Department of Electronic and Electrical Engineering

RES Electronic & Electrical Engineering (MPhil)

Academic Year 2018 - 2022

Advanced digital signal processing technique for asset health monitoring

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A report submitted in partial fulfilment of

the requirements for the degree of Master of Philosophy

Abstract

Asset health monitoring application is critical to ensure structures are operating in a healthy state and damages can be detected earlier for efficient maintenance scheduling to save cost. RAC Foundations has reported that there were more than three thousand bridges identified as substandard bridges in the United Kingdom in 2019. This is due to destructive damage such as deterioration, corrosion, overloading and lack of maintenance etc. These factors have accelerated the deterioration of bridges, reduced performance in normal operation and also potential hazard of bridges at risk of collapse. A figure of an estimated £6.7 billion bill is required to bring substandard bridges back to good condition. In order to improve the bridge health monitoring process and save cost with well-planned inspection schedule, the development of efficient damage detection algorithms is needed.

This study has investigated the current state-of-art in bridge health monitoring applications in terms of types of signals, sensor development and signal processing techniques to extract damage sensitive features. Based on the research outcome in terms of accuracy and efficiency of applications, the author has proposed an advanced digital signal processing technical to develop a vibration-based fault analysis algorithm for early damage detection using optimal filtering. A Spectral Kurtosis (SK) based optimal filter is designed to extract frequencies that are generated by damages. The proposed technique is validated by two applications to detect small defects such as bolt looseness on bolted joint structures as well as applying the technique on bearing fault detection.

The two applications has proved that the proposed technique can detect damages

in both stationary infrastructure such as bridges and operating rotary machine to show its versatility. The results provide confidence that Spectral Kurotsis is capable of detecting non-linear and non-stationary components buried in noisy signal. The outcome has contributed a method to detect small defects that are hard to find and therefore early repair and better maintenance schedule can be achieved to save the cost and ensure structures are operating in a healthy status.

Apart from that, the developed algorithm can also be used to extract features for an automated damage detection application; for instance, feeding the damage sensitive features into machine learning models such as support vector machine and random forest to classify damages. This combined method will reduce the chance of false alarm.

Acknowledgements

I would like to express my sincere appreciation to the supervisory team especially my principal supervisor Professor Wamadeva Balachandran for supervising this project. His support and advice are invaluable that encouraged me to work on this project with the desire to explore the area of advanced signal processing techniques.

I would also like to thank my colleagues and friends from Brunel Innovation Centre through the journey of this MPhil study to make it more enjoyable and memorable.

Finally, I would like to give a special thank to my family for giving company and support during the tough and joy moments.

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Chapter 1

Introduction

Asset health monitoring involves observation of the overall healthiness of a structure that also applies to machinery with condition monitoring on moving components such as gears and bearings. Structural health monitoring (SHM) is defined as a process of implementing a damage identification strategy for various infrastructures such as aerospace, civil and mechanical engineering. The general objectives of the process are to detect structural damage, estimate the remaining service life of a structure and optimise the decision making process for maintenance efforts to reduce replacement costs based on measured data. The need for bridge health monitoring is one such application, and it is discussed in detail below.

Over three thousands bridges were identified at substandard status in the United Kingdom and this has been rising per year reported by RAC Foundations in 2019 [1]. There are several reasons behind; for instance, destructive damages such as deterioration, corrosion, overloading and lack of maintenance etc that accelerated the deterioration of bridges. Resulting in reduced performance in bridge as well as potential hazed of bridges at risk of collapse.

The Genoa tragedy happened in 2018 [2] has raised public concern of need of appropriately planned inspection and maintenance schedule for bridges especially those that have been operating more than few decades. RAC Foundations has also published a figure of an estimated £6.7 billion bill was required to bring substandard bridges back to good condition in 2018 [3]. In order to improve the bridge health monitoring process and save cost with well-planned inspection schedule, the development of efficient damage detection algorithms is needed.

Currently there are different practices of data acquisition and deployment technologies in both industrial and academic sectors [4, 5]. Vibration-based monitoring is one of the most popular methods for analysis, followed by fibre-optic technologies and the popular wireless sensor network for SHM deployments [6, 7, 8]. By definition, monitoring comprises certain procedures that need to be implemented. First, data acquisition is performed to collect data depending on the use of an application. For instance, amplitude, velocity and acceleration are data that describe the characteristic of vibration. Signal processing is then implemented to extract useful data and filter out undesired noise; for instance, time series models, fourier transform and wavelet transform etc. After the processing is completed, different data interpretations (artificial neural network, support vector machine and bayesian classifier etc.,) can then be applied for further feature extraction. Eventually, damage detection of an SHM system can then be established to detect defects in a structure based on measured data comparing to baseline data from previous training data.

Cabling system is widely used in conventional SHM monitoring applications for integrating sensor networks, thanks to their durability and robustness. However, due to the high cost of the cabling system and the lack of flexibility in adding new sensors in the wired SHM systems, there is a need to boost the development of the wireless sensor networks. Due to the massive amount of measurement data on an asset, an advanced signal processing technique is required to increase the computation efficiency as the data analysis will consume a lot of time. This can be achieved by integrating an automated damage detection algorithm into the SHM application for smart monitoring.

1.1 Need for Bridge Monitoring

RAC Foundations has reported in 2019 there are more than three thousand bridges were identified at substandard that could leads to potential risk of collapse and the cost required to bring the bridges back to healthy condition is up to 6 billion pounds [1]. The condition of substandard is defined as if a structure is unable to carry the heaviest vehicles including a lorry of up to 44 tonnes. This is subjected to destructive effects of material aging, deterioration, widespread corrosion in metal structures, increasing traffic volume and overloading. Apart from these factors, an accident caused damage, poorly designed structures and lack of maintenance also accelerates the deterioration of bridges resulting loss of load-carrying capacity.

Highways England has reported over 8,600 bridges with an average age of 37 years old are showing a significant number of structures that need strengthening, rehabilitation or replacement to ensure safety measures for public use [9]. These factors have caught the public interest and numerous news agency have reflected the concern of bridges at risk of collapse [10, 11, 12]. A nearby section of the M4 motorway was urgently closed in 2013 following the discovery of cracks in the 1960s steel structure's welds. The defects were identified on the bearings [13] that were designed to ensure forces can be transmitted through the supporting structure into the foundations and failure can occur if they are not in good condition.

1.2 Bridge Repair and Maintenance Cost

The annual bridge maintenance data published by RAC Foundations has recorded a massive increment that a £6.7 billion bill of the backlog was estimated to bring the stock to a good condition in 2017, and this was double the amount in the previous year [3, 14]. Apart from the figures in the UK, the ACSE (American Society of Civil Engineers) have published a study in regards to the age of bridges and the percentage of structurally deficient bridges in 2017 [14]. Figure 1.1 and Figure 1.2 show that the U.S. has almost 240,000 bridges were over 50 years old and 9.1% of the nation's bridges were structurally deficient in 2016. Considering this is a relatively large number of bridges that requires significant maintenance, rehabilitation or replacement, an estimated backlog of bridge rehabilitation was required for US$123 billion. Due to the poor condition of the critical load-carrying elements induced by deterioration, these bridges are required to be inspected annually.

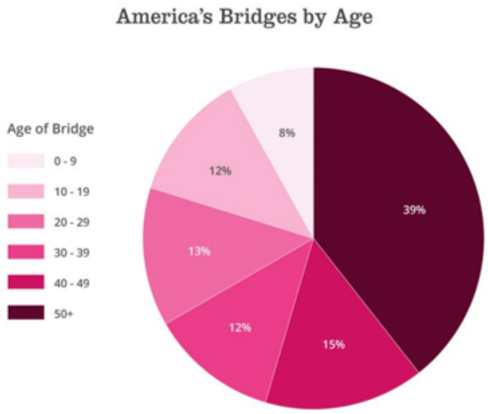

Figure 1.1: America's Bridge by Age [14]

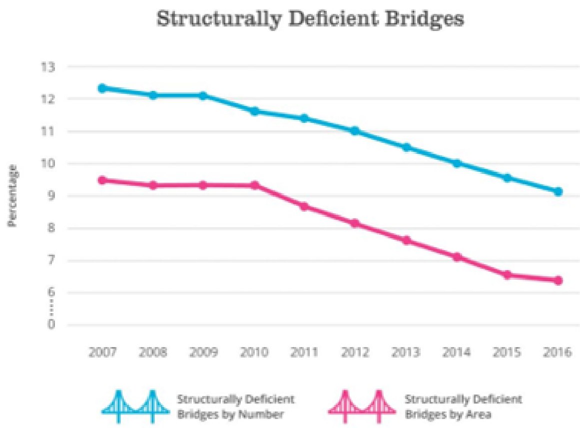

Figure 1.2: Structurally Deficient Bridges in America (2017) [14]

1.3 Bridge Inspection

Bridge inspection is a crucial task to validate the healthy state of the structure which also helps to determine the maintenance plan. After the Genoa tragedy that happened in Italy in 2018 has killed 43 people and left 600 homeless (Figure 1.3) [2], Highways England has urged the need to review bridge inspections in England [15].

Figure 1.3: The Morandi Bridge (Genoa Bridge) Tragedy [15]

RSSB (Rail Safety and Standards Board) [16] has reviewed the current practice for scheduled bridge inspection are subjected to an annual visual examination and a detailed examination by every six years. Despite the frequently scheduled inspections, damages could be hard to detect that the structure suffers from the risk of failure through deterioration in more or less time. Accidents happened to the structure can also accelerate the growth of a defect, and the severity of damages will vary from one structure to another. Consequently, the board has proposed the examination regime to an annual visual examination with a detailed examination every 3/6/9/12/15/18-year period. The interval of detailed examination is determined by the growth time of defect between detectable during examinations and subsequently becoming notifiable depending on working conditions. The proposed regime should enable defects to be identified sooner during regular inspections.

1.4 Aim

The aim of this MPhil research is to develop an advanced signal processing technique focused on bridge health monitoring to extract meaningful features to evaluate state of structure. The data analytic technique is implemented as a fault analysis algorithm for early damage detection.

1.5 Specific Objectives

The research work consists of

- Implementation of literature review on asset health monitoring to investigate the current state-of-the-art, emerging technology and technology gap that is how this research will be able to address the problem of bridge health monitoring;
- Investigation of existing signal processing techniques in asset health monitoring and focus on selection of sensors (e.g. vibration, temperature and pressure etc.,) [17, 18];
- Development of feature extraction algorithms to obtain damage sensitive features [19, 20];
- Establish experiment setup to test and verify the proposed technique to detect small defects such as bolt looseness on bolted joint structures and bearing fault

detection

- Demonstrate the proposed technique is capable of detecting small damage in both stationary and operating structures for early damage detection

1.6 Research Pathway

The pathway of this research study is displayed in Figure 1.4 that consists of three parts of works as literature review of asset monitoring to investigate the current approach of bridge health monitoring and exploring potential damages such as bolt looseness; investigate methodologies to prove the proposed signal processing technique; validate applications results with designed experiments.

This includes six chapters which covers Chapter 1. Introduction of need in asset health monitoring, Chapter 2. Literature review of state-of-the-art health monitoring techniques including cause of damages. Then Chapter 3. Methodology of proposed advanced signal processing technique for two applications of bolt looseness detection and bearing fault detection, Chapter 4. Experimental Results and lastly Chapter 5. Conclusion and recommendations for future works.

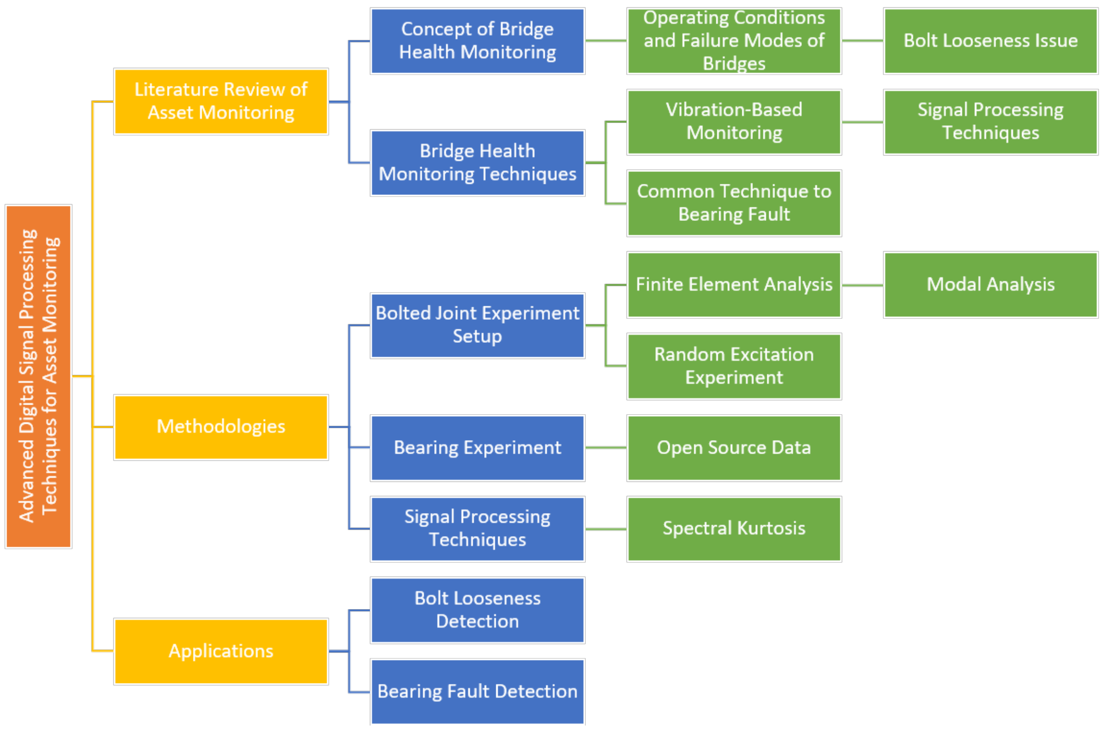

Figure 1.4: Schematic diagram of the research pathway

1.7 Publications

1. Ho, S.K.; Nedunuri, H.C.; Balachandran, W.; Kanfoud J.; Gan, T.-H.; Monitoring of Industrial Machine Using a Novel Blind Feature Extraction Approach. Appl. Sci. 2021, 11, 5792. https://doi.org/10.3390/ app11135792

2. Ho, S.K.; Nedunuri, H.C.; Balachandran, W.; Gan, T.H. Bolt looseness detection using Spectral Kurtosis analysis for structural health monitoring. In Proceedings of the ISMA2020 and USD2020, Leuven, Belgium, 7–9 September 2020; pp. 1215–1221.

Chapter 2

Literature Review

2.1 Bridge Health Monitoring

In bridge health monitoring, the inspections normally start from the key components as structure is likely to fail due to the deterioration or damage to key components that support the bridge. Cristian et al. [21] have implemented a study to understand the deterioration characteristics of bridges that aims to help bridge stakeholders better prioritise bridge maintenance, repairs and rehabilitation. In general, the majority of bridges use steel and concrete as material type of its superstructure. The study has investigated different types of material that superstructure-deficient steel bridges has accounted for over 50% of all types. Due to the long history and popularity of metallic bridges, steel bridges will be focused on in this project.

2.2 Operating Conditions of a Steel Bridge

2.2.1 Bridge Type

Applications of steel bridges can be classified into two main categories from the type of traffic carried and further investigated to the type of structural system. It is used in three main traffic types namely trains, vehicles and pedestrians as well as the type of structural system such as beam, truss and suspension bridge (Figure 2.1). The illustration of structures is presented in Figure 2.2.

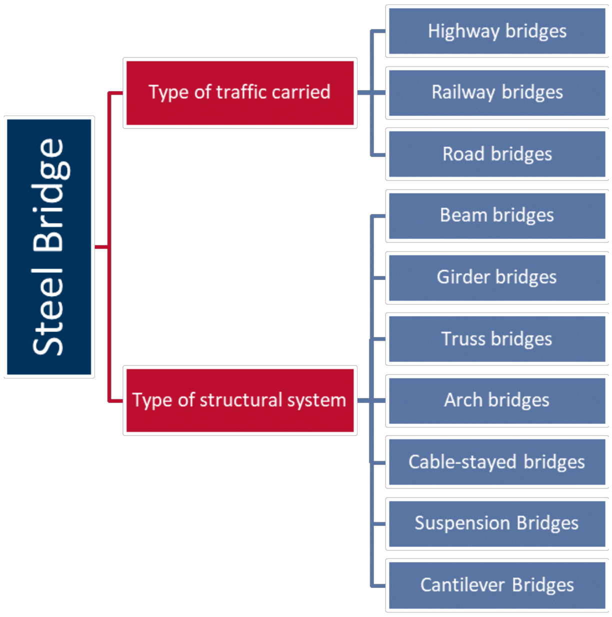

Figure 2.1: Types of Steel Bridge

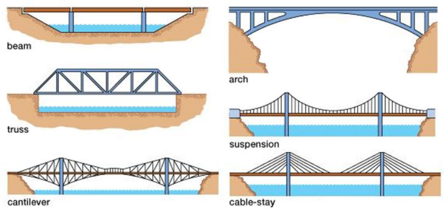

Figure 2.2: Form of Bridge Structures [14]

2.2.2 Bridge Loadings

A bridge is used to form a path to connect places together. During the initial stage to design structures, loading is one of the factors that must take into consideration. The loading describes how the bridge supports its own weight as static load and live load represents moving objects on the bridge such as vehicles, pedestrians and trains. And dynamic load indicates environmental factors such as wind, vibrations and thermal stresses. Figure 2.3 shows a summary of bridge loading and the framed factors introduce vibrational excitation to bridge structure which can be used as a response for structural health monitoring (SHM) purposes.

