# USING 3D SENSING AND PROJECTING TECHNOLOGY TO IMPROVE THE MOBILITY OF PARKINSON'S DISEASE PATIENTS

**A thesis submitted for the degree of**
**Doctor of Philosophy**


**by**

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# Abstract

Parkinson's is a neurological condition in which parts of the brain responsible for movements becomes incapacitated over time due to the abnormal dopamine equilibrium. Freezing of Gait (FOG) is one of the main Parkinson's Disease (PD) symptoms that affects patients not only physically but also psychologically as it prevents them from fulfilling simple tasks such as standing up or walking. Different auditory and visual cues have been proven to be very effective in improving the mobility of People with Parkinson's (PwP). Nonetheless, many of the available methods require user intervention or devices to be worn, charged, etc. to activate the cues.

This research suggests a system that can provide an unobtrusive facility to detect FOG and falling in PwP as well as monitoring and improving their mobility using laser-based visual cues casted by an automated laser system. It proposes a new indoor method for casting a set of two parallel laser lines as a dynamic visual cue in front of a subject's feet based on the subject's head direction and 3D location in a room. The proposed system controls the movement of a set of pan/tilt servo motors and laser pointers using a microcontroller based on the real-time skeletal information acquired from a Kinect v2 sensor. A Graphical User Interface (GUI) is created that enables users to control and adjust the settings based on the user preferences.

The system was tested and trained by 12 healthy participants and reviewed by 15 PwP who suffer from frequent FOG episodes. The results showed the possibility of employing the system as an indoor and on-demand visual cue system for PwP that does not rely on the subject's input or introduce any additional complexities to operate. Despite limitations regarding its outdoor use, feedback was very positive in terms of domestic usability and convenience, where 12/15 PwP showed interest in installing and using the system at their homes.

# Dedication

To my parents, Ali Akbar & Aghdas.

# Acknowledgements

I would like to acknowledge Parkinson's UK foundation for facilitating the process of recruiting PwP for our focus groups. Most importantly, I would like to thank my supervisor, Dr. Konstantinos Banitsas whose comments, observations and ideas have greatly enriched this project.

# Declaration

I hereby declare that this submission is my own work and the use of all material from other sources has been properly and fully acknowledged, and I confirm that this thesis has not been and will not be, submitted in whole or in part to another University for the award of any other degree.

Signature: ………………

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# Abbreviations

| | |
|---|---|
| AAL | Ambient Assisted Living |
| ADC | analogue-to-digital converter |
| ALF | Assisted Living Facilities |
| API | Application Programming Interface |
| CMOS | Complementary metal–oxide–semiconductor |
| DLL | Dynamic-Link Library |
| FOG | Freezing of Gait |
| FPS | Frame per second |
| GUI | Graphical User Interface |
| IR | Infrared |
| MOA-B | Monoamine oxidase-B |
| PCM | pulse code modulation |
| PD | Parkinson's Disease |
| PwP | People with Parkinson’s |
| RGB | Red Green Blue |
| ROS | Robot Operating System |
| SD | Standard Deviation |
| SDK | Software Development Kit |
| SMLD | subject mounted light device |
| SVM | Support Vector Machine |
| ToF | Time-of-Flight |
| USB | Universal Serial Bus |
| VCS | Virtual Cueing Spectacles |
| VGA | Video Graphics Array |
| VGB | Visual Gesture Builder |
| WPF | Windows Presentation Foundation |

# Publications

[1] **A. Amini**; K. Banitsas, “A Prototype System Using Microsoft Kinect to Recognize Freezing of Gait in Parkinson’s Disease Patients,” in International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Chicago, Illinois, USA, 2014.

[2] **A. Amini**, “An Unobtrusive System For Detecting Parkinson’s FOG Episodes,” in 7th Annual Student Research Conference (ResCon’14), London, UK, 2014.

[3] **A. Amini**; K. Banitsas; A. Badii; j.Cosmas, “Recognition of Postures and FOG on Parkinson’s Disease Patients Using Microsoft Kinect Sensor,” in International IEEE EMBS Neural Engineering Conference, Montpellier, France, 2015.

[4] **A. Amini**; K. Banitsas; j.Cosmas, “A comparison between heuristic and machine learning techniques in fall detection using Kinect v2” in 2016 IEEE International Symposium on Medical Measurements and Applications (MeMeA), Benevento, Italy, 2016.

[5] **A. Amini**; K. Banitsas; S. Hosseinzadeh, “A New Technique for Foot-Off and Foot Contact Detection in a Gait Cycle Based on the Knee Joint Angle Using Microsoft Kinect v2” in 2017 IEEE International Conference on Biomedical and Health Informatics (BHI), Orlando, FL, USA, 2017.

[6] **A. Amini**, K. Banitsas, W. R. Young, “Kinect4FOG: Monitoring and Improving Mobility in People with Parkinson’s using a Novel system incorporating the Microsoft Kinect v2” Disability and Rehabilitation: Assistive Technology (Under Review).

[7] **A. Amini**, K. Banitsas, A. A. Amini Maghsoud Beigi, “An Improved Technique for Increasing the Accuracy of Joint-to-Ground Distance Tracking in Kinect v2 for Foot-Off and Foot Contact Detection” The Imaging Science Journal (Under Review).

[8] **A. Amini**, K. Banitsas, “Using Kinect v2 to Control a Laser Visual Cue System for Parkinson’s Disease Patients” Assistive Technology Journal (Under Review).

# Chapter 1: Introduction

## 1.1 Motivation

One of the main physical symptoms among PwP is FOG. Studies have shown that a visual aid projected in front of a patient (e.g. lines, stairs, etc.) experiencing such episodes could be beneficial to the “unfreezing” of those patients.

At the same time and within the last three years, there was an unparalleled bloom in gaming machines capable of detecting the gamer and his/her gestures. The most famous of these is the Microsoft Kinect that, although initially developed as a “wireless joystick”, soon found its way into many other applications, including medicine, healthcare, rehabilitation, etc.

This research proposes a system that takes advantage of the abilities of a Microsoft Kinect, to improve the mobility and locomotion of PwP experiencing FOG episodes. Moreover, it provides a facility for healthcare providers and doctors to monitor the gait performance of their patients remotely. Additionally, the system can detect fall incidents that are common among PwP and inform the people responsible to take further actions if required.

## 1.2 Parkinson’s Disease

Parkinson’s disease (PD), caused by the depletion of dopamine in the substantia nigra, is a degenerative neurological condition affecting the initiation and control of movements, particularly those related to walking [1], [2]. There are many physical symptoms associated with PD including akinesia, hypokinesia, and Bradykinesia [3]. An additional symptom is FOG, usually presenting in advanced stages of Parkinson’s [4]–[7]. FOG is one of the most debilitating and least understood symptoms associated with Parkinson’s. It is exacerbated by several factors including the need to walk through narrow spaces, turning as well as stressful situations [7], [8].

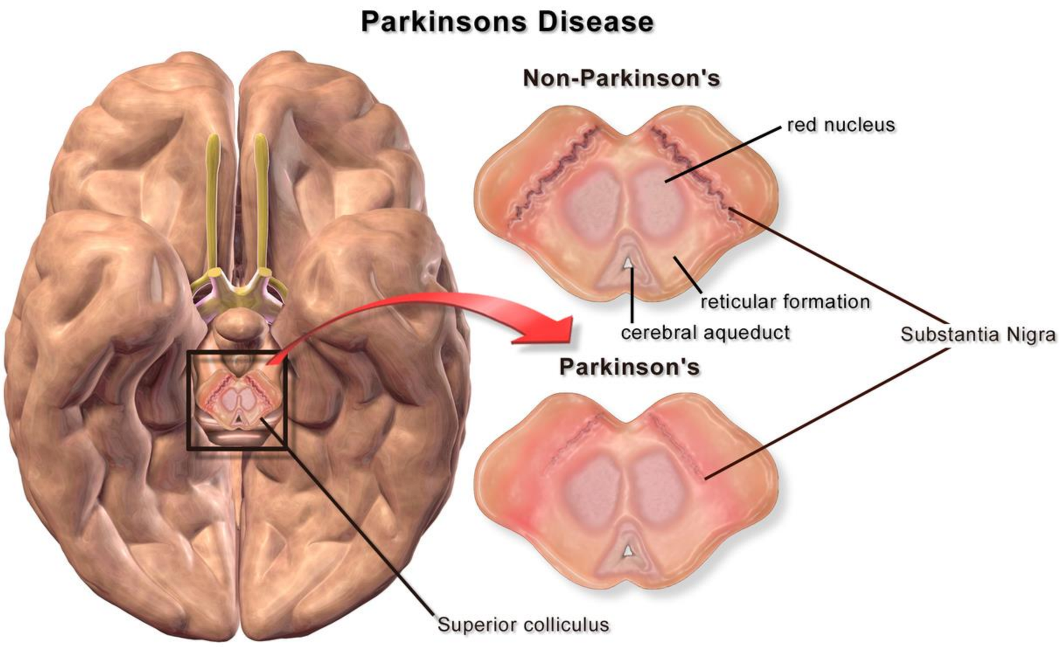



Figure 1:1. The effect of PD (depletion of dopamine in the substantia nigra) on human brain [9]

## 1.3 Freezing of Gait (FOG)

FOG is one of the most disabling symptoms in PD that affect its sufferers by impacting their gait performance and locomotion. FOG is an episodic phenomenon that prevents the initiation or continuation of a patient's locomotion and usually occurs in latter stages of PD where patients' muscles freeze in place as they are trying to move [1], [6], [7], [10].

FOG and associated incidents of falling often incapacitate PwP and, as such, can have a significant detrimental impact at both a physical and psychological level [6]. Consequently, the patient's quality of life decreases and health care and treatment expenditures increase substantially [11]. A research study conducted by the University of Rochester's Strong Memorial Hospital [12] showed that approximately 30 % of PwP experience sudden, unexpected freezing episodes, thus highlighting the high level of dependency that many PwP have on physical or psychological strategies that may assist in alleviating FOG and help people start walking again.

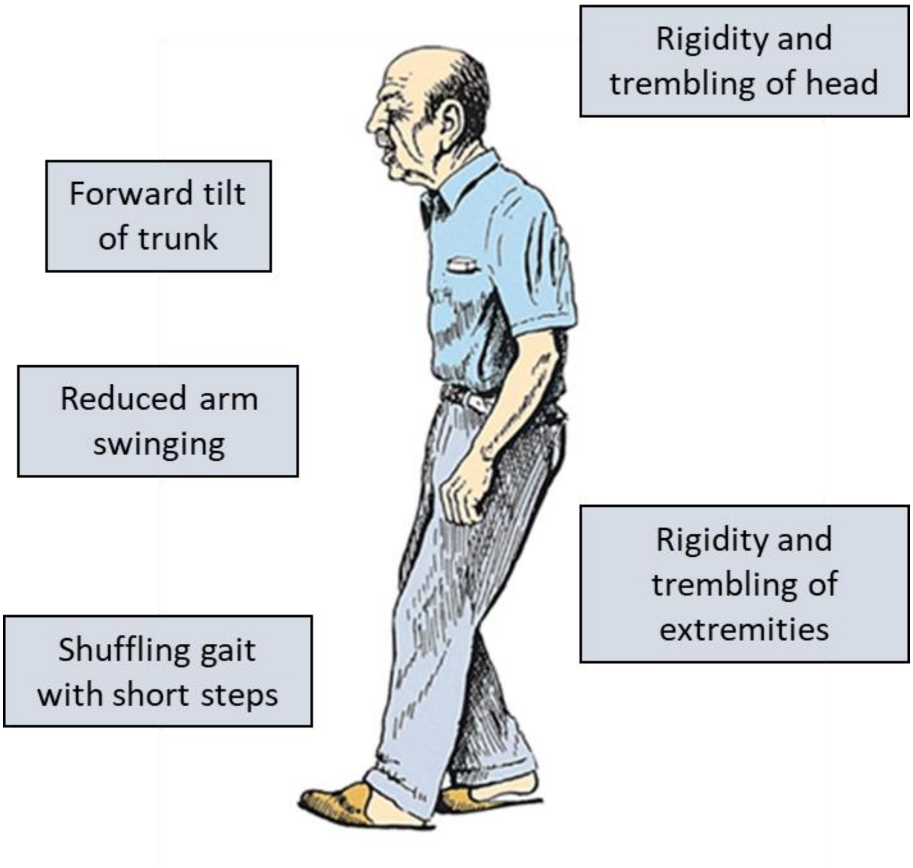



Figure 1:2. PD physical symptoms [9]

## 1.4 Possible Treatments

There is no proven therapy to eradicate the PD or slow down its progression. As a result, the focus of the medical therapy is on the treating or reducing the effect of its symptoms [13]. There are different treatments available to improve PwP living standards and help deal with the symptoms including supportive therapies, medications and surgery.

Supportive therapies focus towards pain relieve using different methods including physiotherapy that relieves joint pain and muscle stiffness as well as exercises and occupational therapy that provide support for day-to-day activities of PwP and programmes that help them maintain their independence. Moreover, supportive therapies also cover dietary advice that would be beneficial to some extent for symptom relieve. Lastly, speech and language therapy can also help PwP improving speech impairment caused by the disease or reduce the patient's swallowing difficulties (dysphagia), also related to PD [14].

Medication are also beneficial in reducing the frequency or effect of PD's main symptoms including FOG and tremors. Nonetheless, there usually are possible short and long-term side effects in these methods. The three types of the mainstream medication for PwP are [14]:

- Levodopa

Levodopa help the increase of dopamine production by the nerve cells; an agent for message transmission between brain parts and nerves responsible of controlling movement. Consequently, this would improve the patient's movement irregularities and locomotion [13] [15].

- Dopamine agonists

These chemical act as a substitute for the imbalanced dopamine level in the brain, that yields similar effect as levodopa. Dopamine agonists could have many side effects including hallucinations and confusion [13], [15].

- Monoamine oxidase-B inhibitors

Monoamine oxidase-B (MOA-B) inhibitors aim at blocking the effect of an enzyme responsible of breaking down dopamine. As a result, the dopamine level would be increased. MOA-B can improve the PD symptoms and can be prescribed to be used alongside other medications such as dopamine agonists or levodopa [13], [15].

Finally, a pulse generator can be surgically implanted into the subject's chest wall connected using wires to a specific part of the brain. This acts as a deep brain stimulation that produces a tiny electrical current which stimulates the brain in order to ease PD symptoms [16].

### 1.4.1 Sensory Stimulation

Many studies suggest that auditory [17]–[20] and visual cues [10], [19]–[31] can improve PwP's gait performance, especially during FOG. Rubinstein et al., [32], observed that in the presence of an external 'movement trigger' (i.e., a sensory cue), a patient's self-paced actions such as walking, can be significantly improved; a phenomenon known as '*kinesia paradoxica*'.

## 1.5 Research Question

This study investigates the question of whether it is feasible to implement an unobtrusive approach for real-time FOG monitoring, by utilising commercially available 3D camera sensors based on the Microsoft Kinect architecture. The research also studied the applicability of using the 3D sensing cameras in conjunction with a moving laser projection system acting as a visual cue with the aim of decreasing the frequency/duration of “freezing” episodes and improving the mobility of patients diagnosed with Parkinson's disease. Studies have shown that such an approach will be beneficiary on reducing the FOG episodes in PwP, both in frequency and in duration. The system can also detect fall incidents that are common among Parkinson’s disease patients and automatically alert relatives/healthcare providers.

## 1.6 Aims and Objectives

The main aim of this study is to research on an affordable, reliable, and unobtrusive system for monitoring/detecting FOG and fall incidents in PwP as well as to provide mobility improvement and locomotion enhancement during a FOG incident using an automatic and dynamic visual cueing system based on laser projection. Additionally, different methods in detecting a subject’s footsteps, an important part in unobtrusive FOG detection, is presented and evaluated.

The individual objectives of the project are:

- To improve PwP locomotion with an automatic and dynamic visual cue system.
- To build a user interface for healthcare providers and doctors to monitor the patients’ activities remotely and get notification should a critical incident such as unrecoverable fall happens.
- To investigate, through a focus group of real PwP on how such a combination of discreet and inexpensive hardware can possibly assist PwP that have frequent FOG episodes.
- To use a 3D sensing technology such as a Microsoft Kinect sensor to detect and monitor PD FOG and fall incidents unobtrusively.

The proposed research focuses on the sensory stimulation therapy and rehabilitations side of the PD treatment using laser-based visual cues. In conjunction with the current system, the project's researchers developed a companion smartphone application and a client software that enables doctors, healthcare providers and family members to monitor and receive notifications regarding possible incidents. Upon the detection of a fall, the system can automatically capture the event alongside an appropriate time stamp and notify a relevant person via email, live video feed (through the smartphone companion app), skype conversation or developed client software.

## 1.7 Contributions to Knowledge

This research study leads to improve upon existing and previous works by:

- Introducing two new footstep detection techniques one based on the subject's knee angle and one based on the subject's ankle vertical height to the ground; Reducing the Microsoft Kinect's intrinsic inaccuracies in skeletal data reading for the subject's ankle vertical height to the ground footstep detection technique; resulting in the increase in accuracy for the footstep detection algorithm by introducing a new correction algorithm.
- Providing an automatic and remotely manageable monitoring system for PwP gait analysis and fall detection.

## 1.8 Thesis Structure

This thesis consists of six chapters supplemented by references and appendices. The outline and a brief description of each chapter are as follow:

**Chapter 2:** This chapter evaluates similar studies carried out in the field. these will be analysed, and their shortcomings will be discussed.

**Chapter 3:** This chapter focuses on the description of technical terms and technologies used in this project. Different technologies will be analysed and evaluated. Their advantages and disadvantages will also be discussed.

**Chapter 4:** This section focuses on the implementation phase of the proposed approach including the execution of the prototype system both in hardware and software level. Moreover, the algorithm employed in this study will also be discussed.

**Chapter 5:** The aim of this chapter is to discuss the outcomes of this research including the empirical results and evaluation of the research study product. The data will be compared against the initial requirements and the aims and objectives of the project and its effectiveness will also be discussed.

**Chapter 6:** In the final chapter the project carried out will be summarised and compared against the initial aims. Additionally, the obstacles and issues encountered during the project development as well as the future works would be discussed.

# Chapter 2: Literature Review

## 2.1 Introduction

This literature review covers the existing research and studies that focused on similar field as this research. Different studies in fall detection, especially in PwP will be analysed; Solutions based on visual cue for locomotion improvement during a FOG for PwP as well as systems for rehabilitations and monitoring of these patients are reviewed. Approaches towards detecting PD symptoms including FOG are discussed including sensor-based and computer vision methods. Moreover, different procedures that help detecting FOG based on computer vision approach such as footstep detection are evaluated. Finally, these studies are then analysed, and their possible shortcomings will be discussed.

## 2.2 The Effect of Visual Cue on PD Locomotion

Many previous studies have developed methods for monitoring FOG behaviours and intervening to improve motor symptoms with the use of external visual cues. Many studies utilised computer vision technologies to minimize the need for patients to wear measurement devices, which can be cumbersome and also have potential to alter a person's movement characteristics. Since the release of the Microsoft Kinect camera several attempts have been made to use the Kinect sensor as a non-invasive approach for monitoring PD-related gait disorders. Many previous research studies have focussed on rehabilitation outcomes and experimental methods for monitoring patients' activities.

For instance, in Takač, et al., [33], a home tracking system was developed using Microsoft Kinect sensors to help PwP who experience regular FOG. The research interconnected multiple Kinect sensors together to deliver a wider coverage of the testing environment. The model operated by collectively gathering data from multiple Kinect sensors into a central computer and storing them in a centralised database for further analysis and processing. The research employed a model based on the subject's histogram colour and height together with the known average movement delays between each camera. Nonetheless, as a Kinect camera produces a raw RGB data stream, analysing multiple Kinect colour data stream for the histogram of colour in real-time requires a very powerful processor and significant amount of computer memory. Moreover, the synchronisation between each camera feed would add extra computation for this approach.

Previous research has demonstrated that dynamic visual cues (such as laser lines projected on the floor) can deliver a profound improvement to walking characteristics in PwP [20]. Furthermore, strong evidence now exists suggesting that it is not only the presence of sensory information (or an external 'goal' for movement) that 'drives' improvements/*kinesia paradoxia*, but rather the presence of continuous and dynamic sensory information. This was first demonstrated by Azulay et al., [34], who showed that the significant benefits to gait gained when walking on visual stepping targets were lost when patients walked on the same targets under conditions when the room was illuminated by strophic lighting; thus making the visual targets appear static. Similar observations have also been made in the auditory domain [3].

In Zhao et al., [35], in order to improve PwP's gait performance, a visual cue system was implemented based on a wearable system installed on subjects' shoes. This system employed laser pointers as visual cues fitted on a pair of modified shoes using a 3D printed caddy. The system consisted of pressure sensors that detect the stance phase of gait and trigger the laser pointers when a freeze occurs.

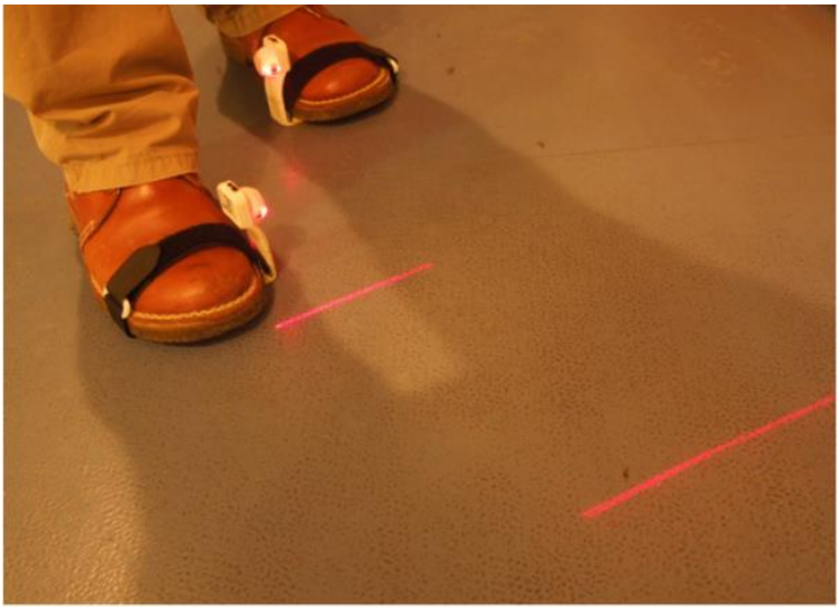


Figure 2:1. A pair of laser-mounted shoes for visual cue [35]

While effective and intuitive to use, the reliance on any attachable/wearable apparatus can be cumbersome and also required users to remember to attach appropriate devices, even around the house; where many people experience significant problems with FOG at times when they are not wearing their shoes.

In another approach based on wearable devices [36], the effect of a subject mounted light device (SMLD) projecting visual step length markers on the floor was evaluated. The study showed that a SMLD induced a statically significant improvement on subjects' gait performance. Nevertheless, it was suggested that the requirement of wearing SMLD might lead to practical difficulties both in terms of comfort and on the potential for the devices impacting on patients' movements characteristics.

In Velik et al., [31], the entire SMLD visual cue system included a backpack consisting of a remotely-controlled laptop (needed to be carried by the subjects). Although the SMLD method was employed, researchers added the 10 seconds on-demand option to the "constantly on" visual cue casting.

Figure 2:2. A SMLD coupled with a controlling laptop and laser line projection system for PD patient's visual cue purposes [31]

Moreover, similar to the aforementioned technologies, the laser visual cues are always turned on, regardless of the subject's FOG status of gait performance. McAuley et al., and Kaminsky et al., [22], [23], proposed the use of Virtual Cueing Spectacles (VCS) that, similar to approaches that project targets on the floor; project virtual visual targets on to a user's spectacles. The use of VCS might eliminate major disadvantages introduced by SMLD (or other wearable approaches), but these systems still need to either be sensitive to a FOG onset, or constantly turned on, even when not required.

In Griffin et al., [30], the effect of real and virtual visual cueing was compared and it was concluded that real transverse lines casted on the floor are more impactful than the virtual counterparts. Nonetheless, using VCS eliminates the shortcomings in other techniques such as limitations in mobility, steadiness and symmetry. VCS also has the advantage of being capable to be used at an external environment when the patient is out and about.

Figure 2:3. A goggle used to project VCS [30]

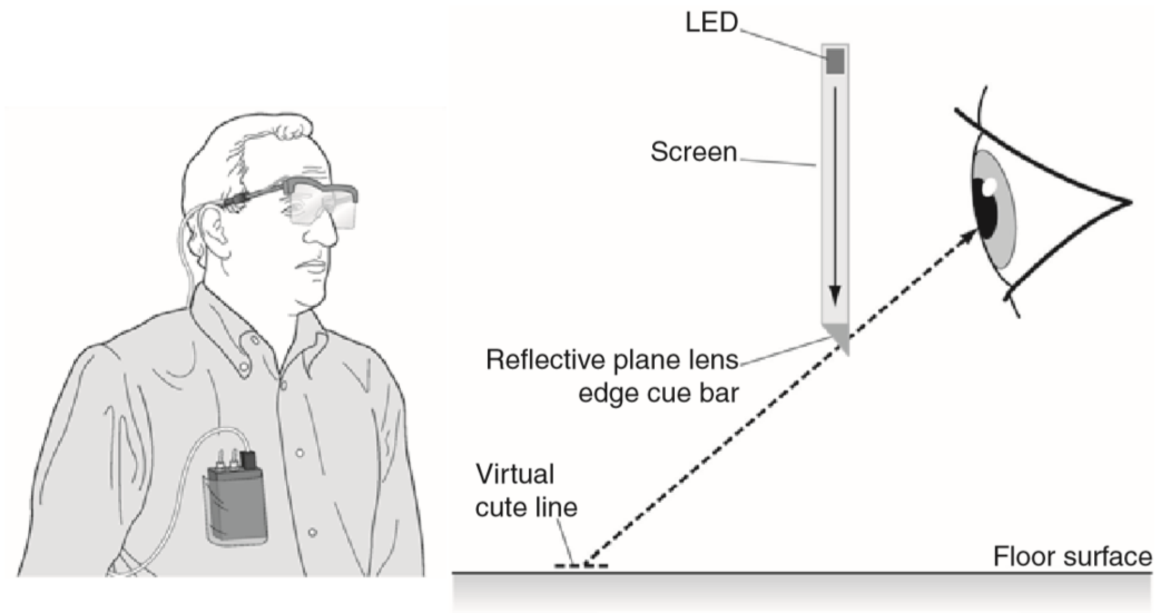



Figure 2:4. A VCS system virtual cue projection mechanism [23]

## 2.3 FOG Monitoring and Detection

Motor-related symptoms of PD have been the subject for assessment and detection in rehabilitation and gait performance analysis research studies. There have been several studies conducted towards the detection and characterising of these symptoms, especially FOG in PwP using on-body sensors and wearables.

For instance, in Tripoliti et al., [37] a combination of six accelerometers and two gyroscopes were placed on the PD patient's body. The research employed four stages and compared its approach against different signal processing techniques and different sensor arrangements in order to achieve the optimal detection success rate.

In Pepa et al., [38], a solution based on a smartphone was used utilising Fuzzy Logic to gather gait related data in case of a FOG, whereas in Mazilu et al., [39], a combination of wearable accelerometer and smartphones were used. Combined with a machine learning technique, this latter approach managed to detect FOG incidents with a 95 % success rate. This research aimed at using auditory cues for mobility improvement of PwP. Once a FOG was detected, the system would provide rhythmic cues to the patient.


Figure 2:5. A pair of accelerometers and a smart phone used for gait analysis and FOG assessments in PwP [39]

In Jovanov et al., [40], an inertial wearable sensor was attached to the patient's shoes for real-time gait monitoring in which upon detection of a FOG incident with an average latency of 332 ms, the prototype system would send acoustic cues to the wireless headset attached to the patient's ear for stimulation. The sensor consisted of a 3-axis accelerometer and 2-rotational gyroscope.

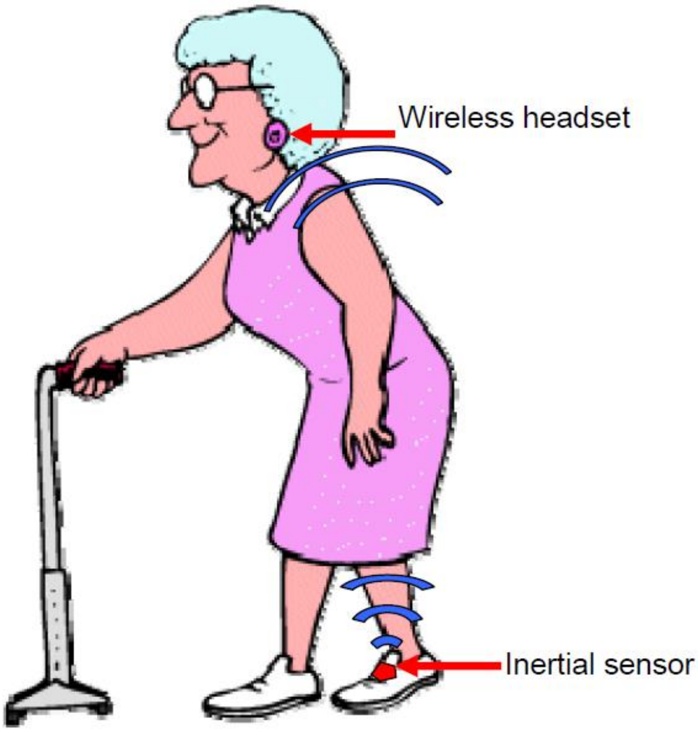



Figure 2:6. Shoe-embedded inertial sensors for FOG assessment and gait performance analysis. Upon a possible FOG detection, a wireless headset would provide auditory cues [40]

In another attempt by Mazilu et al., [41], the correlation between a PD patient's wrist movements and a FOG incident has been examined. The study tried to place the sensor in a more commonly worn area of the body (i.e. wrist) where usually a watch is worn, in order to make the system more acceptable/adoptable and less obtrusive.

In Niazmand et al., [42], accelerometer sensors were embedded in the subject's trousers based on MiMed-Pants in order to achieve a low-profile detection system for FOG. Finally, in Handojoseno et al., [43], a FOG detection technique based on EEG signals was used with relatively low detection rate of 75 %. In summary, the employment of EEG has many limitations such as fixed location and long setup and calibration time.

Since the release of Kinect for Windows SDK, many attempts have been made to use of the Kinect sensor for PD related research. Most of the studies have focused on rehabilitation purposes and experimental ways of monitoring patients' activities.

In Galna et al., [44], a Kinect-based game was developed to encourage patients to conduct daily activities for rehabilitation purposes in which as the user progresses, the difficulty of these activities would increase. The research concluded that most of the participants enjoyed using the system while at the same time could benefit from doing such activities.

Figure 2:7. A Kinect-driven rehabilitation and movement exercise game for PwP [44]

In another study by Palacios-Navarro et al., [45], an augmented reality game was developed based on the Microsoft Kinect for PwP. This tool aimed to help PwP conducting several motion rehabilitation exercises. Nonetheless, the long-term effect and efficiency of the product were not measured while the research concluded that participants showed interest in using the system. Finally in Rocha et al., [46], several body joint data were gathered both from healthy and PD diagnosed subjects based on the Kinect's skeletal data. The data then were analysed, and several gait parameters were extracted. By comparing the healthy subject's gait characteristics and PD counterparts, the study could assess motor-related parameters in PwP. Although the approach proved to have a 96 % success rate in distinguishing PD and non-PD subjects, the system required a lot of data analysis and processing and does not offer a real-time solution.

To our knowledge, these are the most representative research projects related to real-time, non-invasive detection and recognition of PwP symptoms, especially for FOG/tremor incidents. Most of the researchers have concentrated on helping the already diagnosed patients having a better-quality life. They have focused on the rehabilitation process by developing games or monitoring systems. Some used a device or a sensor to be attached to or worn by the patients in order to detect the symptoms.

### 2.3.1 Footstep detection

Detecting footsteps plays an important role in gait cycle analysis and rehabilitation purposes, as many diseases feature physical symptoms, especially gait disorders. Having an unobtrusive gait detection system can significantly improve the accuracy of footsteps analysis, as due to the nature of the case, on-body sensors can sometimes be problematic and have a direct effect on the gait performance and behaviour. Different methods have been used in extracting accurate information related to footstep detection such as pressure-based mapping, in which foot contacts and foot-offs can be detected based on the variance in pressure in different areas of a foot sole [47], [48], inertial-based sensing using different wearable sensors attached to the body [68], [75], [76], instrumented treadmills [51]–[53] and computer vision [54], [55]. Most methods in gait analysis, especially footstep detection, are obtrusive and expensive to implement.

As an alternative approach to the aforementioned techniques, one could consider the employment of unobtrusive depth cameras such as Microsoft Kinect v2. As the Kinect was designed as a replacement for conventional game controllers, it is very effective in reading body joints data, especially from upper extremities that are more active in a gaming session. Nevertheless, due to the Kinect's intrinsic inaccuracies in data acquisition, particularly for lower extremities [56], innovative approaches have been made to compensate these issues. Moreover, due to the nature of some degenerative diseases such as PD that feature gait related symptoms including FOG, minor inaccuracies either greatly affect the data collection or render the entire acquired data unusable.

Since the introduction of the Microsoft Kinect sensor, many studies have been conducted based on the Kinect camera with regards to gait performance analysis [57]–[63]. Nonetheless, the Kinect skeletal-based detection of footsteps in particular, is a challenging feat due to Kinect's margin of error, especially for lower extremities [61]. Additionally there are disadvantages to this method such as higher computational power required for signal analysis and image processing and intrinsic data acquisition inaccuracies, especially in Kinect sensors [64]. Moreover, Kinect v2 in particular, lacks built-in features available in the first iteration of Kinect such as 'Joint Filtering' that could compensate the sensor's erroneous data acquisition to some extent. This led to some innovation methods to compensate the Kinect's aforementioned inaccuracies. For instance, in Ahmed et al., [65], a new Kinect-based gait recognition technique was used in which human gait signatures were analysed using spatio-temporal changes in different skeletal joints' angles. Having a joint relative angle for stride detection eliminates the Kinect sensor's inaccuracies caused the subject's direction or distance from the camera [59], [66]–[68]. The research used the spine joint as the reference point as its relative 3D coordination remains almost stationary during a gait cycle. Nevertheless, by employing such a technique, foot contacts and foot-offs phases will not be directly detected, but instead be estimated based on the distance and angle of skeletal joints.

In Auvinet et al., [69], heel-strikes were estimated by calculating the distance between knees' joint centre along the longitudinal walking axis. To eliminate the Kinect depth-map inaccuracies in localising joints according to a subject's distance from the sensor during a gait cycle (especially for foot contact detection [61]), knee height was estimated based on anthropometric data. In another attempt by Geerse et al., [70], a series of four Kinect v2 sensors were placed in pre-determined locations to compensate each Kinect's depth inaccuracies in farther distances and have an overall wider range of coverage. This method provided promising results but at the expense of using an array of Kinect v2 cameras that required precise alignment between each sensor and increased the cost considerably. Xu et al., [71] used a Kinect camera mounted on a treadmill while the subject performed gait cycles in order to keep the subject's distance to the camera consistent. In Sun et al., [72] a rather innovative technique was employed by putting the subject in a Kinect-mounted cart to keep the subject's distance from the Kinect consistent while walking.

Most of the aforementioned methods can affect gait performance accuracy as they influence the subject's natural way of walking, while others require expensive or difficult-to-implement improvisations. More importantly, some gait performance analysis and step-detection scenarios such as detecting FOG in PwP, mandate precise data reading; minor inaccuracies in joint localisation, may render the entire data reading pointless. This research on the other hand, analyses the data gathered from different subjects in different conditions in order to correct the Kinect's joint-to-ground distance data reading issues according to camera's 3D Cartesian Z-axis.

This research proposed two new techniques in footstep detection, one using skeletal data and plane detection technique and another approach that is solely based on the subject's knee joint angle to determine foot-offs and foot contacts, regardless of the changes of signal acquisition accuracy due to the subject's location or distance to the camera in a 3D environment. The research also evaluated the data gathered from different subjects in different conditions in order to correct the Kinect's joint-to-ground distance data reading issues according to camera's 3D Cartesian Z-axis.

## 2.4 Fall Monitoring and Detection

Similar to the technological developments described above, several attempts have been made to design automated methods for detecting falls in older adults based on a variety of techniques such as wearable devices [73]–[76] and computer vision [77]–[79]. As falls are a major problem in PwP with FOG (during 2017 it was determined to be a top research priority for Parkinson's UK [80]), such developments are particularly relevant, and should ideally be integrated with attempts to provide sensory cues for movement. The Microsoft Kinect was also used as a non-invasive approach for fall detection. Different techniques were used for fall detection such as the use of Kinect depth sensor [79], [81], skeleton tracking [58] and subject-to-floor distance determination. Additionally, some used a single Kinect sensor while some employed a system of multi-Kinect configuration to have a wider coverage. For instance, in Mastorakis et al., [81], the user's body velocity and inactivity was taken into account that made the floor detection unnecessary for the fall detection due to the use of a 3D bounding box (the active area of interest). This removes the need for any environmental pre-knowledge such as a floor's position or height.

