Human Gait Identification and Analysis

A thesis submitted for the degree of Doctor of Philosophy

By

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Abstract

Human gait identification has become an active area of research due to increased security requirements. Human gait identification is a potential new tool for identifying individuals beyond traditional methods. The emergence of motion capture techniques provided a chance of high accuracy in identification because completely recorded gait information can be recorded compared with security cameras.

The aim of this research was to build a practical method of gait identification and investigate the individual characteristics of gait.

For this purpose, a gait identification approach was proposed, identification results were compared by different methods, and several studies about the individual characteristics of gait were performed. This research included the following: (1) a novel, effective set of gait features were proposed; (2) gait signatures were extracted by three different methods: statistical method, principal component analysis, and Fourier expansion method; (3) gait identification results were compared by these different methods; (4) two indicators were proposed to evaluate gait features for identification; (5) novel and clear definitions of gait phases and gait cycle were proposed; (6) gait features were investigated by gait phases; (7) principal component analysis and the fixing root method were used to elucidate which features were used to represent gait and why; (8) gait similarity was investigated; (9) gait attractiveness was investigated.

This research proposed an efficient framework for identifying individuals from gait via a novel feature set based on 3D motion capture data. A novel evaluating method of gait signatures for identification was proposed. Three different gait signature extraction methods were applied and compared. The average identification rate was over 93%, with the best result close to 100%.

This research also proposed a novel dividing method of gait phases, and the different appearances of gait features in eight gait phases were investigated. This research identified the similarities and asymmetric appearances between left body movement and right body movement in gait based on the proposed gait phase dividing method. This research also initiated an analysing method for gait features extraction by the fixing root method.

A prediction model of gait attractiveness was built with reasonable accuracy by principal component analysis and linear regression of natural logarithm of parameters. A systematic relationship was observed between the motions of individual markers and the attractiveness ratings. The lower legs and feet were extracted as features of attractiveness by the fixing root method.

As an extension of gait research, human seated motion was also investigated.

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Abbreviations

SD	standard deviation
PCA	Principle component analysis
k-NN	k nearest neighbour algorithm
3D	three dimensions
2D	two dimensions
L. single support phase	left single support phase
R. single support phase	right single support phase
FA	Fluctuating asymmetry
EGF	subject seated at the front of the Ergokinetic split-seat chair
SOF	subject seated at the front of the standard office chair
EGB	subject seated in the Ergokinetic split-seat chair with their back against lumber support
SOB	subject seated in the standard office chair with their back against lumber support
NF	Neck Flexion
MBF	Mid Back Flexion
HBF	High Back Flexion
SF	Shoulder Flexion
EF	Elbow Flexion
HF	Hip Flexion
HA	Hip Abduction
HAD	Hip Adduction
KF	Knee Flexion

Nomenclature

T	time in one gait cycle
t_{int}	time interval between two frames in recorded data
$\hat{t}_{\text{int}}$	time interval between two frames in data after interpolation
F	feature set including 15 gait features
$PC1$	the first principle component in PCA result
$PC2$	the second principle component in PCA result
$Coe1$	the coefficient of $PC1$
$Coe2$	the coefficient of $PC2$
$(Fr_{\max}, Fr_{\min})$	the frame number with maximum and minimum feature F_i for any feature *i*.
$(P_{\max}, P_{\min})$	the phase number with maximum and minimum feature F_i for any feature *i*.
$(F\_P_{\max,} F\_P_{\min})$	the percentage of a gait phase completed when $Fr_{\max}$ and $Fr_{\min}$ occurs.
$G\_average$	the average gait
$attract$	the attractiveness value of subject

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Chapter 1 Introduction and literature review

Section 1: Introduction

Human gait analysis, the systematic study of human walking, has been developed from early descriptive studies to newer studies involving mathematical analysis and modelling and has become an important part of human motion analysis. Gait analysis has been applied in many areas, including biomechanical, psychological, and security disciplines.

The goal of researchers is to analyse a walker's status based on their gait, such as gender, age, and health (Mather & Murdoch 1994; Nigg et al. 1994; Powers & Perry 1997; Grabiner et al. 2001; Troje 2002; Zhang et al. 2009; Menant et al. 2009a). Furthermore, researchers aim to identify individuals (Foster et al. 2003; Wang et al. 2003; Han & Bhanu 2005; Sarkar et al. 2005; Chellappa et al. 2007). Recently, the use of soft biometrics for recognition has been studied. In (Wang et al. 2005), a video analysis framework using soft biometrics signatures such as skin tone and clothing colour was used for airport security surveillance. In (Moustakas et al. 2010), an efficient framework combining soft biometrics such as "height" and "stride length" with gait features was proposed.

With the development of gait recording techniques, research methods were also advanced. The question that was first proposed in the 1970s, 'Can people recognise their friends or family by gait' has been developed to 'Can we identify a particular person by gait' (Cutting & Kozlowski 1977; Foster et al. 2003; Han & Bhanu 2006; Moustakas et al. 2010). Intuitively, we know that individual gaits are different and include some personal information. Can gait features were used like a 'biometric signature' to identify individuals, similar to the use of DNA or handwriting? This question inspired the research aims of this thesis.

In this research, a novel approach for identifying individuals was proposed based on 3D motion capture data. A novel gait feature set was proposed and evaluated. It was investigated the different influences on gait features from gait phases. A novel gait phases definition was proposed. The similarity and dissimilarity between the left and right sides of the body in gait were investigated. Besides, the relationship between gait and attractiveness was analysed and a predictable model for gait attractiveness was built.

Section 2: Literature review

1.1 History of gait analysis

Gait is defined as "a particular way or manner of moving on foot". Gait analysis was a purely academic discipline in the beginning. Over time, it has been transformed into a useful tool in the diverse fields of physiology, clinical medicine and security. Psychology research (Johansson 1973) would seem to suggest that humans can recognize movement patterns merely from the temporal component. Since the first complete description of the gait cycle given by the Weber brothers in Germany in 1836 (Weber & Weber 1836), gait studies have revealed gait to be related to anatomy, physiology, and biomechanics. From the 1970s to the 1990s, many types of gait analysis research focused on different targets. These studies attempted to reveal the relationship between gait patterns and gender, age, health, wealth, and so on (Mather & Murdoch 1994; Schmitt & Atzwanger 1995; Cho et al. 2004; Boston & Sharpe 2005; Chiu & Wang 2007; Bennett et al. 2008; Røislien et al. 2009; Menant et al. 2009b; Bockemuhl et al. 2010). The biomechanical analysis of gait has been successfully applied in human clinical gait analysis (Whittle 1996).

With the development of motion capture techniques in the last two decades, new research areas have attracted interest. Motion capture techniques provide 3D motion data by motion capture system, whereas videos or cameras only provide 2D image data (3D is abbreviation of three dimensions, 2D is abbreviation of two dimensions). Based on 3D gait data, many medical studies sought to investigate the difference between healthy individuals and patients with specific diseases (Powers & Perry 1997; Rosengren et al. 2009; Zhang et al. 2009). Human identification research also received greater attention with the advent of motion capture techniques, particularly in the field of security (Ma et al. 2006; Shan et al. 2008). Other research has sought to recognize human action, such as walking, jumping, and running. However, gait analysis based on image data has continued since the 1970s (Cutting & Kozlowski 1977; Barton & Lees 1997; Collins et al. 2002; Keren 2003; Jokisch et al. 2006; Bodor et al. 2009).

In addition, much progress has been made in computer-vision-based human motion analysis. Action animation of computer images and game modelling has become more closely related with real gait analysis. Parameterised gait models have employed observation-based physical simulation and kinematic principles (Bruderlin & Calvert 1989; Granieri et al. 1995). Techniques for creating whole-body motions of human and animal characters were applied by generating a natural motion and other constraints such as desired joint angles and joint motion ranges (Yamane 2003). In some studies, the motion of an animated character was created by utilising an existing motion capture database to find a low-dimensional space that captures the properties of the desired behaviour, such as jumping, running, and walking (Safonova et al. 2004).

1.2 The content of gait analysis

Human walking is a simple process that involves a large amount of information.

The analysis of quantitative gait data has mainly focused on topics such as recognition, identification, animation, pattern analysis, and attractiveness, as well as other specific factors.

1.2.1 Gait animation

Gait animation has been observed in a variety application fields, including the fields of computers, game design, advertising, and simulation. Gait animation has attempted to create a virtual human that seems more like a real human. The remaining problem of human motion animation is the requirement for reality and complexity. Human motion animation ranges from very subtle motions such as a smile to whole body motions such as dancing or running. Much previous research has focused on modifying and rebuilding existing motions based on motion capture data. Motion editing methods have been surveyed in (Gleicher 2001). As early as 1978, the generation of synthetic walkers was investigated (Cutting 1978). Research related to articulated figure motion expanded the range of possible motion (Wiley & Hahn 1997). Generating motion with mood, such as a "tired" walk, from a normal motion was studied via Fourier principle methods in (Munetoshi et al. 1995). Research attempted to retarget motion to new characters by re-establishing the constraints while maintaining the frequency characteristics of the original motion (Gleicher 1998). Figures 1.1 and 1.2 illustrate an example of animation.

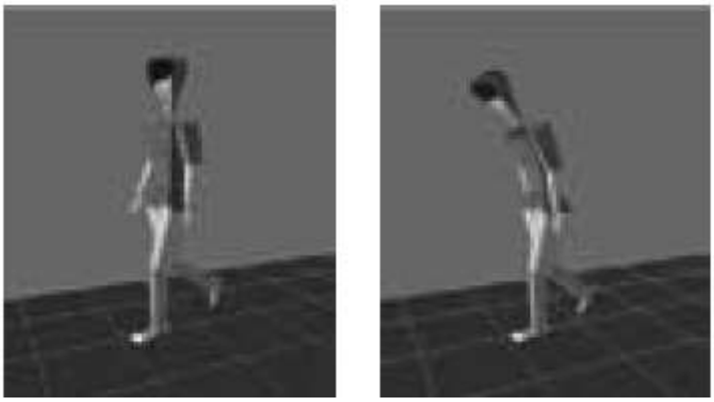


Fig 1.1: The Gait with Mood. left: Normal walk; right: Tired walk (Munetoshi et al. 1995)

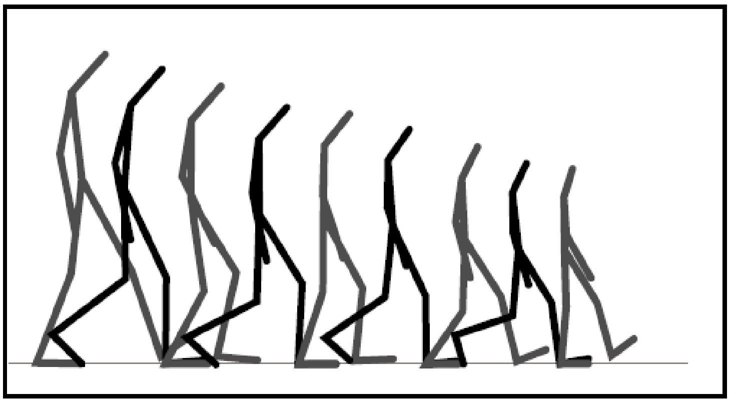


Fig 1.2: The retargeting process, which adapts the motion as the character morphs to 60% of its original size (Gleicher 1998).

1.2.2 Gait attractiveness

Psychologists have long been interested in how people assess the attractiveness of others. Body shape is static, but gait is dynamic. People are continuously perceiving gait attractiveness, whether this perception is conscious or not, because, in real life, human figures are dynamic most of the time and walking is a common movement.

As early as the 1930s, some researchers were considering the factors influencing gait movement attractiveness (Allport & Vernon 1933; Wolff 1935; Eisenberg & Reichline 1939). One study demonstrated that the gaits of dominant women were rated as more attractive than those of non-dominant women, but these results were not conclusive because of methodological difficulties, such as how to present the behavioural component of gait separately (Eisenberg & Reichline 1939). At that time, the media used to record gait was motion picture. After the development of the point-light kinematic display method, it became possible to establish that people can indeed infer various traits of a subject solely on the basis of movement cues from gait (Kozlowski & Cutting 1977; Cutting et al. 1978). Some point-light research investigated the vulnerability cues in the gaits of target choices for assault (Grayson & Stein 1981; Gunns et al. 2002). Experimental results showed that the impression of awkward movement as a kinematic gait quality is related to both a higher feminine impression as well as a higher likelihood of being a target for sexual advances (Sakaguchi & Hasegawa 2006).

Computer animation technology has also provided new methods of gait analysis that have been used to explore gait attractiveness. Johnson and Tassinary (Johnson & Tassinary 2007) found that animated walkers were rated as more attractive by the opposite sex if they exhibited more sex-typical walking movements. The emergence of 3D motion capture techniques has improved the quality of the data that can be used to analyse the gait attractiveness of real human walkers. For example, Provost, Quinsey & Troje (Provost et al. 2008) used motion capture to analyse variations in gait between women at high and low probability of conception and the attractiveness ratings that men assigned to these variations. They found that the gaits of women not using hormonal birth control were slightly more attractive during the luteal stage than in the late follicular stage.

1.2.3 Gait pattern analysis and recognition

Gait is related to a variety of information, including health status, medical disease, age, gender, emotion, and so on. Pattern analysis studies the gait patterns of particular type of subjects to reveal the relationship between this information and gait. Pattern analysis focused on revealing the difference in gait pattern and the factors that affect a particular gait pattern, such as elder gait, female/male gait, patient gait, and so on. For example, much research has focused on the effect of gender on gait (Barclay et al. 1978; Furnham et al. 1997; Troje 2006; Hadid & Pietiknen 2009). Gait of healthy subjects and patients has received increasing attention since the emergence of the motion capture technique (Thornhill & Møller 1997; Allet et al. 2008; Mandeville et al. 2008; Rosengren et al. 2009). In medicine, gait research is normally based on a single type of subject to investigate the difference between their gait and a normal gait. In 1994, Nigg researched the gait characteristics of age and gender (Nigg et al. 1994). Age-related changes in gait were researched in 2001 (Grabiner et al. 2001). In 2009, researchers investigated the effect of walking surfaces, footwear and age on gait (Menant et al. 2009a; 2009b).

Gait recognition is one important part of gait analysis and has attracted much attention since the beginning of gait analysis. Gait recognition is a broad topic that includes gender recognition, age recognition, medical recognition, action recognition, and other recognitions depending on the characteristic used as the classification standard. Gait recognition is highly related to pattern analysis. Pattern analysis analyses the different patterns of different groups, compared the differences in appearance of different groups of walkers, and investigates the factors that affect gait. Gait recognition recognises to which group the walker belongs. For example, there were some common types of recognition, such as gender recognition, age recognition, and health recognition.

1.2.3.1 Gender recognition

Gender recognition systems aim to determine whether the person in a given video is a man or a woman. The traditional method of recognition utilises the face, body shape or gait pattern (Kozlowski & Cutting 1977; Kerrigan et al. 1998). A recently popular identification method is a combination of face and motion (Shan et al. 2008; Hadid & Pietiknen 2009).

In (Kozlowski & Cutting 1977), the first major gender recognition experiment was performed with six walkers (three females and three males) of approximately the same height and weight. This experiment demonstrated that the average gender recognition rate of human observers is 63%. Some alterations, such as arm swing, walking speed, and occluding portions of the body, do not significantly influence the recognition rate. In (Barclay et al. 1978), further study by examining temporal and spatial factors demonstrated that successful gender recognition required approximately two walking cycles and that the rendering speed has a strong influence on recognition.

The shoulder-hip ratio and hip rotation are important features in gender classification by gait. Previous work has indicated that male and female walkers differ in terms of lateral body sway, with males tending to swing their shoulders from side to side more than their hips and females tending to swing their hips more than their shoulders (Kozlowski & Cutting 1977; Mather & Murdoch 1994). In the 1990s, there were many studies of gender analysis based on gait (Mather & Murdoch 1994; Nigg et al. 1994; Furnham et al. 1997; Kerrigan et al. 1998). In 2005 (Lian et al. 2005), a min-max modular support vector machine (M3-SVM) provided a faster response and higher generalisation accuracy than traditional SVMs to solve the gender recognition problem. The M3-SVM module achieved

91.53% accuracy, which is better than the 85.77% accuracy achieved by traditional SVMs in a training database with 786 male samples and 1,269 female samples. In 2008 (Shan et al. 2008), experiments achieved a superior recognition performance of 97.2% recognition of gender by a multimodal gender recognition system in large data sets. It used canonical correlation analysis and SVM to classifier gender.

1.2.3.2 Age recognition

Age affects many features of gait, such as step length, speed and double-support time (Grabiner et al. 2001; Menant et al. 2009a; 2009b). Pelvic rotations in the sagittal, frontal and transverse planes of motion were systematically reduced with age (Van Emmerik et al. 2005). Research has demonstrated that older adults who were transitionally frail differed substantially from other older adults while walking (Kressig et al. 2004). Some research specifically analysed patient age by extracting hip features. All patient age groups displayed a reduced range of hip flexion/extension, knee flexion extension, maximum hip extension, and hip abduction/adduction and a reduced velocity and step length compared to the normal elderly group in experiments (Bennett et al. 2008). Many previous studies have analysed the effect of age on gait with the effect of gender or disease (Nigg et al. 1994; Hijmans et al. 2007; Røislien et al. 2009).

1.2.3.3 Medical recognition

The study of gait for medical applications began in the 1990s (Powers & Perry 1997) and developed rapidly after 2000 as more and more 3D motion data were recorded. Medical recognition mostly focused on the difference between patients and healthy individuals. The research is usually related to a specific sickness, such as CP (Cerebral palsy) or DCD (Developmental Coordination Disorder). Medical applications of gait analysis have attracted the interest of many scientists in the last decade, including the comparison of patients and healthy individuals, the detection of disease, and the evaluation of the effectiveness of a medical treatment (McNally 1998; Newell et al. 2008; Cho et al. 2009; Noort et al. 2009; Zhang et al. 2009).

1.2.3.4 Action recognition

In the specific area of gait recognition, most works have focused on discriminating between different human motion types such as running, walking, jogging, or climbing stairs (Jenn-Jier et al. 2000). Researchers in (Pollick 2003) recognized movement style by extracting features from point light displays. Some research addresses the problem of classification of human activities (walk, run, skip, march, line-walk, hop, side-walk, side-skip) from video, with a greater than 92.8% recognition rate by PCA and eigenvector manifold (Masoud & Papanikolopoulos 2003).

Action recognition also included identifying pedestrians from image and videos. In (Oren et al. 1997), wavelets were used to obtain a characteristic pedestrian template in a single image. In (Rosales & Sclaroff 2000), clustering was employed to recognise several silhouette poses. In (Davis & Tyagi 2006), this approach determines the shortest video exposures required for low-latency recognition by sequentially evaluating a series of posterior ratios for different action classes.

1.2.4 Gait identification

A highly specific area of gait recognition research is gait identification, which identifies individuals. In gait recognition, different subjects are classified among different types. Gait identification research aims to identify individuals. It is only recently that human identification from gait has been focused and become an active area. Early medical studies demonstrated that individual gaits are unique, varying from person to person and difficult to disguise (Murray et al. 1964). Cutting and Kozlowski showed that this personal identification ability also extends to the recognition of friends (Cutting & Kozlowski 1977). Stevenage et al. (Stevenage et al. 1999) demonstrated that humans can identify individuals on the basis of their gait signature, without reliance on body shape, in the presence of lighting variations and under brief exposures. A novel technique for analysing moving shapes is presented using area-based metrics for automatic gait recognition (Foster et al. 2003). This technique is also used to discriminate between male and female subjects.

The field of security has also utilised gait analysis techniques. Scientists have been investigating the use of gait for personal identification and have tried to identify gait signatures that are specific to individuals. Security and biometrics are aimed at identifying an individual through their actions. In 1977, the recognition of friends had already been researched from a medical/behavioural perspective (Cutting & Kozlowski 1977). Later, several attempts were made to investigate the gait recognition problem from the perspective of capturing and analysing gait signals (Barton & Lees 1997). In 2002 and 2003, the identification of individuals was investigated based on walking pattern (Schöllhorn et al. 2002) and area-based metrics (Foster et al. 2003). Researchers have attempted to extract gait signature (Lakany 2008) or some combinations (Ailisto et al. 2006). Most recent work investigating the appropriateness of gait as a biometric for human identification has been performed in the context of the HumanID project sponsored by the U.S. Defense Advanced Research Project Agency (Boulgouris et al. 2005).

1.2.5 Other gait-related analyses

Other research has analysed the influence of different environments on gait, such as walking surface, weight carried, and emotions. Experimental results show that the proposed templates are efficient for human identification in indoor and outdoor environments (Lam et al. 2007). Research in (Vrieling et al. 2008) analysed the difference in the movement of limbs during uphill and downhill walking.

1.3 Research approaches in previous work

1.3.1 Data recording technique

The research methods used in gait analysis have undergone continuous development. Human gait has been studied by using points of light in a technique known as cyclography (Bernstein 1967). In this technique, white tape is attached to the limbs of a walker dressed in a black body suit or small incandescent bulbs are attached to the joints to yields subjects' projections of the cycles of movements over time. Fig 1.3 showed an example of the figure in data recording.

Fig 1.3 Static approximations of the dynamic point-light display (Cutting et al.

1978).

For gait analysis, it is common for high-speed video data to be collected and analysed on a frame-by-frame basis. There have been many studies based on video data. In those studies, the silhouettes of walkers were identified from the background. A silhouette is the image of a person, an object or scene consisting of the outline and a basically featureless interior, with the silhouetted object usually black (Fig. 1.4).

Fig 1.4 Image sequence-background subtraction-image binarisation and normalization (Lam et al. 2007).

With the advent of motion capture technology, the recording of 3D gait data has become another common technique. Data are collected using infrared cameras that track the motion of markers that are placed on the crucial points on body segments. The markers' X, Y, Z coordinates can be recorded. A real-time model of gait will be captured in the motion capture system. Motion capture systems are currently represented by two main groups, optical systems and non-optical systems. Optical systems require the subject to wear a form-fitting suit with markers that reflect light back to the camera’s lens to obtain the markers’ 3D positions. Optical systems use multiple cameras to capture the markers’ exact positions. The more cameras used, the higher the accuracy of the recorded data will be. An optical system usually contains 7-13 cameras.

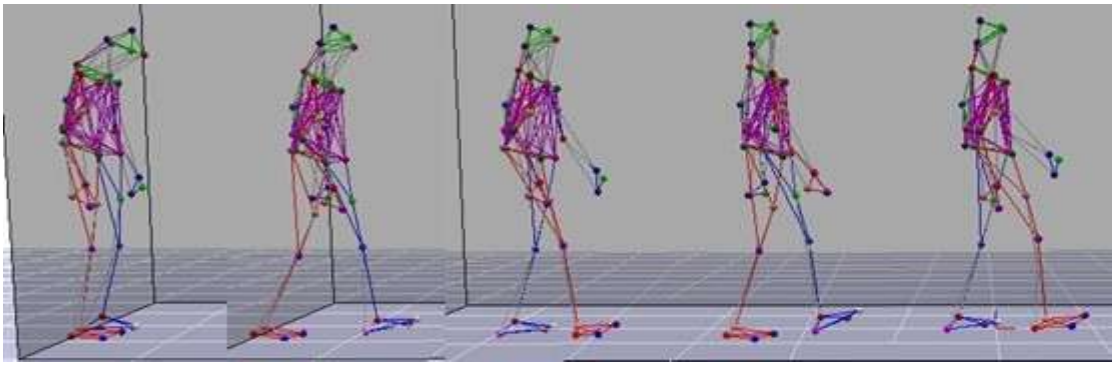


Fig 1.5 Stick figure in a motion capture system with 40 markers.

Recorded data from a motion capture system unquestionably contain more detailed data than that from a video camera. The advantage of video camera data is that the database sample could contain hundreds of people because security cameras provide data easily. For example, gait recognition research based on video images used 114 subjects in (Foster et al. 2003), 126 subjects in (Moustakas et al. 2010), and 80 subjects in (Zhang & Troje 2005). 3D motion capture database samples normally contain only dozens of subjects because more experiment conditions are required. For example, 20 subjects were used in (Rosengren et al. 2009), 37 subjects were used in (Kennedy et al. 2009), 16 subjects were used in (Allet et al. 2008), and 36 subjects were used in (Menant et al. 2009a). Although many important studies have been based on video data, research based on 3D data has attracted more attention in the last two decades, particularly in the fields of medicine and security.

1.3.2 Data Processing Methods

In general, a complete analysis approach for gait data includes the representation method for gait, the analysis method, and the distinguishing method if portions of the research involve recognition or identification. The distinguishing method refers to the method used to recognize or identify gait. Representation and analysis methods differ depending on the dimension of the data.

1.3.2.1 Representation methods

Basically, there are two major approaches in gait analysis: feature-based approaches and model-based approaches (Wang & Singh 2003; Boulgouris et al. 2005). In feature-based approaches, the extracted features are used to represent gait. Silhouettes were commonly used for 2D data (Foster et al. 2003; Wang et al. 2003; Boulgourisa et al. 2006; Barnich & Van Droogenbroeck 2009). In 3D databases, the gait representation was first determined by how many markers were used on the subjects. Those markers were attached at joints. Usually, the number of markers varied from 10 to 40. Some researchers used indicators of joints: degrees of freedom (DOF) (Bockemuhl et al. 2010), joint rotation (Bruijn et al. 2008), joint angles (Ormoneit et al. 2005) and so on. In model-based approaches, mathematical tools such as Fourier expansion and singular value decomposition (SVD) were used to represent gait (Troje 2002; Cunado et al. 2003; Ormoneit et al. 2005). In (Cunado et al. 1999), thigh motion was modelled as a pendulum for representation.

1.3.2.2 Analysis methods

a. Feature-based approach

The main component of the feature-based approach is the extraction of gait features from gait. It is a common method in gait analysis. Techniques such as Fourier transforms, motion energy images, eigenspace transformation, principal component analysis, and canonical space transformation are often used to reduce data dimensionality and generate features for gait analysis.

In research based on video image, silhouettes are the primary features (Foster et al. 2003; Wang et al. 2003; Boulgourisa et al. 2006; Barnich & Van Droogenbroeck

2009). In (Boulgouris & Chi 2007), body component-wise in silhouettes was used. Feature images or templates in silhouette were used in (Masoud & Papanikolopoulos 2003; Lam et al. 2007). Torso length, upper-arm length, lower-arm length, thigh length, calf length, and foot length were used in (Han & Bhanu 2005). Other methods include gait energy images, proposed in 2006 (Han & Bhanu 2006), and composite energy features: clusters of energy filters, to identify gait (Dosil et al. 2008). Clothes, footwear, walking surface, emotional state, and walking speed can also be features (Boulgouris et al. 2005).

Initially, these analyses related to view point. Subsequently, researchers gradually proposed methods that are view point independent (Zhang & Troje 2005; Bodor et al. 2009). Based on motion capture data, more features about body segments are chosen. Hip-knee angles were used as features for gait recognition (Barton & Lees 1997; Cunado et al. 2003). Hip flexion in swing and lower limb joint angles have been studied previously (Vrieling et al. 2008). Arm movement has been received more attention recently. Swinging arm regions were used for gait phase detection (Wang et al. 2009). Arm motion was used in human motion recognition (Ganesh & Bajcsy 2008). The features used in previous research show that limbs and hips are important in gait recognition based on 3D gait data. Furthermore, joint motion trajectories were used to extract gait features as a signature via wavelet (Lakany 2008). Silhouettes are always used in side-view, and curve spread as an efficient descriptor of front-view gait is used in recognition (Soriano et al. 2004).

3D data captured by motion capture systems can produce more accurate identification results because more information is recorded. Many more potential features can be chosen: hip flexion in swing, lower limb joint angles in (Vrieling et al. 2008); velocity in (Kressig et al. 2004; Bennett et al. 2008; Menant et al. 2009a); pelvic rotation and thorax in (Bruijn et al. 2008); arm swing in (Ford et al. 2007); hip-knee angles in (Barton & Lees 1997; Cunado et al. 2003); and motion trajectory in (Wu & Li 2009).

There are different criterions to extract features for different purposes: gender classification, age effect, individual identification, or medical analysis, etc. Appendix 1 listed features which have been used in previous research by the classification of analysis purpose.

Gender-related features: Shoulder-hip ratio and hip rotation are considered important features of gender in gait research (Barclay et al. 1978; Cutting et al. 1978; Johnson & Tassinary 2005; Røislien et al. 2009), as is shoulder sway (Mather & Murdoch 1994). In 2004, Korean scientists investigated this problem with a large sample base (Cho et al. 2004). They used many features such as height, leg length, cadence, pelvic width, speed, step width, stride length, hip joints, and knee joints. Gait curve, hip rotation and foot progression angle were used in (Røislien et al. 2009).

Age related features: Many features such as step length, speed and double-support time were analysed in the gaits of elderly subjects (Menant et al. 2009a; 2009b). Time to last foot contact, total stopping time, stopping distance, number of steps to stop, step length and step width were used in (Menant et al. 2009b). Step width was also used in (Menant et al. 2009a). Many features are used in age analysis, such as velocity in (Kressig et al. 2004; Bennett et al. 2008; Menant et al. 2009a); cadence in (Menant et al. 2009a); double-support time in (Kressig et al. 2004; Menant et al. 2009a); heel horizontal velocity, shoe-floor angle at heel contact, and toe clearance at mid-swing in (Menant et al. 2009a); range of hip flexion/extension, range of knee flexion/extension, maximum hip extension, and range of hip abduction in (Bennett et al. 2008); gait speed in (Nigg et al. 1994; Kressig et al. 2004); stance and swing in (Kressig et al. 2004); ankle joint complexes in (Nigg et al. 1994); and pelvis, head, amplitude of segmental, and joint rotations in (Van Emmerik et al. 2005).

Medical-related features: In medical applications, gait features usually depend on the disease analysed. Features that have been studied previously include the following: stride length in (Wolf et al. 2006; Allet et al. 2008; Zhang et al. 2009); cadence and leg length in (Zhang et al. 2009); joint angle in (Wolf et al. 2006; van den Noort et al. 2009); hip angle and knee angle in (Powers & Perry 1997; van den Noort et al. 2009); shank angle and number of gait cycles in (Rosengren et al. 2009); velocity, gait cycle time, stance phase, thigh and knee range, and sagittal shank in (Allet et al. 2008); double-support time in (Allet et al. 2008; Turner & Woodburn 2008); abduction moment at the knee during gait in (Newell et al. 2008); lower limb joint in (Schache & Baker 2007); sagittal plane in (Schache & Baker 2007; Mandeville et al. 2008); hip abduction, sagittal ROM (range of motion), and pelvic frontal ROM in (Kennedy et al. 2009); gait speed in (Turner & Woodburn 2008); joint motion trajectories, sagittal angles of the hip, knee, and ankle joints in (Lakany 2008); and hip flexion in (Wolf et al. 2006). From this list of features, it is clear that different features are chosen as the focus depending on the disease. Joints are normally important. In additional, gait analysis for medical applications usually uses motion capture data, but some studies have been based on 2D images (Cho et al. 2009).

b. Model-based approach

A fundamental assumption about a model-based approach is that it should offer suitable potential for automatic gait recognition, primarily via computer-based vision. Medical studies are used to develop the model. Naturally, the application of a model will potentially alleviate the restrictions imposed on statistical (area-based) approaches, namely that the extracted metric can be directly attributed to human motion (Cunado et al. 2003).

The model-based approach used mathematical models to represent and analyse gait, not features. In model-based approaches, Hidden Markov Models (HMM) (Sundaresan et al. 2003) were used to model each gait sequence in the database set. In (Cunado et al. 1999; Yam et al. 2002) researchers aimed to accurately model how a subject walks by analysing the motion of the legs. Fourier expansion and PCA were used to represent motion in motion retargeting and animation. Fuzzy clustering is a method for identifying a fuzzy partition of the sample space, i.e., determining the appropriate membership functions. The goal of clustering is to automatically find natural groupings in the data, which has been a traditional problem in automatic pattern recognition.

The statistical techniques reviewed here have been used for many years. PCA can be used to study the entire temporal gait waveform and can detect pathological deviations throughout the gait cycle. As an analysis method, principal component analysis was usually applied to data reduction (Troje 2002; Masoud & Papanikolopoulos 2003; Wang et al. 2003). Some studies have combined PCA with other methods, such as dynamic time warping (Troje 2002) and linear discriminant analysis (Cho et al. 2009). Functional data analysis (FDA) was used in (Røislien et al. 2009). Wavelets as a signal processing method were used in (Lakany 2008). Optimal control models of the human sensorimotor system were used in (Sumitra 2008).

The challenge lies in finding a mathematical model that can connect the high-level goals and intentions of a human subject to the low-level movement details captured by a computer-based vision system. Much progress has been made in computer vision-based human motion analysis since the early days of analysing human motion in terms of groups of rigidly moving points (Flinchbaugh & Chandrasekaran 1981; Webb & Aggarwa 1982).

The advantage is not dependent on a particular feature vector. The disadvantage of model-based approaches is typically the computational complexity. Particularly recently, feature extraction and model building have been used in concert. It is difficult to define a method as purely feature-based or model-based in some cases

1.3.2.3 Distinguishing methods

For gait classification and gait identification, distinguishing methods were needed. Distinguishing methods have included neural networks in (Barton & Lees 1997), a Fourier-based synthesis of gender-specific biological motion for gender classification in (Troje 2002), and elliptical Fourier analysis in (Wolf et al. 2006; Rosengren et al. 2009). A Bayesian classifier model was used in (Bruijn et al. 2008; Zhang et al. 2009). The k-nearest neighbour rule was applied to the Fourier components in (Cunado et al. 2003). A SVM (support vector machine) was used in (Lee & Grimson 2002; Walawalkar et al. 2003; Shan et al. 2008). Several main distinguishing methods for gait analysis are introduced below.

Neutral networks were used to recognise normal walking, a simulation of leg length difference and a simulation of leg weight asymmetry to investigate actual pathological subjects (Barton & Lees 1997). This research used fast Fourier-transformation coefficients of the temporal patterns of the hip-joint angle and knee-joint angle curves of a single step to represent the gait pattern (Barton & Lees 1997).

SVM performs classification by constructing an N-dimensional hyperplane that optimally separates the data into two categories. SVM models are closely related to neural networks. It is an optimal discriminant method based on the Bayesian learning theory that has previously been used successfully for gender classification (Lee & Grimson 2002; Walawalkar et al. 2003; Shan et al. 2008).

Baseline method. Baseline approaches used matching of key gait events to identify their specific relationship with gait. A baseline method was proposed by the University of South Florida that combined area masks, a vertical line, a horizontal line, and a bottom-half line (Foster et al. 2003). Fused motion and static spatio-temporal templates of sequences of silhouette images, motion silhouette contour templates (MSCTs) and static silhouette templates (SSTs) were used in (Lam et al. 2007). Baseline method was used to classify children with cerebral palsy in 2009 (Zhang et al. 2009) and for individual gait recognition (Han & Bhanu 2005).

Bayesian classifier method. A naive Bayes classifier assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature, given the class variable. An advantage of the naive Bayes classifier is that it only requires a small amount of training data to estimate the parameters (means and variances of the variables) necessary for classification. The Bayesian classifier method has been used in many studies (Zhou et al. 2006; Jorge E. Arañaa et al. 2008; Zhang et al. 2009).

The k-nearest neighbour rule. In pattern recognition, the k-nearest neighbour algorithm (k-NN) is a method for classifying objects based on the closest training examples in the feature space. k-NN is a type of instance-based learning, or lazy learning, in which the function is only approximated locally and all computation is deferred until classification. k is a positive integer, typically small. The k-nearest neighbour algorithm is amongst the simplest of all machine learning algorithms: an object is classified by a majority vote of its neighbours, with the object being assigned to the class most common amongst its k-nearest neighbours (Coomans & Massart 1982; Dasarathy 1991; Shakhnarovich et al. 2005). Euclidean distance is usually used as the distance metric for continuous variables. The k-nearest neighbour rule is a popular choice for its simplicity and flexibility in many gait studies (Collins et al. 2002; Foster et al. 2003; Preece et al. 2009).

1.4 Difficulties and Problems in Previous Research

Motion capture techniques have emerged in the last two decades. Previously, all gait analysis research was based on video images. Video-based information is influenced by light, view point, and background. After the development of the point-light kinematic display method, the various traits of a subject could be inferred solely on the basis of movement cues of gait (Kozlowski & Cutting 1977; Cutting et al. 1978). Most gait biometrics employ features derived from side-view videos because limb swings are more pronounced from the side than from the front. However, side-view observations are often impractical and incompatible with the ability of humans to recognize others from front-view gait.

Too many features could be extracted. One difficulty is that the dimensionality of the feature space is much higher than the number of sample spaces in the database. There was no convention to extract features as a gait signature until now. In some studies, features were extracted by mathematical methods, such as general tensor discriminant analysis (Tao et al. 2007), eigenspace transformation with canonical space transformation (Huang et al. 1999), wavelet-based multiscale analysis (Khandoker et al. 2007), and the baseline method for human identification (Collins et al. 2002; Moustakas et al. 2010). Human body segments have also been used to extract features. The extraction of leg angles based on regression analysis has been used as a gait signature (Yoo et al. 2002). Hip angle, angular velocity between human walking and passive dynamic walking have been studied (Preece et al. 2009). In another study, seven components (head, arm, trunk, thigh, front leg, back leg, and feet) were used as features in silhouette gait recognition (Li et al. 2007; Li et al. 2008). Inter-individual variations of hip-joint motion in normal gait was investigated in 1997 (Dujardin et al. 1997). Speed as a gait feature has been studied in (Schmitt & Atzwanger 1995; Chiu & Wang 2007).

The analysis of quantitative gait data has traditionally been a challenging target. From a technical perspective, the main challenges can be summarised as follows.

Data reduction. A gait dataset may consist of kinematic, kinetic, electromyographic, metabolic and anthropometric variables (Chau 2001). Additional parameters such as joint angles, velocities, moments and powers were obtained during the processing of gait data. The need for data reduction is critical. However, there are few guiding rules for determining which variables actually contain useful information. Traditional reduction methods such as factor analysis naively assume linear relationships among gait variables. Due to the issue of dimensionality (Bellman 1961), better presentation methods are needed to summarise massive gait time series and to allow quantitative identification (Mulder et al. 1998). Although some mathematical methods such as principle component analysis and singular value decomposition have been applied, an effective, simple data reduction method is still difficult to construct.

Temporal dependence. Data collected during walking at a self-selected pace has a quasi-periodic temporal dependence (Chau 2001). The gait time series is difficult to model as the traditional assumption of stationary does not hold (West & Griffin 1999). For computation and comparison, the temporal curves are usually parameterised by some time-independent variables, such as peak amplitude, mean value or value at the occurrence of some gait events. Moreover, gait parameters defined on the basis of able-bodied gait signals can be difficult to extract from pathological gait signals (Whittle & Jefferson 1989).

Distance between curves. To verify differences due to specific factors such as age or stride rate and to quantify changes due to different individuals, similarities and differences between gait waveforms need to be investigated (Chau 2001). Complex mathematical derivations have been undertaken to measure differences between gait curves (Leurgrans et al. 1993). However, to date, there is no generally agreed upon distance definition for gait curves, making it difficult to quantitatively compare entire gait waveforms.

Nonlinear relationships. Gait variables generally interact in a complex non-linear fashion, an observation attributable to the intrinsic non-linear dynamics of human movement (Wagenaar & van Emmerik 1996). An example is the relationship between electromyographic (EMG) signal characteristics and muscle force (Davis 1997). Relationships between gait variables are often difficult to describe analytically, and often only subjective descriptions are available (Watts 1994). In this case, researchers must identify new ways to represent and analyse gait data.

1.5 Summary and critical analysis

Since the beginning of gait analysis, interest in gait recognition and individual identification has increased significantly. The prior studies described above strongly support the potential of gait as a useful biometric cue. Researchers were eager to investigate whether gait could be an individual identification characteristic similar to traditional method such as fingerprints and DNA. If so, it will affect the field of security and access control significantly.

Biometrics for security has been extensively researched over the last four decades. Biometric measures include the unique physical or behavioural characteristics of individuals for recognition. Common physical biometrics includes fingerprints, hand or palm geometry and retina, iris, or facial characteristics. Behavioural characteristics include, among others, signature, voice (which also has a physical component), keystroke pattern and gait (Moustakas et al. 2010). Most other biometric techniques require physical contact or proximity to the recording probe. By contrast, gait of a person walking has advantage that it can be captured at a distance without requiring the cooperation or consent of the observed subject. Some studies have used markless motion capture systems to analysis human movement (Corazza et al. 2005; Sundaresan & Chellappa 2005; Mündermann et al. 2006). In addition, gait also has the advantage of being difficult to hide, steal, or fake (Boulgouris et al. 2005). However, there were still some remaining problems in previous research. For example, gait signatures were the combination of gait features with other soft biometrics features for identification with motion capture data; some question such as which features should be extracted and why, which has been insufficiently addressed in studies.These problems will be listed and analyzed in below.

1.5.1 Gait identification based on 3D motion capture is inadequate

In recent years, there has been growing interesting in gait analysis of walking habit based on 3D motion data with the advent of motion capture techniques. Historically, video-image-based research has been an important part of individual identification due to the widespread presence of security cameras. There have been many gait-recognition analyses in the field of medicine, as well as other studies related to gender or age. However, studies identifying individuals based on 3D gait data have been limited compared with the large amount of research based on 2D image data and previous gait recognition research. The 2D gait data derived from video images is easily influenced by view point, camera position, weather (when outside), and other factors. Gait data derived from video images includes only the silhouettes of walkers, which results in the loss of some gait information. Gait data recorded by a motion capture system has the advantage of yielding complete gait information that is view point independent; it also increases the complexity of analysis due to the higher dimension of data. The focus on gait identification has increased at international conferences.

1.5.2 Many previous studies have combined gait features with other characteristics

Some individual identification studies have combined gait and other characteristics as gait signature. For example, in (Moustakas et al. 2010), gait features were combined with soft biometrics such as height and stride length for identification; in (Chellappa et al. 2007; Liu & Sarkar 2007; Shan et al. 2008; Hadid & Pietiknen 2009), gait features were combined with facial features for recognition. These methods increased the recognition rate and were successful at tracking a particular subject when that subject did not change his characteristics, for example, finding a lost person in a place with a high stream of people. The advantage of these methods increased recognition rate. However, it only works on tracking particular subject when that subject didn't change his characteristics imposed, for example, finding some lost person in some place with high stream of people. It does not work for security requirement, for example, tracking some suspicious person who may intend to hide himself by changing his appearance. People may still keep similar way of walking even they changed their appearance. This is the gait pattern of individuals. In this research, gait features for identification will be extracted only from gait, without combination with other soft biometrics, such as height, stride length, or facial features. In this research, the difference between individual gaits and individual identities will be investigated only by gait itself. An efficient set of gait features was proposed in this research, and individual identification was applied by three different methods.

1.5.3 The reason of which gait features were proposed and why is unclear

Extracting gait features as a gait signature is a common method in gait analysis. Many previous studies attempted to extract gait signatures to identify individuals or explain the differences in gait patterns. Until now, there has been no convention for extracting features as a gait signature based on motion capture data. Obviously, the answer to this question should be different for different purposes. There are different ways to extract features for specific purposes: gender classification, age effect, individual identification, or medical analysis, etc. Previous studies have used various features as a signature to analyse gait, to assign subjects to different groups, or even to identify individuals. However, the reasons for choosing these features have received very little attention (Preece et al. 2009). Thus, it is unclear which gait features should be extracted to represent gait and why. The evaluation of the proposed gait features is also lacking. In this research, this question will be answered by using several methods. In addition, a novel analysis and evaluation tool for gait features was proposed.

1.5.4 The research on the relationship between gait attractiveness and accurate 3D motion data is lacking

Static bodies and faces have long been used to study attractiveness and similarity for a long time. Rates of gait attractiveness have been studied in different subject samples, such as women at high and low probability of conception (Provost et al. 2008). Relatively little research has been done into what makes some normal gaits more attractive than others. In this research, the relationship between gait attractiveness and body markers was investigated. The similarities and asymmetric appearances between the left body and the right body in the gait cycle were investigated.

Gait analysis is a complex problem. Gait identification is of special importance for security. This research included gait identification, feature analysis for identification, gait analysis of attractiveness, and a similarity analysis of gait based on 3D motion data. This research also investigated identification methods, gait factors that influence individuals and features that should be extracted for identification by steps. The features in this research were extracted only from gait, the evaluation methods of features were proposed, and the reasons why these features should be extracted were analyzed.

1.6 Outline of Research Work

1.6.1 Research objective and Scope

The prime objectives of this research are to create a novel method to identify individuals by gait and to analyse the differences between individual gaits.

In this research, the identification question was investigated based on 3D gait data. A systematic approach that included a novel gait feature set was proposed to identify individuals, and the identification results were compared with several different methods for extracting gait signatures. The factors that make gait so personal were analysed. For the purpose of analysing the factors for identification, gait features in gait cycle and gait phase were investigated to identify which features should be extracted to represent gait and why. Then, the similarities and asymmetries of gait, and gait attractiveness were investigated As an extension of gait research, human seated motion was also investigated by comparing an Ergokinetic chair with a standard office chair with motion capture technique.

This research could be summarised by four areas: gait identification, gait analysis for identification, similarity in gait, and gait attractiveness.

The specific objectives are:

- to propose a novel set of gait features that is suitable for identifying individuals and that can be extracted only from gait.
- to identify individuals via three different gait signature extraction methods: statistics method, principle component analysis, and Fourier expansion method.
- to analyse the influence of gait phases on individuals.
- to answer the question 'which features should be extracted to represent gait and why'.
- to compare the similarities and differences between the left half of the body and the right half of the body in gait.
- to analyse the relationship between gait attractiveness and movement from different body segments.
- to investigate the differences in seated motion in an Ergokinetic chair and a standard chair.

1.6.2 Research findings and applications

Research findings were stated in four areas: gait identification, gait analysis for identification, similarity in gait, and gait attractiveness.

1.6.2.1 Gait identification

Gait data were normalized by linear interpolation and gait cycle.

It is found that the novel set of gait features is effective for identification and represents individual gaits very well. The identification results given by the three different methods all achieved very high accuracy.

It is found that using average gait as the base gait for identification increased the accuracy, in contrast to using random gait as the base gait.

1.6.2.2 Gait analysis for identification

Two indicators, Consistence degree and Variation degree (defined in Section 3.1.4), were proposed to evaluate gait features for identification.

It is found that features on y-axis are of greater importance for gait than features on z-axis. The Wrist Speed ratio is important for gait. The Head_Topspine angle and Topspine_Root angle are relatively independent of other gait features.

It is found that the fixing root method is an effective method for revealing which part of the human body is more important for distinguishing one person from other people. It is found that motion from the left lower arm, lower legs and feet, and hip are suitable as features for gait recognition.

Novel gait phases and a gait cycle definition were proposed. Two indicators were proposed to evaluate the influence of gait phases on gait features.

It is found that one type of gait features is influenced greatly by gait phases. These features are highly related with walking action, such as knee angles and Heel_toe angles on z-axis. Gait phases do not greatly influence the other type of gait features, which includes elbow angles, Heel_toe angles on y-axis, and Wrist_shoulder angles on y-axis.

It is found that arm-related features exhibit greater freedom/individuality than leg-related features, and gait features on y-axis exhibit more freedom/individuality than gait features on z-axis.

It is found that the posture at which the tibia is vertical or perpendicular to the ground varied greatly for different subjects during the gait cycle. The posture at which maximum knee flexion occurred varied less for different subjects in the gait cycle. The variation in the double-support phase length was intermediate relative to the variation in these two postures.

1.6.2.3 Similarity in gait

In 74.29% of the 35 subjects, the first half-cycle is longer than the second half-cycle. The average length of the first half-cycle is 1.44% longer than that of the second half-cycle. The difference between the first half-cycle and the second half-cycle varied from -8.93% to 7.2% of the gait cycle.

It is found that elbow movement (while the opposite leg is the supporting leg), wrist movement on y-axis (whether the support leg is on the same or opposite side), and foot movement on y-axis (whether the leg is the swing leg or support leg) usually exhibited asymmetry in the gait cycle.

It is found that wrist movement on y-axis exhibited more asymmetry than foot movement on y-axis.

Body movement on y-axis and elbow movement while the leg on the opposite side is the support leg are most likely to be the most asymmetrical body parts in gait.

1.6.2.4 Attractiveness in gait

It is found that a systematic relationship was identified between the motions of individual body markers and the attractiveness rating. A prediction model for the attractiveness rating was built.

It is found that gait attractiveness is much more correlated with the average speed of each body segment than with the average acceleration of each body segment in the gait.

It is found that the extraction of the lower legs and feet by the fixing root method is effective as features of attractiveness. The prediction results for gait attractiveness derived from only ten lower leg and foot markers were compared with the results derived from all 40 markers. The comparative analysis demonstrated that the results could be predicted slightly better by using only lower leg and foot markers than by using all 40 markers.

After the analysis of walking motion, human seated motion was investigated. Compared to the same motion in the standard office chair, subjects seated on the Ergokinetic chair are not required to bend their hips as much and also had more flexibility about hips and legs when completing general actions such as standing and typing.

1.7 Structure

The structure of the thesis is organised as follows:

Chapter 1 introduces the background, reviews the content of gait analysis, the research methods used in previous studies, problems and research aims/objectives.

Chapter 2 explains the methodologies used in this research. It introduces the motion capture system, the gait data captured, and the mathematical methods used.

Chapter 3 is an analysis of gait signature for identification via a feature-based method based on gait normalisation by linear interpolation. A set of gait features was proposed to represent gait. Three different methods were used to extract gait signatures for identification: statistics method, PCA, and Fourier expansion method.

Chapter 4 is the gait phase and gait cycle analysis. It proposed a novel definition of gait phases compared with traditional gait phases. The influences of gait phase on gait features were investigated. The differences between gait phases of individuals were compared.

Chapter 5 provides an explanation for the use of some features to represent gait for identification. It provides a solution for which features should be extracted. The fixing root method was proposed to reveal more information from the relative motion of body parts.

Chapter 6 is a similarity and asymmetry analysis of gait. The left body movement and right body movement were compared in each of the corresponding gait phases. The most asymmetrical body parts of individuals in gaits were investigated.

Chapter 7 is an analysis of gait attractiveness, including model building and verification. Lower legs and feet were extracted as features of attractiveness by the fixing root method and proved effective as features of attractiveness.

Chapter 8 is an extension of gait research. It investigated human seated motion on an Ergokinetic chair and a standard office chair.

Chapter 9 is a conclusion of all of the chapters. It summarises the results in this research from six fields: gait identification, gait feature analysis, gait cycle and phases analysis, similarity analysis in gait, gait attractiveness analysis, and human seated motion on different chairs.

Chapter 2 Methodology

There were some remaining problems in previous gait identification research. The first is the combination of gait features with other soft biometrics features for identification with motion capture data. The other is a question of which features should be extracted and why, which has been insufficiently addressed in studies. The features used in gait classification in medical or pattern analysis based on motion capture data were referred to because of the lack of gait identification based on motion capture data in previous studies. In this research, a novel feature set only related to gait for identification was proposed to represent gait firstly, then those features were analyzed to answer if they can represent the individuality of gait. After that, statistics method, PCA, and Fourier expansion were used to extract gait signatures for identification based on normalized gait cycle. k-NN algorithm was used to identify subjects, and identification results were compared based on different ways.

Furthermore, this research aimed to address which features should be extracted to represent gait and why. The relative motions from different body segments to the Root were analysed via the fixing root method. The Root is located on the back at the upper middle of the pelvis. In this method, the Root was supposed to be virtually fixed by having all subjects walk on a treadmill to identify more factors in individual gait patterns by analysing the relative motion of body segments instead of the trajectory of the whole body moving. For gait recognition, Principal Component Analysis was used to analyse the distribution of markers.

In order to analyse the factors that affect individuality in gait, gait features were investigated by gait phase and gait cycle. The similarities and asymmetric appearances between left body and right body in gait were investigated as well.

In addition, the relationship between gait and gait attractiveness was investigated. This analysis aids in understanding the differences in gait between individuals. One gait attractiveness prediction model was built with an acceptable error rate.

2.1 Experiment and laboratory

3D motion capture techniques make it possible to record vast amounts of spatiotemporal human body motion data and to study human gait kinetics and kinematics in the 3D space and time domain with an accuracy of spacial and temporal resolutions of 1 mm and 1 ms, respectively. In this research, detailed and accurate data were captured by 3D motion capture system.