2.2.3 Bridge Key Components

Bridges are assembled from various core elements which forms the support, allows movement from material expanding and provides a platform for users. These are classified into superstructure, substructure, bearings and connection joints. In convention, concrete is used to form the deck and stone is used to build the piers and abutments due to their characteristic of strong strength. The connection joints for

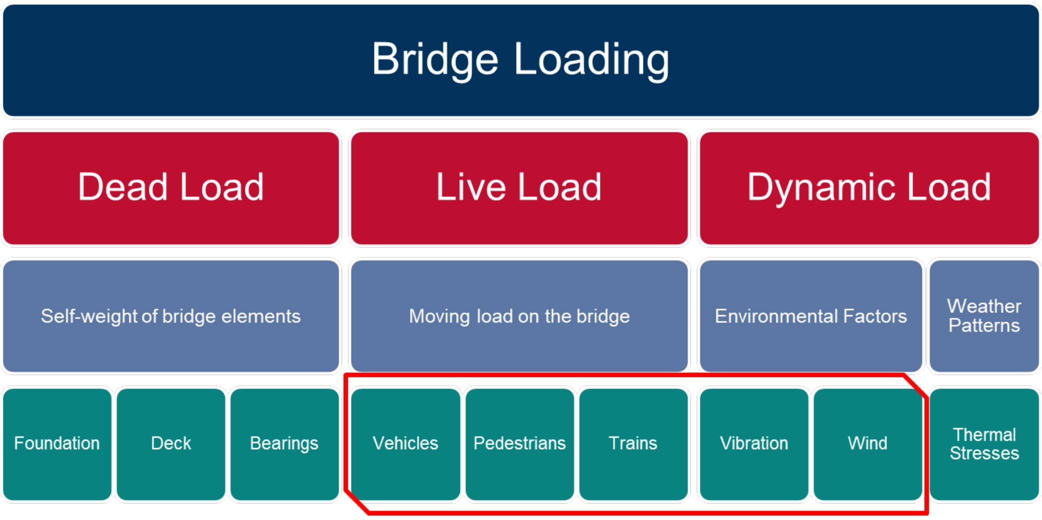

Figure 2.3: Bridge Loading Categories

assembly normally use bolt or rivet as they are easy to assemble and can be replaced if damaged. In order to distribute stress evenly when the bridge is under pressure, bridge bearing is used to provide a resting surface between piers and the deck which allows controlled movements. The key components illustration is presented in Figure 2.4.

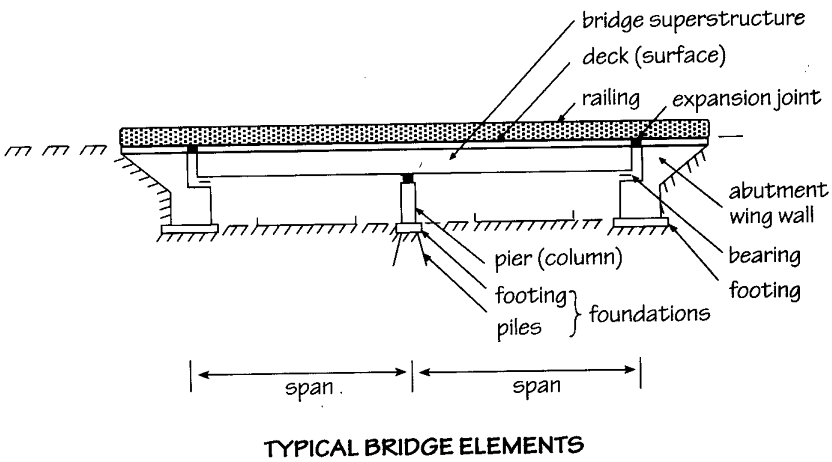

Figure 2.4: Bridge Elements [22]

2.2.4 Environmental Conditions

Bridges are designed to withstand all weather conditions. However, this does not include extreme conditions such as earthquakes and temperature fluctuation. These harsh conditions can introduce damages to the structure; for instance, cracks, corrosion and melting concrete that change structural properties resulting in weaker stiffness and strength of the structure. Furthermore, that also increases the safety hazard for road users. Highways England has published a report on climate adaption risk assessment progress update in 2016 [23], a brief summary of climate change impacts is shown and provides a measure of importance how the hazards affect the road users.

2.3 Bridge Failure Mode

2.3.1 Damage Types

Damage is defined as the deviation in original material or geometric properties of a structure due to cracks, corrosion, loosen bolts, fatigue or broken welds causing displacements, vibrations or undesirable stresses [24]. Research by Cook and Barr [25] have analysed the trend of bridge failure in New York between 1992 and 2014. They have examined 17,460 bridges in their data set and 98 bridges are collapsed. Nearly 50% of the collapsed bridges are classed as structurally deficient which implies weakened structure is prone to failure.

Imhof has gathered a bridge collapse database of 347 failure cases of worldwide metallic bridges in his PhD study on risk assessment of existing structures [26]. The study consists of a time of failure, causes of the bridge collapse, type of failed bridges and stage of failure etc. Imam and Chryssanthopoulos [27] have further investigated Imhof's work to analyse the causes and consequences of bridge failures.

They have classified the causes into seven categories where natural hazards, limited knowledge and design errors are the most commonly encountered causes of collapse in metallic bridges followed by human errors and accidents (Figure 2.5). Aside from the causes, Figure 2.6 illustrates the distribution of failure modes that most frequently found defects are scouring of piers, buckling, fatigue, impact and fracture.

SHM is a vital task for valuable assets. Although bridges are designed to maintain their service and function for a long period of time, defects and damages are inevitable. This could be due to many influences during the service life, such as

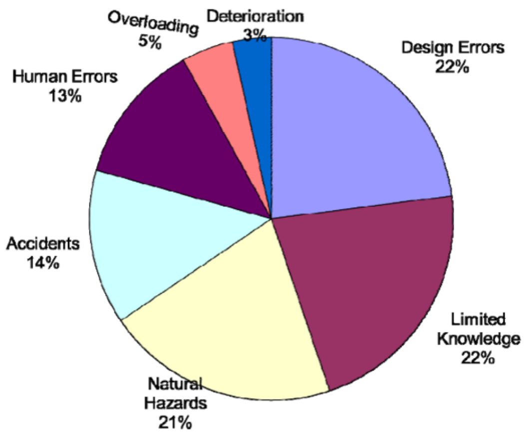

Figure 2.5: Failure Causes Leading to Metallic Bridge Collapses [27]

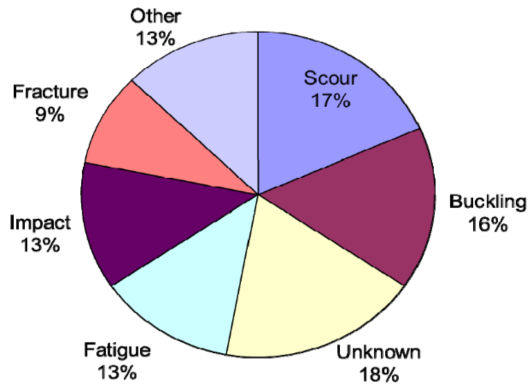

Figure 2.6: Failure Modes Associated with Metallic Bridge Collapses [27]

Table 2.1: Root Cause of Steel Bridge Defects

	Root Cause
Corrosion	Inadequate steel coatings Chloride ingress Water ingress
Crack / Fatigue	Overloading Structural movement / vibration Earthquake impact
Buckling	Overloading Insufficient support Design errors Joint eccentricities & welding deformations

loading flotation, vibration, extreme weather conditions and presence of chlorides in de-icing salts and cycles of freezes and thaw. Table 2.1 shows a summary the type of the major defects in steel bridge with its root causes.

In addition to classifying the failure modes, researchers in Japan have published an article to analyse the deterioration characteristics of steel highway bridges [28]. The inspection was conducted using a new approach for segmental data acquisition which puts structural components and elements into various subdivisions depending on the damage type. The damage type was characterised by material which bolt loosening/loss happens to be one of the major problems in steel members and so bearing malfunctioning and joint spacing malfunctioning as the bolt is used for mounting purposes.

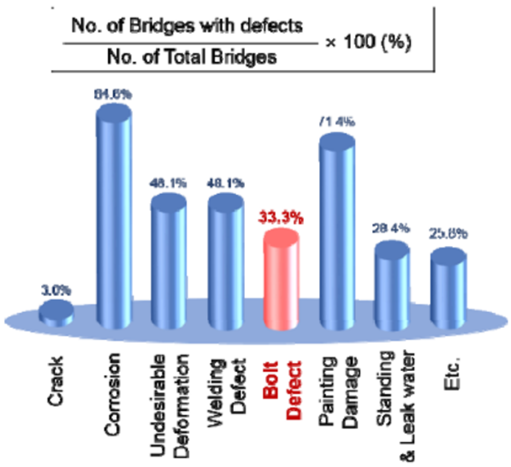

Figure 2.7: Defect Types and Occurrence Rate in Steel Bridge [29]

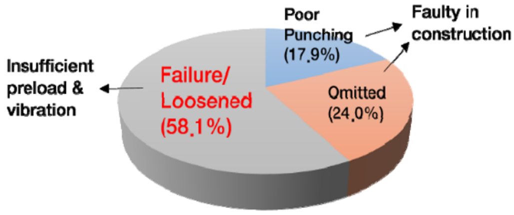

Figure 2.8: Causes of Bolt Defect in Steel Bridge [29]

In the last decade, bolt loosening problem in structural health monitoring has caught interest from both industry and academia and there is a rising trend of commercial products launch and publications. Bolt loosening or missing plays an important role as key member of steel bridge since bolts are used heavily in connection joints and bearings. Park et al. [29] have referred to structural defects report released by Korea Expressway Corporation in 2013, bolt defects were identified in 33.3% of their operating bridges which the major cause was investigated as insufficient preload and vibration (Figure 2.7, 2.8). In accordance to the reported defects, they have developed novel techniques using image processing to detect bolt looseness for bolt joints in steel bridges; however, this approach is limited to local detection and the location of bolts may not be reachable by the camera thus reduces practicality.

2.3.2 Critical Components

Bolts in bearing joints are designed to meet two main criteria: a) yielding and b) fracture. These two examples are presented in Figure 2.9 of both cases which yielding is an inelastic deformation and fracture is a failure of the joint. This failure also applies to the material that the bolt bears against if the stress applied is overloaded.

Bridge maintenance and inspection are normally scheduled regularly depending

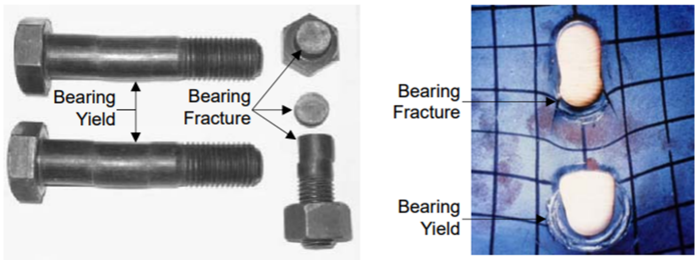

Figure 2.9: Bolted Joint Failure Modes [30]

on the current health state of the structure. However, defects could have developed and grown to an extent that could harm the integrity before inspection or not detectable and it often depends on the experience of the inspector. In order to tackle that, LeBeau et al. [31] have developed a fault tree model to estimate the deterioration rate of bridge element that they calculated the probability of the basic event to occur. Their result shows that bolted joint damage is a major cause and is likely to make a structure to be substandard. Furthermore, Attoh-Okine et al. [32] have implemented an improved version of the fault tree model to estimate the deterioration characteristic of bridge element with Bayesian belief network model. They have developed a more sensitive tool to investigate which components of a bridge have the greatest influence on deterioration. Referring to the two research outcome [31, 32], bolt related elements are found to have a higher probability of contributing to deterioration owing to the consequence of vibration.

2.4 Bolt Looseness Detection Techniques

Bolted Structures

Structural bolting is a popular choice utilised in industrial structures and equipment due to the advantage it can be carried out in a timely manner than welding and with less interrupt during construction. A bolt acts as a fastener which is normally used with a nut to bind materials or objects together with a washer in between to aid distribute stress and force evenly. This tensile force is called preload that generates a compressive force in the bolted joint. If the tension is not maintained, this could pose a problem for common flaws or damages such as fatigue failure, joint separation and self-loosening from vibration in bolted structure.

Bolt looseness

Bolt looseness is a scenario where its tension, axial stress/force are reduced. This can be due to the self-loosening of the nut because of the transverse movement produced by vibration. Apart from vibration, there are other causes of the loose bolt; for instance, 1) under-tightening, 2) embedding, 3) gasket creep, 4) differential thermal expansion and 5) shock. As a result, measurement and estimation of this force can contribute to healthy performance of the structure. The example of preloaded bolts and in the loosened state is presented in Figure 2.10.

Figure 2.10: Preloaded and Loosened Bolting [29, 33]

With regards to the statement from LeBeau et al. [31] and Attoh-Okine et al. [32], bolt looseness is prone to be considerable damage to bolted structure. Their study could have been more persuasive if the researchers had included the variation in stiffness change. A group of researchers in Korea [34] has analysed the contribution of bolt loosening failure to the behaviour of bolted steel plate girder in the lower flange and quantified the structural stiffness has been reduced by approximately 15%-17%. In contrast, to monitor the stiffness change caused by axial force losses, Anginthaya et al. [35] and Xianlong et al. [36] have implemented a parametric study to evaluate the effectiveness of different parameters in bolt looseness detection.

In structural health monitoring and asset monitoring, there are several factors known to determine the healthy performance of a structure. For instance, natural frequency, modal damping ratio and mode shape are popular choices. However, these parameters suffer from some serious shortcomings as they are insensitive to small defects such as the bolt loosening case. In this section, numerous techniques are introduced to improve the effectiveness in bolt looseness detection by extracting meaningful damage sensitive features.

Wang et al. [37] and Nikravesh et al. [38] have reviewed methods for monitoring bolt looseness for the last decade, they have categorised the techniques on the basis of sensing method namely direct and non-direct measurement types. This classification system helps to distinguish the nature of technique and can be broadened to include signal types. Despite most of the reviewed methods are old-fashioned, they are still widely utilised in various industries.

Direct Measurement

Direct measurement means the signal can be analysed without any processing such as direct tension indicator, strain gauges and torque control. The cost of these methods is low and easy to implement with simple theory. The key problem with this method is it possesses low accuracy and is not suitable for situ monitoring.

Indirect Measurement

In contrast, the nature of signals varies from indirect measurement are ranging from impedance, displacement, velocity and acceleration. These signals can be analysed in different domains such as time, frequency and time-frequency depending on applications. This method requires signal processing for analysis and produces acceptable accuracy. Although the classification is easy to understand, it has limited utility with respect to nature of signal as most of structural health monitoring technique requires excessive processing nowadays. Thus, this project has proposed to classify techniques by contact and non-contact type.

2.4.1 Contact Type Techniques

Vibration-based Monitoring

Vibration-based monitoring is one of the most common techniques used for structural health monitoring, especially on monitoring changes to modal parameters. Looseness is a result of a reduction in firmness of joints and structures such that monitoring vibrations and fluctuations of structure's vibration parameter can achieve detection of its occurrence. Referring to Nikravesh et al. [38], structures that possess nonlinear vibration responses are likely to suffer from looseness owing to the existence of flaws and variation in vibrational and dynamic parameters.

One of the advantages of vibration-based monitoring technique is that the recorded signal can be analysed in a variety of domains such as time, frequency and time-frequency. This flexibility makes the technique capable to detect dynamic parameter changes due to flaws. Normally, this is estimated by a damage index to evaluate the severity.

Type of sensors

Displacement sensor

A strain gauge-based relative displacement sensor has been developed to monitor joint conditions in steel truss bridges by Li et al. [39]. It is based on a feasibility analysis to detect bolt looseness by displacement measurements under ambient vibration; however, this technique has a relatively low sensitivity as the detective range is about 1 meter. Apart from that, the sensor may fail to detect other damages that occurred in the structure if they do not emit relative displacement.

Accelerometer

An accelerometer is one of the popular sensor choices in structural health monitoring due to its performance in providing an accurate vibrational response. There are two types of excitation that can be used to evoke and measure the structural response: forced excitation and ambient excitation. By analysing the vibrational feedback of the structure, the information embedded in the signal can then be extracted to show its healthy performance. Furthermore, observation of changes in structural properties is also one of the methods.