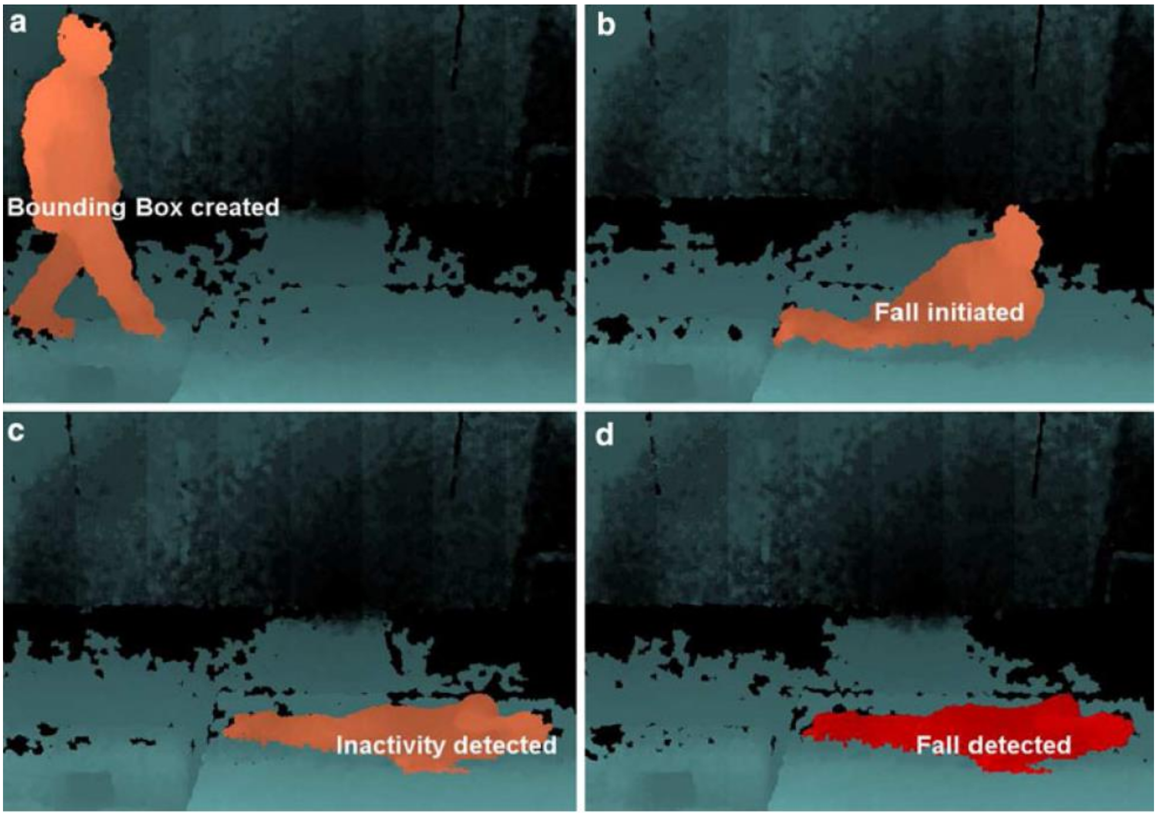



Figure 2:8. Subject's fall and inactivity detection based on 3D bounding box [81]

Moreover, in Stone et al., [77], an algorithm was developed that determines a subject's vertical state in each frame to trigger a detected fall using a decision tree and feature extraction. The research used 454 simulated falls and nine real fall incidents for the trial.

In Gasparrini et al., [79], a set of raw depth data were used to extract human body features using a depth blob technique for each frame and by taking into account the position and distance of each blob from the others. Based on the implemented algorithm, a fall incident will be counted as positive if the head position is close to the ground by a certain threshold. This was feasible because the camera was place on the ceiling facing downwards (Figure 2:9).

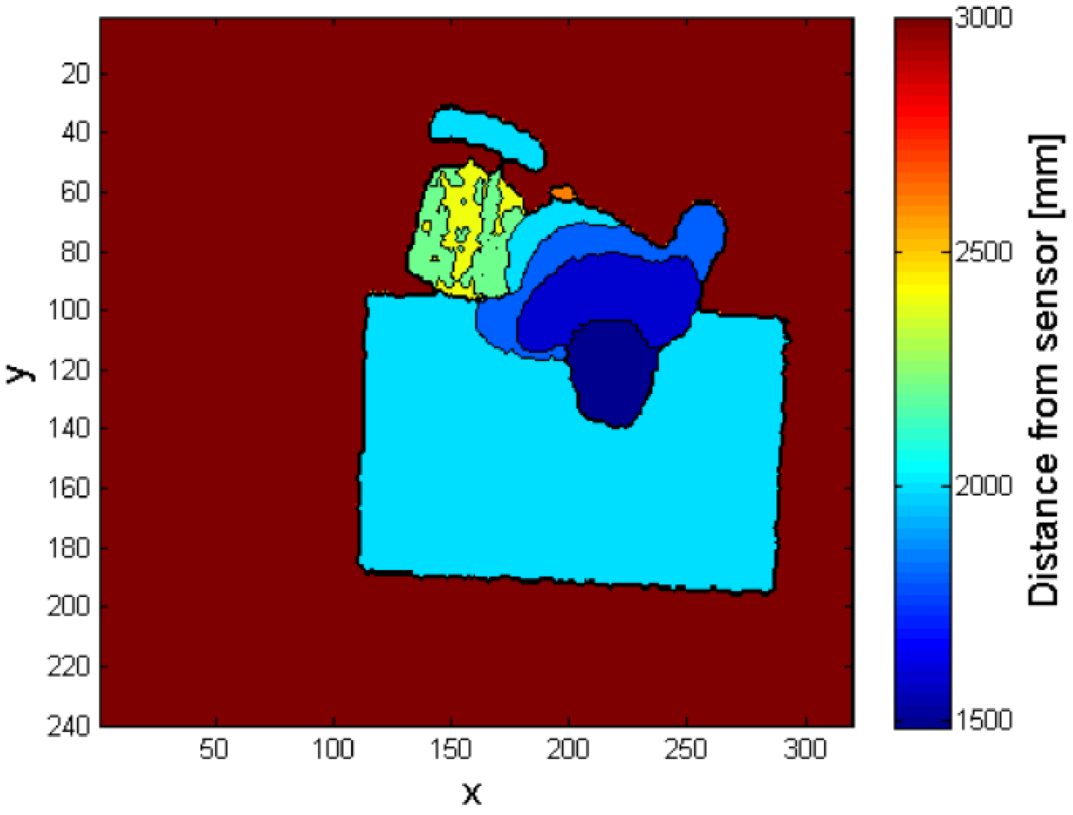



Figure 2:9. A Kinect camera face-down approach for fall detection based on the raw depth data and head-to-floor proximity [79]

Finally in Rusko et al., [82], different machine learning techniques including Native Bays, decision tree and Support Vector Machine (SVM) were used for fall detection in which the decision tree algorithm proved to be more accurate compared to other machine learning techniques used in the study with over 93.3 % success rate in detecting true positive fall incidents.

In the current study, the project's researchers describe a novel integrated system that not only features an unobtrusive monitoring tool for fall and FOG incidents using the Microsoft Kinect v2 camera, but also implements an Ambient Assistive Living (AAL) environment designed to improve patients' mobility during a FOG incident using automatic laser based visual cue projection. Using a dynamically changing laser-based visual cue capable of casting lines according to patients' orientation and position in a room, the system is capable of delivering bespoke and tailored sensory information for each user in a manner that eliminates any need to wear body-worn sensors.

## 2.5 Summary

Footstep detection is an important measurement in rehabilitation and gait analysis studies, as many disorders feature symptoms that directly or indirectly affect patients' gait cycle and walking style. There are different techniques used in detecting footstep and evaluating gait cycles based on on-body sensors that, although accurate, they can affect the subject's walking style and consequently, the data reading as the subject must wear special clothing embedded with on-body sensors during the gait performance analysis. Consequently, an unobtrusive approach based on the Microsoft Kinect v2 sensor would be an ideal method that not only meets the aims and objectives of this research study, but also explores the importance of footstep detection for FOG analysis.

Different fall detection methods have also been reviewed. From on-body sensors to computer vision-based approaches as well as different paths in computer vision-based detection including heuristic and machine-vision. Additionally, the attempts towards analysing and evaluating the effect of different cueing system for FOG as well as detection and characterisation of FOG in PwP have also been reviewed. This laid the foundation of the methodology described in the following chapter to Introduce two new footstep detection techniques one based on the subject's knee angle and one based on the subject's ankle vertical height to the ground; Reducing the Microsoft Kinect's intrinsic inaccuracies in skeletal data reading for the subject's ankle vertical height to the ground footstep detection technique; resulting in the increase in accuracy for the footstep detection algorithm by introducing a new correction algorithm. Moreover, the research would provide an automatic and remotely manageable monitoring system for PwP gait analysis and fall detection.

# Chapter 3: Background of Sensors Technology

## 3.1 Introduction

In this chapter, technologies used throughout this research will be explained and the reason behind their selection will be discussed. This chapter covers an in-depth analysis of the Microsoft Kinect sensor, the main component for receiving data and input for this research. Moreover, all the available drivers and SDKs for the Kinect sensor are evaluated, and the best solution will be chosen accordingly. Additionally, this chapter focuses on different available approaches for utilising Kinect technologies to be used throughout this research. Different systems will be analysed and compared against others. Their advantages and disadvantages will also be evaluated.

## 3.2 Microsoft Kinect

Kinect is an add-on peripheral developed by Microsoft for its Xbox gaming console. It is a motion sensing apparatus that can take human natural body motions as an input. It consists of two cameras/sensors including a colour sensor and an Infrared (IR) depth sensor that receives and interprets IR signals, allowing it to work in the dark. By casting IR lights on objects and calculating the traverse time each beam takes to be bounced back and received by the sensor's IR receiver, a depth map can be drawn making motion sensing technology possible in a 3D environment. Many believe that the original idea of the Kinect sensor came from the previous attempts made by Sony for PlayStation EYE motion camera and Nintendo for Wii remote, which were aimed at broadening the audiences beyond hard-core/typical gamers.

Microsoft has made the Kinect sensor available beyond the Xbox 360 console to home computers with a dedicated Software Development Kit (Kinect SDK) and related documentations [83]. This enabled developers to take advantage of the Kinect sensor hardware capabilities, creating a plethora of innovative applications; many related to medicine and biomedical engineering.

The Kinect sensor (Figure 3:1) has an IR emitter, which casts IR waves on the object that can be later received by the IR depth receiver in order to render 3D images.

Additionally, it features a set of four microphones known as Array Microphone, which are aligned in a specific way to cancel out ambient noise and improve sensitivity in pinpointing the source of the incoming signal.

Finally, yet importantly, it employs a motorised tilt to automatically change the viewing angle based on the user's vertical position.

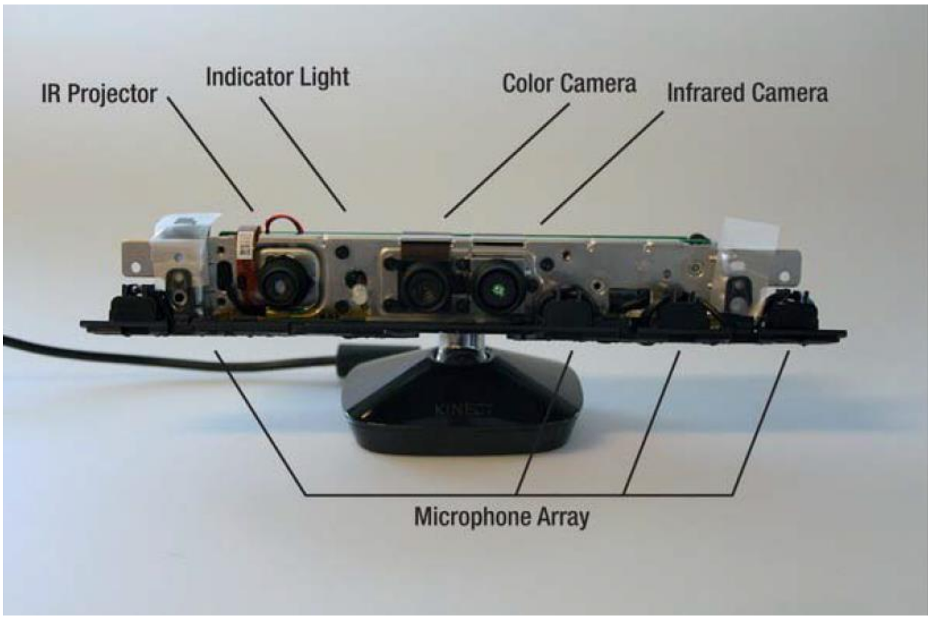



Figure 3:1. Microsoft Kinect v1 internal components [84]

By employing the depth sensor and a microphone array, the Kinect does not require any glove or accessories to be worn by players in order to interpret their movements; unlike other attempts made in movement-based controls.

The RGB sensor in the Kinect receives 2-dimensional colour video feeds for facial recognition and UI purposes. The four-microphone array, which is located along the bottom of the horizontal bar, makes speech recognition possible with echo cancellation and ambient noise suppression. The four microphones used in the Kinect device are arranged in a way that minimise the environmental noise while being able to pinpoint to the source of the voice location [85].

Figure 3:2 demonstrates the Kinect's two sensors, IR emitter and IR depth sensor (monochrome CMOS sensor) that together can capture depth data from the environment [85]. The Kinect, using these two sensors coupled with a trained machine learning algorithm within its SDK, is able to recognise gestures and track body joints and skeleton. The emitter, projects IR light so the receiver can capture the reflected infrared signals for further processing. The emitter casts grid-patterned infrared lights on the target, which leads to the creation of the depth map information by the receiver. The generated depth map contains the information about the position of the object in three dimensions [86].

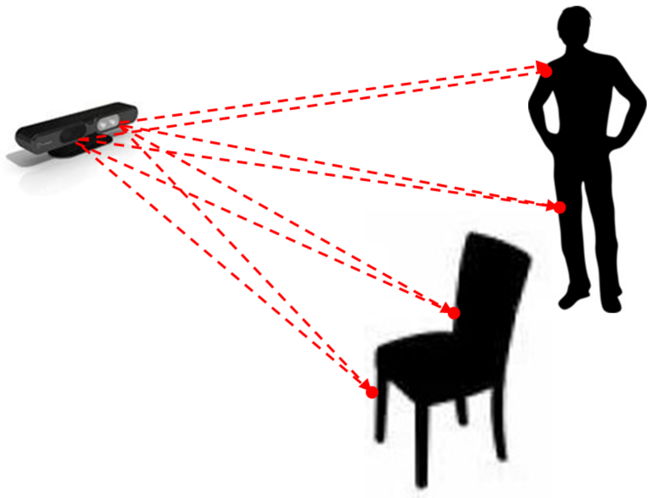


Figure 3:2 Kinect Infrared Depth Sensor [86]

Many other depth-sensing systems similar to the Kinect, determine the depth map of the scene based on the time it takes for the light to return to the receiver after bouncing off objects in the sensor's view also known as Time of Flight (ToF) method. However, the Kinect encodes data in the IR light as it is sent and analyses the distortions in the signal after it returns in order to get a more detailed 3D picture of the scene in addition to the above method [85]. This 3D depth image is then processed in software to perform human skeletal tracking.

The Kinect camera measures the depth data based on a triangulation process [87] in which the IR emitter casts a single beam that splits into multiple beams using diffraction grating in order to construct a dotted pattern of the scenery. The IR receiver then captures the projected pattern, which is then compared against a reference pattern made from a known distance plane saved on the Kinect's memory. Depending on the distance difference of the projected speckles and the reference plane to the perspective centre of the IR camera, the projected speckles' position will be shifted in the baseline direction between the IR emitter and IR receiver. This would result in a disparity image that enables the camera to calculate the distance of each pixel from the corresponding disparity [88].

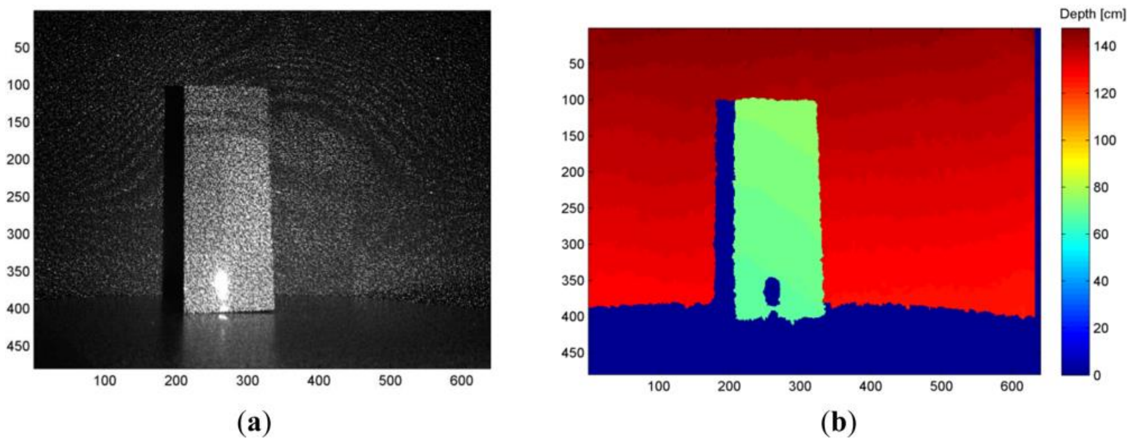



Figure 3:3. Panel (a) is the perceived IR image by the Kinect. Panel (b) represents the depth information for each pixel colour coded based on their distance to the camera [88]

Table 3:1 shows additional Kinect's technical specifications.

Table 3:1. Microsoft Kinect Specifications [85][89]

| Kinect | Value |
|---|---|
| **Viewing angle** | 43° vertical by 57° horizontal field of view |
| **Vertical tilt range** | ±27° |
| **Frame rate (depth and colour stream)** | approx. 30 Hz |
| **Audio format** | 16-kHz, 24-bit mono pulse code modulation (PCM) |
| **Audio input characteristics** | A four-microphone array with 24-bit analogue-to-digital converter (ADC) and Kinect-resident signal processing including acoustic echo cancellation and noise suppression |

| | |
|---|---|
| **Accelerometer characteristics** | A 2G/4G/8G accelerometer configured for the 2G range, with a 1° accuracy upper limit. |
| **Depth Sensor Range** | 1.2 to 3.5 meters |
| **Depth Image Stream** | 320 x 240 16-bit, 30 fps |
| **Angular Field-of-View** | 57◦ horz., 43◦ vert. |
| **Nominal spatial range** | 640 x 480 (VGA) |
| **Nominal spatial resolution (at 2m distance)** | 3 mm |
| **Nominal depth range** | 0.8 m - 3.5 m |
| **Nominal depth resolution (at 2m distance)** | 1 cm |
| **Device connection type** | USB (+ external power) |

### 3.2.1 Open Source Drivers and SDKs

One of the examples of the attempts made in the Kinect open source driver development was OpenNI Framework. It consisted of a series of Application Programming Interfaces (APIs) for the use of programming natural interface peripherals by making use of raw information received from the device's audio/video sensors. Because of its capability on interpreting raw visual and auditory data and due to the fact that the Kinect is in fact a natural interface device, the OpenNI framework became a good candidate for the Kinect open source API/SDK/Driver project. The following figure demonstrates the interaction between each component of a system based on the OpenNI Framework [90].

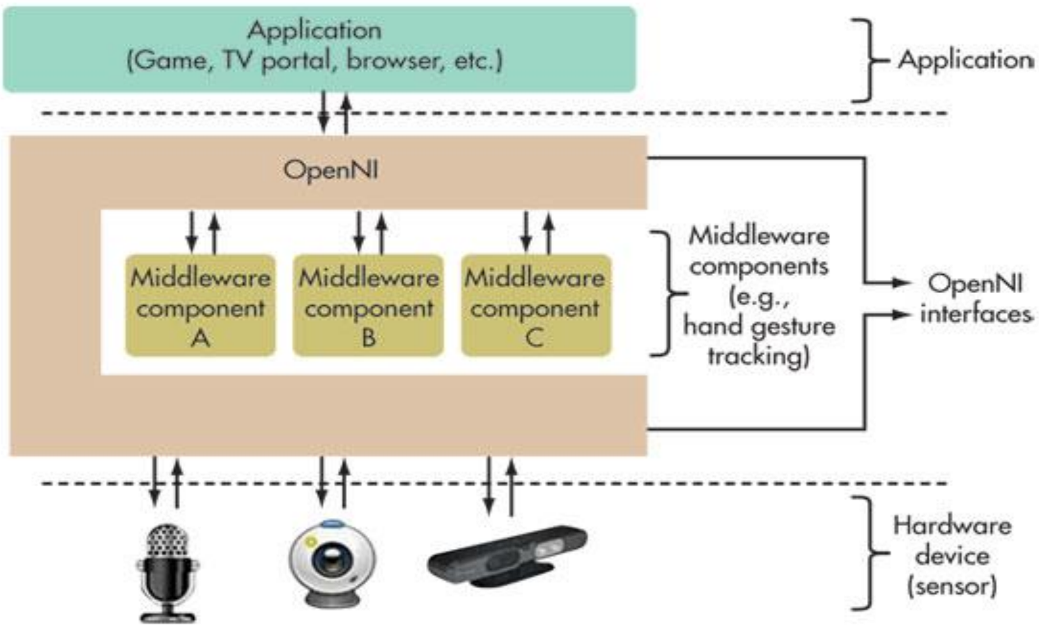


Fig 3. OpenNI provides a layered abstraction for sensors and middleware to provide natural interaction tracking.

Figure 3:4. OpenNI Framework [90]

The OpenNI organisation was responsible for developing the OpenNI framework. OpenNI organisation is a non-profit, industry-driven community founded by PrimeSense that was bought by Microsoft to develop the Kinect sensor.

PrimeSense was also behind the development of the NITE middleware. The NITE middleware can be used in conjunction with the OpenNI API in order to gain access to depth and RGB raw data from the Kinect sensor; it also makes feature detection, joint tracking (skeleton), and gesture recognition possible. Table 3:2 is the list of different open source Kinect drivers and SDKs.

Table 3:2. Open Source Kinect Drivers and SDKs

| Name | Programming Language | Platform | Features |
|---|---|---|---|
| **OpenKinect/libfreenect** [91] | C, Python, actionscript, C#, C++, Java JNI and JNA, Javascript, CommonLisp | Linux, Windows, Mac OS X | -Colour and depth images Colourr and depth images -Accelerometer data -Motor and LED control -Fakenect Kinect simulator (libfreenect) -Record colour, depth, and accelerometer data inthe filee |
| **CL NUI SDK and Driver** [92] | C, C++, WPF/C# | Windows | -Colour and depth images -Accelerometer data -Motor and LED control |
| **Robot Operating System (ROS) Kinect** [93] | Python, C++ | Unix | -Colour and depth images -Motor and LED control |
| **OpenNI/NITE Middleware** [94] | C, C++ | Windows, Linux, Ubuntu | -User identification -Feature detection -Gesture recognition -Joint tracking |

| | |
|---|---|
| | -Colour and depth images<br>-Record colour and depth data in file |

The OpenNI requires calibration before it is able to interpret joint position information. This poses a serious disadvantage for the implementation of this research as due to the nature of these projects, holding a pose for three seconds or more for PwP is a difficult task. NITE implementation also requires a pose called ’psi pose’ before it can function. Figure 3:5 demonstrates the ‘psi pose’.

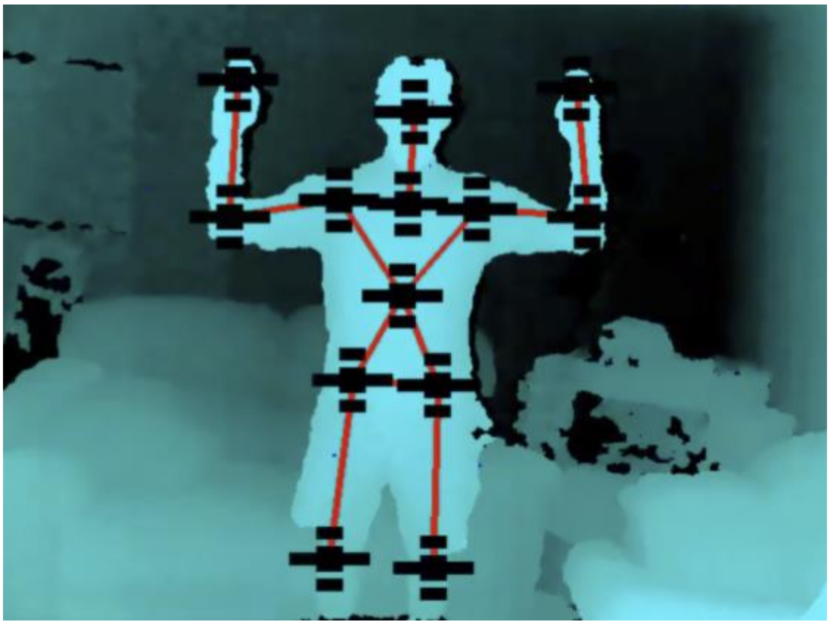


Figure 3:5. Calibration of Psi Pose [95]

As mentioned before, the OpenNI’s calibration requirement is a major drawback for clinical rehabilitation purposes. Additionally, previous attempts made on this topic showed that the calibration of the subject’s arm appeared to be problematic. For instance in [86], it was concluded that the calibration tends to fail if the subject does not hold her/his arms high enough or she/he did not bend the arms at exactly a 90-degree angle. It was also concluded that this level of accuracy is not feasible by most of the patients for this particular project. Developers are still investigating the possibility of removing the calibration for the joint position accusation.

The NITE implementation of OpenNI API can utilise up to 15 joints in which there is a 3x3 matrix for each X, Y and Z angles. Additionally, the orientation may be obtained at any given time; whereas in Microsoft official Kinect SDK, 20 joints can be tracked simultaneously. The following figure shows the joints supported by the NITE implementation alongside with their names, numbers, and orientations [94]. The position directions of each joint including X, Y and Z can be seen in in the figure. From the Kinect sensor's perspective, the negative X, Y and Z axes point to the right, upward and forward (away from the sensor), respectively.

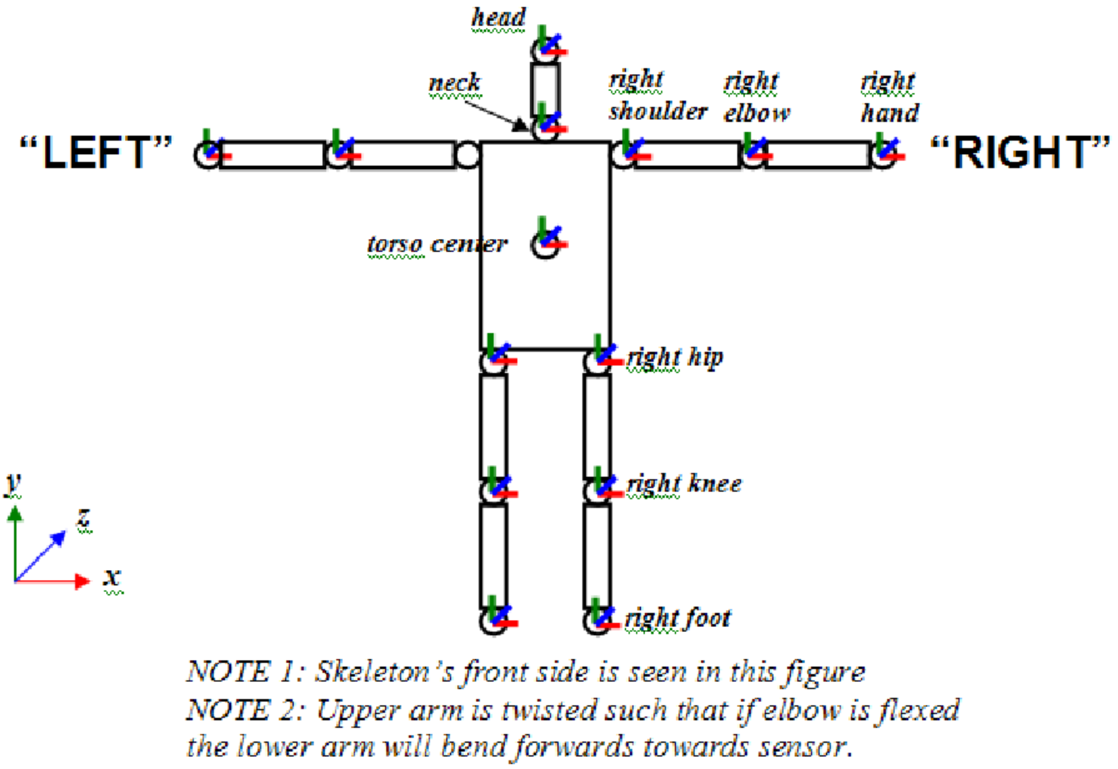



Figure 3:6. NITE Tracked Joints [94]

The NITE/OpenNI also features tools for recording the Kinect raw RGB/depth data and saving them as '.oni' extension for further analysis. The built-in tool provided by the API can play '.oni' files visually. It is also possible to import the exported stored information into other applications [96].

### 3.2.2 Microsoft Kinect SDK for Windows

The Kinect SDK for Windows has several important advantages compared to its open source counterparts discussed above. The following table compares the features and capabilities of one of the well-adapted open source Kinect SDK (OpenNI) with the Microsoft official Kinect SDK [96].

Table 3:3. Comparison of OpenNI and Microsoft Kinect SDK

| **Features** | **OpenNI** | **Microsoft** |
|---|---|---|
| **Raw depth and image data** | Yes | Yes |
| **Joint position tracking** | Yes | Yes |
| **API-supported gesture recognition** | Yes | No |
| **Save raw data stream to disk** | Yes | No |
| **Joint tracking without calibration** | No | Yes |
| **Development in C#** | No | Yes |
| **Audio processing including speech recognition** | No | Yes |
| **Easy installation** | No | Yes |
| **Number of joints available** | 15 | 20 |
| **Quality of documentation** | Adequate | Excellent |

#### *3.2.2.1Kinect for Windows Architecture*

One of the most important advantages of using the Microsoft official SDK for Kinect (Microsoft Kinect SDK for Windows) is the fact that it does not require calibration in order to be able to perform subjects' joint tracking. As mentioned before, other open source SDKs mandate the subject to perform a calibration by holding their arms in a specific position, which proved to be rather impractical and problematic for this project's purpose. The Microsoft Kinect SDK for Windows also delivers results that are more accurate in terms of joint tracking thanks to its ability to track 20 joints at the same time. Moreover, the development in C# programming language for this project had many advantages, since its library documentations and forum community are one of the biggest among different programming languages. Additionally, the Kinect installation and setup are a lot easier and the API samples and documentations are more accessible.

Figure 3:7 shows the components used in Kinect for Windows SDK.

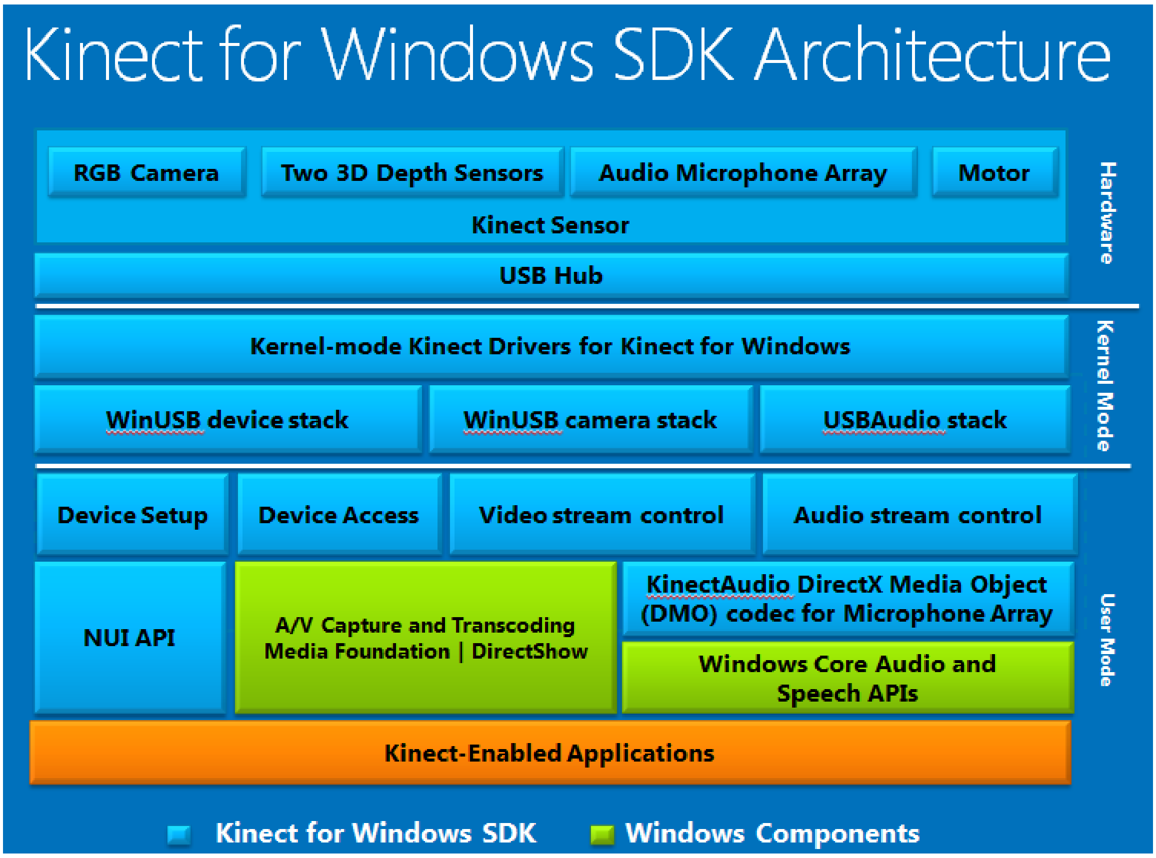



Figure 3:7. Microsoft Kinect for Windows SDK Architecture [97]

There are two different colour image palettes available in the official Kinect SDK including RGB and YUV [98]. There are also different resolutions available to be chosen for the depth and image streams. Although one could manually customise the resolution based on a specific project's needs as well.

The resolution options for the depth map include 640x480, 320x420 or 80x60 pixel frames [98]. During the evaluation, it was observed that each pixel from the depth image feed also contains an indication of which human subject is present at that position in the scenery. This was enabled by using the Microsoft Kinect SDK for Windows machine learning algorithm that can distinguish pixels belonging to a subject from the background [99].

As discussed earlier, the Microsoft Kinect SDK for Windows makes simultaneous 20 joints tracking possible. The figure below demonstrates the position of the joints.

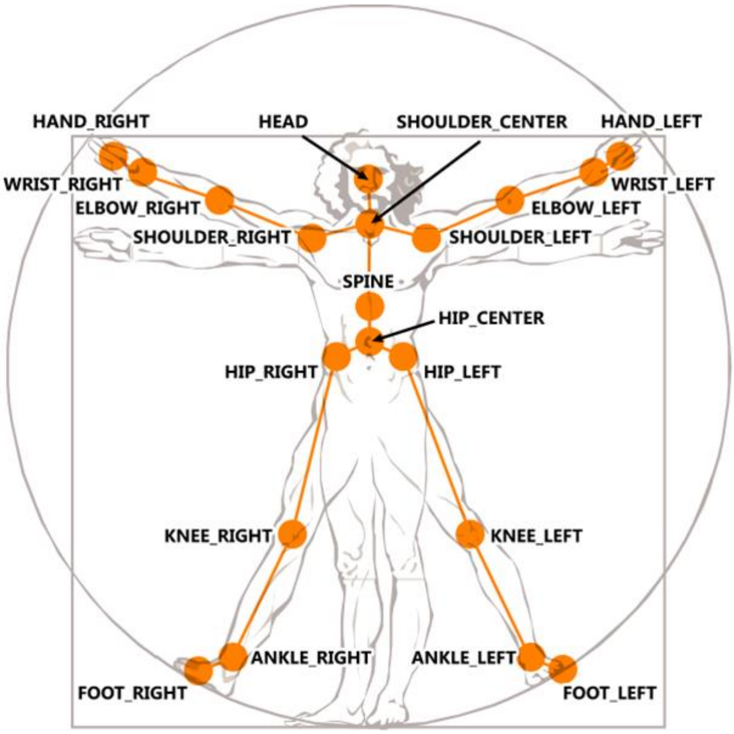



Figure 3:8. Microsoft Kinect SDK for Windows Traceable Joints [100]

### *3.2.2.2 Supported Systems and Languages*

The Microsoft Kinect SDK for Windows supports three programming languages including Visual Basic.NET, C# and C++. The SDK can support Visual Basic.NET and C# by using two dedicated Dynamic-Link Library (DLL) files called 'Microsoft.Kinect.dll' and 'Microsoft.Speech.dll' for visual and audio compatibilities, respectively [84].

For C++ on the other hand, it allows the programming language to access directly the hardware resources without any intermediate DLL files [84].

The system requirements for Microsoft Kinect SDK for Windows are as follow [84]:

**Supported Operating Systems**

Windows 7 or above

**Hardware Requirements**

32-bit (x86) or 64-bit (x64) processor

Dual-core 2.66-GHz or faster processor

Dedicated USB 2.0 bus

2 GB RAM

A Microsoft Kinect for Windows sensor

**Software Requirements**

Microsoft Visual Studio 2010 Express or other Visual Studio 2010 edition or above

.NET Framework 4.0 or above

Note: To develop speech-enabled Kinect for Windows applications, the Microsoft Speech Platform SDK v11 should be installed.