The laboratory has a digital motion analysis system (Fig. 2.1). Gait data were recorded by an optical motion capture system. The system used in this research is an Eagle motion capture system, which was constructed with seven digital cameras, the Eagle Hub, to which all of the cameras were connected and which uplinks to a computer terminal, and EVaRT Real Time software. This software was used for recording, processing, displaying and post-processing data from the camera system. In general, a motion capture session can be summarised by four steps:

a. Studio set-up, setting cameras for multiple captures

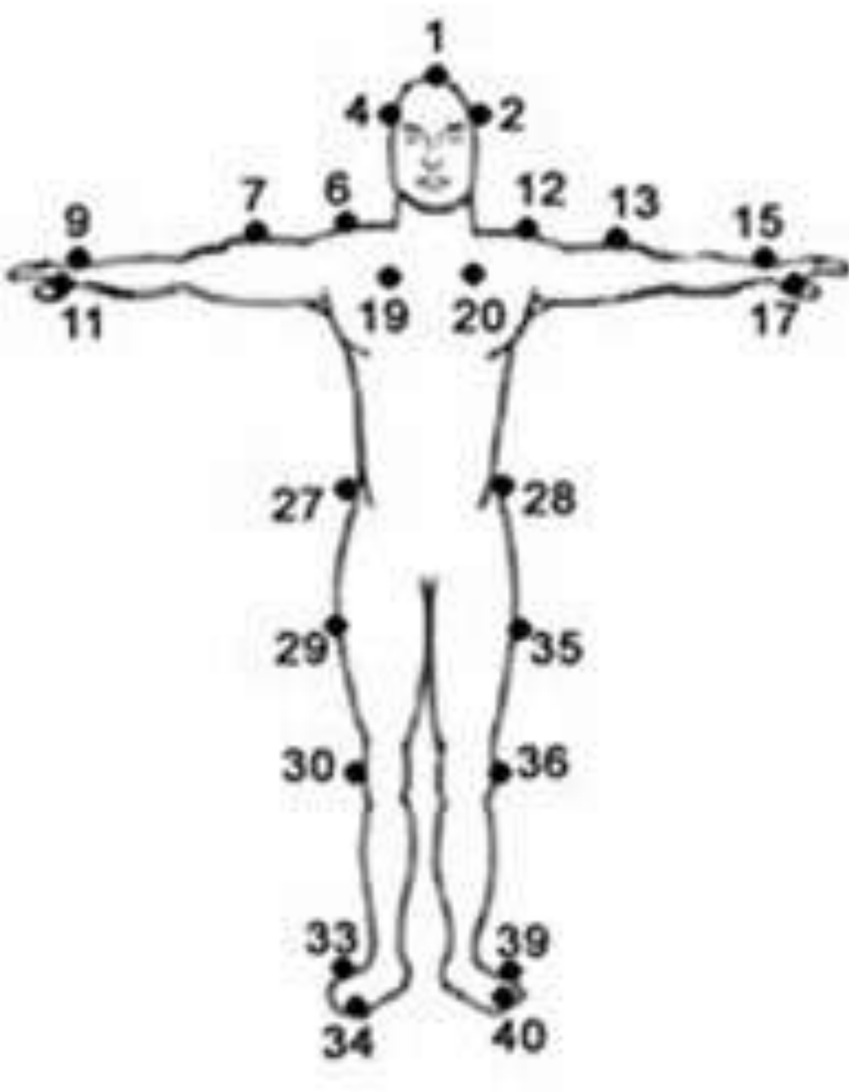
b. Calibration of capture

c. Template and capture of human movement

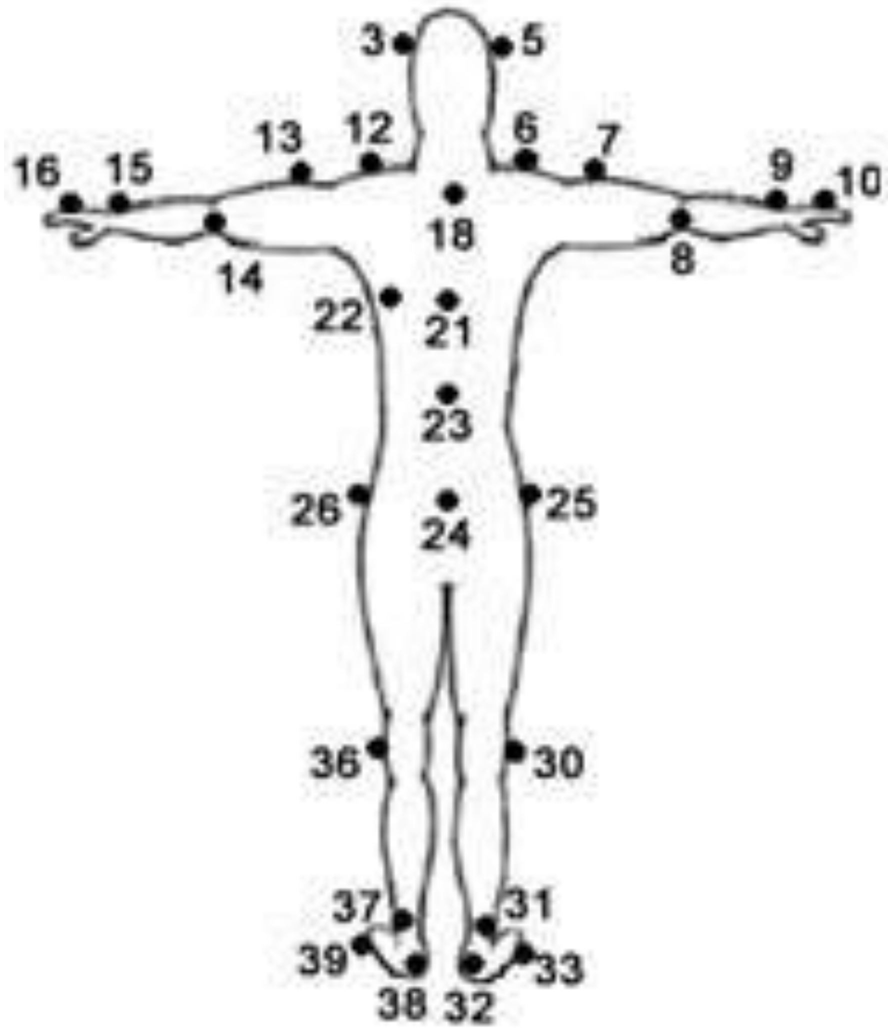
d. Clean-up data in post-processing.

Fig 2.1 Motion capture laboratory

The capture volume was 2 meters wide, 4 meters long and 2.2 meters high and was surrounded by seven cameras. Each subject wore a motion capture suit with 40 reflective markers placed on crucial body segment/joint locations as illustrated in Fig. 7. There are different marker sets in the EVaRT software, depending on the action analysed or the software that the data will be transferred to. The system can capture motions like walking, jumping, running, and dancing with extreme accuracy, to the nearest 2 mm, at up to 200 frames per second. In this research, 40 markers were used to capture gaits, and 31 markers were used for seated motion analysis. Fig 2.2 shows the positions of the 40 markers, and Fig 2.3 shows the positions of the 31 markers.



1. Top_head
2. FrontLeft_head
3. BackLeft_head
4. FrontRight_head
5. BackRight_head
6. Right_shoulder
7. Right_bicep
8. Right_elbow
9. Right_wrist
10. Right_pinky
11. Right_thumb
12. Left_shoulder
13. Left_bicep
14. Left_elbow
15. Left_wrist
16. Left_pinky
17. Left_thumb
18. Top_spine
19. FrontRight_shoulder
20. FrontLeft_shoulder



21. Mid_back
22. MidBack_offset
23. Low_back
24. Root
25. BackRight_hip
26. BackLeft_hip
27. FrontRight_hip
28. FrontLeft_hip
29. Right_thigh
30. Right_knee
31. Right_ankle
32. Right_heel
33. Rightmid_foot
34. Right_toe
35. Left_thigh
36. Left_knee
37. Left_ankle
38. Left_heel
39. Leftmid_foot
40. Left_toe

Fig. 2.2 The positions of the 40 markers on the human body (Evart 5.0 User's Manual)

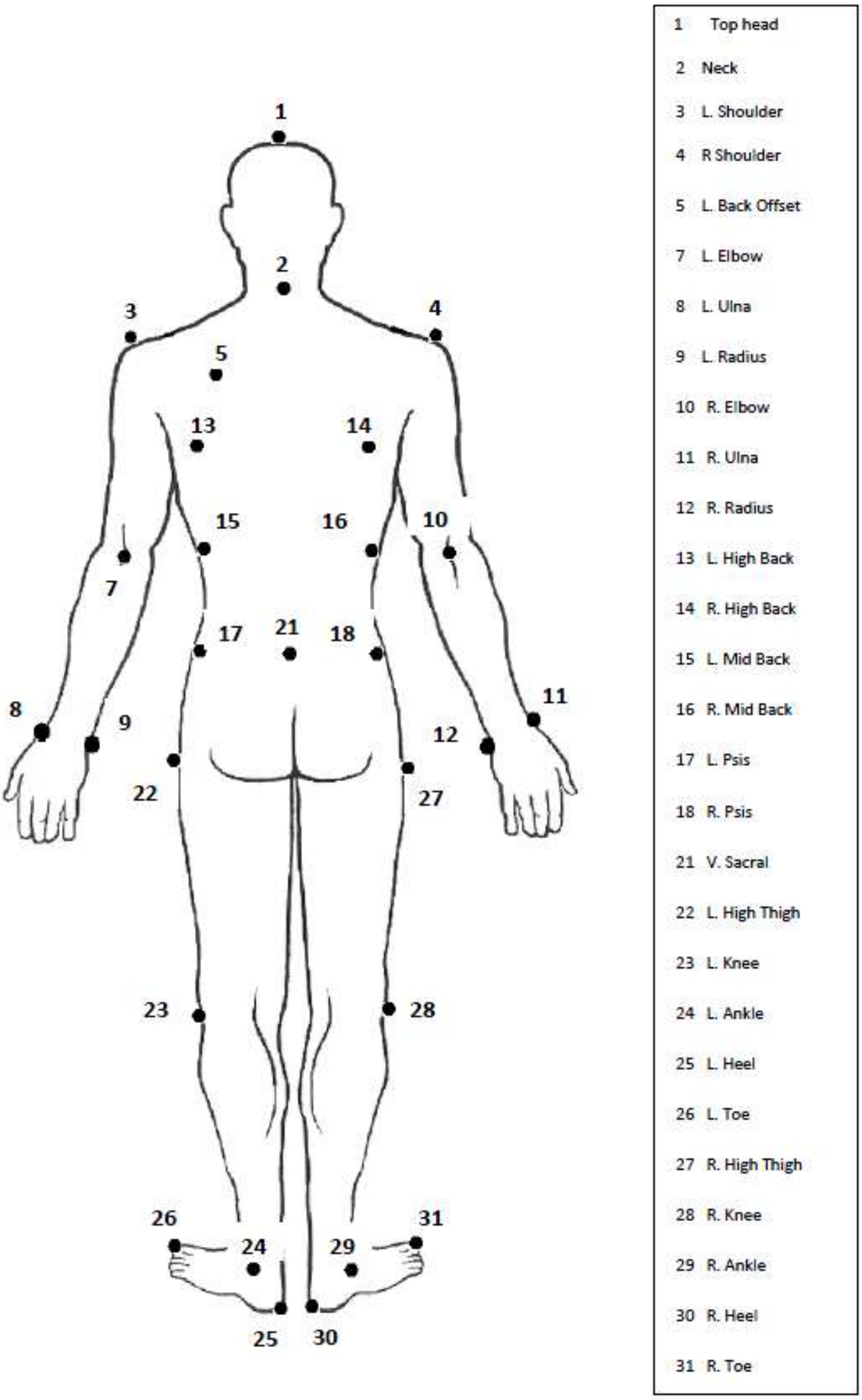


Fig. 2.3a. Back view of custom marker placement for seated motion (Evart 5.0 User's Manual)

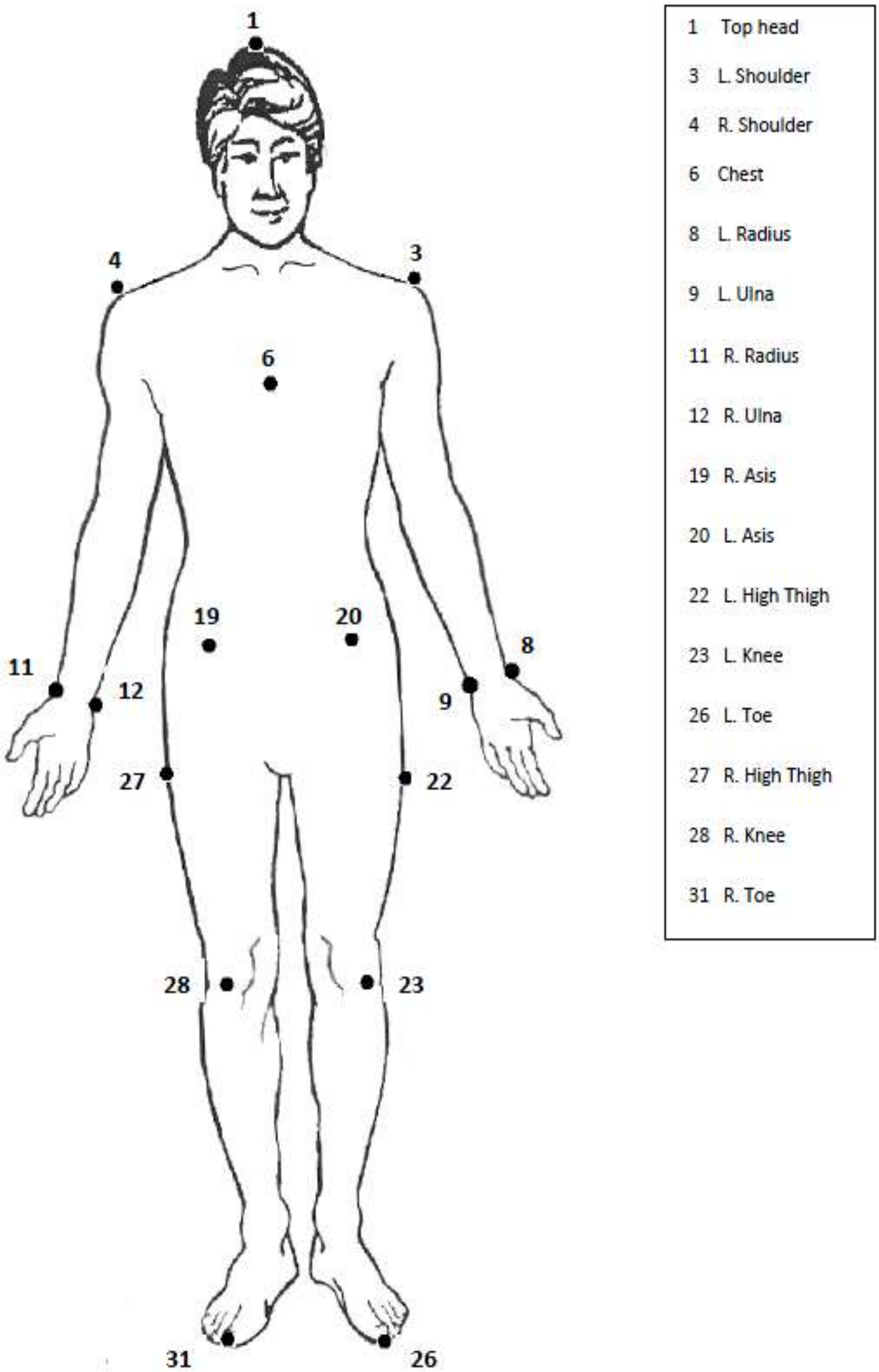


Fig. 2.3 b Front view of marker locations for seated motion (Evart 5.0 User's Manual)

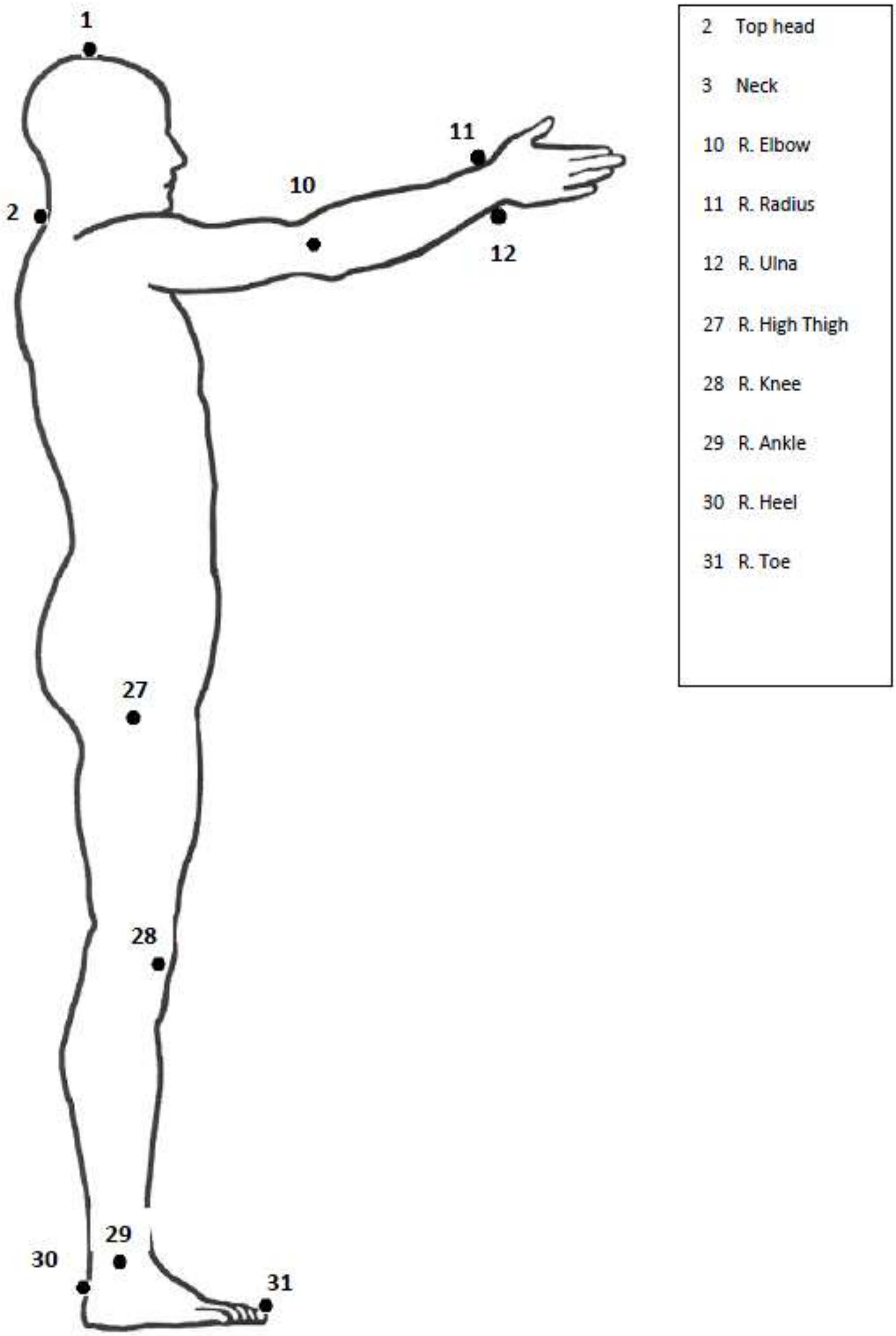


Fig. 2.3 c – Side view of marker locations for seated motion (Evart 5.0 User's Manual)

2.2 Data Captured

Gait data from 35 male students at a British university (Mean age = 26.77, SD = 5.79) recruited via flyers posted around campus were recorded for identification. All motion data were captured indoors. In these experiments, subjects were told to walk freely and naturally at normal speed from one end of the capture volume to the other. 28 subjects, each of them have one gait file limited by experiment conditions; the other 7 subjects, each of them have 6 gait files recorded at different time. Each gait files contained one or two gait cycles. The recorded Root marker (on the back at the upper middle of pelvis) speed for subjects ranged from 913.91mm/s to 2450.33mm/s with a mean of 1552.52mm/s.

Gait data for attractiveness were recorded from 30 male students at a British university (Mean age = 20.83, *SD* = 3.12) recruited via flyers posted around campus. Subjects walked at normal speed, from one end of the capture volume to the other, and then to walk back. One gait file was recorded for each subject. The recorded Root marker (on the back at the upper middle of pelvis) speed for 30 subjects ranged from 666.16 mm/s to 1255.48 mm/s with a mean of 1005.84mm/s.

x axis represented the walking direction, y axis represented the axis perpendicular to x axis, and x-y plane represented the floor plane. z axis represented the subject’s height direction, the axis which is vertical to floor plane.

2.3 Methods

In this research, gait data for identification were first normalized. One gait cycle that started at the same posture was picked from each of the subjects' gait files. Then, one complete gait cycle was normalized to the same frame numbers by linear interpolation.

Gait identification was tested by extracting gait signatures from gait features. In this part, a novel gait feature set was proposed, and individuals were then identified via three different gait signature extraction methods. The identification results were then compared. The three different gait signature extraction methods were the following: statistics method, PCA, and Fourier expansion. The distinguishing method was the k-NN algorithm. PCA is a common analysis method used to reduce the data dimension in gait recognition (Masoud & Papanikolopoulos 2003; Zhang & Troje 2005; Cho et al. 2009; Wu & Li 2009; Bockemuhl et al. 2010). Fourier expansion and Fourier coefficients were used in previous gait analysis (Troje 2002; Wolf et al. 2006). As distinguishing methods, k-NN algorithm is used for identification (Collins et al. 2002; Foster et al. 2003; Preece et al. 2009).

Second, gait features were analysed for identification. Other individual differences were studied in the investigation of the influence of gait phase. One gait cycle was divided into eight gait phases. The appearances of different gait features in gait phases were compared. The question 'which features should be extracted to represent gait and why' were answered by PCA and the fixing root method. The fixing root method is a method to achieve relative motion by coordinate transforming. It will be introduced more detailed in Chapter 5.

Then, the similarities and asymmetries in gait were analysed. The most asymmetrical body part in gait was investigated for individuals. The relationship between gait attractiveness and human body segments was investigated. A linear model was built for the logarithm of gait attractiveness and the logarithm of the makers' speed by PCA and linear regression. Furthermore, gait features for attractiveness were extracted by PCA and the fixing root method. Ten significant markers of the 40 markers for gait attractiveness were selected by the fixing root method. These 10 markers successfully represented all 40 markers with almost identical accuracy.

Finally, human seated motion was also investigated as an extension of gait research.

The methods used in each chapter are different, depending on the aim of each chapter. Thus, the methods used in each chapter are introduced in detail in each chapter. This chapter gives a brief analysis of the methods used throughout the research.

The next part briefly introduces the mathematical methods used in the research.

a. Principle Component Analysis. (used in Chapters 3, 5, and 7)

PCA is used to reduce the dimensionality of a dataset with correlated variables while retaining as much of the variance of the dataset as possible and transforming the dataset into a new dataset with independent variables.

b. linear regression. (used in Chapter 7)

In statistics, linear regression is an approach to modelling the relationship between a scalar variable y and one or more variables denoted X. In linear regression, data are modelled with linear functions, and unknown model parameters are estimated from the data. Such models are called linear models.

c. linear interpolation. (used in Chapter 3)

Linear interpolation is a method of curve fitting with linear polynomials. It is heavily employed in mathematics (particularly numerical analysis) and numerous applications, including computer graphics. It is a simple form of interpolation. Linear interpolation is often used to fill the gaps in a table.

d. Fourier expansion. (used in Chapter 3)

In mathematics, a Fourier series decomposes periodic functions or periodic signals into the sum of a (possibly infinite) set of simple oscillating functions, namely sines and cosines (or complex exponentials).

e. k-NN algorithm. (used in Chapter 3)

In pattern recognition, the k-nearest neighbour algorithm (k-NN) is a method for classifying objects based on closest training examples in the feature space. An object is classified by a majority vote of its neighbours, with the object being assigned to the class most common amongst its k-nearest neighbours

PCA and linear regression were completed by SPSS 16.0, and others were completed by Matlab 2009b.

Chapter 3 Gait Signature for Identification via Feature-based Methods

In this chapter, a novel set of gait features purely extracted from gait as gait features were first proposed to represent gait. The features were then analysed to determine if they could represent personal gait. Then, statistics methods, PCA, and Fourier expansion were used to extract gait signatures for identification based on a normalized gait cycle. A k-NN algorithm was used to identify subjects, and identification results were compared based on different methods.

The data are derived from a gait cycle normalized by linear interpolation. Many previous studies did not incorporate this step. The advantage of normalized gait is that subjects have the same gait cycle, same initial gait pose, and same frame numbers in one gait cycle, which improves the accuracy of individual gait identification.

3.1 Methods

3.1.1 Linear Interpolation and normalization of gait cycle.

Gait data included 35 subjects. For 28 subjects, only one gait file was recorded due to the limitations of the experimental conditions; for the other 7 subjects, 6 gait files were recorded at different times. Each gait file contained one or two gait cycles. x axis represented the walking direction, y axis represented the axis perpendicular to x axis, and x-y plane represented the floor plane. z axis represented the subject’s height direction, the axis which is vertical to floor plane (showed in Fig 3.1).

The gait files contained different lengths for different subjects. The gait data used in this research were constrained to one gait cycle, which started at the same posture and ended at the same posture to avoid extra data that could disturb the accuracy of the identification. Thus, gait cycle normalization included two steps. The first step is to identify a complete gait cycle in a subject's gait with the same gait starting pose. The gait cycle in this research started from the left toe-off posture to the next left toe-off posture (the next left toe-off posture is not included in this gait cycle). The gait cycle is shown in Fig 3.1. The second step is to make the gait cycle includes the same number of frames.

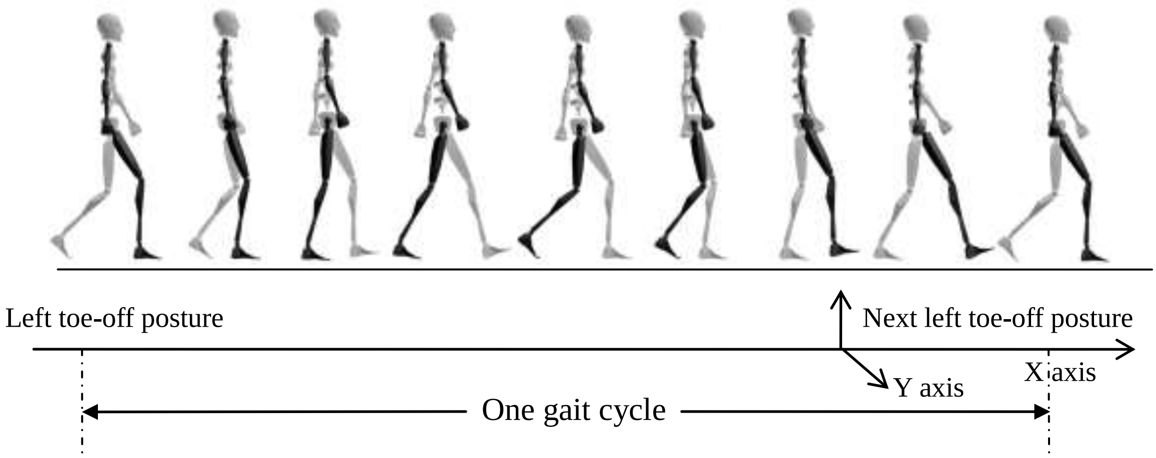


Fig. 3.1 One complete gait cycle

In the original walking data, gait cycles have different numbers of frames because the subjects walked at different speeds. This caused some difficulties when comparing the gaits of two subjects with respect to gait cycle and phase. To analyse gait data more specifically and compare the gait cycle, piecewise linear interpolation was used to normalize the gait cycle.

Based on the linear interpolation of each set of two adjacent frames, the gait cycle was normalized, and each complete gait cycle has the same number of frames for each subject. Linear interpolation is a method of curve fitting with linear polynomials. In the original recording data, one gait cycle may have 60-150 frames. After linear interpolation, one gait cycle has 1500 frames. Time was denoted in a gait cycle as T in the original data, and time in that gait cycle is still T after linear interpolation. The detailed interpolation progress is described below.

i was denoted for markers, *j* for subjects; *i* is from 1 to 40, and j is from 1 to 35. *t* means frame.

Within a gait file for any marker *i*, the coordinate is (X, Y, Z), the gait cycle in the recorded data is $[t_1, t_{n+1})$, the number of frames in this gait cycle is n, and n is different, depending on j. $[t_1, t_{n+1})$ means t_1 is included in the gait cycle, and t_{n+1} is not included in the gait cycle. t_{n+1} is the same posture (the left toe-off posture), with t_1 in the next gait cycle. The new gait cycle after linear interpolation is $[\hat{t}_1, \hat{t}_{1501})$, which means $\hat{t}_1$ is included in the gait cycle, and $\hat{t}_{1501}$ is not included in the gait cycle. The number of frames in the gait cycle after interpolation is 1500. $\hat{t}_{1501}$ is at the same time as t_{n+1}, and $\hat{t}_1$ is at the same time as t_1. t_{int} was denoted as the frame interval (time interval between two frames) in the recorded data. $\hat{t}_{\mathrm{int}}$ was denoted as the frame interval in data after interpolation, and thus

$$T = n \cdot t_{\mathrm{int}} = 1500 \cdot \hat{t}_{\mathrm{int}} \qquad (3.1)$$

So, $$\hat{t}_{\mathrm{int}} = \frac{n \cdot t_{\mathrm{int}}}{1500} \qquad (3.2)$$

The x, y, z coordinates were interpolated separately. X indicates the marker's coordinate in the x-axis. X can be denoted as $X = X(t)$; in this function, t indicates the frame in the recorded data, and X was denoted as $X = \hat{X}(\hat{t})$ after interpolation. $\hat{t}$ indicates the frame in the data after interpolation. In the recorded data, t=t_1,.., t_{n+1}; in the data after interpolation, $\hat{t} = \hat{t}_1$,..., $\hat{t}_{1501}$.

For any two adjacent frames t_f to t_{f+1}, *X0* and *X1* were denoted as $X0 = X(t_f)$ and $X1 = X(t_{f+1})$. *f* indicates the frame number in the recorded data, *f*=1:*n*.

If $\hat{t}$ was supposed to be a continuous function, *num0* is the new frame number in $\hat{t}$ after interpolation for frame t_f. Then,

$X0 = X(t_f) = \hat{X}(\hat{t}_{num0})$, for linear interpolation.

t_f is at the same time as $\hat{t}_{num0}$.

t_f is frame number *f* at time $(f-1)t_{\text{int}}$; $\hat{t}_{num0}$ is frame number *num0* at time $(num0-1)\hat{t}_{\text{int}}$.

So,

$$(f-1)t_{\text{int}} = (num0-1)\hat{t}_{\text{int}} \qquad (3.3)$$

According to equation (3.2) and (3.3), equation (3.4) was derived.

$$num0 = \frac{1500*(f-1)}{n} + 1, \qquad (3.4)$$

num1 was denoted as the frame number in $\hat{t}$ after interpolation for frame t_{f+1}. Then,

$X1 = X(t_{f+1}) = \hat{X}(\hat{t}_{num1})$

Similarly, equation (3.5) was derived.

$$num1 = \frac{1500 * f}{n} + 1, \qquad (3.5)$$

Because $\hat{t}$ was supposed to be a continuous function, *num0* and *num1* are not necessarily integers.

K0 was used as the first interpolated frame number (integer) from frame t_f ($\hat{t}_{num0}$) to frame t_{f+1} ($\hat{t}_{num1}$) after interpolation. *k1* was used as the last interpolated frame number (integer) from frame t_f ($\hat{t}_{num0}$) to frame t_{f+1} ($\hat{t}_{num1}$) in the gait cycle after interpolation.

If *num0* is an integer, then $k0 = num0 + 1$;

otherwise, $k0 = ceil(num0)$. (3.6)

$ceil(num0)$ means the closest integer that is just above num0.

If *num1* is an integer, then $k1 = num1$,

otherwise, $k1 = ceil(num1) - 1$. (3.7)

Subsequently, $\hat{X}(\hat{t})$ will be calculated for all integers from *k0* to *k1*.

$X(t)$ was supposed to be linear in the interval between t_f to t_{f+1}.

So $X(t) = \hat{X}(\hat{t})$, when t=f:f+1, $\hat{t}$ =*num0*:*num1*.

The expression of function $\hat{X}(\hat{t})$ was denoted in a usual representation of a line,

$\hat{X}(\hat{t}) = r \cdot \hat{t} + c$.

Because $X0 = \hat{X}(\hat{t}_{num0})$ and $X1 = \hat{X}(\hat{t}_{num1})$, then

$X0 = r \cdot num0 + c$, $X1 = r \cdot num1 + c$

So $r = \dfrac{X1 - X0}{num1 - num0}$, $c = X0 - r \cdot num0$. (3.8)

Thus, the function expression of $\hat{X}(\hat{t})$ was derived in frames *k0* to *k1* by equations (3.8), (3.4) and (3.5), and the values of *k0* and *k1* were given by equations (3.6) and (3.7). Therefore, the value of $\hat{X}(\hat{t})$ can be obtained when $\hat{t}$ are all the integers from *k0* to *k1*.

$\hat{X}(k)$ was denoted as $\hat{X}(k) = r \cdot k + c$; $k = k0 : k1$ indicates all of the integer numbers from *k0* to *k1*.

$\hat{X}(k)$, $k = k0 : k1$ are the new frames and x-coordinate data after interpolation of the recorded data frame t_f to t_{f+1}.

f is from 1 to *n*, in the same way all the gait cycle was interpolated by steps (t_1, t_2), (t_2, t_3), ..., (t_n, t_{n+1}). The new gait data were then obtained in frame 1 to frame 1501. One gait cycle is frame 1 to frame 1500; frame 1501 is the start frame in the next gait cycle. The new gait cycle data are $\hat{X}(k)$; *k* is 1 to 1500.

For coordinates Y and Z, the interpolation process is similar to that given above.

3.1.2 Definition of gait signature and gait feature

The terms gait feature and gait signature have been frequently used in previous studies. However, the concepts of gait feature and gait signature are not clear. Some features that have been used as gait features in some studies (such as step length and width) have been used as gait signatures in other studies. Some features such as clothing colour and hair colour were defined as 'soft signatures'. Some variables extracted by mathematical methods were referred to as gait features in some studies and gait signatures in other studies. To distinguish between these two terms, a clear concept was given in this research.

Gait features were used represent gait. They state the characteristics in gait. Gait feature data were analysed instead of gait data in feature-based method research. In previous studies, whether silhouette in video data or angles, the DOFs in motion capture data were all gait features based on this definition. In this research, gait features were identified as 14 angles and 1 ratio from gait characteristics.

Gait signatures were used to achieve individual identification. Gait signatures are variables extracted from gait features. The gait signature is the specific statement of personality that makes one subject's gait different with another subject's gait. It is the basis of the distinguishing method. In this research, gait signatures were achieved from three extraction methods for gait features.

3.1.3 Selection of gait features

In previous studies, gait features were proposed directly and, in most cases, without an analysis and evaluation process. There has rarely been an analysis of why these gait features were proposed or an evaluation process of whether these gait features were suitable for representing gait as the basis for identification.

At the beginning of this research, a set of over 20 gait features was proposed as a first step. These gait features are listed below:

1. Head-Topspine angle,

2. Topspine-Root angle,

3-4. Elbow angle (left and right),

5-6. Shoulder angle (left and right),

7-8. Knee angle (left and right),

9-10 Ankle angle

11-12. Heel-toe angle on y-axis (left and right),

13-14. Heel-toe angle on z-axis (left and right),

15-16. Wrist-root distance on y-axis (left and right),

17-18. Wrist--root distance on z-axis (left and right),

19-20. Wrist angle

21. Ratio of Wrist speed (left) to Wrist speed (right).

These gait features were proposed not only on the basis of observations of individual differences in gait from videos of subjects' gaits but also because of features used in previous studies. Subsequently, analysis and filters were applied to these features.

Shoulder angle, ankle angle, and wrist angle were removed because the differences in these features between subjects are not significant. The wrist-root distances on y-axis and z-axis were replaced by wrist-shoulder angles on y-axis and z-axis for consistency with other angle variables. The wrist-shoulder and heel-toe angles were separated into the y-axis and z-axis to separate the influence of walking action and individual gait habits. The definitions of y axis and z axis were shown in Fig 3.1. x axis denoted the walking direction, y axis is the direction from right body to left body, z axis is height direction. An individual gait can be assumed to be constructed by walking action and the individuality of the subject. The body movement on the z-axis is obviously highly influenced by the walking action itself, although the height of the foot in the gait remains a part of the individual gait pattern. The separation of the y-axis and z-axis is appropriate for identifying features that are more closely related to individual gait habits than walking action.

Gait speed is a common feature in previous studies (Grabiner et al. 2001; Menant et al. 2009a; 2009b). It is an effective feature for evaluating the gait of the elderly or some patients. There is a noticeable difference between particular types of subjects, for example, between the elderly and the young. However, it is not a suitable feature for individual identification. The gait features proposed in this research are not speed-related.

Therefore, a new set of 15 gait features was established. The Head-Topspine angle describes the habit of the head to look up or down in the gait. The Topspine-Root angle describes the habit of the upper part of the body in the gait. The Elbow angle describes the habit of the elbow movement in the gait. Heel-Toe angle on y-axis described the habit of how wide the toe is swung away from heel. From top view, Heel-toe angle on y-axis was defined as plus when toe is outside heel, and was defined as minus when toe is inside heel. Heel-toe angle on z-axis described the habit of how cliffy the foot is in gait. From side view, Heel-toe angle on z-axis was defined as plus when toe is above heel, and was defined as minus when toe is under heel. Wrist-shoulder angle on y-axis described the habit of how far away from body the wrist is in gait. From top view, Wrist-shoulder angle on y-axis was defined as plus when wrist is outside shoulder, and was defined as minus when wrist is inside shoulder. Wrist-shoulder angle on z-axis described the habit of how high the wrist is in gait. From side view angle, Wrist-shoulder angle on z-axis was defined as plus when wrist is in front of shoulder, and was defined as minus when wrist is behind shoulder. Ratio of Wrist speed (left) to Wrist speed (right) described the habit of the different movement of left wrist and right wrist. This feature was used because of the phenomenon which was found that most subject's two arms swung in different speed. It is not related to walking speed since it is a ratio of left wrist speed to right wrist speed.

After filtering, the 15 features listed below were chosen as gait features in this research.

Number	Gait Features
1	Head-Topspine angle
2	Topspine-Root angle
3	left Elbow angle
4	right Elbow angle
5	left Knee angle
6	right Knee anglet
7	left Heel-toe angle on y-axis
8	right Heel-toe angle on y-axis
9	left Heel-toe angle on z-axis
10	right Heel-toe angle on z-axis
11	left Wrist-shoulder angle on y-axis
12	right Wrist-shoulder angle on y-axis
13	left Wrist-shoulder angle on z-axis
14	right Wrist-shoulder angle on z-axis
15	Wrist speed ratio (left wirst speedto right wrist speed)

Table 3.1 List of gait features

There were some abbreviations about feature 7-14.

7. left Heel_toe angle on y-axis (abbreviated as Left Heel_toe_y)

8. right Heel_toe angle on y-axis (abbreviated as Right Heel_toe_y)

9. left Heel_toe angle on z-axis (abbreviated as Left Heel_toe_z)

10. right Heel_toe angle on z-axis (abbreviated as Right Heel_toe_z)

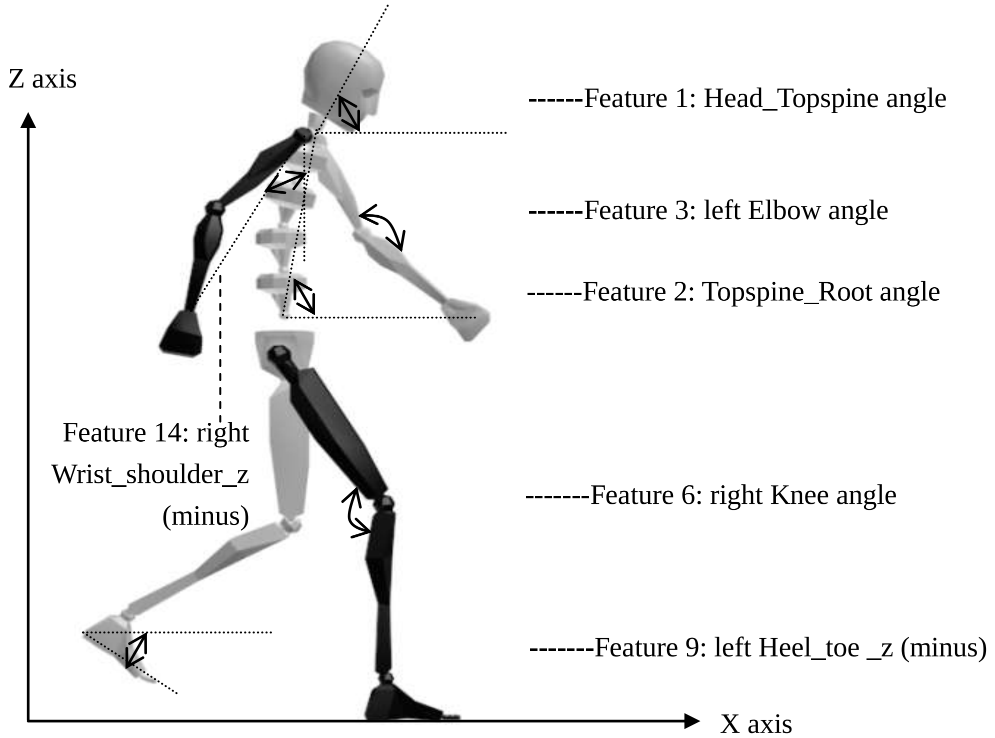
11. left Wrist_shoulder angle on y-axis (abbreviated as Left Wrist_shoulder_y)

12. right Wrist_shoulder angle on y-axis (abbreviated as Right Wrist_shoulder_y)

13. left Wrist_shoulder angle on z-axis (abbreviated as Left Wrist_shoulder_z)

14. right Wrist_shoulder angle on z-axis (abbreviated as Right Wrist_shoulder_z)

Fig. 3.2 showed definition of these features.



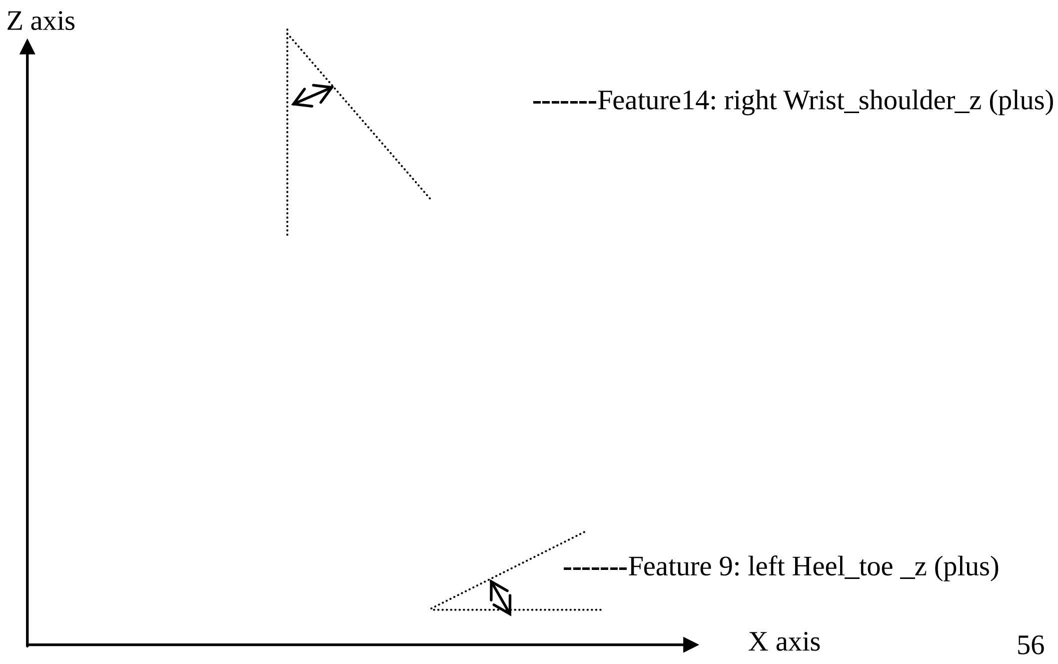


Fig. 3.2 Side view of feature 1, 2, 3, 6, 9 and 14. Feature 4, 5, 10, and 13 were defined as the same way of feature 3, 6, 9, and 14, respectively.

Wrist_shoulder_z was denoted as plus when wrist is in front of shoulder, and as minus when wrist is behind shoulder. The natural posture of wrist is when this angle is 0. Heel_toe_z was denoted as plus when Toe is above heel, and as minus when Toe is under heel. The natural posture of wrist is when this angle is 0.

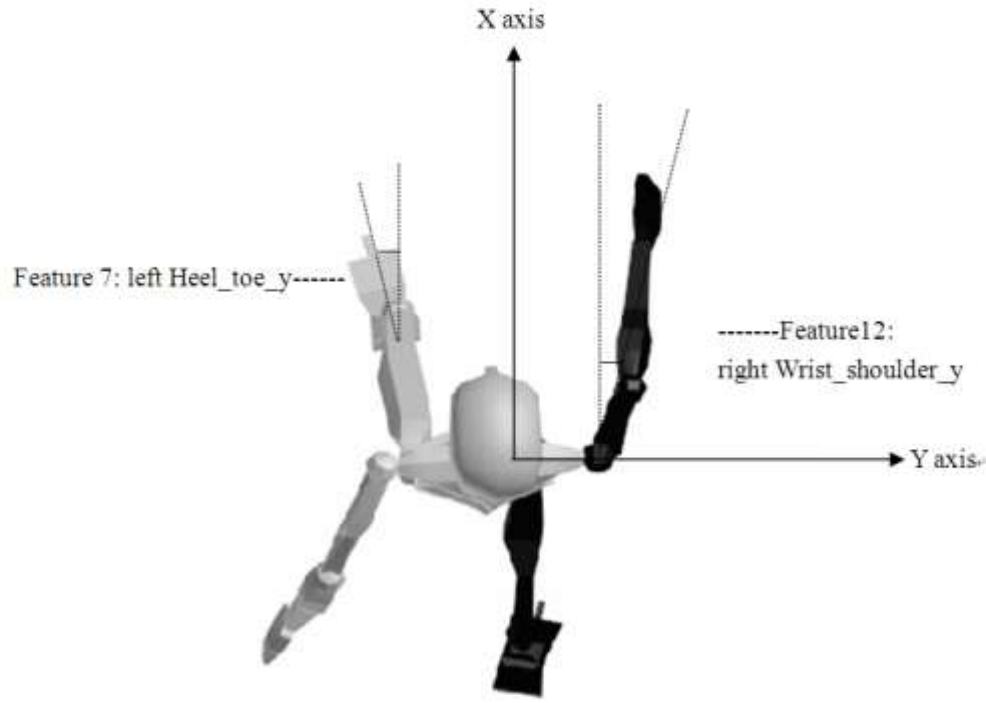


Fig. 3.3 Top view of feature 7 and 12. Feature 8 and 11 were defined as the same way of feature 7 and 12, respectively.

Wrist_shoulder_y was denoted as plus when wrist is outside shoulder, and as minus when wrist is inside shoulder. Heel_toe_y was denoted as plus when Toe is outside heel, and as minus when Toe is inside heel.

3.1.4 Two indicators to evaluate gait features

To analyse the gait features quantitatively, two indicators were designed to evaluate gait features. If a gait feature can be used to distinguish individuals, it should be noticeably different for different people but stable in the same subject at different gaits. To evaluate if these gait features are suitable, two indicators were designed: 'Consistence degree' and 'Variation degree'. The consistence degree evaluates if the gait feature is stable in different gaits for the same subject. The variation degree evaluates if the gait feature is noticeably different in different individuals.

Four variables were used to represent these two indicators: the SD of the mean, the SD of the SD, the SD of the max, and the SD of the min. For any feature of any gait, the mean is the mean value of this gait feature in this gait; the SD is the standard deviation of the mean, which measures dispersion; the max is the maximum value; the min is the minimum value.

In the consistence degree for any gait feature, the 'SD of the mean' measures the dispersion of the mean value of the gait feature in different gaits of the same subject; the 'SD of the SD' measures the dispersion of the SD of the gait feature in different gaits of the same subject; the 'SD of the max' measures the dispersion of the maximum of the gait feature in different gaits of the same subject; the 'SD of the min' measures the dispersion of the minimum of the gait feature in different gaits for the same subject.

In the variation degree for any gait feature, the 'SD of the mean' measures the dispersion of the mean value of the gait feature for different people; the 'SD of the SD' measures the dispersion of the SD of the gait feature for different people; the 'SD of the max' measures the dispersion of the maximum of the gait feature for different people; the 'SD of the min' measures the dispersion of the minimum of the gait feature for different people.

As an ideal gait feature for gait identification, the consistence degree should be small and the variation degree should be large. In section 3.2.1, the evaluation results for the Consistence degree and the Variation degree of these 15 gait features demonstrated that these gait features were ideal and suitable for identification.

3.1.5 Gait signature extraction methods

In this research, 15 gait features were proposed as most significant variables to represent gait, and gait signatures were extracted from gait features to identify individuals. Gait signatures bear the individuality of gait for each subject, and one subject has one unique set of gait signature for identification purpose. Three different methods were applied to extract gait signatures.

3.1.5.1 Statistics method

Statistics method to extract gait signature is the first extraction method in this chapter. Two sets of gait signature were used: the first set is (mean, SD of mean) of gait features as gait signatures, the second set is (mean, SD of mean, maximum, minimum) of gait features as gait signatures. This method was used in section 3.2.2.1 and 3.2.2.2.

3.1.5.2 PCA method

PCA was applied as second extraction method. PCA was used on 1500 frames of one gait cycle. For each subject *j*, features is a matrix F which contain 1500*15 dimensions. 1500 is frame number, 15 is feature number.

$$F = \begin{bmatrix} f_{j,1}^{1} & f_{j,2}^{1} & \cdots & \cdots & f_{j,15}^{1} \\ f_{j,1}^{2} & f_{j,2}^{2} & \cdots & \cdots & f_{j,15}^{2} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ f_{j,1}^{1500} & f_{j,2}^{1500} & \cdots & \cdots & f_{j,15}^{1500} \end{bmatrix}$$

Then the principle components (PC1, PC2,..) were achieved after applying PCA on F. The number of PCs depended on each subject. Then, for any subject *j*,

$$PC1 = \sum_{i=1}^{15} Coe1_{j,i} \cdot f_{j,i}, \quad PC2 = \sum_{i=1}^{15} Coe2_{j,i} \cdot f_{j,i}, \ldots \qquad (9)$$

in that *i* means feature *i*, $f_{j,i}$ means gait feature's data of subject *j*, feature *i*.

Those coefficients $Coe1_{j,i}$, $Coe2_{j,i}$ of PCs represented the contribute degree of each gait features on this subject's gait in one gait cycle. The first two principle components were kept for all 35 subjects since the numbers of PCs are not same. For any feature *i*, the coefficients of PC1 and PC2, $Coe1_{j,i}$, $Coe2_{j,i}$ were used as gait signature. This method was used in section 3.2.2.3.

3.1.5.3 Fourier expansion method

A periodic function $f(x)$ can be expanded to the sum of an infinite series of sines and cosines. The expansion expression of $f(x)$ is:

$$f(x) = a_0/2 + \sum_{n=1}^{\infty}(a_n \cos nx + b_n \sin nx).$$

The coefficients a_n and b_n is determined by equations as below:

$$a_n = (1/\pi)\cdot\int_{-\pi}^{\pi} f(x)\cos nx dx, \quad n=0,1,2,......$$

$$b_n = (1/\pi)\cdot\int_{-\pi}^{\pi} f(x)\sin nx dx, \quad \text{n=1,2,.......}$$

For each feature i, $F_{j,i}(t)$ was denoted as function expression of this feature for subject j. $F_{j,i}(t)$ can be decomposed into a second order Fourier expansion as equation (3.10)

$$F_{j,i}(t) = F0_{j,i} + F1_{j,i}\sin(t) + F2_{j,i}\cos(t) + F3_{j,i}\sin(2t) + F4_{j,i}\cos(2t) + err \tag{3.10}$$

The coefficients in equation (3.10) are determined by:

$F0 = (\int_{-\pi}^{\pi} F_{j,i}(t)dt) / 2\pi$,

$F1 = (1/\pi)\cdot\int_{-\pi}^{\pi} F_{j,i}(t)\sin t dt$,

$F2 = (1/\pi)\cdot\int_{-\pi}^{\pi} F_{j,i}(t)\cos t dt$,

$F3 = (1/\pi)\cdot\int_{-\pi}^{\pi} F_{j,i}(t)\sin 2t dt$,

$F4 = (1/\pi)\cdot\int_{-\pi}^{\pi} F_{j,i}(t)\cos 2t dt$.

So each feature has gait signatures with 5 vectors $(F0_{j,i}, F1_{j,i}, F2_{j,i}, F3_{j,i}, F4_{j,i})$. This method was used in section 3.2.2.4.

3.1.6 k-NN to identify

In pattern recognition, the k-nearest neighbour algorithm (k-NN) is a method for classifying objects based on closest training examples in the feature space. k is usually a positive integer, typically small. If k = 1, then the object is simply assigned to the class of its nearest neighbour. If there were more than one nearest neighbours, the object is assigned to the class which appeared the most times. The best choice of k depends upon the data. Generally, larger values of k reduce the effect of noise on the classification. After choosing gait signatures, Euclidean distance was used as distance between gait signatures of different subjects. For each feature, the subject which has the minimum distance to tested subject was denoted as the nearest neighbour of tested subject on feature *i*. Gait feature set included 15 features, so the tested subject has 15 nearest neighbours for all gait features. At last, the tested subject will be identified as the subject who appeared most times in these 15 nearest neighbours. If there is no such subject, the tested subject will be noted as unable to identify.

The Euclidean distance in three different methods between gait signatures of different subjects were introduced as below:

By statistics method, for any feature *i*, if using (mean, SD of mean) as gait signature, the distance between subject A and subject B in indicator i is

$$\sqrt{(mean_{A,i} - mean_{B,i})^2 + (SD_{A,i} - SD_{B,i})^2} \ .$$

If using (mean, SD of mean, maximum, minimum) as gait signatures, the distance between subject A and subject B in indicator i is

$$\sqrt{(mean_{A,i} - mean_{B,i})^2 + (SD_{A,i} - SD_{B,i})^2 + (SD\max_{A,i} - SD\max_{B,i})^2 + (SD\min_{A,i} - SD\min_{B,i})^2}$$

By PCA method, gait signatures were denoted these as $\left(Coe1_{j,i}, Coe2_{j,i}\right)$, j means subject *j*, and *i* means feature *i*. The distance between subject *A* and subject *B* in feature *i* is

$$\sqrt{(Coe1_{A,i} - Coe1_{B,i})^2 + (Coe2_{A,i} - Coe2_{B,i})^2} \ .$$

By Fourier expansion method, gait signatures were $(F0_{j,i}, F1_{j,i}, F2_{j,i}, F3_{j,i}, F4_{j,i})$. The distance between subject *A* and subject *B* in feature *i* is

$$\sqrt{(F0_{A,i} - F0_{B,i})^2 + (F1_{A,i} - F1_{B,i})^2 + (F2_{A,i} - F2_{B,i})^2 + (F3_{A,i} - F3_{B,i})^2 + (F4_{A,i} - F4_{B,i})^2} \ .$$

The identification process is the following steps:

- Selecting one complete gait cycle from each gait file and each subject.