Forced excitation

In general, forced excitation is implemented by roving an impact hammer to structure. A pulse is then generated and propagated to the structure to evoke a vibration response. A demonstration is conducted to study the characteristic of bolt looseness in both laboratory and field environments [40]. Sun et al. [41] and He et al. [42] have implemented a modal analysis to detect bolt looseness by loosening bolts on a structure and predict the damping ratio by evaluating its pretension force and changes in natural frequencies to identify damages. However, this approach is insensitive to local damage of bolt looseness since changes in modal parameters correlate to variety in structural properties. Therefore, small damage will have a very minor effect contributes to the parameters. This analysis is also called as an input-output method as the processing algorithm requires both the input from the impact hammer and the vibration response from the structure.

Ambient excitation

While performing forced excitation being able to contribute a clear difference in signal when the bolt is loosened, this technique has a huge drawback. It requires stopping the normal operation of bridges so clear evoked response can be measured with less noise. However, it is not practical and not economically efficient in real life. Although the ambient excitation method has the advantage to not disrupt the normal operation of bridges when measuring response, the measured signal is likely to be noisy thus pre-processing is required to filter out the noise and environmental effects. Since the environmental excitation is random and not predictable, it can be treated as white noise. Thus, an output-only signal processing algorithm has been developed to extract features.

Dong et al. [43] and Tanner et al. [44] have implemented studies to monitor bolt group looseness using time-domain analysis to predict damage characteristic parameters. Their approach is capable to provide an estimation of level of looseness by monitoring the bolt's looseness position with amplitude changes in the extracted damage sensitive parameter. Despite joints on bridges, bolting is also popular in wind turbine construction.

A hybrid technique using vibration and impedance responses has been developed to combine global and local damage detection in wind turbine towers

Table 2.2: Comparison between Forced and Ambient Vibration Test

	Forced Vibration Test	**Ambient Vibration Test**
Pros	Provide wide-band input that is able to stimulate different modes of vibration	Can be implemented without affecting operation
	Can apply a large variety of input signals	Low cost
		Non-destructive testing
Cons	Required to stop operation for testing	Strongly depends on the type and characteristic of the equipment used
	Relatively low frequency resolution of the spectral estimates	Suffer from influence of environmental and operational noise
	Requires extremely heavy and expensive equipment for very large and flexible structure	

[45]. The technique detects frequency variation extracted from acceleration response to monitor the structural integrity and classifies damage that occurred at critical components (bolted joints) by analysing the difference in impedance signal. By combining multiple damage detection techniques, efficient methods can be developed in damage detection. This method is also tested to detect bolt looseness in steel girder connections [46]. Table 2.2 is a comparison table stating the advantages and disadvantages of the two techniques.

Deformation-based Monitoring

Load Cell

The load cell is a type of force transducer which converts forces such as tension, compression, pressure or torque into electrical signals that can be analysed. The transducer will output different electrical signal when there is a change of measured force thus able to contribute to damage detection. BoltSafe [47] is a commercial product in the market used to monitor bolt tension force that measures the change of magnetic field. It is installed between the bolt and joint lap surface and reading can be observed in a handheld device (Figure 2.11). This approach can produce accurate tensile force monitoring for each bolt however this might not be cost-effective as it requires one load cell for each bolt and is costly. Alternatively, a patent-pending tension controlled washer [48] has been released to the market which similarly uses a washer with a built-in sensor as a typical contact load cell to estimate changes to the load. However, the contact-based sensing could result in failure due to corrosion, limited load capability.

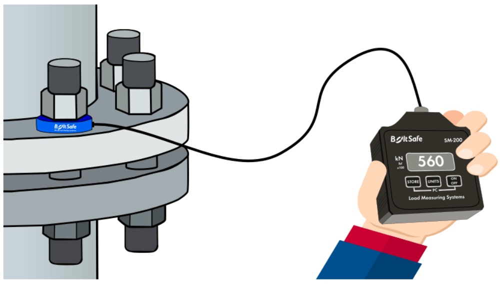

Figure 2.11: Illustration of BoltSafe Tension Monitoring Application [47]

Tension Sensor

Apart from installing sensors to the structure for measurement, the industry has come up with a novel idea to visualise the preload applied to the bolt by using colour. SmartBolts (Figure 2.12) [49] has a direct tension indication system on the bolt head that shows the tensile force by using different ranges of colours ranging from vivid red to gradually turn into black which represents loose and tight respectively. This technique helps inspectors to perform the visual checks for routine maintenance and local monitoring, but this cannot be used for remote monitoring. Similar product Maxbolt (Figure 2.13) [50] has a similar indication system that has a cartridge with a needle embedded in the bolt to show the variation of stress.

Optical-based Monitoring

Fibre Bragg-Grating Sensor

FBG (Fibre Bragg-Grating) is a relatively new material used for tension monitoring that delivers accurate results with a small package size using fibre optic. The sensor provides an indirect fundamental parameter as wavelength to indicate variation in stress using light level and is immune to electromagnetic

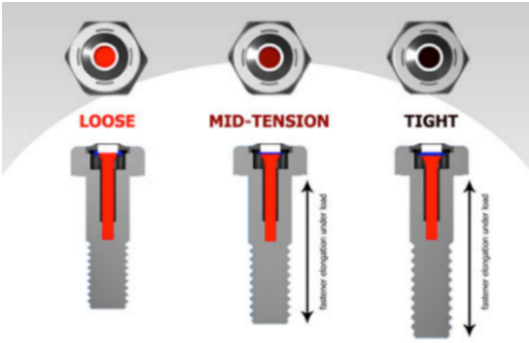

Figure 2.12: SmartBolts Tension Indication System [49]

Figure 2.13: Maxbolt Tension Indication System [50]

interference. Since FBGs can output high sensitivity result, it is very appealing for non-destructive evaluation (NDE) applications; for instance, temperature, strain and vibration measurements. However, FBGs are expensive compared to other sensor and requires calibration before usage.

In 2016, researchers from the USA have developed a bolt tension monitor that has embedded FBG sensor in a bolt shaft [51] (Figure 2.14). Their research recommended this bolt can be used for SHM application and defect detection in joints and structures and can be optimised to for higher clamping load with longer duration of time. Similar to a load cell, FBG can also be embedded to a washer for preload measurement [52] (Figure 2.15).

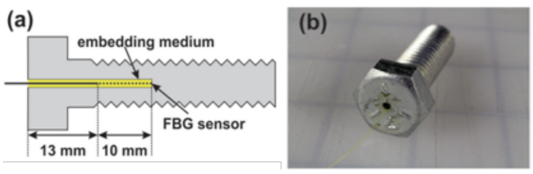

Figure 2.14: FBG Bolt Tension Monitor (a) Cross Section (b) Prototype [51]

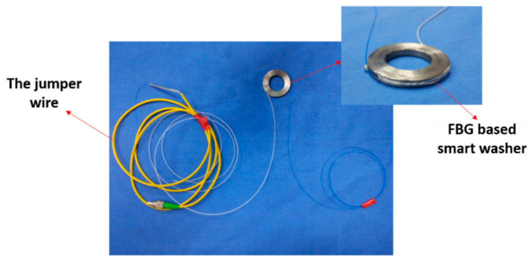

Figure 2.15: FBG-based Smart Washer Prototype [52]

Acoustic-based Monitoring

The concept of acoustic-based monitoring technique relies on a wave propagation approach. Waves are delivered to a structure and the changes indicated in the feedback is evaluated as an index for existence of defect. There are different types of waves can be used either in pulse-echo or transmission methods depending on the application. When there is defect in a structure, the ultrasonic signal will vary from the original. Consequently, by analysing the phenomena such as reflection, scattering of the waves, modulation of signal and energy wastage etc., can identify the location and severity of damage.

Conventional Ultrasound

A novel ultrasonic technique has been developed for stress measurement to estimate the axial force in high-tension bolts [53]. The method analyse the acoustic wave velocity and evaluate the time of flight (TOF) of waves in bolts for stress monitoring. The result is within 5% of error in predicting the axial force in bolts. Apart from scientific study, there are also patents for monitoring bolted joints using ultrasonic waves [54, 55]. Figure 2.16 and Figure 2.17 have illustrated the use cases to detect bolt looseness using bolt displacement and phased array surface acoustic wave (SAW) sensor respectively.

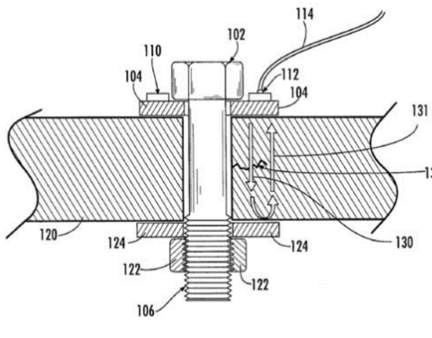

Figure 2.16: Ultrasonic Sensor for Tightness Evaluation [54]

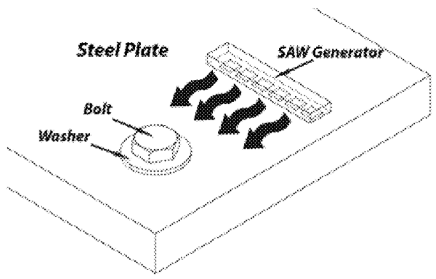

Figure 2.17: Illustration of Ultrasonic Bolt Looseness Detection [55]

Although ultrasonic technique has been a popular choice in SHM application, it poses disadvantages as there is no alerting system available and contact-based ultrasound requires couplant to facilitates the transmission of ultrasonic waves from transducers to structure. This raises problem such as contact corrosion and difficulty for remote monitoring application. In order to ease off the couplant problem, there has been a new sensor called electromagnetic acoustic transducer (EMAT) [56] which generates and detects ultrasound through electromagnetic field and does not require couplant or contact with specimen for axial force measurement.

Guided Waves

The propagation of guided waves is reliant upon the geometry of the testing specimen, and the travel direction of waves is guided by the boundaries of parts or structure. It has the ability to travel long distance inside the structure and cover greater depth in the structure comparing to the conventional ultrasound detection technique. The technique is popularly exploited in on-site inspections for instantaneous monitoring of structure conditions and the low-requency range for stimulation purposes ease of need for high sampling rate equipment which can be costly.

Nevertheless, it has a drawback that it is always subject to energy attenuation as the surface in structure and joints are rough. Researchers in Poland have developed an experimental investigation of damage detection in bolted lap joints using guided waves [57]. However, the results were only observable in the initial time period to show changes of amplitude or phase shift related to different bolt load values.

Impedance-based Monitoring

Considering a system has a fixed value of impedance when the same condition remains, the impedance is dependent on dynamic features and parameters. The appearance of defects such as cracks, decay, corrosion and looseness etc., can affect the value of these parameters and induce variation in the impedance. By utilising the impedance fluctuation, it enables the possibility to diagnose and evaluate the tightness of joints and to estimate the effective axial force in structure. In general, the mechanism of sensors is electrical impedance and electromechanical impedance-based that expose high sensitivity to contact-related defects. However, this technique requires lots of sensor and demonstrates unsatisfactory performance in system with thermal fluctuations or loading.

Piezoelectric sensor

The use of PZT (Piezoelectric) sensor approach is similar to the acoustic-based monitoring method as the impedance change is analysed by comparing the input and output from the actuator and sensor (Figure 2.18). Tao et al. and other researchers have reported studies on using this technique for residual torque estimation in bolted structures [58, 59, 60]. Parvasi et al. [58] have developed a time-reversal technique for bolt preload monitoring that can be used to obtain a simple and practical tightness index (Figure 2.19). However, this technique cannot be used with ambient excitation as external excitation is required thus not possible for remote monitoring as well.

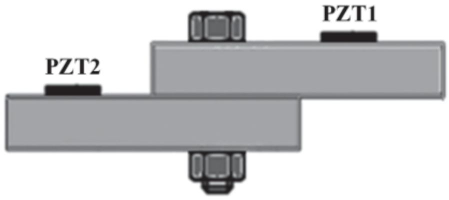

Figure 2.18: Bolted Joint with PZT Sensors [58]

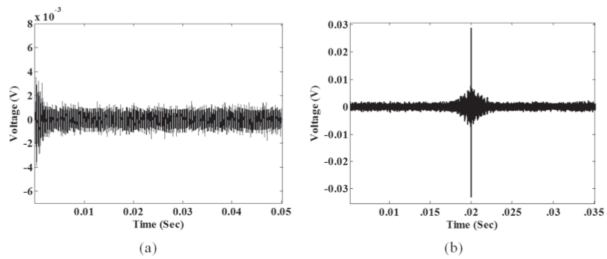

Figure 2.19: Recorded Voltage Response (a) PZT2 in Forward Analysis (b) PZT1 in Reversed Analysis [58]

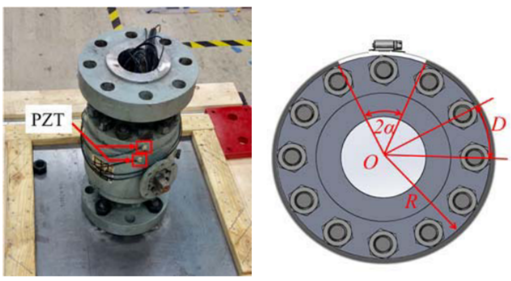

Figure 2.20: Seabed Ball Valve (left) Value (right) Cross-section [61]

A wearable sensor device has been developed for real-time bolted joint monitoring for a flanged valves in oil and gas pipelines [61]. Due to the cylindrical geometry of pipeline, the bolts installed on the connection flange were arranged as a ring. Such that embedding PZT transducers to a collar can achieve tension monitoring if there were any displacement of bolt occurred due to defect or looseness. Photographs of the experimented valve, developed prototype and installed sensor are presented in Figure 2.20, Figure 2.21 and Figure 2.22.

Furthermore, researchers from Japan have invented a smart piezoelectric bolt sensor for bridge health monitoring [62]. The sensor prototype is presented in Figure 2.23 that the piezoelectric cable sensor has used piezo film to wrap the stranded mental wire and the sensor can record vibration response when there is a change in stress level to the bolt body. This is similar to embedding FBG sensor into bolt shaft.

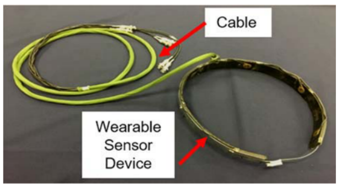

Figure 2.21: Wearable Sensor Device embedded with PZT Transducers [61]

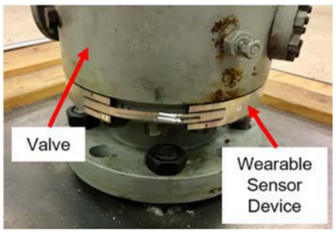

Figure 2.22: Wearable Sensor Device Mounted on Value [61]

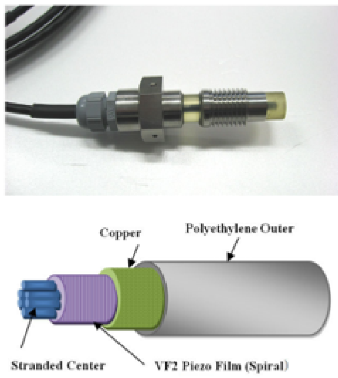

Figure 2.23: The Smart Bolt Sensor [62]

A summary of the contact type techniques for bolt looseness detection can be found in Table 2.3 where vibration-based monitoring has been most effective in maintaining low cost with relatively high accuracy and is suitable to use for remote monitoring applications.

Table 2.3: Contact Type Techniques Comparison

Contact Type Techniques	Vibration-based Monitoring	Deformation-based Monitoring	Acoustic-based Monitoring	Impedance-based Monitoring
Nature of Signal	Displacement, Velocity, Acceleration	Stress	Ultrasonic waves, Guided Waves	Impedance change affected voltage/current
Cost	Low	Low	High	High
Accuracy	High	Low	High	Acceptable
Suitability for remote monitoring	Yes	No	No	Yes
Practicality	High	Low	High	Low

2.4.2 Non-Contact Type Techniques

Optical-based Monitoring

Laser Doppler Vibrometer

Laser detection is known as one of the most accurate measuring technique that gives promising performance in detecting small changes and immune to environmental and operational condition effect. Siringoringo and Fujino have published an experimental study regarding laser Doppler vibrometer for vibration-based monitoring (Figure 2.24) [63]. Such application has presented that the technique is capable of performing modal identification using ambient vibration measurement and a modal-based damage detection algorithm has been developed to analyse bolt looseness. Despite the high precision measurement, modal analysis is insensitive to bolt looseness as the modal parameter does not change more than 10% when the bolt is loosened. This is a relatively high cost and not practical as only the specific location of bolts can be scanned.