### *3.2.2.3 Supported Modes*

There are two types of modes available in the Microsoft Kinect SDK for Windows. The first one is the 'Default' mode, which as the name suggests is ideal for general conditions that sets the viewable depth range to 800mm – 4000mm. The second mode is known as 'Near' mode, which its functionality is similar to 'macro' mode on digital cameras where it focuses on close objects and it sets the viewable depth range to 400mm – 3000mm. In the Near mode, the sensor recognises objects from 40 centimetres to 4 meters away from the IR receiver. Figure 3:9 shows the difference between the Default and Near modes in terms of distance sensitivity [2].

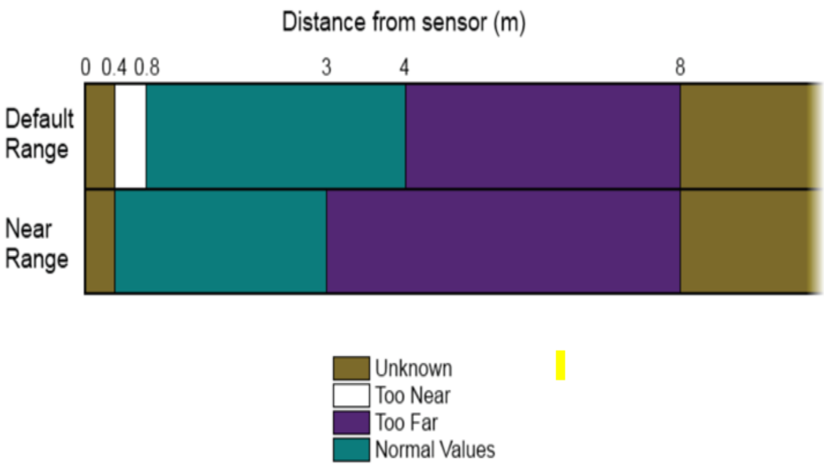



Figure 3:9. Kinect Default vs. Near mode in terms of distance of recognisable objects [101]

For subject's position, the Microsoft Kinect SDK for Windows supports two modes including 'Standing' and 'Seated' mode. The Standing mode is used when almost all the 20 joints are visible to the depth sensor. The Seated mode as the name suggests, is ideal for situations when the subject is seated or only its 10 upper body joints (shoulders, elbows, wrists, arms and head) are visible to the depth sensor [102]. The following figure shows both the Standing and Seated modes including the trackable body joints.

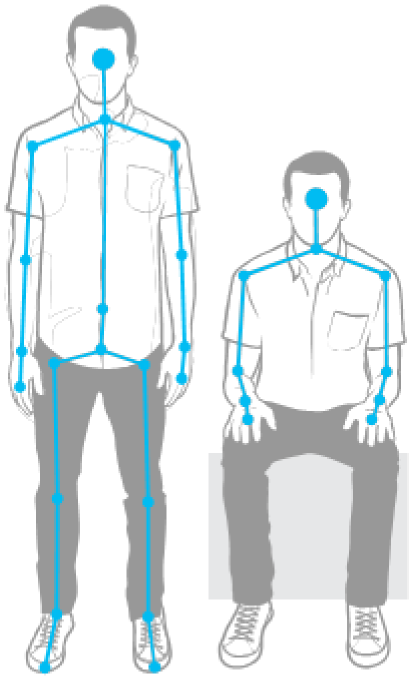


Figure 3:10. Standing vs. Seated modes [102]

The Microsoft Kinect SDK for Windows also provides 'Joint Filtering' in which the joints' position tracked in the skeletal data can be smoothened across different frames in order to improve stability and minimise jittering issues [102]. This can be due to the Kinect's intrinsic inconsistencies or decreases in signal acquisition over longer range that will be discussed in more details in section 2.3.1 Footstep detection.

### *3.2.2.4 The Human Tracking Mechanism*

The mechanism behind the joint tracking system and subject tracking in the Microsoft official SDK recognises joints by processing the data coming from the depth sensor. It first makes up a rough estimation for each pixel in the depth map. Then in adds the probability of that pixel being correct, known as 'Confidence level'. After this, the system is able to select the most likely skeleton for that specific subject. Microsoft employed a machine learning technique in order to improve the Kinect joint and skeleton recognition capability. They used many people around the world and recorded their movements and different poses using the Kinect sensor. They then chose each correct joint position by hand from the stored dataset and fed the information into the algorithm. They even used professional motion capture emitters that can be worn by subjects to improve the accuracy of the Kinect. By collecting and correcting all the information gathered, they trained the algorithm to recognise the body joints successfully in almost all cases [99], [103].

### 3.2.3 Microsoft Kinect v2

The Microsoft Kinect v2 (Figure 3:11) is the second iteration of the Kinect series designed for the Xbox One gaming console as a replacement for conventional gamepads released in 2014 by Microsoft Corporation. It is a ToF camera featuring the ability to process data at two gigabits per second speed making it more accurate compared to its predecessor; its depth and IR sensor resolution have been increased to 512 x 424 and its colour sensor encompasses a 1080p resolution video running at 30 frame per seconds (fps) [104].


Figure 3:11. Microsoft Kinect v2 [105]

The number of skeletal joints that the sensor can detect has been increased from originally 20 to 25 (Figure 3:12). Moreover, the number of concurrent user detection has also been increased from the originally two to six people. The camera's field of view has also been increased, enabling users to operate in a smaller area and closer to the sensor than before. Due to these enhancements, the accuracy of data collection, especially in capturing skeletal information, has been significantly improved. Nonetheless, the Kinect for Windows SDK 2.0 removed many features available to its predecessor such as ‘Joint Filtering’, ‘Standing/Seated mode and Default/Near mode.

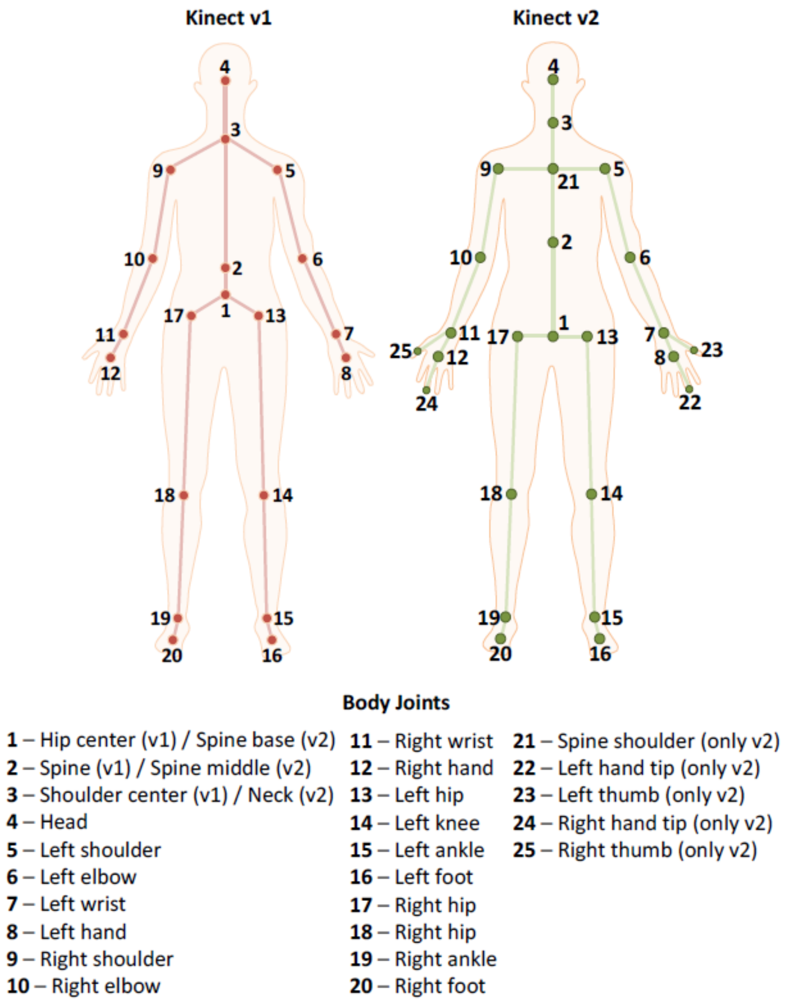



Figure 3:12. Trackable body joints from the skeletal data Kinect v1 vs Kinect v2 [46]

## 3.3 Summary

This chapter aimed at discussing the state of the art of Kinect v1 and v2 sensors’ drivers, API, and SDKs. The technical details and the technologies involved in image recognition process used by the Kinect sensor were discussed. Their advantages and weaknesses over each other have been evaluated concluding that the Microsoft Kinect SDK for Windows has many advantages over other open source SDK tools. It also concluded that the official SDK is the ideal candidate for the project as it can recognise more body joints (25 for Kinect v2) simultaneously and has the ability to track joints without the need of calibration. Additionally, developing application using one of the Kinect SDK supported programming languages (in this case, C#) proved to be a lot easier and the documentations and samples from the community helped to deliver a better-quality software. Thus, thanks to the improvements of the Kinect v2 compared to its predecessor, the Kinect v2 based on Kinect for Windows SDK has been selected for this research.

# Chapter 4: Methodology

## 4.1 Introduction

In this chapter, the research's experimental setup and conditions are explained. Moreover, different types of fall detection methods including heuristic and machine learning approaches are explored in order to find the most reliable method suitable for this study. Furthermore, as a requirement for FOG detection, two approaches in footstep detection one based on the subject's ankles distance to the ground and one based on indirect observation via subject's knees angles during a gait cycle are also evaluated. This chapter also focuses on the software design and hardware prototype for the study including the GUI, serial connection and signal differentiation, and data segmentation. Last but not least, the ethical approval process is also mentioned.

## 4.2 Fall Detection

Automatic fall detection is one of the most widespread research topics in healthcare and AAL as many physical conditions include falls as one of their main symptoms. Having a system that can autonomously detect a fall incident could decrease the risk of injuries and consequently the treatment expenditures. Furthermore, it helps to evaluate gait performance and fall analysis and provides valuable data for further studies.

There have been significant studies such as [73]–[76], [106], [107] with regards to fall detection using different techniques over the past two decades, each with its advantages and drawbacks. Some of the earliest approaches in fall detection were based on wearable devices and attached sensors. Although accurate, they mandate the user to carry extra devices, charge batteries, wear special clothing or sensors to be attached to the body, making them uncomfortable to use. Moreover, these apparatuses may interrupt the normal daily activity and consequently gait performance analyses. In this research study, two different techniques (heuristic and machine learning) were tested and compared using the Microsoft Kinect v2 sensor. The above techniques are fundamentally different in their performance under diverse situations.

### 4.2.1 Heuristic Approach

For the heuristic fall detection approach, an algorithm was developed to track a subject's head 3D Cartesian coordinate location at all times. By using the Kinect skeleton tracking, the spatio-temporal position of each joint, with respect to other joints, can be determined. The proposed system holds the information of the subject head's position and velocity in one second time buffer at all times. This is required to calculate the average velocity of the subject's head. Based on the vector that the subject's head is moving towards and the distance between the head and the floor, a fall incident can be detected if the average velocity reaches 1 m/s and the subject's head distance to ground is less than 10 cm. These thresholds were determined experimentally during the testing phase; after setting different values, the results proved that the above values provided the least false positive detection rate. This minimises the chances for false positives' occurrence by not taking into account low-velocity falls such as laying down or high ground distance incidents such as sitting on a chair. Additionally, the system is designed to distinguish between different types of falls such as critical falls in which the subject is unable to stand up and recover after the incident. This is achievable by adding a timer that can be user-defined to set a threshold for the maximum time elapsed before it reaches a critical falling point.

Figure 4:1 demonstrates the developed fall detection technique using the heuristic approach. It shows a subject has fallen (on the floor) and the system recorded his velocity, direction, and distance to the floor when an object partially blocked the Kinect's camera view. Figure 4:2 shows the system's capability to compensate when the Kinect's camera field of view is partial obstructed.

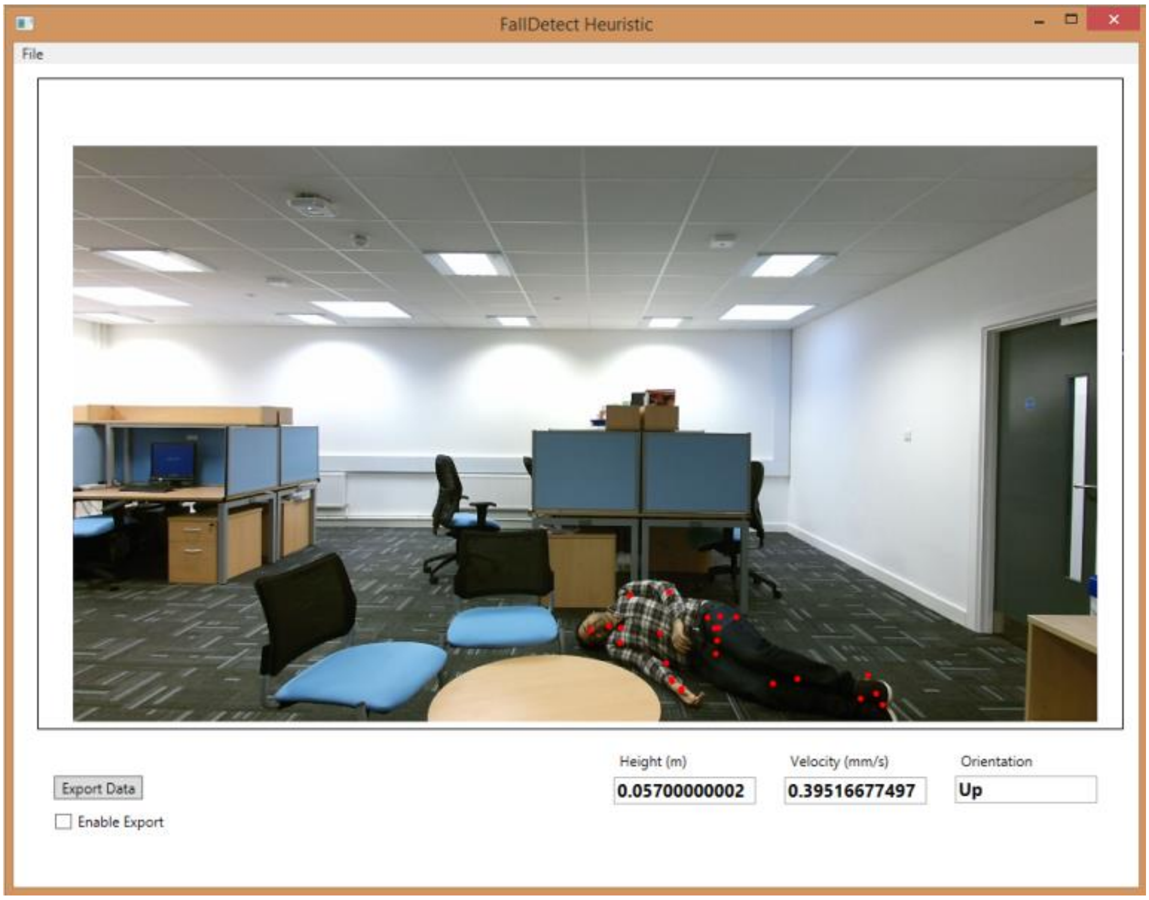



Figure 4:1. Heuristic approach software in action (objects partially blocking the sensor's view)

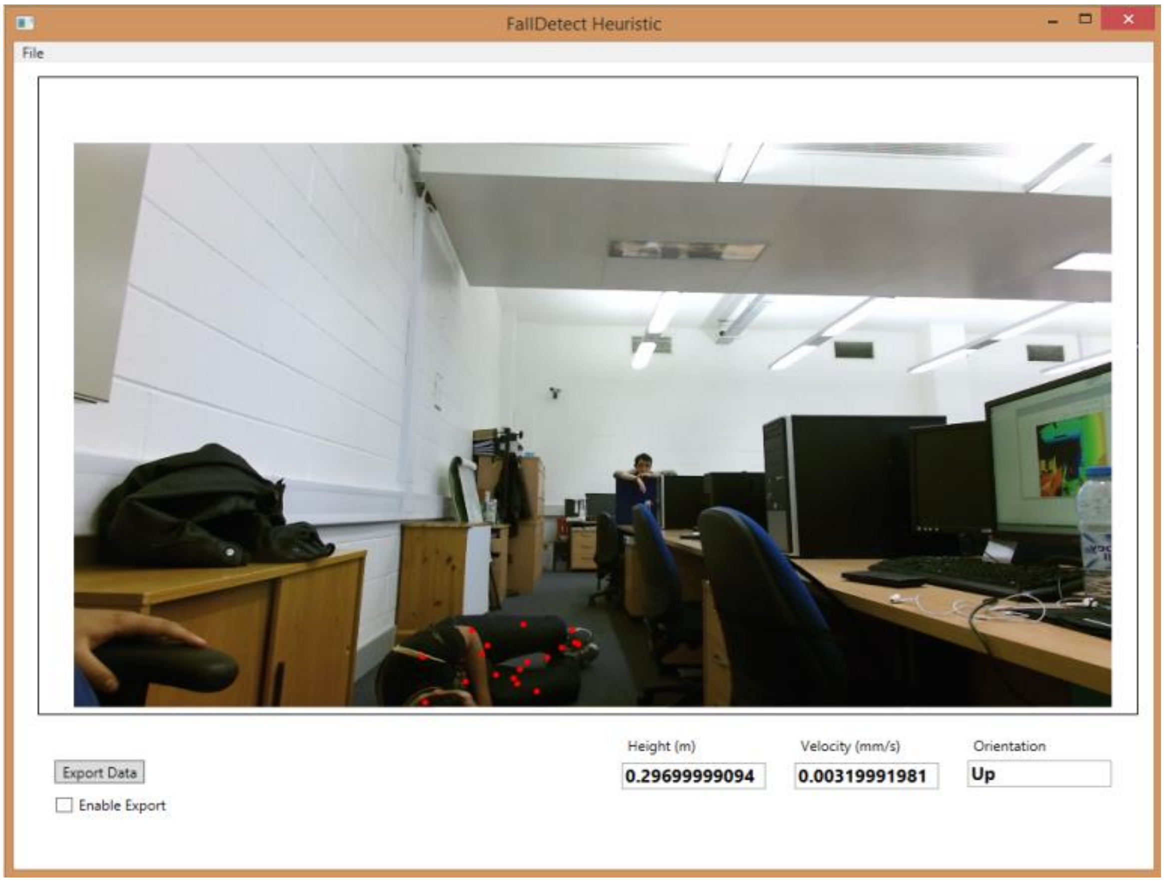



Figure 4:2. Heuristic approach software in action (partial obstructed field of view)

### *4.2.1.1 Floor Detection*

As a part of the heuristic fall detection technique, the detection of the floor is needed in order to calculate the subject's head distance to the ground. A surface floor can be determined by using the scalar equation of plane.

Equation 4:1. The scalar equation of plane

$$\boldsymbol{Ax + By + Cz + D = 0}$$

where $\boldsymbol{A}$, $\boldsymbol{B}$ and $\boldsymbol{C}$ are the components of a normal vector that is perpendicular to any vector in a given plane that are determined by the Kinect once at least a subject is present in a scene and $\boldsymbol{D}$ is the height of the Kinect from the level of the floor. Moreover, $\boldsymbol{x}$, $\boldsymbol{y}$ and $\boldsymbol{z}$ are the 3D coordinates of a joint (subject's head). $\boldsymbol{Ax}$, $\boldsymbol{By}$, $\boldsymbol{Cz}$ and $\boldsymbol{D}$ are also provided by the Kinect SDK once a flat floor is detected by the camera.

Once the floor is determined, the distance of a given joint's 3D Cartesian coordinate location to the floor can be yield as follows:

Equation 4:2. The Kinect's skeletal joint distance to the ground

$$\boldsymbol{d = \frac{Ax + By + Cz + D}{\sqrt{A^2 + B^2 + C^2}}}$$

### *4.2.1.2 Acceleration and Velocity*

To determine the subject's head fall acceleration and velocity, Euclidean distance equation was employed to calculate the distance changes over time.

Equation 4:3. The Kinect's skeletal joint velocity

$$\boldsymbol{\sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2 + (z_i - z_{i-1})^2}}$$

where $\boldsymbol{x_i}$, $\boldsymbol{y_i}$, $\boldsymbol{z_i}$ and $\boldsymbol{x_{i-1}}$, $\boldsymbol{y_{i-1}}$, $\boldsymbol{z_{i-1}}$ are the current and past (one second difference) subject's head 3D Cartesian coordinates, respectively.

## 4.2.2 Machine Learning Approach

For the machine learning approach, an AdaBoostTrigger machine learning technique was implemented. It is an event detection technique that outputs a discrete or binary result. It is based on an AdaBoost machine learning algorithm that operates depending on its dataset and trainings, which combines a series of weak classifiers into a final boosted output [108]. In case of this study, the weak classifiers were determined automatically by the Kinect Visual Gesture Builder (VGB), which is a software developed by Microsoft for Kinect v2 machine learning training purposes [109]. A total of 29 minutes training videos based on 435 GB of 30 fps, 1080p uncompressed RGB and 424p depth data were recorded and stored as a training dataset from the participants. Using Kinect VGB (Figure 4:3), these videos were tagged frame by frame to specify a falling incident's true positive (real fall) and false positive (laying on the floor or sitting on a chair) moments. The details of the number of false positives and true positives performed by the participants are mentioned in section 4.2.3. Even though VGB software is available for developers, it only facilitates the machine learning and training process not the detection phase. Thus, a system was developed to utilise the training set produced by VGB software in order to detect the fall incidents. After the training phase, VGB could automatically generate AdaBoost's weak classifiers based on body joints' vector, velocity, acceleration, and orientation in order to produce a discrete outcome according to the tagged videos. The information was processed to generate a series of weak and strong classifiers and calculate their confidence levels. The generated results were given to the software that was written for the machine learning approach to be compared against the real-time subject's postures. Two factors (velocity and subject's head distance to the ground) were used for the machine learning approach.

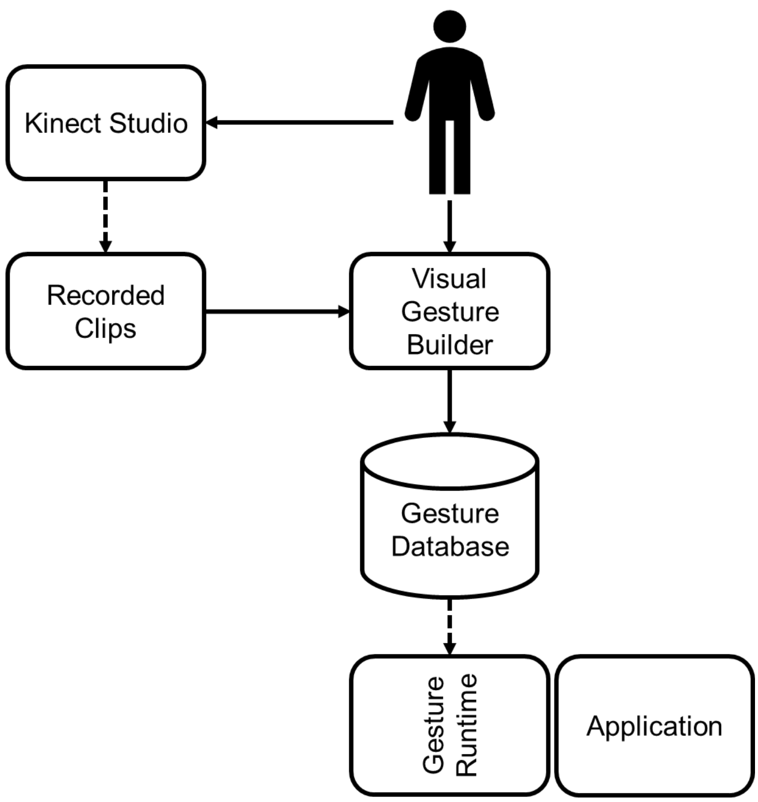



Figure 4:3. Visual Gesture Builder data flow diagram [109]

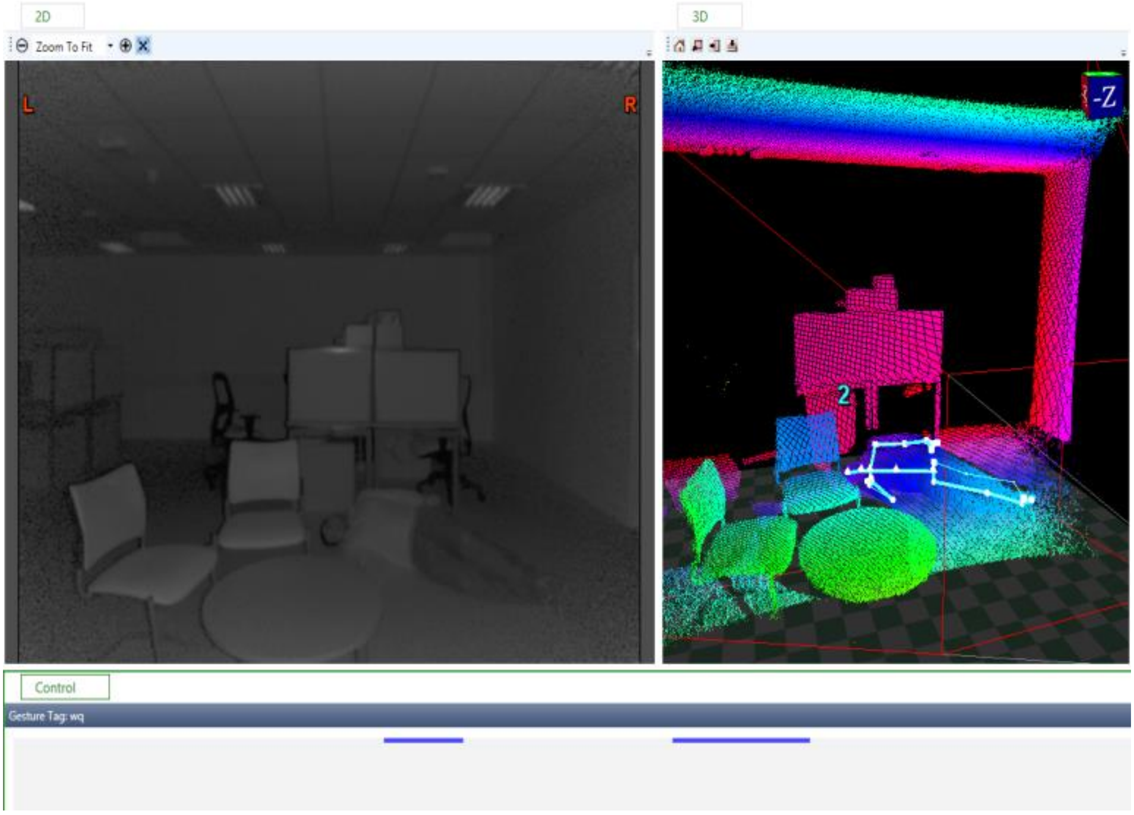



Figure 4:4. Visual Gesture Builder software

Figure 4:4 demonstrates the video tagging training process. On the left, a true positive fall is marked and tagged for training as shown by blue bars at the bottom; on the right, colours represent the distance of 3D objects to the camera.

Figure 4:5 shows the developed software for fall detection using the machine learning approach in action when a fall is about to happen, and the system shows the confidence factors accordingly. Figure 4:6 depict the software behaviour when a false positive fall has happened, and the system shows the confidence factors accordingly.

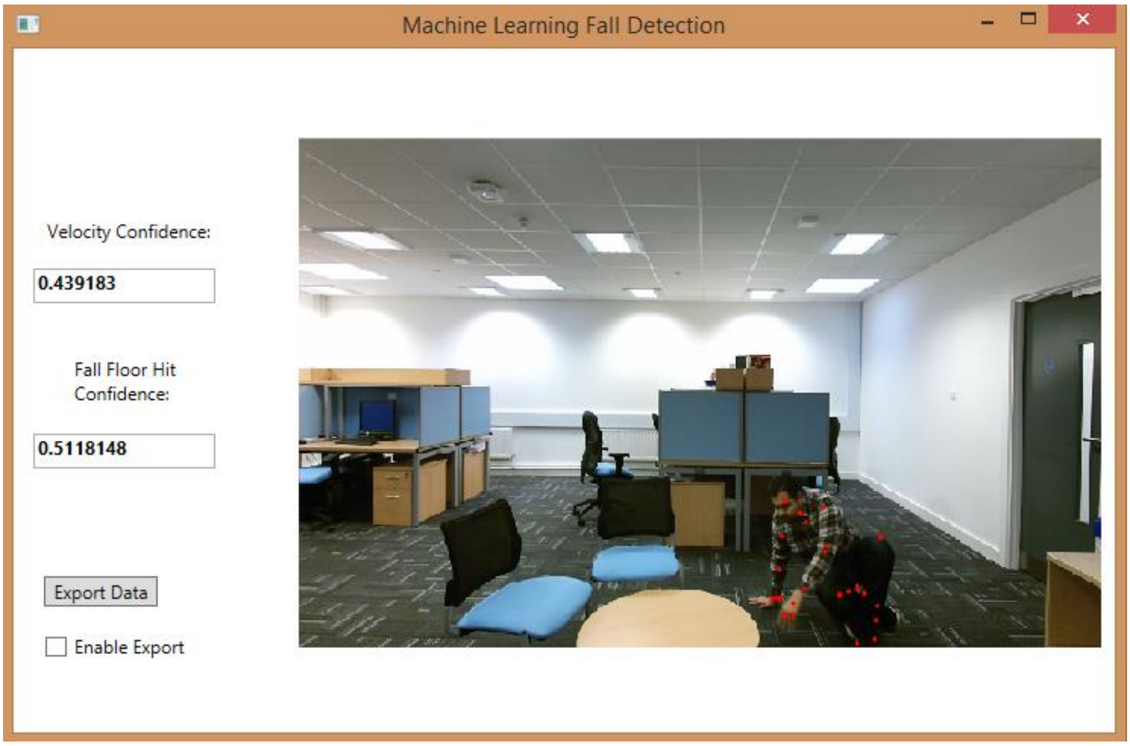



Figure 4:5. Machine learning approach software in action (objects partially blocking the sensor's view)

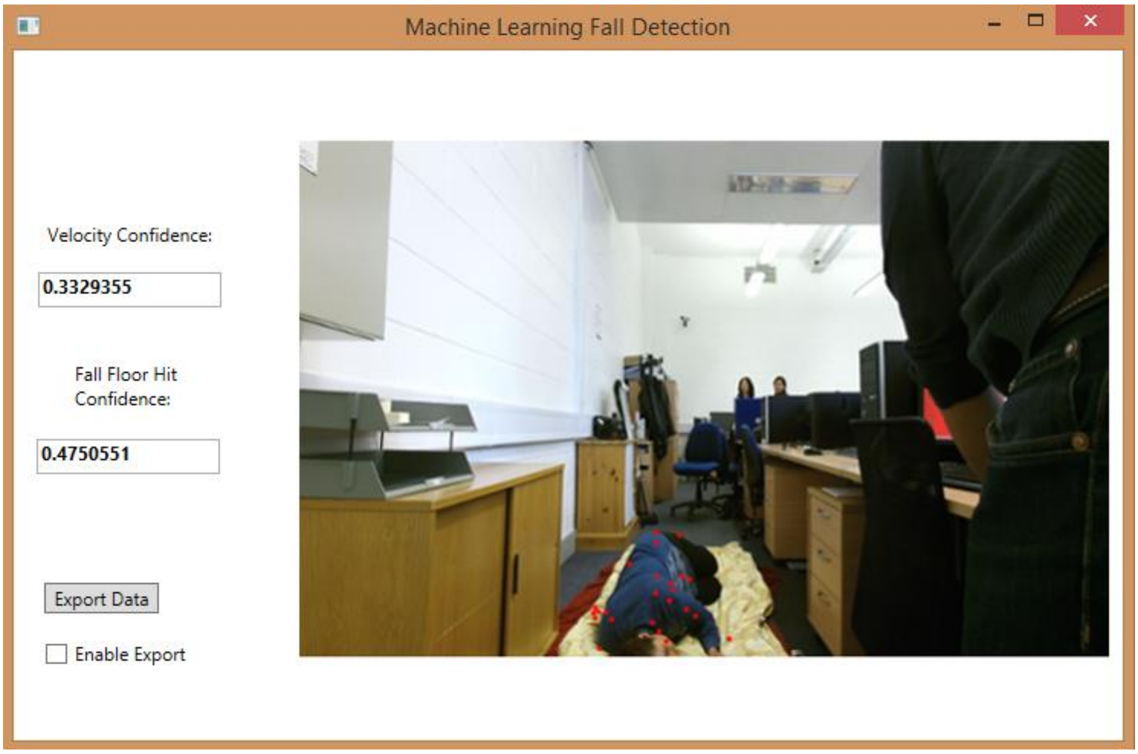



Figure 4:6. Machine learning approach software in action (partial obstructed field of view)

### 4.2.3 Testing Environment and Subjects

The Kinect v2 sensor was placed at a height of one meter facing parallel to the surface. Due to the Kinect v2 wider field of view, subjects were placed at a distance range of one to two and a half meters.

Eleven healthy subjects (Table 4:1) participated in the trial for both heuristic and machine learning approach. For each approach, each subject on average performed six true positive and six false positive fall incidents. False positive incidents were performed by laying down or sitting on the floor. For machine training phase, extra postures were performed by each participant to train the system to detect false positive.

Table 4:1. Test Subjects' Characteristics (n=11; 8 males, 3 females)

| Subject Characteristics | Range | Standard Deviation |
|---|---|---|
| **Age** | 24-31 | 2.34 |
| **Height (cm)** | 163-187 | 8.31 |
| **Ankle Height (cm) with Shoes** | 9.5-12.5 | 1.17 |
| **Weight (kg)** | 51-100 | 16.35 |
| **BMI (kg/m²)** | 17.3-30.1 | 3.83 |

## 4.3 FOG and Footstep detection

The Microsoft Kinect RGB-D sensor has been proven to be a reliable tool for gait analysis and rehabilitation purposes. Although it is accurate for detecting upper body part movements, even the second iteration of the Kinect sensor lacks the accuracy when it comes to lower extremities. As detecting foot-off and foot contact phases of a gait cycle is an important part of a gait performance analysis, using the Kinect for detecting these phases is problematic due to the Kinect's intrinsic inaccuracies.

The detection and analysis of FOG in PwP is an important step towards the main goal of this research study, which is providing dynamic visual cues to the patients during a FOG incident. Thus, two footstep detection techniques were used for this study.

### 4.3.1 Joint Height Footstep detection

Eleven healthy subjects (Table 4:1) participated the trial in which they were asked to walk in pre-defined paths while their skeletal data being captured and analysed by the Kinect camera.

Subjects were asked to walk in pre-defined paths: 12 per subject, by walking towards the camera while having the Kinect camera's angle at 0, 10, 22 and 45 degrees to the ground at Kinect's height of 0.65, 1 and 1.57 metres to the ground, while their skeletal data was captured and analysed by the Kinect camera. The software was written in C# using Kinect for Windows SDK version 2.0.1410.19000. For simplicity, this report only shows the subjects' left ankle throughout the figures.

As an extra step, our Kinect v2 data acquisition was compared against a gold standard Vicon T10 Mocap ToF camera. The Vicon and Kinect v2 recorded each session simultaneously while the frame rate of the recorded data from the Vicon camera was lowered down to match the Kinect v2 approximate 30 frames per second. The Vicon camera was used to ensure that the initial measuring of the subjects' actual ankle height is accurate.

For each test, the first 10 seconds of the subject walking for our system to calculate the correction algorithm were recorded. Subjects were asked to walk towards the Kinect from the distance of 4.33 metres to 1.38 metre to the Kinect camera. The collected data were used in the correction algorithm to rectify the Kinect's intrinsic inaccuracies mentioned previously, in order to provide more accurate subject's joint-to-ground data. Consequently, the results were used to detect subjects' footsteps including foot-offs and foot contacts directly based on their ankles' distance to the ground.

#### 4.3.1.1Correction Algorithm

As mentioned in section 2.3.1, in order to assist the system in correcting the inconsistencies in the footstep detection algorithm, the relation between the subject's ankles Z-coordinates to the Kinect's sensor and subject's ankles distance to the ground was examined.

The first 10 seconds of the Kinect skeletal data, including the subject's ankles height to the ground and subject's ankles distance to the camera for each test subject, were recorded and filtered to include only standstill positions in order to acquire a baseline of calculated ankles' height to the ground. The data was then run through a regression analysis by the developed system to adjust the depth-map correction algorithm, which was based on geometrical transformation. A two-point linear equation was used to estimate the correct ankle's height to the floor at any given time based on the subject's ankle Z-axis distance from the camera.

Equation 4:4. Correlation between a joint's Z-axis and Y-axis

$$\frac{y - y_1}{z - z_1} = \frac{y_2 - y_1}{z_2 - z_1}$$

where $Z$ is the ankle's Z-axis distance to the camera and $\boldsymbol{y}$ is ankle's 3D Euclidean distance to the ground at any given time. After an initial 10 seconds data recording of all trials for the correction algorithm analysis, the value of $\boldsymbol{y}$ in Equation 4:4 was calculated as follows:

Equation 4:5. Corrected value for a joint's Y-axis

$$y = z \times 0.013 \pm 0.05$$

Equation 4:5 is derived from simplifying and substituting numbers collected from the initial 10 seconds of data recording in Equation 4:4.