- Using linear interpolation to get same format gait cycle to normalize those gait cycles.
- using 15 gait features to describe a gait cycle.
- Using statistics method, PCA, Fourier expansion method to extract gait signatures.
- Choosing base gait (random or average gait) and using K-NN algorithm to identify.
- Comparing identify results with different gait signatures and different data sample setup.

3.2 Results

3.2.1 Evaluation of gait features

The computing results showed that these gait features were suitable for distinguish individuals. Table 3.2 showed the Consistence degree and Variation degree of 15 gait features. Figures about the gait features are shown from id 1 to id 7 in Appendix 2. It is obvious that the gait features varied little between different gait files for the same subject, whereas varied much between different subjects.

Gait Features	SD of mean		SD of SD		SD of max		SD of min	
	Consistence	Variation	Consistence	Variation	Consistence	Variation	Consistence	Variation
1	2.16	8.54	0.56	1.46	2.33	8.21	2.11	8.97
2	0.56	2.89	0.17	0.81	0.78	3.06	0.54	3.66
3	0.88	12.43	0.98	3.53	1.18	13.29	2.30	13.23
4	1.04	11.01	1.32	3.01	1.44	11.32	2.95	12.02
5	0.96	9.59	0.67	3.80	1.09	8.80	1.56	13.87
6	0.71	11.33	0.58	4.49	0.99	10.29	1.37	17.33
7	1.45	6.81	1.06	1.81	3.65	10.09	2.58	9.92
8	1.76	7.53	0.78	2.45	4.52	11.98	2.21	7.40
9	0.95	3.89	0.94	3.13	1.23	7.56	2.45	7.44
10	0.90	2.90	0.84	2.99	1.58	6.41	2.72	6.73
11	0.74	2.97	0.41	1.76	1.00	3.99	1.03	4.01
12	0.69	3.38	0.39	1.97	0.87	3.32	0.80	5.44
13	0.94	5.83	1.09	4.14	2.43	8.05	1.23	8.97
14	0.99	5.83	1.56	4.20	2.69	9.23	2.21	7.91
15	0.21	0.80	0.36	1.81	1.25	12.25	0.05	0.13

Table 3.2 Consistence degree and Variation degree of 15 gait features

It is obviously that 15 gait features have low value in Consistence degree and high value in Variation degree. From the measure of dispersion, it showed that these gait features varied little in different gait for the same subject, and varied highly for different people.

3.2.2 Identification results

3.2.2.1 Using (mean, SD of mean) of features as gait signatures

The identification results were compared between random one gait cycle as base gait and average gait cycle as base gait.

First, random gait cycle was used as base gait, and random gait cycle as testing gait. The data sample is for all 35 subjects with some subjects have different gait cycles to choose from. In this way the identification was conducted for 252 times. The accuracy of identification is above 95%. Only 2% is unable to identify. 3% is wrong identifying results.

Secondly, average gait cycle was used as base gait, and random gait cycle as testing gait. All 6 gait cycles of the tested subject were used to get an average gait as base gait. Data sample is still 35 subjects as well. The identification was conducted for 252 times also, and the accuracy of identification is 99%, nearly 100%.

Attempts were also made trying to use less gait cycles to get average gait as base gait. When using 3 gait cycles to get average gait, the accuracy of identification reduced to 97.22%. When using 5 gait cycles to get average gait, the accuracy of identification is 99.60%. The different results were shown in Table 3.3.

Average gait as base gait	identification rate		
	Average gait of 3 gait cycles	Average gait of 5 gait cycles	Average gait of 6 gait cycles
	97.22%	98.41%	99.60%

Table 3.3 the identification results by different average gait as base gait

3.2.2.2 Using (mean, SD of mean, maximum, minimum) of features as gait signatures

Same steps were used as 3.2.2.1. The computing time increased since using more variables. The identify results were almost same. The accuracy of identification is around 95% when using random gait as base gait, nearly 100% when using average gait as base gait.

3.2.2.3 Using coefficients of PCs as gait signatures

PCA as a effective data reduction method was frequently used in gait analysis

(Forbes & Fiume 2005). In (Das et al. 2006), a two-stage PCA extracting gait features was used for recognition. PCA and DTW (dynamic time warping) based classifier method were used in 2009 (Wu & Li 2009). PCA and LDA(linear discriminant Analysis) were used for recognizing patients (Cho et al. 2009). PCA is used to reduce the dimensionality of a data set with correlated variables, while retaining as much variance of the data set as possible, and transforming the data set into a new data set with independent variables.

First, random gait was used as base gait and random gait cycle as testing gait. PCA was performed on 1500 frames for each subject. 2-5 PCs were obtained which occupied 85.6% to 91.2% variance for different subjects. So the 2 first PCs were kept for all subjects. Coefficients of PC1 and PC2 in equation (3.9) were used in k-NN algorithm. The accuracy of identification is 93.25%. Second, average gait were used as base gait and random gait cycle as testing gait. The accuracy of identification is 98.80%.

3.2.2.4 Using Fourier expansion coefficients as gait signatures

Fourier expansion and Fourier coefficients were used in gait animation and recognition before (Gleicher 1998; Troje 2002; Ormoneit et al. 2005). Human motion can be transferred from a walk to a run or changed the motion mood with emotion by Fourier expansions (Munetoshi et al. 1995). The Fourier series has many such applications in electrical engineering, vibration analysis, acoustics, optics, signal processing, image processing, quantum mechanics, econometrics, thin-walled shell theory, etc. In mathematics, a Fourier series decomposes any periodic function or periodic signal into the sum of a (possibly infinite) set of simple oscillating functions, namely sines and cosines (or complex exponentials).

The study of Fourier series is a branch of Fourier analysis. Fourier series were introduced by Joseph Fourier (1768–1830) for the purpose of solving the heat equation in a metal plate.

In this section, Fourier expansion was used on gait features, and then used Fourier coefficients of expansion as gait signature for k-NN algorithm to identify.

The identification is 252 times. The accuracy of identification is above 97% when random gait was used as base gait. The accuracy increased to 99% when average gait of subject was used as base gait.

3.2.2.5 Comparison of different method of extracting gait signatures

Table 3.4 showed the compared results of three extracting gait signature method. Statistics method already got very high identify rate with the simplest calculated dimension. Fourier expansion method got the best result while using random gait as base gait. While using average gait as base gait, all of these three methods achieved very high accuracy. In general, the result of average gait as base gait is better than result of random gait as base gait.

Base gait	identify rate		
	Statistics	PCA	Fourier expansion
random gait	95.24%	93.25%	96.43%
average gait	99.60%	98.80%	99.60%

Table 3.4 Identification results of three extracting gait signature method

3.2.3 Using less features to identify

It is to repeat the identify process with less features. 10 features were used without features 11-15. It was in order to test the effect on identification about some features proposed in this research. Identification was conducted 252 times also. The results were worse. Accuracy of identification decreased from 95% to 83%.

This was conducted by using statistics method and random gait as base gait.

3.2.4 Correct identification rate in the case of data sample doesn't include testing subject

In part 3.2.2.1 to 3.2.2.2, that is the case which data sample include testing subject, and to test if this identification method could right identify that subject. While the testing subject even does not exist in data sample, will it be correctly shown not in this data sample or will be denoted as a wrong person? For verifying this problem, a series of identification were used. The data sample is 34 subjects for now, excluding the subject which used to test. The results showed 60% correct identified that testing gait didn't exist in sample data while using statistics method with (mean, SD of mean) as gait signatures; and 82.54% correct identified that testing gait didn't exist in sample data while using statistics method with (mean, SD of mean, max, min) as gait signatures. These identification rates were based on random gait as base gait. While using average gait as base gait (average 6 gait cycles), the correct identifying rate of testing gait didn't exist in sample data increased to 85.71% with (mean, SD of mean) as gait signatures , and 94.05% with (mean, SD of mean, max, min) as gait signatures.

3.3 Summary

3.3.1 Novel gait features proposed

A novel, effective set of gait features which contained 14 angles and one ratio was proposed to represent individuals’ gait. Some features in this set were used in previous research, such as elbow angles, knee angles. Some features in this set were proposed firstly in this research, such as Wrist_shoulder_y/z angles, Heel_toe_y/z angles, and Wrist speed ratio. Angles were decomposed to y-axis and z-axis to represent gait instead of joint angles only, and a new feature was used -- Wrist speed ratio.

These 15 gait features were evaluated by Consistence degree and Variation degree. Table 3.2 showed the Consistence degree and Variation degree of 15 gait features. It showed that these gait features kept stable in different gait files of the same subjects, and varied much for different people. So these 15 gait features were suitable for individual identification. The identification results also showed that the new set of gait features is very efficient for gait recognition. It could represent individual gait very well.

3.3.2 High accuracy in identification results

3.3.2.1 Effective framework for gait identification

In this chapter, a systematic, practical framework was proposed with high accuracy to identify individuals. The identification result in Table 3.4 is better than previous reported research. The recognition rate was about 75% in 114 subjects in (Foster et al. 2003), 82.5% in 74 subjects in (Wang et al. 2003), the highest recognition rate was 98.8% with best view point (from 45 degree front view) with 80 walkers' 2D image sequence in (Zhang & Troje 2005). The identification framework in this paper included four steps: normalization of gait data, computing gait features, extracting gait signatures from features, and distinguishing by k-NN algorithm.

3.3.2.2 Comparison of three proposed methods of extracting gait signatures

Three different methods were applied to extract gait signatures. Those different methods included:

- Statistics method. Using (mean, SD of mean value), or (mean, SD of mean value, maximum, minimum) as gait signatures.
- PCA method. Using coefficients on PCs of features as gait signatures.
- Fourier expansion method. Using Fourier coefficients as gait signatures.

The highest accuracy of identify was nearly 100% while using average gait as base gait, above 95% while using random one gait as base gait. Statistics method already achieved very high identification rate with the simplest algorithm. Fourier expansion method achieved the best result while using random gait as base gait. PCA method extracted the principle feature combination in 15 features for each subject. It means that the different weights for 15 features on subjects in gait cycle were used to identify. From the results of identification, it was found that Statistics method is better than PCA method. It suggested that the difference of these gait features in different subjects did better for identification than the difference of weights of features in different subjects. Another possible reason of this result is that the removed PCs caused the lower identification results (the removed PCs caused data loss). However, the accuracy rate is still very close in these two methods.

Fourier expansion method showed best result, while statistics method occupied least time in computing.

3.3.2.3 Average gait as base gait is better than random gait as base gait

In general, the identification results which used average gait of subjects as base gait is better than results which used random gait of subjects as base gait. While using average gait as base gait, all of these three extraction methods achieved very high accuracy. It was found that the more gait cycles were averaged as base gait, the higher the accuracy of identification was obtained (shown in Table 3.3).

Besides, using average gait as base gait can also increase the correct identification rate when the subjects is not in data sample than using random gait as base gait. While using average gait as base gait (average 6 gait cycles), the correct identifying rate of testing gait didn't exist in sample data increased from 60% to 85.71% with (mean, SD of mean) as gait signatures , and from 82.54% to 94.05% with (mean, SD of mean, max, min) as gait signatures. For an identifying individual method, there are two functional requirements. One is that the method can pick the correct one when the subject is in data sample. The other one is that the method can identify the subject not there when the subject is not in data sample. This method resolved the first requirement very well. There were very little reported literatures about the second requirement. It is hard to comment the result about the second requirement in this research. It is obviously that using average gait as base gait can increase the rightly identifying rate when the subjects is not in data sample than using random gait as base gait.

3.3.3 Normalized gait data and data sample

The gait data was normalized for one gait cycle by linear interpolation. Each gait cycle has the same frame numbers after interpolation, as well as same starting posture. It improved the accuracy in individual identification.

The data sample in this paper included 35 subjects. It is quite small due to experiment limitation, however 35 subjects’ gait data is a decent sample space for individual identification research based on 3D motion data. In previous research, 20 subjects were used in (Rosengren et al. 2009), 37 subjects were used in (Kennedy et al. 2009), 16 subjects were used in (Allet et al. 2008), and 36 subjects were used in (Menant et al. 2009a). Although the accuracy should decrease when data sample gets much bigger in theory, this identification method is still a significant progress in gait identification research. The other specific property of this data base is that it contained only young, male subjects. The gender and age effects played no part in identification. In a data sample contained very similar subjects, very high identification results were achieved. If the data sample were increased to include all subjects with different age and gender, this identification method will prove even more efficient in theory.

In this chapter, the coherent good results showed the new gait features and identification methods are very effective for gait identification. In next two chapters, gait features were investigated for the purpose of identification. In Chapter 4, the influence on gait features from gait phases and gait cycle were investigated to reveal the secret of the personality of walkers. In Chapter 5, it provided solutions about the question 'which and why these features should be extracted to represent gait'.

Chapter 4 Gait Phase and Gait cycle analysis

Many studies have been dedicated to gait phase. The role of phase has been investigated by gait classification and recognition (Bissacco et al. 2007). Gait phase was used for recognition via a method of phase synchronisation and period-based gait trajectory matching in 2010 (Mori et al. 2010). Some research has focused on analysing three-dimensional kinematics and dynamics in certain gait phases, such as the stance phase or swing phase (Doriot & Cheze 2004; Emborg et al. 2011). Determining how to detect and recognise gait phase has also attracted much interest (Senanayake & Senanayake 2010; 2010; Wang et al. 2010). Gait phase detection in real time requires the accurate timing of feedback as a practical method. An acceptable standard method has not yet been achieved to produce a reliable and accurate system, although many gait phase detection algorithms have been proposed. The aim of this study was to investigate the influence of gait phase on gait features and the difference between the gait phases of individuals.

Certain gait phases, such as the double support phase, have been the focus of study in previous research. Double support time has been shown to be an important feature in the elderly's gait and gait balance (Gabell & Nayak 1984; Allet et al. 2008; Turner & Woodburn 2008).

4.1 Gait phase Classification

4.1.1 Gait cycle and phases in previous research

A normal gait consists of two main phases, the stance phase and swing phase. It is defined by one same leg's moving motion. The stance phase includes two periods of double support and one single support phase. The swing phase is actually the other leg's single support phase. Thus, in each gait cycle, there are two periods of double support and two periods of single support. The double support phase is the period during which both feet are on the ground. The stance phase and swing phase or single support phase are typically the main phases. There are more detailed phases which were divided in the stance phase and swing phase. Previous studies applied various methods of dividing gait phases.

4.1.1.1 Seven phases in gait cycle

In (Perry 1999; M.Nordin & Frankel 2001), one gait cycle was divided into seven phases: Initial Contact (IC), Mid Stance (MSt), Terminal Stance (TSt), Pre Swing (PSw), Initial Swing (ISw), Mid Swing (MSw) and Terminal Swing (TSw). The IC phase is called the loading response in some early literature (Gage 1990; Perry 1990).

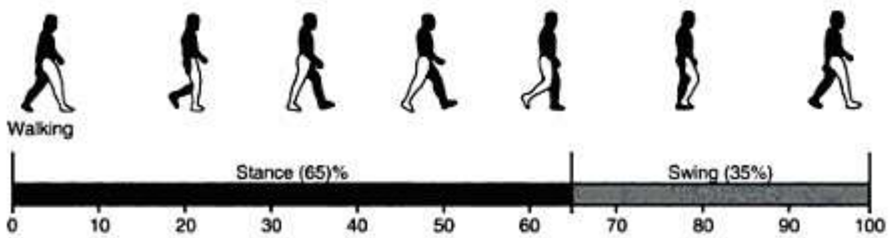


Fig. 4.1 Example of gait cycle in (M.Nordin & Frankel 2001)

Those phases were defined as follows:

- IC (loading response): As its name suggests, this phase begins with initial contact, the instant the foot contacts the ground. (Normally, the heel contacts the ground first. In patients who demonstrate pathological gait patterns, the entire foot or the toes contact the ground initially.) IC ends when the contralateral toe is lifted, when the opposite extremity leaves the ground.

Thus, loading response corresponds to the gait cycle's first period of double limb support.

- Midstance: begins with contralateral toe off and ends when the centre of gravity is directly over the reference foot.
- Terminal stance: begins when the centre of gravity is over the supporting foot and ends when the contralateral foot contacts the ground. During terminal stance, at approximately 35% of the gait cycle, the heel rises from the ground.
- Preswing: begins when the contralateral toe makes initial contact and ends at toe off, at approximately 60 per cent of the gait cycle. Thus, preswing corresponds to the gait cycle's second period of double limb support.
- Initial swing: begins at toe off and continues until maximum knee flexion occurs.
- Midswing: This is the period during which maximum knee flexion is reached and lasts until the tibia is vertical or perpendicular to the ground.
- Terminal swing: begins when the tibia is vertical and ends at initial contact.

4.1.1.2 Eight phases in gait cycle

Eight phases are divided in a gait cycle in (Kerrigan et al. 1998): Initial Contact, Loading Response, Midstance, Terminal Stance, Pre-swing, Initial Swing, Mid-Swing and Terminal Swing. Fig. 4.2 illustrates these eight phases.

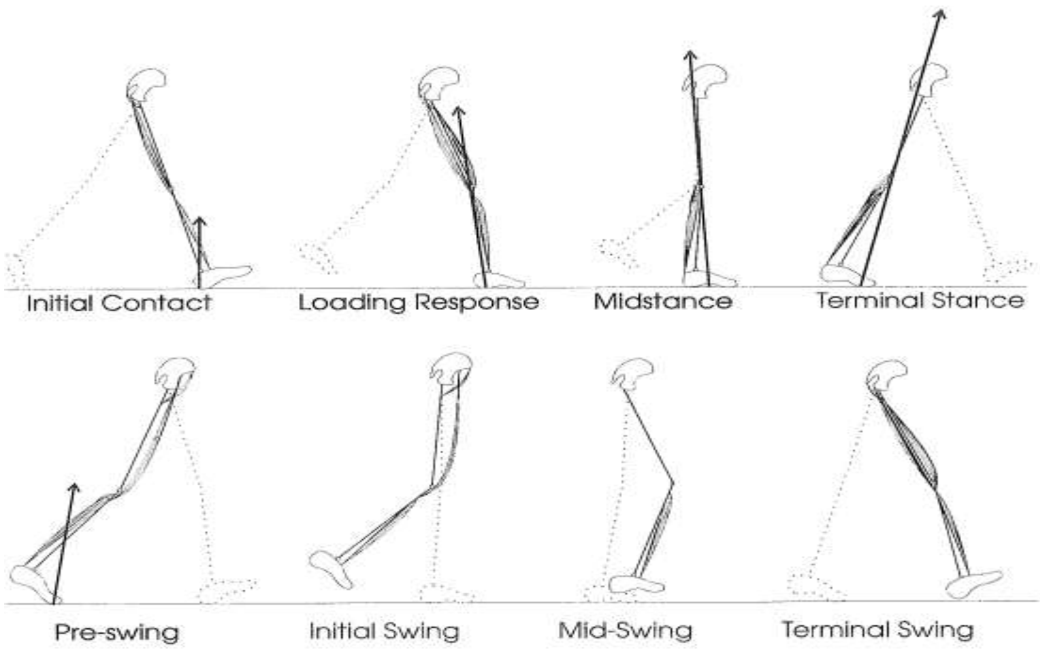


Fig. 4.2 The eight phases of the gait cycle (Kerrigan et al. 1998)

The first three phases in 4.1.1.1 were divided into four phases in section 4.1.1.2. The initial contact phase was added as the first phase in the gait cycle.

In (Inman & et al. 1981), the gait cycle is divided into eight phases as shown in Fig. 4.3. This division of phases is similar to that shown in Fig. 4.2.

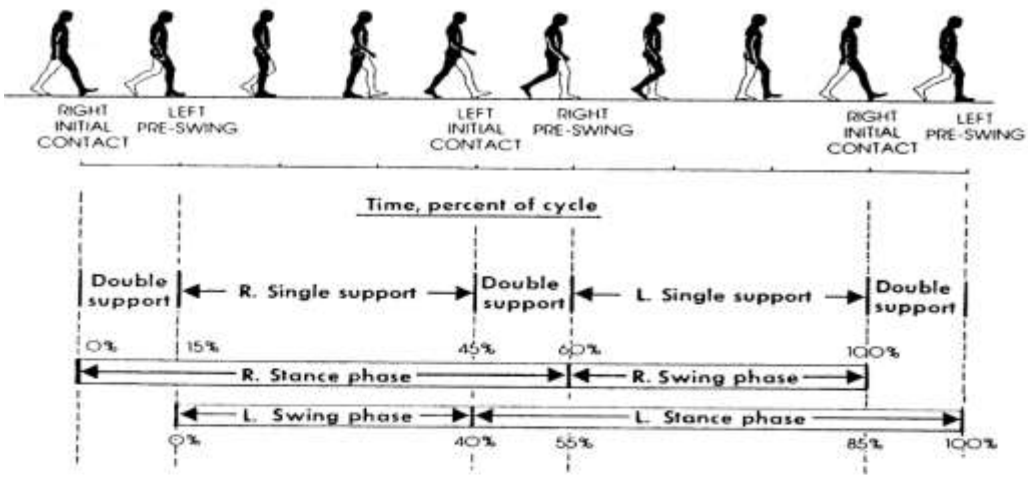


Fig. 4.3 Gait cycle over time (Inman & et al. 1981)

4.1.1.3 Four phases in gait cycle

One gait cycle is divided into four phases in (Pappas et al. 2001). These phases are defined as follows:

- Stance phase: the period when the foot is with its entire length in contact with the ground (angular velocity = 0).
- Heel-off phase: the period following the stance phase during which the front part of the foot is in contact with the ground and its heel is not.
- Swing phase: the period when the foot is in the air (not in contact with the ground) and swings forward.
- Heel-strike phase: the period following the swing phase, which begins with the first contact of the foot with the ground (usually the heel, but not necessarily) and ends when the entire foot touches the ground.

4.1.2 Gait cycle and phases in this research

The traditional definition of the gait cycle is the time interval or sequence of motion occurring from heelstrike to heelstrike of the same foot (DeLisa 1998). Gait cycle consists of a right stance phase and a right Swing phase. The right stance phase included two double support phases and a right single support phase. This way of dividing the gait cycle is good for tracking the same foot's trajectory from motion tracking view; however, the gait cycle is not a centrosymmetric movement cycle. The gait cycle is defined by one same foot's stance phase and swing phase. The stance phase occupies almost 65% of the gait cycle, and the swing phase only occupies approximately 35% of the gait cycle.

In this study, the gait cycle was divided to analyse the movement of the human body movement during the gait cycle and compared the functions of the two legs according to each respective single support phase. The gait cycle was divided in terms of supporting legs and swing legs. Thus, in this chapter, a different gait cycle and gait phases dividing method was proposed. Fig. 4.3 is a clearer gait cycle example than Fig. 4.1. Fig. 4.3 shows one gait cycle and one more phase over time. The traditional gait cycle lasts from the right initial contact posture to the next right initial contact posture. It is composed of a right stance phase (double support phase--right single support phase--double support phase) and right swing phase (left single support phase and double support phase). The gait cycle in this study lasts from the left toe-off posture to the next left toe-off posture, which begins with right single support, followed by double support, and left single support, and ends with double support. They gait cycle in this study is completely symmetrical about the middle of the cycle, as illustrated in Fig. 4.4.

The gait cycle in Fig. 4.4 is divided into two symmetrical half cycles. The first cycle is composed of the right single support phase and double support phase, and the second cycle is composed of the left single support phase and double support phase. The two legs' functions are completely corresponding. Thus, the similarities and differences between the legs with respect to each single support phase and swing phase are easy to discern. The similarities and differences between the left and right sides of the human body can be determined by comparing the first and second cycle.

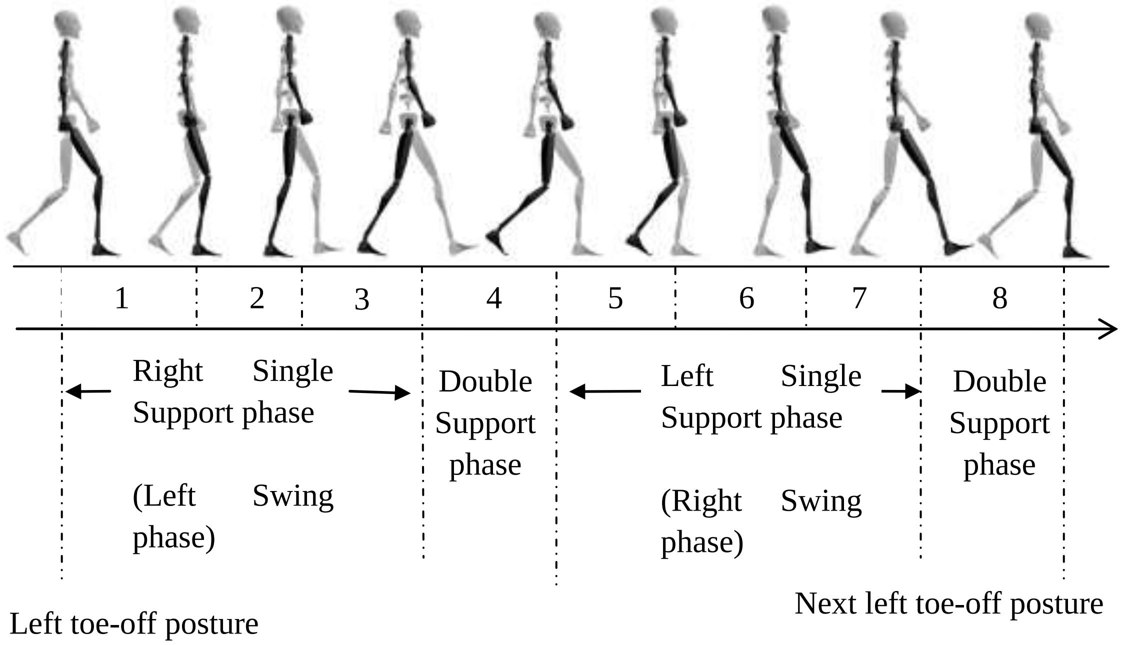


Fig. 4.4 Gait cycle and gait phase used in this research

A new gait cycle was defined as discussed above. The gait cycle starts with the right leg as the support leg, and the posture is left toe off; the cycle is completed at the next same posture. Each single support phase was divided into three shorter phases. Thus, the gait cycle features 8 gait phases. These gait phases as defined in detail as follows:

- 1. Left initial swing: begins with the left toe off of the ground and ends at the posture at which maximum left knee flexion occurs.
- 2. Left mid-swing phase: begins at the posture in which maximum left knee flexion occurs and ends at the posture at which the left tibia is vertical or perpendicular to the ground.
- 3. Left initial contact phase: begins at the posture at which the left tibia is vertical or perpendicular to the ground and ends at the posture at which the left heel makes initial contact with the ground.
- 4. Right pre-swing phase (Double support phase): begins at the posture at

which the left heel makes initial contact with the ground and ends at the right toe off posture.

- 5. Right initial swing phase: begins at the posture with the right toe off the ground and ends at the posture at which maximum right knee flexion occurs.
- 6. Right mid-swing phase: begins at the posture at which maximum right knee flexion occurs and ends at the posture at which the right tibia is vertical or perpendicular to the ground.
- 7. Right initial contact phase: begins at the posture at which the right tibia is vertical or perpendicular to the ground and ends at the posture at which right heel initial contact ground.
- 8. Left pre-swing phase (Double support phase): begins at the posture at which the right heel makes initial contact with the ground and ends at the left toe off posture.

The single support phase begins with the toe off posture and ends with this foot's initial contact posture according to this method of dividing gait cycle phases and methods in previous research. The double support phase is the same according both dividing methods. The difference between this method and the previous method is the gait phases in the single support phase. For example, the gait cycle starts with the right leg as the support leg. In the previous method, the right single support phase (left swing phase) was divided according to variations in the supporting leg‘s stance phase: loading response, mid-stance, terminal stance, etc. Additionally, the right swing phase was divided according to variations of the right leg's swing phase. Obviously, the phases in the right single support phase do not correspond to the right swing phases because two different criteria are used. In the dividing method used in this study, the right single support phase is divided according to variations of the left leg's swing phase: left initial swing phase, left mid-swing phase, left initial contact phase. Moreover, the right swing phase is divided according to variations in the right leg's swing phase: right initial swing phase, right mid-swing phase, right initial contact phase. Therefore, the phases in the right single support phase correspond to the phases in the right swing phase. Using this method of dividing gait phases, the gait cycle is symmetrical about the middle of the cycle. This method is not only suitable for comparing the corresponding stance/swing phases of the two feet, it is also suitable for analysing the similarity in gait between the left and right sides of the body. These eight phases compose two symmetrical half cycles of the swing/stance leg.

One complete gait cycle were selected for every subject which started in the same gait pose. Then, the gait cycle was normalized to the same frame numbers by linear interpolation. The details of the normalisation process were introduced in section 3.1.1.

The subjects were 35 males recruited from a British university. They were told to walk freely. Walking data were recorded by a motion capture system with 7 cameras. Forty markers were used for motion capture (Fig. 2.2). The camera recording speed was 120 frames/s for seven subjects, and 60 frames/s for other 28 subjects.

The same gait features discussed in chapter 4 were used to describe the subjects' gait. Thus, 15 features listed below were obtained. Any posture can be represented as $p = (F_1, F_2, \ldots, F_{15})^T$.

1. Head-Topspine angle,

2. Topspine-Root angle,

3-4. Elbow angle (left and right),

5-6. Knee angle (left and right),

7-8. Heel-Toe angle on y-axis (left and right),

9-10. Heel-Toe angle on z-axis (left and right),

11-12. Wrist-Shoulder angle on y-axis (left and right),

13-14. Wrist-Shoulder angle on z-axis (left and right),

15. Ratio of Wrist speed (left) to Wrist speed (right).

4.2 Data Analysis

The mean, SD of the mean value, maximum, and minimum were calculated in using the 15 gait features. The aim in this chapter is to analyse how gait phases affect these features. The time at which the maximum and minimum values of the features appeared in the gait cycle were investigated. The value of gait features varied even for the same subject. Emotion, gait speed, environment and many other factors will affect the value of gait features. Sometimes, a walker may change gaits on purpose. However, certain habits or so-called gait patterns are more difficult to change than the gait features' value, e.g., which phase will the subject lift his or her foot to the highest level from the ground during the gait cycle, swing his or her arms to the point farthest away from his or her body, raise his or her head to look around, etc. The coordinate mode of the whole body during the gait cycle is more difficult to change. The coordinate mode is the individual gait pattern which was investigated for the purpose of gait identification. In this study, the gait cycle was divided into 8 gait phases; each gait phase has an exact definition and meaning. Thus, the extrema of the gait features revealed the phase in which each subject's gait pattern appeared.

In Chapter 3, the values of gait features were analysed. In this chapter, the gait features' variation with respect to time is analysed. To analyse the time at which gait features' extrema occur, two pairs of variables were used to evaluate the extremum distribution. For any feature i, the frame number with maximum F_i and the frame number with minimum F_i were calculated and denoted as $(Frame_{\max,i}, Frame_{\min,i})$; the phase number with maximum F_i and the phase number with minimum F_i were calculated and denoted as $(Phase_{\max,i}, Phase_{\min,i})$. $(Frame_{\max,i}, Frame_{\min,i})$ will be abbreviated as $(Fr_{\max}, Fr_{\min})$, and $(Phase_{\max,i}, Phase_{\min,i})$ will be abbreviated as $(P_{\max}, P_{\min})$. These two pairs of variables were compared between different gait cycles of different subjects. The first pair of variables is $(Fr_{\max}, Fr_{\min})$. The second pair of variables is $(P_{\max}, P_{\min})$. $(Fr_{\max}, Fr_{\min})$ is too small in dimension to be applied in practice. In theory, the time at which gait features' extrema appear should be limited to a small time interval because the gait cycle of each individual has its own pattern. However, it is very often found that $(Fr_{\max}, Fr_{\min})$ varies even for the same person. Moreover, it is nearly impossible that $(Fr_{\max}, Fr_{\min})$ is the same among different people, as demonstrated by the calculated results. $(Fr_{\max}, Fr_{\min})$ is nearly unrepeatable for each gait. Thus, some improvements were made to evaluate the gait features' extremum distribution.

Instead of using frame numbers to denote when the maximum and minimum value of a feature occurred in the gait phases, a percentage denoted as $(F\_P_{\max,} F\_P_{\min})$ was used. For example, if the maximum value of a gait feature occurred at Frame Number 135, and the phase it belonged to is from Frame Number 100 to 200, then the $F\_P_{\max}$ will be 35%. Thus, $(F\_P_{\max,} F\_P_{\min})$

was used instead of (Fr_{max}, Fr_{min}). F_P_{max} denotes the percentage of a gait phase completed when Fr_{max} occurs. The same applies for Fr_{min}. For example, for subject j, feature i, Fr_{max} is n and Fr_{min} is m, the gait phase during which Fr_{max} occurs is from frame a to frame b, and the gait phase during which Fr_{min} occurs is from c to d. Thus, $F\_P_{max} = \frac{n-a}{b-a} \cdot 100\%$, and $F\_P_{min} = \frac{m-c}{d-c} \cdot 100\%$. Gait phases were divided by the legs' movement function. The number of frames contained in one gait phase varied between different subjects. Thus, (P_{max}, P_{min}) could be different even if (Fr_{max}, Fr_{min}) is the same. $(F\_P_{max,} F\_P_{min})$ avoided the problem of using frame numbers, which are too small and have no specific meanings; on the other hand, it provided a useful tool to study the locations at which the maximum and minimum values of gait features occurred during the gait phases and made the comparisons between different subjects much easier. $(F\_P_{max,} F\_P_{min})$ provided more detailed temporal information in conjunction with (P_{max}, P_{min}).

In the next sections, $(F\_P_{max,} F\_P_{min})$ and (P_{max}, P_{min}) will be analysed of 15 features one by one.

4.2.1. Head-Topspine angle and Topspine-root angle

Head-top spine angle and top spine-root angle were observed to be stable over one gait cycle. Fig. 4.5 is a typical figure for these two angles. For most subjects, this figure shows that the angle curve does not change very much with time. The red curve indicates the head-top spine angle, and the blue curve indicates the top spine-root angle. x axis denotes frame numbers, y axis denotes angles, and the vertical line in figure denotes the dividing frame between gait phases.

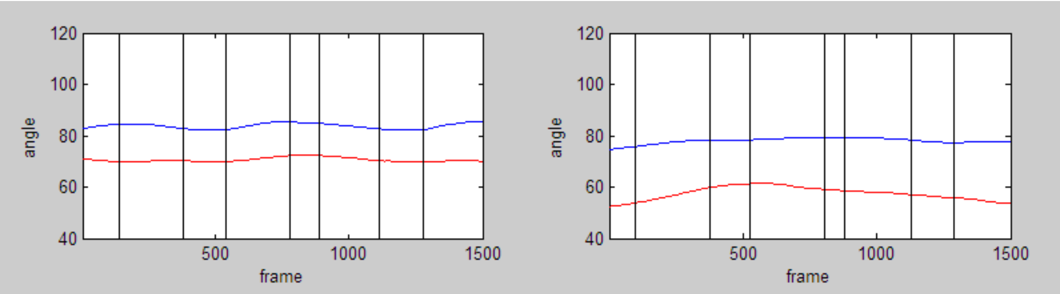


Fig. 4.5 Head-Topspine angle and Topspine-Root angle

The detailed values of the gait features were calculated in Chapter 4, and the average SD on all 70 gait files is only 1.75 for Head-Topspine angle, 1.12 for Topspine-Root angle. Because these two data sets did not show very much variation between different gait phases, the data regarding $(F\_P_{\max,} F\_P_{\min})$ and $(P_{\max}, P_{\min})$ for the two sets will not be analysed any further.

4.2.2. Knee angle

The left knee angle and right knee angle were calculated. The knee angle is defined by three markers: the thigh, knee and heel. Typical knee angle curves are illustrated in Fig. 4.6. x axis denotes frame numbers, y axis denotes angles, and the vertical line in figure denotes the dividing frame between gait phases.

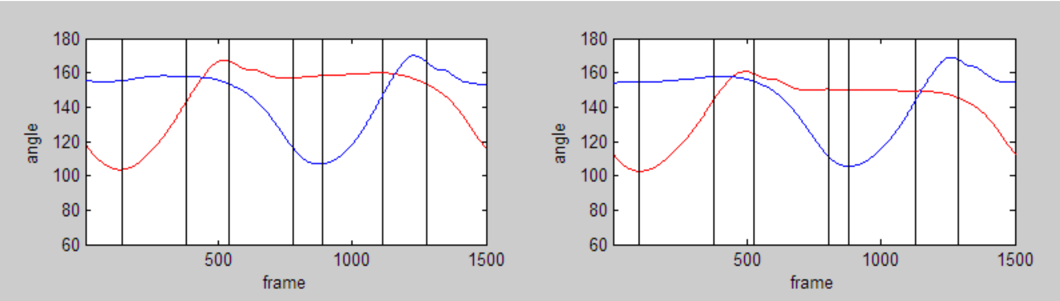


Fig. 4.6 Knee angles (red: left knee angles, blue: right knee angles)

The shapes of the curves of other subjects are similar to those shown in Fig. 4.6. The details of the curves are different between subjects according to their different walking habits.

By the definition of gait phases, Fr_{min} of the left knee angle must be the posture in which gait phase 2 (left mid-swing phase) started and Fr_{min} of the right knee angle must be the posture in which gait phase 6 (right mid-swing phase) started. Thus, for the knee angles, only the gait phase and the percent of the gait phase completed when Fr_{max} is reached need to be calculated.

P_{max} of the left knee angle is concentrated in phase 3. Excluding 2 subjects whose P_{max} occurred in phase 4, there were 94.29% of 35 subjects whose P_{max} occurred in phase 3. P_{max} of the right knee angle is concentrated in phase 7 or 8. The details of P_{max} are listed in Table 4.1. The column named 'per cent of subject' indicates the percentage of the subjects whose maximum or minimum occurred in the corresponding gait phases of all of the subjects.

left knee angle	P max	per cent of subject
	3	94.29%
	4	5.71%
right knee angle	P max	per cent of subject
	7	80.00%
	8	20.00%

Table 4.1 The distribution of P_{max} of knee angle.

Only F_P_{max} will be considered because F_P_{min} is equal to zero. The minima in the left knee angles all occurred in the starting frame of phase 2; the minima in the right knee angles all occurred in the starting frame of phase 6. Table 4.2 shows the data gathered for all subjects.

id	Left Knee		Right Knee	
	P_max	P_F max	P_max	P_F max
1	3	90.57%	7	76.65%
2	3	87.25%	7	87.18%
3	3	75.38%	7	89.40%
4	3	98.46%	7	99.29%
5	3	80.28%	7	79.11%
6	4	0.00%	8	0.00%
7	3	95.51%	7	81.72%
8	3	74.39%	7	77.50%
9	3	87.50%	7	82.08%
10	3	97.08%	7	97.20%
11	3	69.92%	8	2.31%
12	3	71.05%	7	98.73%
13	3	90.97%	7	73.51%
14	3	73.81%	7	77.96%
15	3	89.68%	8	2.62%
16	8	10.65%	8	0.93%
17	3	89.41%	7	94.44%
18	4	3.30%	7	90.36%
19	3	85.59%	7	40.00%
20	3	71.43%	7	55.38%
21	3	80.67%	8	2.01%
22	3	73.98%	7	48.81%
23	3	81.60%	7	56.25%
24	3	66.18%	7	80.00%
25	3	60.32%	8	1.70%
26	3	77.57%	7	76.29%
27	3	67.01%	8	6.85%
28	3	81.90%	7	47.79%
29	3	64.03%	7	51.67%
30	3	84.26%	7	81.82%
31	3	32.94%	7	50.81%
32	3	93.55%	7	97.44%
33	3	71.72%	7	52.03%
34	3	75.86%	7	58.57%
35	3	77.98%	7	62.71%

Table 4.2 F_P_{max} distribution of Knee angles

4.2.3. Elbow angle

The elbow angle is defined by the bicep, elbow and wrist. While the knee angle is an indicator for leg motion during the gait cycle, the elbow angle is an indicator for arm motion during the gait cycle. Elbow angle curvesed they show much greater variations in shape between different subjects than knee angle curves. This is illustrated in Fig. 4.7.

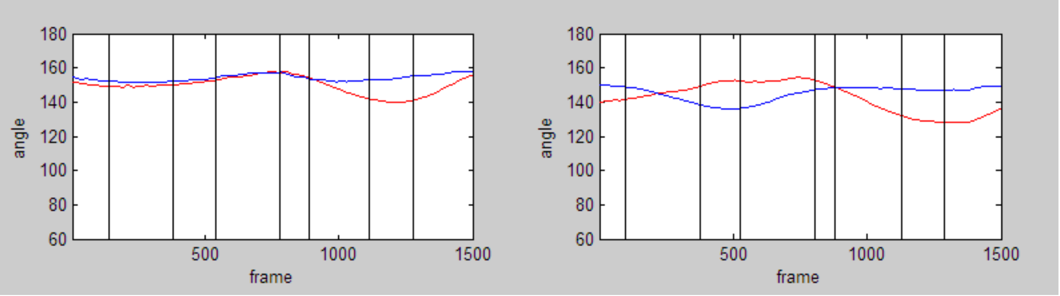


Fig. 4.7 Elbow angles (red: left elbow angles, blue: right elbow angles)

The elbow angles were calculated to investigate the habits of arm motion exhibited while walking. The motions of the arms are less focused than those of the knees which showed in Table 4.3. In other words, elbow angles have more freedom with respect to gait phases than knee angles.

The maximum left elbow angles $P_{\max}$ were concentrated in phases 4 and 5. The minimum left elbow angles were concentrated in phase 7 and 8. The percentage of subjects whose $(P_{\max}, P_{\min})$ for left elbow angles occurred in the most concentrated gait phases was (57.14%, 48.57%). The maximum right elbow angles $P_{\max}$ were concentrated in phases 1 and 8. The minimum right elbow angles were focused in phases 3 and 8. The percentage of subjects whose maximum and minimum right elbow angles occurred in the most concentrated gait phases was (54.29%, 65.71%). The most concentration degree was used to denote indicates the probability of P_{max} occurring in the most concentrated gait phase for all subjects, and the probability of P_{min} occurring in the most concentrated gait phase for all subjects. The most concentration degree is (57.14%, 48.57%) for left elbow angle, and (54.29%, 65.71%) for right elbow angle.

	P max	per cent of subject	P min	per cent of subject
left elbow angle	4	57.14%	8	48.57%
	5	25.71%	7	37.14%
	8	5.71%	2	5.71%
	2	5.71%	1	2.86%
	3	2.86%	3	2.86%
	1	2.86%	6	2.86%
right elbow angle	P max	per cent of subject	P min	per cent of subject
	1	54.29%	3	65.71%
	8	28.57%	8	20.00%
	5	8.57%	2	8.57%
	7	5.71%	1	2.86%
	6	2.86%	5	2.86%

Table 4.3 The distribution of $\left(P_{max}, P_{min}\right)$ of elbow angles

The $(F\_P_{max,} F\_P_{min})$ values of the elbow angles are listed in Table 4.4.

id	Left elbow angle				Right elbow angle			
	P_max	P_min	F_P max	F_P min	P_max	P_min	F_P max	F_P min
1	5	7	21.62%	55.69%	8	2	91.93%	22.08%
2	4	8	77.06%	18.22%	1	3	0.00%	61.74%
3	5	7	60.61%	37.75%	1	4	16.95%	13.19%
4	4	7	91.32%	42.14%	1	4	13.24%	7.85%
5	4	8	95.48%	15.53%	1	3	34.67%	95.07%
6	5	2	22.41%	87.61%	7	1	50.00%	50.00%
7	4	7	85.57%	17.20%	1	3	0.00%	41.03%
8	4	3	90.25%	60.37%	8	4	76.41%	1.69%
9	4	2	79.60%	19.45%	5	3	52.46%	87.50%
10	5	8	0.00%	16.94%	8	4	90.50%	7.85%
11	4	8	50.60%	24.07%	8	3	88.89%	51.22%
12	4	8	81.55%	11.24%	1	3	18.21%	98.42%
13	5	8	21.19%	2.63%	8	4	87.89%	21.55%
14	8	7	99.48%	32.80%	7	3	89.78%	73.81%
15	4	7	96.73%	64.74%	5	8	18.42%	55.90%
16	3	1	65.00%	0.00%	1	3	0.00%	65.00%
17	4	7	75.81%	20.37%	8	2	74.79%	93.10%
18	5	7	3.90%	65.06%	1	3	0.00%	1.27%
19	4	7	90.00%	40.00%	6	3	73.64%	29.73%
20	5	7	8.90%	55.38%	1	3	0.00%	3.17%
21	4	8	81.13%	1.51%	1	3	0.00%	25.21%
22	4	7	91.62%	47.62%	8	3	56.90%	21.95%
23	4	8	56.40%	12.17%	1	3	0.00%	62.40%
24	4	8	45.85%	26.56%	1	3	0.00%	83.09%
25	4	8	49.44%	40.85%	1	3	0.00%	60.32%
26	4	8	47.41%	0.00%	1	3	0.00%	77.57%
27	4	8	49.53%	43.95%	1	3	0.00%	67.01%
28	4	8	62.28%	12.58%	1	3	0.00%	81.90%
29	2	8	87.11%	5.58%	8	4	43.26%	26.13%
30	5	8	11.43%	3.74%	8	4	80.84%	11.27%
31	8	6	66.96%	55.48%	8	2	73.13%	82.59%
32	1	7	0.00%	51.28%	5	3	18.58%	15.05%
33	4	8	71.10%	5.05%	1	3	0.00%	87.59%
34	2	7	38.68%	27.14%	1	3	0.00%	45.52%
35	5	8	6.16%	0.55%	1	3	0.00%	15.60%

Table 4.4 $(F\_P_{max,} F\_P_{min})$ distribution of elbow angles

4.2.4. Heel-toe angle on y-axis and z-axis

This feature is related to the habits expressed by a walker's feet during the gait cycle.

4.2.4.1 Heel_toe_y angles

The curves of the heel-toe angles on the y-axis were rarely similar among the 35 subjects. In some cases, they showed nearly the same shape but different position. In other cases, their shapes were also different (Fig. 4.8).

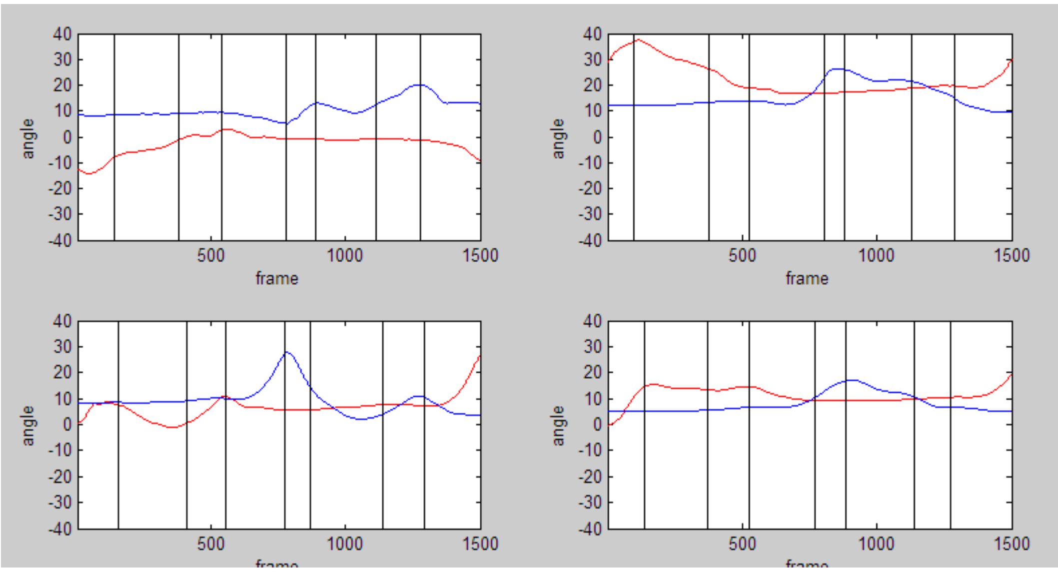


Fig. 4.8 Heel-toe angle on y-axis (red: left Heel_toe_y, blue: right Heel_toe_y)

The phase in which the maximum left heel-toe angle on y-axis is concentrated in phases 1 and 8. The minimum left heel-toe angle on y-axis is concentrated in phase 1. The percentage of maximum and minimum angles $(P_{\max}, P_{\min})$ occurring in these phases is (51.43%, 45.71%). Thus, the most concentration degree is (51.43%, 45.71%) for left heel-toe angle on y-axis.

Such angles for the right foot were calculated as well. The maximum heel-toe angle on the y-axis belongs is concentrated in phase 5. The phases during which the minimum angle occurred are less concentrated. The most concentration degree is (74.29%, 31.43%) for right heel-toe angle on y-axis.

The right heel_toe_y angles were more concentrated than their left counterparts with respect to $P_{\max}$ and $P_{\min}$. The maximum heel_toe_y angles were more concentrated than the minimum heel_toe_y angles. The minimum right heel_toe_y angles were distributed over several different phases. This result indicates that $P_{\min}$ has a weaker relationship with the gait phases than $P_{\max}$ and also suggests that $P_{\min}$ varies more greatly among different individuals than $P_{\max}$, and the left heel_toe_y angles are more characteristic of individiduality than the right angles.

	P max	per cent of subject	P min	per cent of subject
left heel_toe angle on y-axis	1	51.43%	1	45.71%
	8	20.00%	8	20.00%
	3	14.29%	4	14.29%
	2	11.43%	2	8.57%
	4	2.86%	5	8.57%
			6	2.86%
	P max	per cent of subject	P min	per cent of subject
right heel_toe angle on y-axis	5	74.29%	8	31.43%
	6	11.43%	1	22.86%
	7	11.43%	4	17.14%
	8	2.86%	6	17.14%
			5	8.57%
			2	2.86%

Table 4.5 $\left(P_{\max}, P_{\min}\right)$ distribution of Heel_toe_y axis

Table 4.6 showed the distribution of $(F\_P_{\max,} F\_P_{\min})$.

id	Left heel_toe_y angle				Right heel_toe_y angle			
	P_max	P_min	F_P max	F_P min	P_max	P_min	F_P max	F_P min
1	4	1	8.33%	25.18%	8	5	5.83%	6.31%
2	2	4	6.83%	77.06%	5	8	46.58%	99.53%
3	8	1	99.59%	66.95%	7	1	76.82%	0.00%
4	3	1	66.92%	16.53%	5	6	37.27%	80.97%
5	8	2	99.51%	76.56%	5	6	12.24%	73.41%
6	8	1	99.56%	0.00%	6	8	9.16%	99.56%
7	3	1	84.62%	16.35%	5	8	25.81%	99.59%
8	8	1	99.49%	0.00%	7	5	20.00%	20.00%
9	2	1	91.81%	42.96%	6	4	0.00%	72.00%
10	8	1	99.59%	71.34%	7	5	65.73%	33.33%
11	3	1	88.62%	0.00%	6	4	8.21%	88.05%
12	1	1	87.72%	0.00%	6	4	7.94%	44.64%
13	8	2	99.47%	80.93%	5	6	22.03%	81.91%
14	3	1	83.81%	39.62%	5	6	39.05%	74.22%
15	2	4	0.00%	21.03%	5	1	64.91%	85.92%
16	8	2	99.54%	54.59%	7	1	87.01%	55.44%
17	1	1	83.90%	0.00%	5	1	60.20%	33.05%
18	1	5	83.46%	59.09%	5	1	72.73%	0.00%
19	1	1	85.62%	0.00%	5	2	57.14%	0.00%
20	1	1	86.18%	0.00%	5	1	55.48%	42.76%
21	1	1	86.18%	0.00%	5	8	42.86%	99.50%
22	1	5	71.71%	21.17%	5	4	52.55%	6.70%
23	1	8	50.70%	24.34%	5	8	60.98%	99.47%
24	1	5	66.67%	43.55%	5	8	62.10%	99.48%
25	1	8	92.00%	31.49%	5	1	67.38%	56.00%
26	1	8	42.95%	33.33%	5	8	45.97%	99.50%
27	1	6	50.00%	36.98%	5	8	68.49%	99.60%
28	1	8	66.67%	12.58%	5	8	43.44%	99.37%
29	1	4	50.00%	66.83%	5	4	40.44%	25.63%
30	3	8	84.26%	90.65%	5	6	26.43%	19.62%
31	2	8	5.12%	100.00%	5	4	42.31%	32.68%
32	1	8	71.88%	92.37%	5	6	67.26%	67.18%
33	1	4	59.32%	43.93%	5	1	48.91%	0.00%
34	1	4	57.79%	38.58%	5	8	55.56%	52.43%
35	1	1	99.27%	0.00%	5	8	53.42%	87.98%

Table 4.6 $(F\_P_{max,} F\_P_{min})$ distribution of Heel_toe_y axis

4.2.4.2 Heel_toe_z angles

The heel-toe angles on z-axis indicate foot placement on the z-axis while walking. The curves of the heel-toe angles on the z-axis are similar, which is unlike the irregularity observed for angles on the y-axis, likely because the former angles are more affected by the act of walking itself.