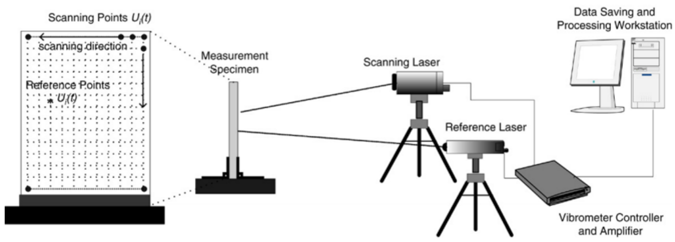

Figure 2.24: Schematic Figure of Data Acquisition using LDV System [63]

Vision-based Monitoring

Washer-based indicator

In contrast to contact-based monitoring, visual inspection is also one of the options for scheduled maintenance. A visual inspection involves a bridge inspector looks for a defect that is visible to eyes; for example, a large damage that can be seen in a distance. Vision-based monitoring is implemented without placing any sensor on the structure and evaluate if the structural integrity is damaged. For instance, there are several patents that bolt looseness is indicated by the deformation of a washer (Figure 2.25), colour indicators inside washers and stress-sensitive sheet when the distance between bolt and joint is increased implying bolt looseness [64, 65, 66].

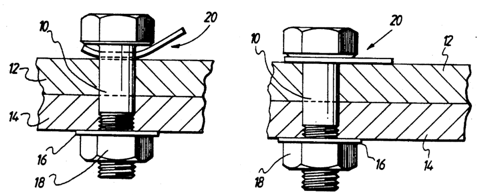

Figure 2.25: Washer-based Indicator [64]

This washer-based indicator enables the inspector to perform the routine check by looking at the bolts and does not require experienced worker that is crucial for other technique to achieve reliable check. However, this technique requires vigilance and is not practical when large numbers of components to be monitored such as complex structures, and bolts are not visible from distance. The application requires remote monitoring is also not achievable.

Image-based technique

Digital signal processing is exploited heavily in recent trends for structural health monitoring owing to its performance for extracting important damage related features. Researchers started to explore the possibility of using image processing techniques to detect bolt looseness by detecting the change of angle and height of bolt [29, 67, 68]. This technique yields a quantitative and tangible analysis of the investigation which is least affected by environmental noises. And the cost is relatively low since the main cost is a camera or can also be a smartphone. It could be difficult to detect changes of bolt due to slight difference in length of bolts in a structure and camera shooting angle requires being level with bolt thus being not practical for complex structure.

Radio Waves Processing-based Monitoring

RFID (Radio-Frequency Identification) Tag

In terms of non-contact type monitoring techniques, radio waves processing is also considered by researchers. Owing to the fact that bolt looseness usually involves rotating bolts and nuts, detection of looseness can then be achieved by monitoring the rotation movement. An RFID tag-based indicator is developed based on the rotation angle of the bolt to enable radio frequency signal propagation to a receiver unit [69].

Initially, the signal cannot be received by the reader if the tag is obscured by a layer of tin foil paper that blocking its propagation. Whereas if the bolt is loosened, such rotation enables the tag's antenna to be exposed for successful signal transmission. A radio frequency signal that carries the corresponding bolt's information is then transmitted to the RFID reader by the tag to identify the location. However, due to the signal blockage by the tin foil, the system fails to detect bolt looseness if the rotational angle does not exceed 20 degrees.

Three different types of non-contact bolt looseness detection techniques are discussed and a comparison is drawn in Table 2.4. It can be seen that the techniques

Table 2.4: Non-Contact Type Techniques Comparison

Non-Contact Type Techniques	**Optical-based Monitoring**	**Vision-based Monitoring**	**Radio Waves Processing-based Monitoring**
Nature of Signal	Optical wave length laser Velocity	Image Tension level	Radio Signal Guided Waves
Cost	High	Low	Low
Accuracy	High	Low	Low
Suitability for remote monitoring	No	No	Yes
Practicality	Low	Adequate	Low

have the potential to detect bolt looseness defects; however, it is not as effective compared to the vibration-based contact type technique thus it is not pursued in this study.

Summary

This section has summarised various types of technique for bolt looseness detection into two categories depending on the sensing method as Contact and Non-Contact type techniques. In contact type, there are four types of technique introduces; for instance, vibration-based, deformation-based, acoustic sensing-based and impedance-based. On the other hand, non-contact types have three types of techniques as optical-based, vision-based and radio waves-based.

Amongst all these discussed methods, vibration-based technique will be focused on in this study as it is the most commonly applied method with acceptable accuracy and suitable for remote monitoring over other techniques. Two comparison tables were presented to compare the techniques regards to their nature of signal, accuracy, cost and suitability for remote monitoring etc. For the recent research trend, researchers are aiming to achieve real-time online monitoring as it is cost-effective and efficient that the quality of monitoring result does not rely on experienced inspectors. In the next section, the data acquisition technique for vibration-based monitoring will be discussed.

2.5 Data Acquisition for Vibration-based Monitoring

Before proceeding to discuss signal processing techniques for bolt looseness detection, it is crucial to investigate how vibrational signals can be captured as good as possible. In this section, data acquisition systems will be discussed in terms of sensor, measurement unit, data resolution and sensitivity, sampling rate and frequency range. Machine vibration is a key element for structural health monitoring so there is massive interest in acquiring, analysing and quantifying this parameter for improving reliability, life, quality control, productivity and safety against catastrophic failure [70]. Vibration is characterised into three variables: Displacement, Velocity and Acceleration. The performance of sensors are depending on the vibration signal frequency range where displacement sensors are used for low-frequency range, velocity sensors to pick up middle range and accelerometers for higher-frequency range.

Moreno-Gomez, Perez-Ramirez, Dominguez et al. have reviewed sensors used in structural health monitoring in 2017 [4]. Reviewed sensors are grouped into three categories as Kinematical (movement of structure), Mechanical (change of structural properties) and Ambiental (environmental effect). Their study has summarised accelerometer is a popular choice for damage detection and system identification due to its advantage for easy installation to the structure and accuracy.

2.5.1 Data Acquisition System

In order to enable remote monitoring applications for cost-effective and efficient manner in structural health monitoring, researchers and industries have investigated various data acquisition techniques. This can be grouped into two types: (1) separated sensors connected to data acquisition system and (2) microelectromechanical sensor chip embedded to data acquisition system circuit board. Different types have their own advantages and disadvantages depending on the application and will be discussed in the following:

Table 2.5: Accelerometers Performance Criteria

Study	**Accelerometer**	**Sensitivity**	**Bandwidth (Hz)**
Yusa & Sawada [40]	PCB 608A11	100 mV/g	0.5 - 10000
Sun & Liao [41]	PCB 320C03	10 mV/g	1 - 6000
He & Zhu [42]	PCB U352C66	100 mV/g	1 - 4000
Nguyen, Huynh et al. [45]	PCB 333B52	1 V/g	0.5 - 3000
Abdeljaber, Avci et al. [71]	PCB 393B04	1000 mV/g	0.06 - 450
Avci, Abdeljaber et al. [72]	PCB 393B04	1000 mV/g	0.06 - 450

Integrated Circuit Piezoelectric (ICP)-based

Taking into account when selecting sensors for certain applications, sensitivity and its relative frequency range are the top priority concerns as they dominate the quality of the captured signal. The ICP-based accelerometer has a built-in microelectronic that converts a high-impedance charge signal by a piezoelectric sensing element into processor-readable low-impedance voltage signal. Table 2.5 has summarised the used accelerometers in the reviewed studies regarding their performance in signal sensitivity and frequency bandwidth. What stands out in the table is the frequency have a wide range with a relatively low-pass band as low as 0.06 Hz, as a large structure has low natural frequencies identified and observing such changes can correlate to existing defect modified its structural properties. When considering the data acquisition system, a measurement unit is required to convert the electrical signal from analogue to digital format that can be used by a processor. There are few criteria needs to be considered:

- Data Resolution
- Sampling Rate
- Number of Channels available

Table 2.6: Data Acquisition Systems

Study	Data Acquisition System	Data Resolution	Sampling Rate	Num. of Ch.
Yusa & Sawada [40]	NI-9233-USB	24-bit	25 kS/s	4
Sun & Liao [41]	VTI EMX (4251)	24-bit	204.8 kS/s	8
He & Zhu [42]	LMS 36-Ch Spectral Analyser	24-bit	204.8 kS/s	4
Nguyen, Huynh et al. [45]	HBM's QuantumX-MX840A	24-bit	40 kS/s	8
Abdeljaber, Avci et al. [71]	ME'scopeVES	24-bit	250 kS/s	32
Avci, Abdeljaber et al. [72]	TROMINO ENGY Wireless Sensing Unit	24-bit	250 kS/s	3

These parameters are crucial when capturing data in vibration signal as the data resolution dominates how much detail can be captured, and the sampling rate should be at least double the signal frequency to qualify for aliasing effect. As such, the higher the sampling rate the finer signal can be recorded and more channels available can ease of synchronisation problem for different sensor channels. As discussed, Table 2.6 shows different data acquisition system used in other studies and all of them are capable to achieve high resolution of 24-bit data with a relatively high sampling rate.

Microelectromechanical (MEMS)-based
In contrast to the ICP-based data acquisition system, the MEMS-based system has the advantage of arranging sensing units with the acquisition system integrated into a portable sensor node enabling a wireless senor network for structural health monitoring applications.

MEMS is a microelectromechanical sensor device fabricated using microelectronic techniques that form a micro-meter range mechanical sensing structure using silicon to measure physical parameters such as acceleration. Over the two decades, researchers have investigated the feasibility of a wireless sensor network by building a modular sensor node [44, 46, 73].

A module consists of a MEMS-based accelerometer board, processing board and a battery pack to power the unit. The monitoring system uses a sensor board to detect bolt looseness and report alert to the processing board wirelessly when an event is triggered. This sensor technology enables the deployment of a dense array of sensors feasible and affordable at the cost of producing a sizable sensor network for large and complex structures. Sabato, Niezrecki and Fortino have published a review paper on wireless MEMS-based accelerometer sensor boards for structural vibration monitoring [5].

Study (-)	Accelerometer (-)	Noise-Density ($10^{-3} m \cdot s^{-2} \cdot Hz^{-0.5}$)	Sensitivity ($mV \cdot m^{-}1 \cdot s^{2}$)	Sensing Range ($m \cdot s^{-2}$)	BW (Hz)	Acc. Res. ($10^{-3} m \cdot s^{-2}$)	ADC (bit)	ADC Res. ($10^{-3} m \cdot s^{-2}$)	Transmission (-)
Pakzad [24]	SD-1221	0.05	203.96	±0.98	0.1 - 25	**0.31**	16	0.22	Multi-hop
Cho [51]	CXL02LF	1.37	101.98	±19.61	0 - 50	**12.28**	16	0.75	Multi-hop
Swartz [54]	CXL01LF	0.69	203.96	±9.81	0.03 - 25	**4.34**	16	0.37	Multi-hop
Park [35]	SD-1221L	0.05	203.96	±19.61	0.1 - 100	**0.62**	16	0.45	Single-hop
Nagayama [61]	LIS3L02DQ	1.03	67.30	±19.61	0 - 56	**9.75**	-	-	Multi-hop
Rice [63]	LIS3L02AS4	0.49	67.30	±19.61	0 - 50	**4.39**	16	0.68	Multi-hop
Jo [66]	SD-1221L	0.05	203.96	±1.96	0 - 15	0.24	16	**0.37**	Multi-hop
Whelan [28]	LIS2L02AL	0.29	67.30	±19.61	0 - 50	2.63	12	**10.88**	Single-hop
Meyer [55]	LIS2L06AL	0.88	22.43	±58.84	0 - 100	11.16	12	**32.65**	Multi-hop
Bocca [59]	LIS3L02DQ	1.03	67.30	±19.61	0 - 56	**9.75**	16	0.68	Single-hop
Chae [36]	AC310-002	0.13	203.96	±19.61	0 - 300	**2.79**	16	0.37	Single-hop
Hu [72]	SD-1221	0.05	203.96	±0.98	0 - 50	0.44	12	**4.31**	Multi-hop
Sabato [38]	SF1600	0.003	122.37	±29.42	0 - 1500	**0.14**	-	-	Single-hop
Kohler [73]	SF1500	0.003	122.37	±29.42	0.1 - 1500	**0.14**	24	0.003	Multi-hop

Figure 2.26: Summary of Wireless MEMS-based Accelerometer Sensor Board between 2006 & 2016 [5]

Figure 2.26 presents a summary on wireless MEMS-based developed sensor board over the decades between 2006 and 2016. It has presented majority of developed boards have a relatively low sensitivity (∼20mV/g VS 100mV/g) and 8-bit less resolution compared to ICP-based accelerometers. However, the performance should be adequate since the device is designed as a portable sensor unit with an embedded microprocessor thus energy-consuming high-performance components is not preferred.

Table 2.7: Signal Processing Techniques for Structural Health Monitoring

Techniques	Good SNR Ratio	Good Resolution (T-F Domain)	Computational Efficiency	No Calibration	Nonlinear Signal Analysis	Ambient Excitation Input
Statistical Time Series (TS)					Y	
Fast Fourier Transform (FFT)			Y	Y		
Short-Time Fourier Transform (STFT)			Y	Y		Y
Wavelet Transform (WT)	Y	Y	Y	Y	Y	
Hilbert-Huang Transform (HHT)	Y	Y			Y	Y
Spectral Kurtosis (SK)	Y	Y		Y	Y	Y

2.6 Signal Processing Techniques

So far this study has focused on the background of bridge health monitor, techniques and sensors used for data acquisition. The following section will discuss how useful information can be extracted by implementing digital signal processing and utilise it for damage detection. In regards to the development of signal processing techniques used for structural health monitoring, there are review papers published recently to analyse their advantages and disadvantages [70, 19, 74].

2.6.1 Feature Extraction Criteria

Table 2.7 summarises some of the popular signal processing techniques and compared their performance in some of the key aspects which is important. The key areas are as follows:

Key Aspects	Description
Good SNR Ratio	Assess the level of the desired signal to the level of background noise
Good Resolution (T-F Domain)	A view of the signal represented over time and frequency that provides location of frequency at the time domain
Computational Efficiency	Taking into account the resources required to implement the algorithm in the processor
No Calibration	Input parameter required to calibrate algorithm for performance
Nonlinear Signal Analysis	Ability to analyse nonlinear signal that does not obey superposition and scaling properties
Ambient Excitation Input	Able to analyse response evoked by ambient excitation and qualified as an output-only algorithm

With respect to the developed techniques, it can be categorised into two types as feature extraction and pattern recognition that focus on filtering useful information and investigate the correlation between data and gather them together respectively. Fast Fourier Transform (FFT) is the oldest technique used in digital signal processing to convert discrete samples from the time domain to the frequency domain. The quality of the digitising conversion process is highly dependent on the sampling rate of the recorded signal due to the aliasing effect resulting in false frequency components takes place. However, since FFT detect the variation in frequency signals content over time. It cannot be used to analyse nonlinear signals and monitor structures subjected to dynamic excitations. Therefore, there is a need to develop advanced digital processing technique to extract useful information. A brief introduction of the aforementioned techniques will be discussed in this section.

2.6.2 Signal Processing Techniques for Bolt Looseness Detection

The concept of structural health monitoring is to perform system identification to estimate its modal parameters such as natural frequencies, modal shape and damping ratio from data measurement. The estimation has a close relationship to structural properties and can be used as a baseline reference. Any damage that changes the integrity of the structure can be detected by observing variation in the parameters.

The key problem with this approach is that system response to local damage has relatively low sensitivity, for example, bolt looseness issues in large structures can hardly be detected. The failure can also be owing to poor data quality, signal processing techniques have difficulties in handling non-stationary signals and low sensitivity of modal parameters to present structural damage that suffers from fluctuations in environmental conditions. The following part will focus on how researchers developed different techniques to detect bolt looseness by monitoring the loss of preload on the bolt.

Time Series Analysis

Time Series (TS) Analysis is an approximately mathematical model based on a set of input–output measurements characterised into linear and nonlinear statistical TS models. It is the one of the earliest models used for structural condition assessment. In time series analysis, it is normally based on evaluating the variant in time-domain features; for instance, standard deviation, peak, mean and root mean square of signal to detect damage. It is often to combine features with a statistical analysis approach. Researchers have simulated structure damage using cantilever metal beam or truss structure representing bolted joint of the bridge with tightened and loosened case [48, 75, 76]. The developed technique is based on the residual error of auto regression model from its standard deviation as a damage sensitive feature (DSF).

Another study has implemented a two-stage damage detection algorithm that monitors signal correlation between sensors for global damage detection. Once an alert is triggered, a local damage detection algorithm that combines time series analysis and statistical hypothesis testing is used for damage localisation. However, the mentioned techniques only focus on simple damage cases for bolt looseness. Dong et al. [43] have implemented an experimental study to monitor bolt group looseness where multiple damage cases are investigated and showed effective results for detecting damages. One major drawback of these time series analysis techniques is that they rely on threshold-based detection to distinguish health and damage cases and the looseness of the bolt cannot be quantified.

Wavelet Transform

Wavelet Transform (WT) is a technique that provides time-frequency analysis of signals that consists of a collection of elementary scale functions called wavelets. The wavelets collection consists of different discrete–time low and high-pass filters that can be dilated and shifted individually. Owing to its advantages in computational efficiency and time localisation, WT is utilised extensively in SHM applications. It is a relatively new technique that has caught loads of interest in the civil and mechanical engineering field due to its ability in delivering time-frequency analysis with good resolution. Academic researchers have utilised wavelet analysis for damage detection of a steel frame structure with bolted joints [77]. The vibration responses of joints is utilised to calculate wavelet coefficients to represent health and loosened connection structure and damage can be detected by observing differences between them. Zhang, Yan, Yang et al. [68] have proposed to use Daubechies (DB) wavelet, an orthogonal wavelet to detect bolt looseness with an assembly tightness quantitative index. This quantitative index is used to detect different assembly tightness degrees of the bolted rotor and it can accurately detect six different damage cases. However, the authors failed to quantify the energy distribution to the actual remaining torque of the bolts which is essential in evaluating the severity of damage caused by looseness.