The following equation was then used to correct the depth map stream data reading. By applying the corrected $\boldsymbol{y}$ value yielded from Equation 4:5 to the following equation, the true value of the $\boldsymbol{d}$ can be calculated as follows:

Equation 4:6. Joint distance-to-ground correction technique

$$\hat{d}_i = d_i + (l - z_i)\frac{y_i}{z_i}$$

where $\hat{\boldsymbol{d}}_i$ is the corrected estimate of ankle's distance to ground for the $i$th stride, $\boldsymbol{d}_i$ is the Kinect's measured distance of the subject's ankle yielded from Equation 4:2, $\boldsymbol{z}_i$ is the ankle's Z-axis distance from the Kinect, and $\boldsymbol{y}_i$ is the correction factor for the $i$th stride. $\boldsymbol{l}$ is the maximum visible distance of Kinect in Z-axis and remains consistent. All the values are in meters as detected by the Kinect's depth sensor.

#### *4.3.1.2 Footstep detection Algorithm*

Kinect skeleton data were used to calculate ankles' joint 3D Cartesian coordinate locations. Once a joint was localised using Kinect skeleton data, the surface floor was determined based on the scalar equation of planes (Equation 4:1).

As Figure 4:7 demonstrates, ankles and feet are the only Kinect-discoverable joints having significant displacement changes in relation to gait cycles while retaining least errors compared to the movements of a human upper extremities. As mentioned previously, although some studies [57] discussed methods based on joints' anterior and posterior displacement changes, this proposed method can be used in scenarios that joints' anterior and posterior displacement changes have little correlation with gait cycles such as FOG incidents in PwP. As observed during the study, Kinect's detection of ankles was less susceptible to noise and inaccuracies compared to feet. A filter was applied to the signal in order to acquire a baseline of subjects' ankles and feet height only in a stand-still position. An average inaccuracy was calculated based on the deviation between the estimated ankles' height and the actual ankles' height. Moreover, the inaccuracy between the estimated feet's height and the actual feet's height was also calculated. The results showed 25.69 % and 44.43 % inaccuracies for all subjects' ankles and feet, respectively. Moreover, according to [56], it was concluded that in the lower extremities, a subject's feet are more susceptible to noise due to their close distance to large planar surfaces. Thus, subjects' ankles were chosen to evaluate and track footsteps.

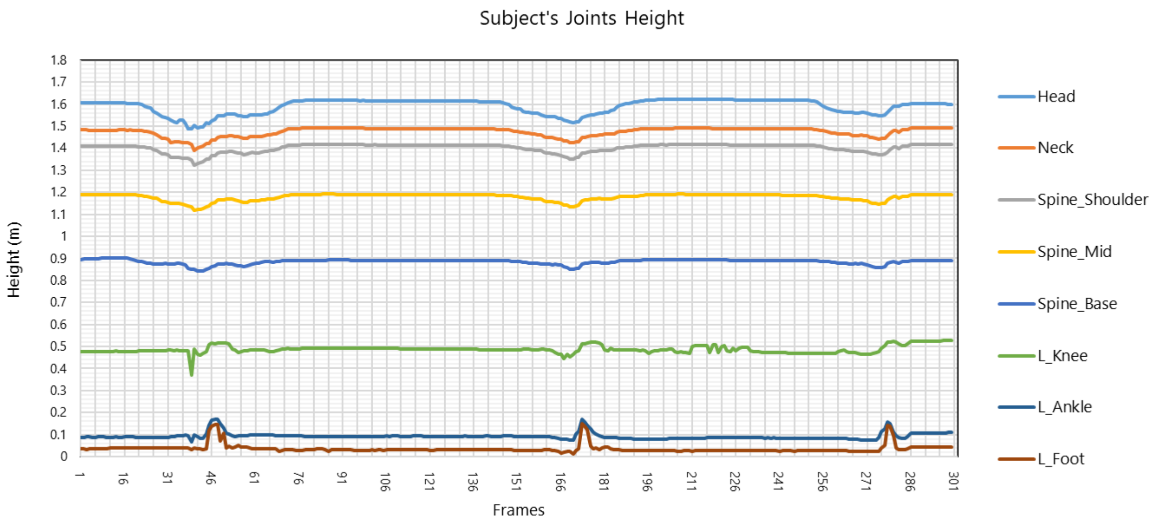



Figure 4:7. Subject's joints height to the ground in a gait cycle

A foot-off event is considered to have occurred when a foot's ankle 3D Euclidean distance from the floor has increased to more than a particular threshold based on the actual ankle's height. Consequently, a foot contact event is triggered when the ankle 3D Euclidean distance from the floor of the same foot has returned to its original value in a time period of more than 250 ms. The empirically 250 ms timing threshold was set to avoid the false positives flag ups due to the Kinect inconsistencies and noise. The Euclidean distance of an ankle's 3D Cartesian coordinate location from the ground can be yielded based on Equation 4:2.

Figure 4:8 demonstrates the subject's footstep detection process including foot-offs and foot contacts. The algorithm loops at approximately 30 frames per second while the Kinect camera is tracking the subject's movements.

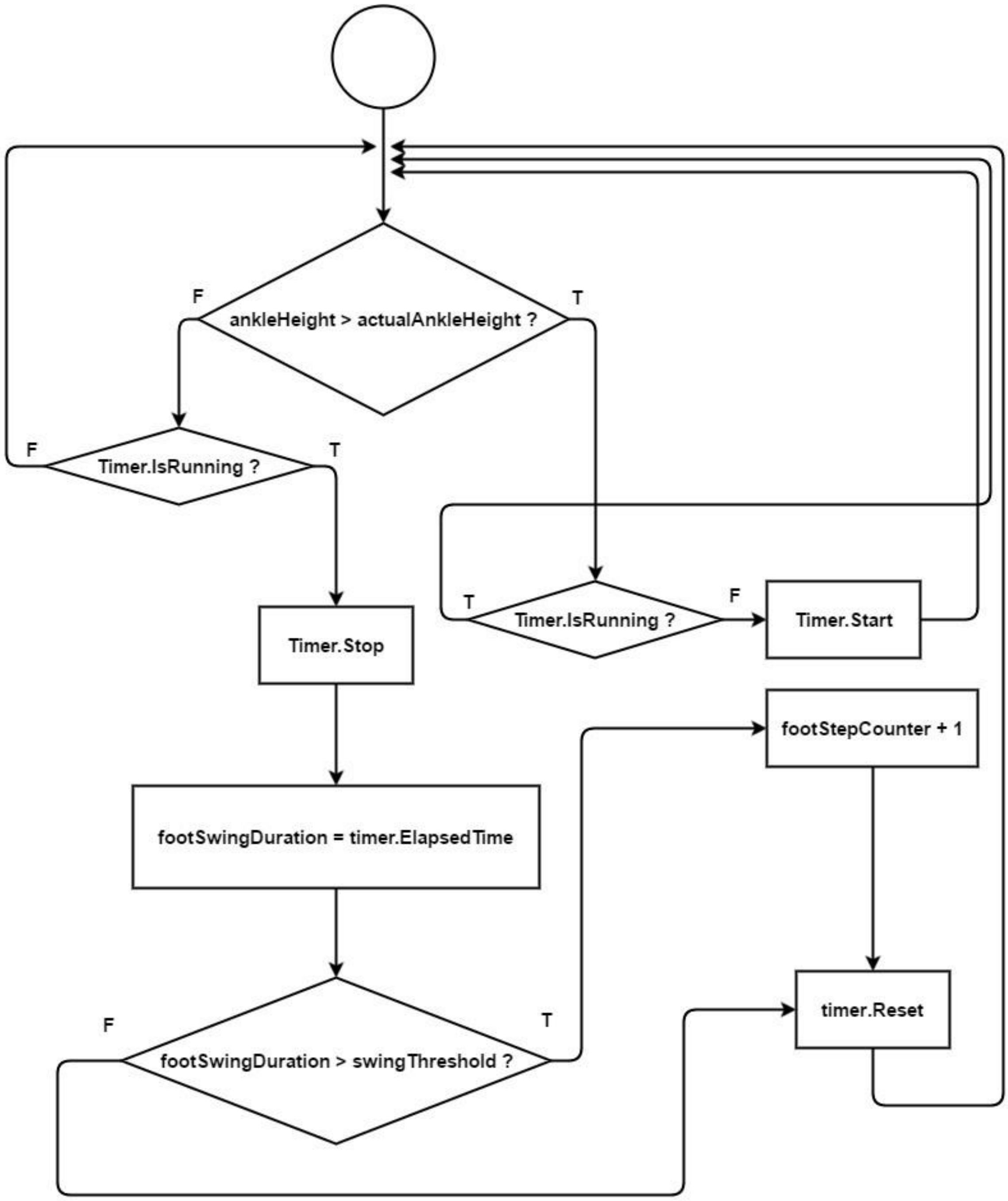



Figure 4:8 Foot step detection algorithm flowchart

Figure 4:9 shows the calculated height of a subject's ankle using Equation 4:2 (before the correction was applied). The algorithm checks whether the subject's ankle height value is greater than the actual size of the subject's ankle. If the result was true, the algorithm then starts a timer to calculate the swing time. As soon as the initial condition becomes false, the algorithm then stops the timer and increment the number of footstep for each foot. Subjects were asked to move towards the Kinect camera and remain still at different distances from the Kinect's lens optical centre. The Kinect RGB feed was then aligned with its depth/skeleton feed using the Kinect coordinate mapping technique. The figure demonstrates the Kinect's inaccuracies in detecting a subject's ankle distance to the ground. Even in standstill posture, as the subject's Z coordinates (depth) to the Kinect's sensor changes, the Kinect reads different value of the subject's ankle distance to the ground.

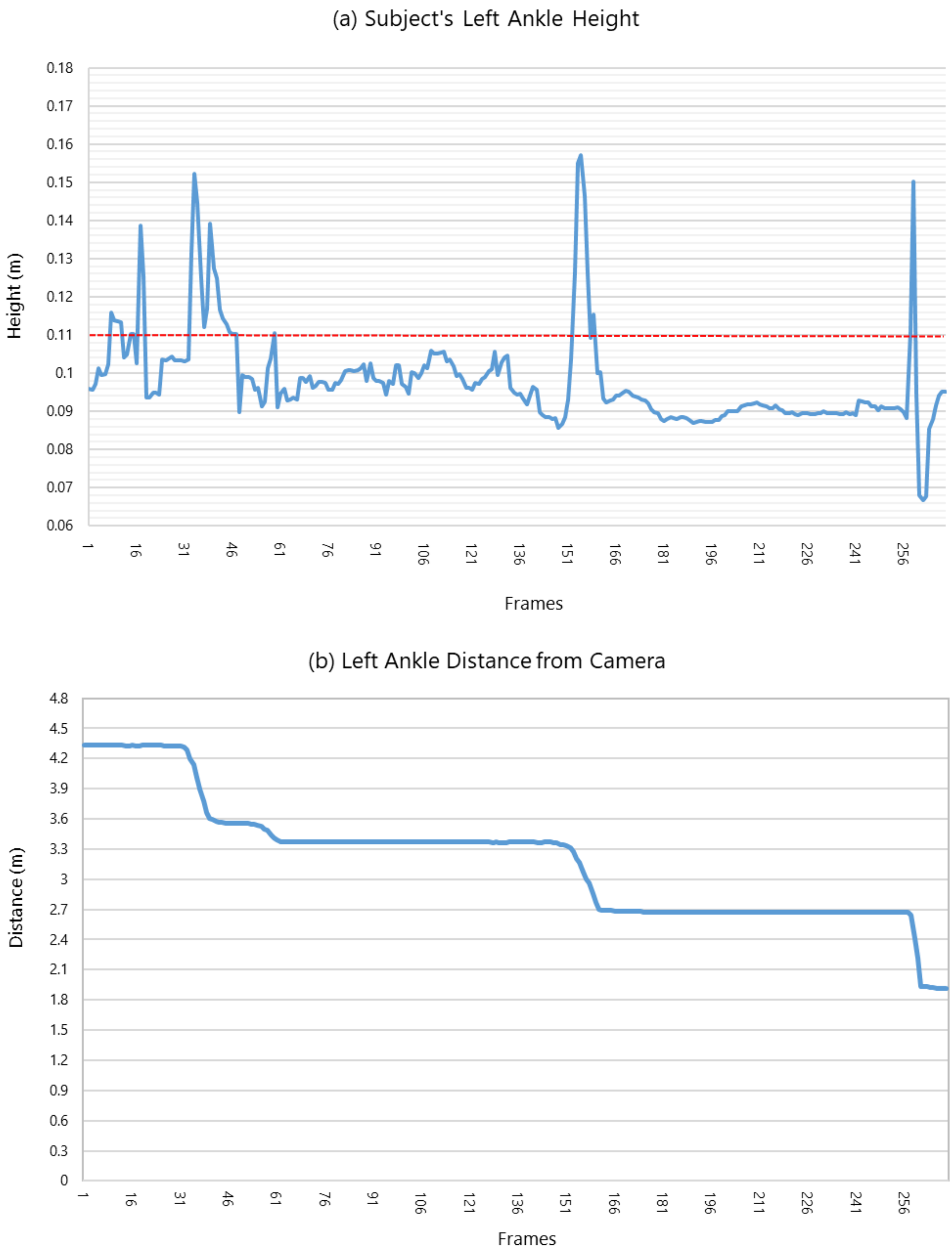



Figure 4:9. Panel (a) shows a subject's left ankle height to the ground at different distances from the Kinect camera. Panel (b) shows the subject's ankle Z-axis distance from the Kinect camera

Figure 4:9 Panel (a) shows a subject's left ankle height to the ground at different distances from the Kinect camera while the subject is walking towards the Kinect camera before the correction was applied. The peaks in Panel (a) show the steps taken by the subject. The dotted line represents the subject's actual ankle height in a stand still position. Panel (b) shows the same subject's ankle Z-axis distance from the Kinect camera during the same walking session.

It was observed that not only the subject's ankles height was changing in accordance to its Z-axis distance from Kinect camera, but also the calculated distance of the ankle from the floor was not consistent even in a stand-still position. The study showed that as the subject's ankle Z-axis distance from the Kinect camera decreases, the subject's calculated ankle height to the ground also decreases.

### 4.3.2 Knee Angle Based Footstep detection

#### *4.3.2.1 Angle Determination*

As studies previously noted, the Kinect skeletal joints relative 3D coordinates data reading are less susceptible to noise and inaccuracies compared to their distance to the ground data acquisition [4,13–15]. Thus, for each leg, a knee joint angle was determined by considering the location of the neighbouring joints such as hip and ankle in the Cartesian coordinate. The hip, the knee and the ankle position in a Cartesian space are defined with three vectors, with the Kinect being at the origin of the 3D space. This vector definition is expressed in Equation 4:7.

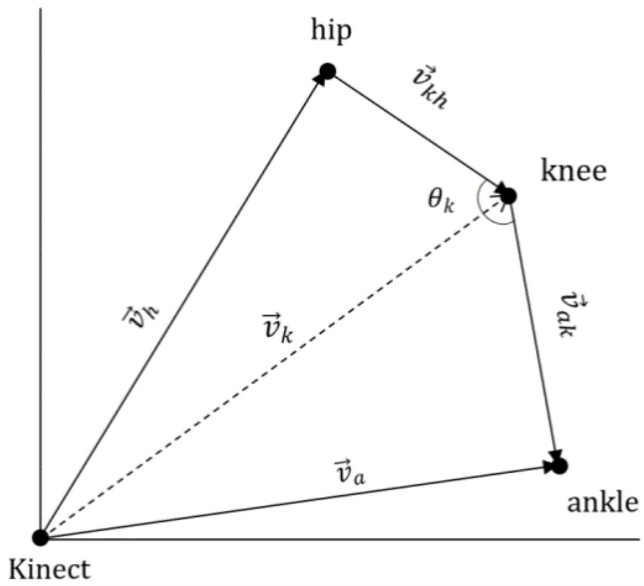



Figure 4:10. Determination of $\boldsymbol{\theta}$ using hip and ankle joints

Equation 4:7. Knee joint 3D angle determination

$$\vec{v}_{kh} = \vec{v}_k - \vec{v}_h$$

$$\vec{v}_{ak} = \vec{v}_a - \vec{v}_k$$

$$\theta_k = \cos^{-1}(\vec{u}_{kh} \cdot \vec{u}_{ak})$$

Were $\vec{v}_{kh}$ and $\vec{v}_{ak}$ are the 3D vectors connecting the subject's hip to the knee and knee to the ankle, respectively that is also depicted in Figure 4:10. Moreover, $\vec{u}_{kh}$ and $\vec{u}_{ak}$ are the unit vectors of $\vec{v}_{kh}$ and $\vec{v}_{ak}$, respectively.

#### *4.3.2.2 Footstep detection Algorithm*

A foot-off event is considered to have occurred when the knee angle of one foot has decreased to less than a particular threshold, which was experimentally acquired to be 170 degrees. Moreover, a foot contact is triggered when the knee angle of the same foot has returned to its original value (170 > θ ≤ 180) within a time period of more than 200 ms. The 200 ms timing window was set to avoid the false positives flag ups due to the Kinect inconsistencies and noise.

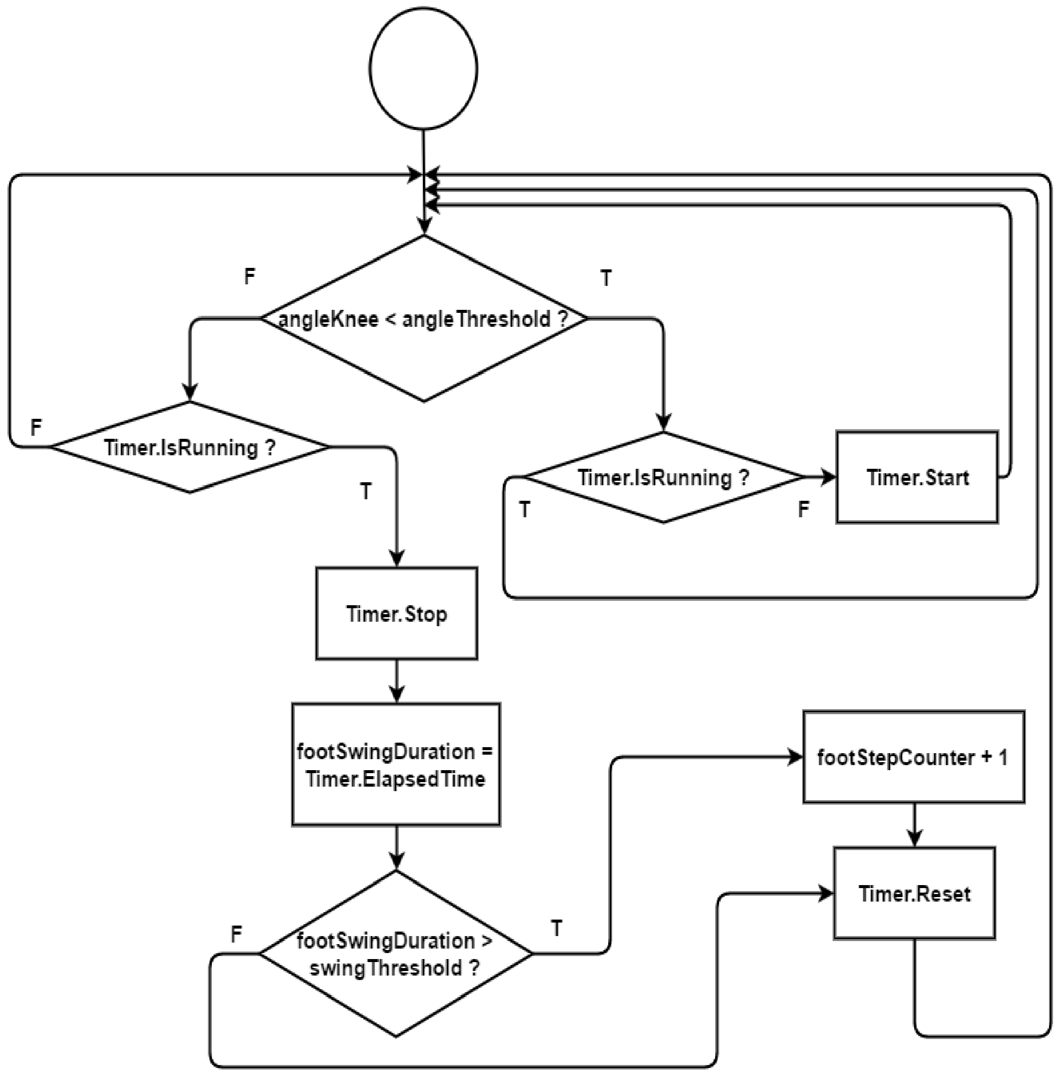



Figure 4:11. Step detection (foot-off and foot contact) process flowchart

Figure 4:11 demonstrates the subject's footstep detection process including foot-offs and foot contacts. The algorithm checks whether the subject's knee angle value is lesser than the defined threshold. If the result was true, the algorithm then starts a timer to calculate the swing time. As soon as the initial condition becomes false, the algorithm then stops the timer and increment the number of footstep for each foot. The algorithm loops at approximately 30 frames per second while the Kinect camera is tracking the subject.

## 4.4 Software Development

The proposed system also includes a comprehensive Graphical User Interface (GUI) that enables doctors and healthcare providers gather important information about a patient's gait performance such as stride time, steps in a given time and total number of steps in real-time. This data can be recorded and later exported to a patient's database profile for future analysis and evaluations.

The developed software can also enable a user to log in and observe the patient's status as well as provide support should the patient require. Figure 4:12 illustrates the network diagram facilitating the relay of video streams via the internet to the smartphone and client applications.

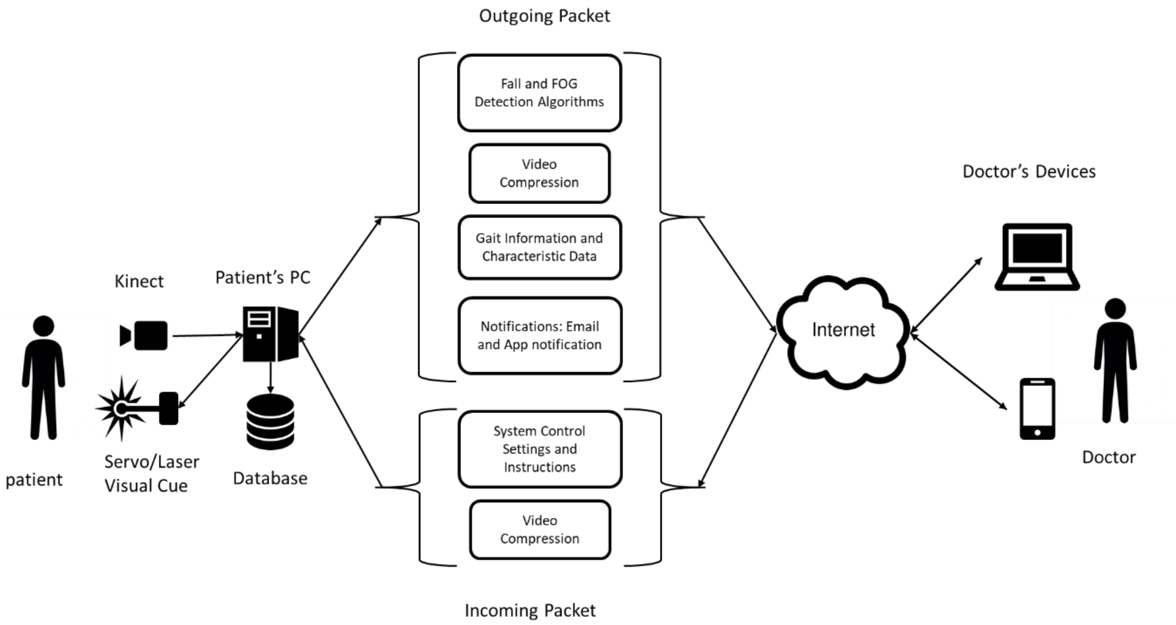



Figure 4:12. Network connection diagram including outgoing and incoming data packets over the internet

A smartphone companion application was also developed for Universal Windows Platform (UWP), that provided notification and a live video stream of a patient to be monitored.

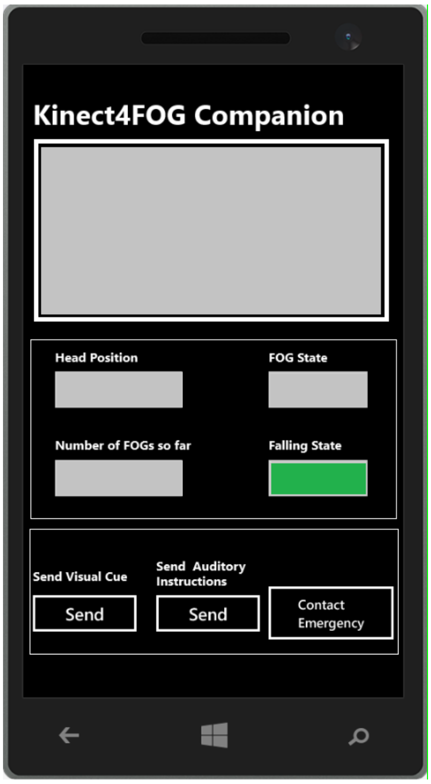



Figure 4:13. Design of the system's companion smartphone application

Figure 4:13 shows the design of the system's smartphone companion application for healthcare providers, doctors and carers. The application provides vital information about the subject including the number of FOG incidents as well as notification to the user if a critical fall incident occurs. Moreover, it provides the remote user the ability to send visual or auditory cues during a FOG incident or contact emergency services. Based on the user preference, the system can contact a person in-charge via email or notifications in the companion smartphone application including a live stream of the incident and the time stamp of the incident's date and time. A carer, once notified, can also initiate a Skype conversation where he/she can talk to the patient and provide further support. The carer or the person in-charge can be a member of a user defined list in the app setting so only the users who are added can gain access to the patient's information and provide remote support.

### 4.4.1 FOG Detection

In a past study, [58] we have implemented a process of FOG detection in using the gait cycle and walking pattern detection techniques published in [57], [110]. Once the developed system detects a FOG incident, it will turn on the laser-based visual cues and start determining the appropriate angles for both vertical and horizontal servo motors. After passing a user-defined waiting threshold or disappearance of the FOG incident, the system returns to its monitoring phase by turning off the laser projection and servo motors movements. Figure 4:14 shows the GUI for the developed system application.

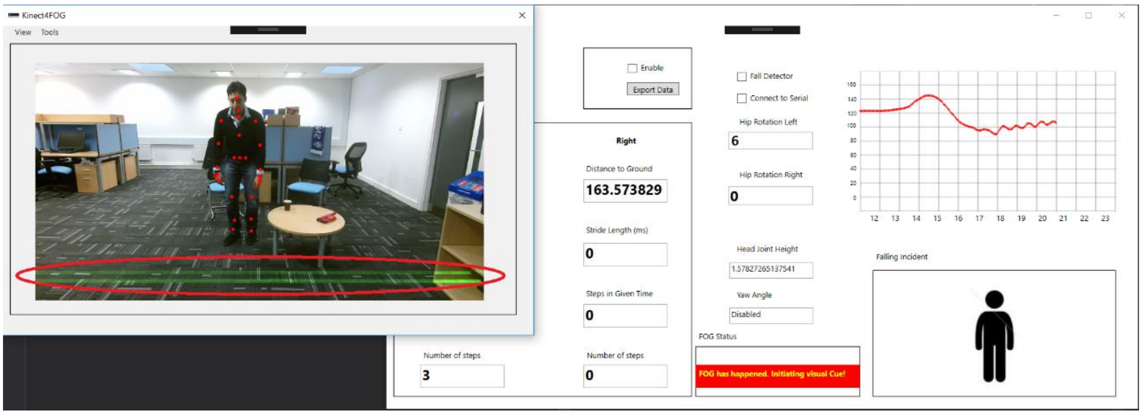



Figure 4:14. Graphical User Interface for the developed software

The left window shows a PD patient imitator during his FOG incident. The right window shows that the subject is being monitored and his gait information is being displayed to healthcare providers and doctors. As it can be seen in the ‘FOG Status’ section displayed in the red rectangle, the system has detected a FOG incident and activated the laser projection system to be used as a visual cue stimulus. The red circled area shows the projection of laser lines in front of the subjects according to its feet distance to the camera and body direction. The developed system also allows further customisation including visual cues distance adjustments to the front of the patient.

During the initial testing phase, 11 healthy subjects were invited, consisting of both males and females ranging from ages 24-31, with the age mean of 27 and (SD) of 2.34, mean height of 174.45 and (SD) of 8.31 cm ranging from 163 to 187 cm. They were asked to walk in pre-defined paths: 12 paths per subject, walking towards the camera and triggering a FOG incident by imitating the symptom while having the Kinect camera positioned at a fixed location. The subjects' skeletal data were captured and analysed by the Kinect camera in real-time. The room that was used for conducting the experiments consisted of different living room furniture to mimic a practical use case of the device. This not only yields more realistic results, but also tests the system in real-life scenarios where the subject is partially visible to the camera and not all the skeletal joints are being tracked.

## 4.5 Hardware Development

### 4.5.1 Servo Motors Angle Detection

The Kinect v2 was used to determine the subjects' location in a 3D environment and localise the subject's feet joints to calculate the correct horizontal and vertical angles for servo motors. To determine the subject's location, Kinect skeletal data were used for joints' 3D coordinate acquisition. A surface floor can be determined by using the vector equation of planes (Equation 4:1). This is necessary to automate the process of calculating the Kinect's height to the floor that is one of the parameters in determining vertical servo angle.

For vertical angle determination, the subject's feet 3D coordination was determined and depending on which foot was being closer to the Kinect in Z-axis, the system selects that foot for further calculations. Once the distance of the selected foot to the camera was calculated, the vertical angle for the servo motor is determined using the Pythagorean theorem, as depicted in

Figure 4:15. The subject's skeletal joints' distance to the Kinect on the Z-axis is defined in a right-handed coordinate system, where the Kinect v2 is assumed to be at origin with a positive Z-axis value increasing in the direction of Kinect's point of view.

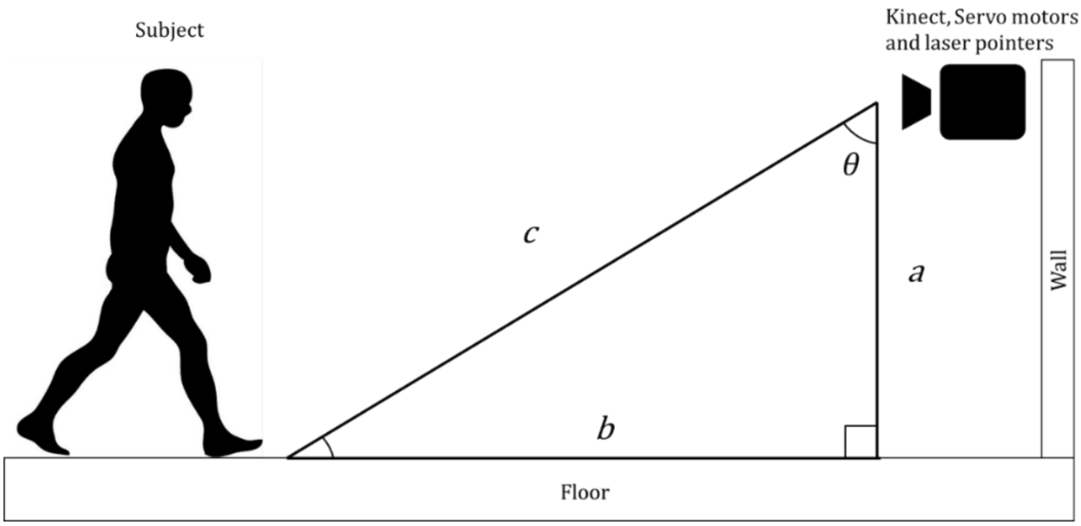



Figure 4:15. Vertical angle determination

where ***a*** is the Kinect's camera height to the floor that is the same as variable ***D*** from Equation 4:1 and ***c*** is the hypotenuse of the right triangle, which is the subject's selected foot distance to the Kinect camera in the Z-axis. ***θ*** is the calculated vertical angle for the servo motor. Note that the position offsets in X and Y axes between the Kinect v2 camera and laser pointers/servo motors were taken into account to achieve the most accurate visual cue projection.

Figure 4:18 illustrates a subject's lower extremities Z-axis distance to the Kinect camera (Figure 4:15 variable c) while the subject is moving towards the camera. It shows that the Kinect v2 determines a joint's Z-axis distance to the camera by considering its height to the ground. i.e. the higher the value of a joint's Y-axis to the camera's optical centre is, the farther the distance it has, to the camera in the Z-axis. This indicates that unlike the Kinect's depth space, the Kinect skeletal coordinate system does not calculate Z-axis distance (Figure 4:15 variable c) in a perpendicular plane to the floor and as a result, the height of the points that in this case are joints, are also considered.

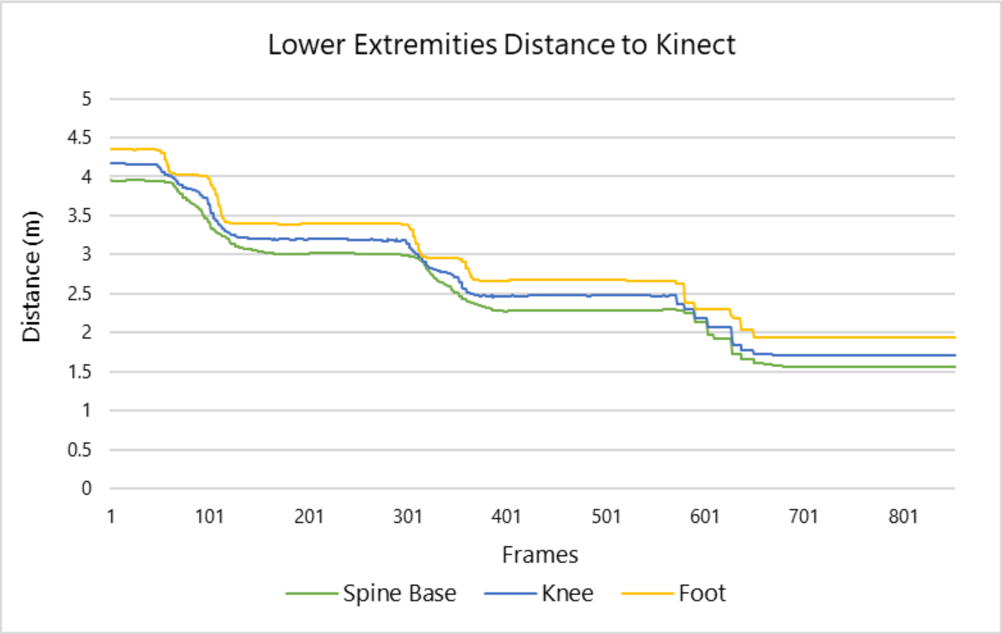



Figure 4:16. Subject's lower body joints distance to the Kinect camera in the Z-axis during a walking session

To test the Kinect v2 accuracy in determining both vertical and horizontal angles according to the subject's foot distance to the Kinect camera and body orientation, a comparison between the aforementioned Vicon and Kinect camera was performed.

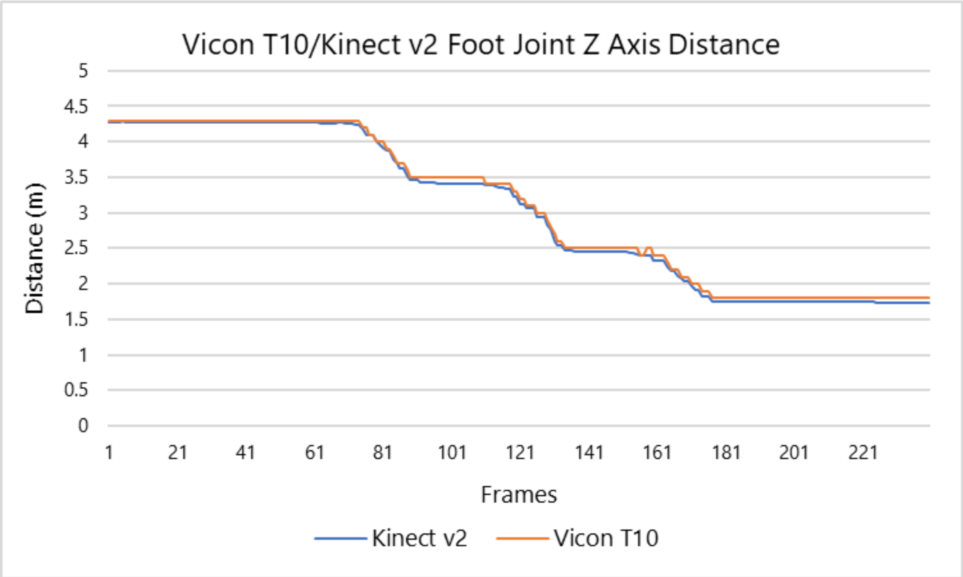



Figure 4:17. Subject's left foot distance to the camera in Z-axis using Kinect v2 and Vicon T10

The above figure shows the Kinect v2 accuracy in determining a subject's joint (left foot) distance to the camera in Z-axis after applying our suggested correction algorithms compared to a gold standard motion capture device (Vicon T10). It was concluded that Kinect v2 skeletal data acquisition accuracy was very close (98.09 %) to the industry standard counterpart. The random noise artefacts in the signal were not statistically significant and did not affect the vertical angle determination.