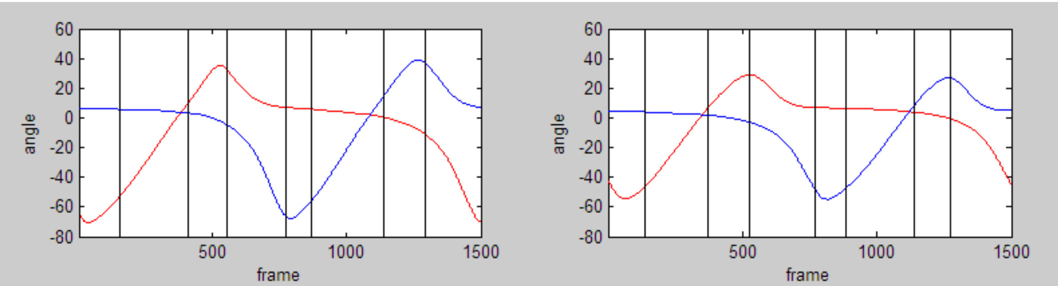


Fig. 4.9 Heel-toe angle on z-axis (red: left Heel_toe_z, blue: right Heel_toe_z)

P_{max} of left Heel-toe angle was concentrated on phase 3. P_{min} of left Heel-toe angle was concentrated on phase 1, or 8. P_{max} and P_{min} of the right Heel-toe angles are concentrated in phase 7 and phase 5, respectively. The subjects' heel-toe angles showed a very high concentration of P_{min} and P_{max} in these phases. Table 4.7 and Table 4.8 present the detailed results obtained for (P_{max}, P_{min}) and $(F\_P_{max,} F\_P_{min})$ details, respectively.

The maximum and minimum distributions of the left heel_toe_z angles are similar to those observed for the knee angles. This result suggests that the variation in the heel_toe_z angles over time is very closely related to the gait phases, especially P_{min} of the right heel_toe_z angles. The minimum heel_toe_z angle indicates that the toe is at the lowest level along the heel plane because it is negative. The concentrate degree is (88.57%, 80.00%) for left heel_toe_z angles, and (82.86%, 100%) for right ones.

The heel-toe angle on z-axis is highly correlated with the gait phases. The value of this gait feature varied between individuals; however, the time variation of this gait feature is mostly determined by act of walking.

left heel_toe angle on z axis	P max	per cent of subject	P min	per cent of subject
	3	88.57%	1	80.00%
	4	11.43%	8	20.00%
right heel_toe angle on z axis	P max	per cent of subject	P min	per cent of subject
	7	82.86%	5	100%
	8	17.14%		

Table 4.7 $(P_{\max}, P_{\min})$ distribution of Heel_toe_z axis

id	Left heel_toe_z angle				Right heel_toe_z angle			
	P_max	P_min	F_P max	F_P min	P_max	P_min	F_P max	F_P min
1	3	1	91.19%	50.36%	7	5	77.25%	6.31%
2	3	8	87.25%	99.53%	7	5	87.18%	19.18%
3	3	1	62.81%	50.00%	7	5	89.40%	40.40%
4	4	1	7.44%	33.88%	8	5	7.22%	37.27%
5	3	8	80.28%	99.51%	7	5	79.11%	12.24%
6	4	1	0.00%	50.00%	7	5	99.26%	41.38%
7	3	1	96.15%	17.31%	7	5	81.72%	44.09%
8	3	8	75.00%	99.49%	7	5	77.50%	20.00%
9	3	8	87.50%	99.53%	7	5	82.08%	21.31%
10	3	1	97.08%	28.66%	8	5	7.44%	49.63%
11	3	1	69.92%	33.33%	8	5	2.31%	18.39%
12	3	1	98.95%	38.01%	7	5	98.73%	33.33%
13	3	8	87.74%	99.47%	7	5	88.08%	40.68%
14	3	1	84.29%	19.81%	7	5	89.78%	20.00%
15	4	1	1.87%	42.96%	8	5	2.62%	29.82%
16	3	8	78.75%	99.54%	7	5	87.66%	32.81%
17	3	1	89.41%	50.00%	7	5	94.44%	20.41%
18	4	1	3.30%	49.61%	7	5	66.27%	59.09%
19	3	1	85.59%	56.85%	7	5	10.00%	36.73%
20	3	1	54.76%	57.24%	7	5	23.08%	40.41%
21	3	1	79.83%	43.42%	7	5	66.67%	41.96%
22	3	1	73.98%	42.76%	7	5	48.81%	52.55%
23	3	1	81.60%	33.80%	7	5	56.25%	42.28%
24	3	1	66.18%	33.33%	7	5	80.00%	42.74%
25	3	1	60.32%	36.80%	8	5	1.70%	51.06%
26	3	1	77.57%	42.95%	7	5	76.29%	28.23%
27	3	1	67.01%	33.33%	8	5	6.85%	36.99%
28	3	1	81.90%	33.33%	7	5	47.06%	42.62%
29	3	1	64.03%	37.65%	7	5	51.67%	39.71%
30	3	1	65.74%	50.00%	7	5	81.82%	41.43%
31	3	1	41.76%	19.74%	7	5	50.81%	26.92%
32	3	8	93.55%	99.58%	7	5	74.36%	19.47%
33	3	1	71.72%	39.83%	7	5	69.92%	48.18%
34	3	1	75.86%	57.14%	7	5	59.29%	34.34%
35	3	1	78.90%	49.64%	7	5	62.71%	53.42%

Table 4.8 $(F\_P_{max,} F\_P_{min})$ distribution of Heel_toe_z axis

4.2.5. Wrist-shoulder angles on y-axis and z axis

These 4 features represent the habits associated with arm motion during the gait cycle.

4.2.5.1 Wrist_shoulder_y angles

The curve shapes of the wrist-shoulder angles on y-axis were rarely similar, as shown in Fig. 4.10.

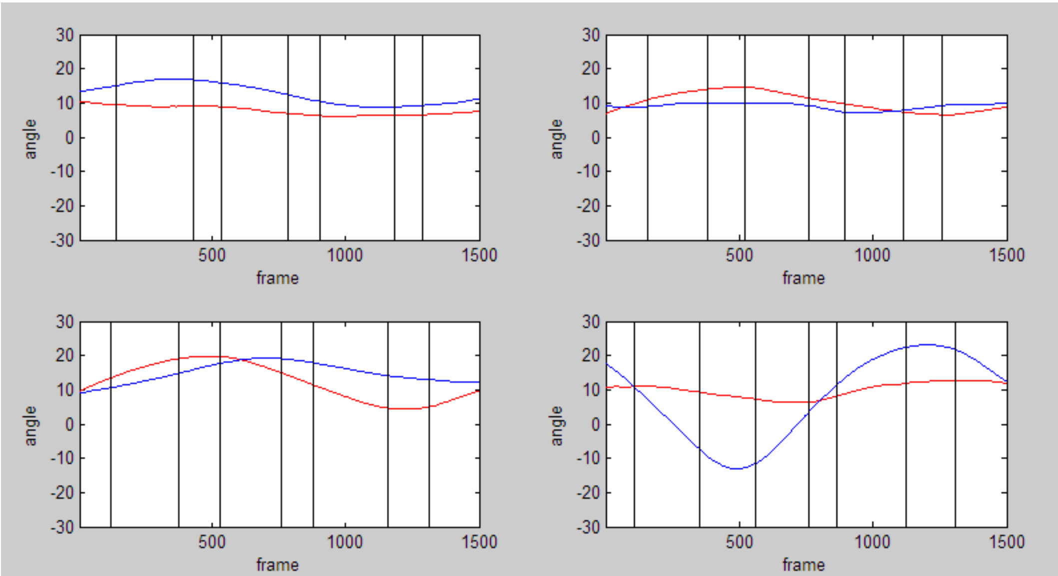


Fig. 4.10 Wrist_shoulder angles on y-axis (red: left Wrist_shoulder_y, blue: right Wrist_shoulder_y)

Compared with the features concerning the legs, the wrist-shoulder angles have fewer limits. Moreover, compared with the wrist-shoulder angles on the z-axis, the wrist-shoulder angles on the y-axis have more freedom on individuality.

P_{max} and P_{min} of the wrist-shoulder angles on the y-axis are not concentrated in any phase. They are distributed in as many as 6 or 7 phases. The highest degree of concentration of the left Wrist_shoulder_y angles is only (34.29%, 31.43%) and that of the right angles is (45.71%, 37.14%). Table 4.9 showed (P_{max}, P_{min})

distribution of Wrist_shoulder_y angles. $(F\_P_{\max,} F\_P_{\min})$ distribution of Wrist_shoulder_y angles were show in Appendix 3.

	P max	per cent of subject	P min	per cent of subject
left Wrist_shoulder angle on y-axis	8	34.29%	6	31.43%
	2	31.43%	4	28.57%
	3	17.14%	7	17.14%
	1	14.29%	5	14.29%
	5	2.86%	1	2.86%
			2	2.86%
			8	2.86%
	P max	per cent of subject	P min	per cent of subject
right Wrist_shoulder angle on y-axis	4	45.71%	8	37.14%
	6	34.29%	2	25.71%
	5	5.71%	1	22.86%
	1	5.71%	3	8.57%
	2	2.86%	6	5.71%
	3	2.86%		
	7	2.86%		

Table 4.9 $(P_{\max}, P_{\min})$ distribution of Wrist_shoulder_y angles

4.2.5.2 Wrist_shoulder_z angles

The curve shapes of the wrist-shoulder angles on the z-axis are similar in most cases. There were few subjects have significant difference in curve shapes, as shown in Fig. 4.11.

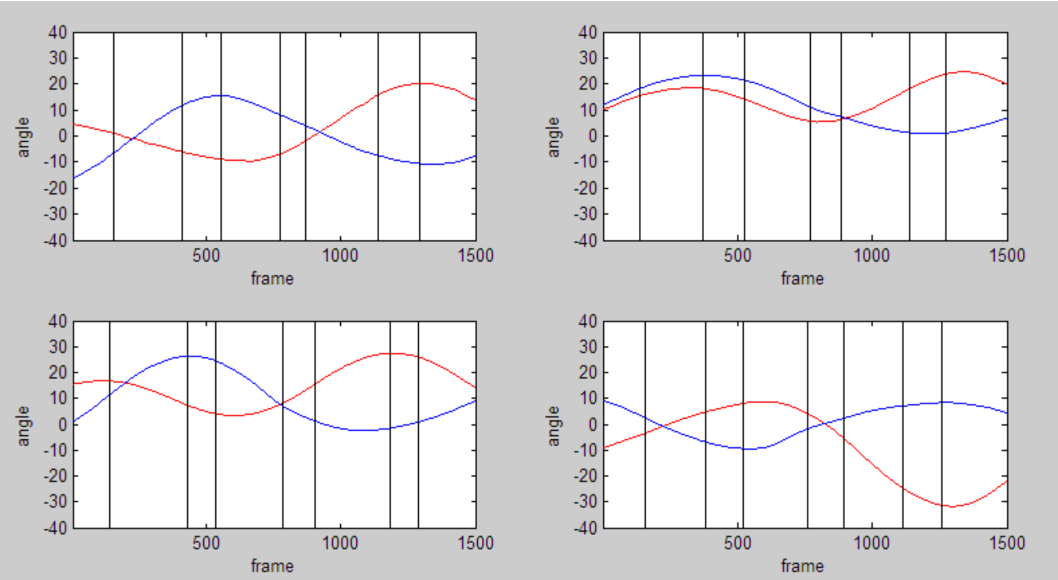


Fig. 4.11 Wrist_shoulder angles on z-axis (red: left Wrist_shoulder_z, blue: right Wrist_shoulder_z)

The minimum and maximum wrist_shoulder_z angles were more concentrated than the angles on the y-axis. Nearly half of all subjects' $P_{\max}$ occurred in phase 7 (left wrist_shoulder_z) and phase 3 (right wrist_shoulder_z), and $P_{\min}$ occurred in phase 4 (left wrist_shoulder_z). Details regarding $(P_{\max}, P_{\min})$ and $(F\_P_{\max}, F\_P_{\min})$ are shown in Table 4.10 and Appendix 3, respectively.

The concentration degree is (45.71%, 42.86%) for left wrist_shoulder_z angles, and (54.29%, 34.29%) for the right angles. The maximum and minimum wrist_shoulder_z angles were more concentrate than the wrist_shoulder_y angles in gait phases. This finding indicates that the features exhibit a greater degree of freedom/individuality on the y-axis than on the z-axis. $(F\_P_{max,} F\_P_{min})$ distribution of Wrist_shoulder_z angles were listed in Appendix 3.

	P max	per cent of subject	P min	per cent of subject
left Wrist_shoulder angle on z axis	7	45.71%	4	42.86%
	6	28.57%	3	34.29%
	8	22.86%	2	8.57%
	4	2.86%	8	5.71%
			1	5.71%
			5	2.86%
	P max	per cent of subject	P min	per cent of subject
right Wrist_shoulder angle on z axis	3	54.29%	8	34.29%
	2	22.86%	7	22.86%
	4	17.14%	6	20.00%
	1	2.86%	1	17.14%
	8	2.86%	3	2.86%
			4	2.86%

Table 4.10 (P_{max}, P_{min}) distribution of Wrist_shoulder_z angles

4.2.6. Wrist-speed ratio

The wrist-speed ratio is a novel feature which was proposed in this research and is defined as the ratio of the left wrist speed to the right wrist speed. Through motion capture data, it was found that most subjects swung their left arms and right arms at different speeds. Some subjects swung their left wrist much faster than their right wrist. The figure plotted for this feature shows a step line curve, as shown in Fig. 4.12.

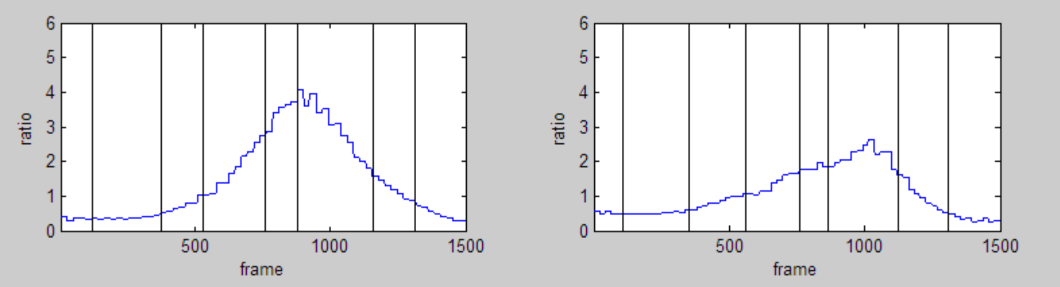


Fig. 4.12 Wrist speed ratio (left wrist speed/right wrist speed)

(P_{max}, P_{min}) of the wrist speed ratio showed a reasonable degree of concentration. The maximum wrist speed ratio was distributed in 3 phases: phases 6, 5,and 4. The minimum wrist speed ratio was less concentrated.

	P max	per cent of subject	P min	per cent of subject
Wrist speed ratio	6	57.14%	2	42.86%
	5	22.86%	8	31.43%
	4	20.00%	1	22.86%
			6	2.86%

Table 4.11 (P_{max}, P_{min}) distribution of Wrist speed ratio (left/right)

$(F\_P_{max,} F\_P_{min})$ distribution of Wrist speed ratio (left/right) were shown in Appendix 3.

4.2.7 Gait phase length

The percentage represented by each phase in the gait cycle is only an approximate value; there are no fixed rules for defining this value. This percentage varied among individuals. The gait phase length was also indicative of the walking habits of the subjects. The stance phase usually lasts approximately 65% of the cycle, the swing phase approximately 35% and each period of the double support phase approximately 10%.

In a previous study (Inman & et al. 1981), the right single support phase lasts 30% of the gait cycle, the left single support phase 40% of the gait cycle, and each double support phase 15% of the gait cycle. In (M.Nordin & Frankel 2001), the stance phase was observed to last 65% of the gait cycle and swing phase 35% of the gait cycle. This means that the single support phase last 35% of the gait cycle because one foot’s swing phase is the other foot's single support phase. In (Perry 1992), it was observed that the stance phase lasts 60% of the gait cycle, the swing phase lasts 40% of the gait cycle, and the double support phase lasts 10% of the gait cycle.

In this study, more detailed results were obtained. The duration of the right single support phase (36.24%) is nearly the same as that of the left single support phase (35.33%). The average duration of the double support phase is 14.22%. In other words, the left swing phase lasts 36.24% of the gait cycle and the right swing phase lasts 35.33% of the gait cycle. The right stance phase lasts 64.67% of the gait cycle. These results are more similar to those reported in (M.Nordin & Frankel 2001). The durations of the right single support phase (36.24%) and the following double support phase (14.48%) are slightly longer than those of the single support phase (35.33%) and the following double support phase (13.95%). Table 4.12 presents the average gait phases length, average single support length and average double support length. Table 4.13 presents the lengths of all gait phases for the 35 subjects.

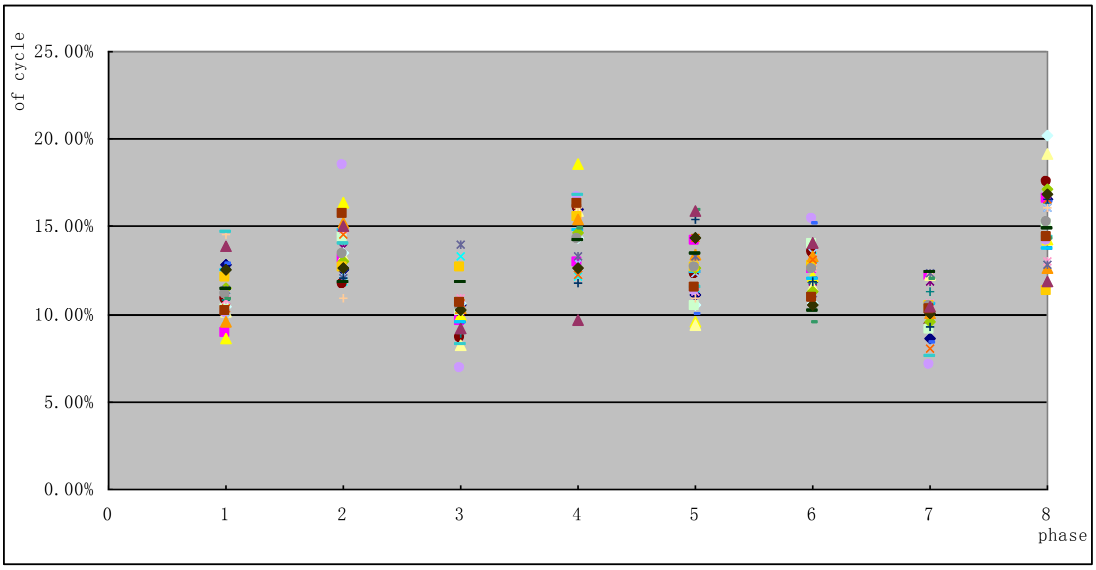


Fig. 4.13 Phase length of 35 subjects

phases	R. Single Support			Double Support	L. Single Support			Double Support
	1	2	3	4	5	6	7	8
average length	9.13 %	18.10%	9.02 %	14.48%	8.01 %	19.5 1%	7.81 %	13.95%
	36.24%			14.48%	35.33%			13.95%

Table 4.12 Average phase length over one gait cycle

1	2	3	4	5	6	7	8
9.27%	16.00%	10.60%	16.00%	7.40%	14.73%	11.13%	14.87%
6.53%	18.53%	9.93%	18.60%	4.87%	16.87%	10.40%	14.27%
7.87%	15.40%	13.27%	12.13%	6.60%	18.60%	10.07%	16.07%
8.07%	14.47%	8.67%	16.13%	10.73%	15.07%	9.33%	17.53%
10.13%	17.07%	9.47%	14.73%	6.53%	17.80%	10.53%	13.73%
9.07%	15.60%	10.20%	16.47%	7.73%	16.73%	9.07%	15.13%
6.93%	15.27%	10.40%	12.93%	6.20%	19.73%	12.40%	16.13%
9.20%	16.47%	10.93%	15.73%	7.67%	16.33%	10.67%	13.00%
9.00%	19.53%	6.93%	16.67%	8.13%	18.53%	7.07%	14.13%
10.47%	15.00%	9.13%	16.13%	9.00%	14.60%	9.53%	16.13%
9.40%	19.27%	8.20%	16.73%	5.80%	18.67%	7.53%	14.40%
11.40%	13.27%	12.67%	15.53%	8.60%	16.80%	10.47%	11.27%
7.67%	17.13%	10.33%	15.47%	7.87%	18.80%	10.07%	12.67%
7.07%	16.40%	14.00%	13.27%	7.00%	17.07%	12.40%	12.80%
9.47%	15.07%	10.33%	14.27%	7.60%	17.60%	10.40%	15.27%
12.87%	13.07%	10.67%	16.27%	8.53%	13.93%	10.27%	14.40%
7.87%	21.27%	5.67%	16.53%	6.53%	22.93%	3.60%	15.60%
8.47%	21.00%	5.27%	14.13%	10.27%	21.73%	5.53%	13.60%
9.73%	20.00%	7.40%	14.67%	6.53%	24.53%	4.67%	12.47%
10.13%	21.53%	8.40%	11.07%	9.73%	23.67%	4.33%	11.13%
10.13%	19.73%	7.93%	14.13%	7.47%	23.53%	3.80%	13.27%
10.13%	20.00%	8.20%	11.93%	9.13%	23.40%	5.60%	11.60%
9.47%	18.67%	8.33%	14.07%	8.20%	21.20%	7.47%	12.60%
9.40%	19.00%	9.07%	13.67%	8.27%	21.47%	6.33%	12.80%
8.33%	20.47%	8.40%	11.87%	9.40%	20.73%	5.13%	15.67%
10.40%	18.40%	7.13%	15.47%	8.27%	20.47%	6.47%	13.40%
9.20%	20.33%	6.47%	14.27%	9.73%	20.73%	2.73%	16.53%
9.20%	18.93%	7.00%	15.20%	8.13%	21.87%	9.07%	10.60%
10.80%	17.07%	9.27%	13.27%	9.07%	22.20%	4.00%	14.33%
10.93%	18.60%	7.20%	14.20%	9.33%	21.07%	4.40%	14.27%
5.07%	19.53%	11.33%	13.67%	6.93%	20.07%	8.27%	15.13%
8.53%	21.00%	6.20%	14.07%	7.53%	21.73%	5.20%	15.73%
7.87%	19.60%	9.67%	11.53%	9.13%	20.80%	8.20%	13.20%
10.27%	19.13%	9.67%	13.13%	6.60%	19.53%	9.33%	12.33%
9.13%	21.53%	7.27%	12.93%	9.73%	19.33%	7.87%	12.20%

Table 4.13 Gait phase lengths of 35 subjects

Fig. 4.13 shows the length of each phase for the 35 subjects. Phases 4 and 8 are double support phases, phases 1-3 are left swing phase/right single support phase, and phases 5-7 are right swing phases/left single support phase. Fig. 4.13 and Table 4.13 reveal notable differences within different subjects with respect to these variables. Some people prefer to stand on two legs for longer periods than others. Some people prefer to use a more near-vertical angle when their feet are in contact with the floor. By these characteristics that are hidden in people's walking habits, a specific individual's gait cycle can be described. For example, the double support phase length was often used to describe the features of elders' gait. Normally, this length should be longer in elders than in younger walkers. Although the subjects in this data sample were all young adults, the double support phase length still differed greatly, from 10.6% to 18.60%. The right single support phase length varied from 31.20% to 40.07%, and the left single support phase length varied from 32.00% to 39.07%.

Table 4.14 shows the SD of each gait phase of the 35 subjects. The gait phase length varied much more in phases 6, 7, and 2, 3 than in phases 1, 5. This means that in the single support phase, the length from the toe-off posture to the posture in which maximum knee flexion occurs varied less between different subjects. In other word, the time at which the tibia is vertical or perpendicular to the ground varied more between different subjects. This produced a high variation in the gait phase length of phases 2, 3 and 6, 7 because the posture in which tibia is vertical or perpendicular to the ground occurs at the end of gait phases 2 and 6 and at the beginning of gait phases 2 and 7.

Gait phase	1	2	3	4	5	6	7	8
SD	1.50	2.41	2.06	1.73	1.36	2.81	2.73	1.69

Table 4.14 SD of each gait phase length

4.3 Summary

4.3.1 Database of normalized gait data

In this study, the gait data were normalized by linear interpolation and were compared based on gait cycle and gait phases. Each gait cycle featured the same frame numbers for all subjects, which eliminated the effect of walking speed on different subjects. Walking speed is not a stable feature for individual identification because it is too easy to change. The gait pattern over the gait cycle is more stable than speed for a single subject. In this chapter, the location of certain postures that occurred during the gait cycle is the main focus. The normalized gait cycle made it easy to compare those locations in the corresponding gait cycles and phases of different subjects.

4.3.2 Clear gait cycle and gait phases definition

In previous research, the gait cycle was defined by the movement of one same foot; thus, the gait cycle was constructed according to one foot's stance phase and the same foot's swing phase. There were different ways of dividing the gait cycle into several phases. Seven phases and eight phases have been used in previous research. The name and definition of each gait phase may be different, but the phases also share much in common. Certain postures, such as the toe off posture and initial contact posture, were typically used as to separate gait phases. The criteria for defining gait phases are the variation in the supporting leg’s movement in the stance phase and the variation in the swinging leg in the swing phase. The advantage of these criteria is that they allow for the analysis of a single one same foot's movement over the gait cycle. The disadvantage is that the gait phases are not symmetrical about the middle of the cycle because it is divided by different criteria in stance phase and swing phase. Thus, it is difficult to analyse the corresponding movement of each support leg and swing leg.

In this study, novel definitions of the gait cycle and gait phases were proposed (section 4.1.2). The goal was to compare body's movement according to the corresponding stance phases/swing phases of two feet, instead of tracking the same foot's movement, as in previous research. The cycle was divided into eight phases: left initial swing phase, left mid-swing phase, left initial contact phase, double support phase (right pre-swing phase), right initial swing phase, right mid-swing phase, right initial contact phase, double support phase (left pre-swing phase). Each of the eight gait phases was clearly defined in section 4.1.2. These eight phases composed two half cycles symmetrical about the middle of the whole gait cycle.

4.3.3 Proposed indicators about the influence from gait phases

In the last chapter, 15 gait features were proposed to identify individuals. The identification results are better than those in previous reported research. In this chapter, the variation in the gait features over time is analysed. To investigate the time at which the gait features' maximum and minimum values occurred, two pairs of indicators were proposed to evaluate the extremum distribution. These indicators are denoted as $(P_{\max}, P_{\min})$ and $(F\_P_{\max}, F\_P_{\min})$.

Using these two pairs of indicators, the extremum distributions of the gait features on gait phases were analysed. These indicators were used to evaluate how the gait features of the various phases varied.

4.3.4 Some gait features have more individuality

According to the distribution of (P_{max}, P_{min}), gait features can be divided into two kinds. One kind of gait feature is highly correlated with the act of walking, which means that the (P_{max}, P_{min}) of such features are influenced very much by the gait phases. These features include the knee angles and heel_toe angles on z-axis because gait phases are defined by leg movement. The difference in these gait features between individuals affected the values of these features but not their appearance in the gait phases. The other kind of gait feature is not strongly influenced by gait phase. Such features include the elbow angles, heel_toe angles on y-axis, and wrist_shoulder angles on y-axis. The features associated with movement along the y-axis exhibit a higher degree of freedom and are more characteristic of individuality. The swinging of the arms connotes more individuality/freedom than the swinging of the legs during walking.

Thus, regarding the influence of gait phase on gait features, two important results were obtained: features associated with arm movement are more indicative of individuality than those associated with leg movement; and features associated with movement along the y-axis are more characteristic of individuality than those associated with movement along the z-axis.

4.3.5 Gait phase length between individuals

The lengths of the gait phases in one gait cycle vary because subjects' walking habits are different. More-detailed phase data for different subjects were obtained compared to those obtained in previous research. With respect to the average phase length, the right single support phase lasted 36.24% of the gait cycle, the left single support phase lasted 35.33% of the gait cycle, and the average double support phase lasted 14.22% of the gait cycle. Table 4.16, shows that the average right single support phase lasts 0.91% longer than the average left single support phase. The average length of phase 4 is 0.53% longer than the average length of phase 8.

The gait phase length varied greatly between different individuals. The double support phase length varied from 10.6% to 18.60%. The right single support phase length varied from 31.20% to 40.07%. The left single support phase length varied from 32.00% to 39.07%. Table 4.17 shows that the gait phase length varied much more in phases 6, 7, and 2, 3 than in phases 1, 5. This finding suggests that the time at which the tibia is vertical or perpendicular to the ground varied greatly between different subjects. The time at which maximum knee flexion occurred varied less between different subjects. The range of variation in the double support phase length was between the variations in these two postures.

Chapter 5 Gait analysis about Gait features via PCA and fixing root method

In chapter 3, two indicators were proposed to evaluate whether certain gait features were suitable for identification. These two indicators were referred to as Consistence degree and Variation degree. Consistence degree was used to evaluate whether a certain gait feature could remain stable between different gait cycles of the same subject. Variation degree was used to evaluate whether a certain gait feature varies noticeably between different people. These two indicators provided a novel quantitative tool to evaluate gait features, answering the question "why should these features be extracted from the gait", instead of only proposing a few gait features to use.

Although there have been many previous studies on the determination of which bodily features are the most important in gait analysis, the question regarding which features should be extracted from the human gait has not been convincingly answered. Previous studies rarely analysed or evaluated the reason why certain gait features are used, although many different gait features have been proposed in feature-based research. The analysis in Chapter 3 inspired the solution about how to evaluate the proposed gait features. In Chapter 4, the effects of gait phases on gait features were studied. In this chapter, the answer to the question "which should these features be extracted to represent gait and why" will be further investigated.

The analysis of gait features described in this chapter aimed to find which gait features should be extracted and analyse the effect of different body segments on gait. This analysis was divided into two parts. First, the average gait and PCA were used to analyse gait features. Second, the fixing root method and PCA were used to analyse the significance of the relative motion of different body segments with respect to gait.

5.1 Methods

5.1.1 Average gait

The data sample included 35 subjects: 28 subjects each had one gait file, and 7 subjects each had six gait files, which were captured at different times. After normalization by linear interpolation (section 3.1.1), each gait cycle featured the same frame numbers. Thus, 70 normalized gait cycles were obtained in total. The average gait is the mean gait of these 70 gait cycles.

The average gait was denoted as $G\_average$. It is a complete gait cycle, which includes 1500 frames. The 15 gait features (F_i) proposed in Chapter 3 were calculated for the average gait $G\_average$. Gait features for the average gait was denoted as follows:

$$F\_average = (F_1\_average, F_2\_average, ..., F_{15}\_average)$$

where $F_i\_average$, (i=1:15) indicates feature i for average gait $G\_average$.

Thus, $F\_average$ is a 1500x15 matrix.

5.1.2 PCA on average gait

PCA is a useful and common data reduction method and was applied to $F\_average$ to investigate the relationship between different gait features. The principle component PC_k is a linear combination of $F_i\_average$.

$$PC_k = \sum_{i=1}^{15} C_{i,k} F_i\_average$$ (5.1), *k* is determined by the PCA results.

This revealed the common weights of the 15 gait features over one gait cycle. Principal component analysis (PCA) is a mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables to a set of values of uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined such that the first principal component has as high a variance as possible (that is, it accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it be orthogonal to (uncorrelated with) the preceding components. Principal components are guaranteed to be independent if the data set is jointly normally distributed. PCA is sensitive to the relative scaling of the original variables.

PCA was invented in 1901 by Karl Pearson (Pearson 1901). Today, it is mostly used as a tool in exploratory data analysis and for creating predictive models. PCA can be performed by the eigenvalue decomposition of a data covariance matrix or singular value decomposition of a data matrix, usually after mean centring the data for each attribute. The results of a PCA are usually discussed in terms of component scores (the transformed variable values corresponding to a particular case in the data) and loadings (the weight by which each standardised original variable should be multiplied to obtain the component score).

5.1.3 Fixing Root method

In a separate study, the data sample was composed of 30 subjects. These subjects were thirty male students from a British university whose mean age was 20.83. The marker set was composed of 40 makers, as shown in Fig. 2.2. The subjects were told to walk freely and naturally at normal speed, from one end of the capture volume to the other, and to then walk back. The recorded Root marker (on the back of the upper middle of the pelvis) speed for the 30 subjects ranged from 666.16 mm/s to 1255.48 mm/s, with a mean of 1005.84 mm/s. The gait data for each subject covered one to two cycles without normalization.

Fixing root method is that through some coordinate transforming, subjects can be considered as walking at the starting point all the time, as if they have a fixed root. Root marker was assumed to be virtually fixed, almost as if the subjects were walking on a treadmill (but not exactly the same), which helped to analyse the relative motion of body segments instead of the trajectory of the whole body's movement. The root marker was located on the walker's lower back at the upper centre of the pelvis; see Fig. 2.2.

$M_i^j(t:x,y,z)$ was used to denote the coordinates of the marker *i* on subject *j* at frame number *t*. The Root marker was the 24th marker for every subject. $M_{24}^j(1:x,y,z)$ denotes the initial coordinates of the Root marker for subject *j*. When Root marker was fixed, every marker's new coordinates were obtained using the following formula.

$$Mfix_i^j(t:x,y,z) = M_i^j(t:x,y,z) - \left(M_{24}^j(t:x,y,z) - M_{24}^j(1:x,y,z)\right) \qquad j=1,\ldots,30; i=1,\ldots,40; t=1,\ldots,t_{end} \tag{5.2}$$

After obtaining the new coordinates of the markers, the speed and acceleration of all 39 markers were calculated except for the Root marker for every frame. Then, average speed of all frames was obtained for every marker for each subject. It was denoted as $\overline{Ms}_i^j$, where j denotes the subject number, and i denotes the marker number. Then, the following matrix was obtained:

$$\overline{Ms} = \begin{bmatrix} \overline{Ms}_1^1 & \overline{Ms}_2^1 & \cdots & \overline{Ms}_{40}^1 \\ \overline{Ms}_1^2 & \overline{Ms}_2^2 & \cdots & \overline{Ms}_{40}^2 \\ \cdots & \cdots & \cdots & \cdots \\ \overline{Ms}_1^{30} & \overline{Ms}_2^{30} & \cdots & \overline{Ms}_{40}^{30} \end{bmatrix}_{30\times 39} \tag{5. 3}$$

$\overline{Ms}$ is the average speed matrix of the 39 markers (except Root) for the 35 subjects. Thus, only 39 markers were left instead of 40 markers. The 24th marker (Root) was removed because its displacement, speed and acceleration were all zero after fixing the Root marker. An example of a subject's gait after fixing the Root marker is shown in Fig. 5.1.

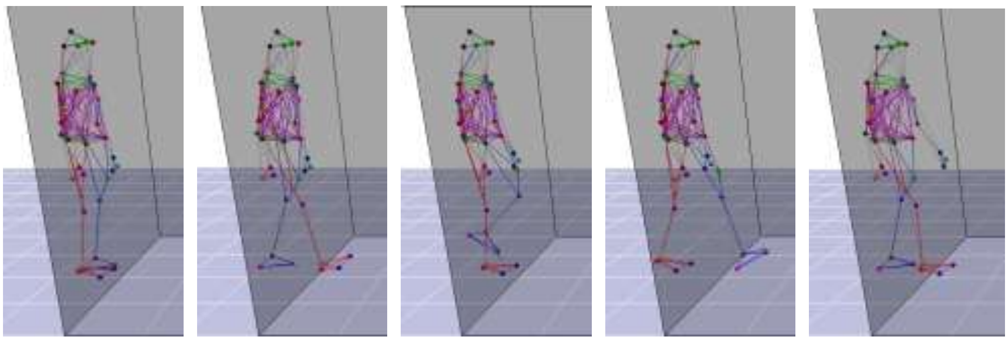


Fig. 5.1 An example of a subject with fixed Root marker

5.1.4 PCA with Fixing Root method

The method of fixing the Root marker was applied to obtain more information about the subjects' gaits. Gait speed is always one of the features used in gait analysis. The relative motion of different body segments may reflect more useful information than walking speed. For this reason, the fixing root method was used. The effect of walking speed was nearly eliminated after fixing the Root markers, thus gait data should focus on relative movement of each segment of the human body and reflect the signature of each gait pattern.

PCA analysis was applied on $\overline{\overline{Ms}}$ to investigate which markers are the most important as gait features. This revealed the relationship between the 40 markers on the 30 subjects. With the PCA results, it can be analysed that which segments are the most important to relative motion during the gait cycle.

5.2 Results

5.2.1 PCA on average gait

Four principle components were extracted after applying PCA on $F\_average$. The results of principle components are shown in Table 5.1. Four principle components occupied 95.16% of the variance in the gait data before PCA, meaning that these four principle components can represent the original gait data very well.

Total Variance Explained						
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.29	41.95	41.95	6.29	41.95	41.95
2	3.77	25.12	67.07	3.77	25.12	67.07
3	2.99	19.91	86.98	2.99	19.91	86.98
4	1.23	8.18	95.16	1.23	8.18	95.16

Extraction Method: Principal Component Analysis.

Table 5.1 Four principle components of average gait

Thus, equation (5.1) becomes (5.3):

$$PC_k = \sum_{i=1}^{15} C_{i,k} F_i\_average, \quad k{=}1{:}4 \qquad (5.3)$$

Table 5.2 shows the coefficients $C_{i,k}$ for PC_k, in equation (5.3), and Table 5.3 shows the coefficients $C_{i,k}$ after sorting in descending order for each PC_k.

Features	Coefficients of Principle Components			
	Pc1	Pc2	Pc3	Pc4
1	0.68	0.22	0.06	0.64
2	0.57	0.60	0.15	0.49
3	0.48	-0.42	-0.73	0.23
4	0.03	0.98	-0.19	-0.01
5	0.52	-0.37	0.75	0.04
6	-0.81	-0.18	0.45	0.24
7	-0.71	-0.14	-0.50	-0.30
8	0.76	0.26	-0.10	-0.35
9	0.42	-0.61	0.66	-0.08
10	-0.78	-0.04	0.61	0.00
11	-0.91	0.17	-0.18	0.23
12	0.89	-0.19	0.31	-0.21
13	-0.11	0.78	0.56	-0.26
14	0.06	-0.96	-0.22	0.12
15	0.91	0.14	-0.26	-0.23

Extraction Method: Principal Component Analysis.

a. 4 components extracted.

Table 5.2 The coefficients of Principle Components

Coefficients of Principle Components in descending order							
Feature	Pc1	Feature	Pc2	Feature	Pc3	Feature	Pc4
Left Wrist_shoulder_y	-0.91	Right Elbow	0.98	Left Knee	0.75	Head_Topspine	0.64
Wrist_speed_ratio	0.91	Right Wrist_shoulder_z	-0.96	Left Elbow	-0.73	Topspine_Root	0.49
Right Wrist_shoulder_y	0.89	Left Wrist_shoulder_z	0.78	Left Heel_toe_z	0.66	Right Heel_toe_y	-0.35
Right knee	-0.81	Left Heel_toe_z	-0.61	Right Heel_toe_z	0.61	Left Heel_toe_y	-0.30
Right Heel_toe_z	-0.78	Topspine_Root	0.60	Left Wrist_shoulder_z	0.56	Left Wrist_shoulder_z	-0.26
Right Heel_toe_y	0.76	Left Elbow	-0.42	Left Heel_toe_y	-0.50	Right knee	0.24
Left Heel_toe_y	-0.71	Left knee	-0.37	Right knee	0.45	Wrist_speed_Ratio	-0.23
Head_topspine	0.68	Right Heel_toe_y	0.26	Right Wrist_shoulder_y	0.31	Left Wrist_shoulder_y	0.23
Topspine_Root	0.57	Head_Topspine	0.22	Wrist_speed_ratio	-0.26	Left Elbow	0.23
Left Knee	0.52	Right Wrist_shoulder_y	-0.19	Right Wrist_shoulder_z	-0.22	Right Wrist_shoulder_y	-0.21
Left Elbow	0.48	Right knee	-0.18	Right Elbow	-0.19	Right Wrist_shoulder_z	0.12
Left Heel_toe_z	0.42	Left Wrist_shoulder_y	0.17	Left Wrist_shoulder_y	-0.18	Left Heel_toe_z	-0.08
Left Wrist_shoulder_z	-0.11	Wrist_speed_ratio	0.14	Topspine_Root	0.15	Left knee	0.04
Right Wrist_shoulder_z	0.06	Left Heel_toe_y	-0.14	Right Heel_toe_y	-0.10	Right Elbow	-0.01
Right Elbow	0.03	Right Heel_toe_z	-0.04	Head_Topspine	0.06	Right Heel_toe_z	0.00

Table 5.3 Coefficients of Principle Components in descending order

In PCA analysis, the most important criteria to determine the number of components to retain is the interpretability criteria. The rules for the interpretability criteria determine whether the variables in a component share the same conceptual meaning, and variables in different components seem to be measure different constructs; moreover, the results reveal a “simple” structure, which means that most of the variables have relatively large coefficients with respect to only one component, and most of the components have relatively large coefficients with respect to some variables and small coefficients for the remaining variables.

The PCA results meet the above criteria very well. Table 5.3 shows that Pc1 focused on Wrist_shoulder_y, Wrist speed ratio, Right Knee, Heel_toe_y, Right Heel_toe_z, Head_Topspine, and Topspine_Root.

Pc2 focused on Right Elbow, Wrist_shoulder_z, Left Heel_toe_z, Topspine_Root, and Right Heel_toe_z.

Pc3 focused on Left Knee, Left Elbow, Heel_toe_z, and Left Wrist_shoulder_z.

Pc4 focused on Head_Topspine and Topspine_Root.

Pc1 is the most important principle component, which occupied 41.95% of the total variance. It has the most gait features for which the absolute value of $C_{i,k}$ is above 0.5 on PC_k. This suggests that Pc1 is a composite indicator for the gait cycle and focuses on features associated with y-axis and the Wrist speed ratio.

Pc2 occupied 25.12% of the total variance and focused on features associated with z-axis and Right Elbow. Pc3 occupied 19.91% of the total variance and focused on Left Knee, Left Elbow, and Left Wrist_shoulder_z, which suggests that Pc3 is an indicator that describes the features about the left side of the body.

Pc4 is the last principle component, which occupied only 8.18% of the total variance. It is clear that Pc4 is determined mainly by the two relatively stable gait features Head_Topspine and Topspine_Root.

5.2.2 PCA by Fixing Root method

PCA was used to find the most important markers in the $\overline{\overline{Ms}}$ matrix. Based on the markers' speed $\overline{Ms}$ after fixing the Root marker, 7 principal components were obtained, which occupied 89.36% of the total variance (Table 5.4). There were three principal components that occupied over 10% of the total variance, which together accounted for 67.04% of the total variance.

Total Variance Explained						
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	15.32	39.27	39.27	15.32	39.27	39.27
2	6.88	17.65	56.92	6.88	17.65	56.92
3	3.95	10.12	67.04	3.95	10.12	67.04
4	3.04	7.79	74.83	3.04	7.79	74.83
5	2.53	6.48	81.32	2.53	6.48	81.32
6	1.74	4.46	85.78	1.74	4.46	85.78
7	1.40	3.58	89.36	1.40	3.58	89.36

Extraction Method: Principal Component Analysis.

Table 5.4 Seven principle components obtained by fixing root method

By comparing the highest coefficients of the first three principal components obtained by PCA, the results were presented in Table 5.5. The markers that appear to be important in Pc1 are clearly those associated with the motions of lower left arm. These markers include the biceps, pinky, wrist, thumb, etc. In the coefficients of Pc2, it is found that the markers focus on the lower legs. In the coefficients of Pc3, all four hip segment markers were related to the top in terms of coefficient value. The distinct and concentrated distribution of the markers that have the highest coefficients for the principal components is extraordinary. PCA was performed also on these gait data without fixing the Root marker. Only two principal components were obtained; the first captured 83.09% of the total variance, and the second captured 12.14% of the total variance. The 10 markers with the highest coefficient values in Pc1 were inspected (Table 5.6) and found that the distribution was not as concentrated as that shown in Table 5.5. Thus, it shows that the fixing root method is effective method to find the relationship among human body and gait; moreover, the significance of the lower left arms (biceps, pinky, wrist and thumb), lower legs (knee, heel, ankle, toe and foot), and hips was revealed using this method. This analysis was performed only to study the subjects' gait and not for any other classification purposes. The results suggest that arms, legs and hips could be extracted as gait signatures for gait recognition.

PC1		PC2		PCA3	
Left_Thumb	0.85	RightMid_Foot	0.77	BackRight_Hip	0.78
Left_Wrist	0.82	Left_Toe	0.72	FrontLeft_Hip	0.75
Left_Pinky	0.80	Right_Ankle	0.72	FrontRight_Hip	0.69
BackRight_Head	0.88	Right_heel	0.71	BackLeft_Hip	0.67
Right_Bicep	0.79	LeftMid_Foot	0.68	MidBack_Offset	0.63
BackLeft_Head	0.77	Left_Heel	0.67	Right_Thigh	0.31
FrontLeft_Shoulder	0.77	Left_Ankle	0.66	Low_Back	0.28
Left_Bicep	0.77	Right_toe	0.64	Left_Elbow	0.18
Mid_Back	0.77	Left_Knee	0.59	Left_Toe	0.17
Top_Spine	0.75	Right_Knee	0.56	LeftMid_Foot	0.16

Table 5.5 Markers with ten highest coefficients in PC1, PC2 and PCA3 determined by fixing Root marker

Midback	0.998
Midback_offset	0.998
Root	0.998
BackRght_hip	0.998
FrontRight_hip	0.998
Top_spine	0.997
BackLeft_hip	0.997
FrontLeft_hip	0.997
FrontRight_shoulder	0.996
FrintLeft_shoulder	0.996

Table 5.6 Markers with ten highest coefficients in PCA1 determined without fixing Root marker

5.3 Summary

In this chapter, a solution was provided to the question, “Which features should be extracted to represent gait and why?” Via principle component analysis, the question was investigated beyond the scope of the analysis in section 3.2.1. The analysis was divided into two parts. First, PCA was performed on the average gait of 35 subjects to investigate the influence of the gait features proposed in Chapter 3 on the gait cycle. Second, PCA was performed for the 30 subjects according to the markers' speed to analyse the effect of the relative motion of different body segments on gait with the fixing root method.

5.3.1 The different effects of gait features on gait cycle

As mentioned in section 5.2.1, the average gait was one gait cycle containing 1500 frames. PCA was applied on the 15 gait features of the average gait. The PCA results reveal the different weights of these 15 gait features on the one gait cycle.

According to the PCA results, the features associated with y-axis and the Wrist speed ratio are most important in the gait cycle, followed by the features associated with z-axis, the features associated with the movement of the left side of the body, and finally Head_Topspine and Topspine_Root. The features associated with y-axis include left Wrist_shoulder_y, right Wrist_shoulder_y, and left Heel_toe_y. The features associated with z-axis include left Wrist_shoulder_z, right Wrist_shoulder_z, left Heel_toe_z, and right Heel_toe_z. These results are consistent with those presented in Chapter 4. It was found that the features associated with y-axis have more freedom/individuality than those features associated with z-axis, as described in Chapter 4. The analysis described in this chapter also revealed that the y-axis features are more important to gait than the z-axis features.

PCA results also suggest that the gait features separately associated with y and z axes are important (Wrist_shoulder_y/z, Heel_toe_y/z); the Wrist Speed ratio is also important. These features describe the walking habits of the lower arms and lower legs.

Head_Topspine and Topspine_Root angle are relatively independent of the other gait features.

5.3.2 The different influence of body segments on gait

In section 5.2.2, the Root marker was assumed to be fixed and used PCA to investigate the relative motion of different body segments to reveal the most important gait features. In Pc1, the three variables with the largest coefficients were concentrated in the lower left arm, followed by other variables concentrated around the left shoulder. In Pc2, all 10 variables associated with the lower legs and feet were among the top 10 variables exhibiting large coefficients. Meanwhile in Pc3, all four variables associated with the hip exhibited the largest coefficients, followed by the variable MidBack_Offset; all of the remaining variables with coefficients are less than or equal to 0.31 which can be ignored. The PCA results of this study provide a simplified structure to reveal the most important features/characteristics of gait, and which are the movement associated with the lower left arm, lower legs and hip.

PCA has been used for gait analysis on many occasions, for example in (Carriero et al. 2009; Muniz & Nadal 2009; Samantha et al. 2010), but no reported literature has been found to apply PCA to investigate the relative motion of all body segments with respect to a specific body point. Although there are previous studies that have applied PCA to gait on a treadmill (Das et al. 2006), the normal gait for people walking naturally on the ground is different from that for people walking on a treadmill. The gait in this section is absolute relative motion that cannot be achieved by walking on a treadmill because there is no absolutely fixed point on the human body. By the fixing Root method, the influence of walking speed was removed, and gait data were fully focused on the relative movement of each body segment; therefore, there was a greater chance of finding the most natural gait features.

Many previous studies on gait feature extraction are based on video images, and features used for gait recognition are usually identified around a silhouette (Boulgouris et al. 2005), for example, moving shapes are used to obtain a sequence of silhouettes of walking subjects (Foster et al. 2003). Using 3D motion capture data, detailed gait features regarding body segments' movement and rotation could be obtained; for example, hip-knee angles were used as features for gait recognition (Barton & Lees 1997; Cunado et al. 2003), and hip flexion in swinging and lower limb joint angles were studied (Vrieling et al. 2008). Leg motion has been identified as a core feature for gait recognition (Das et al. 2006). Arm motion has recently received more attention; for example, the swinging of the arms was used for gait phase detection (Wang et al. 2009), the effect of arm swinging on the local and global stability of steady-state gait were studied (Bruijn et al. 2010), and through extra features produced from the motion of the arms, gait recognition has been considerably enhanced (Tafazzoli & Safabakhsh 2010). The results of these previous studies are consistent with the findings from PCA and the fixing Root method. Furthermore, the findings in section 5.2.2 provide analytical support for choosing the motion of the left lower arm, lower legs and feet, and hips as features for gait recognition.

In the last chapters, gait identification, the analysis of gait feature extraction and evaluation, and the analysis of gait phases were performed. All of these analyses were performed for the purpose of gait identification. In the next two chapters, further content regarding gait will be analysed. In chapter 6, the similarity between the left and right sides of the human body with respect to gait will be investigated. In chapter 7, gait attractiveness will be discussed.

Chapter 6 Similarity Analysis in Gait Cycle

In the past 20 years, a large portion of literature has explored associations between fluctuating asymmetry and human health, attractiveness, intelligence and other qualities. Fluctuating asymmetry (FA) refers to the observation of a random deviation from perfect symmetry in the bilateral structures of bilaterally symmetric organisms (Palmer & Strobeck 1986; Palmer 1994; Watson & Thornhill 1994). Research aimed at finding links between FA and human health has been achieved some success. FA has been proved to be positively associated with a number of chromosomal abnormalities and genetic diseases, including cleft-lip, Down's syndrome, fragile X syndrome, and scoliosis (Thornhill & Møller 1997). However, some studies have found that there are no consistent associations between FA and other health measure, including fitness (VO_2 max), blood pressure (BP), and lung function (Tomkinson & Olds 2000). FA has also been shown to be unrelated to the frequency and severity of diseases (Hume & Montgomerie 2001; Rhodes et al. 2001).

The association between FA and attractiveness has been a common theme among FA analyses. It is believed that small deviations from bilateral symmetry could be used as an index of a potential partner's suitability. A number of studies have suggested that a symmetric human face is more attractive than an asymmetric face (Grammer & Thornhill 1994; Thornhill & Gangestad 1995; Rhodes et al. 1998). However, other studies have reported opposite results. Symmetry was actually more associated with less attractiveness than was asymmetry because perfect facial symmetry appears abnormal, whereas asymmetry is normal (Langlois et al. 1994; Swaddle & Cuthill 1995; Kowner 1996). The role of FA has also been extended to the whole body. Some studies have suggested that more symmetric human males are more attractive or are able to attract more sexual partners (Thornhill & Gangestad 1994; Brown et al. 2008). Some other studies found evidence that suggested a role of symmetry in the perception of the attractiveness of the human female body (Tovée et al. 2000).

Human fluctuating asymmetry in sports receives less attention. Previous research has shown that higher FA is associated with poorer locomotor trait design and performance in several species, including humans (Thomas 1993; Manning & Pickup 1998; Møller et al. 1999).

In this chapter, the similarities and asymmetric appearances were investigated of gait. The same set of gait features in Chapter 3 was used. The gait cycle and gait phase definitions in Chapter 4 were also used. The left body movement and right body movement was compared in each of the corresponding gait phases. The most asymmetric body part of individuals in their gaits was also investigated.

6.1 Methods

6.1.1 Data sample

The subjects included 35 male students at a British university recruited via flyers that were posted around campus. The gait data were normalized to the gait cycle using linear interpolation. The data sample is the same as described in Chapter 4. The definitions of gait cycle and gait phases are also the same as in Chapter 4. Eight gait phases were divided in one gait cycle (Fig 4.4). The gait cycles were divided into two half cycles. Each half cycle contained four gait phases. The first half of the cycle corresponds to the right leg as the supporting leg and the left leg as the swinging leg. The second half of the cycle corresponds to the left leg as the supporting leg and the right leg as the swing leg. The first half of the cycle was denoted as cycle 1 and the second half of the cycle was denoted as cycle 2.

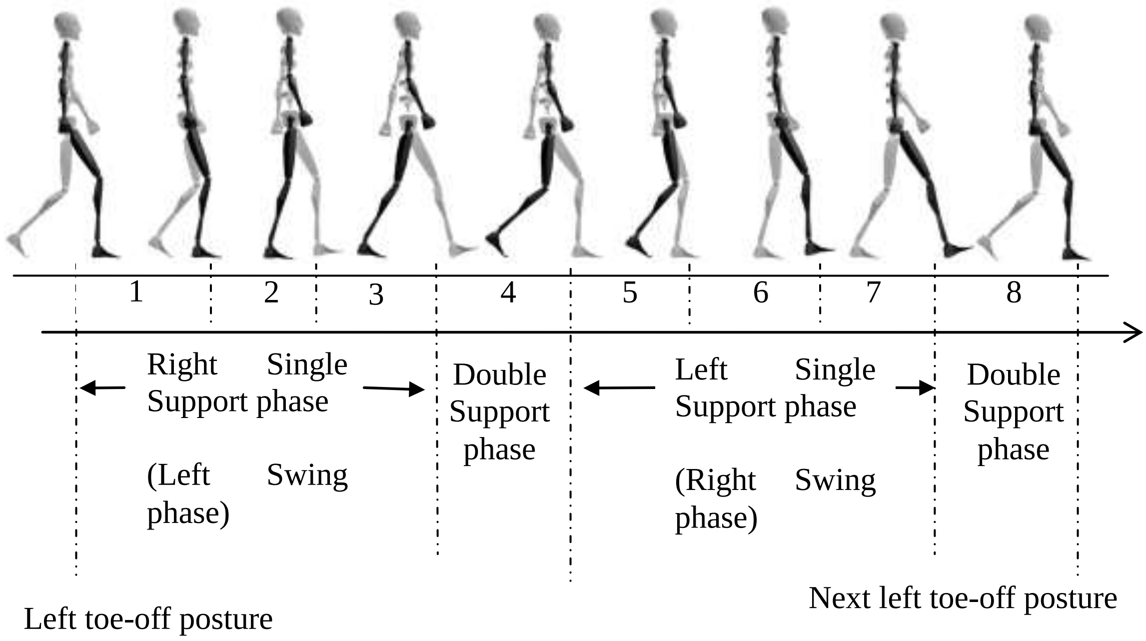


Fig. 4.4 Gait cycle and gait phase used in this research

Cycle 1 was constructed of a R. single support phase/L. swing phase and one double support phase (phase 4). Cycle 2 was constructed of a L. single support phase/Right swing phase and one double support phase (phase 8).