Another weakness is that only a specific spectrum is analysed therefore events that occurred in other bandwidth will be missed to detect. Apart from using wavelets for structural health monitoring, Nayak and Panigrahi have present a novel technique called S-Transform by implementing modifications of Short-Time Fourier Transform (STFT) and wavelet for feature extraction in data mining [78]. STFT is an extension of FFT that is capable of analysing non-stationary signals by segmenting signals into small windows where each window is analysed with FFT. This segmentation approach enables STFT capable to represent the variation of signal frequency contents as signal changes in time. This technique provides a broadband analysis which focuses on both low and high frequency transient signal by offering a variable window that is inversely proportional to frequency.

Combinational of Different Techniques

Empirical Mode Decomposition, Hilbert Transform and Wavelet

Hilbert-Huang Transform (HHT) is an adaptive signal processing technique capable of analysing stationary, nonstationary and transient signals. The technique is implemented based on two stages that use empirical mode decomposition (EMD) with the Hilbert spectral transform (HT). This helps to separate different frequency components in a noisy signal which is useful to detect damage. Owing EMD's ability to analyse the non-stationary signals, Xu et al. [79] have utilised the technique and extended its application to detect damage in bolted joints. Their approach has evaluated the structural dynamic response to identify the nonlinear system behaviour induced by bolt looseness. The technique is a combination of techniques such as Hilbert transform and wavelet analysis to decompose a measured signal into intrinsic mode functions (IMF) that represents a hidden oscillation mode with its own characteristic time scale. These IMF can then be used as damage feature indices for bolt looseness detection that correspond to looseness level by torque.

Another example uses a similar approach with the combination of these techniques whereas the application is developed to detect damage of cracks with travelling loads applied [80]. Although the technique is targeted to analyse the non-stationary and nonlinear signal, the processed result is insensitive to crack depth and suffers from operational and environmental noise. Apart from monitoring bolted joints on bridges, pedestal looseness is one of the issues that introduce damage to the wind turbines. An et al. [81] have established a technique that based on ensemble empirical mode decomposition (EEMD) and Hilbert transform to analyse vibration signals using IMFs. The presented technique shows the effective results to detect looseness whereas it is insensitive to the location of defects. Other drawbacks are it does not quantify the state of damage and high-frequency component is not noticeable.

Spectral Kurtosis

Spectral Kurtosis (SK) is a statistical spectral analysis technique that can be used to characterise non-stationary time signals. This is based on the spectral analysis of the time series analysis feature Kurtosis and is an enhancement to the classic power spectrum density (PSD). Antoni has introduced the concept of the technique and formalised it by giving it a theoretical definition [82]. Although there are other definitions of SK [83], they agree that the technique is capable of detecting non-stationary components in noisy transient signals by finding a closed-form relationship in regards to noise-to-signal ratio.

The technique has caught much interests in the past decade due to its performance in identifying non-stationary components induced by damage, most of the applications are focused on the health diagnosis of rotating machines in respect to bearing damage that has a noisy periodic operational effect [84, 85, 86]. However, there is currently no report of use in application for detecting bolt looseness and can be investigated.

2.6.3 Common Techniques to Bearing Fault

In conventional asset condition and health monitoring applications, it is aimed to extract defect sensitive features for damage detection. The extracted features are then used to compare to baseline operational data to distinguish the severity of detected damage. This is also a common approach used for bearing fault detection as defect tends to omit abnormal patterns in the periodic operational signal.

During normal operation, non-stationary components are often found buried in time-series vibrational signals that are generated by the abnormal patterns [87]. However, it is a challenging task to extract the non-stationary components. Given these components are unknown, there is a demand for efficient algorithms that are capable to distinguish the abnormal vibrational pattern and classify the cause of damage.

Despite multiple researchers have reported that SK is effective in detecting bearing faults and characterising the induced vibrational responses, there are few gaps that remain unsolved; for instance, fault alarm caused by spikes in signal, scalability of SK estimates and the high noise level. Siu et al. [88] have proposed a novel blind feature extraction technique to address these problems and provide an early damage detection solution to optimise the efficiency of maintenance cost. The detail of this work is described in the later chapter as an additional application to bolt looseness detection.

2.7 Machine Learning for Bridge Health Monitoring

2.7.1 Overview of Machine Learning Algorithms

Machine learning applications have received massive interest in the recent decades due to its effective and intelligence approach to solve problems associated with uncertainties and complex problems. Researchers from academia have investigated the possibility to emerge artificial intelligence (AI) algorithms with existing signal processing techniques to aid structural health monitoring. The following section focus on an overview of machine learning methods utilised for bridge health monitoring.

Figure 2.27 illustrates a flow chart of machine learning practice in SHM with five stages. Machine learning requires massive amount of data to train a model in learning features and result prediction. Therefore, the first stage is to acquire vibration data from sensors and it is important to implement pre-processing since noisy signal can affect accuracy of model and normalisation to adapt dynamic range amplitude. After that, the aforementioned digital signal processing techniques such as WT, HHT and SK are implemented to extract damage sensitive feature for use with AI algorithms for damage detection. And finally, the predicted result are used for decision making.

There are many machine learning techniques exists and been tested to prove feasibility in predicting damage in structures. This section will briefly introduce the key methods reviewed in machine fault predictions and structural damage monitor-

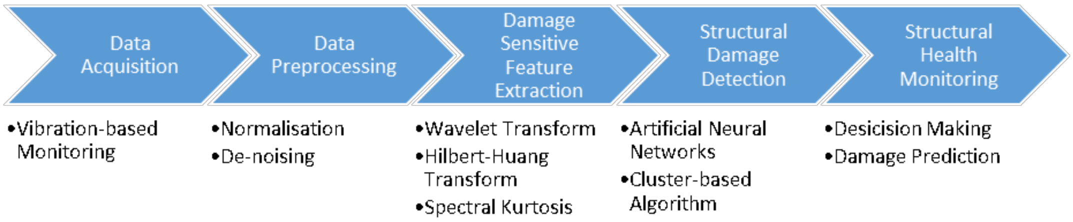

Figure 2.27: Flow Chart of Machine Learning Approach of SHM

ing and the summary is shown in Figure 2.28. AI algorithms can be categorised as feature extraction by analysis correlations between data and put them into different buckets where classifier relies on labelled data to output result into different types according to input data. Apart from this approach, algorithms can also be grouped as unsupervised and supervised learning where algorithms requires data labelling or not to output result. For instance, feature extraction algorithm is unsupervised learning and classifier requires labelled data to distribute data to different types of output.

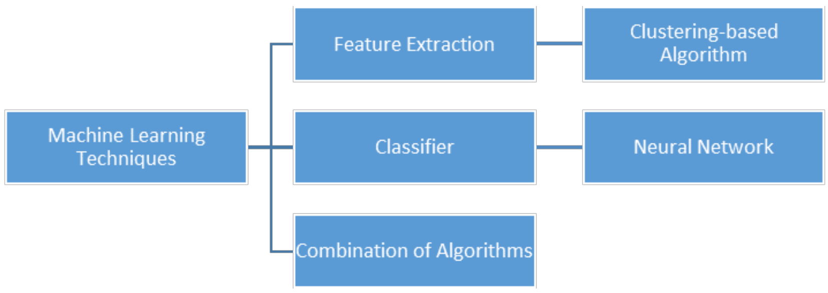

Figure 2.28: Overview of Machine Learning Algorithm in SHM

Due to the fact that machine health monitoring looks for nonstationary component and its deviation from healthy and damaged states system response, machine learning methods used for machine fault diagnosis can be applied to structural health monitoring application as well. Zurita et al. have reviewed AI methods used for vibrational machine diagnosis [89]. The review has briefly introduced feature extraction techniques such as principle component analysis (PCA) and genetic algorithm (GA). Then extracted feature can be fed to different classification techniques for fault diagnosis. Another review for AI in rotating machinery has also discussed similar approached in addition to other techniques such as k-Nearest neighbour, Navie

Bayes classifier with their theoretical background and their application [90]. The authors summaries the performance amongst the techniques (Figure 2.29) that deep learning shows a better all rounded performance in managing accuracy, robustness to noise and dealing with overfitting problem. Han et al. [91] have evaluated the performance of random forest (RF), artificial neural network (ANN) and support vector machine (SVM) applications for machinery fault diagnosis and argues that RF provides the best performance in terms of classification accuracy, stability and robustness to features.

Performance comparison of AI algorithms.

	ANN	SVM	*k*-NN	Naive Bayes	Deep learning
Accuracy in general	***	****	**	*	****
Classification speed	****	****	*	****	**
Robustness to noise	**	**	*	***	****
Dealing with overfitting	*	**	***	***	***
Physical explanation	*	*	***	****	*
Robustness to parameters	*	*	***	****	**

Figure 2.29: Performance Comparison of AI Algorithms Review [90]

2.7.2 Clustering-based Algorithm

As a data-driven machine learning approach, clustering-based algorithm is a technique used to extract and distribute features as pattern recognition. For instance, bridge components deteriorate before damage become detectable. Thus researchers have used Bayesian network approach to estimate deterioration of fatigue cracking of girders and corrosion of bearings [32]. The model is developed for prognostic health monitoring system that based on probability analysis to investigate the types of bridge elements have largest influence on structure deterioration. Apart from Bayesian network, there are also other choices such as K-means and Fuzzy clustering for bridge health monitoring [92, 93, 94]. Figure 2.30 is a flowchart showing the approach of a clustering-based algorithm for SHM that involves five stages. This starts from retrieving vibration data from bridge and a series of digital signal processing to extract features, masking data with K-means envelop for outliner removal and characterise system behaviour from estimated damage sensitive index. One of the concern from these clustering algorithms is that damage state data might not be available from existing structure. However, the detection can be achieved by estimating the density of feature vectors by assuming the structure is healthy and evaluate consistency with new feature vectors.

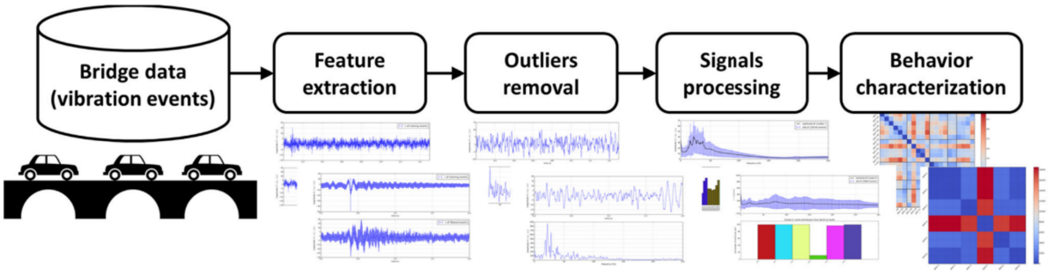

Figure 2.30: Flowchart of Clustering Based Approach for SHM [92]

2.7.3 Convolutional Neural Network

Convolutional neural network (CNN) is one of the advancement in deep learning applications which received lots of interest and achieved outstanding result in the domain of computer vision. It has been utilised for applications such as image analysis classification, image video recognition and natural language processing. Figure 2.31 is an illustration of CNN showing the information processing procedures consists of input images, feature learning and classification. The algorithm analyse input images with a kernel to assign importance to different objects in image and distinguish variation from one to other. During the feature learning process, the convolution layer goes deeper to extract high level features such as edges, colours and gradient orientation. Meanwhile, the convolved feature is reduced in dimensionality compared to input and is feed to normal neural network to implement classification process to distribute output to different classes.

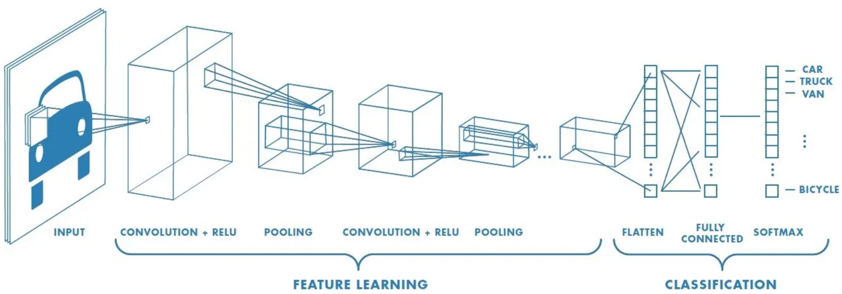

Figure 2.31: Illusration of Convolutional Neural Network [95]

In regards to bolt looseness detection using deep learning, researchers have established an application using image detection technique to monitor loosening angle with CNN [96]. Although the application achieved good result with 91.4% of accuracy, the minimum recognition rotation angle of bolt has to be greater than 10°. In addition, the same group of researchers have developed an autonomous monitoring technique by detecting variation of bolt looseness by the angel and height with images [68]. The deployed real-time application is presented in Figure 2.32. Despite the good result of model, this technique requires image position correction and suffer from contrast level of image if environment lighting is dark.

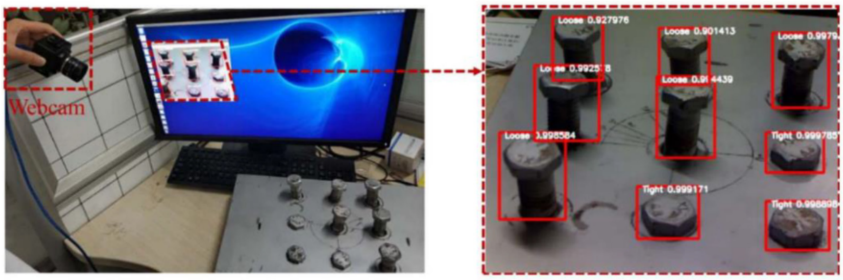

Figure 2.32: CNN Deployed Real-time Bolt Looseness Detection Algorithm [68]

2.7.4 Combination of AI Techniques

Owing to the fact that every machine learning technique has their own characteristics, researchers have started to investigate the possibility in merging various approach together to achieve better performance to predict damage in structures. For instance, Bandara et al. [97] have implemented frequency response function (FRF) based damage identification using PCA and pattern recognition. Due to fact that FRF suffers from requirement of large amount of data and complexity, the use of PCA could reduce dimension of data and remains important information. And damage sensitive features are feed to pattern recognition algorithm for damage detection. However, this approach cannot be used for ambient excitation monitoring technique as FRF requires input and output signal to detect defect. Another example uses combination of Bayesian, NN and SVM to apply supervised learning method to extract features from raw data and detect damages [98].

2.8 Emerging Technologies

2.8.1 Artificial Intelligence in SHM

In the recent decades, AI algorithms have received lots of interest from academia and industry coming up with the idea of industry 4.0 applied to health monitoring applications for machines and structures. Eraliev et al. [99] have developed a vibration-based bolt looseness detection application using machine learning algorithms such as Random Forest, Decision Tree, SVM and K Neighbours Classifier etc.

Although their findings has provided an insight how artificial intelligence can be used to detect bolt looseness, the experiment is limited to controlled experiment as excitation is delivered by AC motor and the used signal processing technique STFT might not extract transients buried in noisy signal effectively.

Salehi and Burgueno have reviewed the emerging technologies used in structural health monitoring and focused on machine learning methods [100]. They have analysed the trend and diversity of different techniques and their population between 2009 and 2017. In the study, the research trend based on publications is diversified into two categories as learning & recognition based and stochastic optimisation and reasoning respectively which Machine Learning and Neural Network occupy the most population than Fuzzy Logic and Decision Tree.

For a better understanding of how AI is used in different applications, Figure 2.33 has presented that both pattern recognition and machine learning methods are utilised in SHM heavily for damage detection due to their ability in spotting deviation in features caused by damage. The authors have summarised the emerging applications would be Data-driven SHM and IoT (Internet of Things) SHM (Figure 2.34).