The subject's body direction that determines the required angle for the horizontal servo motor can be found via the calculation of rotational changes of two subject's joints including left and right shoulders. The subject's left and right shoulder joints' coordinates were determined using skeletal data and then fed to an algorithm to determine the body orientation as follows:

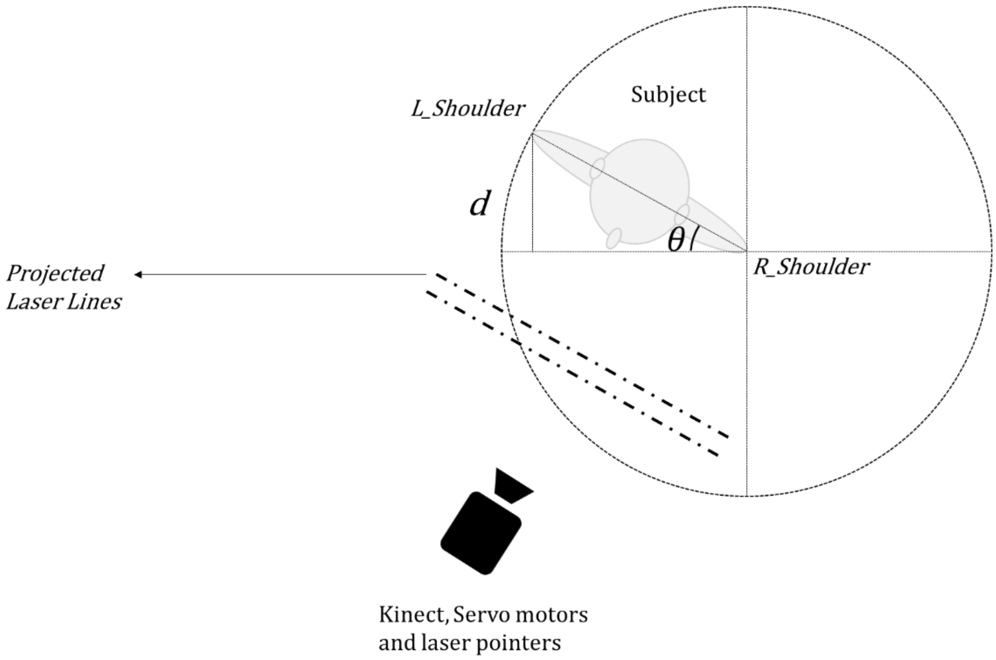



Figure 4:18. Horizontal angle determination (note that Kinect sees a mirrored image thus shoulders are reversed)

Equation 4:8. Horizonal Servo Motor Angle Determination

$$\theta_H = |90 \pm (\sin^{-1}|\text{shoulderA-shoulderB}|)|$$

where ***d*** in Figure 4:18 is the Z-axis distance difference to the camera between the subject's left and right shoulders.

Once the ***d*** based on the Equation 4:8 was calculated, the angle for the horizontal servo motor ($\theta_H$) can be determined by calculating the inverse sine of $\theta$. Depending on the subject's direction of rotation to the left or right, the result would be subtracted or added from/to 90, respectively. This is because, in order to cast laser lines in front of the subject, the horizontal servo motor should rotate in reverse compared to the subject's body rotation.

### 4.5.2 Motor Control

A serial connection was needed to communicate with the servo motors controlled by the Arduino Uno microcontroller. The transmitted signal by the developed application needed to be distinguished at the receiving point (i.e. Arduino microcontroller) so each servo motor can act according to its intended angle and signal provided. A multi-packet serial data transmission technique similar to [111] has been developed. The data were labelled at the transmitter side, so the microcontroller can distinguish and categorise the received packet and send appropriate signals to each servo motor. The system loops through this cycle of horizontal angle determination every 150 ms. This time delay was chosen as the horizontal servo motor does not need to be updated in real-time due to the fact that a subject is less likely to change its direction in very short intervals. This ensures less jittery and smoother movement of horizontal laser projection.

### 4.5.3 Design of the Prototype System

A two-servo system was developed using an Arduino Uno microcontroller and two class-3B 10mW 532nm wavelength green line laser projectors as shown in Figure 4:19a; green laser lines have been proven to be most visible among other laser colours used as visual cues [112]. An LCD display has also been added to the design that shows all the information with regards to vertical and horizontal angles to the user. Figure 4:19c shows the developed prototype system used in the experiment at different angles including the Kinect v2 sensor, pan/tilt servo motors, laser pointers and the microcontroller. Figure 4:19b shows the top view of the prototype system including the wiring and voltage regulators. A 3D printed caddy was designed to hold the laser pointers (Appendix J).

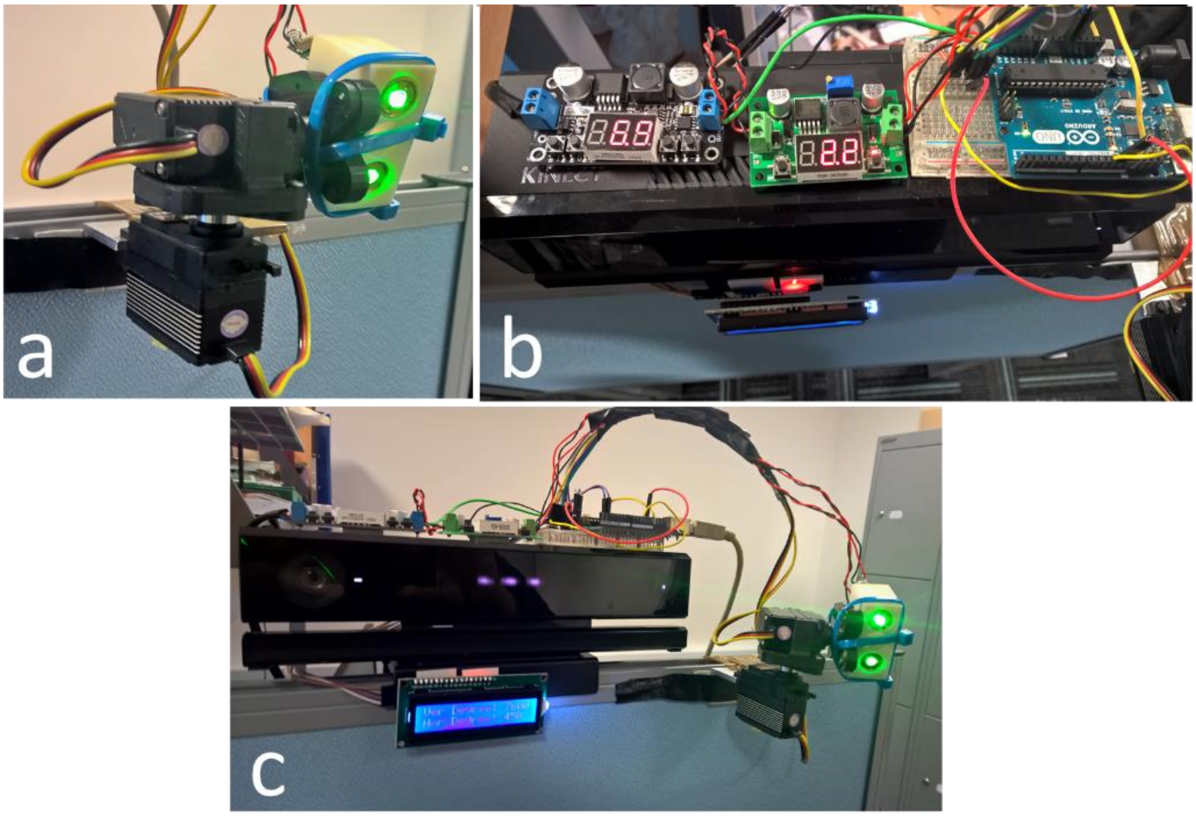



Figure 4:19. Developed prototype of the automatic visual cue system. a) The two step motors controlling the horizontal and vertical alignment of the system. b) A top view of the Kinect v2 combined with the micro controller and voltage regulators c) A view of the prototype system in action

As mentioned before, a micro controller based on Arduino Uno was employed to controller the movement of both horizontal and vertical servo motors as well as providing signals to the laser pointers. The board was also used to provide information to the LCD panel during the monitoring phase. Figure 4:20 illustrates the schematic diagram of the designed prototype hardware and the connection between each component.

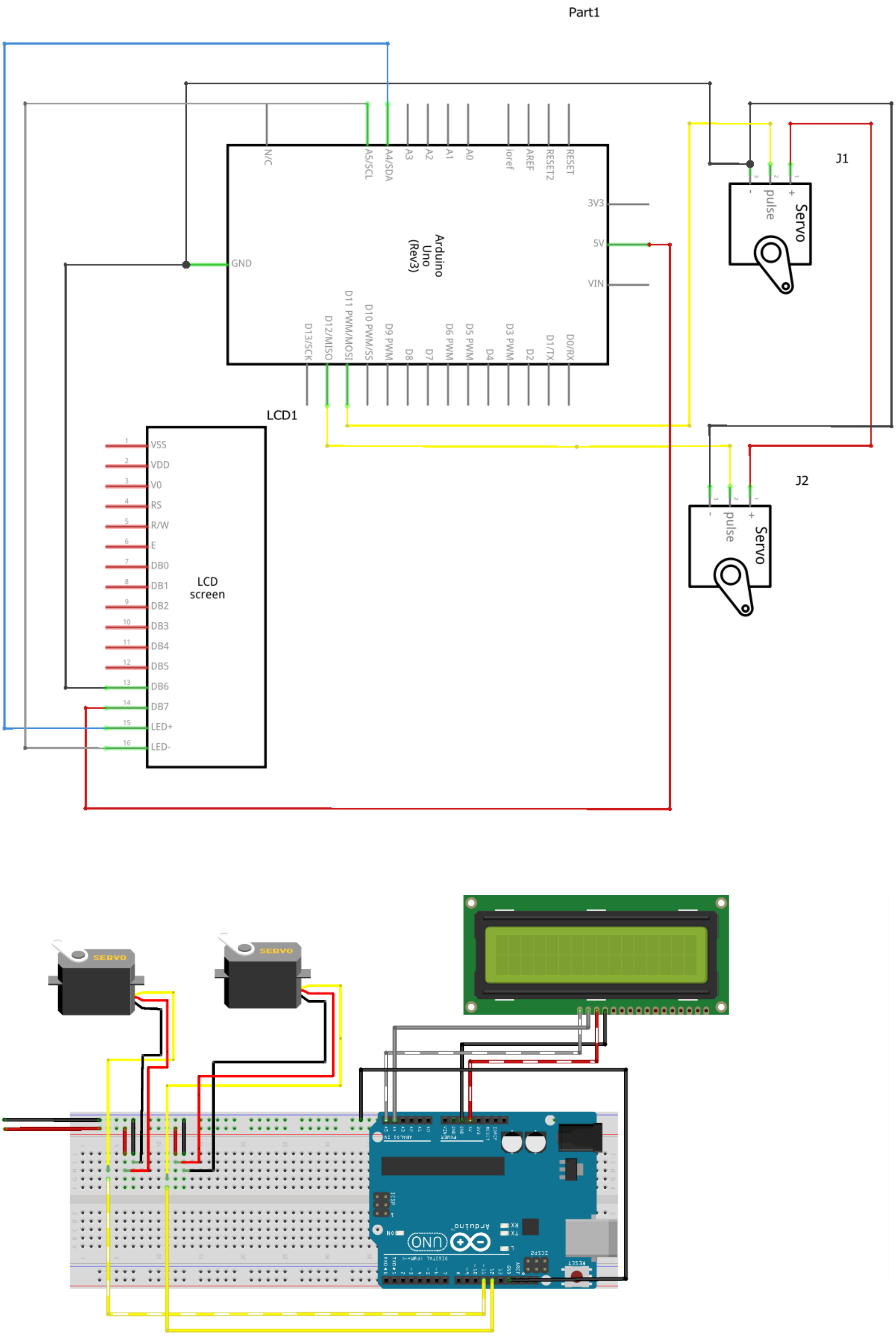



Figure 4:20. Schematic diagram of the designed prototype hardware

## 4.6 Focus Group and Patients Participation

Once the prototype system including the hardware, software and algorithms were chosen for the study, PwP where invited to participate in a focus group. The aim of the focus group was to review the functionality and performance of the developed system and provide valuable feedback on how to improve the prototype system. Fifteen PwP (12 male, 3 female) participated in the focus group in which seven PwP volunteered to directly interact with and evaluate the system. The 15 volunteers were split up in to three groups of five people.

They were invited to attend an event where the system's capabilities were demonstrated in terms of monitoring patient's FOG status, fall-detection, and providing sensory cues for improving locomotion during FOG. Participants were provided the opportunity to experience the system themselves as an option. They were allowed to walk towards the camera while being monitored, assess the system's capabilities for visual cues projection and observe the dynamic laser lines in action, as majority suffer frequent FOG. Moreover, the falling incidents were simulated by a healthy adult to demonstrates the system's fall detection and live support capabilities. Seven of those 15 participants tested the system. Nonetheless, all 15 of them observed the prototype system in operation. Seven patients who volunteered to test the system were split in to three groups, attending in three different sessions.

Participants were recruited from local support groups managed by Parkinson's UK (Appendix E). Potential participants were given written information about the study and were invited to participate (Appendices F and G). They were reminded that they were under no obligation to take part and could withdraw at any time. All participants provided written and informed consent (Appendix C). All investigations were carried out according to the principles laid down by the Declaration of Helsinki of 1975, revised in 2008. Ethical approval for the research was granted by Brunel University London's ethics committee (Appendices B and D). A risk assessment investigation was also conducted in order to assess the testing environment and laser projection system (Appendix A).

The population age of the 15 PwP participating in the focus group ranged from 54-78, with a standard deviation (SD) of 8.01 years of having PD, population (SD) of 4.99 ranging from 0.5 to 18 years and daily FOG frequency population (SD) of 4.31 ranging from 3 to 20 episodes (Table 4:2). The aim of the focus group was to review the developed system functionality and performance. During the sessions, those who volunteered to test the system were instructed to walk towards the camera in pre-defined paths within the distance range of 4.33 meters to 1.38 meter while their gait and locomotion were being tracked by the developed system. The Kinect was placed perpendicularly at a height of 1.57 meters from the ground.

Table 4:2. Patients Participants (* indicates those who volunteered to try them system)

| Patient | Gender | Age | Years of PD | Average Daily FOG occurrence |
|---|---|---|---|---|
| **S 1** | Male | 60 | 9 | 3 |
| **S 2*** | Female | 54 | 7 | 5 |
| **S 3** | Male | 77 | 7.5 | 5 |
| **S 4*** | Male | 72 | 18 | 15 |
| **S 5** | Male | 74 | 8 | 20 |
| **S 6*** | Male | 73 | 14 | 10 |
| **S 7** | Male | 70 | 10 | 10 |
| **S 8** | Male | 72 | 2 | 5 |
| **S 9*** | Female | 72 | 17 | 10 |
| **S 10** | Male | 76 | 12 | 5 |
| **S 11*** | Male | 70 | 10 | 10 |
| **S 12** | Female | 78 | 0.5 | 10 |
| **S 13*** | Male | 71 | 5 | 5 |
| **S 14*** | Male | 92 | 2 | 10 |
| **S 15** | Male | 70 | 8 | 10 |
| **Mean** | N/A | 72.06 | 8.66 | 8.86 |

## 4.7 Summary

This chapter provided the methodology used for conducting this study including the implementation of different approaches required by this research. For fall detection, two different methodologies including heuristic and machine learning were used. In order to estimate FOG events, footsteps occurrences were also explored using two different methods one based on knee angle and one based on the subject's ankles height to the floor, in which a new correction algorithm was introduced to address the Kinect's intrinsic inaccuracies. Moreover, the prototype design of the system including the software and hardware was developed during this stage and put on test. Several PwP were also invited to test the prototype as part of a focus group. The detailed information about the results of the experiments will be explained in the next chapter.

# Chapter 5: Results and Discussion

## 5.1 Introduction

This capture covers the results and data found during this research. The conditions for each experiment conducted in this study will be indicated and analysed. Moreover, this chapter includes the comparison of the results of this study against previous findings in related studies mentioned in the literature.

## 5.2 Experimental Setup

### 5.2.1 System Specifications

The system's hardware specifications used in all the computations and collection of the data phases as well as the machine learning and testing process are as follow:

**Model:** Viglen Genie Full

**CPU:** Intel (R) Core(TM) i7-4790 CPU @ 3.60GHz

**Internal Memory (RAM):** 24.00 GB (23.8 usable) DDR3 in Dual Channel mode

**Graphics Card:** AMD FirePro W5000 (2 GB VRAM)

**System Type:** 64-bit Operating System, x64-based processor

**Operating System:** Windows 8 Enterprise upgraded to Windows 10 Education

The developed software was written in C# using Kinect for Windows SDK version 2.0.1410.19000 while the companion smartphone application was based on Windows 10 Mobile (10.0; Build 10240) and the client software was developed using Windows Presentation Foundation (WPF).

### 5.2.2 Testing Environment

A testing environment was used to carry out the trials as below:

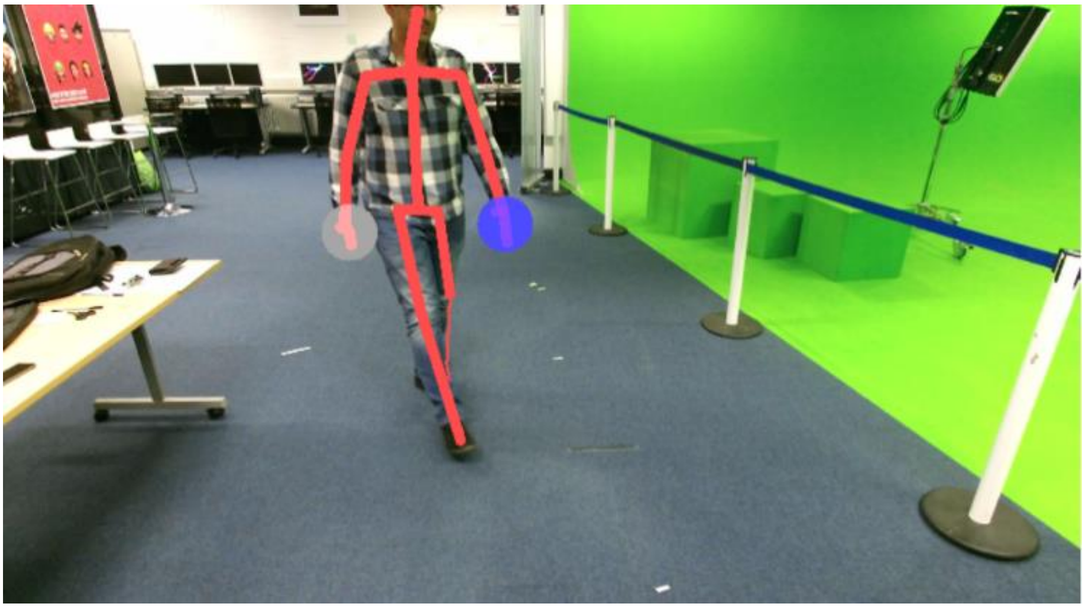


Figure 5:1. The testing environment: the subject is walking diagonally towards the Kinect camera while his body joints are being tracked

The Kinect sensor was setup at different angles ranging from 0 to 45 (0, 10, 22 and 45) degrees to the ground and at different heights 0.65, 1 and 1.57 meters in order to identify any possible differentiation in results based on the camera angle and height factors.

For further evaluation of the system, its outputs had to be compared for accuracy to a system considered as a golden standard. A series of eight synchronised Vicon T10 motion capture cameras providing full room coverage were used alongside the Kinect v2 camera. The test subjects were asked to walk in a pre-determined path while their skeletal joints were being monitored by both the Kinect v2 and Vicon cameras. Subjects also performed upper-body rotation while being in a stand still position for the Kinect's horizontal angle calculation.

Figure 5:2a shows the process of collaborating virtual markers attached to a subject for Vicon cameras where a subject in a T-pose for her ankles height, as well as her joints' position to be calculated by both Vicon and Kinect systems. The Vicon cameras and Kinect v2 captured each session simultaneously while the frame rate of the recorded data from the Vicon cameras was lowered down to match the Kinect v2 at approximately 30 frames per second.

Figure 5:2b and Figure 5:2c show real-time 3D data representation of both the Vicon cameras and Kinect v2, respectively.

Note that the motion capture suit used in the experiment were intended for the Vicon cameras only as the Kinect v2 does not require any special clothing for its skeletal detection system to function. Subjects were also asked to wear normal clothing after the initial ankle measurement phase while their movements were being recorded by Kinect v2 in different situations (camera heights and angles).

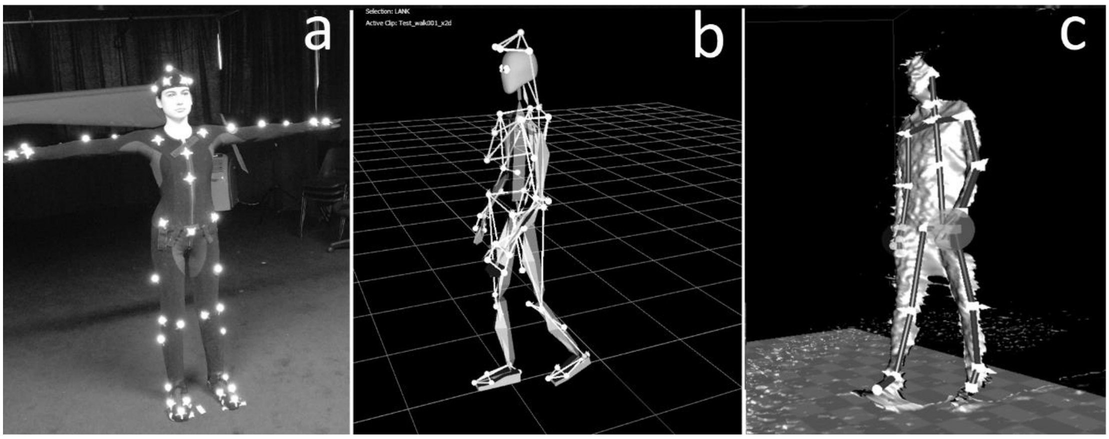



Figure 5:2. 3D data acquisition using Kinect v2 and Vicon T10 cameras

### 5.2.3 Test Cases

For the trial testing, 11 subjects (Table 4:1) participated by walking in pre-determined paths in 12 walking sessions including diagonally walking towards the camera, while their body data was being recorded and analysed by the system using Kinect v2.

## 5.3 Kinect v1 Frame Rate Analysis

The frame rate information was collected based on different options in the software to determine the impact of each feature on the system performance as well as the frequency of obtaining the joint positions. It was clear that if the sampling rate decreases, there will not be enough data for the system's algorithms to operate effectively. The minimum frame rate required by the system to determine the joint positions was low (between 5 to 10 FPS). It was observed that the use of depth imaging of the API decreases the frame rate by a huge factor. The following table compares the obtained data frame rate from the system concerning different settings.

Table 5:1. Frame rate comparison of different Kinect v1 capturing settings

| Frame Rate Analysis | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| Depth Image 640x480 | | ✓ | | ✓ | | ✓ | | ✓ |
| Depth Image 320x240 | ✓ | | ✓ | | ✓ | | ✓ | |
| One Subject in the Scene | ✓ | ✓ | | | ✓ | ✓ | | |
| Two Subject in the Scene | | | ✓ | ✓ | | | ✓ | ✓ |
| Live Coordination Feed Enabled | | | | | ✓ | ✓ | ✓ | ✓ |
| Minimum Frame Rate (FPS) | 29 | 27 | 22 | 15 | 5 | 0 | 0 | 0 |
| Average Frame Rate (FPS) | 29.5 | 28.9 | 25.4 | 16 | 6 | 0 | 0 | 0 |
| Maximum Frame Rate (FPS) | 30 | 30 | 27 | 23 | 8 | 0 | 0 | 0 |

The following diagram demonstrates the effect of each capturing setting on the system performance.

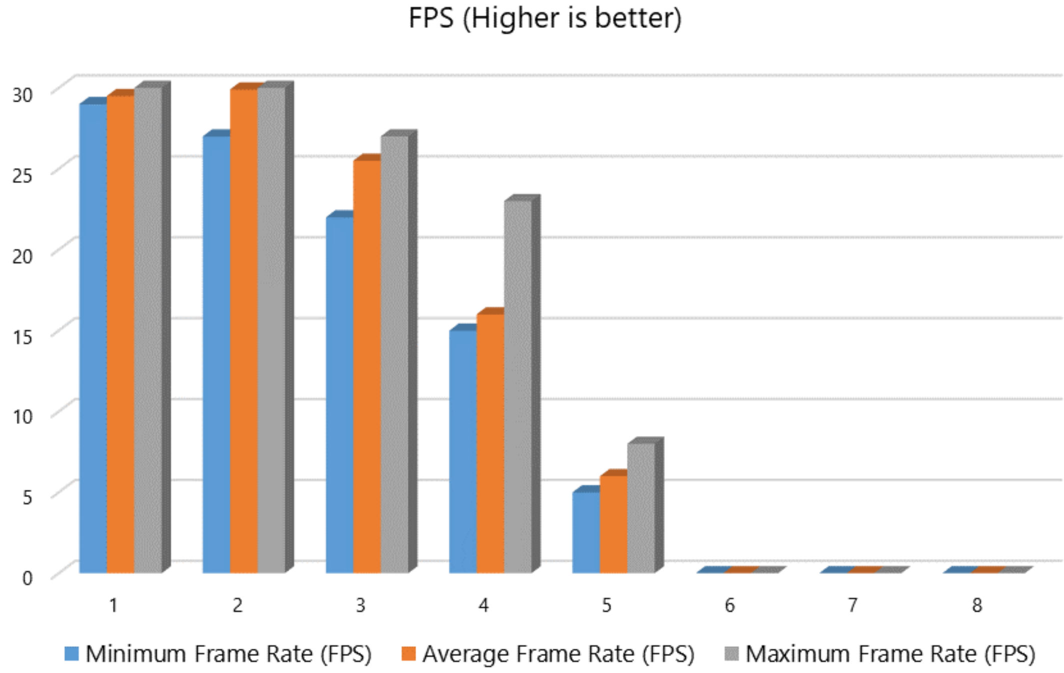



Figure 5:3. System Performance in FPS

It was observed that when a second subject enters the field of view, the frame rate dropped significantly. The system needs to do extra data processing for the second individual and consequently, it slows down the overall system's performance. Currently there is no control over the number of tracking joint in the API. Moreover, when the 'Live Data Feed' check box is enabled, the system halted although it did not crash. The current implementation of the Kinect v1 sensor was not capable of handling live feed information of three joints each in 3D.

As the result, either a very low resolution (320x240) had to be chosen to be used in the final implementation of the application or one had to go with Kinect v2. As mentioned before, although Kinect v2 has higher resolution (1080p) for its RGB data stream and has many improvements over Kinect v1, it is missing a lot of built in features in its API such as 'Joint Filtering'. Nonetheless, by implementing the developed correction algorithm, especially for the Joint-to-Ground footstep detection technique, many of these missing features could be compensated. Thus, the Kinect v2 was chosen for the use of this study as its advantages outweighs its disadvantages.

## 5.4 Fall Detection

During the experimentation stage of this research study, two different fall detection approaches for the system have developed and evaluated. One based on a heuristic design and one based on machine learning technique using AdaBoostTrigger. Same dataset were used to train the machine learning algorithm and test the heuristic method.

For heuristic approach, as expected, the system showed good results with high accuracy. Although each subject's fall incident had different characteristics in terms of velocity and postures, the implemented algorithm detected 95.42 % of falls successfully. Figure 5:4 shows a subject's head fall velocity as detected by the system.

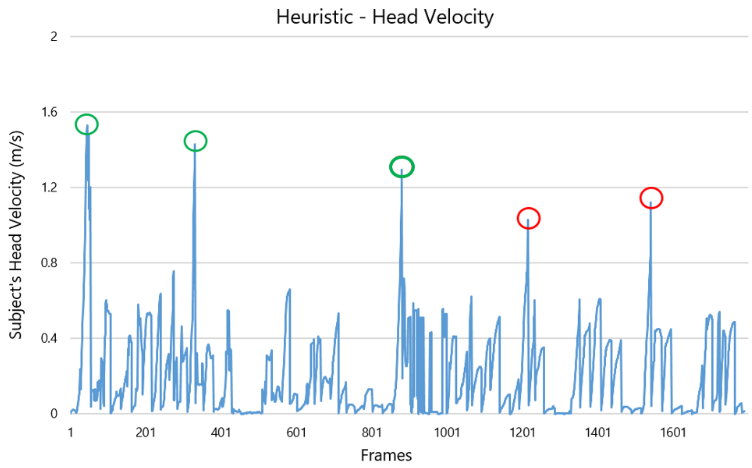



Figure 5:4. Heuristic – Subject's head fall velocity (true positives and false positives are shown as green and red circles, respectively)

As the above figure shows, there are five major falls with considerable velocity detected by the system. These data then were analysed by the algorithm and compared to the subject mean head's Y-axis height (Figure 5:5) to eliminate false positives. Note that the subject's height is measured as a 3D Cartesian coordinate point located in the middle of the head.

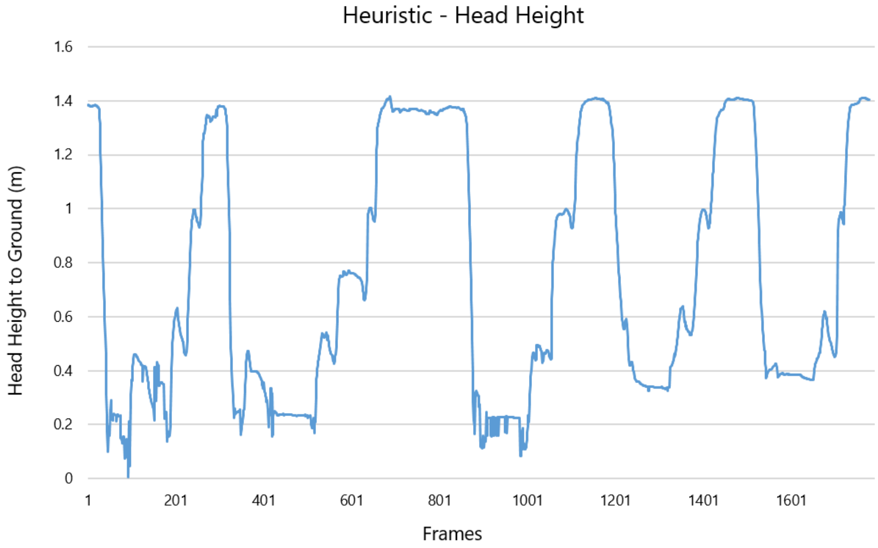



Figure 5:5. Heuristic – Subject’s head height to floor

In order for the system to detect a falling incident with higher accuracy, the signal was filtered, normalised and the earlier-mentioned thresholds such as velocity, acceleration and the subject’s head distance to ground were set in order to ignore false positives. A conditional statement was applied to ignore signals when the subject’s head distance to the ground is higher than 10 cm or its velocity is less than 1 m/s. Figure 5:6 shows the same subjects’ falling incidents after correction. Note that the whole process is automatic and done in real-time by the developed system.

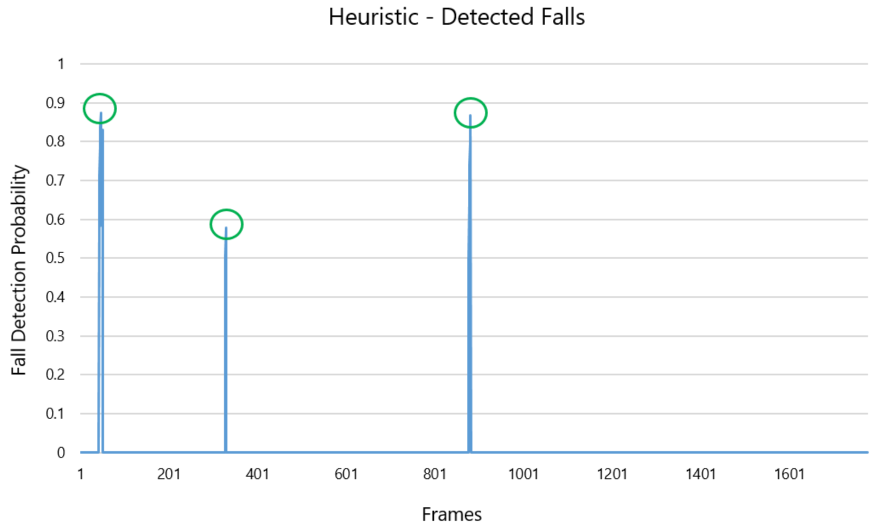



Figure 5:6. Heuristic – Filtered true positive fall detection’s confidence level (true positives are shown as green circles)

As the above figure illustrates, the system managed to detect three discrete fall incidents during the trial for the subject. The Y-axis shows the system's confidence in fall detection with one being the absolute certainty. As the set of instructions for fall detection algorithm was implemented in software, the heuristic approach showed a similar result in both scenarios (one with objects partially blocking the sensor's view and one with partial obstructed field of view). Nonetheless, in partial obstructed field of view condition, the accuracy of true positive detection was lower depending on whether the subject's fallen body was fully seen by the Kinect. In both conditions, the obstructed joints' 3D Cartesian coordinate location tracking was compensated and predicted using 'inferred' state enumerate, a built-in feature in the Kinect SDK. By implementing the 'inferred' joint state, the joint data were calculated, and its location was estimated based on other tracked joints.

For machine learning approach, two factors were taken into account. The system was built to calculate both velocity and the subject's head closeness to the ground by importing false positive, false negative and true positive tagged-video samples. Results show that our system (mentioned in 4.2.3) required about 18 minutes to calculate and process all training videos including 11 subjects' fall incidents in different conditions and 11 subjects' false positive training videos. Overall, 435 GB of 30 fps, 1080p uncompressed RGB and 424p depth video data were processed by the system for a total of 29 minutes training videos. Figure 5:7 shows the likelihood of the same subject reaching the threshold fall velocity as a confidence level zero to one. False positives are shown with red circles.

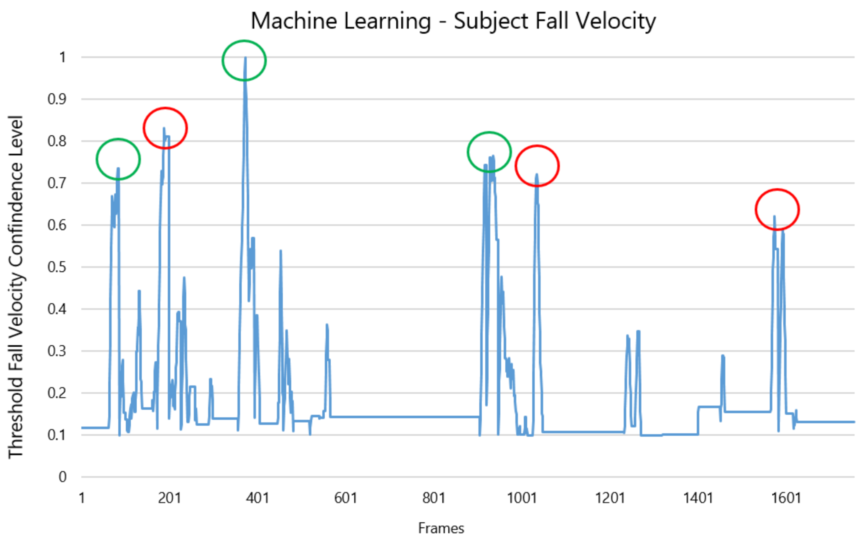



Figure 5:7. Machine learning – Subject's fall velocity threshold confidence level (false positives and true positives are shown as red and green circles, respectively)

Figure 5:8 shows the confidence level for detecting the same subject's distance to the ground as a fall incident happens.

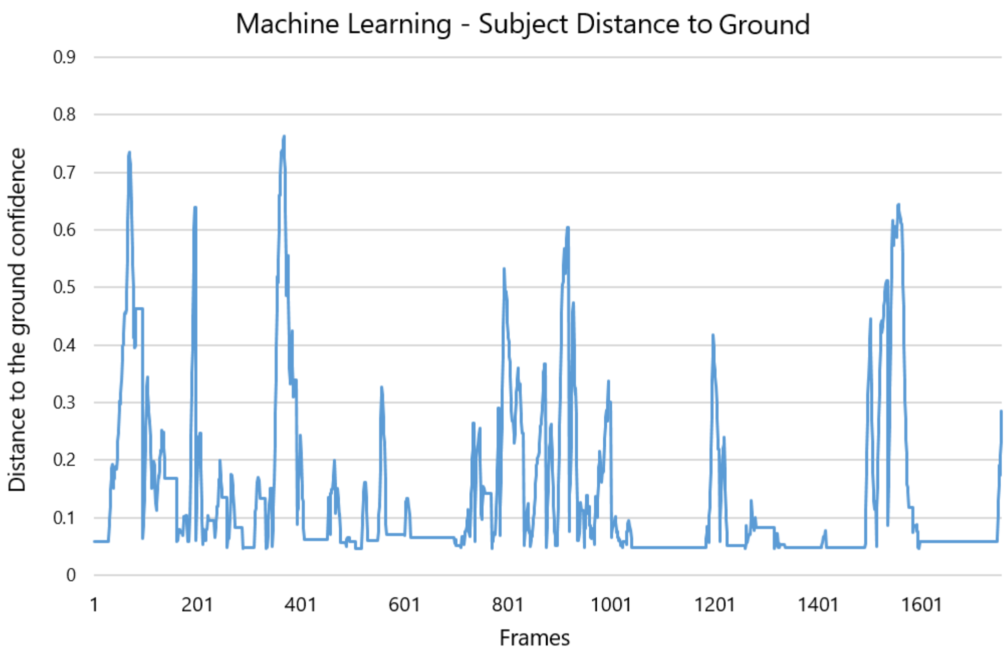



Figure 5:8. Machine learning – Subject's distance to the ground confidence level

As the above figure demonstrates, the machine learning approach proved to be less accurate compared to the heuristic method due to the limited number of subject's samples [113].