Cycle 1 started at the left toe off posture and ended on the right toe off posture; cycle 2 started at the right toe off posture and ended at the following left toe off posture.

6.1.2 Similarity measures

Feet, ankles, knee, hands, wrists, and elbows were the common factors investigated in previous research (Gangestad & Thornhill 1997; Tovée et al. 2000). Knee angles and elbow angles have been analysed in many studies in the literature on gait (Zhang et al. 2009; Menant et al. 2009b).

Combined with gait phase, the relationship between the left and right parts of the human body during walking can be analysed. Gait cycle is a similar regularly repeating action. In this research, the length of cycle 1 and cycle 2 was first compared. The length of a half cycle refers to the percentage of the half cycle occupied in one complete gait cycle. Next, the 15 gait features were investigated. Because the research aim is to identify the similarity between the left and right body in gait cycle, the features of the left body during cycle 1 should be compared with the features of the right body during cycle 2. For example, for knee angles, the left knee angle in cycle 1 should be compared with right knee angle in cycle 2 because the left leg is the swing leg in cycle 1 and the right leg is the swing leg in cycle 2. To compare the two legs' appearances as the swing leg, the left knee angle in cycle 1 and the right knee angle in cycle 2 should be compared. Thus, features that express the same function or the same situation should be compared.

For the same reason, left Heel_toe_y in cycle 1 and right Heel_toe_y in cycle 2 were compared as the swing legs' features. left Heel_toe_z in cycle 1 and right Heel_toe_z in cycle 2 were compared. Left Heel_toe_y in cycle 2 was compared with right Heel_toe_y in cycle 1 as the support legs' features. Left Heel_toe z in cycle 2 and right Heel_toe z in cycle 1 were also compared for the support legs' features. Left knee angles in cycle 2 and right knee angles in cycle 1 were not considered, as there was not much difference in the support phase. The left leg is the support leg in cycle 2, and the right leg is the support leg in cycle 1.

Wrist_shoulder_y and Wrist_shoulder_z are similar to Heel_toe_y and Heel_toe_z. Left Wrist_shoulder_y and left Wrist_shoulder_z in cycle 1 describe the left arm's movement while the right leg is the support leg. These features correspond to right Wrist_shoulder_y and right Wrist_shoulder_z in cycle 2, which describe the right arm's movement while the left leg is the support leg. In other words, it describes arm movement while the opposite leg is the support leg. Left Wrist_shoulder_y and left Wrist_shoulder_z in cycle 2 describe the left arm's movement while the left leg is the support leg, and right Wrist_shoulder_y and right Wrist_shoulder_z in cycle 1 describe the right arm's movement while the right leg is the support leg. Left Wrist_shoulder_y/z in cycle 2 and right Wrist_shoulder_y/z in cycle 1 describes arm movement while the leg of the same side is the support leg.

Elbow angles are similar to Wrist_shoulder angles. Head_Topspine angle, Topspine_Root angle, and Wrist speed ratio were not considered because these three features cannot be divided into left or right body.

Eleven indicators of comparison were used, as listed below. Left 1 signifies the left feature in cycle 1, and right 2 signifies the right feature in cycle 2. Thus, Elbow angle (left 1: right 2) signifies the left Elbow angle in cycle 1: right Elbow angle in cycle 2.

1. Elbow angle (left 1: right 2)
2. Elbow angle (left 2: right 1)
3. Knee angle (left 1: right 2)
4. Heel_toe_y (left 1: right 2)
5. Heel_toe_y (left 2: right 1)
6. Heel_toe_z (left 1: right 2)
7. Heel_toe_z (left 2: right 1)
8. Wrist_shoulder_y (left 1: right 2)
9. Wrist_shoulder_y (left 2: right 1)
10. Wrist_shoulder_z (left 1: right 2)
11. Wrist_shoulder_z (left 2: right 1)

6.2 Results

6.2.1 Gait phase difference between cycle 1 and cycle 2

Table 4.16 shows the detailed data of each of the gait phases of the 35 subjects. The average length of cycle 1 was 50.72% of the gait cycle, and the average length of cycle 2 was 49.28% of the gait cycle. Cycle 1 occupied almost the same percentage as cycle 2. Of the 35 subjects, 74.29% exhibited a longer cycle 1 compared with cycle 2. The average length of cycle 1 was 1.44% longer than cycle 2. The difference between cycle 1 and cycle 2 varied from -8.93% to 7.2% of the gait cycle.

6.2.2 Similarity/asymmetry between body parts that played the same function in gait

The correlation coefficients between the 11 comparisons in section 6.1.2 were calculated. The averages of the absolute values of the correlation coefficients for 35 subjects are listed in Table 6.1 in descending order. The results for all subject are shown in Table 6.2. The table shows that Elbow angle (left 1: right 2), Wrist_shoulder_y (left 1: right 2), Wrist_shoulder_y (left 2: right 1), and Heel_toe_y (left 1: right 2) had lower correlation coefficients than other features. The most similar features were Heel_toe_z (left 2: right 1), Heel_toe_z (left 1: right 2), and Knee angles (left 1: right 2).

Feature	Correlation coefficients
Heel_toe_z(left 2:right 1)	1.00
Heel_toe_z(left 1:right 2)	0.99
knee(left 1:right 2)	0.98
Elbow(left 2:right 1)	0.91
Wrist_shoulder_z(left 2:right 1)	0.90
Wrist_shoulder_z(left 1:right 2)	0.85
Heel_toe_y(left 2:right 1)	0.74
Heel_toe_y(left 1:right 2)	0.69
Wrist_shoulder_y(left 2:right 1)	0.69
Wrist_shoulder_y(left 1:right 2)	0.68
Elbow(left 1:right 2)	0.66

Table 6.1 Average correlation coefficients of the 35 subjects

Comparison of the swing leg as the left or right leg:

The Comparison of the swing leg as the left or right leg is described by Knee (left 1: right 2), Heel_toe_y (left 1: right 2), and Heel_toe_z (left 1: right 2). Knee (left 1: right 2) and Heel_toe_z (left 1: right 2) are highly similar, with correlation coefficients nearly equal to 1. Heel_toe_y is less similar, with a correlation coefficient of only 0.69. These results signify that Knee movement and foot movement on the z-axis are highly similar between the left and right leg as the swing leg. Foot movement on the y-axis displayed an asymmetry between the left leg and the right leg as the swing leg.

Comparison of the support leg as the left or right leg:

The Comparison of the support leg as the left or right leg is described by Heel_toe_y (left 2:right 1) and Heel_toe_z (left 2:right 2). Heel_toe_z (left 1:right 2) are highly similar, with correlation coefficients are all nearly equal to 1 for most subjects. Heel_toe_y is less similar, with a correlation coefficient of only 0.74. These results signify that foot movement on the z-axis is highly similar between the left and right leg as the support leg and that foot movement on the y-axis is asymmetric between the left and right leg as the support leg.

Comparison of arm movement while the opposite leg is the support leg:

It is described by Elbow (left 1: right 2), Wrist_shoulder_y (left 1: right 2), and Wrist_shoulder_z (left 1: right 2). Wrist_shoulder_z (left 1: right 2) exhibited a higher similarity, with a correlation coefficient of 0.85. Wrist_shoulder_y (left 1: right 2) displayed less similarity, with a correlation coefficient of 0.68. Elbow (left 1: right 2) had the lowest similarity in all features, with a correlation coefficient of 0.66. These results signify that elbow movement is highly asymmetric between the swing of the left and right arms while the opposite leg is the support leg. Wrist movement on the y-axis was also asymmetric between the swing of the left and right arms while the opposite leg is the support leg. Wrist movement on the z-axis was similar between the swing of the left and right arms while the opposite leg is the support leg.

Comparison of arm movement while the leg of the same side is the support leg:

It is described by Elbow (left 2: right 1), Wrist_shoulder_y (left 2: right 1) and

Wrist_shoulder_z (left 2: right 1). Elbow (left 2: right 1) and Wrist_shoulder_z (left 2: right 1) had a high similarity, with correlation coefficients 0.91 and 0.90. Wrist_shoulder_y (left 2: right 1) had a less similar correlation coefficient of 0.69. These results indicate that elbow movement and wrist movement on the z-axis are similar between left and right arm swing while the leg of the same side is the support leg. Wrist movement on the y-axis displayed an asymmetry between the left and right arm's swing while the leg of the same side was the support leg.

The comparison of gait features:

From the analysis above, Wrist_shoulder_y was largely asymmetric between the left and right sides. Heel_toe_y exhibited a decent asymmetry between the left and right sides. Wrist_shoulder_z had little asymmetry between the left and right sides. Heel_toe_z and Knee were highly similar between the left and right sides.

Elbow angle is an interesting feature. Elbow (left 2: right 1) had high similarity, but Elbow (left 1: right 2) had the most asymmetry. This result signifies that left elbow movement and right elbow movement are very similar when the leg of the same side is the support leg but that they are very asymmetric when the opposite leg is the support leg.

id	Elbow angles		Knee angle	Heel_toe_y		Heel_toe_z		Wrist_shoulder_y		Wrist_shoulder_z	
	Left1: right2	Left2: right1	knee	Left1: right2	Left2: right1	Left1: right2	Left2: right1	Left1: right2	Left2: right1	Left1: right2	Left2: right1
1	0.90	0.33	0.95	0.74	0.72	0.96	1.00	0.67	-0.04	0.87	0.59
2	-0.32	0.98	0.99	0.95	0.27	0.98	0.99	-0.10	-0.16	0.92	0.98
3	-0.37	0.95	1.00	0.48	0.91	1.00	1.00	0.98	0.48	0.82	0.96
4	0.64	0.89	0.96	-0.77	-0.48	0.97	0.99	0.99	0.99	1.00	1.00
5	0.98	0.98	0.96	0.20	0.97	0.98	0.99	0.86	1.00	0.98	1.00
6	-0.36	-0.77	0.99	0.00	0.82	0.99	1.00	-0.96	0.47	-0.49	0.37
7	0.62	0.91	0.99	-0.86	-0.21	0.98	0.99	0.42	-0.77	0.89	0.84
8	0.49	0.98	0.99	0.73	-0.60	0.99	1.00	-0.06	0.84	-0.74	1.00
9	-0.86	0.86	0.99	0.36	0.44	0.99	1.00	0.28	-0.63	-0.33	0.98
10	0.62	0.99	0.99	0.86	-0.53	1.00	1.00	0.27	-0.92	0.93	1.00
11	0.84	1.00	0.97	0.36	0.74	0.98	0.99	0.65	0.98	0.97	1.00
12	0.95	0.99	0.99	0.55	0.43	0.99	1.00	-0.47	0.07	0.93	1.00
13	0.87	0.98	0.99	0.91	0.98	0.99	1.00	-0.82	-0.69	0.94	0.96
14	-0.52	0.73	1.00	0.22	0.69	1.00	1.00	-0.41	-0.95	-0.93	0.55
15	-0.96	-0.66	0.99	0.57	0.97	0.99	0.99	0.59	0.12	0.45	-0.19
16	0.52	0.98	0.88	0.49	0.08	0.95	1.00	0.81	0.79	0.62	0.98
17	0.92	0.95	0.99	0.76	0.97	0.99	1.00	0.93	0.92	0.94	0.93
18	0.93	0.81	0.98	0.96	0.92	0.99	1.00	0.95	0.95	0.99	0.91
19	0.71	0.97	0.97	0.54	0.99	0.97	0.99	0.53	0.51	0.78	1.00
20	0.70	0.96	1.00	0.75	0.99	1.00	1.00	0.54	0.52	0.94	0.99
21	0.93	0.96	0.99	0.58	0.93	0.99	1.00	0.56	0.71	0.98	1.00
22	0.82	0.98	1.00	0.83	0.96	1.00	1.00	0.44	0.47	0.98	0.99
23	0.77	0.98	1.00	0.99	0.91	1.00	1.00	0.99	1.00	1.00	0.99
24	0.46	0.98	1.00	0.98	0.98	1.00	1.00	0.99	1.00	1.00	0.98
25	0.49	0.94	0.99	0.95	0.96	0.99	1.00	0.92	0.99	0.98	0.96
26	0.43	1.00	0.99	0.98	0.83	0.99	1.00	0.96	1.00	0.99	1.00
27	0.30	0.93	1.00	0.94	0.91	1.00	1.00	0.93	1.00	0.97	0.93
28	0.59	0.97	1.00	0.96	0.94	1.00	1.00	0.91	0.99	1.00	0.98
29	0.74	0.94	0.99	1.00	0.91	0.99	1.00	-0.12	-0.95	0.99	0.98
30	0.63	0.96	1.00	0.55	-0.41	0.99	1.00	0.97	0.96	0.96	0.93
31	0.38	0.60	0.97	0.31	-0.70	0.99	1.00	0.99	0.98	-0.27	0.70
32	0.82	0.95	1.00	0.47	0.18	1.00	1.00	0.85	-0.06	0.62	0.97
33	0.93	0.99	1.00	0.87	0.88	1.00	1.00	0.28	-0.03	0.82	1.00
34	-0.06	0.94	0.92	0.93	0.90	0.94	0.99	0.67	0.94	0.81	0.92
35	0.63	0.96	0.99	0.80	0.94	0.99	1.00	0.77	0.39	0.93	0.99

Table 6.2 Correlation coefficients of features between the left body and the right body

6.2.3 Similarity/asymmetry differences among individuals

In the last section, the general similarities and asymmetries in gait were analysed. For individuals, the appearance of similarity and asymmetry differs. In Table 6.3, the 'max' column contains the maximum correlation coefficient value of the features, the 'min' column contains the minimum correlation coefficient value of the features, the 'min of abs value' contains the minimum absolute value of correlation coefficients of features, and the 'interval' column contains the distance between the max and min values. Table 6.3 is sorted by the 'interval' column in descending order.

Except Knee (left 1: right 2), Heel_toe_z (left 1: right 2), and Heel_toe_z (left 2: right 1), all of the features have individuals with nearly no correlation regarding the respective feature. The values of the min of absolute correlation coefficients varied from 0.00 to 0.33 for these features. For Wrist_shoulder_y, Elbow, Wrist_shoulder_z (left 1: right 2), and Heel_toe_y, there were some subjects for which these features were highly positively, some subjects for which these features were highly negatively correlated, and some subjects for which there was nearly no correlation among these features. For Wrist_shoulder_z (left 2: right 1), this feature was highly positively correlated for some subjects and nearly uncorrelated for some subjects, but there were no subjects with a highly negative correlation for this feature. For the features Knee and Heel_toe_z, almost all of the subjects were highly positively correlated.

Features	max	min	min of abs value	interval
Wrist_shoulder_y(left 1:right 2)	0.99	-0.96	0.06	1.95
Wrist_shoulder_y(left 2:right 1)	1.00	-0.95	0.03	1.95
elbow(left 1:right 2)	0.98	-0.96	0.06	1.94
Wrist_shoulder_z(left 1:right 2)	1.00	-0.93	0.27	1.93
Heel_toe_y(left 1:right 2)	1.00	-0.86	0.00	1.85
elbow(left 2:right 1)	1.00	-0.77	0.33	1.77
Heel_toe_y(left 2:right 1)	0.99	-0.70	0.08	1.69
Wrist_shoulder_z(left 2:right 1)	1.00	-0.19	0.19	1.19
knee(left 1:right 2)	1.00	0.88	0.88	0.12
Heel_toe_z(left 1:right 2)	1.00	0.94	0.94	0.06
Heel_toe_z(left 2:right 1)	1.00	0.99	0.99	0.01

Table 6.3 Similarity/asymmetry differences among different subjects

6.2.4 The most asymmetric body parts in gait

Table 6.4 shows the feature with minimal correlation for each subject. The minimal correlation is that which has the minimum absolute value of correlation coefficients. The table shows the most asymmetric body parts in gait for each subject. For example, for subject 1, the minimal correlation appeared for Wrist_shoulder_y (left 2: right 1), which means wrist movement on y-axis between the left and right sides were the most asymmetric while the leg of the same side was the support leg in gait.

id	min correlation	Feature
1	-0.04	Wrist_shoulder_y(left 2:right 1)
2	-0.10	Wrist_shoulder_y(left 1:right 2)
3	-0.37	elbow(left 1:right 2)
4	-0.48	Heel_toe_y(left 2:right 1)
5	0.20	Heel_toe_y(left 1:right 2)
6	0.00	Heel_toe_y(left 1:right 2)
7	-0.21	Heel_toe_y(left 2:right 1)
8	-0.06	Wrist_shoulder_y(left 1:right 2)
9	0.28	Wrist_shoulder_y(left 1:right 2)
10	0.27	Wrist_shoulder_y(left 1:right 2)
11	0.36	Heel_toe_y(left 1:right 2)
12	0.07	Wrist_shoulder_y(left 2:right 1)
13	-0.69	Wrist_shoulder_y(left 2:right 1)
14	0.22	Heel_toe_y(left 1:right 2)
15	0.12	Wrist_shoulder_y(left 2:right 1)
16	0.08	Heel_toe_y(left 2:right 1)
17	0.76	Heel_toe_y(left 1:right 2)
18	0.81	elbow(left 2:right 1)
19	0.51	Wrist_shoulder_y(left 2:right 1)
20	0.52	Wrist_shoulder_y(left 2:right 1)
21	0.56	Wrist_shoulder_y(left 1:right 2)
22	0.44	Wrist_shoulder_y(left 1:right 2)
23	0.77	elbow(left 1:right 2)
24	0.46	elbow(left 1:right 2)
25	0.49	elbow(left 1:right 2)
26	0.43	elbow(left 1:right 2)
27	0.30	elbow(left 1:right 2)
28	0.59	elbow(left 1:right 2)
29	-0.12	Wrist_shoulder_y(left 1:right 2)
30	-0.41	Heel_toe_y(left 2:right 1)
31	-0.27	Wrist_shoulder_z(left 1:right 2)
32	-0.06	Wrist_shoulder_y(left 2:right 1)
33	-0.03	Wrist_shoulder_y(left 2:right 1)

34	-0.06	elbow(left 1:right 2)
35	0.39	Wrist_shoulder_y(left 2:right 1)

Table 6.4 The most asymmetric body part in the gait cycle for each subject

There were 9 subjects, 25.71% of all of the subjects, for which the most asymmetric body part appeared as Wrist_shoulder_y (left 2: right 1). There were 8 subjects, 22.86% of all of the subjects, for which the most asymmetric body part appeared as Elbow (left 1: right 2). The distribution of the most asymmetric body part for all of the subjects is shown in Table 6.5.

Wrist movement on the y-axis while the leg of the same side is the support leg, elbow movement while the opposite leg is the support leg, and wrist movement on the y-axis while the opposite leg is the support leg are the most possible asymmetric body parts in gait. Foot movement of the swinging leg on the y-axis and foot movement of the support leg on the y-axis are the least asymmetric body parts in gait. There were no subjects for whom the most asymmetric body part was Knee, Heel_toe_z, or Wrist_shoulder_z (left 2: right 1).

Body movement on the y-axis (Wrist_shoulder_y, Heel_toe_y), and Elbow movement while the opposite leg is the support leg were highly likely to be the most asymmetric body part in gait.

feature with greatest asymmetry in gait	subject numbers	percentage among all subjects
Wrist_shoulder_y(left 2:right 1)	9	25.71%
elbow(left 1:right 2)	8	22.86%
Wrist_shoulder_y(left 1:right 2)	7	20.00%
Heel_toe_y(left 1:right 2)	5	14.29%
Heel_toe_y(left 2:right 1)	4	11.43%
elbow(left 2:right 1)	1	2.86%
Wrist_shoulder_z(left 1:right 2)	1	2.86%

Table 6.5 The distribution of the most asymmetric body parts in gait for all subjects

6.3 Summary

6.3.1 Similarity/asymmetry between the left body and the right body when performing the same function

The similarity and asymmetry between the left body and right body movement in gait were investigated. For 74.29% of the 35 subjects, cycle 1 was longer than cycle 2. The average length of cycle 1 was 1.44% longer than cycle 2. The difference between cycle 1 and cycle 2 varied from -8.93% to 7.2% of the gait cycle.

The similarity/asymmetry between the left body and right body was calculated according to four parts: leg movement as the swing leg, leg movement as the support leg, arm movement while the opposite leg is the support leg, and arm movement while the leg of the same side is the support leg. The similarity/asymmetry between the left and right body in arm movement while the opposite leg is the support leg refers to the similarity comparison between left arm movement in cycle 1 and right arm movement in cycle 2. The similarity/asymmetry between the left and right body in arm movement while leg of the same side is the support leg refers to the similarity comparison between left arm movement in cycle 2 and right arm movement in cycle 1.

Leg movement as the swing leg: Knee movement and foot movement on the z-axis are highly similar between the left leg and the right leg as the swing leg. Foot movement on the y-axis displayed an asymmetry between the left leg and the right leg as the swing leg.

Leg movement as the support leg: Foot movement on the z-axis was highly similar between the left leg and the right leg as the support leg, and foot movement on the y-axis displayed an asymmetry between the left leg and the right leg as the support leg.

Arm movement while the opposite leg is support leg: Elbow movement displayed a high asymmetry between the left and right arm swing while the opposite leg was the support leg. Wrist movement on the y-axis also had an asymmetry, and wrist movement on the z-axis was similar between the left and right arm swing while the opposite leg was the support leg.

Arm movement while the leg of same side is the support leg: Elbow movement and wrist movement on the z-axis were similar between the left and right arm swing while leg of the same side was the support leg. Wrist movement on the y-axis was asymmetric between the left and right arm swing while the leg of the same side was support leg.

From the above results, elbow movement while the opposite leg was the support leg, wrist movement on the y-axis both when the opposite and same-side legs were support legs, and foot movement on the y-axis for both the swing leg and the support leg showed an asymmetry in the gait cycle.

Elbow movement while the leg of the same side was support leg, wrist movement on the z-axis for both the opposite and same-side leg as the support leg, foot movement on the z-axis for both the swing and support leg, and knee movement showed high a similarity in the gait cycle.

Wrist movement on the y-axis had less similarity than foot movement on the y-axis.

6.3.2 The similarity/asymmetry of gait features

From the point of view of the proposed gait features, Wrist_shoulder_y had a high asymmetry between the left and right sides. Heel_toe_y had a decent asymmetry between the left and right sides. Wrist_shoulder_z had little asymmetry between the left and right sides. Heel_toe_z and Knee were highly similar between the left and right sides.

Elbow (left 2: right 1) had a high similarity, but Elbow (left 1: right 2) displayed the greatest asymmetry. This result signifies that left elbow angle and right elbow angle are very similar when the leg of the same side is the support leg, but they are very asymmetric when the opposite leg is the support leg.

For different subjects, the similarity/asymmetry appearance varied very little for the features Knee and Heel_toe_z (almost all were highly positive correlated), they varied highly for Wrist_shoulder_y, Elbow, Heel_toe_y, and Wrist_shoulder_z when the opposite leg was the support leg (from a highly negative correlation to a highly positive correlation), and they varied from uncorrelated to highly negatively correlated for Wrist_shoulder_z when the leg of the same side was the support leg.

6.3.3 The most asymmetric body part for individuals in gait

There were 9 subjects, 25.71% of all of the subjects, for which the most asymmetric body part appeared for Wrist_shoulder_y (left 2: right 1). Wrist movement on the y-axis while leg of the same side was the support leg was most frequently identified as the most asymmetric body part in gait.

Wrist movement on the y-axis while leg of the same side was the support leg, elbow movement while the opposite leg was the support leg, and wrist movement on the y-axis while the opposite leg was the support leg were the body parts most likely to be asymmetric in gait.

Foot movement on the y-axis for the swing leg and foot movement on the y-axis as the support leg were the least likely body parts to be asymmetric body part in gait.

There were no subjects for whom the most asymmetric body part in gait was Knee, Heel_toe_z, or Wrist_shoulder_z (left 2: right 1).

Body movement on the y-axis (Wrist_shoulder_y and Heel_toe_y), and Elbow movement while the opposite leg is the support leg were the most likely body parts to be asymmetric in gait.

In Chapter 4 and 5, it is found that features on the y-axis had more individuality than features on the z-axis, and arm-related features had more individuality than leg-related features. The results of the similarity analysis of gait are consistent with the conclusions in the last two chapters. Wrist movement on the y-axis had more asymmetry than foot movement on the y-axis. Wrist movement on the z-axis, foot movement on the z-axis, and knee movement are very similar in gait. In addition, elbow movement while the opposite leg is the support leg also had high asymmetry in gait. In next Chapter, the relationship between gait attractiveness and body segments was investigated.

Chapter 7 Gait Attractiveness and Gait Features for Attractiveness

Facial and bodily attractiveness has received a great deal of attention in psychology, particularly from evolutionary psychologists who suggest that the cognitive mechanisms for perceiving attractiveness of the opposite sex are species-typical, sexually selected adaptations for finding high quality mates (Thornhill & Gangestad 1999; Fink & Penton-Voak 2002; Rhodes et al. 2003). For example, faces and bodies that display higher left-right symmetry (an indicator of biological quality) are perceived as more attractive (Thornhill & Gangestad 1994; Gangestad & Thornhill 1997; Rhodes et al. 2005; Brown et al. 2008), as are faces and bodies that exhibit greater sex-typicality (Rhodes et al. 2003; Brown et al. 2008).

One possible influence on male gait attractiveness is gait speed. Research suggests that males with a higher social status tend to walk faster (Jahoda et al. 1933; Schmitt & Atzwanger 1995). If high status men walk faster, then it follows that faster male gaits should be more attractive to females because social status is one of the most important aspects of what makes a male attractive to females (Davies & Shackelford 2008).

In the current study, the detailed and accurate data provided by 3D motion capture were utilised to investigate whether a systematic relationship exists between the motions of individual body markers and gait attractiveness. It was also examined that which body marker movements are the most important in determining gait attractiveness. Finally, it was investigated that whether it is the speed or the acceleration of body markers that is most correlated with gait attractiveness ratings. PCA and linear regression were used to choose some particular markers as features determining the attractiveness value of gait by the fixing root method. The effectiveness about the features extracted for attractiveness was verified by comparing the results with those results by all markers.

7.1 Methods

7.1.1 Subjects and data acquisition

The subjects included 30 male students at a British university (mean age = 20.83, *SD* = 3.12) who were recruited via flyers posted around campus. Gait data were collected by a seven camera motion capture system from Motion Analysis at a rate of 60 frames per second. The capture volume was 2 meters wide, 4 meters long and 2.2 meters high. Each subject wore a form-fitting motion capture suit, with 40 reflective markers placed on crucial body segment/joint locations, as illustrated in Fig. 2.2 and below: TopHead, FrontLeft_Head, BackLeft_Head, …, Leftmidfoot, Lefttoe. Subjects were told to walk freely and naturally at normal speed, from one end of the capture volume to the other, and then to walk back. The recorded Root marker (on the back at the upper middle of pelvis) speed for 30 subjects ranged from 666.16 mm/s to 1255.48 mm/s with a mean of 1005.84 mm/s.

1. Top_head
2. FrontLeft_head
3. BackLeft_head
4. FrontRight_head
5. BackRight_head
6. Right_shoulder
7. Right_bicep
8. Right_elbow
9. Right_wrist
10. Right_pinky
11. Right_thumb
12. Left_shoulder
13. Left_bicep
14. Left_elbow
15. Left_wrist
16. Left_pinky
17. Left_thumb
18. Top_spine

19. FrontRight_shoulder
20. FrontLeft_shoulder
21. Mid_back
22. MidBack_offset
23. Low_back
24. Root
25. BackRight_hip
26. BackLeft_hip
27. FrontRight_hip
28. FrontLeft_hip
29. Right_thigh
30. Right_knee
31. Right_ankle
32. Right_heel
33. Rightmid_foot
34. Right_toe
35. Left_thigh
36. Left_knee
37. Left_ankle
38. Left_heel
39. Leftmid_foot
40. Left_toe

The recorded data for each subject were the coordinates of 40 markers in the 3D space at each frame (60 frames per second) during walking. These data, after post-processing, were presented to evaluators to assess the gait attractiveness of each walker. The walkers were presented in random order in a 3D stick figure format (Fig. 7.1). The gait motion video was presented using EVaRT software from Motion Analysis on the computer screen using a 360 degree rotation feature, such that different viewing angles could be viewed by the evaluators. The evaluators were 32 female students from a British university (mean age = 20.28, SD = 3.38). They rated the attractiveness of each gait by drawing a vertical line on a 100 mm scale ranging from “unattractive” to “attractive”. Because Cronbach's α, a measure of agreement between raters, was reasonable (0.78), gait attractiveness ratings were averaged for each walker. Table 7.1 showed the gait attractiveness value of each subject.

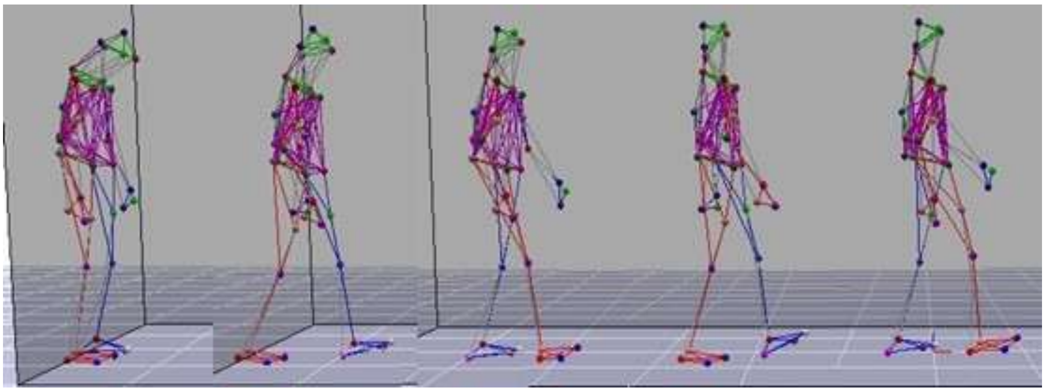


Fig. 7.1 Gait cycle of stick person (id16)

subject id	1	2	3	4	5	6	7	8
attractiveness value	32.60	40.60	29.67	40.27	45.97	45.50	29.10	49.13
subject id	9	10	11	12	13	14	15	16
attractiveness value	40.10	42.83	32.97	32.23	36.57	42.07	33.23	46.13
subject id	17	18	19	20	21	22	23	24
attractiveness value	34.80	49.37	50.53	42.67	47.50	44.20	37.90	42.50
subject id	25	26	27	28	29	30		
attractiveness value	43.97	42.40	42.80	39.70	36.77	49.90		

Table 7.1 Attractiveness value of 30 subjects.

M_j^i is denoted as number j marker attached to ID number i subject, $1 \le i \le 30,\ 1 \le j \le 40$. For example, M_1^3 refers to the first mark of id_3, which is the Tophead marker of subject id_3. Thus, for each frame, there is a set $\{M_1^i, \ldots, M_{40}^i\}$. $M_j^i = [M_{jx}^i, M_{jy}^i, M_{jz}^i]$, representing the 3D coordinates of M_j^i on the x, y, and z axes.

$Ms_j^i,\ 1 \le i \le 30,\ 1 \le j \le 40$ is denoted as the speed of M_j^i, and Ms_j^i is defined by equation (6.1).

$$Ms_j^i = \sqrt{\left(Ms_{jx}^i\right)^2 + \left(Ms_{jy}^i\right)^2 + \left(Ms_{jz}^i\right)^2} \qquad (7.1)$$

In this equation, Ms_{jx}^i is M_j^i marker's speed along the x-axis, and Ms_{jy}^i and Ms_{jz}^i are M_j^i marker's speed along the y-axis and the z-axis, respectively.

$\overline{Ms}_j^i$ is defined as the average Ms_j^i for all frames; thus, a matrix $\overline{Ms}$ was obtained to state average marker speeds as follows.

$$\overline{Ms} = \begin{bmatrix} \overline{Ms}_1^1 & \overline{Ms}_2^1 & \cdots & \overline{Ms}_{40}^1 \\ \overline{Ms}_1^2 & \overline{Ms}_2^2 & \cdots & \overline{Ms}_{40}^2 \\ \cdots & \cdots & \cdots & \cdots \\ \overline{Ms}_1^{30} & \overline{Ms}_2^{30} & \cdots & \overline{Ms}_{40}^{30} \end{bmatrix}_{30\times 40}$$

In the same way, $Macc_j^i$ and $\overline{Macc}_j^i$ are denoted as M_j^i marker's acceleration and average acceleration. In this case, $Macc_j^i$ is defined by equation (7.2).

$$Macc_j^i = \sqrt{\left(Macc_{jx}^i\right)^2 + \left(Macc_{jy}^i\right)^2 + \left(Macc_{jz}^i\right)^2} \qquad (7.2)$$

Therefore, the matrix $\overline{Macc}$ contains the average marker accelerations as follows.

$$\overline{Macc} = \begin{bmatrix} \overline{Macc}_1^1 & \overline{Macc}_2^1 & \cdots & \overline{Macc}_{40}^1 \\ \overline{Macc}_1^2 & \overline{Macc}_2^2 & \cdots & \overline{Macc}_{40}^2 \\ \cdots & \cdots & \cdots & \cdots \\ \overline{Macc}_1^{30} & \overline{Macc}_2^{30} & \cdots & \overline{Macc}_{40}^{30} \end{bmatrix}_{30\times 40}$$

Finally, a data set was denoted to contain every subject's gait attractiveness average rating,

$$attract = [32.6, 40.6, \ldots, 49.9]^T{}_{30\times 1}$$

7.1.2 Principle component analysis

These data were then analysed in steps. First, the principal component analysis was conducted, and two principal components were obtained. Based on the two principal components, a linear regression analysis was carried out to produce a linear expression of the attractiveness ratings in terms of the speeds of the 40 different markers.

7.1.3 Linear regression

Linear regression was the first type of regression analysis to be rigorously studied and used extensively in practical applications, because models that depend linearly on their unknown parameters are easier to fit than models that are non-linearly related to their parameters and because the statistical properties of the resulting estimators are easier to determine. Linear regression was used to predict attractiveness, and verified the linear regression results.

In this research, the linear regression result was drawn using only 25 subjects' motion and attractiveness data as samples, leaving 5 unused subjects to verify this method. This process was repeated eight additional times, each time using different sets of 25 sample subjects and 5 verification subjects. For each iteration, a different linear regression equation with two principal components was drawn from the 25 sample subjects, and the equation was verified using the 5 unused subjects. Then, the correlation between attractiveness ratings and marker speed/acceleration were analysed. In the end, which markers are important for determining gait attractiveness were analysed

7.1.4 Fixing root method

The fixing root method was introduced and applied in Chapter 5. Root is on the back at the upper middle of pelvis. There are some speed-related features about root that have been analysed for motion retargeting (Gleicher 1998), motion synthesis (Kwon & Shin 2005; Meredith & Maddock 2005), and animation (Chai & Hodgins 2007). Root was also used as a special external point to gait pose (Forbes & Fiume 2005). In this method, Root was considered to be virtually fixed, like all subjects walking on a treadmill, in order to better understand individual gait by analysing the relative motion of the body segments rather than the trajectory of entire moving body.

Every markers' new coordinates was achieved by the following formula.

$$Mfix_j^i(t:x,y,z) = M_j^i(t:x,y,z) - \left(M_{24}^i(t:x,y,z) - M_{24}^i(1:x,y,z)\right)$$
$$i = 1,\ldots,30; j = 1,\ldots,40; t = 1,\ldots,t_{end}$$

PCA and linear regression were performed on the gait data after the fixing root method to investigate which features should be extracted for gait attractiveness. Then, the difference was compared between the analyses derived from the use of all of the markers with the results using only the markers of the extracted features.

7.2 Results

7.2.1 Correlation of attractiveness ratings with marker speed/acceleration

The correlation coefficients between attractiveness ratings *attract* and the marker speed matrix were obviously higher than the correlation coefficients between *attract* and the marker acceleration matrix.

It is evident that the attractiveness ratings are more closely related to marker speed than to acceleration. The average correlation coefficient between attractiveness and the speed of the 40 markers was 0.64, with the highest value reaching 0.74, whilst the average correlation coefficient between attractiveness and the acceleration of the 40 markers was only 0.21, with the highest value only 0.47.

Because attractiveness is correlated more with marker speed than with acceleration, the main concern in the following sections is the relationship between the attractiveness matrix *attract* and the marker speed matrix.

7.2.2 Principal Component Analysis (PCA) and linear regression results

In this section, 25 subjects were used as the data sample and left 5 subjects unused to verify the robustness of the method. Principal components were calculated by using the correlation matrix and every principal component was extracted with an eigenvalue over 1. The matrix $\overline{S}$ is the original data. SPSS extracted two principal components with eigenvalues of 33.24 and 4.86. The cumulative variance of these two components reached 95.23% of the total variance. The first component captured 83.09% of the total variance, and the second captured 12.14% of the total variance. These high percentages indicated that these two components express the original variables well. The two extracted principal components are linear combinations of the 40 original variables, which are the markers' average speed, $\overline{Ms}_j,\ \ 1 \le j \le 40$. A coefficient matrix of these two principal components is shown in Table 7.2.

Component Matrix of markers in PCA

Markers\coefficient	C1	C2	Markers\coefficient	C1	C2
Top_Head	0.979	-0.007	Mid_Back	0.998	0.005
FrontLeft_Head	0.989	-0.020	MidBack_Offset	0.998	0.015
BackLeft_Head	0.991	-0.015	Low_Back	0.984	-0.050
FrontRight_Head	0.988	0.022	Root	0.998	-0.002
BackRight_Head	0.989	0.028	BackRight_Hip	0.998	-0.003
Right_Shoulder	0.994	0.054	BackLeft_Hip	0.997	0.003
Right_Bicep	0.983	0.157	FrontRight_Hip	0.998	-0.008
Right_Elbow	0.764	-0.070	FrontLeft_Hip	0.997	0.008
Right_Wrist	0.859	0.396	Right_Thigh	0.960	-0.242
Right_Pinky	0.769	0.541	Right_Knee	0.894	-0.410
Right_Thumb	0.795	0.514	Right_Ankle	0.761	-0.581
Left_Shoulder	0.994	-0.040	Right_heel	0.705	-0.597
Left_Bicep	0.986	-0.119	RightMid_Foot	0.795	-0.554
Left_Elbow	0.962	-0.231	Right_Toe	0.842	-0.506
Left_Wrist	0.868	-0.412	Left_Thigh	0.975	0.185
Left_Pinky	0.824	-0.439	Left_Knee	0.880	0.430
Left_Thumb	0.824	-0.446	Left_Ankle	0.710	0.685
Top_Spine	0.997	0.008	Left_Heel	0.679	0.711
FrontRight_Shoulder	0.996	0.031	LeftMid_Foot	0.729	0.657
FrontLeft_Shoulder	0.996	-0.010	Left_Toe	0.771	0.603

Table 7.2 Component Matrix of markers in PCA

Two principal components were named as Pc1 and Pc2, and was calculated to obtain two data sets:

$$Pc1 = \overline{Ms}C1 = \sum_{j=1}^{40} C1_j \overline{Ms}_j$$

$$Pc2 = \overline{Ms}C2 = \sum_{j=1}^{40} C2_j \overline{Ms}_j \qquad (7.3)$$

where C1 is the coefficient matrix for Pc1, and C2 is the coefficient matrix for Pc2, as listed in Table 7.2.

Then, linear regression was carried out between Pc1, Pc2, and attractiveness with Pc1 and Pc2 as independent variables and attractiveness *attract* as an induced variable. The regression results showed that attractiveness has no obvious linear relation with Pc1 and Pc2 because the coefficient values of Pc1 and Pc2 were too small compared with the constant coefficient. This result probably occurred because the scale of Pc1 and Pc2 is too large in comparison with the attractiveness rating values. Therefore, the regression method was improved by using ln(Pc1), ln(Pc2), and ln(attract) for the linear regression. The square of the multiple correlation coefficients is 0.564, and the standard error of the estimation is 0.113. Therefore, the regression equation is acceptable. The linear relationship among ln(Pc1), ln(Pc2) and ln(attract) was highly significant ($P < 0.001$).

The regression equation can be expressed as follows,

$$\ln(attract\_value) = 0.829 * \ln(Pc1) + 0.003 * \ln(Pc2) - 5.044 \qquad (7.4)$$

Combining equation (7.3) and (7.4), *attract_value* can be further expressed by the speed of the 40 markers as:

$$\ln(attract\_value) = 0.829 * \ln(\sum_{j=1}^{40} C1_j \overline{Ms}_j) + 0.003 * \ln(\sum_{j=1}^{40} C2_j \overline{Ms}_j) - 5.044 \qquad (7.5)$$

As equation (7.5) is only a more detailed expression of equation (7.4), in the following, equation (7.4) was used as an abbreviation of equation (7.5).

According to equation (4), the unused 5 subjects' data were employed to verify the regression function. The average error between the predicted attractiveness value by equation (7.4) and the real value was 9.27%. Equation (7.4) was also used to calculate the 25 subjects' attractiveness values from the data sample one by one.

The average error between the real attractiveness value and the value calculated by equation (7.4) in the data sample was 8.56%. Note that these 25 subjects are the data sample from which equation (7.4) was derived. The average error difference for predicting a new, unknown gait motion was only 0.71%.

To further test the robustness of this predicting method, the data sample and the unused subjects were substituted another eight times. Each time, five subjects were randomly withheld for verification, and the other 25 subjects comprised the data sample. After repeating this random verification procedure eight times, it is found the regression results to be very similar. Each time, first two principal components were extracted (only two were produced) from the 40 marker speed matrix. The eigenvalues were close to those of the original principal components, and the percentages of total variance explained by these two components were all above 90%. These results suggest that the markers have stable patterns regardless of sample differences. Furthermore, the resulting linear regression equations (7.6) to (7.13) were very similar to each other as well as to equation (7.4).

$$\ln(attract\_value) = 0.879 * \ln(Pc1) + 0.002 * \ln(Pc2) - 5.525 \qquad (7.6)$$

$$\ln(attract\_value) = 0.875 * \ln(Pc1) - 0.002 * \ln(Pc2) - 5.520 \qquad (7.7)$$

$$\ln(attract\_value) = 0.815 * \ln(Pc1) + 0.003 * \ln(Pc2) - 4.892 \qquad (7.8)$$

$$\ln(attract\_value) = 0.862 * \ln(Pc1) + 0.001 * \ln(Pc2) - 5.391 \qquad (7.9)$$

$$\ln(attract\_value) = 0.891 * \ln(Pc1) + 0.003 * \ln(Pc2) - 5.677 \qquad (7.10)$$

$$\ln(attract\_value) = 0.833 * \ln(Pc1) + 0.006 * \ln(Pc2) - 5.081 \qquad (7.11)$$

$$\ln(attract\_value) = 0.850 * \ln(Pc1) - 0.001 * \ln(Pc2) - 5.244 \qquad (7.12)$$

$$\ln(attract\_value) = 0.802 * \ln(Pc1) + 0.005 * \ln(Pc2) - 4.756 \qquad (7.13)$$

The average error in predicting attractiveness in the eight additional verification procedures was 8.58%, and the average error in calculating attractiveness from the data sample was 8.75% when both ln(Pc1) and ln(Pc2) were used in the linear regression. The results of these eight verification procedures are listed in Table 7.3.

verify time	Regression including ln(Pc1) & ln(Pc2)		Regression only including ln(Pc1)	
	error in estimating data	error in data sample	error in estimating data	error in data sample
1	7.756%	9.089%	7.484%	9.287%
2	5.445%	8.620%	5.654%	8.789%
3	9.241%	8.581%	10.704%	8.711%
4	8.090%	8.990%	8.424%	9.142%
5	6.889%	9.240%	6.255%	9.571%
6	10.980%	8.201%	10.485%	8.790%
7	10.887%	8.800%	10.575%	8.762%
8	9.379%	8.490%	10.455%	8.801%
average	8.583%	8.751%	8.755%	8.982%

Table 7.3 The verification results of the eight repeated analyses using different sample data and verification data

7.2.3 PCA and linear regression on acceleration and attractiveness

The same method was used to analyse the relationship between marker acceleration and gait attractiveness. The only difference in the analysis was that the data which corresponded to acceleration not speed. PCA were applied and every principal component with an eigenvalue over 1 were extracted. Nine principal components were extracted, which together explained 87.43% of the total variance. This value is less than the total variance that was explained by only two components. These nine components were named PCac1, PCac2,…, PCac9, and carried out linear regression between PCac1, PCac2, …, PCac9 and attractiveness with PCac1, PCac2, …, PCac9 as independent variables and attractiveness as the induced variable. The regression results showed no obvious linear relationship between *attract* and $\{PCac_i\}$. The linear regression between ln(PCac1), ln(PCac2), … , ln(PCac9) and ln(attract) showed the same result. These results suggested that gait acceleration is not related to gait attractiveness.

7.2.4 Features for gait attractiveness

Using the same method in Section 7.2.3, a linear regression equation was obtained between a subject's gait attractiveness and natural logarithm of the extracted principal components after the fixing root method. The only difference from the methodology described in section 7.2.3 is that previously 40 markers were used in matrix $\overline{Ms}$ and extracted two principal components, whereas in this section, 39 markers were used in matrix $\overline{Ms}$ after the fixing root method and extracted seven principal components. An example of enter method linear regression is below:

$$\begin{aligned}\ln(attract) &= 0.758*\ln(Pc1)+0.239*\ln(Pc2)-0.004\ln(Pc3)+0.006\ln(Pc4) \\ &+0.034\ln(Pc5)-0.096\ln(Pc6)-0.005\ln(Pc7)-5.128\end{aligned} \tag{7.14}$$

Five subjects were randomly selected to comprise the testing database, and the other 25 subjects were used as the data sample to obtain a linear regression equation similar to the equation above. The process was repeated 8 times. Three times it was not able to obtain effective linear regression results. Three times, good linear regression results were obtained using the stepwise method, shown by equations (7.15) and (7.17) as follows.

$$Ln(attract) = 0.851Ln(Pc2)-3.762 \tag{7.15}$$

(The average error was 8.35% in the sample data and 5.57 % in the estimating data.)

$$Ln(attract) = 0.746Ln(Pc2) - 2.878 \qquad (7.16)$$

(The average error in the sample data was 10.03%, and the average error in the estimating data was 7.57 %.)

$$Ln(attract) = 0.694Ln(Pc2) - 2.400 \qquad (7.17)$$

(The average error was 9.68% in the sample data and 9.97% in the estimating data.)

On all other occasions, linear regression equations were still obtained, but the results were not acceptable. Errors in the verification database were above 15%. There was no stable linear relationship between the markers and attractiveness after fixing root. This result indicated that there were no Ln equations that could predict attractiveness value. However, although the regression results were not satisfactory, they still provided some useful clues. When using the stepwise method, all the linear regression equations related only to Pc2. This result suggests that Pc2 is highly related to attractiveness. In the coefficients of PCA2, it is found that the markers focused on the lower legs, including all of the markers on the lower legs (shown in Table 5.5, centre columns). These 10 markers were R/L knee, R/L ankle, R/L heel, R/L toe, and R/L mid_foot. These results suggested that the lower leg features could be extracted for gait attractiveness.

7.2.5 Verification of lower leg features in gait for attractiveness

To verify the correlation that was suggested in the previous section between lower leg motion and attractiveness values, the accuracy of predicting attractiveness values from the motions of all of the 40 markers was compared as opposed to just ten markers from around the lower leg area only. The only difference is that ten markers were used from the lower legs without fixing root in $\overline{Ms}$, whereas 40 markers were used without fixing root as the database in Section 7.2.2. This time, two principal components were still extracted, which occupied over 97% of the total variance, and then used linear regression on the natural logarithm of these two principal components and natural logarithm of gait attractiveness. The resulting square of multiple correlation coefficients was 0.546, and the standard error of the estimation was 0.115; thus, the regression equation is acceptable. The linear relationship between ln(PCA1), ln(PCA2), and ln(attract) was highly significant, with a P (probability) value of regression below 0.001. One example of the regression equation is shown below.

$$\ln(attract\_value) = 0.794 * \ln(Pca1) - 0.003 * \ln(Pca2) - 3.507 \tag{7.18}$$

To test the robustness of the above regression equation and to make a comparison with Section 7.2.2, the equation was verified eight times. Each time, five subjects were randomly selected to comprise the testing database and the other 25 subjects were used as the data sample. Each time, the resulting linear regression equations were very similar to each other as well as to equation (7.18). These results suggested that the lower leg markers had stable patterns with gait attractiveness. the results of using lower leg markers was compared with the results of using all 40 markers from the entire body, and the results are listed in Table 7.4.

verify time	Regression with 40 markers		Regression with only leg markers	
	error in estimating database	error in data sample	error in estimating database	error in data sample
1	7.76%	9.09%	7.49%	9.08%
2	5.45%	8.62%	5.48%	8.63%
3	9.24%	8.58%	8.71%	8.83%
4	8.09%	8.99%	7.16%	9.15%
5	6.89%	9.24%	5.74%	9.43%
6	10.98%	8.20%	9.59%	8.66%
7	10.89%	8.80%	8.98%	8.76%
8	9.38%	8.49%	9.30%	8.72%
average	8.58%	8.75%	7.81%	8.91%

Table 7.4 Verification results comparing the use of all 40 markers and only leg markers

The left part of Table 7.4 is the results of using all 40 markers, and the right part is the results of using ten markers around the lower leg area only. The results show that the error in the testing database was smaller using only the lower leg markers than for using all 40 markers for every verification. The average error in predicting attractiveness was only 7.81% when only the leg markers were used. The results of these comparisons show that using lower leg markers as features for gait attractiveness is adequate.

7.3 Summary

7.1 Attractiveness correlated positively with speed but was uncorrelated with acceleration

Gait attractiveness is much more correlated with the average speed of each body segment in the gait cycle than with the average acceleration of each body segment in the gait cycle. The correlation coefficients between attractiveness and average speed of all 40 markers were much higher than those between attractiveness and average acceleration. PCA extracted two principal components from the original data matrix, $\overline{Ms}$, and the cumulative variance of these two components reached 95.23% of the entire variance. This result signifies that these two components represent the original data matrix $\overline{Ms}$ very well. Further regression analysis showed that there is an obvious linear relation among ln(Pc1), ln(Pc2), and ln(attract). In contrast, PCA extracted nine principal components from the original data matrix $\overline{Macc}$ with much lower eigenvalues, which explained less cumulative variance, and the regression analysis showed no linear relationship among ln(PCac1),… , ln(PCac9) and ln(attract). This sharp contrast in the analysis results strongly suggests that attractiveness is much more correlated with speed than with acceleration.

The speed of different body segments has been considered a feature in gait analysis, especially with regard to age and gender identification (Nigg et al. 1994; Røislien et al. 2009; Menant et al. 2009a). Here, it is found that speed is also correlated with attractiveness.

7.2 Linear equation of ln(PC1) and ln(PC2) predicted ln(attract value) with reasonable accuracy

One of the main motivations for this research was to investigate whether there is a systematic relationship between the motions of individual body markers and attractiveness ratings. It is found that such a pattern does exist, and it can be expressed as a linear equation of the natural logarithm of attractiveness rating value, the natural logarithm of two principal components extracted from the 40-marker speed matrix, and a constant (equation (7.4)). Principal components analysis (PCA) had been used for action recognition (Masoud &

Papanikolopoulos 2003), gait recognition (Troje 2002), and some motion data representations (Wu & Li 2009). Cho et al. (Cho et al. 2009) recently used a combination of PCA and linear discriminant analysis for medical applications of gait recognition. In this case, PCA and linear regression revealed the pattern between attractiveness ratings and individual marker speeds. The robustness of this method was further verified eight times by randomly substituting the subjects who composed the data sample and the verification group, a procedure which produced very similar results to the original analysis (equations (7.6)—(7.13)). This implies that for a specific subject group and a specific evaluator group, if PCA and linear regression are used to generate an equation similar to equation (4), then the gait attractiveness ratings of any further new subjects in this group can be predicted with reasonable accuracy (around 10%) based on their gait motion data.

7.3 Features for gait attractiveness

Using PCA and the linear regression method, it was found that PC2 is high related to gait attractiveness. The 10 markers with highest coefficients of PC2 are clearly located around the lower legs and feet. This result suggests that features can be extracted from the lower legs and feet to be used for gait attractiveness.

To verify this, the effectiveness of predicting attractiveness in gait was compared by using leg and feet markers as opposed to by using all 40 markers in linear regression equations similar to (7.18). The leg and feet markers that used for features were the 10 markers with the highest coefficients of PC2: R/L knee, R/L ankle, R/L heel, R/L toe, and R/L mid_foot. The comparative analysis showed that the results could be predicted slightly better by using only lower leg and feet markers than by using all 40 markers. Thus, instead of using 40 markers, ten markers from lower legs and feet can be used to fully represent and predict attractiveness values. The relationship between the movement of the lower legs and feet and attractiveness could not be revealed without the fixing root method.

In next chapter, human seated motion will be investigated beyond gait with motion capture techniques.

Chapter 8 A study on Human Seated Motion

As an extension of walking motion research, this chapter is aim to investigated human seated motion by comparing the seated motion on an Ergokinetic split seat chair and a standard chair. A special marker set was designed for this purpose.