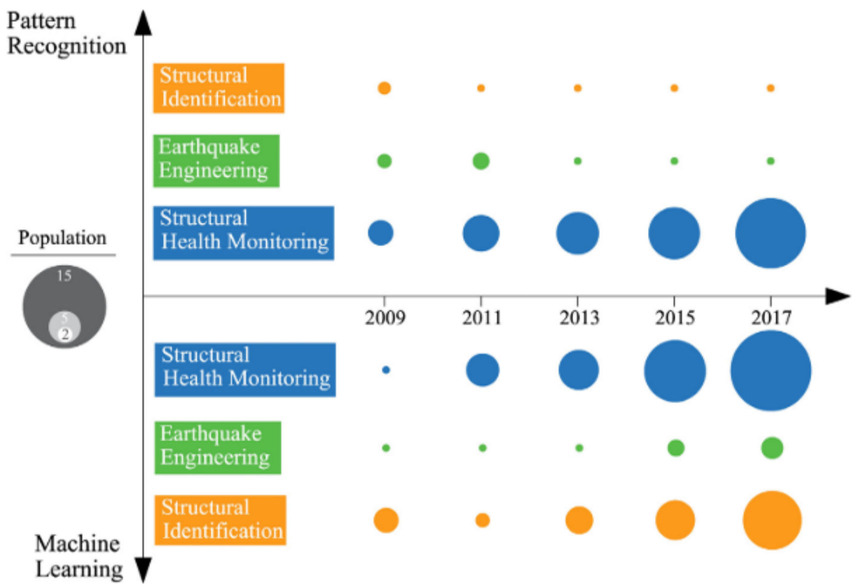

Figure 2.33: Research Publications on Use of Machine Learning and Pattern Recognition [100]

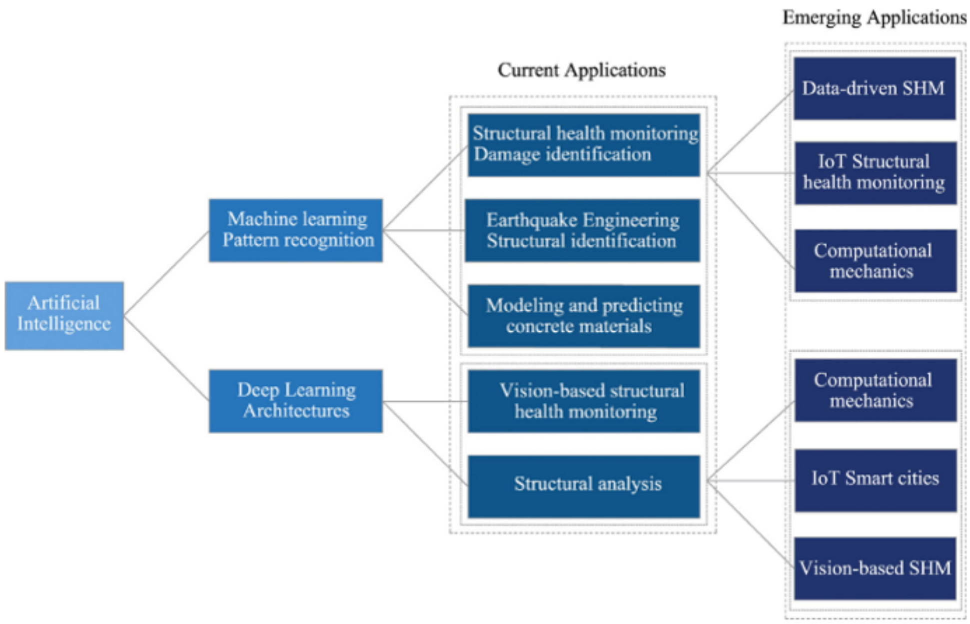

Figure 2.34: Artificial Intelligent Application in Structural Engineering [100]

2.8.2 Internet of Things – Wireless Sensor Network

In order to achieve Industry 4.0 with digital twin real-time remote monitoring, it is important not to neglect the hardware required for data acquisition and wireless communications between devices. In general, there are two types of the communication protocol for SHM applications used for data acquisition as wired and wireless networks that measurements are transmitted through cables or radio frequencies respectively. Although wired sensor network has been proved to have better tolerance in noise and better quality of signal with faster speed, the cost of system equipment such as cable and acquisition unit is costly and difficult to perform maintenance tasks. Consequently, industry and academia have started to investigate the feasibility of wireless sensor networks to enable remote structural health monitoring with IoT technology [72, 73, 101].

These wireless SHM applications have emerged many sensor nodes with the embedded systems running damage detection algorithm onsite with a lower cost and ease of manpower of inspection task. In addition to IoT enabled SHM, there is also the new trend of sensing devices predicted for health monitoring that researchers suggested that smartphones can be utilised due to their advantages for development-friendly software platforms, real-time monitoring with internet & cloud storage and affordable for big-data collection [102].

2.9 Technology Gap

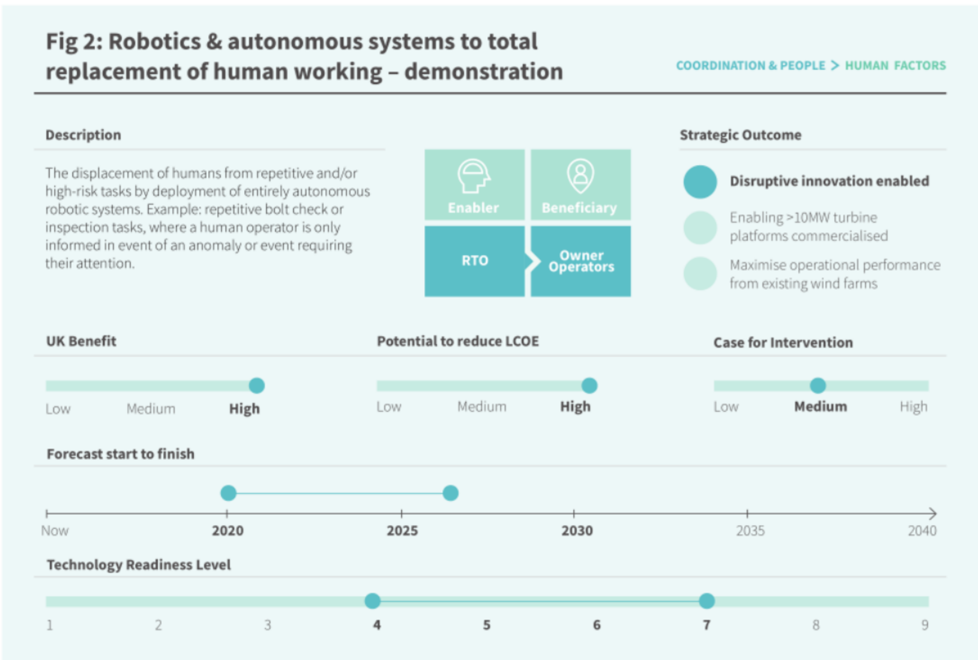

Figure 2.35: Autonomous Bolt Check Roadmap [103]

Having discussed the emerging technologies in bridge health monitoring, the final section of this literature review addresses the existing technology gaps in damage detection. A case study and review regarding the deployment of smart SHM has pointed out that it is a challenge to retrieve a damaged structural model in real life unless simulated and it is vital to develop advanced sensors to solve the problem [74].

In addition, wireless sensing technologies with the high sampling rates and accuracy should also be developed. Referring to the data-driven SHM trend, the development of machine learning algorithms is crucial with advanced signal processing techniques is required. Consequently, a journal article has explored the possibility of feature extraction using domain knowledge [104]. It is recommended that the selection of feature extraction should depend on the nature of the signal.

In bolt looseness detection, it is also predicted that microcontroller based sensing devices for data pre- and post-processing and local decision making for alerts (use of ML algorithms) will be the trend [105]. Offshore Wind Innovation Hub has released an innovation roadmap that also stated there is a need for enabling remote monitoring for repetitive bolt check or inspection tasks where a human operator is only informed in the event that requires their attention within the duration of 2020 and 2027 (Figure 2.35) [103].

To summarise the findings in this literature review, it has presented the need of sensor advancement to contribute high quality recorded data from structure, effective pre- and post data processing to remove noise, efficient digital signal processing technique to extract damage sensitive features and finally combining techniques with machine learning models to establish an automated early damage detection application. In this study, an advanced digital signal processing technique is proposed to address the requirement aiming to detect small defects that are hard to detect in structure by applying optimal filtering to extract useful information. The developed work will contribute a key role in damage detection application as the accuracy of damage sensitive feature dominate the effectiveness of an application that could cause false alarm resulting in delayed repair along with increased maintenance cost.

Chapter 3

Methodologies

3.1 Proposed Signal Processing Techniques

In nature, there are three types of signals namely periodic time, aperiodic time and random signals that present different characteristics of certain patterns over time or no pattern respectively. In conventional digital signal processing, Fourier Transform is widely used to convert signal from time domain to frequency components; however, it cannot be used to detect non-stationary signal thus discrete Fourier transform is utilised to analyse aperiodic signal.

Signals captured in real world is full of noise and in random format therefore other technique such as PSD (Power Spectral Density) is used for analysis. PSD is a technique used to display the distribution of signal frequency components visually. It shows the percentage of the overall signal power that each frequency component contributes to the signal. Since the PSD estimates are dependent on choice of window size and overlap can affect the accuracy, these limitations make it challenging to use PSD for non-stationary signal processing. Therefore, an advanced signal processing technique Spectral Kurtosis is proposed in this study to identify non-linear and non-stationary frequency components generated by damage in structure.

3.1.1 Spectral Kurtosis

Spectral Kurtosis (SK) is a statistical spectral analysis tool that can be used to indicate the presence of non-stationary signal buried in a time-series signal. It is proficient in characterising non-stationary frequency component of a signal while compressing Gaussian noise and stationary component by utilising it's fouth-order cumulant based Kurtosis statistical parameter. This technique has caught many interests due to its effectiveness in detecting non-stationary components produced by damage; for instance, the majority of the applications are focused on fault detection and diagnosis of rotating machinery [37, 86, 106].

SK was originally used as a supplement tool to PSD to detect random frequency buried in noisy signal. Despite its capability is suited to many detection problems, it was rarely used until a mathematical approach was published by Antoni to connect the missing theoretical proof and validated with vibration-based condition monitoring applications [82]. Although there are other definition of SK, Vrabie et al. [83] agrees that the technique has the ability in detecting non-stationary components in noisy transient signals. The SK estimates can be calculated by finding the relationship in terms of the signal-to-noise ratio (SNR) in detecting transient fused with additive noise. SK can be calculated based on the second ($S_{2,x}$) and fourth ($S_{4,x}$) spectral moments of a vibration signal, $x(t)$ as

$$SKx(f)\frac{S_{4,x}}{S_{2,x}} - 2 \tag{3.1}$$

The spectral moments can be estimated as

$$S_{n,x} = \langle |PS(f)|^n \rangle \tag{3.2}$$

where $PS(f)$ is the Fourier power spectrum of the signal, $x(t)$.

3.1.2 Wiener Filter and Envelop

Once the SK estimates are processed, a Wiener filter can be obtained by applying a statistical threshold using

$$W(f)\frac{1}{1+\rho(f)} \tag{3.3}$$

where $\rho(f)$ is the signal-to-noise ratio.

An adaptive threshold is applied to the Wiener filter using a proportion of the SK estimate's maximum value, this approach can eliminate the need of baseline data which is a preferred method in general. Furthermore, an envelope is then generated by calculating the inverse of the extracted feature that can be used as a damage sensitive filter for bolt looseness detection.

3.1.3 Spectral Kurtosis Feature Extraction

The methodology is presented in Figure 3.1 that uses Equation 3.1, 3.2, 3.3 to extract an SK-based Wiener Filter and an SK residual squared envelope. The generated envelope can be applied to the raw vibrational signal directly to extract damage sensitive index. Extracted feature can then be used as an input to machine learning model for an automated damage detection decision-making tool. This can be achieved by implementing a peak tracking operation on the extracted Hilbert envelope. By using this method, damage can also be localised by comparing the amplitude of peaks against the sensor channel location as damage tends to generate stronger response to nearby sensor.

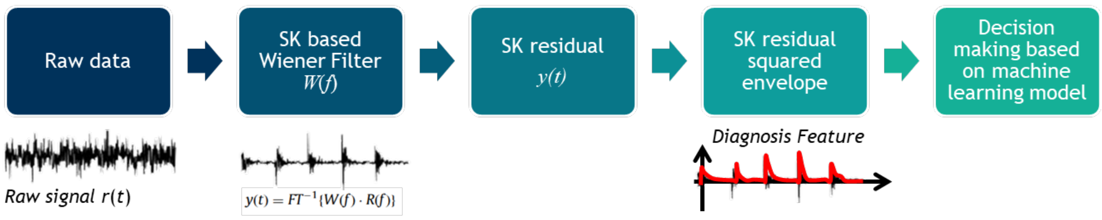

Figure 3.1: SK feature extraction and filtering methodology (Sketch from [84])

The proposed approach is demonstrated and validated with two applications with designed experiments to detect bolt looseness and bearing fault to prove the effectiveness.

3.2 Application 1: Bolt Looseness Detection Algorithm

Experiments are carried out to validate the proposed method to detect bolt looseness. A bolted structure is designed to simulate the girder assembly part of a bridge under normal operation. Firstly, a finite element analysis (FEA) is conducted to observe the system behaviour of the designed bolted structure in order to estimate the modal parameters such as natural frequencies. This simulation is performed to provide an insight how structure behaves under normal operation between healthy and damaged cases by loosening bolt.

3.2.1 Finite Element Model Simulation

A finite element model of the bolted structure is developed for modal analysis to investigate the system fundamental movement and the first five vibration modes are estimated using simulation software ANSYS. The designed model is presented in Figure 3.2 when all the bolts are fixed and configured to a fixed support mount.

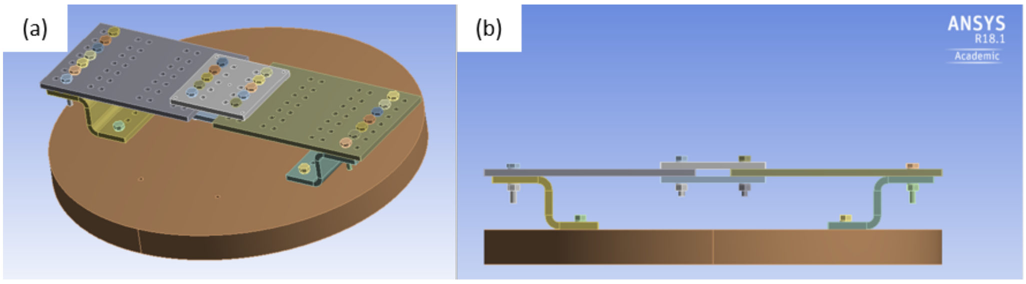

Figure 3.2: Finite Element Model of Bolted Structure (a) Top view (b) Side view

A modal analysis is implemented to simulate both healthy and damaged cases by removing a bolt and compare their natural frequencies to indicate the change of structural properties. The simulated result of the first five vibration modes is showed in Figure 3.3 where the difference of natural frequencies of both cases is almost negligible (less than one percent).

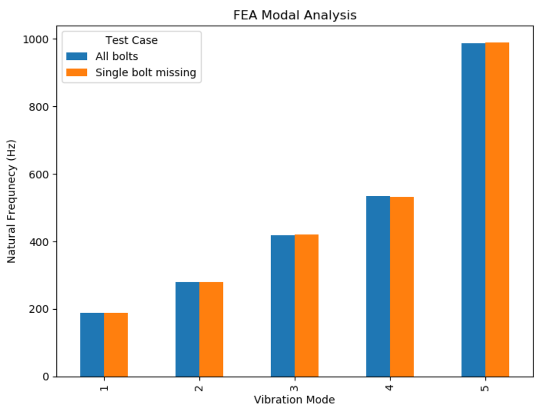

Figure 3.3: Modal Analysis of FE model with first five natural frequencies

Figure 3.4 presented the maximum displacement location of the bolted structure for the simulated first five vibration modes for both healthy (a - e) and damaged (f-j) case. It was clear that despite a bolt at

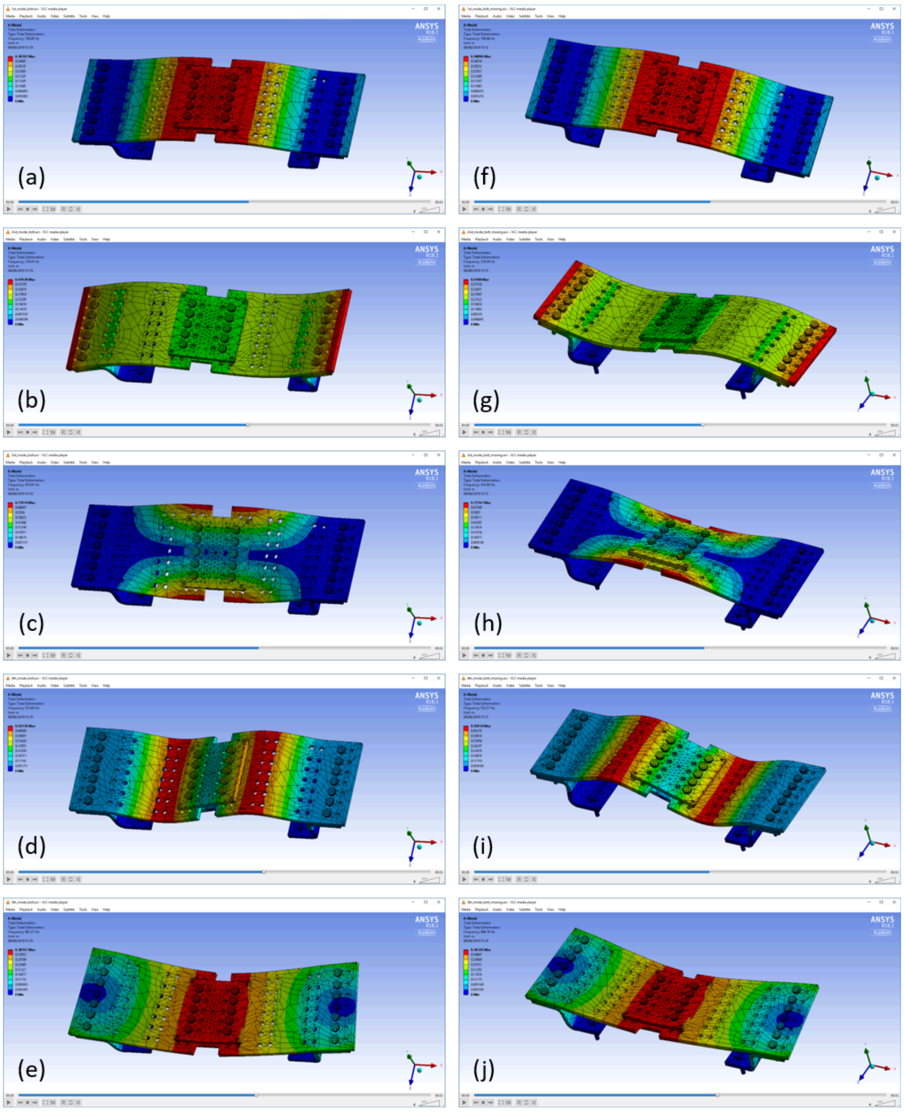

Figure 3.4: First five vibration modes of bolted structure (a)-(e) Healthy (f)-(j) Damage Cases

bottom left is removed as damage in the structure, the change in structural property was minor and the results were identical for both cases. This simulation approach has proved small defect such as bolt looseness is difficult to detect as the severity of damage is not enough to change the structure properties such as stiffness and mass to be detectable. Therefore, there is a need to develop an advanced signal processing technique to detect small damage in large structure before it grows to be detectable to save maintenance cost.