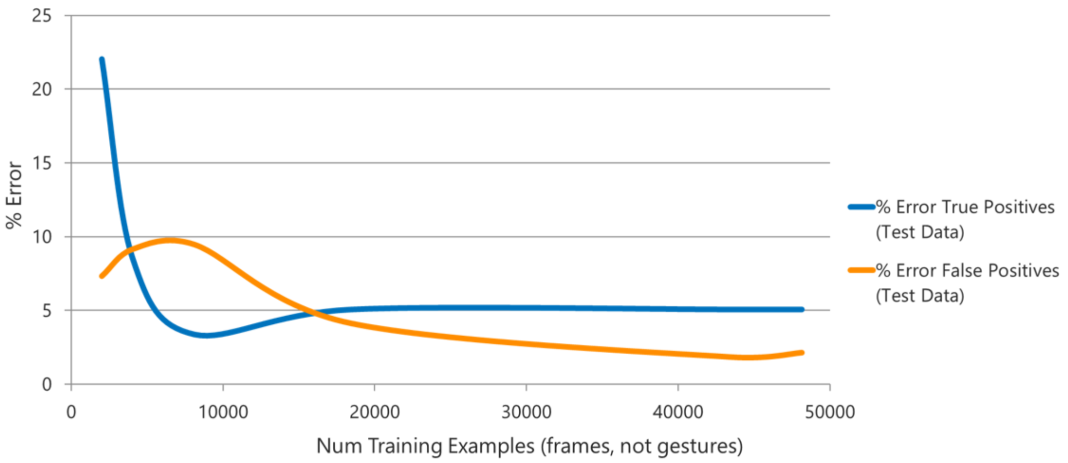



Figure 5:9. Number of true positives and flase positives detected by Kinect based on the size of the training dataset [113]

The accuracy of an AdaBoostTrigger algorithm is highly dependent on the number of training samples. Nevertheless, by introducing a second confidence factor into the equation and merging both confidence factors, the system managed to cancel out most of the false positives. Figure 5:10 shows the combined confidence level for the subject's fall on the floor and fall velocity. The graph shows that once the two signals are combined, most of the false positive detection was weakened and consequently, the successful detection signals have been boosted and normalised. The green circles show true positive fall incidents with highest confidence level whereas the red circle indicates an error in picking up a false positive incident as a true positive.

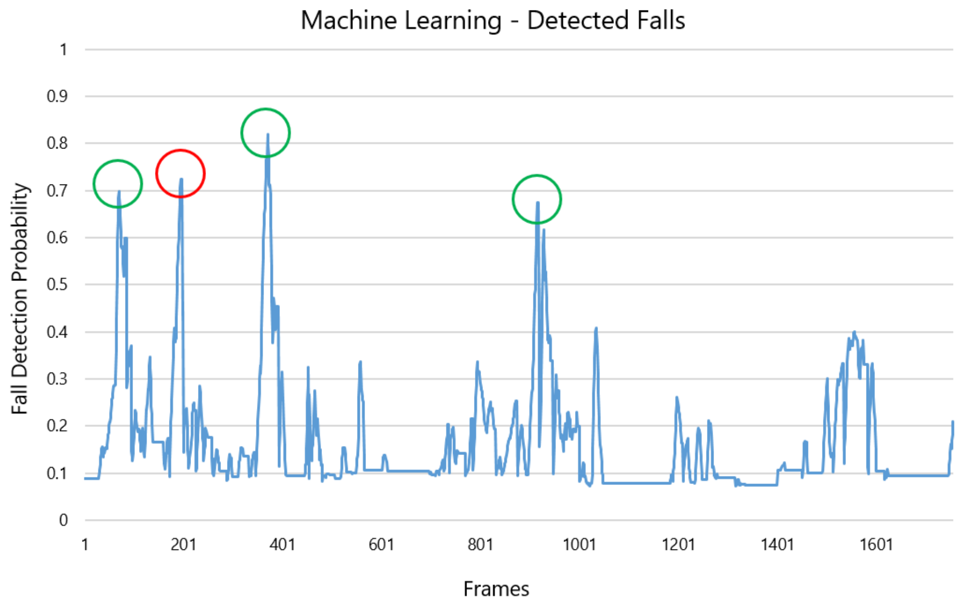



Figure 5:10. Machine learning – Fall detection overall confidence from combining the threshold fall velocity and distance to the floor factors (false positives and true positives are shown as red and green circles, respectively)

Figure 5:11 shows the data once the system passed it through a filter to ignore signals, which either of the probability levels (threshold fall velocity or subject's distance to ground) is below 60 %.

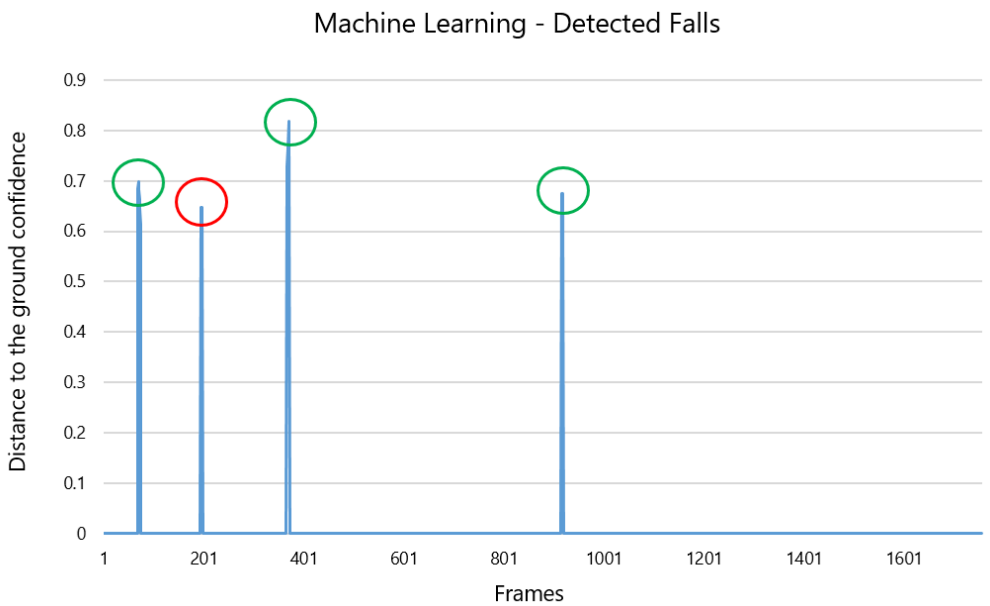



Figure 5:11. Machine learning – Filtered fall detections' confidence level (true positives and false positives are shown as green and red circles, respectively)

Combining two sets of conditions achieved a slightly higher detection rate. Nevertheless, in order to observe a noticeable improvement in detection of true positives, the number of dataset and training data should be significantly increased [113]. Overall, the system behaved differently for each testing trial. The algorithm managed to detect a maximum of 88.33 % of true positive falls successfully.

Table 5:2 shows the results for each fall detection approach true positive success rate for each participant.

Table 5:2. Heuristic and machine learning fall detection success rate comparison

| **Fall Detection Approach** | **Heuristic (%)** | **Machine Learning (%)** |
|---|---|---|
| **S1** | 94.98 | 88.12 |
| **S2** | 95.11 | 87.98 |
| **S3** | 95.62 | 88.21 |
| **S4** | 95.24 | 88.65 |
| **S5** | 95.10 | 87.86 |
| **S6** | 95.16 | 88.03 |
| **S7** | 96.21 | 88.45 |
| **S8** | 96.02 | 88.92 |
| **S9** | 95.35 | 88.37 |
| **S10** | 95.72 | 88.82 |
| **S11** | 95.21 | 88.29 |
| **Average** | **95.42** | **88.33** |

## 5.5 FOG and Footstep Detection

As a part of FOG detection for the developed system, two footstep detections capable of detecting of foot-offs and foot contacts phases of a gait cycle were developed and evaluated. One approach was based on direct footstep detection technique using subject's ankles distance to the ground and another based on the subject's knees angle. For the former approach, due to the Kinect's intrinsic inconsistencies in data stream, a correction algorithm was also developed and applied to maximise accuracy.

### 5.5.1 Ankle Distance to Ground Approach

Figure 5:12 shows that after the correction technique based on the two-point linear equation was applied, the data reading proved to be consistent, and the calculated ankle's height was closer to the actual measured height (in the most commonly used range of 1.6 to 2.9 metres from the Kinect camera), regardless of the subject's location to the camera. The dotted line represents the subject's actual ankle height in stand still position

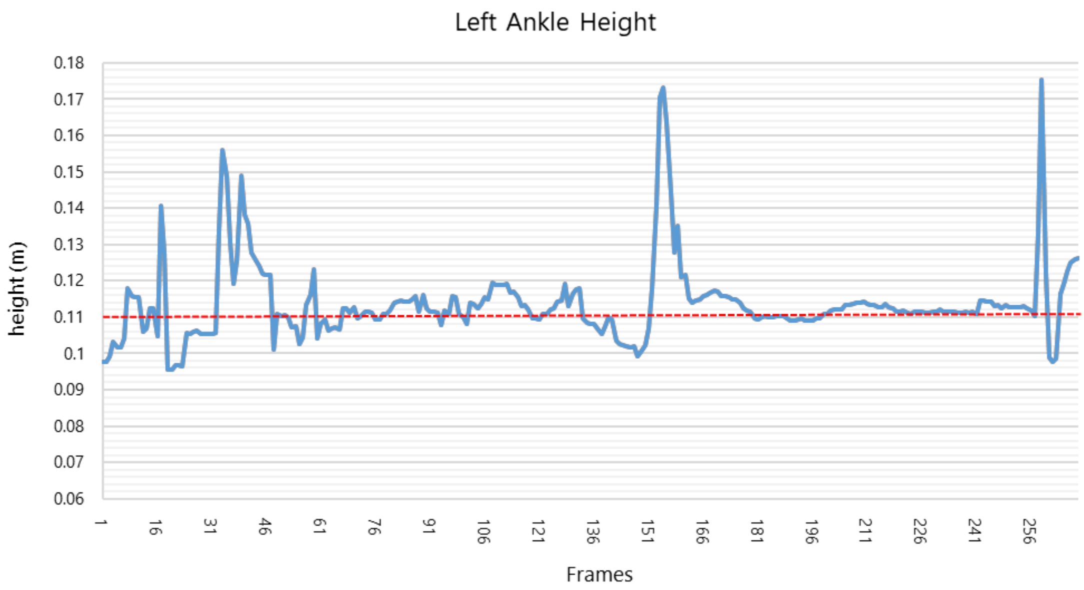
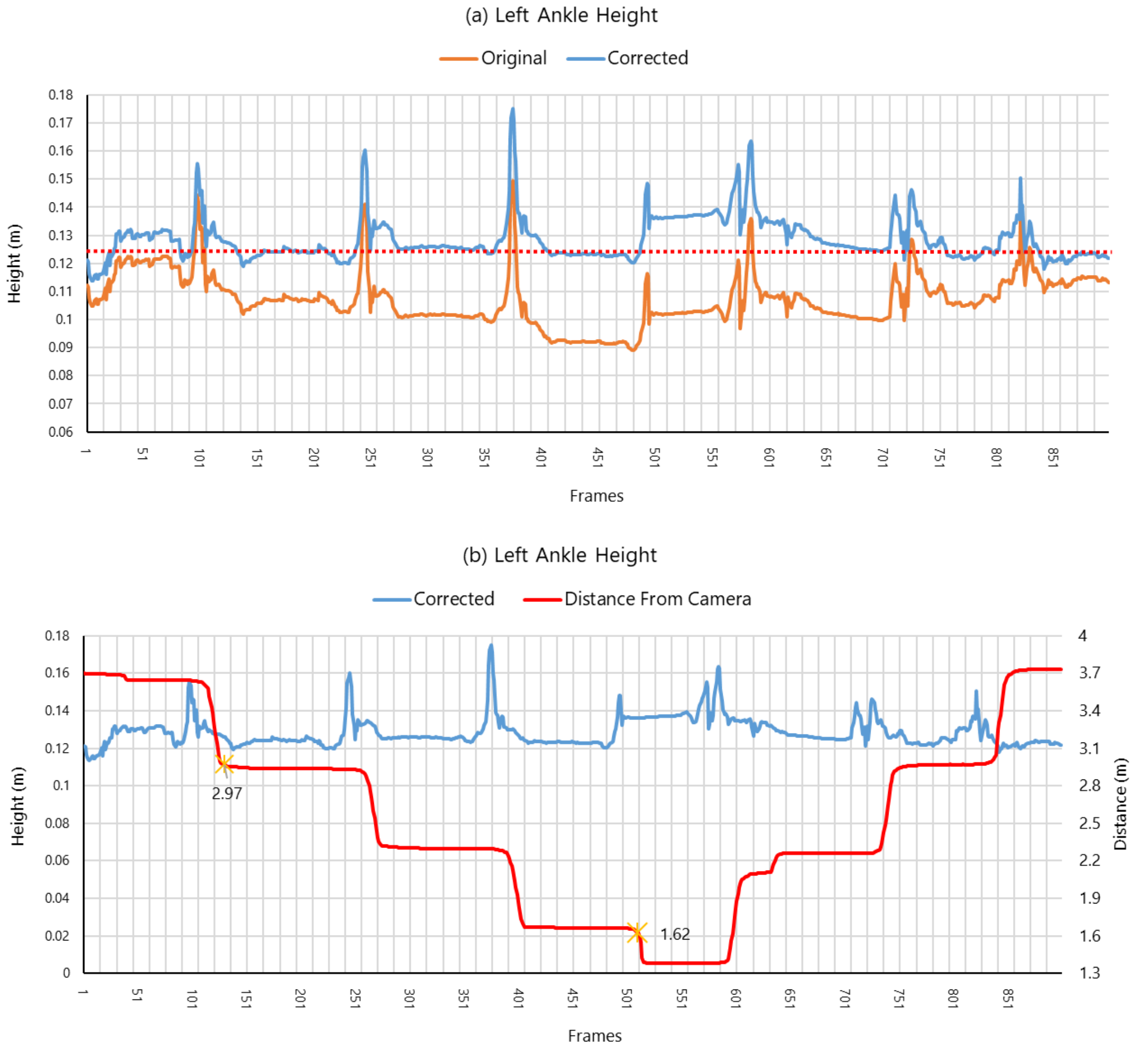



Figure 5:12. Subject's left ankle height to the ground at different distances from the Kinect camera after correction algorithm was applied. The dotted line represents the subject's actual ankle height in stand still position



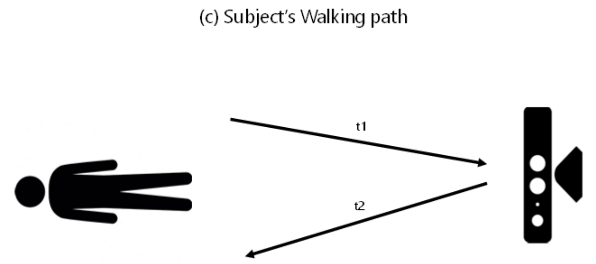
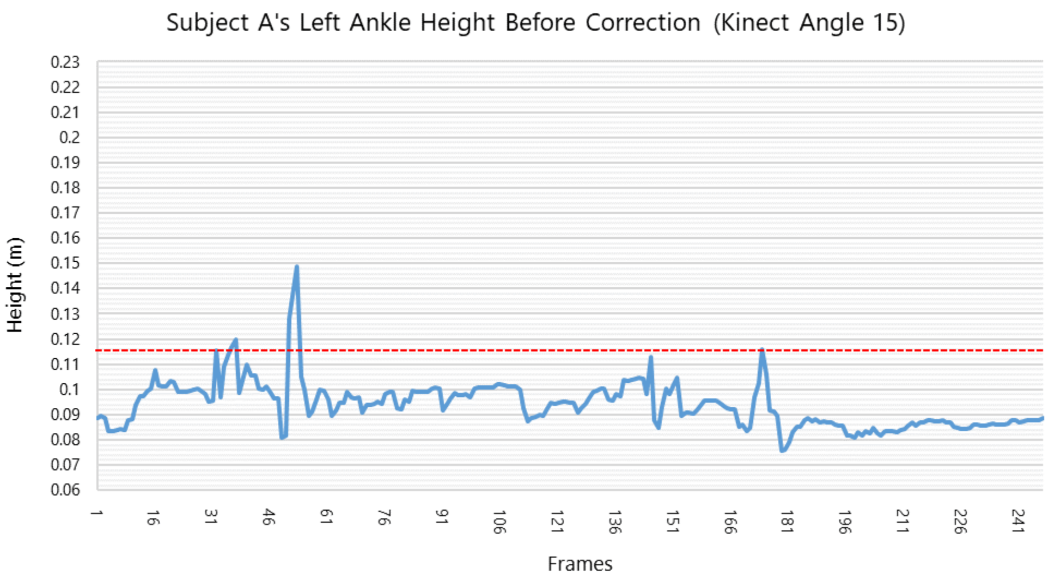



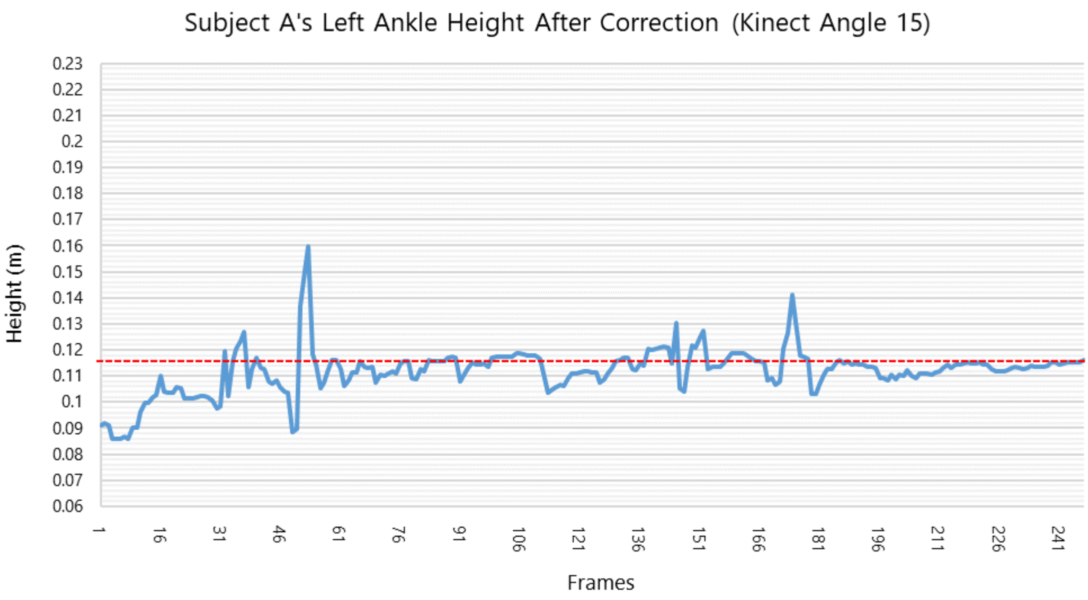

Figure 5:13. Comparison between the original and corrected subject ankle's height and the effect of the joint to the camera.

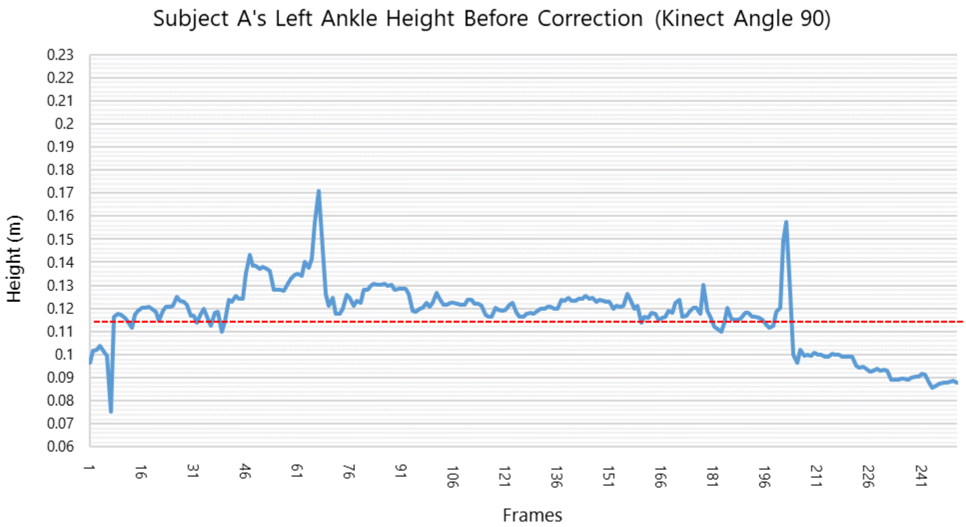
Figure 5:13 Panel (c) shows a subject's walking path towards the Kinect camera. The walking path consisted of two phases (t1) walking towards the Kinect camera and (t2) moving away from the Kinect camera. The subject was at 45 degrees in reference to the Kinect cameras. Figure 5:13 Panel (b) shows the subject's left ankle height to the ground and its Z-axis distance to the Kinect camera. The result showed that the ankle's angle to the Kinect's camera references point does not affect the data reading and the correction algorithm. Panel (a) compares the subject's left ankle height to the ground during gait analysis in both scenarios (with and without the correction being applied). The dotted line represents the subject's actual ankle height in stand still position.

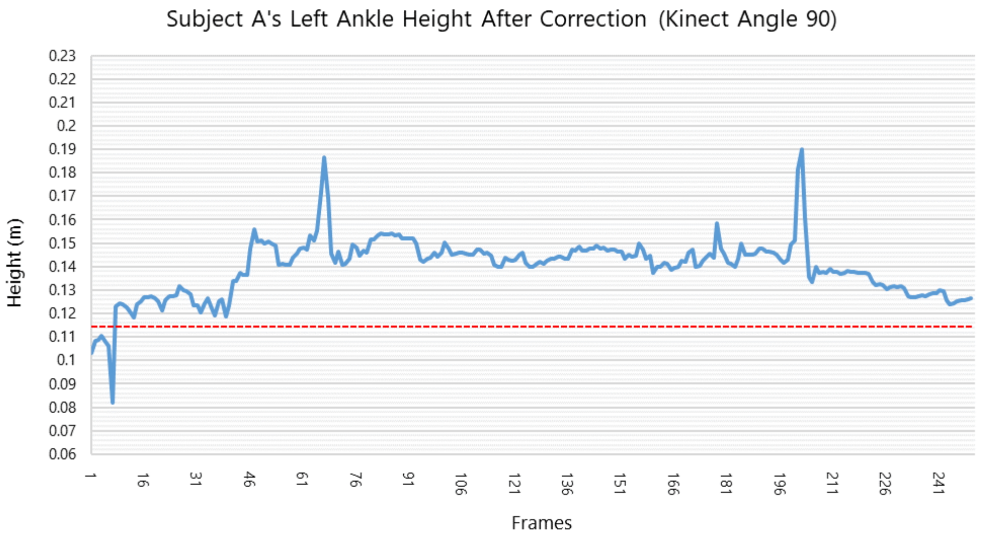
It was observed that the Kinect's height to the ground did not have any impact on the data collection whereas its angle to the floor proved to have a statistically significant effect on the data collection and readings. While the Kinect's data collection and consequently the proposed correction algorithm accuracy were at their highest when the Kinect's angle to the floor was within the range of 15±3 and 45±3 degrees, angles higher/lower than this range proved to be problematic and inaccurate. A possible explanation would be the effect of the Kinect's limited field of view on covering subjects' joints and detecting floor plane during the entire gait cycle.

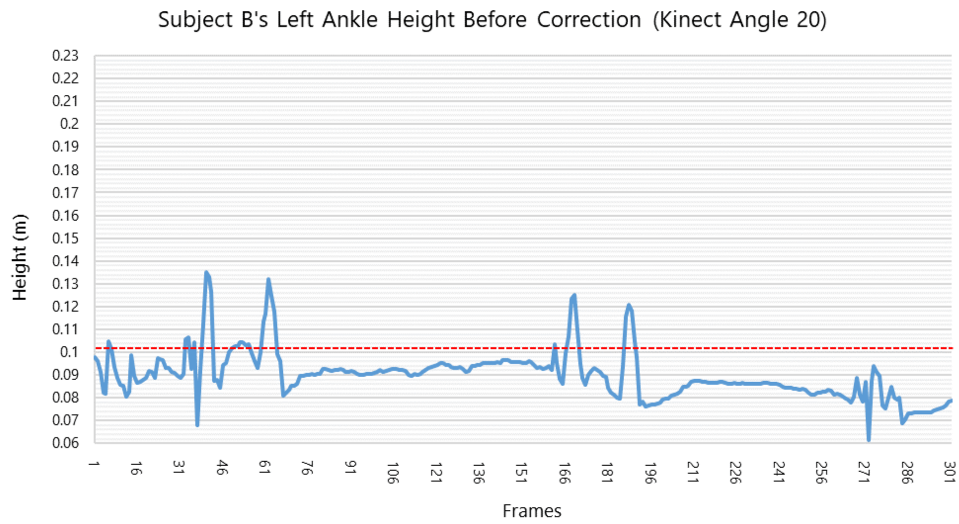
Figure 5:14 illustrates the effect of different Kinect's angle to ground on its data collection accuracy and the proposed correction algorithm. The corrected data was then used to calculate the gait characteristics and the number of footsteps.

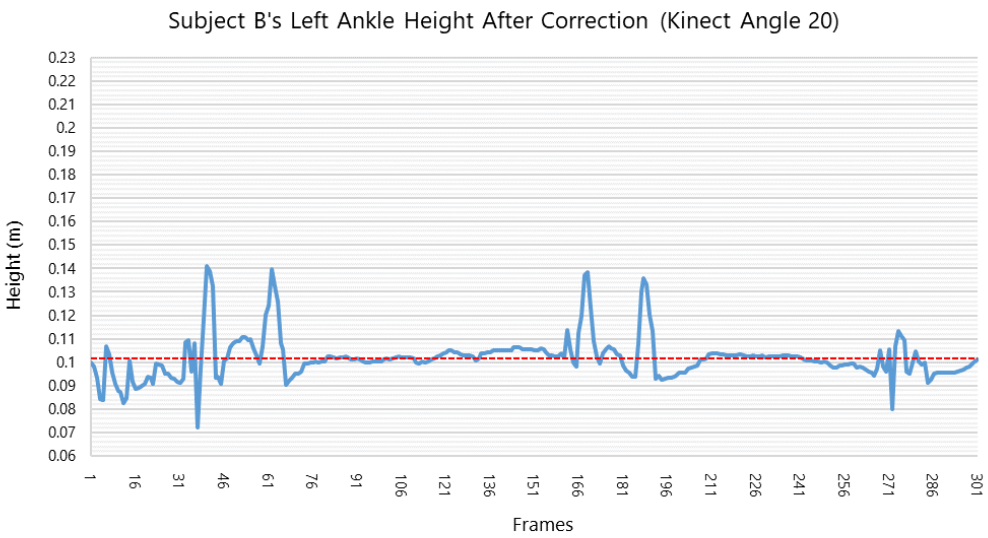



Subject A's Left Ankle Height After Correction (Kinect Angle 15)
Height (m)
0.23
0.22
0.21
0.2
0.19
0.18
0.17
0.16
0.15
0.14
0.13
0.12
0.11
0.1
0.09
0.08
0.07
0.06
1
16
31
46
61
76
91
106
121
136
151
166
181
196
211
226
241
Frames


Subject A's Left Ankle Height Before Correction (Kinect Angle 90)
Height (m)
0.23
0.22
0.21
0.2
0.19
0.18
0.17
0.16
0.15
0.14
0.13
0.12
0.11
0.1
0.09
0.08
0.07
0.06
1
16
31
46
61
76
91
106
121
136
151
166
181
196
211
226
241
Frames


Subject A's Left Ankle Height After Correction (Kinect Angle 90)
Height (m)
0.23
0.22
0.21
0.2
0.19
0.18
0.17
0.16
0.15
0.14
0.13
0.12
0.11
0.1
0.09
0.08
0.07
0.06
1
16
31
46
61
76
91
106
121
136
151
166
181
196
211
226
241
Frames


Subject B's Left Ankle Height Before Correction (Kinect Angle 20)
Height (m)
0.23
0.22
0.21
0.2
0.19
0.18
0.17
0.16
0.15
0.14
0.13
0.12
0.11
0.1
0.09
0.08
0.07
0.06
1
16
31
46
61
76
91
106
121
136
151
166
181
196
211
226
241
256
271
286
301
Frames


Subject B's Left Ankle Height After Correction (Kinect Angle 20)
Height (m)
0.23
0.22
0.21
0.2
0.19
0.18
0.17
0.16
0.15
0.14
0.13
0.12
0.11
0.1
0.09
0.08
0.07
0.06
1
16
31
46
61
76
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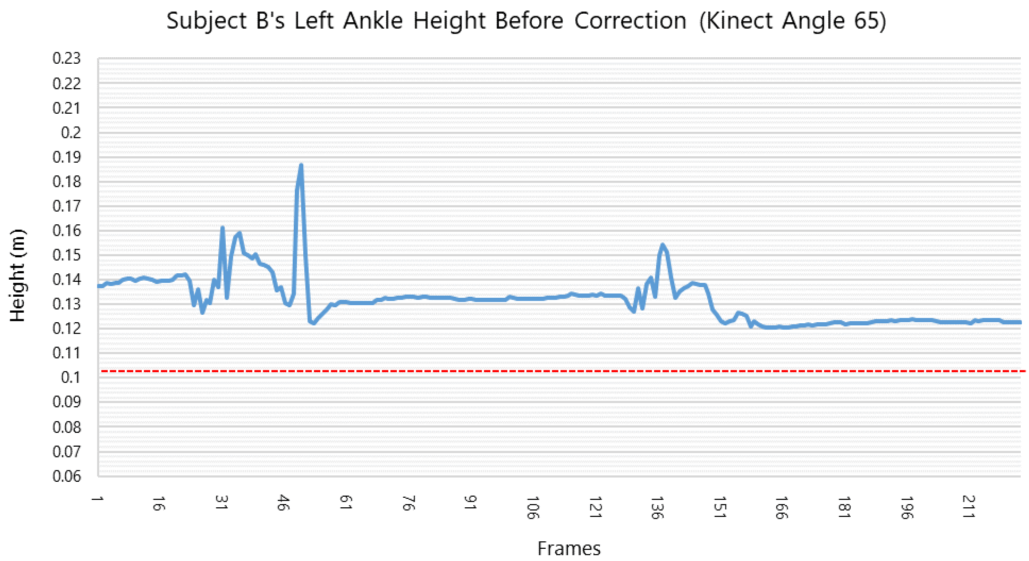
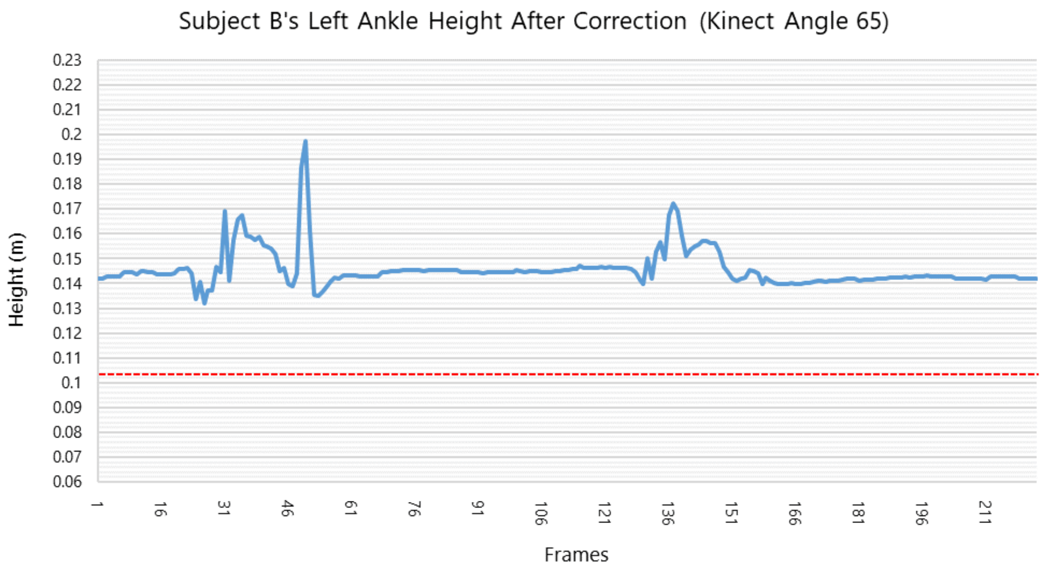
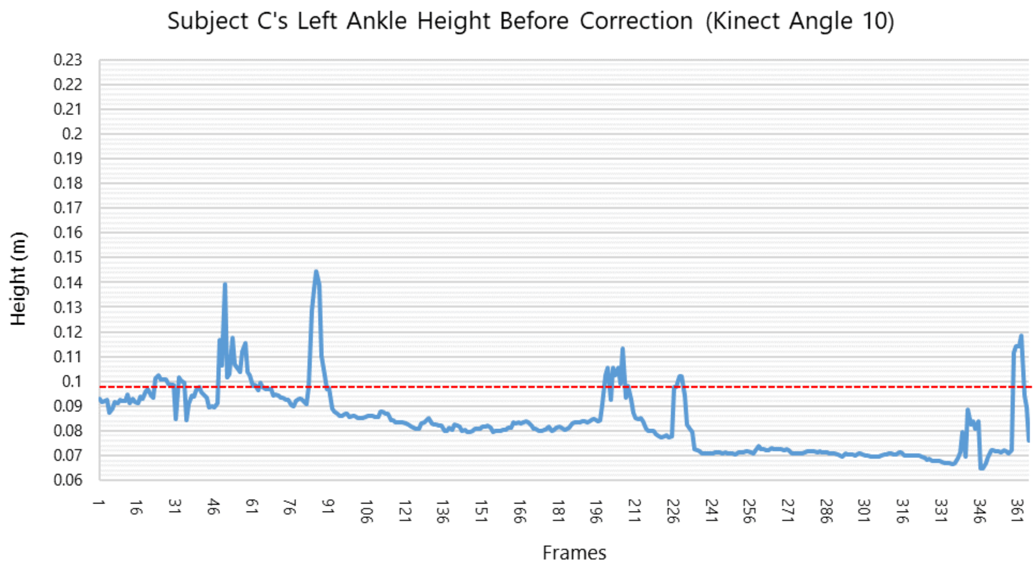
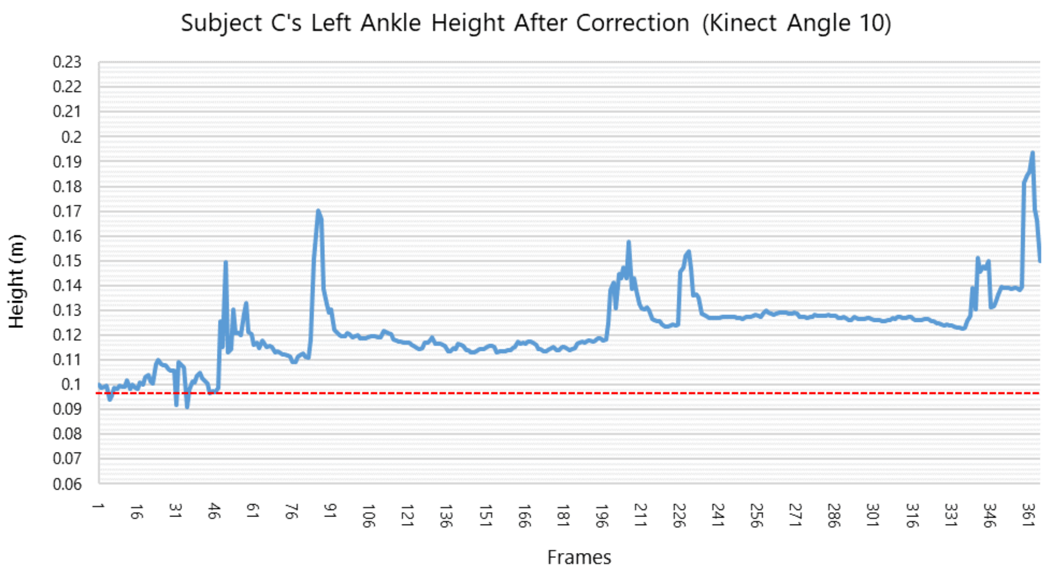
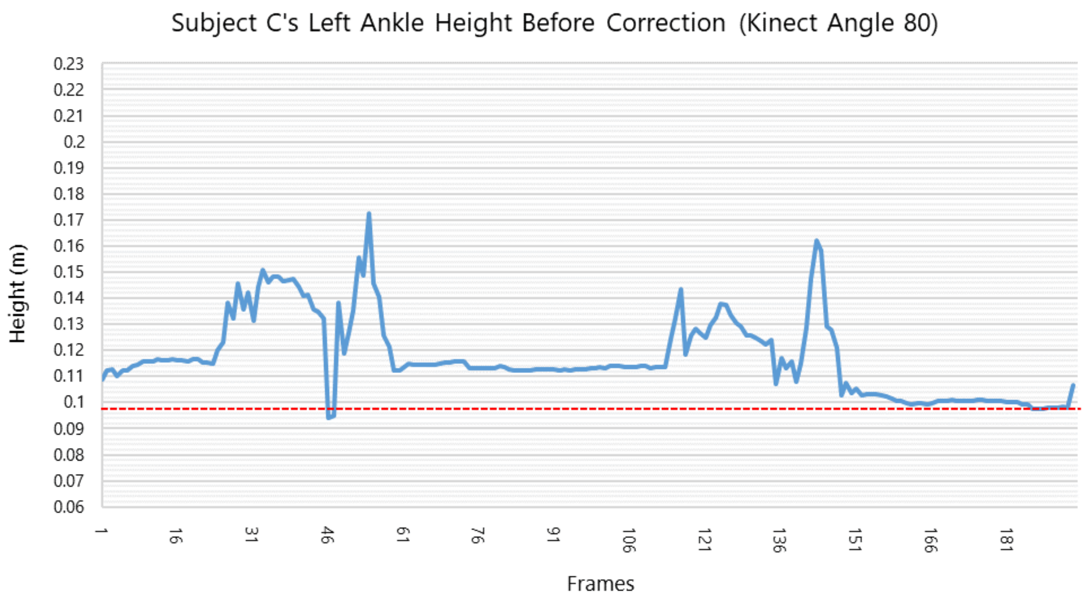
256
271
286
301
Frames


Subject B's Left Ankle Height Before Correction (Kinect Angle 65)
Height (m)
0.23
0.22
0.21
0.2
0.19
0.18
0.17
0.16
0.15
0.14
0.13
0.12
0.11
0.1
0.09
0.08
0.07
0.06
1
16
31
46
61
76
91
106
121
136
151
166
181
196
211
Frames


Subject B's Left Ankle Height After Correction (Kinect Angle 65)
Height (m)
0.23
0.22
0.21
0.2
0.19
0.18
0.17
0.16
0.15
0.14
0.13
0.12
0.11
0.1
0.09
0.08
0.07
0.06
1
16
31
46
61
76
91
106
121
136
151
166
181
196
211
Frames


Subject C's Left Ankle Height Before Correction (Kinect Angle 10)
Height (m)
Frames


Subject C's Left Ankle Height After Correction (Kinect Angle 10)
Height (m)
Frames



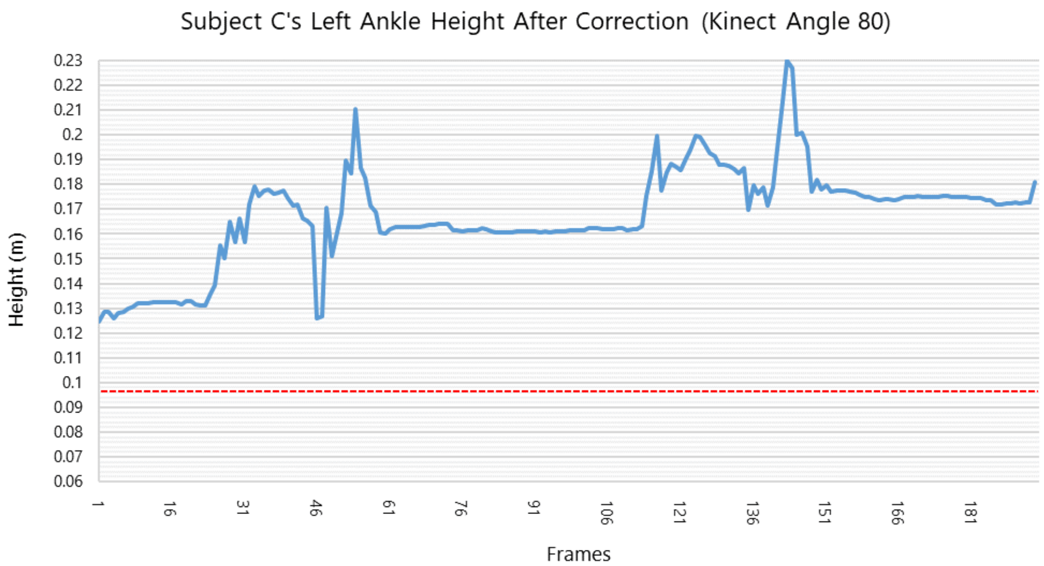




Figure 5:14. Kinect data collection accuracy before and after the correction algorithm being applied at different angle to the ground. The dotted line represents the subject's actual ankle height in stand still position.