8.1 Method

8.1.1 Data captured

Data sample is 17 subjects. A custom marker set was used to analyze in greater detail the back motion of each participant. The custom marker set is composed of 31 markers instead of the 40 marker set used for gait recording. A total of 8 markers were placed on the back to investigate the hip, lower back and high back movement specially. The Custom marker set used is displayed in the Fig 2.3.

A set of 8 workstation motion tasks were designed and introduced in Section 8.1.2. Each subject was asked to repeat the tasks again 4 times by different sitting position and different chair seated.

Once whilst seated in the standard office chair with their back against lumber support (SOB). Once seated at the front of the standard office chair (SOF). Once whilst seated in the Ergokinetic split-seat chair with their back against lumber support (EGB). Once seated at the front of the Ergokinetic split-seat chair (EGF).

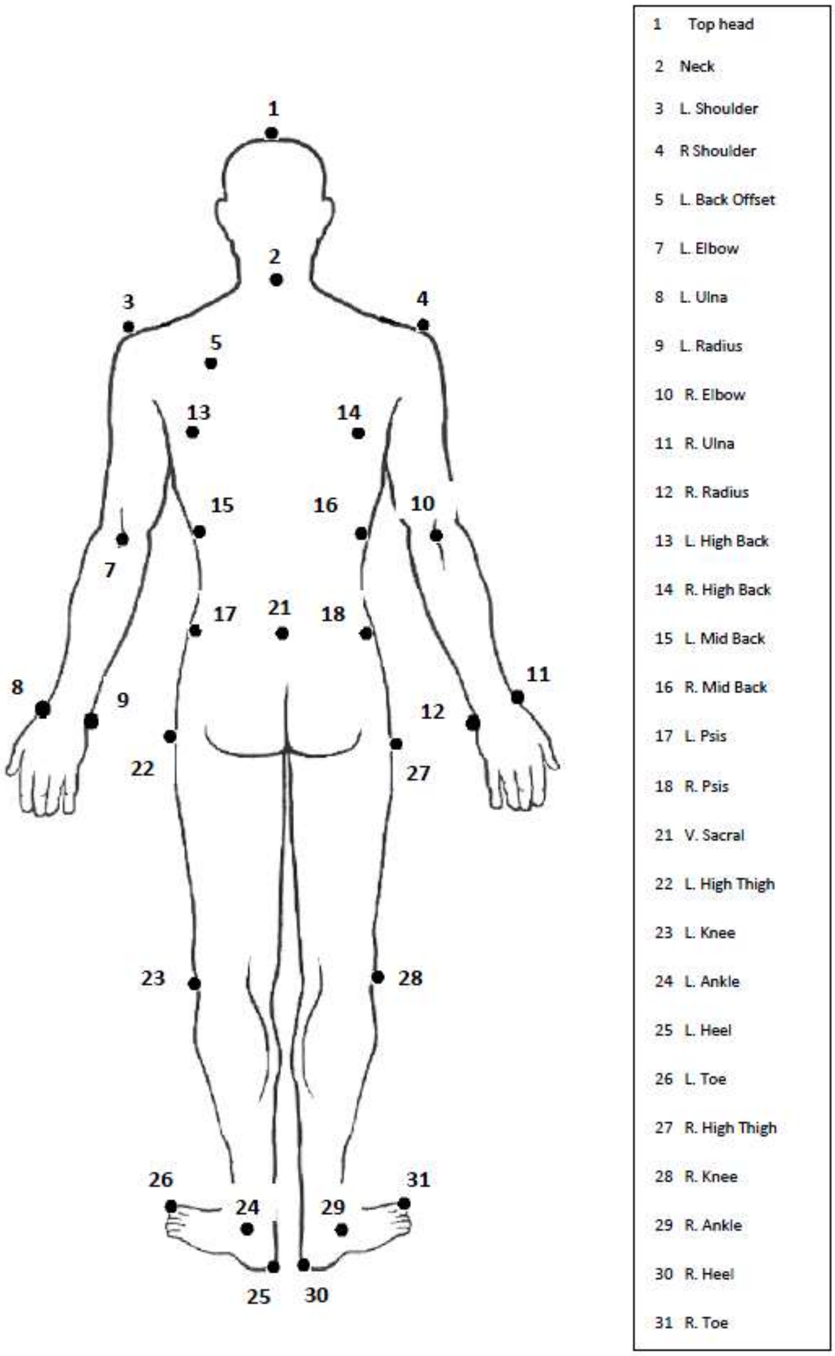


Fig. 2.3a Back view of marker locations for seated motion. (Evart 5.0 User's Maneual)

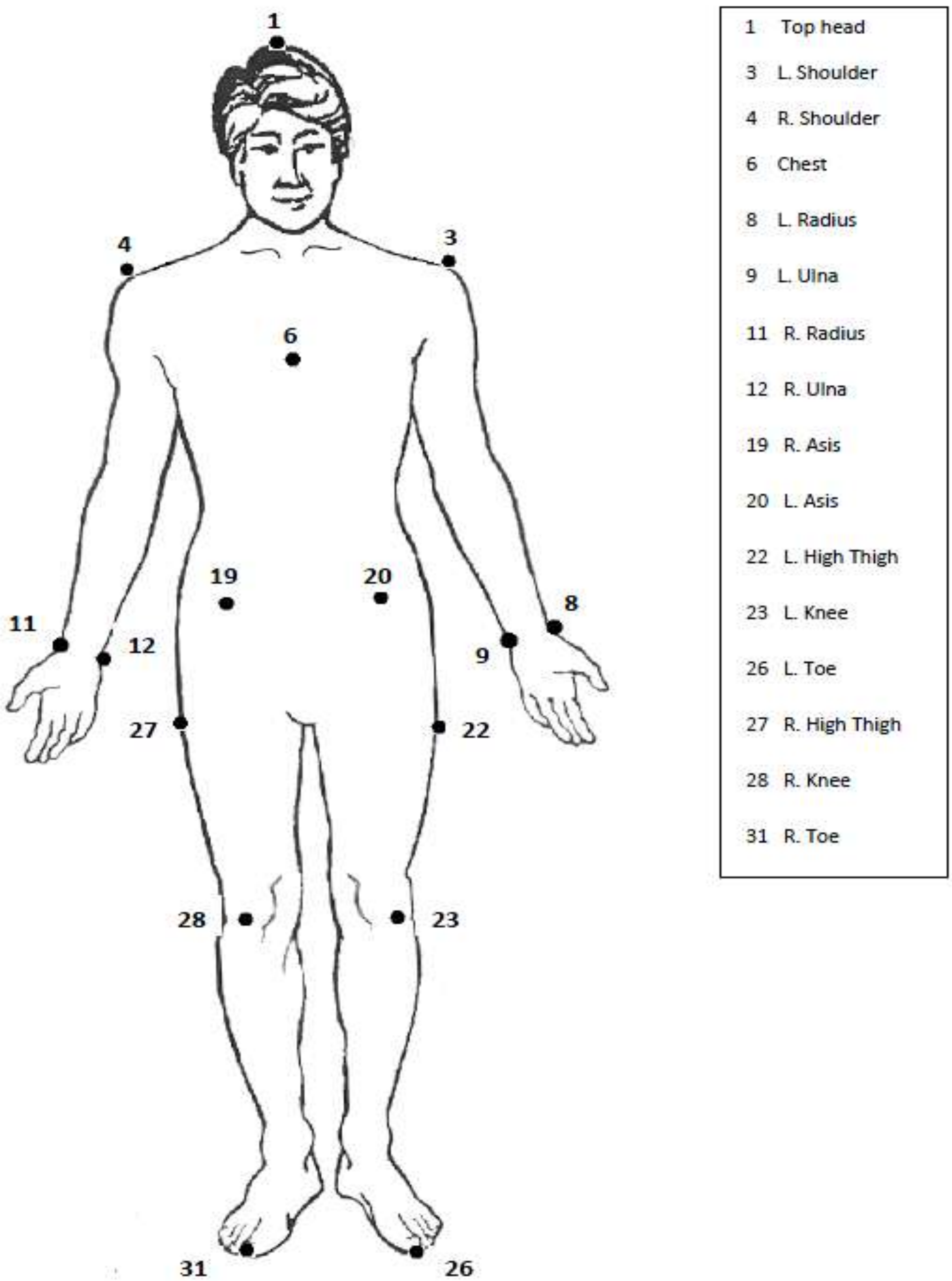


Fig. 2.3b Front view of marker locations for seated motion (Evart 5.0 User's Maneual)

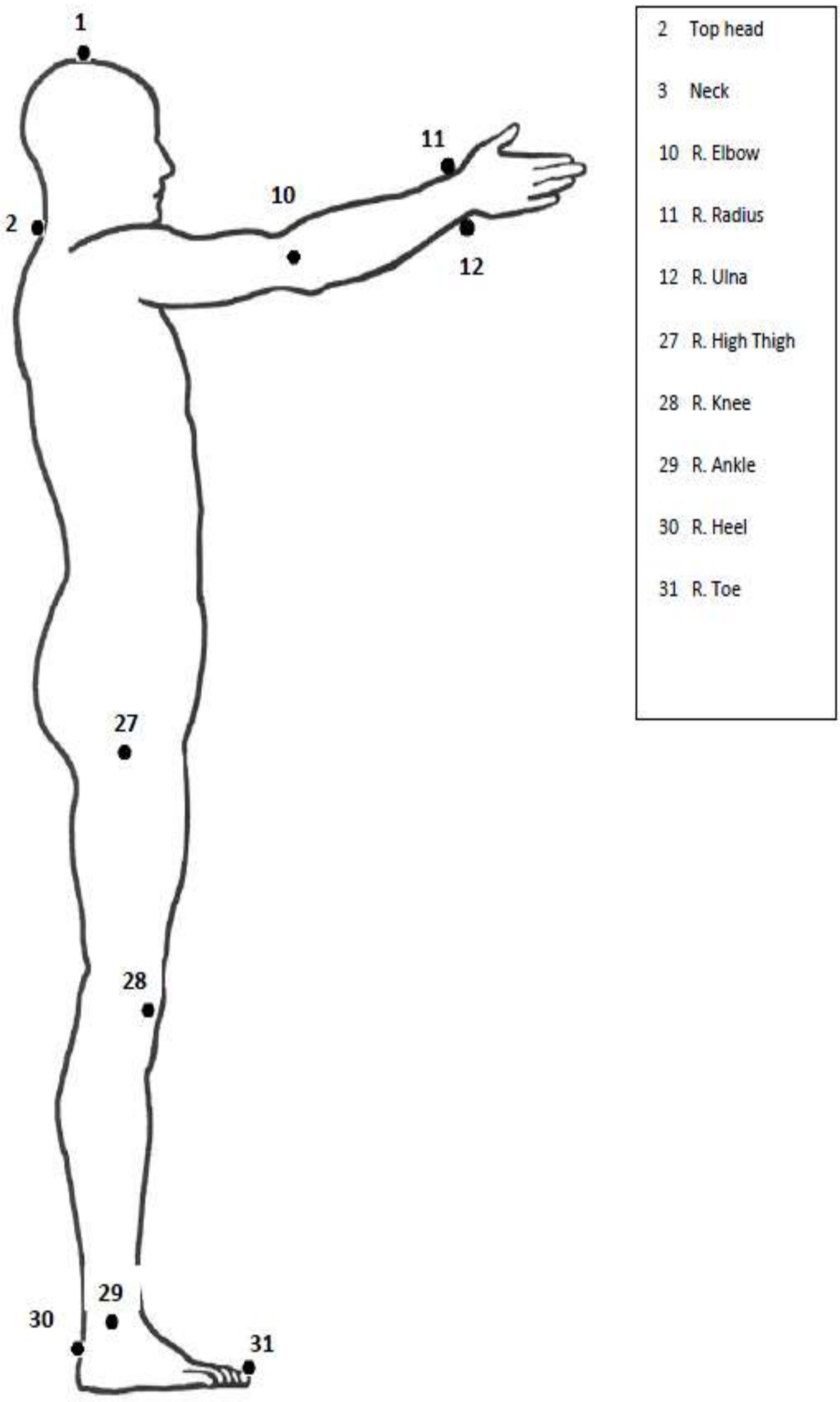


Fig. 2.3c Side view of marker locations for seated motion (Evart 5.0 User's Maneual)

8.1.2 Motion tasks

8 motion tasks which were frequently used were selected in order maximise the number of subjects capable of being captured in the shorter capture time.

1. Stand up and sit down in one cyclic motion.

2. Lean as far to the left and then to the right without support.

3. Reach to file cabinet (located behind/right to the participant). Due to the nature and size of a filling cabinet, camera line of site will be affected, due to this a suitable prop will be substituted maintaining the same height and reach properties.

4. Reach to paper on the floor (front/left).

5. Reach for a glass of water on desk (front/left to the participant), move it to your mouth, then place it back to the original position on desk.

6. Reach for a telephone on desk (front/right to the participant), move it towards your ear, hold for 5 seconds, then return it to the original position on desk.

7. Move a mouse in a square motion around the perimeter of a piece of white A4 paper, taped to the desk top (whilst seated). Two pieces of A4 paper will be placed to accommodate for right and left handed participants.

8. Type at a keyboard (whilst seated). Participants will be asked to type 1 paragraph of text displayed in front of them.

8.1.3 Indicators definition

Twenty joint angels were designed to compare the seated motion on Ergokenitic chair and standard chair. The Fig 8.2 showed the angles and their identification on the biomechanical model in the sagittal (first and third) and in the frontal second planes.

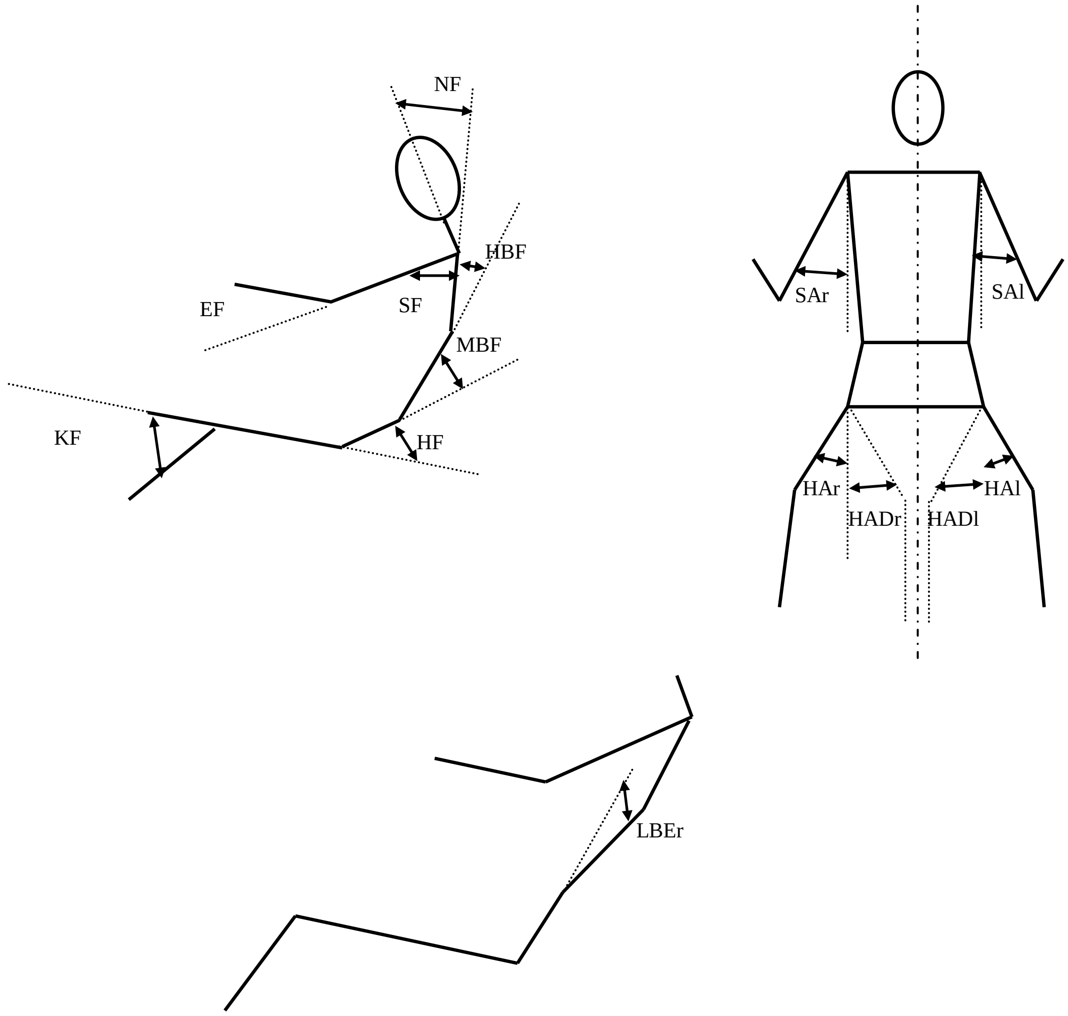


Fig. 8.1 Angle identification on biomechanical models: the first and third figure is angles in the sagittal plane, the second figure is angles in the frontal planes

The definition of 20 joint and their abbreviations are listed below:

Neck Flexion ⇨ (NF): the angle between the line of marker Top Head and Neck and the extension line of marker Neck and V.sacral.

Left Mid Back Flexion ⇨ (MBFl) : the angle between line of marker L.Midback and L.Highback and the extension line of marker L.Midback and a virtual marker constructed by L.Asis and L.Psis.

Right Mid Back Flexion⇨ (MBFr) the angle between line of marker R.Midback and R.Highback and the extension line of marker R.Midback and a virtual marker constructed by R.Asis and R.Psis.

Left High Back Flexion ⇨ (HBFl) the angle between line of marker L.Highback and L.Shoulder and the extension line of marker L.Lowback and L.Highback.

Right High Back Flexion ⇨ (HBFr) the angle between line of marker R.Highback and R.Shoulder and the extension line of marker R.Lowback and R.Highback.

Left Shoulder Flexion ⇨ (SFl) the angle between the line of marker L.Shoulder and L.Elbow and the line of marker L.Shoulder and L.Asis.

Right Shoulder Flexion ⇨ (SFr) the angle between the line of marker R.Shoulder and L.Elbow and the line of marker L.Shoulder and R.Asis.

Left Shoulder Abduction ⇨ (SAl) the angle between the line projected to body plane of marker L.Shoulder and L.Elbow and a virtual line which parallel to central body line.

Right Shoulder Abduction ⇨ (SAr) the angle between the line projected to body plane of marker R.Shoulder and R.Elbow and a virtual line which parallel to central body line on body plane.

Left Elbow Flexion ⇨ (EFl) the angle between the line of marker L.Elbow and Left virtual wrist constructed by L.Radius and L.Ulna and the extension line of marker L.Shoulder and L.Elbow.

Right Elbox Flexion⇨ (EFr) the angle between the line of marker R.Elbow and Right virtual wrist constructed by R.Radius and R.Ulna and the extension line of marker R.Shoulder and R.Elbow.

Left Hip Flexion ⇨ (HFl) the angle between line of marker L.Lowback and a virtual marker constructed by L.Asis and L.Psis and the extension line of marker L.Knee and the virtual marker constructed by L.Asis and L.Psis.Right Hip Flexion ⇨ (HFr) the angle between line of marker R.Lowback and a virtual marker constructed by R.Asis and R.Psis and the extension line of marker R.Knee and the virtual marker constructed by R.Asis and R.Psis.

Left Hip Abduction ⇨ (HAl) the angle between the line projected to body plane of marker L.Knee and the virtual marker constructed by L.Asis and L.Psis and a virtual line which parallel to central body line, when left leg moved outside of body.

Right Hip Abduction ⇨ (HAr)) the angle between the line projected to body plane of marker R.Knee and the virtual marker constructed by R.Asis and R.Psis and a virtual line which parallel to central body line, when right leg moved outside of body.

Left Hip Adduction ⇨ (HADl) the angle between the line projected to body plane of marker L.Knee and the virtual marker constructed by L.Asis and L.Psis and a virtual line which parallel to central body line, when left leg moved inside of body.

Right Hip Adduction ⇨ (HADr) the angle between the line projected to body plane of marker R.Knee and the virtual marker constructed by R.Asis and R.Psis and a virtual line which parallel to central body line, when right leg moved inside of body.

Left Knee Flexion ⇨ (KFl) the angle between the line of marker L.Knee and L.Heel and the extension line of marker L.Knee and L.High Thigh.

Right Knee Flexion ⇨ (KFr) the angle between the line of marker R.Knee and R.Heel and the extension line of marker R.Knee and R.High Thigh.

Right Mid Back Hyperextension ⇨ (MBEr) (Applicable for 3 motion task only) the angle between line of marker R.Midback and R.Highback and the extension line of marker R.Midback and a virtual marker constructed by R.Asis and R.Psis, when R.Highback move behind R.Midback.

For each chair type and each workstation task, computations of the above angles were completed using the following steps:

- Computation of the mean value, related standard deviations(SD), maximum value, and minimum value of a single subject;
- Computation of the mean angles, SD of mean angles by averaging all the 17 subjects.
- Computation of the average maximum angles, and average minimum angles of all the 17 subjects.

Finally, the obtained mean angles, SD, maximum angles, and minimum angles in motion tasks 1-8 of EGF, EGB, SOF and SOB were the basis for comparing the Ergokinetic chair and standard chair.

For this purpose, denotations ‘<’ or ‘>’ = 2-4 degree in difference, ‘<<’ or ‘>>’ =

4-8 degree, and '<<<' or '>>>' = above 8 degree.

8.2 Data Analysis

Workstation motion task 1

See table 1 in appendix 3 for full comparison of workstation motion task 1 in table form. There were not many common differences between the Ergokinetic chair and the standard office chair. However the mean angles of KFl and KFr.

$KFl_{EG} < KFl_{S}$; $KFr_{EG} > KFr_{S}$;

The maximum of KF on the Ergokinetic chair is higher than on the standard chair, and the minimum of KF on the Ergokinetic chair is lower than on the standard chair. That means the available scale of knee flexion on the Ergokinetic chair is more than on the standard chair.

Workstation motion **task 2**

See table 2 in appendix 3 for full comparison of workstation motion task 2 in table form. In this action, shoulder flexion has a distinct difference when sitting at the front of chair. Shoulder flexion is close when sitting the back of chair.

$SFl_{EGF} \gg SFl_{SOF}$; $SFr_{EGF} \gg SFr_{SOF}$;

And, $Max_{SFl\_EGF} \ggg Max_{SFl\_SOF}$; $Max_{SFr\_EGF} \ggg Max_{SFr\_SOF}$;

Results showed that when participants twist their bodies, the arms get higher in location for EGF than in SOF.

Workstation motion task 3

See table 3 in appendix 3 for full comparison of workstation motion task 3 in table form. In this action, there is a clear difference in posture of the back and hips between the Ergokinetic chair and standard chair. These differences however are less when sitting at the back of the chair than in the front of chair.

$HF_{EG} < HF_{S}$; $HAl_{EGF} \gg HAl_{SOF}$; $HAl_{EGB} > HAl_{SOB}$;

$MBFl_{EGF} \gg MBFl_{SOF}$; $MBFl_{EGB} \gg MBFl_{SOB}$;

$MBFr_{EGF} > MBFr_{SOF}$; $MBFr_{EGB} \approx MBFr_{SOB}$;

These results suggest that subjects bend the mid back much more instead of bending hips in order to reach the file cabinet located to the back right of the Ergokinetic chair. In summary Mid back bent more in the Ergokinetic chair than in standard chair, while the hips hips bend less in Ergokinetic chair than in standard chair. Specifically, hyperextension was computed for the right mid back.

$MBEr_{EGF} \gg MBEr_{SOF}$; $MBEr_{EGB} > MBEr_{SOB}$;

Subjects had more hyperextension for the right mid back in the Ergokinetic chair than in the standard chair.

The movement of higher back was almost identical with both chairs.

$SFl_{EGF} \gg SFl_{SOF}$; $SFl_{EGB} > SFl_{SOB}$;

The Left shoulder flexion for EGF is 6 degrees more than SOF, 3 degrees more with EGB than on SOB. The right shoulder flexion was also similar between both chairs.

It is similar phenomenon occurred in action 2. When a subject's body was twisted, their shoulder flexion was of higher value in the Ergokinetic chair than in the standard chair.

Workstation motion task 4

See table 4 in appendix 3 for full comparison of workstation motion task 4 in table form. For this motion, the hip flexion was relatively close in comparison however the hip abduction/adduction showed obvious differences between the two chairs.

$HAl_{EGF} \gg HAl_{SOF}$; $HAl_{EGB} > HAl_{SOB}$; $HAr_{EGF} \approx HAr_{SOF}$; $HAr_{EGB} < HAr_{SOB}$;

$HADl_{EGF} \ll HADl_{SOF}$; $HADl_{EGB} \gg HADl_{SOB}$; $HADr_{EGF} \gg HADr_{SOF}$; $HADr_{EGB} \gg HADr_{SOB}$;

Hip adduction occurred when the knee moved towards the centre of the body. There were no static rules in hip abduction and adduction. The only thing that can be stated is that the hips have a wider varied scale in the Ergokinetic chair than in the standard chair.

$MBFl_{EGF} \gg MBFl_{SOF}$; $MBFl_{EGB} \approx MBFl_{SOB}$; $MBFr_{EGF} > MBFr_{SOF}$; $MBFr_{EGB} \approx MBFr_{SOB}$;

The above shows that in general the subjects' mid back bends more in EGF than in SOF, however subjects were almost the same in EGB and in SOB.

The difference in high back and shoulder movement were minimal. Right shoulder flexion in EGF motions, was 3 degrees higher than in SOF motions.

Workstation motion task 5

See table 5 in appendix 3 for full comparison of workstation motion task 5 in table form. In this action, the movement of the hips, mid back and high back were clearly different between the Ergokinetic chair and standard chair.

$MBFl_{EGF} > MBFl_{SOF}$; $MBFl_{EGB} \approx MBFl_{SOB}$; $MBFr_{EGF} > MBFr_{SOF}$; $MBFr_{EGB} \approx MBFr_{SOB}$;

The same applied to high back flexion.

$HFr_{EG} < HFl_S$; $HFr_{EG} < HFr_S$;

Similar to that shown in action 3, subjects bend their mid back and high back much more instead of bending hips in order to reach the glass of water on desk in the Ergonetic chair. In this motion and motion 6, hip adduction was not accounted for, since there were very few subjects that had this angle.

$SFr_{EGF} \gg SFr_{SOF}$;

When reaching for the glass, subjects right shoulder flexion was higher in EGF than in SOF, but close in EGB and SOB.

Workstation motion task 6

See table 6 in appendix 3 for full comparison of workstation motion task 6 in table form. Motion task 6 is very similar with motion task 5.

$MBFl_{EGF} > MBFl_{SOF}$; $MBFl_{EGB} \approx MBFl_{SOB}$; $MBFr_{EGF} > MBFr_{SOF}$; $MBFr_{EGB} > MBFr_{SOB}$;

$HBFr_{EGF} > HBFr_{SOF}$; $HFr_{EG} < HFl_S$; $HFr_{EG} < HFr_S$;

Mid back bends further in Ergokinetic chair than in standard chair, hips bend less in Ergokinetic chair than in standard chair. The left high back moved almost the same distance between both chairs. Right high back bends much more in EGF than in SOF, same in EGB and SOB.

$HAl_{EGF} \gg HAl_{SOF}$; $HAl_{EGB} > HAl_{SOB}$; $HAr_{EGF} > HAr_{SOF}$; $HAr_{EGB} \approx HAr_{SOB}$;

Results show that subject's knees moved more away from centre of the body in the Ergokinetic chair than in the standard chair.

$SFl_{EGF} > SFl_{SOF}$;

It is an interesting and consistent rule that subjects had higher right shoulder flexion when they were getting something at left in the Ergokinetic chair than in standard chair, and had higher left shoulder flexion when they were getting something towards the right in the Ergokinetic chair than in the standard chair, excluding when they were picking something up from on the floor.

Workstation motion task 7

See table 7 in appendix 3 for full comparison of workstation motion task 7 in table form.. While moving the computer mouse on the desk with right hand, the left mid back flexion was higher when seated in the Ergokinetic chair than in the standard chair.

$MBFl_{EG} > MBFl_{S}$; $MBFr_{EG} \approx MBFr_{S}$;

$HBFr_{EGF} > HBFr_{SOF}$; $HFl_{EGB} < HFl_{SOB}$; $HFr_{EGB} < HFr_{SOB}$;

Results also showed that the hip bent less in the Ergokinetic chair than in the standard chair whilst seated to towards the back of the chair.

$SFl_{EGF} > SFl_{SOF}$; $SFl_{EGB} \approx SFl_{SOB}$; $SFr_{EGF} > SFr_{SOF}$; $SFr_{EGB} < SFr_{SOB}$;

Left shoulder flexion was increased in the Ergokinetic chair than in the standard chair while using the right hand to move the mouse. The right shoulder flexion was different however it had a higher value in EGF than in SOF, but had lower value in EGB than in SOB.

$HAl_{EGF} > HAl_{SOF}$; $HAl_{EGB} > HAl_{SOB}$; $HAr_{EGF} > HAr_{SOF}$;

$HAr_{EGB} \approx HAr_{SOB}$;

Overall subject's knees moved more away from the centre of the body in the Ergokinetic chair. Results showed that there was more freedom about hip abduction in the Ergokinetic chair than in the standard chair.

Workstation motion task 8

See table 8 in appendix 3 for full comparison of workstation motion task 8 in table form. This action is very similar with just sitting in still motion.

$MBFl_{EGF} > MBFl_{SOF}$; $MBFl_{EGB} \approx MBFl_{SOB}$; $MBFr_{EGF} \approx MBFr_{SOF}$; $MBFr_{EGB} < MBFr_{SOB}$;

$HBFr_{EGF} > HBFr_{SOF}$; $HFl_{EGB} < HFl_{SOB}$; $HFr_{EGB} < HFr_{SOB}$;

Results showed that the hip bent less whilst seated in the Ergokinetic chair than in standard chair when sitting at the back of chair, but almost the same whilst seated in the front of chair. The right high back flexion had little difference when sitting in the front of chair. The left mid back bent more in EGF than in SOF, but the right mid back bent less in EGB than in SOB.

$SFl_{EGF} \approx SFl_{SOF}$; $SFl_{EGB} < SFl_{SOB}$; $SFr_{EGF} > SFr_{SOF}$; $SFr_{EGB} < SFr_{SOB}$;

Left shoulder flexion had lower value in EGB than in SOB. Right shoulder flexion had higher value in EGF than in SOF, but had lower value in EGB than in SOB.

$HAl_{EGF} > HAl_{SOF}$; $HAl_{EGB} \approx HAl_{SOB}$; $HAr_{EGF} > HAr_{SOF}$; $HAr_{EGB} < HAr_{SOB}$;

There were no clear distinction in shoulder flexion and hip abduction differences in action 8. One thing which can be stated is that most hip angles varied scale was wider in the Ergokinetic chair than in standard chair since most of maximum hip angles were higher in Ergokinetic chair than in standard chair.

8.3 Results

8 common workstation motion tasks were designed in order to investigate the human seated motion difference on Ergokinetic split seat chair in comparison with

a standard office chair. After analyzing all the results of 2nd motion study, a clear difference the two chairs became apparent. After examination of all joint angles across the 8 workstation motion tasks, some common ground was summarized for the seated motion on the Ergokinetic chair.

8.3.1 More HF, less MBF

The main distinct difference between the Ergokinetc chair and the standard chair showed mainly at the hips, mid back and high back. Each of the above was affected by the different designs present in both chairs. Overall the subject's hips bent less whilst completing the motion tasks seated in the Ergokinetic chair than in standard chair. Subjects were inclined to bend their mid backs and higher backs instead of their hips. This difference is very obvious in some actions which leads subjects to change their centre of gravity whilst reaching for the items on the desk (left/front or right/front), as well as something behind. The difference is more apparent when subjects sitting at the front of chair than sitting at the back of chair.

8.3.2 Wider varied scale

In some other motions, subjects showed wider varied scale about hip angles including hip abduction and hip adduction. In additional, subjects had almost the same hip flexion but very different hip abduction and adduction results when asked to pick an item up of the floor. Subjects have much more freedom about how they position their hips and legs in the Ergokinetic chair when completing these actions.

8.3.3 Higher shoulder flexion

Subjects have a higher shoulder flexion value in most actions. When twisting their body, left/right shoulder flexion were both higher. When reaching for a glass of water in the left front on desk, right shoulder flexion was higher in the Ergokinetic chair than in standard chair. For the opposite type of motion, reaching to answer the telephone at the front right on the desk, the left shoulder flexion was higher in ergo chair than in standard chair.

Elbow and knee angles didn't have much difference between the chairs. .

8.4 Summary

According to the above analysis, the difference between seated motion on the Ergokinetic chair and standard office chair are clear.

Subjects seated in the Ergokinetic chair are not required to bend their hips as much as needed to, in order to carry out the same motion in the standard office chair. When a change in centre of the gravity occurs, the Ergokinetic chair offers more support which protects the hips. Thus, the mid back bends instead of hips. The Ergokinetic chair offers greater support and motion advantages surrounding the hip area of the human body.

Subjects seated on Ergokinetic chair also had more flexibility about hips and legs when completing general actions such as standing, typing etc.

Subjects seated on Ergokinetic chair increase balance as subject gained a higher level of shoulder flexion on the opposite arm when completed the reaching workstation motion tasks.

The results showed that the difference of seated motion between Ergokinetic chair and standard chair is more obvious when the subjects were seated towards the front of the chair, over sitting against the back lumber support.

Little difference was noticed with elbow, knee and lower leg movements in seated motion between the Ergokinetic chair and standard office chair.

Chapter 9 Conclusion

In this thesis, the main work encompassed gait identification and gait analysis of individuals. First, a novel approach for identifying individuals was proposed. This identification method achieved very high accuracy in a data sample with very similar subjects. Then, a solution was provided to the question: which of these features should be extracted to represent gait and why. A novel gait cycle and its corresponding phases were defined. The influence of gait features from the gait phases was investigated.

In addition, the relationship between gait and attractiveness was analysed and a predictable model for gait attractiveness was built. The similarity and dissimilarity between the left and right sides of the body in gait were investigated. This research showed the most asymmetric body parts in each subjects' in gait and revealed the common similarities and asymmetric appearances in gait among different subjects.

As an extension of gait research, human seated motion was also investigated by comparing subjects seated in an Ergokinetic chair with those seated in a standard office chair using motion capture technique. A special set of markers were designed for the seated person to evaluate seated motion.

The results were summarised in six fields: gait identification, gait feature analysis, gait cycle and phase analysis, similarity analysis in gait, gait attractiveness analysis, and the human seated motion on different chairs.

9.1 Progress achieved in gait identification

9.1.1 Novel gait features proposed

A novel, effective set of gait features, which contained 14 angles and one ratio, was proposed to represent the gait of individuals. These 15 gait features were evaluated according to Consistence degree and Variation degree. Table 3.2 shows the Consistence degree and Variation degree of 15 gait features. *The results showed that these gait features remained stable in different gait profiles of the same subjects but varied greatly for different people.* Therefore, these 15 gait features were suitable for individual identification. *These identification results also showed that the new set of gait features are very suitable for gait identification.* The features were able to describe gait features about individuals well.

The influence of gait phases and similarities in gait were analysed using this set of gait features as well. Gait signatures were extracted from this set of gait features using three different methods, and the signatures yielded high accuracy in individual identification. This set of gait features included 14 angles and 1 ratio, which are listed in Table 3.1.

Some features in this set have been utilised in previous research, such as elbow angles and knee angles. Some features in this set were proposed in this study, such as Wrist_shoulder_y/z, Heel_toe_y/z, and Wrist speed ratio. Angles were separated on the y-axis and z-axis to represent gait instead of only joint angles in this research. The following research about gait features also showed that these features described the individuality of gait.

9.1.2 Normalized gait data as a database and Data sample with very similar subjects

The gait data was normalized by gait cycle and linear interpolation. Each gait cycle had the same frame numbers after interpolation and the same starting posture. Interpolation and normalized gait data improved the accuracy of individual identification and significantly helped in the analysis of gait cycles and phases.

The data sample in this paper included 35 subjects. The specific property of this data base is that it contained only young, male subjects. The gender and age effects played no part in identification. *In a data sample contained very similar subjects, very high identification results were achieved.* If the data sample were increased to include all subjects with different age and gender, the identification methods will prove even more efficient in theory.

9.1.3 High accuracy in identification results

In this thesis, a systematic and practical method was proposed with high accuracy to identify individuals. The results of this identification procedure are better than previous reported literature. This method used k-NN algorithm as the distinguishing method, 15 gait features as represent method, and several different methods to extract gait signatures. Then the identification results were compared. The different methods were as follows:

- Statistical method using (mean, SD of mean value) or (mean, SD of mean value, maximum, minimum) as gait signatures.
- PCA method using coefficients on PCs of features as gait signatures.
- Fourier expansion method using Fourier coefficients as gait signatures.

The highest accuracy of identify was nearly 100% while using the average gait as the base gait, and the accuracy was above 95% while using the random one gait as the base gait. Table 3.3 in Chapter 3 shows the identification results. The accuracy is much higher than that reported previous research. The identification rate is about 75% in 114 subjects in (Foster et al. 2003), 82.5% in 74 subjects in (Wang et al. 2003). The statistics method achieved a very high identification rate using the simplest calculated dimension. The Fourier expansion method achieved the best result while using the random gait as the base gait. While using the average gait as the base gait, each of the three methods achieved a very high accuracy.

In general, the identification results that used the average gait of the subjects as the base gait were better than the results that used the random gait of the subjects as the base gait. In addition, using average gait as the base gait can also increase the correct identification rate when the subjects is not in the data sample compared with using random gait as the base gait.

9.2 Progress achieved in gait analysis regarding gait features

9.2.1 Mathematical tools for evaluating gait features

To evaluate the gait features using a quantitative method, two indicators were designed to evaluate gait features. These two indicators were proposed as 'Consistence degree' and 'Variation degree'. Consistence degree evaluated whether the gait feature remained stable in different gaits for the same subject. Variation degree evaluated whether the gait feature was noticeably different for different people. If a gait feature is suitable for distinguishing individuals, it should have a noticeable difference for different people while remaining stable among different gaits for the same subject.

The set of gait features in this thesis were evaluated by these two indicators. These gait features all had a high Variation degree and a high Consistence degree.

9.2.2 The importance of different gait features in the gait cycle

To provide a solution to the question of which features should be extracted to represent gait, the average gait of 70 gait cycles was analysed via PCA, as described in Chapter 5. Four principle components were extracted. Pc1 is a composite indicator of the gait cycle and focused on features on y-axis and Wrist speed ratio. Pc2 focused on features on z-axis and Right elbow. Pc3 is an indicator that focused on left Knee, left elbow, and left Wrist_shoulder_z. Pc4 focused on Head_Topspine and Topspine_Root.

Thus, f*eatures on y-axis have higher importance in gait than features on z-axis. Wrist speed ratio is important in gait. Head_Topspine and Topspine_Root angle are relatively independent of other gait features.* These results show the varying importance of gait features in the gait cycle and provided a simplified structure to represent gait for identification.

9.2.3 The significance of relative motion from different body segments by the fixing root method

In a separate study, PCA and the fixing root method were used to investigate the relative motion of different body segments in order to answer the question of which features should be extracted to represent gait. By the fixing root method, the influence of walking speed was removed, and gait data were fully focused on the related movement of each body segment. Therefore, this method provided a greater chance for identifying natural gait features.

PCA were applied on gait after the fixing root method. In Pc1, the three variables with largest coefficients were concentrated on the lower left arm, which were followed by other variables located around left shoulder. In Pc2, all 10 variables on the lower legs and feet corresponded to the largest coefficients. However, in Pc3, all four variables on the hip corresponded to the largest coefficients, which were followed by the variable Midback_offset. The remaining variables with coefficients equal to or less than 0.31 were ignored. *The PCA results in this study provided a simplified structure for revealing the most important features/characteristics of gait, which were found to be movements of the left lower arm, the lower legs, and the hip.* The method provided an analytical solution for choosing the motion of left lower arm, the lower legs and feet, and the hip as features for gait recognition.

9.3 Progress achieved in the analysis of gait cycles and phases

9.3.1 Novel gait phases and gait cycle definition

A novel dividing method of gait phases and gait cycle was provided in this research with a clear statement of definition. Gait phases were divided by two feet as they corresponded to the stance phase or the swing phase, instead of tracking the movement of the same feet, as reported in previous research. The traditional gait phases were constructed by the stance phase of one foot and the swing phase of the same foot by the two different criteria: the variation of the supporting leg in the stance phase and the variation of swing in the swing phase. It is difficult to analyse the corresponding movement of each support leg and swing leg by this division of gait phases because the phases in the Right single support phase are not symmetrical with the phases in the Left single support phase.

The gait cycle that was used in this research encompasses the left toe off posture to the next left toe off posture. The gait cycles were divided into eight gait phases by the following definitions.

- 1. Left initial swing: begins at the left toe off posture and ends at the posture at which the maximum left knee flexion occurs.
- 2. Left mid-swing phase: begins at the posture at which the maximum left knee flexion occurs and ends at the posture at which the left tibia is vertical or perpendicular to the ground.
- 3. Left initial contact phase: begins at the posture at which the left tibia is vertical or perpendicular to the ground and ends at the posture at which the left heel makes initial contact with the ground.
- 4. Right pre-swing phase (Double support phase): begins at the posture at which the left heel initial contact ground and ends at the right toe off posture.
- 5. Right initial swing phase: begins at the right toe off posture and ends at the posture at which the maximum right knee flexion occurs.
- 6. Right mid-swing phase: begins at the posture at which the maximum right knee flexion occurs and ends at the posture at which the right tibia is vertical or perpendicular to the ground.
- 7. Right initial contact phase: begins at the posture at which the right tibia is vertical or perpendicular to the ground and ends at the posture at which the right heel initial contact ground.
- 8. Left pre-swing phase (Double support phase): begins at the posture at which the right heel initial contact ground and ends at the left toe off posture.

The difference between this method and the previous method is the gait phases in the single support phase. The Right single support phase is divided by the variation of the left leg's swing. Therefore, *the phases in the Right single support phase correspond to phases in the Left single support phase (Right swing phase).*

By this method of dividing gait phases, the gait cycle is symmetrical from the middle of the cycle. This method is appropriate not only for comparing the body movement of the corresponding stance/swing phase of the two feet but also for analysing the similarity in gait between the left body and the right body. These eight phases constructed two half symmetrical cycles of the swing/stance leg.

9.3.2 Two indicators for evaluating the influence from gait phases

The two indicators $(P_{\max}, P_{\min})$ *and* $(F\_P_{\max,} F\_P_{\min})$ *were proposed to evaluate the influence on gait features from the gait phases.* $(P_{\max}, P_{\min})$ signify the phase number with the maximum value for feature i and the phases number with the minimum value for feature i. $(F\_P_{\max,} F\_P_{\min})$ refers to the percentage of a gait phase completed when $Fr_{\max}$ and $Fr_{\min}$ occur. $Fr_{\max}$ and $Fr_{\min}$ are the frame number with maximum F_i and the frame number with minimum F_i, respectively.

9.3.3 The different influences on gait features from gait phases

In this research, the influences on gait features from gait phases were analysed. Two findings can be summarised from this research. Arm-related features were less influenced by the gait phases than leg-related features. Features on y-axis were less influenced by gait phases than features on z-axis. Therefore, *arm-related features have more freedom/individuality than leg-related features, and gait features on y-axis have more freedom/individuality than gait features on z-axis.* These findings are consistent with the PCA results of average gait described in Section 9.2. Gait features on y-axis were affected more by gait than gait features on z-axis.

9.3.4 Differences in the length of gait phases for different subjects

Detailed and exact data of the length of gait phases were obtained for 35 subjects. The average gait phase lengths of the single support phase and the double support phase were nearly with the previous data. The gait phase lengths of individuals differed greatly. The gait phase lengths varied much more in phases 6, 7, 2, and 3 than in phases 1 and 5, which showed that the postures where the tibia is vertical or perpendicular to the ground varied greatly for different subjects in the gait cycle. *The posture at which the maximum knee flexion occurred varied less for different subjects in the gait cycle. The variation of double support phase length was between the variations of these two postures.*

9.4 Progress achieved in similarity analysis in gait

9.4.1 Gait half cycle length difference

Based on the research in Chapter 4, one gait cycle was divided into two half cycles. The first half cycle comprised phase 1 to phase 4 and was denoted cycle 1. It was constructed by the Right single support phase and the following double support phase. The second half cycle comprised phase 5 to phase 8 and was denoted cycle 2. It was constructed by the Left single support phase and the following double support phase.

There were 74.29% of the 35 subjects for which cycle 1 was longer than cycle 2. The average length of cycle 1 was 1.44% longer than cycle 2. The difference between cycle 1 and cycle 2 varied from -8.93% to 7.2% of the gait cycle.

9.4.2 Evaluation of similarity and asymmetry in gait

The similarity and asymmetry was investigated between the left body and the right body movement in gait. *The similarity/asymmetry between the left and right body was analysed by comparing the appearance of body parts while performing the same function.* Therefore, it was calculated according to four components: leg movement of the swing leg, leg movement of the support leg, arm movement while the opposite leg was the support leg, and arm movement while leg of the same side was the support leg.

Eleven indicators of comparison were used in Chapter 6. Left 1 refers to the left feature in cycle 1, and right 2 refers to the right feature in cycle 2. Knee angle (left 2: right 1) was not considered because there was not much difference in the support phase.

The similarity/asymmetry of the leg movement of the swing leg was described by indicators 3, 4, and 6. The similarity/asymmetry of the leg movement of the support leg was described by indicators 5 and 7. The similarity/asymmetry of arm movement while the opposite leg was the support leg was described by indicators 1, 8, and 10. The similarity/asymmetry of arm movement while the leg of the same side was the support leg was described by indicators 2, 9 and 11.

9.4.3 Similarity/asymmetry of body part movement in gait

In general, *elbow movement (while the opposite leg was the support leg*), *wrist movement on the y-axis* (when both the opposite and same-side leg was the support leg), and *foot movement on y-axis* (for both the swing leg and the support leg) usually showed an asymmetry in the gait cycle.

Elbow movement while the leg of the same side was the support leg, *wrist movement on the z-axis* (when both the opposite and same-side leg was the support leg), *foot movement on z-axis* (for both the swing leg and the support leg), and *knee movement* showed a high similarity in gait cycle.

In addition, wrist movement on the y-axis was more asymmetric than foot movement on the y-axis.

For different subjects, the similarity/asymmetry appearance varied very little for the Knee and Heel_toe_z features (almost all had a high positive correlation), varied highly for Wrist_shoulder_y, elbow, Heel_toe_y, and Wrist_shoulder_z when the opposite leg was the support leg (ranging from a high negative correlation to high positive correlation), and varied from no correlation to a high negative correlation for Wrist_shoulder_z when the leg of the same side was the support leg.

9.4.4 The most asymmetric body parts in gait for individuals

The most asymmetric body part in gait was investigated for 35 subjects. Table 6.4 and Table 6.5 show each subject's data and the summarised data. Table 6.5 shows the numbers of subjects with the most asymmetric body parts and the corresponding feature, and the percentage of all 35 subjects.

Wrist movement on the y-axis while same-side leg is support leg, elbow movement while the opposite leg is the support leg, and wrist movement on the y-axis while the opposite leg is the support leg are the most possible asymmetric body part in gait.

Foot movement of the swing leg on the y-axis, and foot movement of the support leg on the y-axis are the body parts least likely to be asymmetric in gait.

There were no subjects for whom the most asymmetric body part in gait was Knee, Heel_toe_z, or Wrist_shoulder_z (left 2: right 1).

In summary, body movement on the y-axis (Wrist_shoulder_y and Heel_toe_y), and Elbow movement while the opposite leg is the support leg have a high possibility of being the most asymmetry body part in gait.

9.5 Progress achieved in gait attractiveness

9.5.1 Predictable gait attractiveness value with reasonable accuracy

Here, *a predictable model for gait attractiveness based on markers' average speeds derived via PCA and linear regression is proposed.* This research is a continuation of previous research on the relationship between walking speed and walkers' status (Schmitt & Atzwanger 1995; Chiu & Wang 2007). Although speed is not a suitable feature for identification individuals because it is too easy to change or fake, speed is still a very useful feature which reflects much information from gait such as walker's age, emotion. A systematic relationship between the motions of individual body markers and attractiveness rating was found. This relationship can be expressed as a linear equation of the natural logarithm of the attractiveness rating value, the natural logarithm of two principal components extracted from the 40-marker speed matrix and a constant (such as equation (7.4)).

$$\ln(attract\_value) = 0.829 * \ln(Pc1) + 0.003 * \ln(Pc2) - 5.044 \qquad (7.4)$$

PCA and linear regression revealed the pattern between attractiveness rating and individual marker speed. The robustness of this method was further verified eight times by randomly substituting the subjects who composed the data sample and the verification group, a procedure that produced very similar results to the original analysis. *The average error in predicting attractiveness in the eight additional verification procedures was 8.58%, and the average error in calculating attractiveness from the data sample was 8.75%.*

These results imply that for a specific subject group and a specific evaluator group, if PCA and linear regression are used to generate an equation similar to equation (4), then the gait attractiveness ratings of any further new subjects in this group can be predicted with reasonable accuracy (around 10%) based on their gait motion data.

9.5.2 Attractiveness correlated positively with speed but was uncorrelated with acceleration

Gait attractiveness was much more correlated with the average speed of each body segment than with the average acceleration of each body segment in gait. The correlation coefficients between attractiveness and average speed of all of the 40 markers are much higher than those between attractiveness and average acceleration. The PCA results on marker speeds and marker accelerations also verified these results. PCA extracted two principal components from the marker speeds, with the cumulative variance reaching 95.23% of the total variance. In contrast, PCA extracted nine principal components from marker acceleration, with cumulative variance reaching 87.43% of the total variance. Furthermore, the regression results show no obvious linear relationship between *attract* and these nice principle components, and no linear relationship between ln(attract) and ln(PCac1), ln(PCac2), … , ln(PCac9).

9.5.3 Using lower leg and feet features as gait features for attractiveness

Via PCA and the linear regression method, it was found that features can be extracted from the lower legs and feet for gait attractiveness. The effectiveness of predicting the results of gait attractiveness using only ten lower leg and feet markers was compared as opposed to using all 40 markers. The comparative analysis showed that the results could be predicted slightly better by only using the lower leg and feet markers than by using all 40 markers. The average error decreased from 8.58% to 7.81%. *This result signifies that instead of using 40 markers, ten markers from the lower legs and feet can be used to fully represent and predict attractiveness values.* Comparing the results revealed the effectiveness of the features for gait attractiveness that chosen by fixing root method and PCA.

The relationship between the movement of the lower legs and feet and attractiveness could not be revealed without the fixing root method. The method of fixing root revealed more information on gait by utilising the relative motion from different body segments.

9.6 Progress achieved in seated motion

9.6.1 A systemic evaluation process for Ergokinetic chairs

A new set of markers, 8 common workstation motion tasks and 20 joint angles, were proposed to evaluate human seated motion after the analysis of walking motion. The seated motion of 17 subjects was compared between the subjects sitting on an Ergokinetic chair and a standard chair. The Ergokinetic chair is a newly designed chair with a split seat.

9.6.2 Differences in the seated motion between Ergokinetic chairs and standard office chairs

A noticeable difference between seated motions on the different chairs was found.

Subjects seated on the Ergokinetic chair were not required to bend their hips as much as is typically needed to carry out the same motion in a standard office chair. When a change in the centre of the gravity occurs, the Ergokinetic chair offers greater support, which protects the hips. Thus, the mid-back bends instead of the hips. The Ergokinetic chair offers greater support and motion advantages surrounding the hip area of the human body.

Subjects seated on the Ergokinetic chair also had more flexibility around the hips and legs when completing general actions, such as standing and typing.

Subjects seated on the Ergokinetic chair exhibited increased balance, as they gained a higher level of shoulder flexion on the opposite arm when completing the reaching workstation motion tasks.

The results showed that the difference in seated motion between the Ergokinetic chair and the standard chair was more obvious when the subjects were seated towards the front of the chair rather than sitting against the back lumber support.

Little difference was noticed in elbow, knee, and lower leg movements during seated motion between the Ergokinetic chair and the standard office chair.

9.7 Future work

Research in this area has many possible applications in security. Most previous research related with gait in regard to security focused only on 2D image data acquired via security cameras. More research based on 3D data recorded by motion capture systems has recently emerged. Normally, motion captured databases, which have been used in previous research for identifying individuals, only contain several tens of subjects, whereas 2D databases could have over several hundreds of subjects. It is obvious that 3D data includes more complete and accurate data compared with 2D data. The database contained 35 subjects, which is sufficient for this study, although a larger database would be more helpful in practice for future research.

In this thesis, two main aims were completed: gait identification, and analysis of gait features for identification which answer the question of which of the extracted features represent gait and why. The identification results were achieved with high accuracy in a data sample with very similar subjects. It suggests that this identification method is very effective and successful. Two indicators were proposed to evaluate gait features whether are suitable for identification. The minor aims of gait attractiveness analysis and similarity analysis in gait were also completed. In addition, an extra task related to human seated motion was completed.

This period of gait research has been completed. There are numerous continuing research studies based on the current results. For example, my 15 gait features were shown to describe gait well. The fixing root method and PCA analysis suggested that the features derived from the left lower arms, the lower legs, and the hips should be used. Then, the number of features needed by only retaining the gait features could be minimised related to the left lower arms, the lower legs, and the hips from the 15 features. This procedure shortens the computing time for analysing large gait databases. This study is only one possible avenue of continued research. Gait identification is still in a starting stage. A complete approach of gait included the represent method, the analysis method, and the distinguish method. In the future, analysis method could be improved by focusing on improved signal processing methods. The distinguish method could also be improved. k-NN algorithm was chosen because of the ease of application and the limitations of the small database. However, a self-training model could be realised if a larger database is acquired. After the analysis of gait attractiveness and fluctuating, it was begun to consider that whether attractiveness or asymmetry could be included as gait features for identification. Would these features significantly increase the accuracy rate to provide useful information or waste computing time by generating superfluous information? These are interesting questions that provide avenues for future work.