3.2.2 Experiment Setup

In order to verify the simulated FEA result, a bolted structure was manufactured accordingly using structural steel material as close to a real bridge structure. The assembly had 28 M10 type bolts arranged in evenly spaced row to assemble eight components together. Two square lap cover metal plates (150mm×150mm×10mm) were used to sandwich two rectangle cover metal plates (300mm×200mm×10mm) using two rows of bolts as highlighted in Figure 3.5a. This bolted structure was installed on an electro-magnetic vibration testbed (Data Physics GW-V2644 shaker controller) using a pair of S-shape brackets (200mm×150mm×75mm) using four columns of bolts (Figure 3.5b). The weight of the structure was approximately 18.5 kg.

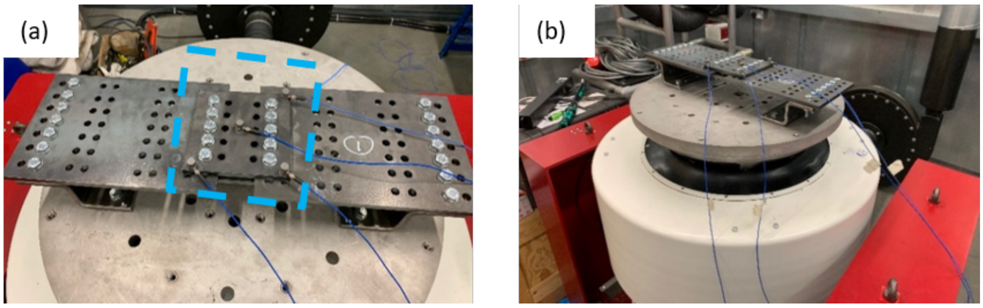

Figure 3.5: Bolted structure experimental setup (a) Bolted Assembly (b) Assembly mounted on vibration test-bed

The vibration testbed was configured to operate under controlled excitation and transferred to the bolted structure. Vibration data was captured by using a National Instruments cDAQ-9234 module with a NI9171 data acquisition chassis from three stud mounted piezoelectric accelerometers on the top plate. A PC was connected to both shaker controller and DAQ unit for data exchange and computation purposed. The data acquisition system was deployed with a LabVIEW program to interface the DAQ unit for sampling the vibration data at 5 kHz. The test setup schematic is presented in Figure 3.6. The locations of the three channels of sensors (ACC0 – ACC2) and loosened bolt (red bolt at the bottom left) located on the centre plate is illustrated in Figure 3.7.

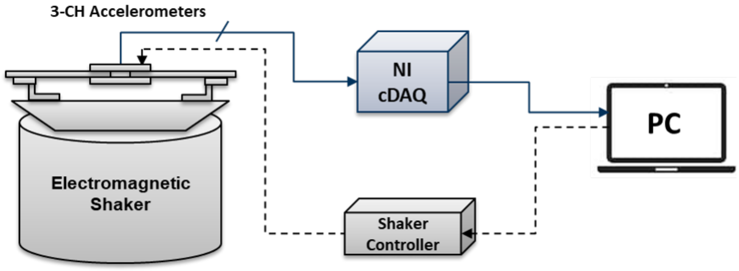

Figure 3.6: Bolt looseness detection experimental system schematic

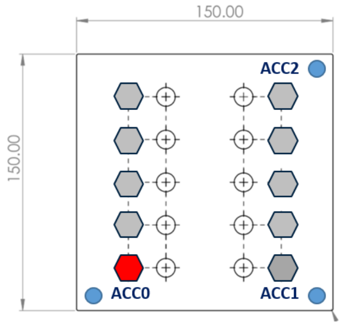

Figure 3.7: Sensor locations and bolt arrangement

3.2.3 Multi-Mode Input Excitation Profile

In order to simulate a bridge excitation profile under normal operation as close to real life, an excitation profile was required for the electromagetic shaker controller. A combination of multiple stationary components with a broadband baseline random excitation was considered for this purpose. Referring to the FEA numerical simulated modal analysis result in Session 3.2.1, the first three vibration modes were observed as below 500 Hz and this information was utilised to select the bandwidth of the input excitation profile. The traffic passing on the bridge was generated by using two stationary components and this assumption was proven to be a true scenario and the findings were reported by many researchers [107, 108, 109, 110]. The baseline broadband random vibration was matched with the excitation bandwidth with two stationary components with centre frequency located at 50 Hz and 110 Hz. These patterns represent vibration induced by moving vehicles with wind and ambient environmental excitation. The profile details and input excitation model were presented in Table 3.1 and Figure 3.8 respectively.

Table 3.1: Multi-mode vibration modelling profile

	Multi-mode vibration components
Frequency Range	5 Hz - 500 Hz
Sinusoidal Stationary	48 Hz - 60 Hz (0.5 g^2/Hz)
Component	96 Hz - 120 Hz (0.25 g^2/Hz)
Random Broadband	5 Hz - 500 Hz
Amplitude	2.4 g

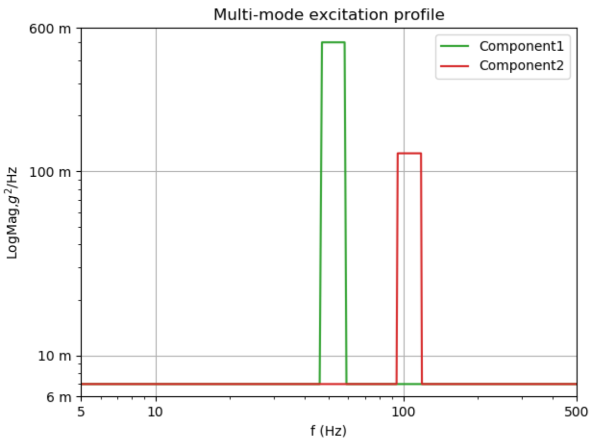

Figure 3.8: Multi-mode excitation profile

3.3 Application 2: Bearing Fault Early Detection Algorithm

Although SK has been a popular choice in damage detection applications, it can also be used as a novel blind feature extraction approach for industrial machine monitoring application. There were many diverse algorithms developed to solve the Blind Source Separation (BSS) problem; however, this was a challenging task for rotating machinery as the complexity of frequency combinations was higher due to the oil lubricant fluid interaction.

In general, the presence of abnormal patterns in the vibration data often indicate an abnormal behaviour that might cause issues to the process or the processing unit. These abnormal patterns induce non-stationary components that were fused in transient vibration signal and were difficult to filter. Due to the diversity of BSS applications, Pal et al. [111] have summarised the fundamental approach and classified this into four types as below:

- Temporal Structure, Non Whiteness;
- Mutual Independence, Non-Gaussianity and ICA (Independent Component Analysis)
- Non-stationary, Time-varying variance;
- Time-Frequency, Spectral/Spatial diversities;

Apart from Antoni and Randall's approach in using SK for rotating machine diagnostics [84], many researchers have implemented enhancement in adaptive SK [112], SK-based optimal filter [113], wavelet-based SK [114], combination of PPCA (probabilistic principal component analysis) and SK [115], correlated EEMD and SK [116]. Nevertheless, there were few gaps remains unsolved as listed in Table 3.2.

Table 3.2: Unsolved problems in previously reported SK applications

	Unsolved Problems	**Cause**
1	Fluctuation of SK estimates due to spikes in signals	Rolling element tend to introduce spikes in vibration data frequently
2	Scalability of SK estimates analysis pipeline	Datasets from reported approach are specified to certain applications and cannot be generalised to other machinery datasets
3	Inaccurate SK estimates due to noisy signal	Low SNR in vibration signal can cause false alarm and potential engineering failures

This study had proposed an enhanced Spectral Kurtosis filtering technique to address the above mentioned problems by applying a combination of spike subtraction, stationary wavelet waveforms and automated change detection algorithms. The detail of the implementation was described in Session 3.3.2.

3.3.1 Description of Experiments and Data Acquisition

A set of open-source vibration data for bearing damage experiment published by the NASA prognostic centre [117] was used in this study to prove the effectiveness of the proposed SK enhancement technique. The test setup was graphically presented in Figure 3.9 that consists of four Rexnord ZA–2115 double row bearings installed on a shaft. A constant rotation speed of 2000 RPM was configured for an AC motor coupled to a shaft to operate. A radial load of 2721.55 kg was applied on the shaft and bearing using a spring mechanism to speed up the deterioration process.

Regards to the data measurement process, four pairs of PCB 353B33 accelerometers were installed to capture the $x-$ and $y-$ axes vibration response of the four bearings as presented in Figure 3.9. The measurements were stored as individual files of a one second duration of vibration measurements with 20,480 samples. The data was captured every 10 minutes using a sampling frequency of 20 kHz. A run to failures experiment was conducted aiming to operate and exceed the designed lifetime of the bearing as more than 100 million revolutions. This dataset had been widely used by many researchers to validate their proposed techniques and a summary of comparison of the published literature findings against the proposed method was presented in Table 3.3.

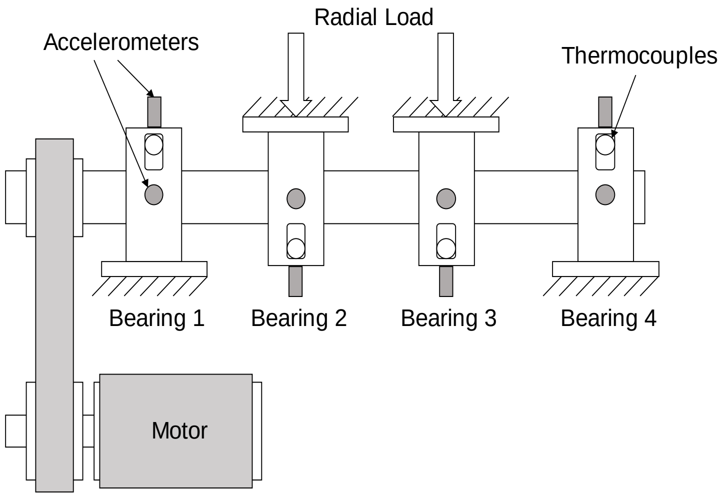

Figure 3.9: IMS bearing test set up and sensor's configuration

Table 3.3: Comparison of signal processing techniques using the NASA IMS bearing data

Study	**Qiu et al. [118]**	**Wang et al. [119]**	**Yu [120]**	**Proposed Method**
De-noising	No	No	No	Stationary Wavelet Transform
Filtering	Wavelet Transform	Packet Wavelet Transform	Hidden Markov Model	Wiener Filter
Decomposition	Singular Value Decomposition	Empirical Mode Decomposition	Dynamic Principal Component Analysis	Spectral Kurtosis
Prior Knowledge to Failure	No	No	No	No
Automated Detection	No	No	No	Change detection using SK estimate

A weak signature detection algorithm was developed by Qiu et al. [118] and Wang et al. [119] using wavelet-transform while Yu [120] had used hidden Markov model for filtering damage sensitive coefficients. Their proposed algorithms have managed to detect defect pattern that was seven days earlier than the inspection day. Although their proposed techniques were capable to detect defects and prior knowledge to failure were not needed, they were prone to noisy signal as prior de-noising process was missing. For instance, the trend forecast developed by Wang et al. [119] use of the 10th IMF (Intrinsic Mode Function) from EMD (Empirical Mode Decomposition) generates a coarse result. This made the filtering process very sensitive to noise level and false alarm are likely to happen. Therefore, the author has proposed an pre-processing algorithm for this application in order to eliminate unwanted noise at the initial stage.

3.3.2 Pre-Processing Algorithms

Multiple pre-processing algorithms were developed by the author in order to address the de-noising process mentioned in session 3.3.1. A spike subtraction algorithm is a denoising technique that is particularly effective for non-stationary signals and considered initially. It works by restoring each data point of the signal by its median estimated over a fixed window length, thereby removing any spikes or transient noise in the signal. This method is useful for denoising signals that contain a large amount of noise or artifacts, as it can effectively reduce these unwanted components without significantly affecting the underlying signal. Additionally, this technique is computationally efficient and can be applied in real-time applications. This algorithm had addressed the fluctuation issue in data due to random events that do not represent a defect. Apart from that, a wavelet transform-based decomposition process was also proposed to ensure the SNR of signal was high and improve the accuracy of diagnosis.

The proposed SK approach can benefit from the combination of these techniques to improve its reliability and adaptability in an industrial setting as well as its scalability of the analysis pipeline. The author had developed a change detection algorithm to enable automated detection for the early diagnosis of bearing defects. Since the proposed approach was targeted to detect abnormal patterns induced by damage, the analysis pipeline can be generalised and applied to other rotary machine applications such as gearboxes and wind turbines.

Spike Subtraction Algorithm for Abnormal Event Detection

The spike subtraction algorithm was implemented by obtaining the median of the data vector estimated over a fixed window length to restore each data point. This filtering process ensures the spikes in signal were eliminated, and false alarms were significantly minimised. This was because fluctuation in a signal that is irrelevant to defect will generate a peak in the SK estimates thus fused noise to the SK spectrum. The filtered result of the vibration response of a bearing with defects was presented in Figure 3.10. Despite the algorithm having eliminated some spikes in the signal (highlighted by arrows), it was still fused with additive noise that could lead to a false alarm. Consequently, an alternative de-noising algorithm was considered to improve the signal-to-noise ratio.

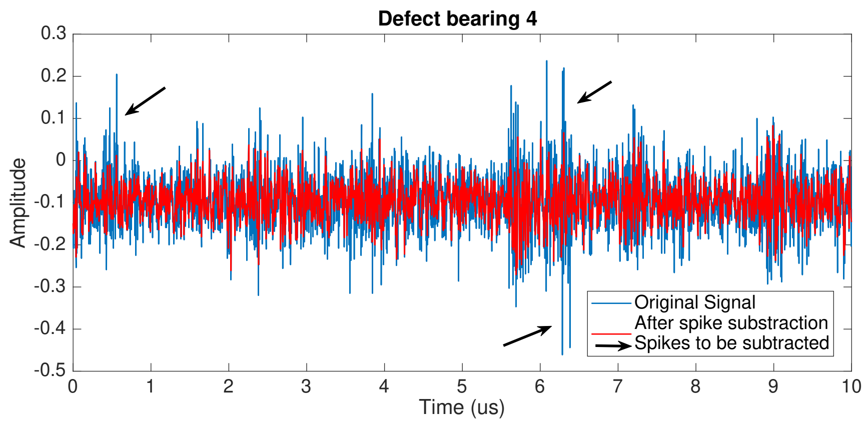

Figure 3.10: Demonstration of spike subtraction algorithm on open source IMS bearing data set

Wavelet Decomposition

Apart from compressing noise in a signal, it was critical to extract signal patterns from a noisy signal. In general, data captured with high sampling frequency was highly sensitive to the noise level. Stationary Wavelet Transform (SWT) is considered in this study for noise elimination. The Stationary Wavelet Transform (SWT) is a powerful signal processing technique that offers several advantages over the Power Spectral Density (PSD) method for denoising purposes. Firstly, SWT can effectively reduce noise and artifacts in non-stationary signals that change over time [121]. Secondly, SWT can accurately capture the local variations in signal frequency components, making it more suitable for the analysis of signals with abrupt changes in frequency content [122]. Additionally, SWT can be used with a variety of mother wavelets, allowing for greater flexibility and control over the denoising process [123]. Overall, the advantages of SWT make it a popular choice for denoising applications in fields such as biomedical signal processing and image analysis.