Table 5:3 presents the Kinect v2 inaccuracies comparison for both before and after the correction algorithm was applied. It is clear that the margin of error varies between different subjects, which can be explained by different Kinect behaviour in data collection based on subjects' different shoes and trousers types, as well as colours and materials. Nonetheless, the difference between subject's actual and calculated ankle height deviation for all subjects fall under the estimated margin of this study.

Table 5:3. Kinect v2 accuracy in detecting subjects' ankle height before and after the correction algorithm being applied

| **Subject Number** | **Ankle Height Inaccuracies without Correction (%)** | | **Ankle Height Inaccuracies with Correction (%)** | |
|---|---|---|---|---|
| | **Right** | **Left** | **Right** | **Left** |
| 1 | 23.45 | 23.78 | 4.02 | 4.38 |
| 2 | 14.56 | 16.62 | 3.60 | 4.78 |
| 3 | 29.36 | 28.28 | 5.91 | 5.03 |
| 4 | 30.11 | 34.40 | 7.50 | 8.26 |
| 5 | 31.47 | 29.44 | 3.52 | 5.51 |
| 6 | 25.01 | 21.79 | 1.56 | 1.38 |
| 7 | 23.19 | 23.05 | 7.73 | 8.42 |
| 8 | 29.49 | 29.55 | 3.74 | 4.97 |
| 9 | 31.31 | 29.57 | 5.52 | 6.86 |
| 10 | 30.02 | 29.18 | 8.19 | 8.97 |
| 11 | 15.09 | 16.55 | 2.68 | 3.01 |
| Average | **25.73** | **25.65** | **4.90** | **5.59** |
| Standard Deviation | **5.87** | **5.48** | **2.10** | **2.24** |

A correction algorithm was applied to subjects' ankles distance to the floor in order to compensate for the Kinect's v2 inconsistencies in joints' localisation, which ultimately made footstep detection based on skeletal data and plane detection techniques possible. The initial ankle's height data reading inaccuracies were decreased after the correction algorithm was applied from 25.72 % and 25.66 % (R/L ankle) to about 5.59 % and 4.91 % on average, among all subjects, therefore, resulting in greater accuracy in footstep detection from the original 42.06 % and 43.65 %, to 79.37 % and 80.16 % on average, for right and left ankles, respectively, among all subjects. It was studied that the effective range for the correction algorithm was between 1.6 to 2.9 metres from the Kinect camera; in which before and after this range, the data reading inaccuracies returned back to the original values. Moreover, although the Kinect's height did not affect the data reading, the camera's angle had a statistically significant effect: it was observed that while the camera's angle to the floor facing downward is within the range of 15±3 and 45±3 degrees, the data were also at their highest accuracy. This can be due to the fact that angles lower than 15±3 and higher than 45±3 degrees cannot cover most of the subject's joints and detecting floor plane in a frame due to the Kinect's limited field of view.

### 5.5.2 Knee Angle Approach

Eleven subjects were asked to walk in pre-determined paths while their skeletal data was captured by Kinect v2, which was placed at different heights and angles to the ground. Figure 5:15 illustrates a subject's walking session and knee joints behaviour during a gait cycle. It shows that in a standstill pose or a during foot contact phase, the knee joint angle remains approximately at 176 degrees. The acquired signal required no further processing as it had low Signal to Noise Ratio (SNR) for gait performance analysis resulting in a low latency, low-resource consumption footstep detection.

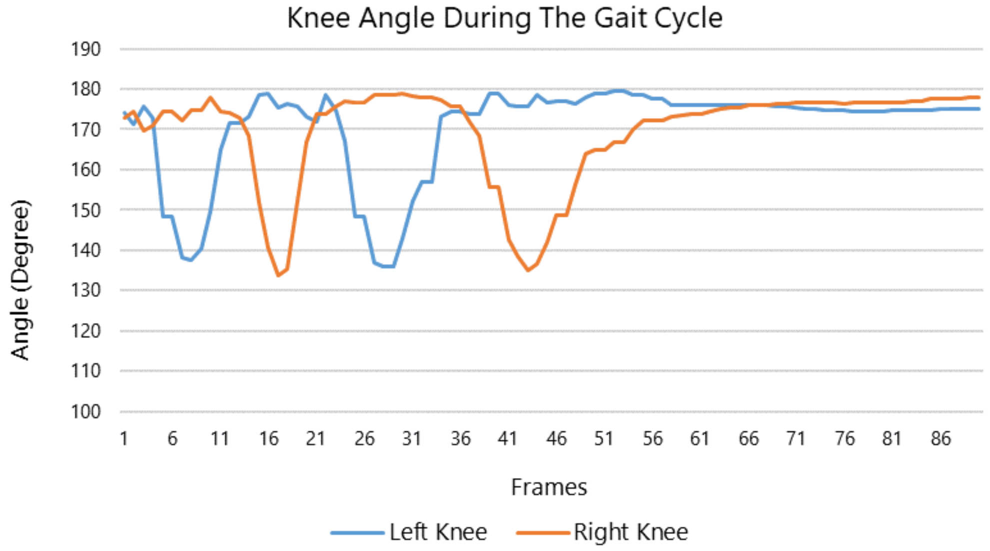



Figure 5:15. Knee joint angle value during a gait cycle

Figure 5:16 shows the same subject's walking session, walking towards the Kinect v2 camera. It indicates that the knee joint angle reading remained unaffected by the joint's distance-to-Kinect changes, as it is relative to the subject's skeletal joints. The subject's right knee data was omitted in the figure for simplicity.

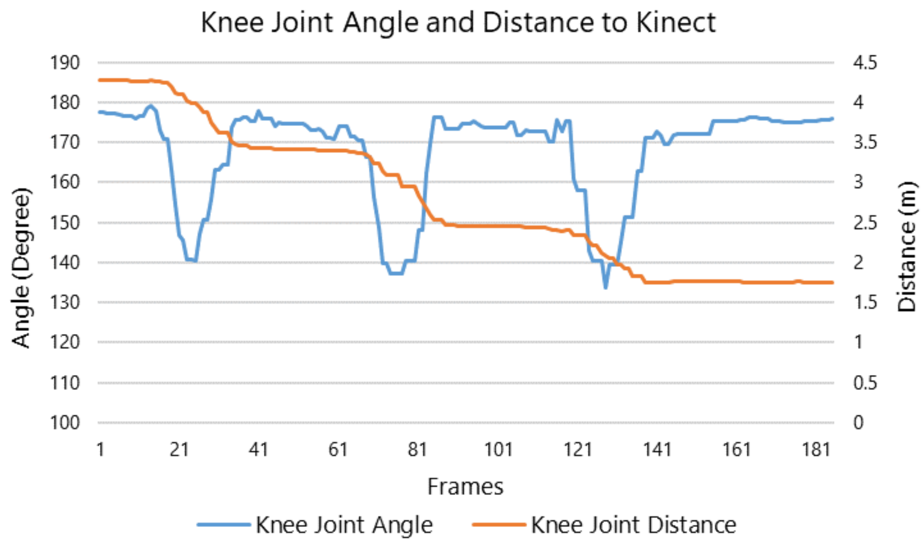



Figure 5:16. Knee joint angle and its distance to the camera during a gait cycle

The Knee joints angle performance during a gait cycle was compared against a different footstep detection method based on the subject's ankle joints distance-to-ground (Figure 4:9), in order to evaluate how the footstep detection accuracy has improved. The following figure shows the same walking session based on the subject's ankle joint distance-to-ground.

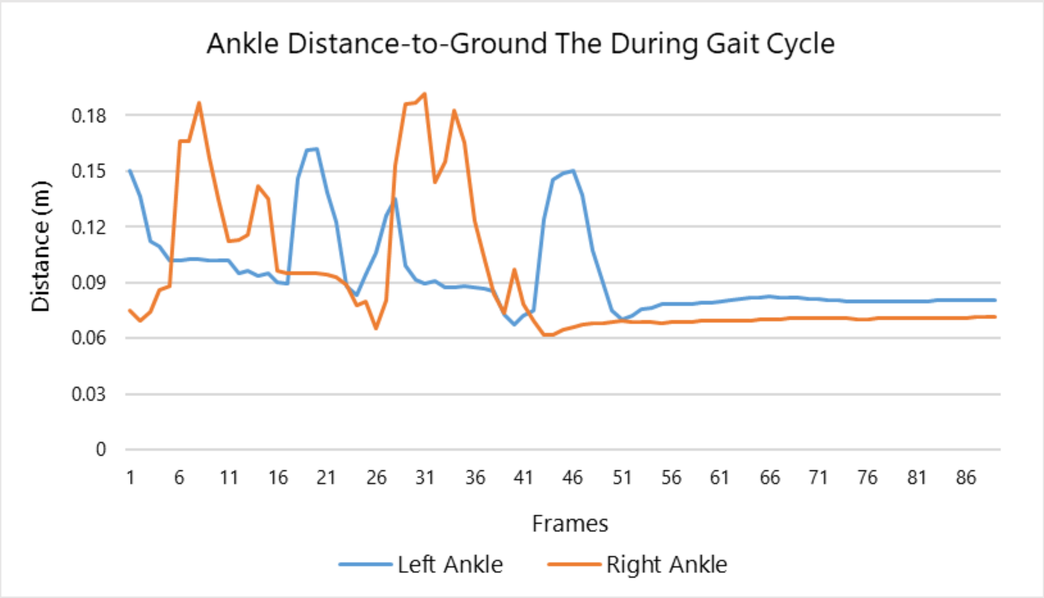



Figure 5:17. Ankle joint distance-to-ground value during a gait cycle

As Figure 5:17 illustrates, not only joints height to the ground detection by the Kinect v2 is noisy and less accurate, but also inconsistent and highly dependent on subject's distance to the camera due to the Kinect's aforementioned issues.

As mentioned previously, the Kinect v2 camera was placed at different distances and angles compared to the ground plane. It was observed that different heights from the ground (including 0.65, 1 and 1.57 meters) did not have any effect on the knee joint angle measurement as long as the subject was within the Kinect v2 detection range. Different Kinect camera angles (0, 10, 22 & 45 degrees compared to the ground plane) were also studied, in order to determine the possibility of different outcomes. It was concluded that similar to the Kinect's height, the camera's angle did not have a significant effect on the measurement of the knee joint angle. Nonetheless, it was observed that as soon as a knee's next closest joint (such as hip or ankle) becomes undetected due to an obstruction or limited field of view, the knee joint angle reading becomes unreliable. Thus, this study did not cover the effect of angles larger than 45 degrees to the ground due to the Kinect's limited field of view.

It was also concluded that the footstep detection using solely the knee joint angle is a reliable method to detect foot-offs and foot contacts phases of a gait cycle. The system showed 86.37 % and 86.67 % accuracy for left and right foot, respectively, compared to the ankle joint distance-to-ground detection algorithm accuracy of 43.65 % and 42.06 % for left and right foot, respectively. Moreover, the proposed method had less footstep detection latency (200 ms) compared to the 250 ms delay in the ankle joint distance-to-ground detection algorithm.

## 5.6 Laser System

As mentioned in the previous chapter, at the centre of this research is the creation of a visual aid (a set of laser lines) to be projected in front of the patient experiencing a FOG incident, in an attempt to provide a visual stimulant to assist him/her taking the next step. The implementation of this relies in a set of two independent servo motors (capable of moving horizontally and vertically) being able to project the laser lines in front of the patient. This would mean that the position and the orientation of the subject within the space have to be read and taken into account.

Figure 5:18 demonstrates the calculated vertical angle based on the subjects' feet joints distance to the Kinect camera in Z-axis. The right foot has been omitted in the graph for simplicity.

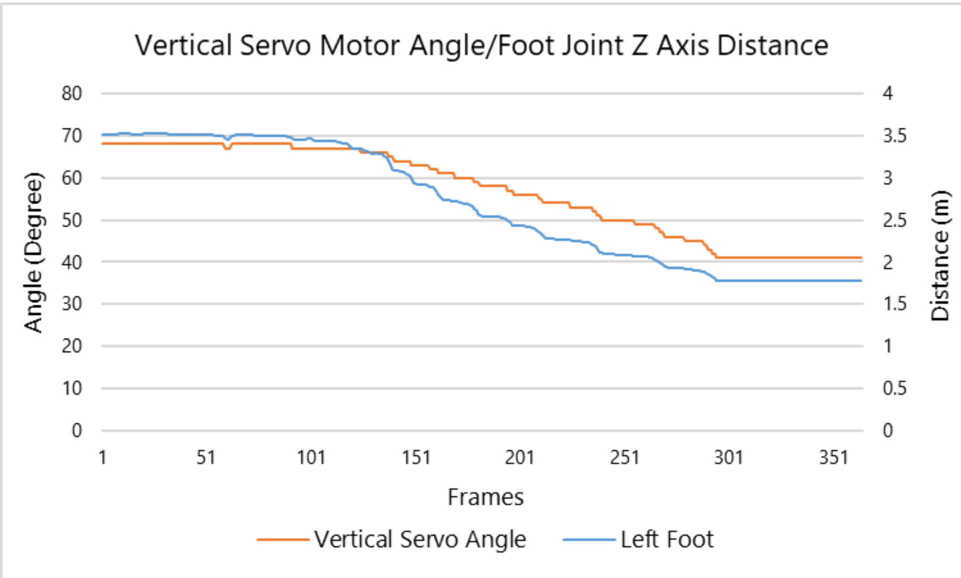



Figure 5:18. Vertical servo motor angle relation to the subject's foot joint distance to the Kinect camera in Z-axis

As Figure 5:18 demonstrates, the system provides highly accurate responses based on the subject's foot distance to the camera in Z-axis and the vertical servo motor angle.

Subjects were also asked to rotate their body in front of the Kinect camera to test the horizontal angle determination algorithm and as a result the horizontal servo motor functionality. Figure 5:19 shows the result of the calculated horizontal angle using Equation 4:8 for left and right direction.

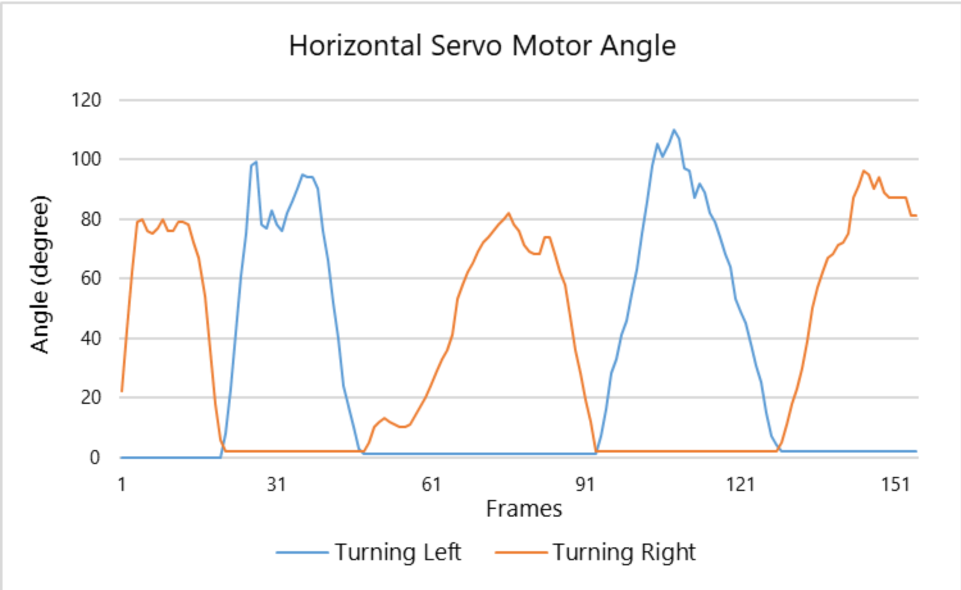



Figure 5:19. Horizontal servo motor angle changes according to the subject's body orientation and direction during a test

Figure 5:19 shows how the system reacts to the subject's body orientation. The horizontal angle determination proved to be more susceptible to noise compared to the vertical angle calculation. The subject was asked to face the camera in a stand still position while rotating their torso to the left and to the right in turns. This is due to the fact that as the angle increases to more than 65 degrees, the farther shoulder to the camera would be obstructed by the nearer shoulder and as a result, the Kinect should compensate by approximating the whereabouts of that joint. Nonetheless, this did not have any significant impact on the performance of the system.

A series of pan/tilt servo motors have been used alongside laser line projectors to create a visual cuing system, which can be used to improve the mobility of PwP. The use of the system eliminates the need to carry devices, helping patients to improve their mobility by providing visual cues. It was observed that this system can provide an accurate estimation of the subject's location and direction in a room and cast visual cues in front of the subject accordingly. The Kinect's effective coverage distance was observed to be between 1.5 to 4 meters form the camera, which is within the range of the area of most of the living rooms, thus making it an ideal device for indoor rehabilitation and monitoring purposes. To evaluate the Kinect v2 accuracy in calculating the vertical and horizontal angles, a series of eight Vicon T10 cameras were also used as a golden standard.

As a future improvement addressing to increase coverage of the system, the two servo motors can be mounted on a rail attached to the ceiling capable of moving around and projecting the lines in front of the patient.

## 5.7 Focus group try outs and used feedback

Fifteen patient having Parkinson's and experiencing frequent FOG were provided by the Parkinson's UK institute, following an ethical approval by the University. The participants, were instructed to walk towards a fix-positioned Kinect v2 camera in a pre-determined path within the distance range of 4.33 meters to 1.38 meter in a room hired for the focus group event (Figure 5:20) while their gait and their movements were analysed by the developed system. Figure 5:20 shows the process of testing the system by one participant while simulating a FOG. Images are from the point of view of the Kinect camera.

Figure 5:20. A PD patient volunteering to try out the system’s capabilities in detecting FOG. Visual cues are projected in front of him, on the floor based on his whereabouts

Figure 5:21 shows the design of the system’s smartphone companion application for healthcare providers, doctors and carers. The application provides information about the subject including the number of estimated FOG incidents as well as a notification to a carer if a critical fall incident occurs. Moreover, it provides the carer with the ability to send visual or auditory cues during a FOG incident or contact emergency services. Based on the user preference, the system can contact a relevant person via email or through notifications in the companion smartphone application including a live stream of the incident and the time stamp of the relevant date and time. An approved carer, once notified, can also initiate a Skype conversation where he/she can talk to the patient and provide further support. Figure 5:21 shows the system behaviour when a fall incident occurs. As Figure 5:21 depicts, the developed software was designed as an open-ended solution on an UWP, that can provide other types of cues such as auditory cues to the patients. However, while feasible, such additions are beyond the scope of this specific study.

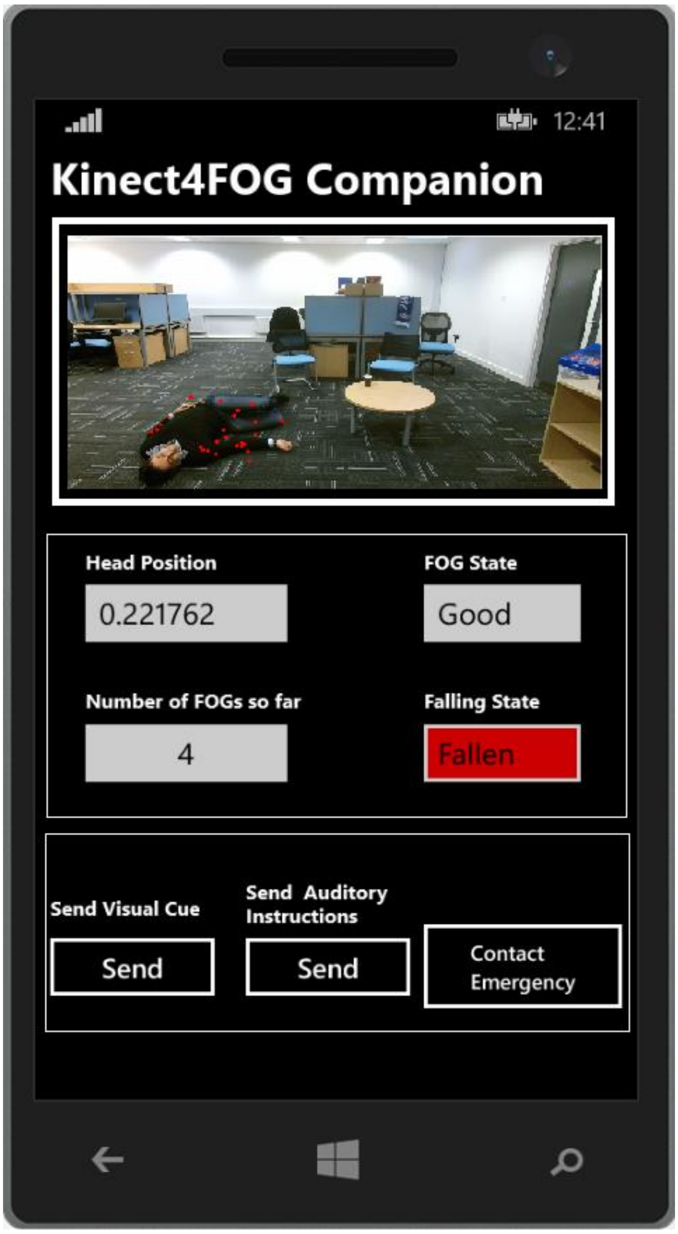



Figure 5:21. System's companion smartphone application in action

At the end of the session, participants were asked to provide feedback (Appendix H and I) and complete a survey form in which the results are listed in the following table:

Table 5:4. Focus Group Questioner Feedback

| Question | Strongly agree (%) | Agree (%) | Neither agree nor disagree (%) | Disagree (%) | Strongly disagree (%) |
|---|---|---|---|---|---|
| The system would be easy to use. | 33.3 | **46.6** | 13.3 | 6.6 | 0 |
| The system FOG detection was accurate. | 20 | **66.6** | 13.3 | 0 | 0 |
| Auditory cue would also be beneficial to be implemented. | 20 | **46.6** | 20 | 13.3 | 0 |
| The system fall detection was accurate. | **53.5** | 47 | 0 | 0 | 0 |
| I am concerned about my privacy when I use the system at home. | 0 | 0 | 20 | **40** | **40** |
| The overall system was helpful in improving my mobility, especially during a FOG. | 26.6 | **53.3** | 20 | 0 | 0 |
| The visual aid was helpful in increasing my mobility and walking performance. | 13.3 | **86.6** | 0 | 0 | 0 |
| I would use the system in my house. | **40** | **40** | 20 | 0 | 0 |

The results obtained in the above table related to fall detection are based on demonstration made by a healthy participant not the volunteers. When asked about the healthcare provider remote communication method with the patient during a critical fall incident, eight patients suggested a telephone call while six suggested a Skype video call and one remained neutral. While the prototype system cost £137.69 to build excluding the controlling PC, patients suggested that they would be willing to pay between £150-500 to have the system installed in their homes. Nevertheless, if the prototype is released as a commercial device, other economic factors including insurance, maintenance, and the necessity to install multiple systems in different rooms would inevitably escalate the price. Finally, when asked about possible improvements to the final product, eight of the patients suggested that a hybrid/portable method that can also provide outdoor visual cues, would be very beneficial while seven wanted it to be as simple as possible to keep the cost down and have a separate device for outdoor purposes.

The QR code (Appendix K) demonstrates the use of our system in action upon detection of a FOG event by providing visual cues and notifications to doctors and carers.

## 5.8 Summary

This chapter provided the empirical results and findings for the research verifying the hypothesise provided in the previous chapter. After an in-depth analysis of the Kinect v1 capabilities and its performance, it was concluded the Kinect v2 introduces more advantages over its predecessor including higher frame rate and resolution. Despite the fact that the Kinect v2 SDK was in beta phase and missing a lot of built-in features, as the advantages of using it, outweighed its shortcomings, thus, the Kinect v2 was chosen for this project. Moreover, for fall detection, as mentioned before, due to the limited training dataset, and also due to the relative simplicity of the detection (fall), heuristic approach was proven to be more accurate in detecting true positive falls compared to the machine learning counterpart. Additionally, as discussed, for footstep detection and consequently the FOG tracking for patients, the knee angle method was chosen as the preferred method for this study due to the fact that it lacks the inaccuracies and limitation of the other method, which was based on the subject's ankle height to the ground. Combined with the developed hardware and software interface, the chosen methods yielded promising results when the system was demonstrated to the focus group and tested by some of the volunteers, based on their feedback.

# Chapter 6: Conclusions and Future Work

The aim of this study was to Introduce two new footstep detection techniques one based on the subject's knee angle and one based on the subject's ankle vertical height to the ground; Reducing the Microsoft Kinect's intrinsic inaccuracies in skeletal data reading for the subject's ankle vertical height to the ground footstep detection technique; resulting in the increase in accuracy for the footstep detection algorithm by introducing a new correction algorithm. Moreover, this research aimed to provide an automatic and remotely manageable monitoring system for PwP gait analysis and fall detection. The results of which would lead to the development and evaluation of an integrated system capable of detecting falls and FOG, providing visual cues orientated to a user's position, and providing a range of communication options. Based on the patients' feedback, and in accordance with previous research studies, it was concluded that our system can indeed be helpful and used as a replacement to alternative, potentially less-capable technologies such as laser canes and laser-mounted shoes. Due to the system being an open-ended, proof of concept, the system's coverage is limited to only one axis. Nonetheless, future improvements can eliminate this constraint by mounting the laser pointer, servo motors and the Kinect camera on a circular rail attached to the ceiling capable of moving/rotating in accordance to the subject position and direction in a room. Although this research was focused solely on the automatic projection of dynamic visual cues, the system was designed to accommodate additional features in future developments, such as auditory cues.

## 6.1 Conclusion

Overall, based on the patients' feedback, the system represents a viable solution for detecting fall incidents and providing help during a critical fall when the patient is unattended. Furthermore, the system has the capacity to provide an unobtrusive and automatic visual cue projection when needed at home during a FOG episode.

This study set out to explore the possibility of implementing an integrated system based on Microsoft Kinect v2 capable of unobtrusively detecting falls and FOG while providing remote support to the patients using developed applications. The system was designed to provide visual cues in a form of laser lines in front of the patient upon the detection of FOG in order to improve locomotion. Additionally, this research set out to conduct a comparison between different Kinect's open source APIs such as OpenNI/NITE against the official Microsoft Kinect SDK for Windows and investigated advantages and disadvantages for each SDK. It was concluded that that the Microsoft official SDK for Windows was ideal for the implementation of our project, as it does not require calibration before the joint tracking process can take place. Nevertheless, OpenNI/NITE implementation proved to have a reliable and more consistent joint tracking capabilities as well as a built-in support for streamed image saving to the local disk for further analysis.

As mentioned before, the project's researchers gathered joint coordination data from our test subjects (male and female) with different heights, body builds, and walking styles. During our analysis, it was found that our developed system was able to identify the movement phases (e.g. moving, standing, sitting, etc.). Our evaluations suggested that the consistency and stability of joint position tracking data using Kinect v1 were acceptable when only one subject was present in the field of view. However, the system efficiency, performance and consequently the sampling rate dropped exponentially when an additional subject appeared in the field.

Moreover, the ideal testing environment for such a project was investigated. By studying the past projects reports and our experimental results it was concluded that the increase in the subject's distance from the sensor helped the consistency of the joint tracking process. However, a distance further than 3.5 meters proved to be problematic where the system was no longer able to identify different joint positions. As mentioned earlier, the optimal subject's distance from the Kinect v1 sensor was in the range of 2 to 2.5 meters. The ideal location of the camera was proved to be at the height of 2.2 meters facing downward.

The rotation of the subject in different angles caused a huge decrease in the system consistency to track joints. It was observed that having two or three Kinect sensors interconnected to each other might solve the issue, as there would be a 360-degree coverage of the testing environment. Nevertheless, this approach would require extra computation and preparations in terms of calibration between the cameras as well as time synchronisation between data feeds from each camera.

The type and the colour of the subject's clothes did not appear to make a significant impact on the joint tracking quality. Nevertheless, more investigation is required towards the effect of clothing on the Kinect's recognition capabilities.

The aforementioned limitations of the Kinect v1 and the hardware enhancements and improvements including a wider field of view, farther coverage, and higher resolution in depth and colour data of the Kinect v2 proved it to be a better candidate for the use on this project. Consequently, , a Kinect v2 has been used for gait performance analysis and evaluation due to its higher accuracy.

For fall detection, two different approaches including heuristic and machine learning (using AdaBoostTrigger algorithm) based on Microsoft Kinect v2 sensor were implemented and evaluated. The efficiency and accuracy of both were compared against one another in similar conditions.

Heuristic approach showed higher accuracy in terms of detection of true positive falls as it works independent to the number of pre-operation training videos. Heuristic algorithms are very efficient for discrete detections such as falls, as long as the detection case is simple enough to be implemented algorithmically. On the other hand, AdaBoostTrigger machine learning approach effectiveness is greatly dependent on the number of training samples. Correct and accurate sample tagging plays a significant role in reducing latency and increasing accuracy. Nevertheless, the overall success rate of a machine learning algorithm with a small training dataset can be increased by implementing and combining more confidence factors.

Overall, the machine learning approach is ideal for detections that are more sophisticated in terms of body movements and require a lot of thresholding and variables such as complex and continues body gestures or gait disorders, but for simpler cases such as fall detection, its disadvantages outweigh its benefits; mainly due to its increased needs for system resources (i.e. CPU and memory) to process information beforehand. Moreover, video tagging is a painstaking task and requires a lot of time and training data.

Thus, it is concluded that for fall detection with a small number of training samples (11), the heuristic approach provides results that are more accurate. Nonetheless, by increasing the number of training data, the accuracy of the machine learning algorithm would also be increased. Machine learning approach accuracy would be significantly higher in complex scenarios where a continuous and sophisticated gesture needs to be detected.

Although the attempts undertaken on this research helped improving the accuracy of footstep detection and joint 3D localisation at different distances, using only a single Kinect v2 sensor and based on the ankle joint distance-to-ground, which can be used in various gait analysis projects. It was concluded that for FOG symptom detection in PwP, which requiring a higher accuracy in data reading for footstep detection due to the nature of the symptoms, a more accurate technique is needed, hence the implementation of a knee angle footstep detection.

In this thesis, a novel low-latency and low-resource approach in detecting footsteps including foot-offs and foot contacts phases of a gait cycle based on a subject's knee joint angle was also introduced. It was concluded that neither the camera's height nor its angle to the ground has a significant impact on the data acquisition of the subject's knee joint angle, and as a result, on the footstep detection process. Nonetheless, the detection of the proposed system was limited to the Kinect v2 practical skeletal distance coverage (1.6 to 4 meters). Moreover, the system showed a consistent measurement, as long as none of the knee's neighbouring joints (joints that are needed to be calculated for knee joint angle determination) is obstructed or undetected by the Kinect v2 camera.

Overall, due to the low latency and high accuracy of this technique and the fact that the system's accuracy is unaffected by the Kinect v2 intrinsic inaccuracies or its height or angle, the proposed system can be used for gait assessment scenarios that require a high level of accuracy as it is capable of detecting subtle movements.

The results of this research also verified that it is possible to implement an automatic and unobtrusive FOG monitoring and mobility improvement system while being reliable and accurate at the same time. Nonetheless, there are many limitations to this approach including the indoor aspect of it and the fact that it requires the whole setup including the Kinect, servos, and laser projectors to be included in the most communed areas of a house such as the living room and the kitchen. Having said that, the affordability (the entire setup except the controlling PC will cost £137.69), and ease of installation would still make it a desirable solution should more than one setup need to be placed in a house. Nevertheless, the system's main advantages such as real-time patient's monitoring, improved locomotion and patient's mobility, unobtrusive and intelligent visual cue projection, make it in overall, a desirable solution that can be further enhanced for future implementations.

Additionally, the results of this research demonstrate the viability of using an automatic and unobtrusive system for monitoring and improving the mobility of PwP based on the Microsoft Kinect camera. The implementation of a visual cuing system based on laser lines for improving FOG incidents in PwP has been developed and reviewed by 15 PwP. Feedback provided regarding the usability of the system showed promising results. All the participants either 'agreed' or 'strongly agreed' with the fact that the system's visual cues are helpful in increasing their mobility and walking performance. 86.6 % of those who tested the system, were satisfied with the system's FOG detection whereas 13.3 % neither agreed or disagreed about the system's competency in detecting FOG incidents.

Overall, compared to current commercially available alternative devices, this system provides a broadly affordable solution while, theoretically, providing a means of improving patients' mobility unobtrusively. Moreover, this solution is one of the few that can function in an automated fashion, both in terms of event detection, cue provision and when establishing communication with third parties. The user does not need to wear something, charge a device, carry anything or switch it on or off. The ease of use and simple installation process compared to other available solutions can make the system a desirable solution for indoor assisting purposes as suggested by participants in the current study.