In addition, there are factors regarding the space of the gait data that may be improved. Although 35 subjects is not a small database compared with other gait analyses based on the motion capture system. In theory, research results could greatly differ when the database is enlarged to hundreds or even thousands subjects. In additional, the multi-gait cycles of one subject were captured at different times within same day, which is a limitation of the experimental environment. A more realistic application for the future would be to capture gait on different days for one subject.

Gait identification has attracted increasingly more attention recently and has substantial potential for application in many areas.

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*Gait analysis and identification***,** Hong, Jie; Kang, Jinsheng; Price, Michael E.***, 18th International Conference on Automation and Computing (ICAC),*** 2012. pp. 1-6.

Appendices

Appendix 1: A list of gait features in previous research

Table 1 Gait features related to medical research

features	articles	Published year
Stride length	Gait classification in children with cerebral palsy by Bayesian approach	2009
	Reliability of diabetic patients' gait parameters in a challenging environment	2008
	Automated feature assessment in instrumented gait analysis	2006
Cadence	Gait classification in children with cerebral palsy by Bayesian approach	2009
Leg length	Gait classification in children with cerebral palsy by Bayesian approach	2009
Joint angle	Evaluation of clinical spasticity assessment in Cerebral palsy using inertial sensors	2009
	Automated feature assessment in instrumented gait analysis	2006
Hip angle	Evaluation of clinical spasticity assessment in Cerebral palsy using inertial sensors	2009
Knee angle	Evaluation of clinical spasticity assessment in Cerebral palsy using inertial sensors	2009
Shank angle	Differences in gait complexity and variability between children with and without Developmental Coordination Disorder	2009
asymmety of gait cycles	Differences in gait complexity and variability between children with and without Developmental Coordination Disorder	2009
Velocity	Reliability of diabetic patients' gait parameters in a challenging environment	2008
Gait cycle time	Reliability of diabetic patients' gait parameters in a challenging environment	2008
Stance phase	Reliability of diabetic patients' gait parameters in a challenging environment	2008
Double support time	Reliability of diabetic patients' gait parameters in a challenging environment	2008
	Characterising the clinical and biomechanical features of severely deformed feet in rheumatoid arthritis	2008
Sagittal shank	Reliability of diabetic patients' gait parameters in a challenging environment	2008

Thigh and knee range	Reliability of diabetic patients' gait parameters in a challenging environment	2008
Abduction moment at the knee during gait	Detecting differences between asymptomatic and osteoarthritic gait is influenced by changing the knee adduction moment model	2008
lower limb joint	On the expression of joint moments during gait	2007
Sagittal plane	On the expression of joint moments during gait	2007
	The effect of total knee replacement surgery on gait stability	2008
hip abduction	Femoroacetabular impingement alters hip and pelvic biomechanics during gait Walking biomechanics of FAI	2009
Sagittal ROM(range of motion)	Femoroacetabular impingement alters hip and pelvic biomechanics during gait Walking biomechanics of FAI	2009
pelvic frontal ROM	Femoroacetabular impingement alters hip and pelvic biomechanics during gait Walking biomechanics of FAI	2009
Gait speed	Characterising the clinical and biomechanical features of severely deformed feet in rheumatoid arthritis	2008
joint motion trajectories	Extracting a diagnostic gait signature	2008
sagittal angles of the hip, knee, and ankle joints	Extracting a diagnostic gait signature	2008
Hip flexion	Automated feature assessment in instrumented gait analysis	2006
left and right boundaries on silhouettes	A vision-based analysis system for gait recognition in patients with Parkinson's disease	2009

Table 2 Gait features related to age research

features	articles	Published year
Time to last foot contact	Rapid gait termmination: Effects of age, walker surfaces and footwear	2009
Total stopping time	Rapid gait termmination: Effects of age, walker surfaces and footwear	2009
Stopping distance	Rapid gait termmination: Effects of age, walker surfaces and footwear	2009
Number of steps to stop	Rapid gait termmination: Effects of age, walker surfaces and footwear	2009
Step length	Rapid gait termmination: Effects of age, walker surfaces and footwear	2009
	Effects of walking surfaces and footwear on temporo-spatial gait parameters in young and older people	2009
	Gait kinematics of age-stratified hip replacement patients—A large scale, long-term follow-up study	2008
	Temporal and spatial features of gait in older adults transitioning to frailty	2004
Step width	Rapid gait termmination: Effects of age, walker surfaces and footwear	2009
	Effects of walking surfaces and footwear on temporo-spatial gait parameters in young and older people	2009
velocity	Effects of walking surfaces and footwear on temporo-spatial gait parameters in young and older people	2009
	Gait kinematics of age-stratified hip replacement patients—A large scale, long-term follow-up study	2008

	Temporal and spatial features of gait in older adults transitioning to frailty	2004
cadence	Effects of walking surfaces and footwear on temporo-spatial gait parameters in young and older people	2009
Double-support time	Effects of walking surfaces and footwear on temporo-spatial gait parameters in young and older people	2009
	Temporal and spatial features of gait in older adults transitioning to frailty	2004
Heel horizontal velocity	Effects of walking surfaces and footwear on temporo-spatial gait parameters in young and older people	2009
Shoe-floor angle at heel contact	Effects of walking surfaces and footwear on temporo-spatial gait parameters in young and older people	2009
Toe clearance at mid-swing	Effects of walking surfaces and footwear on temporo-spatial gait parameters in young and older people	2009
Range of hip flexion/extension	Gait kinematics of age-stratified hip replacement patients—A large scale, long-term follow-up study	2008
Range of knee flexion/extension	Gait kinematics of age-stratified hip replacement patients—A large scale, long-term follow-up study	2008
	Gait characteristics as a function of age and gender	1994
Maximum hip extension	Gait kinematics of age-stratified hip replacement patients—A large scale, long-term follow-up study	2008
Range of hip abduction	Gait kinematics of age-stratified hip replacement patients—A large scale, long-term follow-up study	2008

Gait speed	Temporal and spatial features of gait in older adults transitioning to frailty	2004
	Gait characteristics as a function of age and gender	1994
Stance	Temporal and spatial features of gait in older adults transitioning to frailty	2004
swing	Temporal and spatial features of gait in older adults transitioning to frailty	2004
Ankle joint complexes	Gait characteristics as a function of age and gender	1994
pelvis	Age-related changes in upper body adaptation to walking speed in human locomotion	2005
Head	Age-related changes in upper body adaptation to walking speed in human locomotion	2005
Amplitude of segmental	Age-related changes in upper body adaptation to walking speed in human locomotion	2005
joint rotations	Age-related changes in upper body adaptation to walking speed in human locomotion	2005

Table 3 Gait features related to gender research

features	articles	Published year
Height	Gender differences in three dimensional gait analysis data from 98 healthy Korean adults	2004
Leg length		
Cadence		
Pelvic width		
Speed		
Step width		
Stride length		
Hip joints		
Knee joints		
Gait curve	Simultaneous estimation of effects of gender, age and walking speed on kinematic gait data	2009
Hip rotation		
Foot progression angle		
shoulder–hip ratio	Temporal and spatial actors in gait perception that influence gender recognition	1978
	A biomechanical invariant for gait perception	1978
center-of-moment	Temporal and spatial actors in gait perception that influence gender recognition	1978
	A biomechanical invariant for gait perception	1978
Shoulder sway	Gender discrimination in biological motion displays based on dynamic cues	1994
LBP (Local Binary Pattern)	Combining appearance and motion for face and gender recognition from videos	2009
	Gender Recognition Using a Min-Max Modular Support Vector Machine	2005
	Fusing gait and face cues for human gender recognition	2008
silhouettes	Fusing gait and face cues for human gender recognition	2008

1D: Gait features related to identification

features	articles	Published year
Composite energy features: clusters of energy filters (based on 2D image)	Motion representation using composite energy features(Dosil et al. 2008)	2008
Silhouettes (2D)	Automatic gait recognition using area-based metrics(Foster et al. 2003)	2003
	Frontal-view gait recognition by intra- and inter-frame rectangle size distribution(Barnich & Van Droogenbroeck 2009)	2009
	Gait recognition using linear time normalization(Boulgourisa et al. 2006)	2006
	Silhouette Analysis-Based Gait Recognition for Human Identification(Liang et al. 2003)	2003
Body component-wise in silhouettes(2D image)	Human gait recognition based on matching of body components(Boulgouris & Chi 2007)	2007
Feature image(2D image)	A method for human action recognition(Masoud & Papanikolopoulos 2003)	2003
Clothes, footwear, walking surface, emotion condition(2D image)	Gait Recognition: A challenging signal processing technology for biometric identification(Boulgouris et al. 2005)	2005
Walking speed(2D image)	Gait Recognition: A challenging signal processing technology for biometric identification(Boulgouris et al. 2005)	2005
silhouette templates(based on 2D image)	Human gait recognition by the fusion of motion and static spatio-temporal templates (Lam et al. 2007)	2007
Hip flexion in swing	Uphill and downhill walking in unilateral lower limb amputees(Vrieling et al. 2008)	2008
velocity	Uphill and downhill walking in unilateral lower limb amputees(Vrieling et al. 2008)	2008
	An application of neural networks for distinguishing gait patterns on	1997

	the basis of hip-knee joint angle diagrams	
Lower limb joint angles	Uphill and downhill walking in unilateral lower limb amputees(Vrieling et al. 2008)	2008
Pelvic rotation	Coordination of leg swing, thorax rotations, and pelvis rotations during gait: The organisation of total body angular momentum(Bruijn et al. 2008)	2008
thorax	Coordination of leg swing, thorax rotations, and pelvis rotations during gait: The organisation of total body angular momentum(Bruijn et al. 2008)	2008
Arm swing	Arm constraint and walking in healthy adults	2007
Hip-knee angles	An application of neural networks for distinguishing gait patterns on the basis of hip-knee joint angle diagrams	1997
	Automatic extraction and description of human gait models for recognition purposes	2003
15 markers(no special features)	Decomposing biological motion: A framework for analysis and synthesis of human gait patterns	2002
Motion trajectory	Flexible signature descriptions for adaptive motion trajectory representation, perception and recognition	2009
upper leg	Automatic extraction and description of human gait models for recognition purposes	2003
Torso length, upper arm length, lower arm length, thigh length, calf length, and foot length (based on 2D image silhouettes)	Performance prediction for individual recognition by gait	2005

Appendix 2: Figures for gait featur es within six different gait files for the same subject

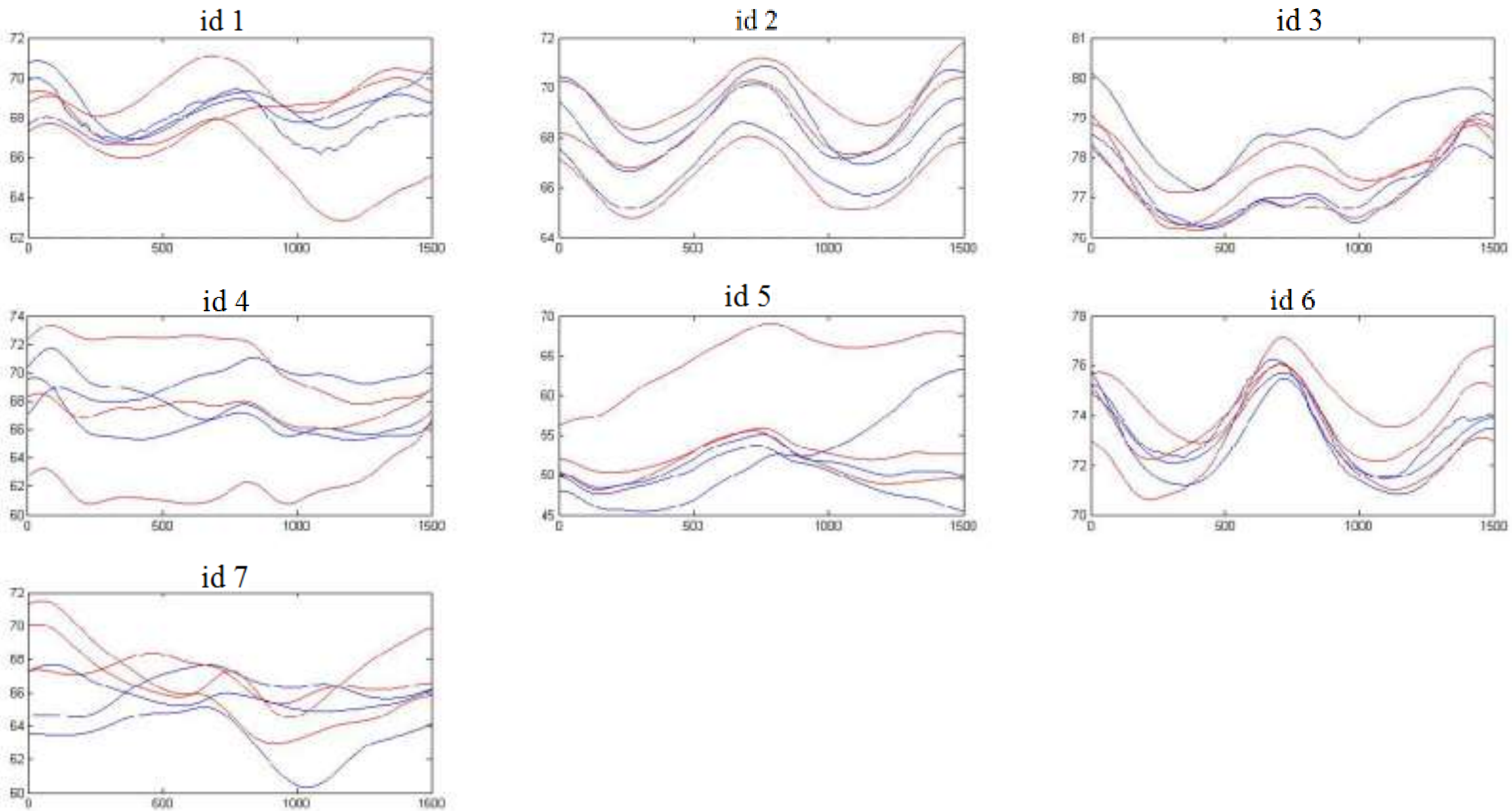


Fig. 1 Head_Topspine angle curve for six different gait cycles for the same subject (id 1 to id 7): x axis denotes frame numbers, y axis denotes angles degree.

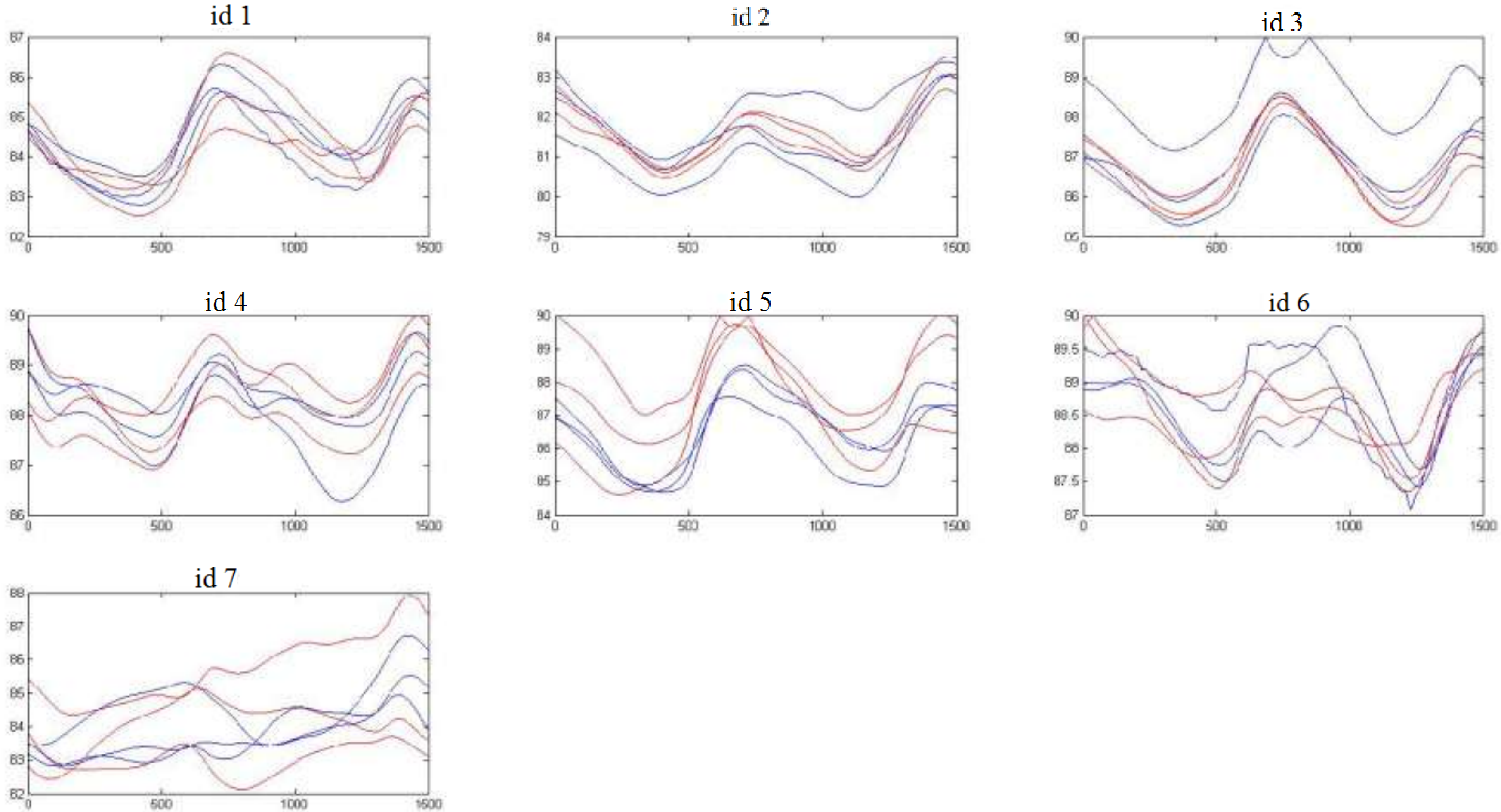


Fig. 2 Topspine_Root angle curve for six different gait cycles for the same subject (id 1 to id 7): x axis denotes frame numbers, y axis denotes angles degree. (The curves on Fig. 1 and Fig. 2 showed waves because the y axis was limited to an interval within 15 degrees.)

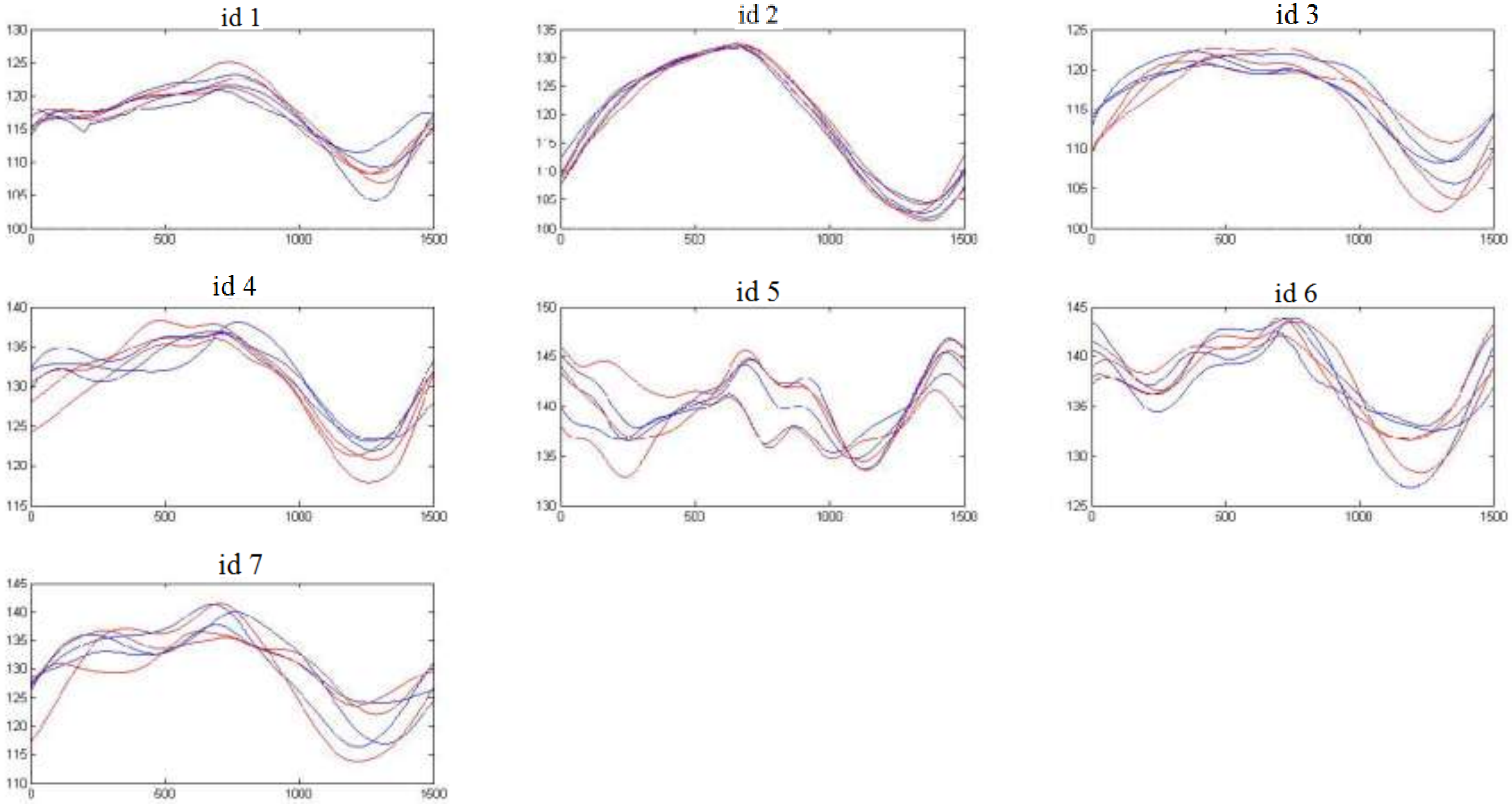


Fig. 3 Left elbow angle curve for six different gait cycles for the same subject (id 1 to id 7): x axis denotes frame numbers, y axis denotes angles degree.

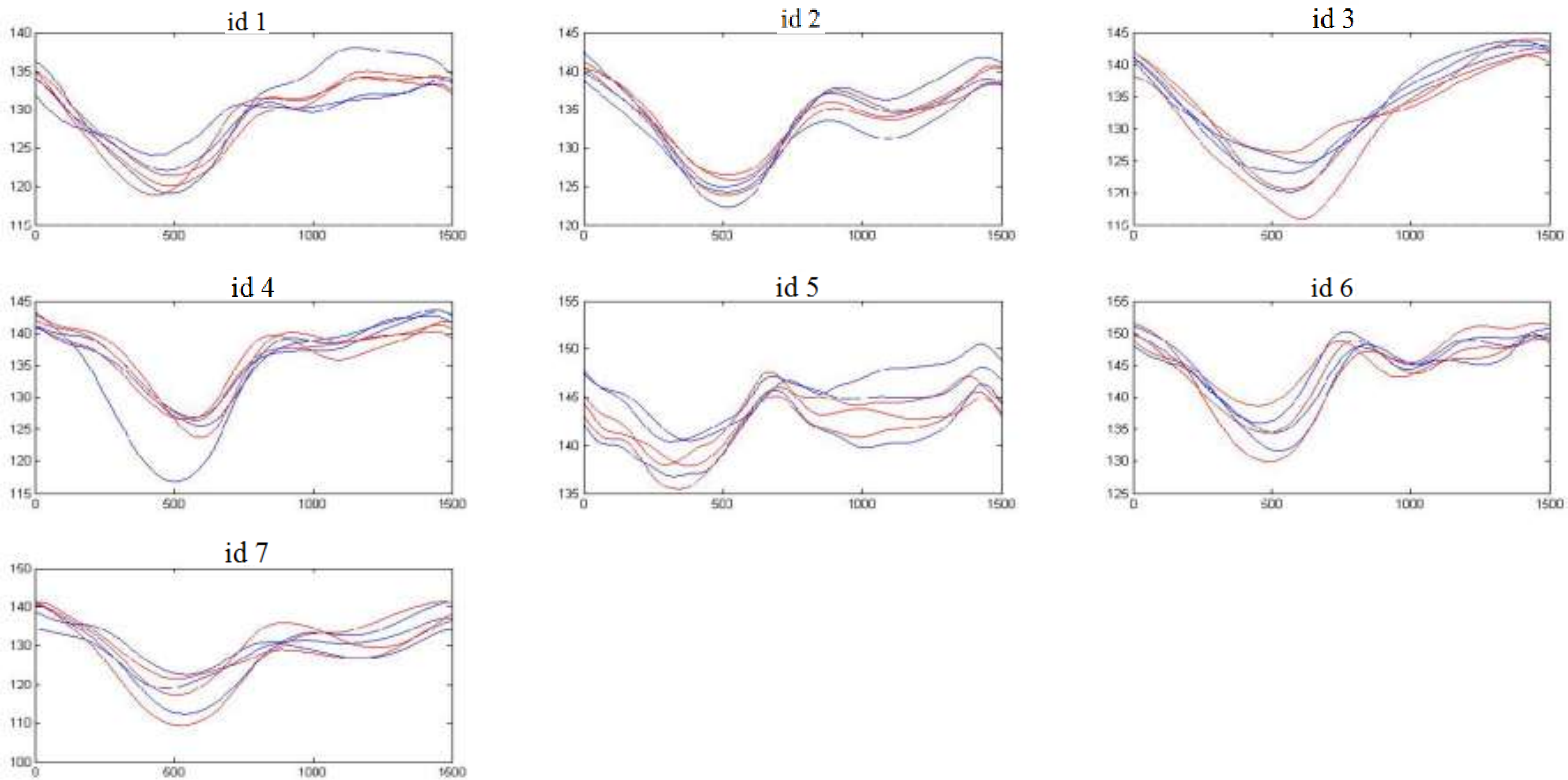


Fig. 4 Right elbow angle curve for six different gait cycles for the same subject (id 1 to id 7): x axis denotes frame numbers, y axis denotes angles degree.

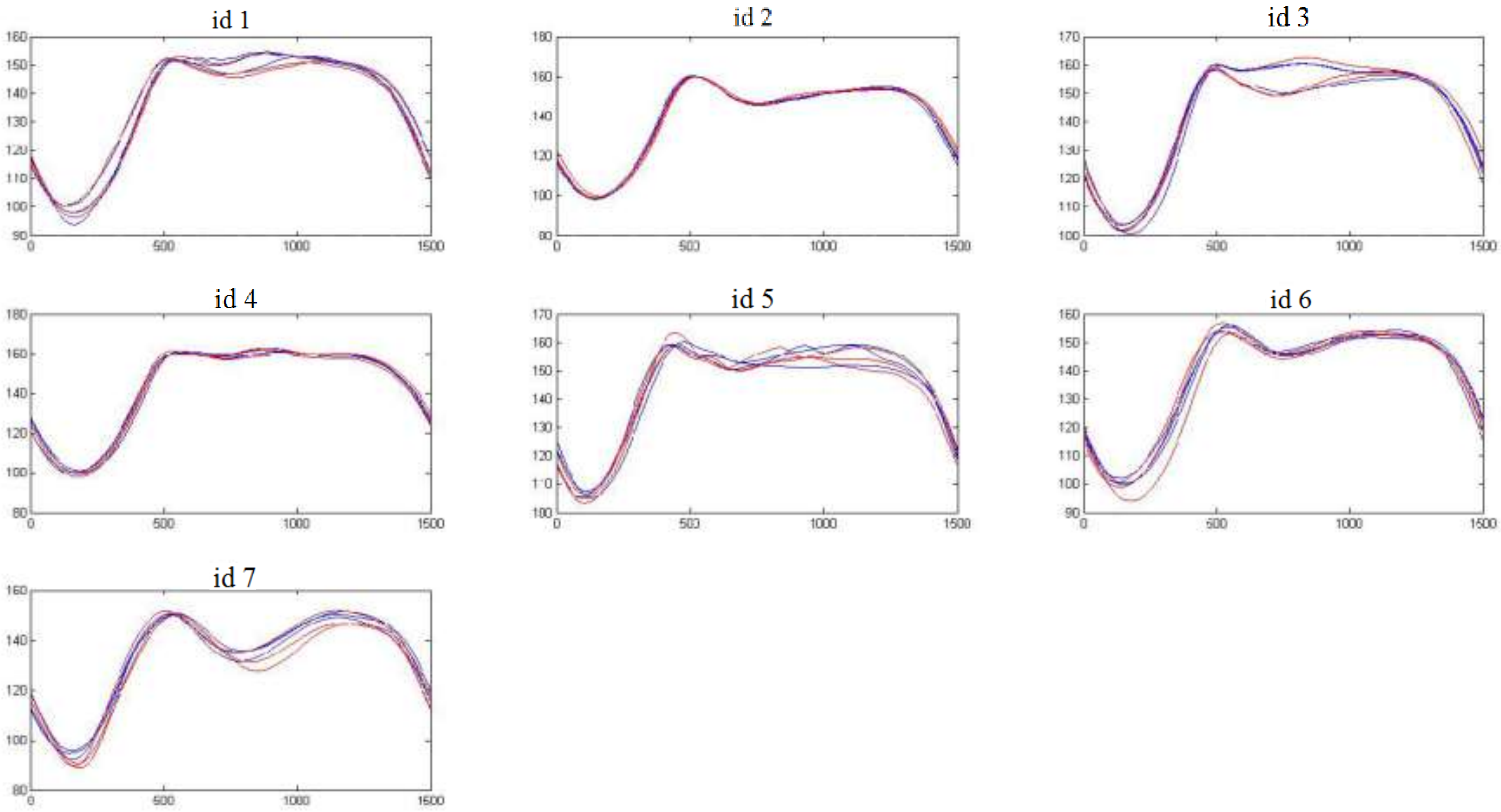


Fig. 5 Left knee angle curve for six different gait cycles for the same subject (id 1 to id 7): x axis denotes frame numbers, y axis denotes angles degree.

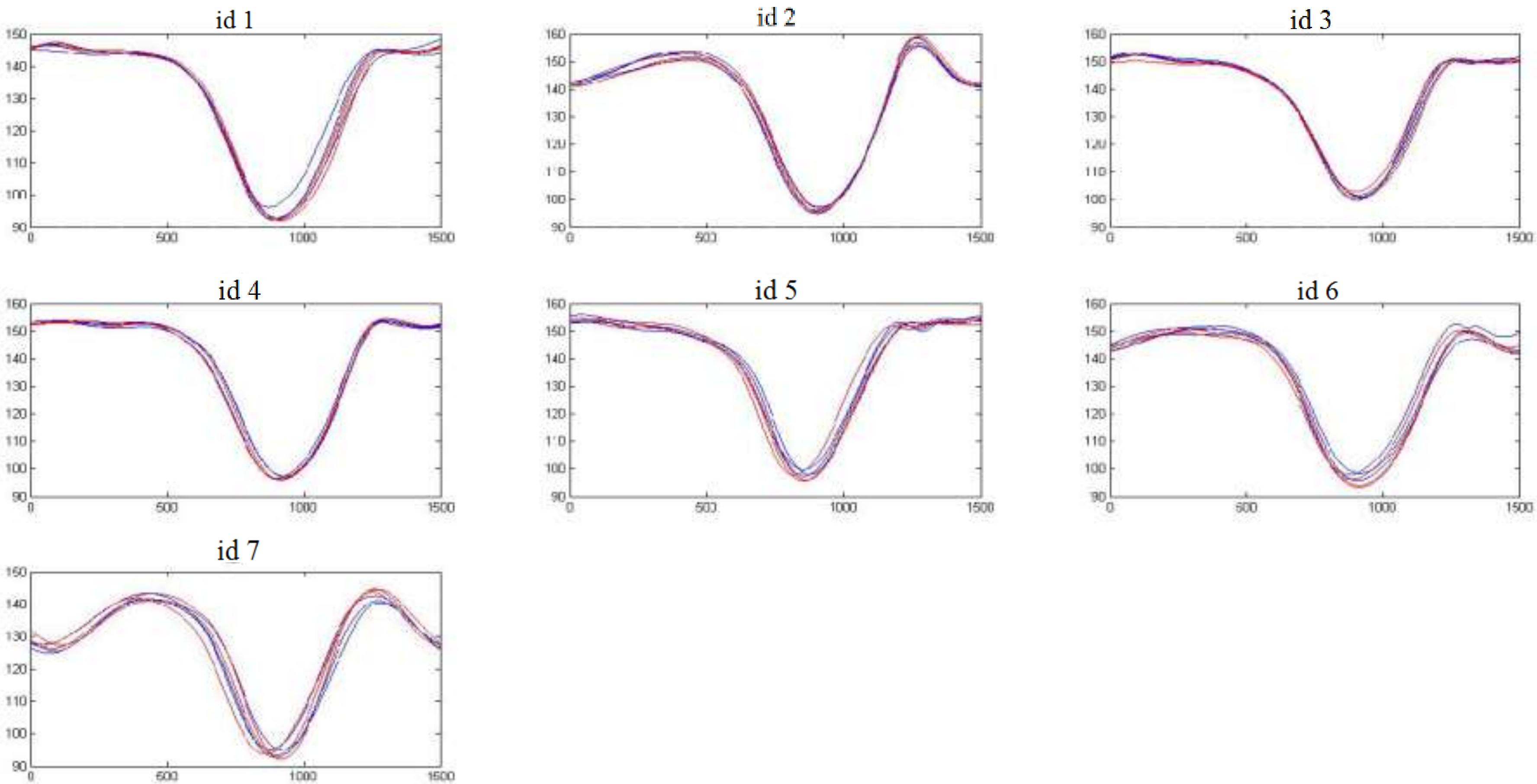


Fig. 6 Right knee angle curve for six different gait cycles for the same subject (id 1 to id 7): x axis denotes frame numbers, y axis denotes angles degree.

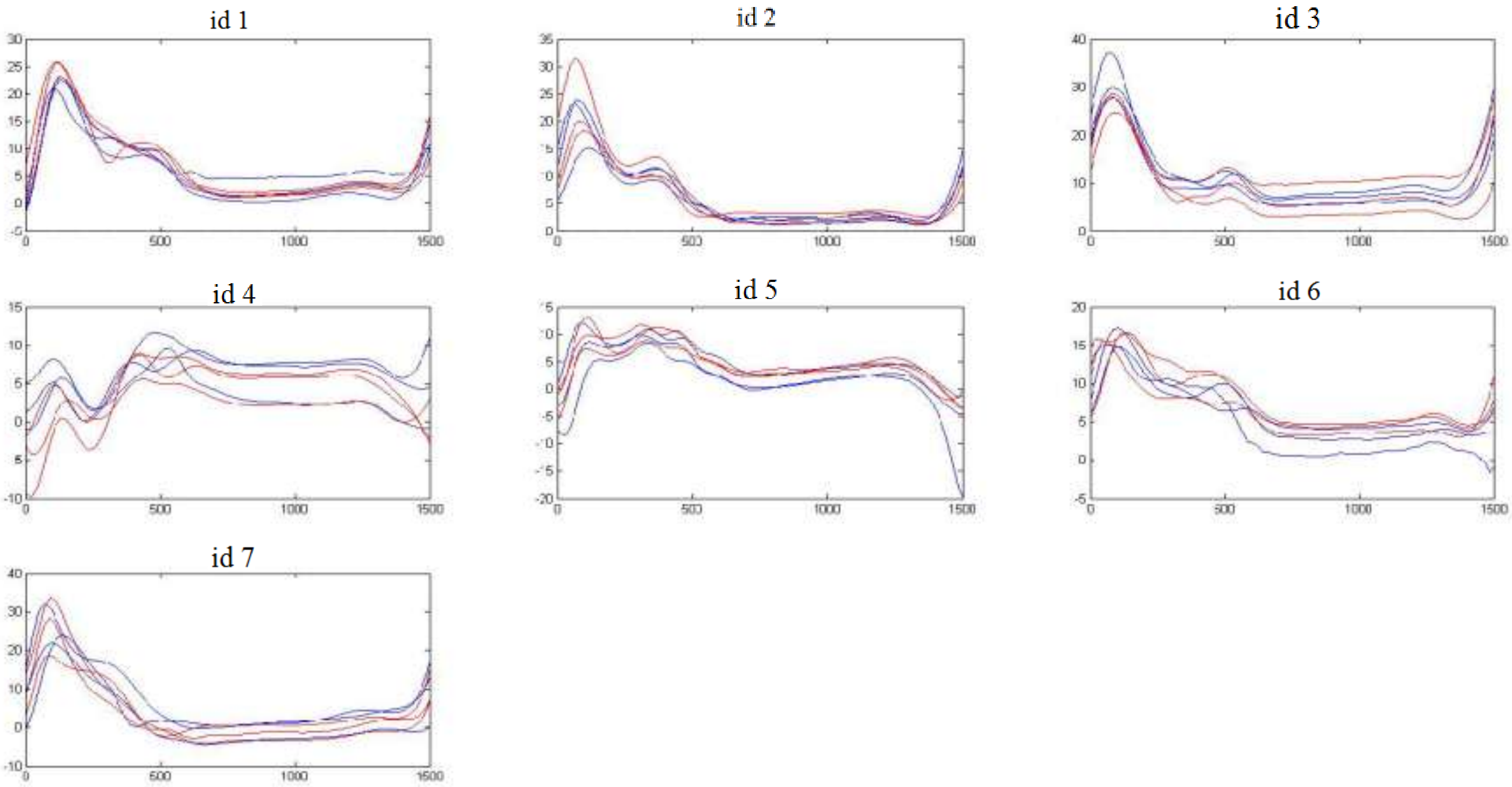


Fig. 7 Left Heel_toe_y angle curve for six different gait cycles for the same subject (id 1 to id 7): x axis denotes frame numbers, y axis denotes angles degree.

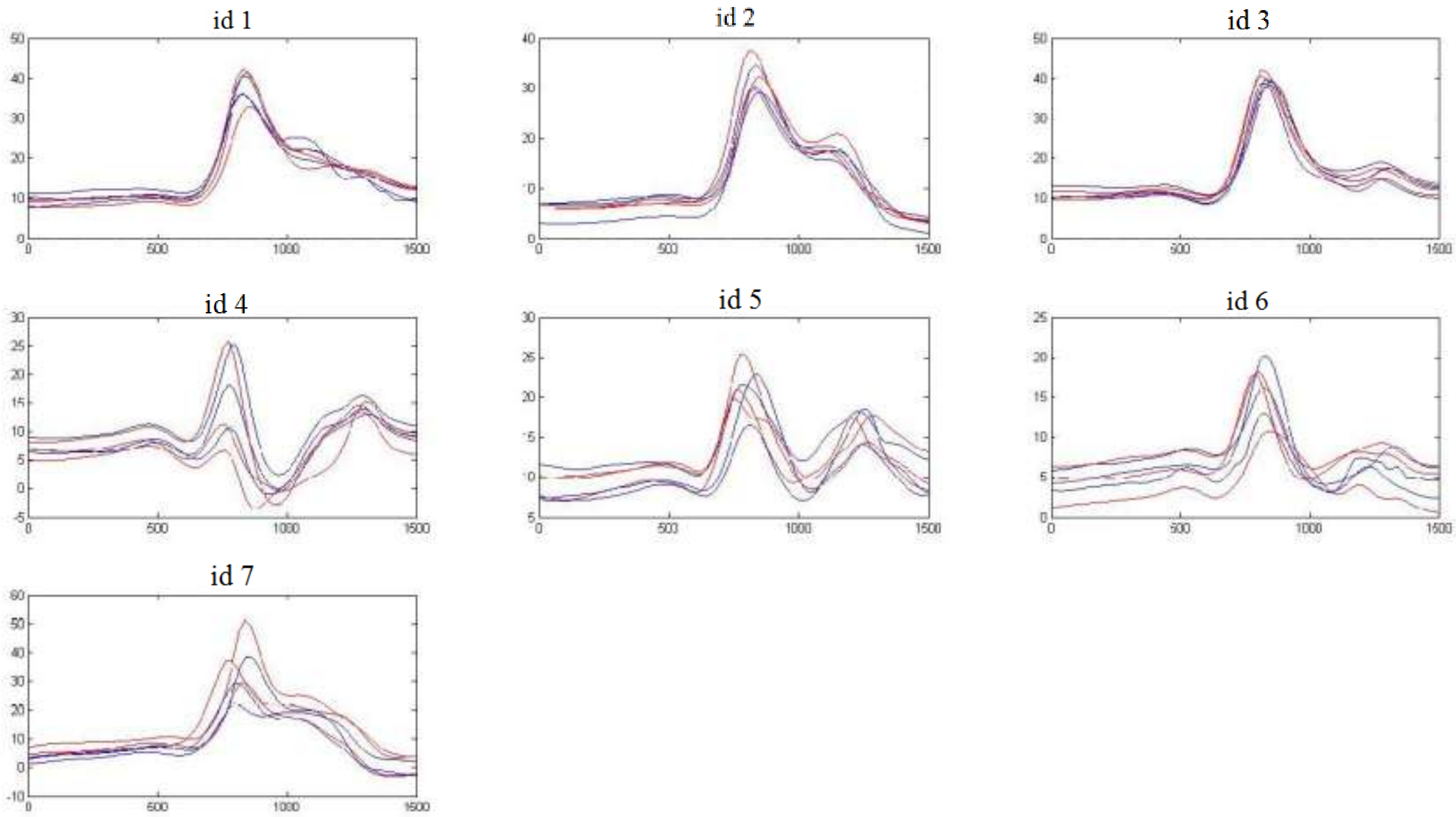


Fig. 8 Right Heel_toe_y angle curve for six different gait cycles for the same subject (id 1 to id 7): x axis denotes frame numbers, y axis denotes angles degree

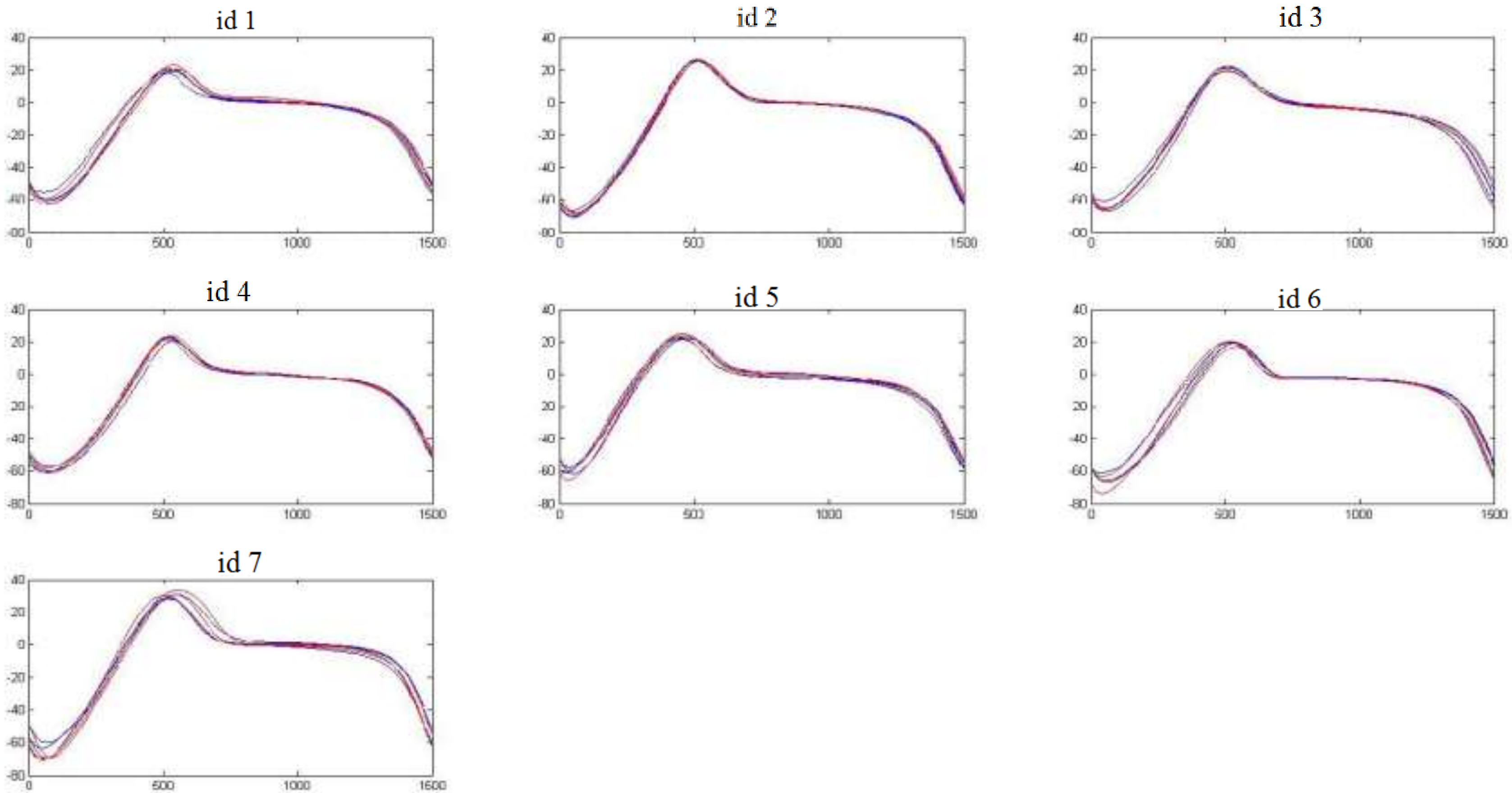


Fig. 9 Left Heel_toe_z angle curve for six different gait cycles for the same subject (id 1 to id 7): x axis denotes frame numbers, y axis denotes angles degree

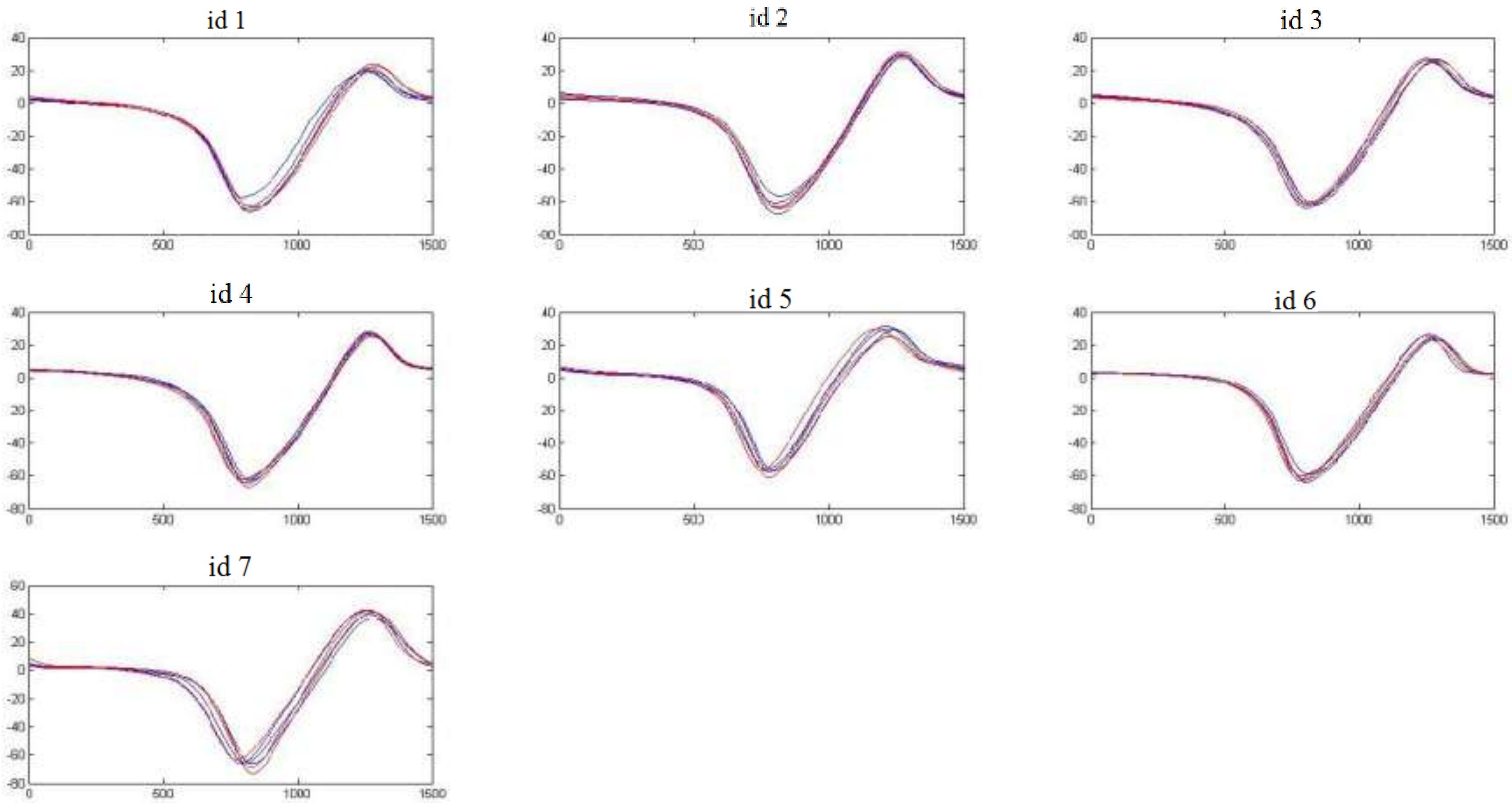


Fig. 10 Right Heel_toe_z angle curve for six different gait cycles for the same subject (id 1 to id 7): x axis denotes frame numbers, y axis denotes angles degree

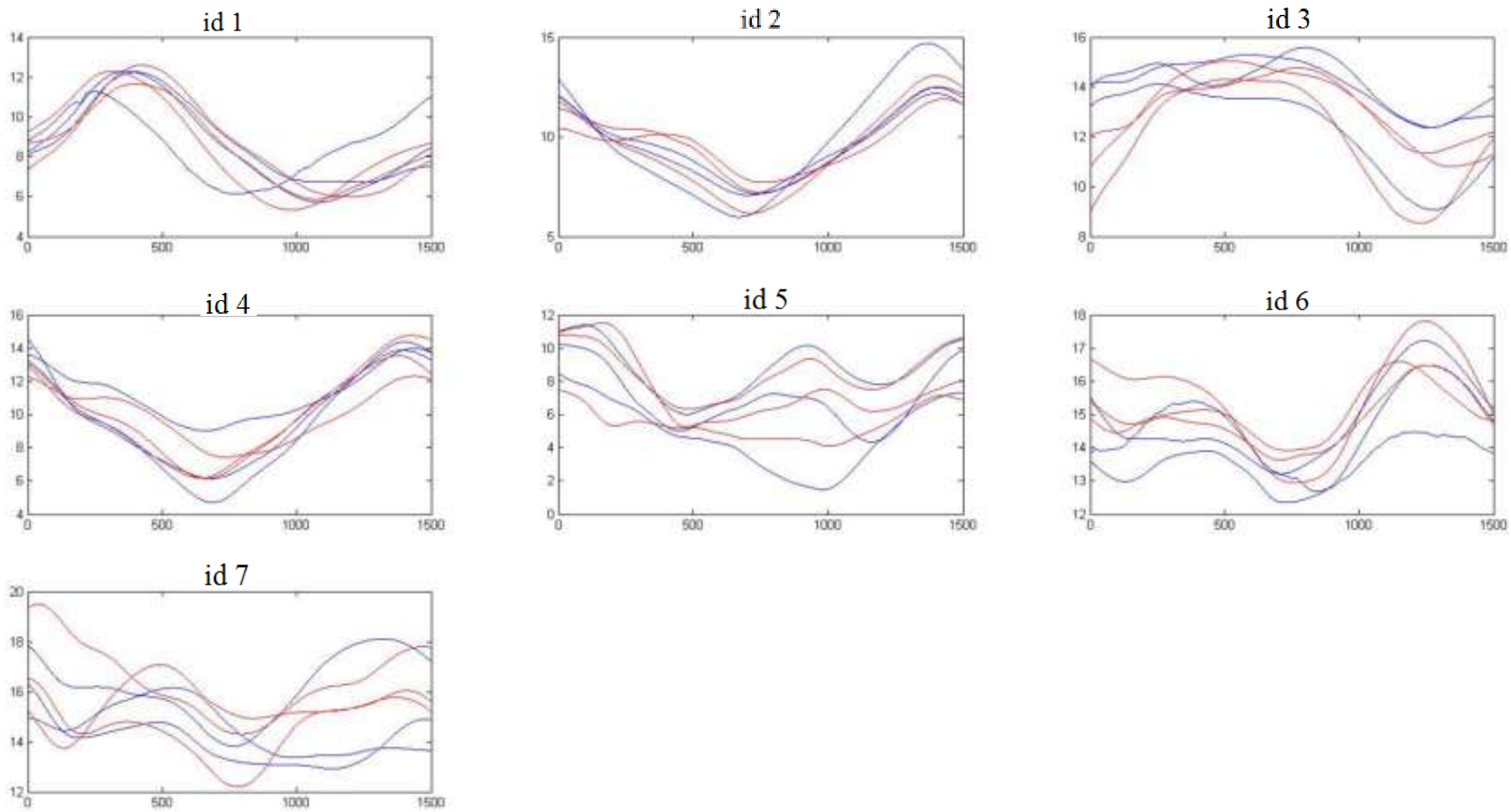


Fig. 11 Left Wrist_shoulder_y angle curve for six different gait cycles for the same subject (id 1 to id 7): x axis denotes frame numbers, y axis denotes angles degree

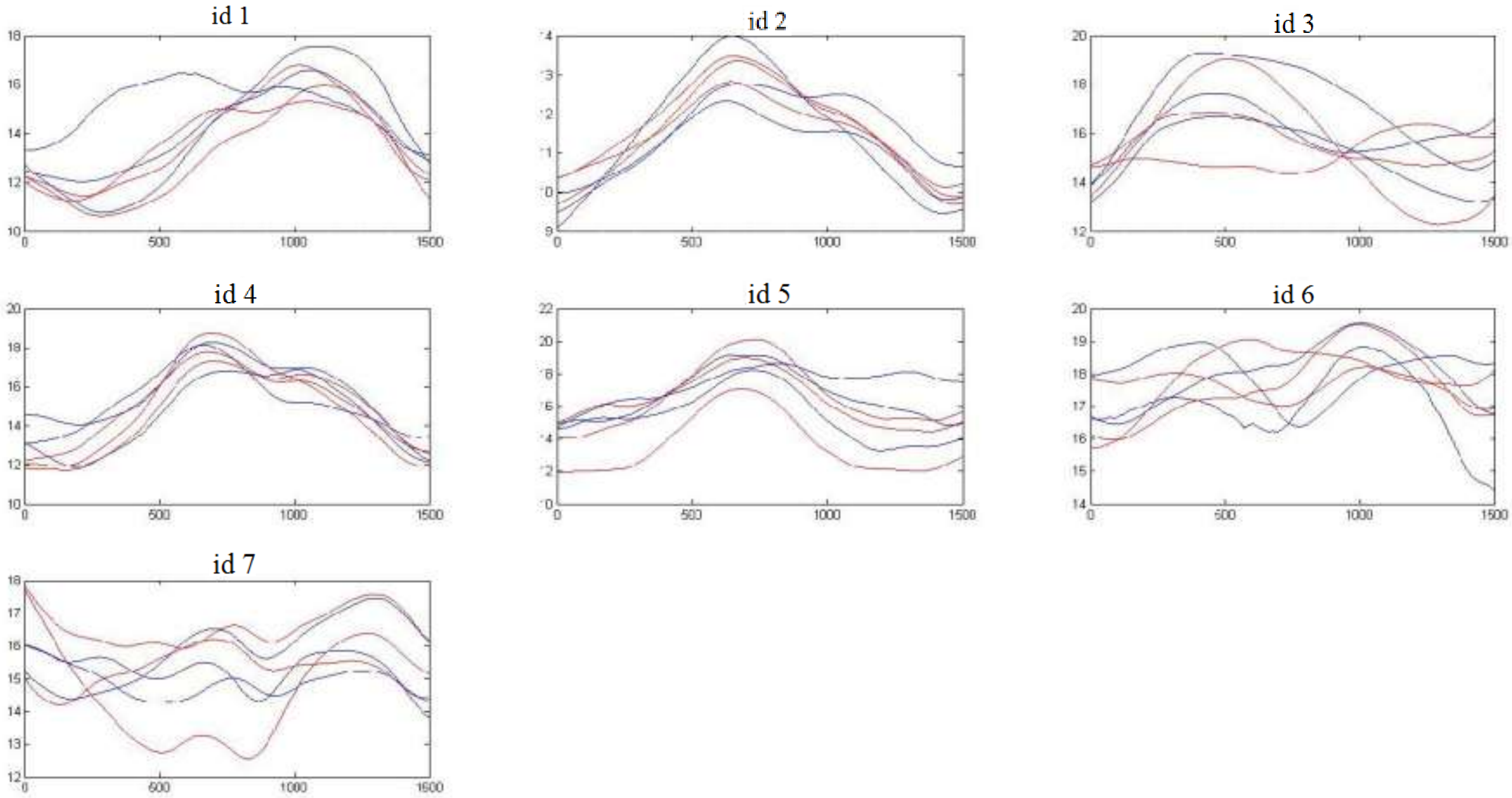


Fig. 12 Right Wrist_shoulder_y angle curve for six different gait cycles for the same subject (id 1 to id 7): x axis denotes frame numbers, y axis denotes angles degree

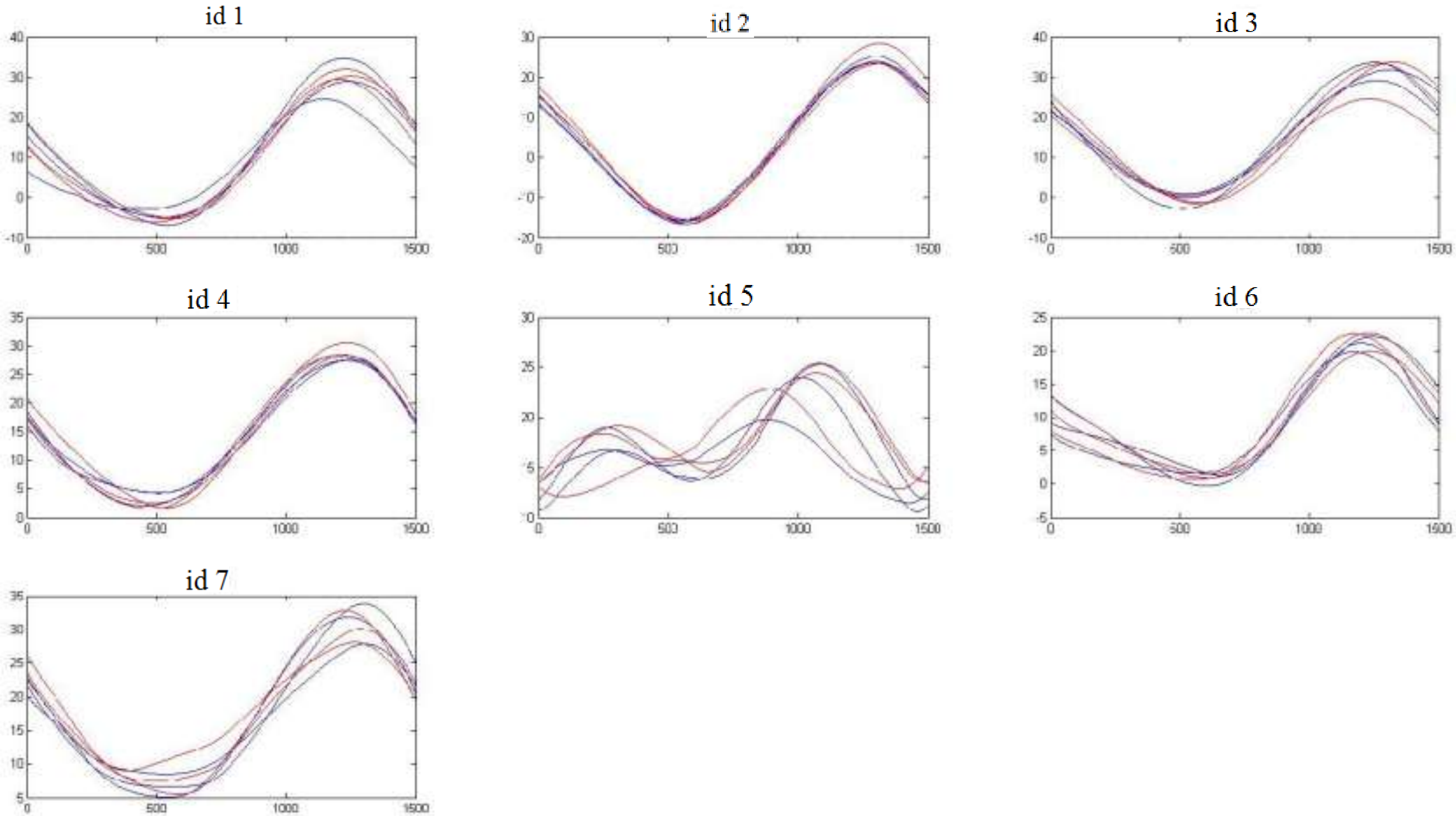


Fig. 13 Left Wrist_shoulder_z angle curve for six different gait cycles for the same subject (id 1 to id 7): x axis denotes frame numbers, y axis denotes angles degree

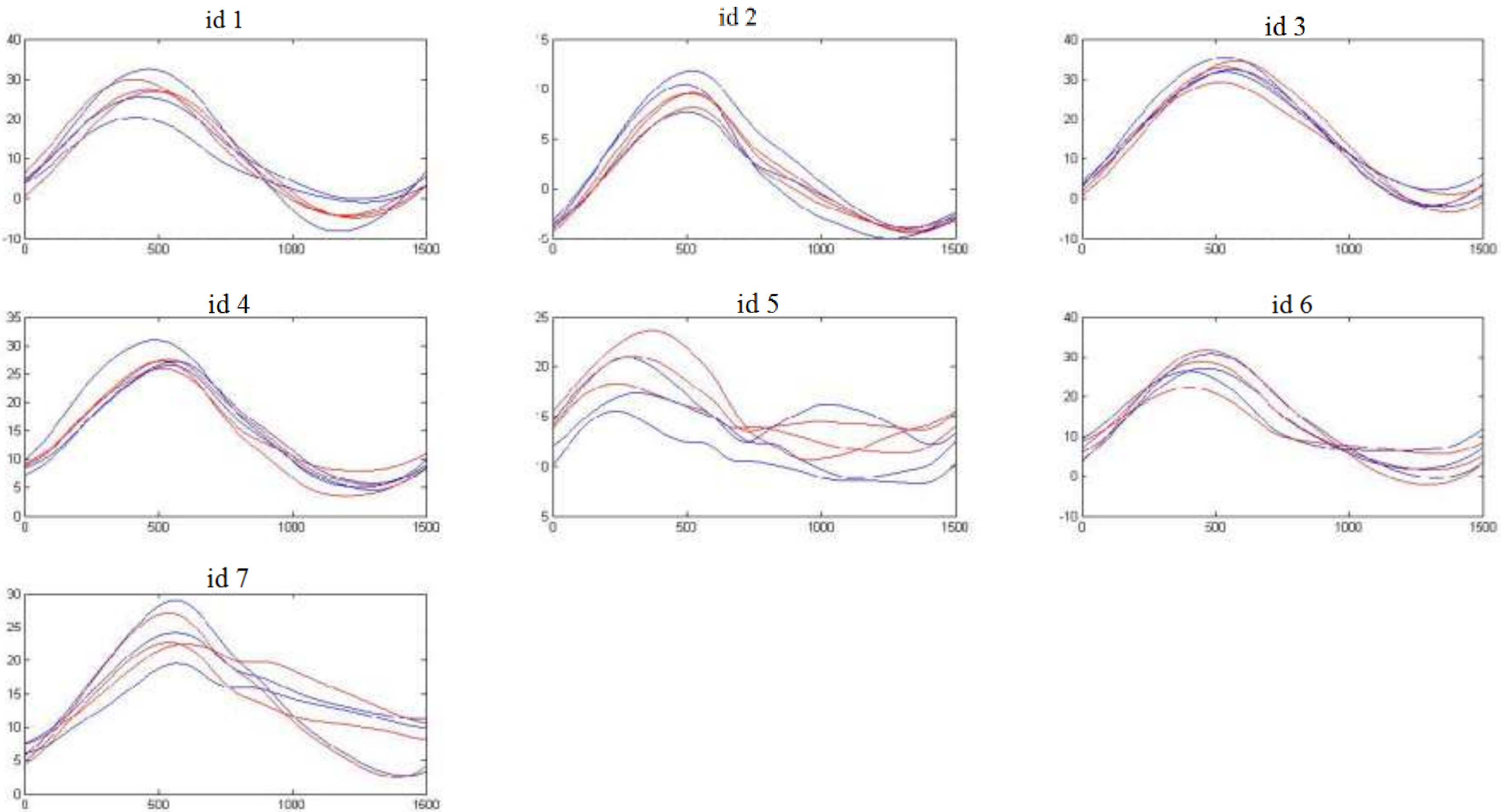


Fig. 14 Right Wrist_shoulder_z angle curve for six different gait cycles for the same subject (id 1 to id 7): x axis denotes frame numbers, y axis denotes angles degree

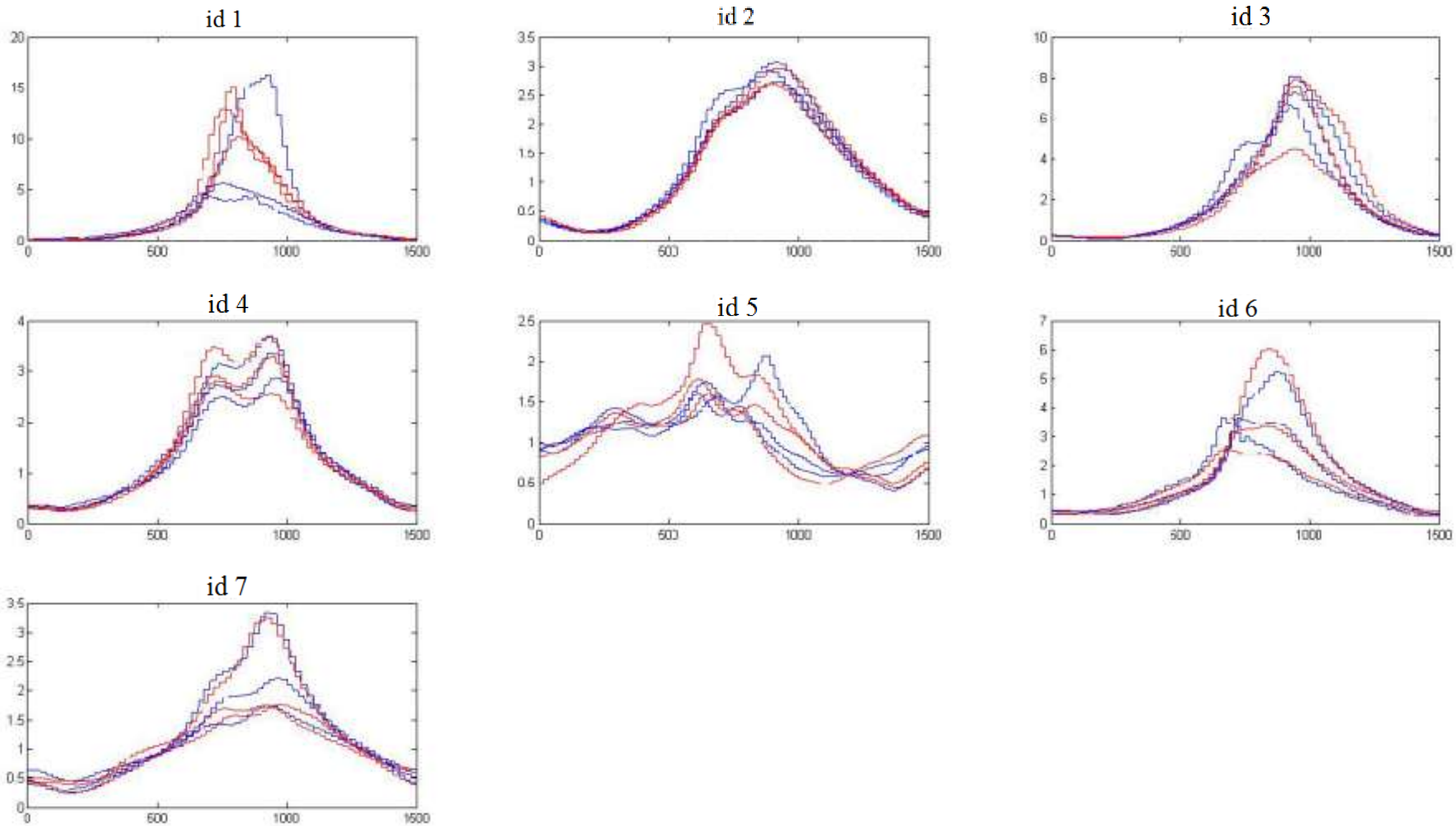


Fig. 15 Wrist speed ratio curve for six different gait cycles for the same subject (id 1 to id 7): x axis denotes frame numbers, y axis denotes ratio

Appendix 3: Some $(F\_P_{max,} F\_P_{min})$ distribution tables for gait features

Table 1 $(F\_P_{max,} F\_P_{min})$ **distribution Wrist_shoulder_y angles**

id	Left Wrist_shoulder_y angle				Right Wrist_shoulder_y angle			
	P_max	P_min	F_P max	F_P min	P_max	P_min	F_P max	F_P min
1	2	7	50.83%	56.29%	6	1	31.67%	0.00%
2	3	7	48.32%	37.18%	6	8	46.25%	54.67%
3	1	6	0.00%	98.92%	4	8	89.01%	91.70%
4	8	4	23.19%	49.59%	4	8	49.59%	30.80%
5	8	4	57.77%	56.11%	4	8	36.65%	36.41%
6	8	2	80.18%	38.89%	6	2	45.42%	58.55%
7	2	4	37.12%	50.52%	6	3	81.42%	41.03%
8	2	6	84.21%	56.33%	4	1	70.34%	50.00%
9	1	6	0.00%	34.53%	2	6	72.01%	83.09%
10	3	8	81.02%	16.53%	4	6	44.63%	30.59%
11	2	6	89.27%	75.36%	6	2	58.57%	65.05%
12	3	1	42.11%	0.00%	5	2	16.28%	32.66%
13	3	7	72.90%	42.38%	4	1	71.12%	0.00%
14	8	4	0.52%	88.94%	7	3	55.38%	73.81%
15	3	7	37.42%	25.64%	6	1	15.53%	85.21%
16	8	5	60.19%	67.19%	5	2	16.41%	65.31%
17	2	5	37.30%	0.00%	4	8	28.23%	99.57%
18	2	6	60.32%	26.07%	6	2	38.96%	26.98%
19	2	7	83.33%	10.00%	6	2	62.23%	48.67%
20	2	6	87.31%	79.44%	6	2	55.21%	40.56%
21	2	6	73.31%	55.52%	6	2	49.29%	21.96%
22	2	6	80.00%	49.57%	6	2	43.59%	7.33%
23	8	4	24.87%	56.87%	4	1	45.50%	0.00%
24	8	4	51.04%	80.00%	4	8	57.07%	88.02%
25	8	4	60.43%	75.84%	4	8	36.52%	80.00%
26	8	4	55.22%	86.21%	4	8	47.41%	66.67%
27	8	4	62.50%	92.52%	4	1	60.75%	0.00%
28	8	5	56.60%	5.74%	4	8	52.19%	85.53%
29	5	7	25.74%	86.67%	3	1	5.76%	0.00%
30	8	4	71.03%	50.23%	4	8	69.01%	99.53%
31	1	6	0.00%	45.51%	4	8	47.80%	80.18%
32	2	5	81.27%	99.12%	6	8	44.79%	99.58%
33	1	6	0.00%	82.69%	1	8	0.00%	99.49%
34	1	5	28.57%	11.11%	4	1	60.91%	85.71%
35	3	6	77.98%	31.38%	1	3	0.00%	77.98%

Table 2 $(F\_P_{max,} F\_P_{min})$ **distribution Wrist_shoulder_z angles**

id	Left Wrist_shoulder_z angle				Right Wrist_shoulder_z angle			
	P_max	P_min	F_P max	F_P min	P_max	P_min	F_P max	F_P min
1	7	4	35.33%	59.17%	2	8	65.42%	45.29%
2	7	2	62.18%	98.20%	3	8	48.32%	0.00%
3	7	3	50.33%	52.76%	3	7	72.86%	63.58%
4	7	4	56.43%	15.70%	4	7	7.44%	85.00%
5	8	4	4.85%	46.61%	3	1	95.77%	0.00%
6	8	5	29.96%	22.41%	3	7	10.46%	66.18%
7	6	4	98.99%	58.76%	2	8	75.11%	50.00%
8	8	1	5.13%	0.00%	3	8	89.02%	5.13%
9	6	4	97.12%	25.60%	3	6	14.42%	62.23%
10	4	8	35.12%	16.94%	1	4	0.00%	7.44%
11	8	4	24.07%	3.98%	4	1	3.59%	0.00%
12	7	4	98.73%	35.62%	3	7	98.95%	84.71%
13	7	3	72.85%	87.74%	4	1	1.72%	0.00%
14	7	1	21.51%	0.00%	3	7	73.81%	55.38%
15	7	4	90.38%	20.56%	8	3	100.00%	37.42%
16	7	3	73.38%	65.00%	3	7	51.88%	17.53%
17	6	2	80.52%	99.06%	2	7	92.79%	94.44%
18	6	3	97.24%	55.70%	2	6	87.30%	90.80%
19	6	3	96.20%	86.49%	3	6	11.71%	79.35%
20	6	3	92.11%	54.76%	2	6	94.43%	85.63%
21	6	3	98.58%	62.18%	2	6	95.61%	98.58%
22	6	3	93.16%	74.80%	3	6	39.02%	99.15%
23	7	4	98.21%	11.37%	3	8	81.60%	11.64%
24	8	4	2.60%	0.49%	3	8	65.44%	14.58%
25	8	3	11.91%	96.83%	3	8	59.52%	31.49%
26	7	4	77.32%	18.53%	3	8	77.57%	10.95%
27	8	4	16.53%	6.54%	3	8	43.30%	6.85%
28	7	4	80.88%	21.93%	4	7	1.32%	97.79%
29	7	3	53.33%	64.03%	3	8	92.81%	5.58%
30	7	3	50.00%	65.74%	4	8	1.41%	4.21%
31	6	8	10.30%	66.52%	2	8	51.88%	40.09%
32	6	4	95.40%	6.16%	2	6	86.98%	95.09%
33	8	3	5.05%	87.59%	4	1	3.47%	0.00%
34	7	2	59.29%	77.00%	3	1	61.38%	0.00%
35	7	4	82.20%	0.00%	3	1	99.08%	0.00%

Table 3 $(F\_P_{max,} F\_P_{min})$ distribution of Wrist speed ratio (left/right)

id	Wrist speed ratio			
	P_max	P_min	F_P max	F_P min
1	4	8	67.08%	69.96%
2	4	1	81.36%	43.88%
3	6	8	28.67%	85.06%
4	6	2	7.52%	13.36%
5	6	2	69.29%	13.28%
6	4	8	95.95%	95.15%
7	6	8	13.51%	44.21%
8	6	8	3.67%	77.95%
9	5	8	97.54%	85.38%
10	6	1	0.91%	51.59%
11	5	2	73.56%	9.34%
12	6	2	33.73%	51.76%
13	6	1	3.19%	27.83%
14	6	8	58.20%	80.73%
15	5	8	83.33%	94.32%
16	5	2	50.00%	35.20%
17	4	8	66.94%	73.08%
18	5	1	17.53%	62.99%
19	6	1	16.30%	76.03%
20	5	1	17.12%	16.45%
21	4	1	83.49%	46.71%
22	5	1	47.45%	74.34%
23	6	2	12.89%	17.50%
24	6	2	4.66%	27.37%
25	6	2	7.40%	20.85%
26	6	2	1.30%	21.01%
27	5	2	94.52%	23.28%
28	6	2	14.94%	32.04%
29	6	2	13.21%	16.02%
30	6	8	10.44%	96.73%
31	4	6	35.12%	91.69%
32	4	8	63.51%	66.53%
33	6	2	20.51%	21.77%
34	6	2	12.63%	8.36%
35	6	2	20.34%	5.57%

Appendix 4: Comparison results of motion tasks

Table 1 – Workstation Motion Task 1

Angles	EGF				SOF				EGB				SOB			
	average	SD	max	min	average	SD	max	min	average	SD	max	min	average	SD	max	min
Neck Flexion	19.00	7.99	49.26	0.44	16.66	7.16	50.66	0.21	17.69	8.02	54.83	0.72	17.03	7.52	54.11	0.16
Lowback Flexion-Left	33.83	9.59	54.57	4.72	31.93	9.51	55.49	4.97	34.13	9.39	60.22	4.24	33.92	9.15	57.85	4.92
Lowback Flexion-Right	46.99	8.98	77.24	16.72	46.57	9.48	78.36	15.63	47.48	8.01	74.10	19.91	48.51	9.07	76.01	15.54
Highback Flexion-Left	49.56	11.60	74.59	24.42	52.44	10.93	74.02	26.54	49.08	10.48	73.71	21.58	49.84	11.34	80.13	22.12
Highback Flexion-Right	55.24	9.28	82.74	31.88	55.29	6.48	68.88	29.27	53.17	6.60	71.59	26.30	54.24	6.62	76.83	25.52
Shoulder Flexion-Left	26.42	11.93	78.70	5.06	24.48	9.18	67.45	6.03	25.82	4.58	63.89	10.36	23.77	4.60	55.13	6.29
Shoulder Flexion-Right	29.56	10.49	78.65	7.32	27.70	8.28	64.32	7.86	28.59	4.29	57.48	9.40	27.69	5.50	49.44	10.66
Shoulder Abduction-Left	21.47	6.89	66.05	0.68	19.19	4.58	46.82	2.65	23.13	7.10	74.10	2.49	21.09	5.48	66.39	0.00
Shoulder Abduction-Right	22.78	7.07	65.76	4.51	20.21	5.39	50.20	4.23	24.86	6.77	80.61	4.98	22.69	5.89	64.57	6.03
Elbow Flexiion-Left	66.27	13.57	126.94	37.59	65.94	13.44	127.41	36.90	68.81	13.77	125.43	35.32	68.85	14.47	125.58	32.33
Elbow Flexiion-Right	63.52	13.32	118.80	34.43	62.00	12.97	120.59	34.68	65.90	12.14	120.56	34.42	65.70	12.86	121.80	31.49
Hip Flexion-Left	34.45	4.73	79.37	1.01	34.41	4.38	82.04	0.33	35.93	4.94	85.65	0.72	35.59	4.41	87.34	0.23
Hip Flexion-Right	34.32	6.02	80.53	0.11	33.82	5.13	85.86	0.37	35.44	6.68	86.52	0.72	35.16	5.74	88.37	0.11
Hip Abduction-Left	12.17	8.27	69.55	0.01	10.46	7.51	60.98	0.00	10.87	7.22	58.84	0.00	10.71	8.10	63.56	0.00
Hip Abduction-Right	9.52	7.08	57.96	0.00	8.55	4.61	34.89	0.00	8.91	5.10	43.23	0.00	9.13	7.09	43.52	0.00
Hip Adduction-Left	1.93	1.86	8.41	0.00	2.16	3.19	20.20	0.00	2.20	2.52	15.69	0.01	1.91	1.58	12.95	0.00
Hip Adduction-Right	3.58	4.76	26.36	0.00	3.74	4.28	23.82	0.00	3.54	4.62	23.97	0.01	4.53	5.19	30.52	0.00
Knee Flexion-Left	57.25	5.95	106.60	3.27	60.17	9.97	103.80	5.19	54.27	6.52	100.52	2.95	57.61	6.31	98.27	11.68
Knee Flexion-Right	67.12	6.52	113.22	17.61	69.37	8.92	111.70	20.11	63.64	7.02	108.88	16.76	66.70	6.72	106.39	19.01

Table 2 – Workstation Motion Task 2

Angles	EGF				SOF				EGB				SOB			
	average	SD	max	min	average	SD	max	min	average	SD	max	min	average	SD	max	min
Neck Flexion	20.55	9.29	55.29	0.37	19.69	7.03	45.59	2.55	23.65	10.28	63.80	2.43	23.08	10.09	61.11	2.30
Lowback Flexion-Left	38.59	9.33	77.63	19.10	34.67	8.94	70.07	14.16	40.45	8.19	76.71	15.98	38.71	7.95	73.70	13.29
Lowback Flexion-Right	52.93	9.26	77.13	26.18	51.73	9.80	83.84	22.49	53.91	8.46	85.94	31.84	54.82	9.43	87.96	25.27
Highback Flexion-Left	51.97	12.26	81.35	28.31	51.69	10.00	76.05	30.40	51.53	11.20	77.50	28.40	52.18	11.55	84.27	29.67
Highback Flexion-Right	57.40	8.55	84.11	40.54	55.53	6.59	73.25	38.21	55.98	6.59	78.11	40.25	56.89	5.58	74.03	40.00
Shoulder Flexion-Left	27.24	12.11	70.33	7.93	21.87	6.15	39.82	3.75	25.49	7.49	62.35	5.85	23.81	7.10	50.21	5.13
Shoulder Flexion-Right	29.68	11.80	66.69	7.50	25.84	7.09	48.48	10.10	27.62	8.15	52.89	11.32	27.22	7.82	51.17	4.71
Shoulder Abduction-Left	25.16	5.99	71.80	0.00	25.89	6.08	72.09	0.00	25.97	7.51	79.24	0.00	26.28	6.14	79.31	0.00
Shoulder Abduction-Right	25.51	6.57	77.35	0.01	24.44	5.01	72.87	0.00	25.50	7.33	87.11	0.01	25.56	5.46	71.72	0.00
Elbow Flexiion-Left	73.97	20.46	121.24	34.16	70.30	17.44	114.91	37.07	75.64	20.86	128.89	33.99	73.62	19.36	123.45	36.42
Elbow Flexiion-Right	70.10	18.99	117.98	32.16	69.78	17.85	121.07	31.93	72.50	20.23	129.01	32.63	71.56	20.18	122.80	30.55
Hip Flexion-Left	30.36	9.35	73.33	6.62	30.18	7.34	53.37	8.38	29.26	12.54	92.82	4.01	29.71	8.49	66.28	9.18
Hip Flexion-Right	30.74	8.91	63.25	11.34	29.97	6.69	54.90	12.11	29.05	12.94	69.31	4.77	28.74	8.68	61.00	2.17
Hip Abduction-Left	28.44	14.97	92.09	0.03	26.07	13.21	69.18	0.00	27.43	15.64	74.21	0.00	26.30	14.74	81.52	0.01
Hip Abduction-Right	26.26	12.68	77.97	0.03	26.36	11.92	59.58	0.02	24.10	14.40	75.06	0.00	26.84	15.32	74.81	0.00
Hip Adduction-Left	10.38	7.56	30.74	0.01	11.21	5.70	34.79	0.02	4.36	4.39	16.12	0.01	7.73	7.12	39.16	0.02
Hip Adduction-Right	15.53	7.14	39.11	0.04	10.04	8.57	39.71	0.00	10.44	7.92	39.83	0.01	15.86	5.83	53.89	0.02
Knee Flexion-Left	91.80	7.00	111.46	74.80	90.75	7.47	109.07	67.72	86.59	6.17	103.82	71.07	87.65	6.89	101.30	65.96
Knee Flexion-Right	100.40	5.91	118.65	83.00	98.45	7.44	114.83	75.88	95.12	5.88	115.45	78.81	95.23	6.47	115.39	69.06

Table 3 – Workstation Motion Task 3

Angles	EGF				SOF				EGB				SOB			
	average	SD(of average)	max	min	average	SD	max	min	average	SD	max	min	average	SD	max	min
Neck Flexion	24.48	7.47	49.33	1.84	21.59	6.93	37.58	1.47	25.08	7.09	51.28	5.49	24.72	7.55	40.62	5.25
Lowback Flexion-Left	40.04	11.23	63.40	10.06	33.99	10.79	51.49	6.77	37.67	11.04	59.42	7.63	34.24	11.57	58.28	7.13
Lowback Flexion-Right	49.89	8.09	73.81	22.47	47.60	8.14	73.58	28.71	48.16	8.45	77.78	31.15	47.99	7.14	63.94	24.84
Highback Flexion-Left	47.10	12.73	74.25	26.25	47.22	12.10	72.77	24.19	47.92	13.59	74.59	24.88	48.20	12.94	81.01	25.67
Highback Flexion-Right	54.20	9.21	82.33	31.02	51.87	7.30	72.31	32.94	53.22	7.66	82.70	22.78	53.59	7.82	74.68	34.85
Shoulder Flexion-Left	30.47	20.61	127.82	5.48	24.62	7.98	50.24	5.65	27.04	8.39	52.82	4.68	25.59	8.06	45.64	4.72
Shoulder Flexion-Right	62.51	9.70	108.13	6.70	63.00	9.68	112.52	11.07	61.72	9.31	106.71	9.52	62.64	8.51	109.34	6.11
Shoulder Abduction-Left	28.45	12.80	85.39	0.06	25.74	9.36	50.20	0.02	24.83	9.58	51.33	0.02	26.82	9.93	53.04	0.00
Shoulder Abduction-Right	39.27	12.81	94.11	0.02	41.12	14.93	103.95	0.13	43.07	11.64	102.43	3.52	44.09	12.04	103.46	4.45
Elbow Flexiion-Left	67.58	16.85	123.71	28.41	65.57	16.58	103.29	29.93	75.25	21.76	130.39	30.89	68.78	17.57	125.48	29.56
Elbow Flexiion-Right	69.48	10.57	136.66	33.31	67.63	12.62	142.36	36.03	75.27	12.54	149.47	37.07	71.42	14.25	145.27	35.89
Hip Flexion-Left	23.93	10.86	58.06	3.80	27.24	8.48	61.61	7.46	24.97	13.25	68.15	0.25	26.35	10.20	60.21	3.08
Hip Flexion-Right	24.74	9.05	54.83	2.88	28.55	7.11	49.47	11.94	24.94	11.05	55.32	4.93	28.22	9.42	55.21	9.82
Hip Abduction-Left	30.78	15.73	74.37	0.06	23.93	16.16	69.16	0.01	26.25	15.12	70.73	0.02	23.70	12.26	60.87	0.01
Hip Abduction-Right	25.04	12.74	58.06	0.00	29.29	12.88	61.59	0.01	29.55	13.88	56.87	0.05	30.72	15.01	59.37	0.03
Hip Adduction-Left	8.38	7.56	33.23	0.02	7.61	5.75	25.79	0.01	12.42	13.56	46.93	0.01	10.39	10.08	42.86	0.00
Hip Adduction-Right	6.46	8.21	36.45	0.00	8.80	8.94	42.65	0.05	20.85	11.52	39.40	0.11	11.96	11.43	41.95	0.02
Knee Flexion-Left	90.26	7.18	107.59	74.74	89.03	7.53	104.17	73.22	88.15	5.54	101.30	76.42	89.00	6.08	100.68	75.16
Knee Flexion-Right	100.26	7.95	115.06	76.41	96.47	8.84	110.77	78.18	94.75	7.07	109.42	71.11	94.94	6.85	114.10	80.89
Lowback Hyperextension-l	46.01	6.95	60.34	20.84	41.18	6.72	53.25	23.42	43.35	9.80	64.92	30.78	38.80	6.17	53.08	23.32

Table 4 – Workstation Motion Task 4

Angles	EGF				SOF				EGB				SOB			
	average	SD(of average)	max	min	average	SD	max	min	average	SD	max	min	average	SD	max	min
Neck Flexion	21.59	7.40	43.45	1.76	19.98	7.72	48.05	0.41	21.12	8.03	46.74	0.42	20.29	7.82	48.26	0.06
Lowback Flexion-Left	54.47	10.97	81.23	19.05	50.51	11.44	83.02	3.67	53.12	11.33	81.62	2.93	51.73	11.11	80.90	4.76
Lowback Flexion-Right	55.96	9.50	78.59	31.47	53.95	10.16	77.65	26.15	56.12	9.33	76.23	28.97	55.63	8.82	72.81	28.98
Highback Flexion-Left	43.34	10.39	75.29	16.67	42.85	10.15	75.45	14.90	44.11	13.64	83.31	15.00	41.60	12.23	82.95	15.19
Highback Flexion-Right	57.58	8.29	82.72	40.26	55.90	6.18	70.34	40.59	56.74	6.91	73.16	40.55	56.10	5.54	71.98	40.66
Shoulder Flexion-Left	42.40	8.77	77.44	3.39	40.09	5.63	76.09	6.78	43.09	9.50	82.02	10.07	41.88	6.12	73.19	5.32
Shoulder Flexion-Right	33.82	12.06	80.39	10.66	30.04	5.70	46.73	11.55	34.42	12.81	93.56	11.76	32.78	7.09	53.99	8.13
Shoulder Abduction-Left	15.73	10.31	87.75	0.00	13.14	4.83	43.55	0.00	17.27	12.07	93.30	0.02	15.82	5.74	50.07	0.03
Shoulder Abduction-Right	50.87	15.65	125.49	3.75	50.83	7.92	113.14	6.75	49.79	13.60	115.75	6.23	52.99	13.13	134.44	4.11
Elbow Flexiion-Left	62.45	11.09	115.47	37.88	63.53	10.22	125.43	37.73	67.17	13.85	135.58	41.09	63.81	9.60	127.62	36.92
Elbow Flexiion-Right	79.35	17.11	110.46	40.54	81.66	17.74	116.61	39.19	81.81	18.65	119.33	37.41	84.93	20.02	116.26	40.83
Hip Flexion-Left	51.21	9.11	103.81	11.82	51.84	11.53	110.83	14.59	53.31	12.70	115.20	2.40	54.83	9.80	108.64	15.56
Hip Flexion-Right	43.86	8.24	75.57	13.13	43.37	7.70	76.36	11.96	44.26	9.44	76.88	4.28	45.68	8.27	79.17	10.33
Hip Abduction-Left	27.20	16.22	79.04	0.04	21.74	14.25	63.63	0.04	21.71	17.14	72.76	0.01	18.54	14.60	63.52	0.01
Hip Abduction-Right	26.37	11.81	59.10	0.06	27.35	8.58	52.13	0.06	25.08	9.94	44.46	0.03	27.30	12.59	55.36	0.01
Hip Adduction-Left	8.61	10.37	43.49	0.02	14.84	7.95	40.53	0.02	7.77	7.85	38.31	0.01	9.22	6.50	39.98	0.00
Hip Adduction-Right	15.63	5.74	28.57	0.06	6.39	5.21	22.18	0.00	16.70	1.72	25.08	0.26	9.40	6.18	25.16	0.09
Knee Flexion-Left	92.30	8.42	113.13	74.44	91.40	8.60	103.97	72.88	88.10	6.91	106.47	73.88	89.00	7.16	105.16	72.09
Knee Flexion-Right	96.32	7.38	113.55	76.44	92.80	8.95	107.73	66.74	91.50	6.24	108.75	74.52	90.88	7.62	103.61	67.83

Table 5 – Workstation Motion Task 5

Angles	EGF				SOF				EGB				SOB			
	average	SD(of average)	max	min	average	SD	max	min	average	SD	max	min	average	SD	max	min
Neck Flexion	20.73	6.02	38.34	5.70	20.72	6.74	44.13	6.23	21.34	7.33	38.68	3.20	21.77	6.62	39.77	2.56
Lowback Flexion-Left	42.58	8.52	68.04	17.29	40.19	8.81	63.57	13.10	42.80	8.93	68.73	17.63	41.67	9.63	67.17	10.93
Lowback Flexion-Right	51.78	5.24	73.15	34.10	48.17	8.02	65.54	13.82	50.44	6.55	71.98	33.54	50.54	7.35	69.47	32.38
Highback Flexion-Left	40.66	11.43	70.29	19.50	38.69	8.82	70.19	17.63	39.92	9.26	73.54	20.04	39.57	9.31	77.62	16.60
Highback Flexion-Right	57.65	7.65	79.61	40.72	55.73	7.26	66.33	38.14	57.53	6.80	72.32	41.77	56.19	7.18	73.98	39.23
Shoulder Flexion-Left	50.13	5.77	69.61	11.64	49.82	5.40	70.35	9.95	49.56	4.79	71.82	9.67	49.54	4.43	71.69	9.04
Shoulder Flexion-Right	35.96	14.36	101.30	14.77	30.83	5.90	45.69	8.12	33.04	5.65	45.42	13.12	31.94	6.19	71.17	18.12
Shoulder Abduction-Left	39.06	5.96	71.44	2.12	39.22	6.70	71.78	2.31	39.81	6.01	74.99	2.20	39.41	5.27	74.67	0.08
Shoulder Abduction-Right	26.60	8.74	74.59	9.08	25.59	6.12	40.21	5.86	25.54	5.75	42.34	4.77	25.79	7.10	67.53	9.39
Elbow Flexiion-Left	97.55	6.73	157.29	45.31	97.66	6.46	159.13	47.05	99.48	6.76	160.25	42.04	95.71	6.02	157.47	40.03
Elbow Flexiion-Right	89.13	20.72	150.59	43.65	90.07	16.31	120.16	38.07	93.69	16.20	127.51	45.69	83.16	18.10	125.31	43.84
Hip Flexion-Left	34.89	8.11	65.46	11.19	36.50	8.58	64.46	15.03	35.27	9.20	69.83	12.33	37.44	7.59	69.64	3.87
Hip Flexion-Right	29.68	8.14	53.17	6.14	32.48	8.23	57.10	11.89	30.31	9.42	53.29	6.97	32.85	6.95	55.09	10.75
Hip Abduction-Left	26.30	15.56	64.42	0.00	23.73	12.32	53.22	0.00	24.94	16.59	64.37	0.00	24.15	16.25	70.10	0.00
Hip Abduction-Right	24.74	13.55	55.97	0.07	22.90	11.43	50.57	0.01	22.61	12.90	48.29	0.00	25.54	12.69	56.18	0.06
Hip Adduction-Left	7.34	6.18	20.59	0.01	8.39	6.36	20.94	0.00	3.91	4.53	16.82	0.00	8.75	4.88	24.65	0.01
Hip Adduction-Right	8.17	6.90	18.06	0.01	2.73	2.53	8.11	0.05	7.87	9.74	22.54	0.00	9.93	10.52	22.08	0.03
Knee Flexion-Left	94.11	9.32	108.67	72.84	93.32	8.17	107.58	78.22	87.22	7.67	100.60	69.50	89.26	6.49	99.83	74.52
Knee Flexion-Right	100.03	9.24	113.73	80.04	97.57	6.66	107.30	83.56	94.33	7.40	104.00	75.88	93.39	7.30	102.44	71.22

Table 6 – Workstation Motion Task 6

Angles	EGF				SOF				EGB				SOB			
	average	SD(of average)	max	min	average	SD	max	min	average	SD	max	min	average	SD	max	min
Neck Flexion	19.67	6.29	38.34	1.60	18.52	6.56	36.34	0.31	19.24	6.09	39.20	0.21	17.70	6.10	43.09	0.22
Lowback Flexion-Left	35.75	8.81	55.48	19.46	33.08	8.19	48.52	11.91	35.51	9.25	52.85	14.71	34.07	8.15	52.98	15.95
Lowback Flexion-Right	60.26	8.75	80.48	34.77	58.56	10.06	82.07	25.70	59.71	9.18	78.41	32.92	57.82	14.01	86.45	13.60
Highback Flexion-Left	51.71	10.62	71.21	29.91	51.04	10.41	71.68	30.54	51.71	10.98	74.88	31.15	51.73	11.41	69.50	29.34
Highback Flexion-Right	44.23	11.92	85.12	20.15	40.97	6.69	70.39	22.00	41.29	6.67	73.26	18.62	40.92	6.03	71.56	21.32
Shoulder Flexion-Left	30.77	14.70	85.73	10.62	26.49	5.13	44.59	14.67	27.86	6.17	50.00	10.41	26.82	7.48	48.21	7.61
Shoulder Flexion-Right	50.03	5.32	73.53	15.36	49.43	4.23	70.12	11.20	48.84	4.10	75.20	13.74	51.56	5.27	76.73	14.26
Shoulder Abduction-Left	20.90	7.77	43.42	4.21	19.34	6.51	40.79	1.71	20.54	6.88	45.10	4.30	21.04	7.82	41.40	3.66
Shoulder Abduction-Right	34.31	6.40	60.81	2.28	34.32	7.36	66.76	8.55	35.43	5.27	60.95	3.71	36.35	5.96	64.16	7.01
Elbow Flexiion-Left	89.65	22.73	144.09	42.00	91.85	15.20	134.93	42.66	88.67	19.50	124.77	39.58	89.58	17.34	120.83	40.08
Elbow Flexiion-Right	96.85	5.83	157.24	47.00	98.25	8.00	157.79	45.30	95.51	5.43	156.94	45.41	95.90	7.47	157.54	43.53
Hip Flexion-Left	34.18	8.12	54.72	8.61	35.29	7.91	59.51	16.34	35.93	8.33	57.40	12.82	37.45	8.36	60.94	8.29
Hip Flexion-Right	35.86	8.00	69.13	6.90	36.78	8.36	69.78	13.48	36.61	9.23	70.70	9.16	39.07	8.31	69.15	10.43
Hip Abduction-Left	26.38	15.35	70.23	0.00	20.59	13.55	55.15	0.01	22.43	14.81	67.86	0.00	19.48	14.20	62.51	0.00
Hip Abduction-Right	25.79	14.51	59.05	0.00	22.20	12.34	47.42	0.00	23.57	11.79	51.12	0.03	25.35	14.49	61.59	0.01
Hip Adduction-Left	4.48	3.15	12.51	0.02	6.91	4.71	17.00	0.03	4.90	4.09	16.16	0.01	5.88	3.08	20.36	0.01
Hip Adduction-Right	8.47	6.21	18.38	0.00	7.21	1.22	16.47	0.01	8.56	8.59	19.89	0.03	13.19	2.32	23.03	0.01
Knee Flexion-Left	93.46	9.69	109.86	71.99	92.94	8.80	110.84	78.03	87.07	7.50	102.77	69.12	88.48	6.12	100.26	75.06
Knee Flexion-Right	100.56	9.00	113.63	81.65	98.75	7.47	112.60	85.82	94.66	7.52	105.39	78.23	93.91	7.24	104.87	74.10

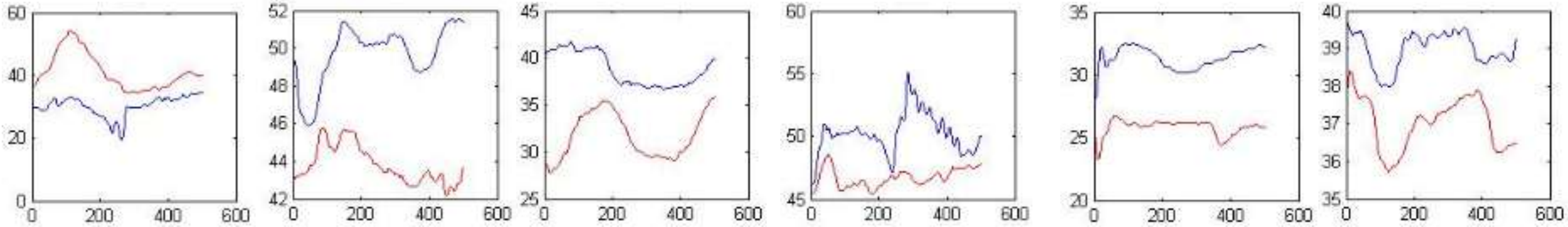
Table 7 – Workstation Motion Task 7

Angles	EGF				SOF				EGB				SOB			
	average	SD(of average)	max	min	average	SD	max	min	average	SD	max	min	average	SD	max	min
Neck Flexion	28.22	7.36	43.71	2.16	27.04	6.48	43.38	2.24	28.23	6.03	45.51	10.08	27.72	7.00	43.94	3.20
Lowback Flexion-Left	36.67	9.76	55.40	19.49	33.36	9.79	49.51	11.48	36.01	9.94	54.02	17.10	33.40	9.27	50.44	12.94
Lowback Flexion-Right	54.40	8.18	71.15	35.33	53.56	8.46	73.82	30.87	55.43	10.40	84.00	32.29	56.87	9.36	81.29	35.83
Highback Flexion-Left	51.85	11.66	71.91	30.83	51.01	11.30	69.04	29.18	52.55	12.11	71.42	28.86	53.23	12.29	69.46	28.86
Highback Flexion-Right	51.25	9.46	81.06	28.92	48.86	5.97	69.52	27.17	49.24	6.13	72.45	32.64	48.53	6.04	72.27	29.45
Shoulder Flexion-Left	30.02	13.66	83.73	10.68	27.02	7.11	46.09	11.05	27.39	7.52	40.14	11.22	25.91	7.34	49.21	9.74
Shoulder Flexion-Right	39.59	7.17	63.85	19.08	36.48	3.64	52.44	9.70	36.57	3.94	54.26	14.42	38.65	4.76	60.50	19.55
Shoulder Abduction-Left	21.17	7.43	42.89	6.05	21.33	6.92	38.05	2.32	20.90	7.72	33.73	4.06	21.49	7.57	49.47	3.26
Shoulder Abduction-Right	33.87	5.29	50.75	10.15	32.49	5.28	54.04	9.36	33.04	5.08	51.69	5.33	33.50	6.17	55.16	10.39
Elbow Flexiion-Left	88.50	23.06	129.50	37.76	93.29	16.46	134.08	46.47	89.62	19.10	117.61	40.28	86.55	17.68	124.99	35.83
Elbow Flexiion-Right	85.07	7.49	128.59	46.86	83.61	5.61	129.14	46.88	82.37	8.41	125.38	42.39	81.07	7.74	126.77	43.72
Hip Flexion-Left	30.70	9.45	51.45	12.28	31.27	8.13	48.60	18.17	30.06	9.40	51.84	12.30	32.08	8.66	46.17	13.57
Hip Flexion-Right	29.97	9.03	56.11	10.45	31.06	8.17	54.94	14.94	29.55	10.58	56.93	7.04	31.91	9.03	53.17	9.58
Hip Abduction-Left	28.68	14.61	64.18	1.99	23.89	13.86	56.19	0.00	27.17	17.22	65.43	0.01	25.60	15.06	60.85	0.00
Hip Abduction-Right	25.53	14.48	55.85	0.01	23.54	10.30	45.79	0.06	25.86	10.70	44.22	3.97	26.68	13.12	54.63	0.01
Hip Adduction-Left	16.04	17.31	38.10	2.30	5.48	2.29	8.89	0.00	3.44	1.39	13.24	0.01	3.80	2.69	11.87	0.02
Hip Adduction-Right	7.70	7.16	19.43	0.01	5.11	2.83	10.50	0.03	11.50	8.30	21.28	1.76	9.28	9.26	21.46	0.02
Knee Flexion-Left	93.73	9.47	110.22	71.55	93.38	9.13	110.50	78.10	87.20	7.45	98.23	69.32	88.50	6.31	98.00	71.66
Knee Flexion-Right	101.20	9.01	113.83	82.11	99.35	7.62	113.72	86.75	94.97	7.51	103.66	78.29	94.24	7.14	103.74	74.33

Table 8 – Workstation Motion Task 8

Angles	EGF				SOF				EGB				SOB			
	average	SD(of average)	max	min	average	SD	max	min	average	SD	max	min	average	SD	max	min
Neck Flexion	32.43	9.04	53.07	14.26	35.57	7.16	51.89	22.31	32.09	8.74	50.11	17.76	31.36	7.83	50.29	7.95
Lowback Flexion-Left	38.48	9.42	59.49	23.17	36.73	8.54	51.93	21.88	38.64	10.40	61.02	22.10	38.71	10.08	59.71	18.46
Lowback Flexion-Right	54.68	9.60	69.32	33.92	53.62	10.10	70.48	28.72	55.80	11.33	73.36	35.96	57.06	11.30	75.00	34.93
Highback Flexion-Left	44.63	11.61	64.88	24.68	44.22	10.48	60.55	26.80	44.70	11.15	62.56	26.57	43.41	11.58	62.15	23.05
Highback Flexion-Right	49.14	9.75	79.86	28.81	47.05	6.02	59.39	34.15	46.82	6.40	63.69	28.24	45.74	6.60	60.28	26.68
Shoulder Flexion-Left	32.82	9.92	63.29	18.94	30.70	6.29	43.19	16.31	30.30	6.24	44.44	20.21	32.39	8.19	48.07	14.35
Shoulder Flexion-Right	26.43	11.19	66.53	14.17	24.21	5.83	41.84	13.41	23.82	4.46	45.99	16.46	27.61	6.59	46.71	12.79
Shoulder Abduction-Left	22.08	7.72	37.90	3.95	21.14	6.95	37.71	1.79	20.72	6.61	37.21	6.61	21.83	8.33	45.02	5.37
Shoulder Abduction-Right	20.82	7.02	40.49	10.80	21.29	7.20	43.60	5.07	19.17	6.48	40.26	7.95	21.24	8.12	45.84	7.80
Elbow Flexiion-Left	99.69	8.55	124.75	86.11	100.42	7.93	125.97	81.93	97.03	8.12	116.05	81.76	96.24	10.16	119.69	75.54
Elbow Flexiion-Right	95.93	9.25	114.16	82.05	96.25	8.35	115.52	76.32	93.62	8.90	112.02	72.82	93.29	10.52	116.67	71.40
Hip Flexion-Left	33.98	9.17	52.51	22.07	35.05	9.37	55.02	21.25	34.94	9.98	55.81	16.44	37.01	8.84	50.01	18.51
Hip Flexion-Right	30.23	7.80	48.06	14.00	31.35	8.69	52.05	17.73	30.21	9.61	52.24	11.18	33.48	8.86	50.60	14.00
Hip Abduction-Left	26.34	14.15	56.13	2.26	23.24	13.35	54.49	2.59	25.26	17.31	58.58	0.00	24.90	11.40	43.86	5.22
Hip Abduction-Right	27.04	12.73	50.57	3.58	23.17	11.25	45.07	0.00	25.39	10.25	39.61	6.49	29.54	11.62	54.24	8.10
Hip Adduction-Left	15.75	16.34	36.75	4.75	8.05	2.79	12.62	5.33	5.92	3.45	10.00	0.00	7.64	5.23	16.43	1.70
Hip Adduction-Right	8.72	8.26	18.57	2.45	5.00	6.19	10.22	0.00	12.24	9.20	20.02	5.36	10.76	7.26	16.17	4.08
Knee Flexion-Left	94.44	9.33	108.24	72.59	94.90	11.06	124.68	79.24	87.75	7.44	97.27	70.16	89.10	6.61	98.63	71.65
Knee Flexion-Right	99.12	8.76	113.80	81.96	98.85	9.60	124.51	82.01	93.68	7.49	103.23	77.33	92.89	7.26	101.89	73.59

Appendix 5: Some examples of seated motion



(a) Hip Flexion (left); (b) Hip Flexion (right); (c) Midback Flexion (left); (d) Midback Flexion (right); (e) Shoulder Flexion (left); (f) Shoulder Flexion (Right)

x axis denotes frame numbers, y axis denotes degree. Blue curve- Ergokinetic chair ; Red curve- Standard Office Chair.

(a)-(c): graphical examples to showing that Hip Flexion less, and mid back flexion is higher in the Ergokinetic chair than in the standard office chair in workstation motion task 5.

(d)-(f): is an example showing shoulder flexion to be higher at the side opposite to which the participant reaches for an item on the desk.

(e): is SFl for action 6 (reach for something right/front). (f): is SFr for action 5 (reach for something left/front).