## 6.2 Future Work

This research laid the foundation to explore the feasibility of commercially available apparatuses such as Microsoft Kinect sensor as a home monitoring service for PwP as a rehabilitation fall detection tool. It also provided the possibility of using an automatic and unobtrusive system to deliver on-demand visual cues based on laser lines in front of a patient regardless of one's position and orientation in a room to improve one's locomotion and gait performance during a FOG incident. As a next step, one could improve the system's coverage with a series of this implemented system to be installed in PwP houses to cover most of the communal areas or areas where the patient experiences the FOG the most. One could also investigate the possibility of using such systems attached to a circular rail on a ceiling that can rotate and move according to the patient's location, this removes the need for extra setup in each room as the system can cover one direction at the current stage. As mentioned before, this system was designed as an open-ended platform to provide variety of supports for PwP in the future including auditory cues. The system's capabilities in providing such cues and the effect of them on PwP can also be explored. Moreover, by coupling the system with other available solutions such as laser-mounted canes or shoes, patients can use the implemented system when they are at home while using other methods for outdoor purposes. This requires integration at different levels such as smartphone application and visual cues in order for these systems to work as intended.

Additionally, with the introduction of augmented reality apparatuses such as Microsoft HoloLens, one could use Microsoft Kinect and the developed algorithms to detect FOG in PwP while using the HoloLens to provide visual/auditory cues to the patient. The implemented algorithms used in this research study can also be improved, especially for machine learning fall detection. As mentioned before, by having larger training dataset, the accuracy of the machine learning algorithm in detecting true positive falls can be significantly improved. One could also use the principal of Kinect-based machine learning tools including VGB, to implement complex detection systems such as machine learning based FOG detection.

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# Appendices

# A. Laser Project Registration and RA Class 3B-4 Form & risk assessment

Brunel University London

**Class 3B and 4 Lasers, Project Registration and Risk Assessment**

Class 3B and Class 4 lasers are capable of causing eye injury to anyone who looks directly into the beam or its specular reflections. In addition, diffuse reflections of a high-power (Class 4) laser beam can produce permanent eye damage. High-power laser beams (Class 4) can burn exposed skin, ignite flammable materials, and heat materials that release hazardous fumes, gases, debris, or radiation. Equipment and optical apparatus required to produce and control laser energy may also introduce additional hazards associated with high voltage, high pressure, cryogenics, flammable materials, toxic fluids, noise and other forms of radiation. Thus, each proposed experiment or operation involving a laser must be evaluated to determine the hazards involved and the appropriate safety measures and controls required to reduce the risk to an insignificant or low level. **A copy of this assessment must be sent to the Radiation Protection Office before the start of a project.**

**(Please complete one form per equipment and return to the Radiation Protection Office)**

| | | | |
|---|---|---|---|
| **1. School/Dept** | Electronic & Computer Engineering | **1.1 Room Number** | HWLL 307-02 |
| **2. Project Supervisor:** | Dr. Banitsas | | |
| **3. Names of personnel who use the laser system:**<br>Mr. Amin Amini Maghsoud Bigy | | | |
| **4. Brief description of the project:** | | | |
| Optimisation of systems for Parkinson's patient treatment. Through the use of a collimated laser projected on the floor, we attempt to stimulate the patient's brain in order to alleviate the debilitating effects of the disease. | | | |
| **5. Equipment Description:** | | | |
| Class of laser | 2M (cylinder is the same as the 3M one but the driving circuit is 2M, limiting its power to 5mW max)<br>3B (10 or 30mW max) | | |
| Model and Serial No. | OFL196/197/198 | | |
| Type (e.g. He-Ne) | N/A | | |
| Power Used | 3 Volts (Can be lowered down) | | |
| Max Output Power | 5mW/30mW | | |
| Wavelength Range | 532nm | | |
| Pulse Energy Used | Not mentioned in the specs | | |
| Pulse Length | Not mentioned in the specs | | |
| Pulse Repetition Rate: | Not mentioned in the specs | | |
| Specify Beam Diameter and Shape | Visible Green Line Laser | | |
| Beam termination/stop | Beam is spread to about 4 meters when mounted on a 2 meter post | | |
| **6. Equipment Location:**<br>Room No: | HWLL 307-02 | | |
| Laser warning sign on door and area | Available | | |

**Is the laser beam totally enclosed? No**

Is there a safety interlock? **No**

| | |
|---|---|
| Is there a Fail/Safe Design in place? Yes | Both at hardware and software level. Details are mentioned in the following section. |

Describe any other safety feature that is in place:

- There are both software and hardware kill switches designed to avoid direct eye contact as well as to apply instant shutdown.
- Eyewear will be used during the experimentation. Below is the details for the eyewear:
  Laser Safety Goggles EP1 190-540nm and 800-2000nm (Blue, Green, Infrared (IR) and Blu-ray Lasers).
- The whole system including the laser modules can only be used with the research computer, which is password protected and only operable in the presence of the main researcher.
- Laser modules will be placed in container to ensure that the minimum 3cm distance is being considered.
- Laser modules are only being used when nobody is presence in the room (usually at weekends) and only for a very short period of time. The rest of the project does not need the lasers to be on.
- When not being used, laser modules are kept safe in a locker.
- The input voltage for the laser modules can be lowered down for experimental purposes to have the minimum effect.
- Laser safety signs will be put in place.
- The laser will be facing a wall so the chance of direct or indirect contact will be zero.

## 7. Identification of Hazards Associated with Laser Radiation

| | | |
|---|---|---|
| 7.1 | **Are open or partially enclosed beams used during the following?**<br><br>Initial setting up and beam alignment;<br>Addition of new optical elements;<br>Day to day operation;<br>Maintenance | <br><br>**Yes**<br>**No**<br>**Yes**<br>**No** |
| If you have replied **"Yes"** to any of the above, please provide an appropriate protocol/operating procedure giving details of how the radiation risks are controlled. Enter the title of the protocol and attach to this assessment. You must also complete the Section 9 of this document. | | |
| | | |

## 8. Identification of Hazards Additional to the Laser Hazards

| | | |
|---|---|---|
| **8.1** | **Electrical Hazards**<br>*Most lasers contain high-voltage power supplies and often large capacitors/capacitor banks that store lethal amounts of electrical energy.*<br>**Are any special precautions/procedures required?** | **No** |
| 8.2 | **Are laser dyes used?**<br>*Laser dyes are often toxic and/or carcinogenic chemicals dissolved in flammable solvents*<br>Give details, if "yes". | **No** |
| **8.3** | **Are compressed gases and/or toxic gases used?**<br>*Hazardous gases may be used in laser applications, i.e., excimer lasers (fluorine, hydrogen chloride)*. | **No** |
| **8.4** | **Are cryogenic fluids used?**<br>*Cryogenic fluids can create hazardous situations. Adequate ventilation must be provided.* | **No** |
| **8.5** | **Is there a potential for fumes/vapours/Laser Generated Air Contaminants?**<br>*When laser beams are sufficiently energised to heat up a target, the target may vaporise, creating hazardous fumes or vapours that may need to be captured or exhausted.* | **No** |
| **8.6** | **Is there a potential for significant UV/visible radiation?**<br>*UV and visible radiation may be generated by laser discharge tubes, pump lamps or plasmas. The levels produced may be an eye and* ***skin hazard*** | **No** |
| **8.7** | **Is there a potential for explosion?**<br>*High-pressure arc lamps, filament lamps, and capacitors may explode if they fail during operation. Laser targets and some optical components also may shatter if heat cannot be dissipated quickly enough.* | **No** |
| **8.8** | **Is there an ionising radiation hazard?**<br>*X-rays can be produced from two main sources, high voltage vacuum tubes of laser power supplies such as rectifiers, thyratrons, and electric discharge lasers. Any power supplies that require more than 15 kV may produce x-rays.* | **No** |
| **8.9** | **Other potential hazards not identified above, Please specify** | |

## 9. Controlling Risks

If you have replied **"Yes"** to any of the above, please complete the following section and provide an appropriate protocol/operating procedure a COSHH and/or other assessments, giving details of how the associated risks are controlled, using additional paper as necessary.

| Hazard/Risks No | Control Measures | Remaining Risks | | |
|---|---|---|---|---|
| | | Insignificant | Low | Medium |
| Minimal risk of overexposure of retina to the laser. | Eye wear, hardware kill switch, software kill switch, physical barrier, physical limitations, operation time | | | |
| Please enclose COSHH and other protocols as appropriate | | | | |

As the supervisor of this project I am satisfied that appropriate steps have been taken to put in place the identified controls, reducing the risk to an insignificant level.

**Supervisor's Signature:** **Date** 15/01/2016

N.B. If there are any changes in the procedure then the above RA musd and resubmitted to the RPO.

# B. Approval Letter from Brunel for inviting Parkinson's patients

Brunel University London

College of Engineering, Design and Physical Sciences Research Ethics Committee
Brunel University London
Kingston Lane
Uxbridge
UB8 3PH
United Kingdom

www.brunel.ac.uk

7 November 2016

**LETTER OF APPROVAL**

Applicant: Mr Amin Amini Maghsoud Bigy

Project Title: Using 3D sensing and projecting technology to improve the mobility of patients with Parkinson's disease

Reference: 4311-LR-Nov/2016- 4354-2

Dear Mr Amin Amini Maghsoud Bigy

The Research Ethics Committee has considered the above application recently submitted by you.

The Chair, acting under delegated authority has agreed that there is no objection on ethical grounds to the proposed study. Approval is given on the understanding that the conditions of approval set out below are followed:

- The agreed protocol must be followed. Any changes to the protocol will require prior approval from the Committee by way of an application for an amendment.

Please note that:

- Research Participant Information Sheets and (where relevant) flyers, posters, and consent forms should include a clear statement that research ethics approval has been obtained from the relevant Research Ethics Committee.
- The Research Participant Information Sheets should include a clear statement that queries should be directed, in the first instance, to the Supervisor (where relevant), or the researcher. Complaints, on the other hand, should be directed, in the first instance, to the Chair of the relevant Research Ethics Committee.
- Approval to proceed with the study is granted subject to receipt by the Committee of satisfactory responses to any conditions that may appear above, in addition to any subsequent changes to the protocol.
- The Research Ethics Committee reserves the right to sample and review documentation, including raw data, relevant to the study.
- You may not undertake any research activity if you are not a registered student of Brunel University or if you cease to become registered, including abeyance or temporary withdrawal. As a deregistered student you would not be insured to undertake research activity. Research activity includes the recruitment of participants, undertaking consent procedures and collection of data. Breach of this requirement constitutes research misconduct and is a disciplinary offence.

Zhao Hua

Professor Hua Zhao

Chair

College of Engineering, Design and Physical Sciences Research Ethics Committee
Brunel University London

Page 1 of 1

## C. Consent Form for Focus Group participation

Brunel University London

CONSENT FORM

*The participant should complete the whole of this sheet*

*Please tick the appropriate box*

| | YES | NO |
|---|---|---|
| Have you read the Research Participant Information Sheet? | ☐ | ☐ |
| Have you had an opportunity to ask questions and discuss this study? | ☐ | ☐ |
| Have you received satisfactory answers to all your questions? | ☐ | ☐ |
| Do you understand that you are free to withdraw from the study: | | |
| • at any time? | ☐ | ☐ |
| • without having to give a reason for withdrawing? | ☐ | ☐ |
| • (where relevant, adapt if necessary) without affecting your future care? | ☐ | ☐ |
| (Where relevant) I agree to my interview being recorded. | ☐ | ☐ |
| (Where relevant) I agree to the use of non-attributable direct quotes when the study is written up or published. | ☐ | ☐ |
| Do you agree to take part in this study? | ☐ | ☐ |

**Signature of Research Participant:**

**Date:**

**Name in capitals:**

Witness statement (if necessary)

I am satisfied that the above-named has given informed consent.

Witnessed by:

Date:

Name in capitals:

| | |
|---|
| Researcher name: A. Amini |
| Supervisor name: Dr. K. Banitsas |

## D. Approval of collaboration with Parkinson's UK

Amin Amini Maghsoud Bigy

From: Konstantinos Banitsas
Sent: 01 November 2016 14:25
To: Amin Amini Maghsoud Bigy
Subject: FW: (RSN-London) Have your say - a new technology for improving freezing

Follow Up Flag: Follow up
Flag Status: Flagged

---

**From:** Isabelle Abbey-Vital
**Sent:** 11 October 2016 3:40 PM
**To:** Sophie Mclachlan
**Subject:** (RSN-London) Have your say - a new technology for improving freezing

Research Support Network
Have your say

PARKINSON'S UK
CHANGE ATTITUDES.
FIND A CURE.
JOIN US.

Hello,

Dr. Konstantinos Banitsas, from Brunel University is developing a new technology to monitor and actively assist people affected by Parkinson's to overcome freezing of gait, and he wants to invite from people affected by Parkinson's in London to help his develop this.

## Background

Research has shown that visual and/or audio cues can assist individuals overcoming episode of freezing of gait. Dr Banitsas has developed a new technology that is based on a type of sensor that can identify an individual's position and heading.

When the sensor detects a freezing episode, it will project a series of laser lines in front of the individual in an attempt to help un-freeze their motion.

## How can you get involved?

The researchers plan to run focus group meetings with local people affected by Parkinson's throughout November to help them to shape this technology to be ready to take forward into a research project.

The aims of the focus groups are to:

- Give you an opportunity to see how the technology works
- Have an opportunity to try it yourself and make suggestions

1

- Provide feedback on how useful you think the technology is, how easy you think it would be to use, and any issues you can identify

These will be held at Brunel University and your time and travel expenses will be reimbursed for attending the meeting. Partners and carers are welcome to accompany you along to the meeting.

The information that you provide will be used to develop a research proposal for testing the effectiveness of this technology for the wider use for the Parkinson's community.

### Who are they looking for?

People with Parkinson's who experience freezing episodes and who are able and willing to travel to Brunel University for a focus group meeting that will last approximately 2 hours.

If you are interested in attending please email Konstantinos on Konstantinos.Banitsas@brunel.ac.uk or call him on 01895266886 at the latest by Friday 29 October.

Please be aware spaces will be allocated on a first-come-first-serve basis.

Please do not hesitate to contact me should you have any questions about this opportunity.

Best wishes,
Isabelle

### How can you help?

Dr Banitsas would like to involve people affected by Parkinson's in developing this technology, to help identifying an issues with the system that might need improving.

They would like to invite you to attend focus group meeting at Brunel University, at a time convenient for you where you will:

- Have an opportunity to see and test the technology
- Provide feedback on the technology – including how useful it might be to you, how easy you think it would be to use
- Identify issues with the technology

### Who do they need?

If you are

They would like to invite you to attend focus group meeting, at a time convenient for you where

Felicity wants to hear from people affected by Parkinson's in Northern Ireland to know if you think this study is important. To share your views please answer the below questions and email them to f.hasson@ulster.ac.uk by Friday 26 August.

1. Do you think this proposed study is needed?
2. Is there anything else you think it should focus upon?
3. Do you have any other comments or suggestions?

2

If you have any questions, please contact Dr Felicity Hasson on f.hasson@ulster.ac.uk or call 028 90 36 6895.

Best wishes,

Isabelle

Isabelle Abbey-Vital
Research Involvement Officer
Parkinson's UK
Tel: 020 7963 9327
Email: iabbey-vital@parkinsons.org.uk

The Excellence Network Awards celebrate the services doing fantastic work driving up standards of care for people affected by Parkinson's. Encourage the professionals you know to enter by 28 October 2016.

Parkinson's UK, 215 Vauxhall Bridge Road, London SW1V 1EJ
parkinsons.org.uk | facebook.com/parkinsonsuk | twitter.com/parkinsonsuk



3

# E. Patient and Public Involvement Request Form

PARKINSON'S[UK] CHANGE ATTITUDES. FIND A CURE. JOIN US.

## Patient and Public Involvement (PPI) request form

We can support good quality research which has potential deliver benefits for people affected by Parkinson's. We assess each request to ensure it meets our required standards. We need to fully understand the purpose of the research and how the information gathered will be used.

Ultimately it will be at the discretion of the Parkinson's UK research team whether the research is eligible for support and how this is provided.

For more information please refer to our **'Research Support Policy'**.

**If you want to involve people affected by Parkinson's in your research but are not sure of where to start, see our PPI Resource for Researchers or email us at researchinvolvement@parkinsons.org.uk for tips and advice.**

**By helping to involve people affected by Parkinson's through PPI, Parkinson's UK is not taking any responsibility for the research and is therefore not liable for any claims concerning negligence, harm or oversight that might arise during the course of the research.**

**Please return your completed form to researchinvolvement@parkinsons.org.uk**

| **Contact details** | | | |
|---|---|---|---|
| Name | **Dr. Konstantinos Banitsas** | | |
| Job Title | **Senior Lecturer, Researcher** | | |
| Research Institution | **Brunel University** | Department | **Electronic & Computer Engineering** |
| Telephone | **01895266886, 07890450501** | Email | **Konstantinos.Banitsas@brunel.ac.uk** |

| **Background to your research** | |
|---|---|
| Plain English title | **Using Microsoft's Kinect system to assist Parkinson's patients having frequent FOG episodes** |
| A plain English description of the study and its aims (max 250 words; including research area, projected study length if known and any suitable links to online information about the research) | |

Recently, at Brunel University, we have developed a system that can not only monitor a patient experiencing FOG but can actively assist him/her on overcoming those symptoms. It is based on Microsoft's Kinect sensor, a small box having two cameras, that can identify the position and heading of the patient. It will constantly monitor the patient's attitude and when it detects a FOG episode, it will project a series of laser lines in front of the patient in an attempt to un-freeze his/her motion. In addition, the system can support a fall detection where if the user does not respond within a preset time frame, it will initiate a Skype conversation with a designated. The following videos provide some information of our research

https://youtu.be/j2HNjq4pw5M

https://youtu.be/xrXCzRYMNw8

The focus group study to evaluate this system, will take place at Brunel University within November and will last

1

| | |
|---|---|
| about two weeks | |
| How will your research help people affected by Parkinson's in the future? (in 2 or 3 sentences) | |
| Research has shown that visual and/or auditory cues can assist overcoming a FOG episode. As this is system that requires nothing to be worn, charged, carried, etc, it is envisioned that when installed in a patient's premises, it will help by reducing the effects of FOG episodes. | |
| Have you secured funding for your research? If yes, who is supplying the funding? If no, when and where are you applying for funding? | |
| A budget has set aside to be used for the patients that will participate in this research. This is part of the IDEA project funding, supported by Brunel University's Healthcare technologies research group | |
| Do you have ethical approval for your study at this stage? (If yes, please provide this as an attachment). Please refer to INVOLVE's statement on the requirements for ethical approval for PPI. | Not yet. it is submitted pending approval within the next few days |
| **PPI in your research** | |
| At what stage of your research would you like to involve people affected by Parkinson's? (please see all that apply) | |
| ☐ Identifying and prioritizing<br>☐ Commissioning<br>☑ Designing and managing<br>☐ Undertaking | ☐ Disseminating<br>☐ Implementing<br>☑ Evaluating impact<br>☐ Other (please specify): |
| How would you like to involve people affected by Parkinson's in your project? (such as completing a survey, attending focus/steering groups, reviewing documentation) | |
| Attending focus groups, fill out surveys, provide feedback after testing the prototype | |
| What will you be asking the PPI contributors to do? | |
| Provide feedback and identify issues that might need improving. Also, suggest new functions that we can include to our system | |
| Are you looking for people with specific characteristics or experience? (such as early-onset, experience of participating in research) | |
| As this prototype is mostly addressing patients experiencing often FOG, It will be beneficial to prioritise involving more of those | |
| What will be the expected time commitment for PPI volunteers? | How many people fitting the criteria are you looking for? |
| 2-3 hours | 5-15 |
| Are you looking for people who live in a specific location? (e.g. city/region or UK-wide) | When is the deadline for recruiting PPI contributors? |

2

| | | |
|---|---|---|
| London, preferably west London | End of Oct 2016 so we can invite patients within Nov 2016 | |
| Will PPI expenses be reimbursed? | | Yes. Also they will be compensated with £50 |
| Does this PPI role require ethical approval? (If so please provide a copy) | | Yes, a copy will follow in the next few days |

| Feedback and Acknowledgement |
|---|
| How do you plan to feedback to the PPI contributors on the impact they have had? |
| Through emails |
| How will you inform those taking on the PPI role of the research outcomes once the study is complete? |
| **Emails of results and journal papers** |
| How do you plan to acknowledge the PPI contributors? (as a contributor, co-applicant, authorship) |
| as a contributor |

# F. Invitation to Focus Group Days

## <u>Invitation to our focus group</u>

### Using MS Kinect to reduce FOG episodes

Dear Participant,

Thank you very much for agreeing to assist us with the evaluation of our prototype. This research aims at reducing the symptoms of Freezing Of Gait for people affected by Parkinson's disease. Your participation will help us improve our prototype and possibly add new functions to it before making it available to the healthcare providers.

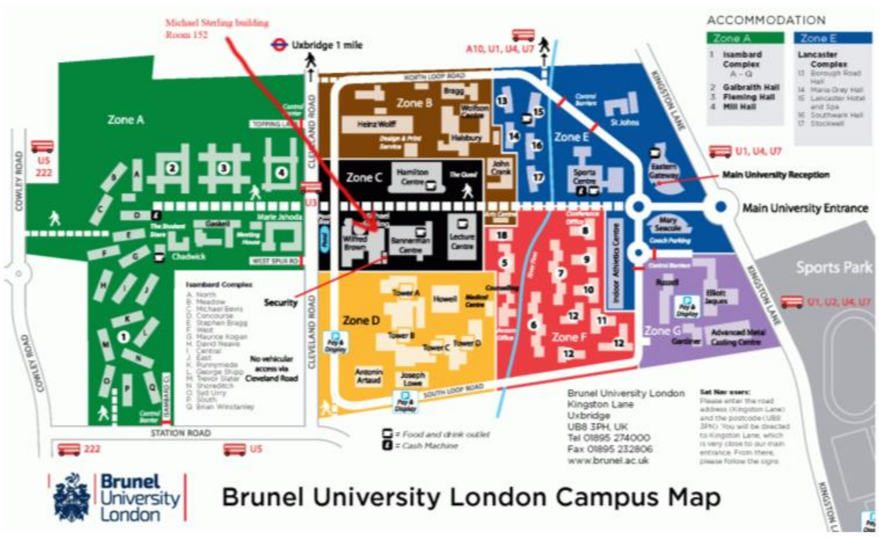
There are three dates in November that the meetings will take place: Monday 21th, Monday the 28th and Tuesday the 29th. By now, I would have already called all of you and you would have decided on one of these three dates.

The time for the focus group would be 10am

Below are some information about your visit to Brunel University:

### How to find us:

Brunel University is located near the town of Uxbridge. The post code is UB8 3PH. Depending on your mode of travel, you may find the following useful:




**Travelling by car:**

> From the M4: Leave the M4 at Junction 4, follow signs to Uxbridge (A408) and Brunel University. Those taking the M25 should join the M4 or M40.

From the A40/M40: At Swakeleys Roundabout take B483 exit to Uxbridge. Follow signs across two mini-roundabouts.

**Parking**

To avoid paying for parking, you must first report to the University's main reception, at the Eastern Gateway building (on the right side of the attached map). They will ask you for the registration of your car and the name and telephone number of the person you are visiting at Brunel (Dr. Konstantinos Banitsas, 66886). They will then give you a parking permit for the day with a code that will open the gate. Please park at any parking space indicated by a red dot. If you have any problems, please call me on my mobile (07890450501) and I will send a student to assist you.

**Travelling by bus:**

From Uxbridge bus station (next to underground station)
U3 (alight Cleveland Road)
U1 to West Drayton, U4 and U7 (alight Kingston Lane)
From Heathrow Central
A10 Heathrow Fast, every 15 minutes, journey time approx. 25 minutes (alight The Greenway and use river footpath to campus)
From West Drayton railway station
U3 (alight Cleveland Road)
U1 (alight Kingston Lane)

**Travelling by train**

By underground (London Transport)
Take the westbound Metropolitan Line to Uxbridge (approx. 40 mins from Baker Street station).
Or take the westbound Piccadilly Line to Uxbridge (approx. 45-50 mins from Earl's Court station).
You can then take a taxi, bus (see above for recommended bus services) or walk to campus.

**Travelling by rail**

West Drayton (First Great Western Link) is the nearest mainline station, approx 1.5 miles from the campus.
Services run from London Paddington (approx. 20 mins journey time) or from the West (Bristol).
West Ruislip Station (Chiltern Railways) is the mainline service from London Marylebone (approx. 20 mins journey time) and the North (Aylesbury, Banbury and Birmingham) and is approx. 4 miles from the campus.From the M4
Leave the M4 at Junction 4, follow signs to Uxbridge (A408) and Brunel University. Those taking the M25 should join the M4 or M40.
From the A40/M40
At Swakeleys Roundabout take B483 exit to Uxbridge. Follow signs across two mini-roundabouts.
From the M4
Leave the M4 at Junction 4, follow signs to Uxbridge (A408) and Brunel University. Those taking the M25 should join the M4 or M40.
From the A40/M40
At Swakeleys Roundabout take B483 exit to Uxbridge. Follow signs across two mini-roundabouts.

## Where is the meeting taking place

The focus groups will convene at the Michael Sterling building, first floor, room 152. This is at the centre of the map attached and is also indicated with a red arrow. There is a lift that you can use if needed. Please allow some time to find the building as the Brunel University campus is quite large. I will be standing by in case you have any problems. You can use my mobile phone number (07890450501) so I can send one of my students to assist you.

### What to expect on the day

We will meet in the above mentioned room. There will be about five patients in each group, many with their carers. You will be given a simple statement to sign indicating that you accept to participate in this focus group. My students and I will give you a demonstration of our system. You are not required to try it yourselves but if you feel like it, you are free to do so.

I am interested in your feedback about how to make this system better and more tailored to your needs.

At the end, we will distribute a questionnaire and ask for your opinion.

All the information will be anonymised and kept in a secure server.

The plan is that the meeting will last for about two hours. After that you will be free to go. If you need a taxi, we would be happy to call one for you or help you in any other way possible.

### Travelling expenses

Apart from a £50 gift card that you will get as a gesture of appreciation for helping us out with our research, you will be compensated for your travelling expenses as well.

If you came by car, please provide me with a

If you used train or bus, please

Finally, if you have used a taxi, please keep receipts

Sincerely yours

Dr. Konstantinos Banitsas

# G. Invitation to Participate to the focus groups

Dr. Konstantinos Banitsas
Department of Electronic & Computer Eng
College of Engineering, Design & Physical sciences
UB8 3PH, Uxbridge
Tel. 01895266886
Mob. 07890450501
konstantinos.banitsas@brunel.ac.uk

**Invitation to participate in the evaluation of a prototype system**

**designed to assist FOG in Parkinson's disease patients**

As you may know, at Brunel University a number of research groups are investigating on ways of assisting Parkinson's disease patients on their everyday tasks. Recently we have developed a system that can not only monitor a patient but can actively assist him/her on overcoming the common symptom of Freezing Of Gait (FOG). Before starting our research, we have talked to patients such as yourselves and they have explained that for several of the methods used so far, the patient has to wear something, carry a device, remember to charge it, etc; something considered as a nuisance.

We have developed a completely novel approach. It is based on Microsoft's Kinect sensor, a small box having two cameras, that can identify the position and heading of the patient. It will constantly monitor the patient's attitude and when it detects a FOG episode, it will project a series of laser lines in front of the patient in an attempt to un-freeze his/her motion. In addition, the system can support a fall detection where if the user does not respond within a preset time frame, it will initiate a Skype conversation with a designated carer. All these are achieved without any wires, charging processes or anything that has to be put on or carried.

I have given two demonstrating videos of our prototype to Mrs. Jeanne Phillips so you can have an initial idea of our research.

**We need your help to evaluate our system!**

We would be delighted to have you visiting Brunel University and trial this system. We would like to hear what you like about this or how the system can be improved (or add new features to it).

The whole visit should not take more than 1-2 hours. You will be compensated for your travelling expenses. Food will also be available on the day and a cash/voucher for £50 will also be given for your participation.

Please communicate either with me or with Mrs. Jeanne Phillips if you are interested in helping this research. Further details about the times and venues will be given following your responses.

Thank you in advance

Dr. Konstantinos Banitsas

# H. Participant Information Sheet

**PARTICIPANT INFORMATION SHEET**

**Using 3D sensing and projecting technology to improve the mobility of patients with Parkinson's disease**

**Invitation Paragraph**

You are being invited to take part in a focus group to investigate the effectiveness of using Microsoft Kinect camera for improving the mobility of Parkinson's disease sufferers based on visual cues. Before you decide, it is important for you to understand why the research is being done and what it will involve. Please take time to read the following information carefully and discuss it with others if you wish. Ask me/us if there is anything that is not clear or if you would like more information. Take time to decide whether or not you wish to take part. Each participant will be given a copy of the information sheet and a signed consent form to keep.

**What is the purpose of the study?**

Parkinson's disease:
Parkinson is a progressive neurological condition in which part of the brain becomes progressively more damaged over many years. Brain's nerve cells make a vital chemical called Dopamine in order to be able to communicate with each other and send signals to their neighbour nerve cells; it helps the brain to perform its important tasks such as: Controlling movement and motor functions and possibly other functions related to feeling and mood.
A research conducted by the University of Rochester's Strong Memorial Hospital (Presented at the American Academy of Neurology's 51st annual meeting, Apr 1999) shown that about 30% of Parkinson's disease sufferers experience a sudden freeze (FOG) where patients' muscles literally freeze in place as they are trying to walk. (rochester.edu, 1999).
The cause of the freezing which affects about 500,000 adults in only the United States is still a mystery. But scientists have realised that using laser pointers with regards to the patient's position and coordinates can be effective to overcome the problem by stimulating their brains functionality. Figure below demonstrates how simple guiding lines can help overcome the FOG moments.
The idea is to develop a system to employ 3D-sensing capabilities of a set of interconnected Kinects alongside with 3D laser projectors to
1. Detect the (FOG) moment using image processing techniques.
2. Help the patient to overcome the problem by projecting laser patterns or auditory cues based on the patient's 3D position.
3. detect falling and subsequently calling a healthcare provider or a person in charge to monitor the incident in real-time and act accordingly.
By using a Kinect camera, we will be able to pin point a patient's 3D position in a room. The system then uses this information to determine the patient's direction and its path. Using image processing techniques, the FOG moment will be detected and then the laser projectors will be informed to cast 3D patterns in front of the patient with regards to its intention and direction. The pattern can be a path, a highly visible grid on a stair case or a set of flashing indicators on both objects and the floor.

We conclude that by binding the Kinect capabilities (or "Kinect for Xbox One" which is more precise but yet to be released) with a laser projection system, it is possible to unfreeze patients experiencing FOG. Lasers can be useful as the patterns are not fixed and can be changed based on different situations.

At this point, we are going to present our system's capabilities to patients diagnosed with Parkinson's disease for evaluation and feedback purposes.

The recording process should not take more than one day.

**Why have been invited to participate?**

The trial requires participants with the following characteristics:

- Diagnosed with Parkinson's Disease
- Experiencing FOG symptoms
- No significant visual impairment
- No other neurological condition that may impact on walking (e.g. stroke, MS)
-

In the case that the participant wishes to try out the system, we need him/her to be able to:

- walk independently with or without a walking aid (stick)
- walk 10 m repeatedly (with rest breaks)

**Do I have to take part?**

As participation is entirely voluntary, it is up to you to decide whether or not to take part. If you do decide to take part, you will be given this information sheet to keep and be asked to sign a consent form. If you decide to take part, you are still free to withdraw at any time and without giving a reason.

**Where is the showcase event location?**

The event will take place at Brunel University London Michael Sterling Building room 152 (MCST152)

**On what dates and at what time should I be available if I take part?**

We have three days available for you to choose starting from 10:00 for two hours as follows:

- Monday 21st of November 2016
- Monday 28th of November 2016
- Tuesday 29th of November 2016

**What will happen to me if I take part?**

The showcase will take two hours of a specific day. You will be given a choice of three different days. If you decide to try out the system, you will be walking in pre-defined paths and evaluate our system capabilities in improving your mobility in case of a Freezing of Gait (FOG) incident. At the end of the trial, you will be providing the researchers with your opinion and feedback on how useful the system is and how our prototype system can be improved. The event will be taking place at Brunel University London Your time will be compensated with a £50 gift card and your travelling expenses will be paid.

**What do I have to do?**

. Just give your opinion on our prototype. If you decide to try it out, you will be walking through corridors for a very short period of time.

**What are the possible disadvantages and risks of taking part?**

There would not be any significant risks involved.

**What if something goes wrong?**

You are encouraged to take a friend/relative with you at the time of this study

**Will my taking part in this study be kept confidential?**

The evaluation feedback gathered from all participants will be released in further reports as possible journal publications or conference proceedings. Any information will be kept on an encrypted hard drive in a secure locker and will be deleted after five years. Nobody apart from the project main researcher would have access to the raw data. There will not be any identifiable information save/recorded during the whole trial process.

**What will happen to the results of the research study?**

The result of this participation including improvement feedback will be gathered from all participants in the trial and will be released in further reports as possible journal publications or conference proceedings.

**Who is organising and funding the research?**

The whole project will be conducted at Brunel University London by the project's main researcher and the project supervisor.

**What are the indemnity arrangements?**

N/A as this is a focus group

**Who has reviewed the study?**

Brunel University London Research Ethics Committee.

**Include a passage on the University's commitment to the UK Concordat on Research Integrity**

'Brunel University is committed to compliance with the Universities UK Research Integrity Concordat. You are entitled to expect the highest level of integrity from our researchers during the course of their research.'

**Contact for further information and complaints**

Should you had any question, query or complain, please contact:

Project supervisor:

Dr. Konstantinos Banitsas (konstantinos.banitsas@brunel.ac.uk)

Project main researcher:

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**References:**

1. Healthwise. (2010). What is Parkinson's disease? Available: http://www.webmd.com/parkinsons-disease/tc/parkinsons-disease-topic-overview. [Accessed: 12-06-2013].

2. Healthwise. (2010). Dopamine. Available: http://www.webmd.com/hw-popup/dopamine [Accessed: 12-06-2013].
3. Evaluation of Kinect joint tracking for clinical and in-home stroke rehabilitation tools. (Undergraduate dissertation). Retrieved from NetScale Laboratory.
4. Microsoft. (2013). Kinect for Windows Sensor Components and Specifications. Available: http://msdn.microsoft.com/en-us/library/jj131033.aspx [Accessed: 09-06-2013].

# I. Participant Feedback Form

**Thank you for your participation in the focus group. Please answer the following questions:**

1. **Participant Information:**

**Age:**

**Gender:**

**How long have you been diagnosed with Parkinson's disease?**

**How often do you experience Freezing of a Gait (FOG), if any, per day?**

**What methods, if any, do you use to improve your mobility during a FOG incident?**

2. **The system was easy to use.**

☐ Strongly disagree ☐ Disagree ☐ Neither agree not disagree ☐ Agree ☐ Strongly agree

3. **The accuracy of the system is efficient.**

☐ Strongly disagree ☐ Disagree ☐ Neither agree not disagree ☐ Agree ☐ Strongly agree

4. **Apart from visual aids, I would consider auditory aids such as music to be helpful.**

☐ Strongly disagree ☐ Disagree ☐ Neither agree not disagree ☐ Agree ☐ Strongly agree

5. **Using a similar laser technology for projecting 3D staircases is also helpful.**

☐ Strongly disagree ☐ Disagree ☐ Neither agree not disagree ☐ Agree ☐ Strongly agree

6. **The system fall detection was accurate.**

☐ Strongly disagree ☐ Disagree ☐ Neither agree not disagree ☐ Agree ☐ Strongly agree

7. **Which method do you prefer the system to use in order to contact a doctor or a healthcare provider in case of fall incidents?**

☐ Calling ☐ Skype ☐ SMS

8. **If you were to pay for this, what would be your estimate of cost?**

**£………..**

9. **What methods do you use to assist you during your FOG incidents?**

10. **I am concerned about my privacy when I use this system.**

☐ Strongly disagree ☐ Disagree ☐ Neither agree not disagree ☐ Agree ☐ Strongly agree

11. **In which room/area around your house do you experience FOG the most?**

12. **In which scenarios do you experience FOG the most?**

13. **What additional functionalities would you like the prototype to have if any?**

14. **What functions in the prototype do you think might be unnecessary if any?**

15. **The overall system was helpful in improving my mobility, especially during a Freezing of Gait (FOG)**

☐ Strongly disagree ☐ Disagree ☐ Neither agree not disagree ☐ Agree ☐ Strongly agree

16. **The visual aid was helpful in increasing my mobility and walking performance**

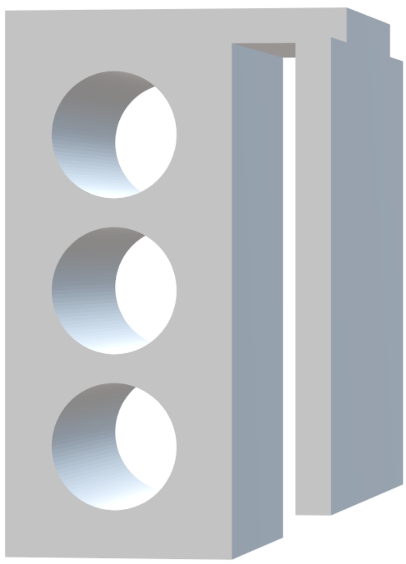
☐ Strongly disagree ☐ Disagree ☐ Neither agree not disagree ☐ Agree ☐ Strongly agree

17. **I would use the system in my house**

☐ Strongly disagree ☐ Disagree ☐ Neither agree not disagree ☐ Agree ☐ Strongly agree

18. **Do you have any suggestions for making the system more effective and comfortable?**

J. 3D design for laser pointers' mount



K. QR code for the system's demonstration video https://tinyurl.com/kinect4pwp