Wavelet Transform provides a flexible decomposition process that various formats of wavelet that can be applied to signals that has its distinct characteristics thus can be adapted to different signal to extract the patterns. This approach can compress noise while maintaining the impulsiveness of the data. Figure 3.11 has presented a comparison between two sets of health and defect bearing and the effectiveness of using SWT processing to compress the noise in signals. In order to evaluate the noise compression performance of the de-noising algorithm, PSD analysis is used to evaluate the spectra of the signal before and after the de-noising process. The result presented in Figure 3.12 showed that the PSD estimates have dropped significantly after the 1 kHz frequency range in both healthy and defect data. It can be observed that the noise level in the healthy data between 1 kHz and 9 kHz is almost negligible, presented an effective noise compression.

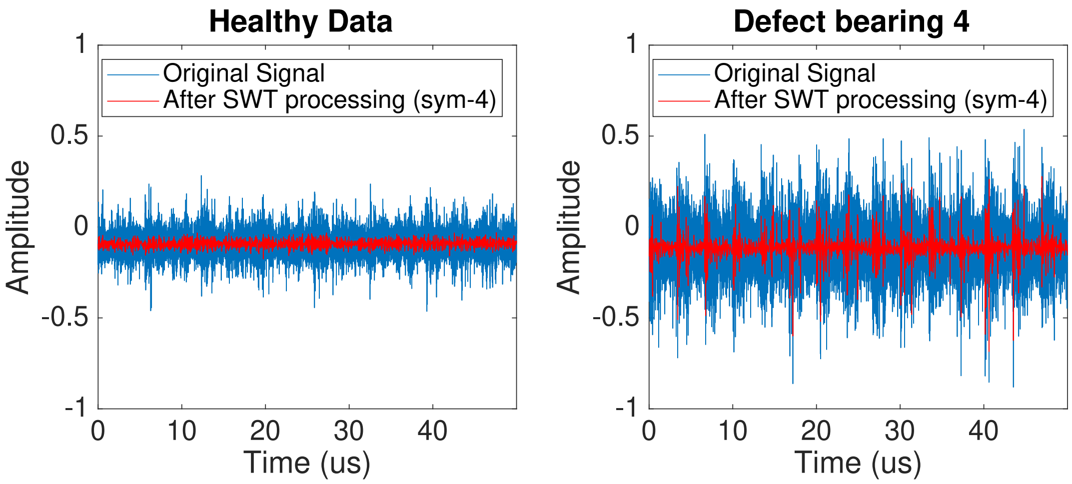

Figure 3.11: Before and after de–noising using Stationary Wavelet Transform

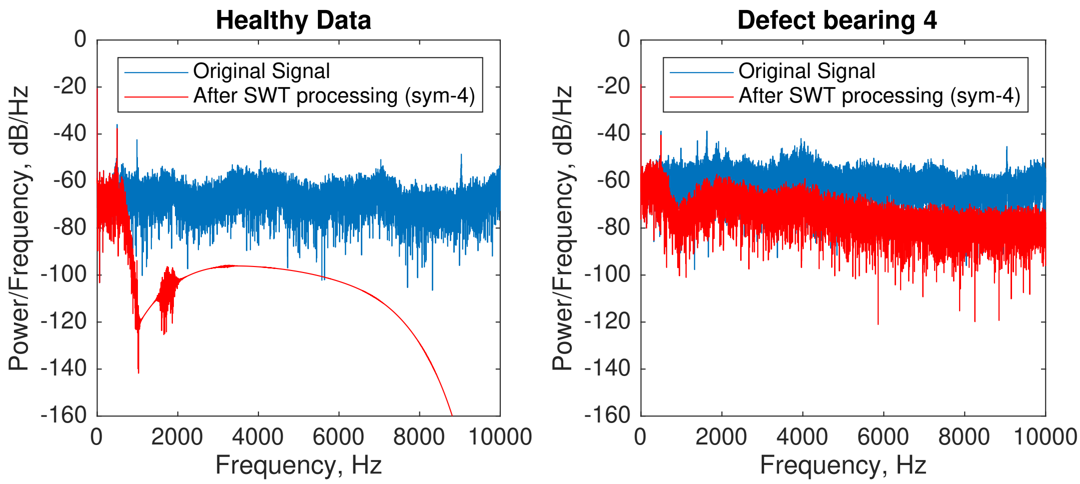

Figure 3.12: PSD estimate of before and after de-noising using Stationary Wavelet Transform

Rotating Machine Generated Weak Vibration Signatures

In general, rotating machinery generates a consistent pattern of vibration response under normal operation. However, bearing faults tends to produce abnormal pattern as weak vibration signature; for instance, a cyclo-stationary random component as shown in Figure 3.13. These signals were buried in a vibration signal mixed with other signal components such as input shaft frequencies and higher-order harmonics due to load fluctuation and difficult extracting. The motivation of the proposed 2 stages pre-processing and feature extraction algorithm was to extract these weak signatures from signals to distinguish damage sensitive features and identify early fault characteristics and results were discussed in the next chapter.

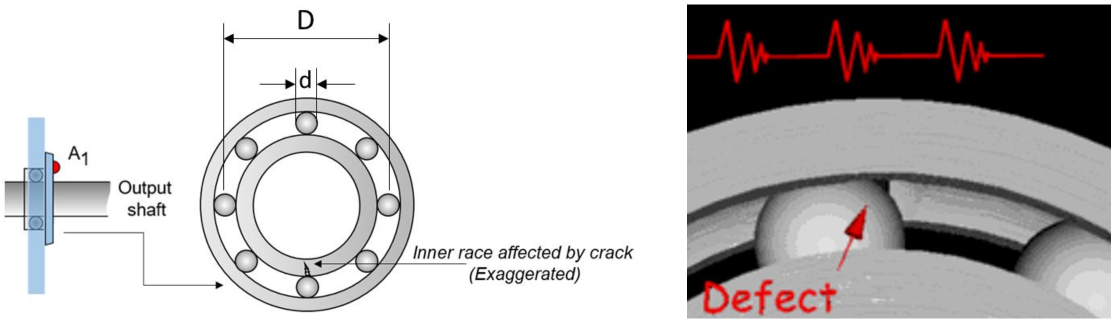

Figure 3.13: (Left) Bearing configuration with rolling elements [124] (Right) Signal expected due to bearing fault

Summary

This chapter had discussed the methodologies perused in this study by covering the theoretical background of the proposed SK-based signal processing technique to prove it can be used to detect small defect such as bolt looseness that was hard to detect. The proposed technique consists of multi stages that a initial SK-based Wiener filter was applied to raw vibration data from sensor to extract the SK residual. An adaptive threshold is then applied to the Wiener filter based on the SK's estimate's maximum value to eliminate the need of baseline data for damage detection. Eventually, an Hilbert envelope was then generated that can be applied directly to raw vibration data as a damage sensitive filter for bolt looseness detection. Two applications were design to validate the proposed techniques. This includes the bolt looseness detection algorithm and bearing fault early detection algorithm.

The author had designed a finite element model of a bolted structure to simulate a modal analysis in order to observe the structure's system behaviour under healthy and damaged cases. The damaged case is simulated by removing a single bolt in the bolted joint. The modal analysis had provided an insight of the structure's structural property such as natural frequencies and maximum displacement of the first five vibration modes. The simulated result had proven that small defects cannot be detected by monitoring structural properties as the changes in both natural frequencies and maximum displacement were almost neglectable. Therefore, there is a need to develop an efficient signal processing technique to detect small defect.

An experiment was designed to verify the simulated finite element model by manufacturing a bolted structure accordingly in order to simulate a bridge structure as close as possible. The simulated result was then used as a reference to design a bridge excitation profile to control the vibration testbed. A combination of multiple stationary components with a broadband baseline random excitation was considered for this purpose to mimic a bridge under normal operation and traffic induced by vehicles and environmental noise.

The proposed technique was also validated by an bearing fault early detection application by addressing the missing gaps of the explored literature findings of existing equivalent usage of SK-based algorithms. This consists of improving the scalability, adaptability and reliability of the algorithm to solve the noisy signal issue. The author had therefore proposed an enhanced SK-based filtering technique by implementing multiple pre-processing algorthms for de-noising purpose and decomposition. An spike subtraction algorithm was considered; however, the processed result was not satisfactory that the signal was still fused with additive noise that could cause false alarm. SWT was then pursued due to its effectiveness in reducing noise and the provided flexibility in choosing various mother wavelet to fit different signal needs along with the control over the denoising process. The performance of the proposed SWT technique was then validated using PSD analysis and effective result was showed by evaluating the signal's spectra before and after de-noising process. The results of the two applications were covered in the following chapter.

Chapter 4

Experimental Results

4.1 Bolt Looseness Detection

To ensure the repetitiveness of the experiment result, the baseline data of all bolts tight cases were measured multiple times. All bolts were tightened to 45Nm torque, referring to the maximum torque load of property class 8.8 of M10 size bolt to present a healthy condition of the bolted structure. The controlled excitation from the input excitation profile showed stable operating performance and repeatable excitation.

Vibration signals were recorded for 40 seconds duration under the controlled excitation. This baseline data was labelled as a tight bolt (healthy) dataset. The bolt near sensor ACC0 was later loosened to less than 10Nm tension to simulate a defect in the structure, and the same excitation was applied. A weak rattling effect was generated by the loss of pressure of the bolt that produced non-linear and non-stationary vibration components. This phenomenon have changed the structural properties so that the local stiffness of the structure was reduced, and weak signatures were transferred to the system through washers.

This experiment aimed to extract these weak signatures using Spectral Kurtosis estimates; it was because conventional signal processing techniques such as conventional signal processing techniques such as FFT and PSD were not suitable for extracting non-linear and non-stationary signals.

The time-series data presented in Figure 4.1 illustrated the healthy (all bolts tight) and unhealthy (ACC0 bolt loose) state of the structure respectively. There

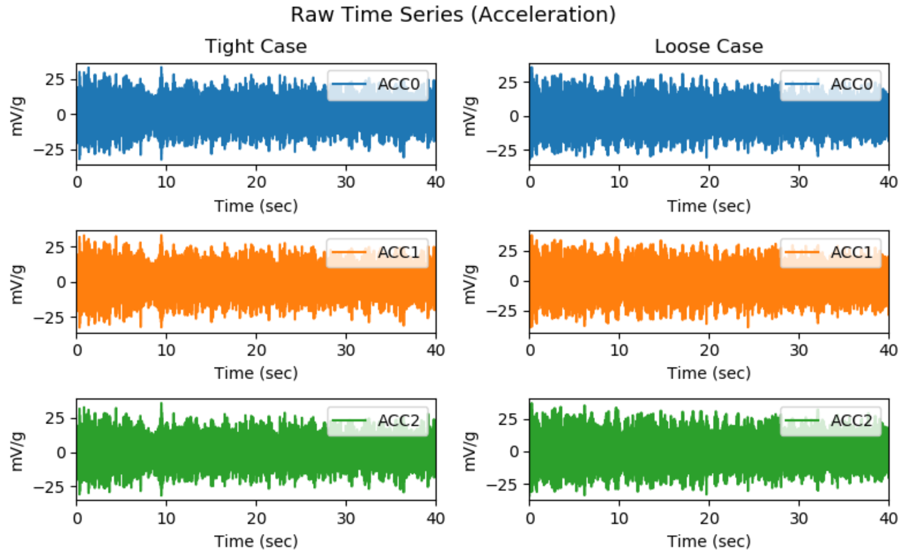

Figure 4.1: Raw time domain data for tight bolt case (left) and ACC0 loose bolt case (right)

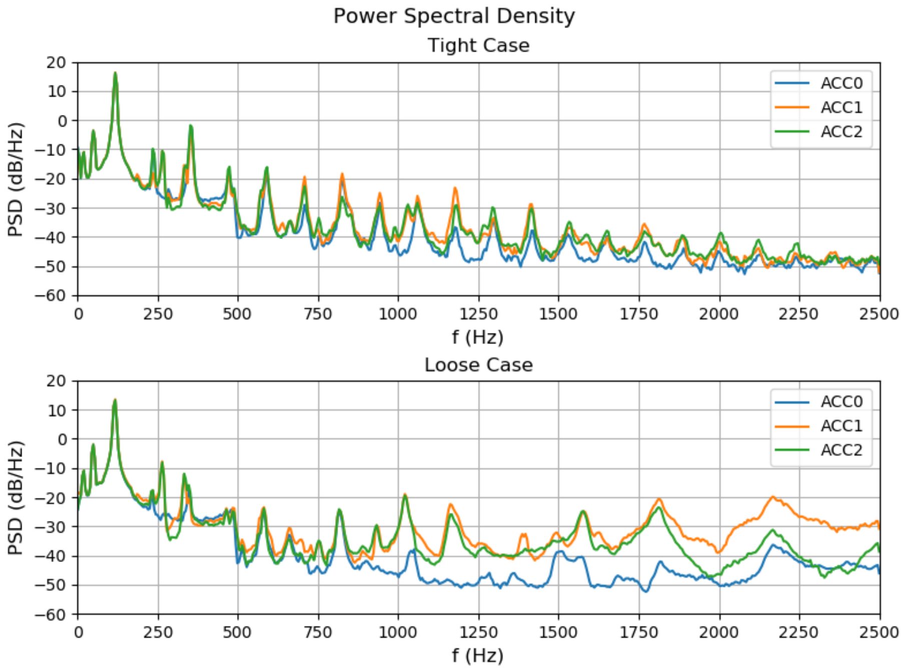

Figure 4.2: PSD graph of tight and loose case

was no clear indication of the simulated defect. To further analyse the vibration signals, PSD analysis is implemented, and the estimate was presented in Figure 4.2. A trivial irregularity was detected by the PSD estimates after frequency at 500 Hz in the data; however, the result cannot differentiate the looseness clearly. Thus, further processing was required to detect the damage.

The SK estimates presented in Figure 4.3 extracted the presence of multiple non-stationary components corresponded to the response of the three individual bolts on the bolt joint. A 5% statistical threshold was applied to the SK estimates to filter out the non-linear components buried in the signal using a Wiener filter. The Wiener filter shown in Figure 4.4 was used as a band-pass filter to extract vibration corresponding to the rattling effect from raw vibration data. The result had indicated between the healthy and single bolt loosen case; there was a new frequency component captured at 350Hz near the ACC0 accelerometer while ACC1 and ACC2 show the identical result. The extracted feature of these non-stationary components was later presented using a Hilbert envelope (Figure 4.5), which clearly indicated that looseness can be detected using the proposed technique.

To further elaborate the result, a peak tracking operation was implemented on the Hilbert envelope in Figure 4.6. To summarise the findings, non-stationary behaviour induced by the loosened bolt was captured distinctively with ACC0 using the proposed technique. In contrast, a weaker peak response was detected from the next accelerometer ACC1, which was 135 mm away from the loosened bolt. Furthermore, this phenomenon can also be observed from ACC2, which was diagonally opposite to the ACC0 location with the weakest signature.

This trend showed the amplitude of peaks can be used to localise the loosened bolt where the peaks gradually decrease the futher away from the defect; In contrast, the response of the healthy case from all three accelerometers indicated a negligible peak. The proposed approach can also be implemented without baseline data to detect the looseness defect.

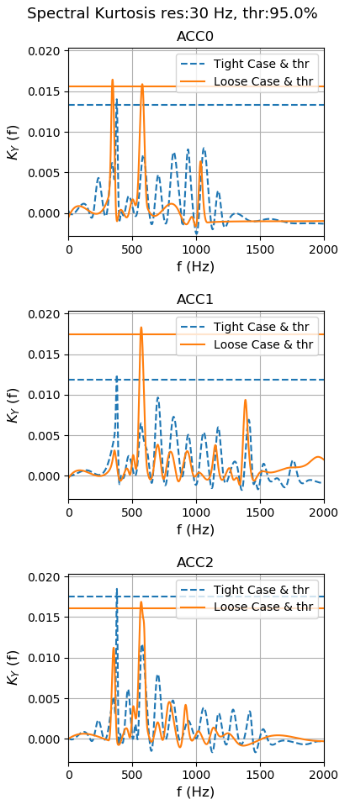

Figure 4.3: SK estimates

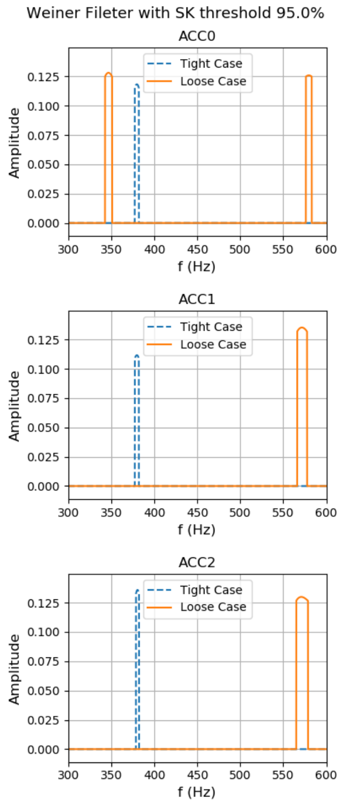

Figure 4.4: Wiener filter of SK

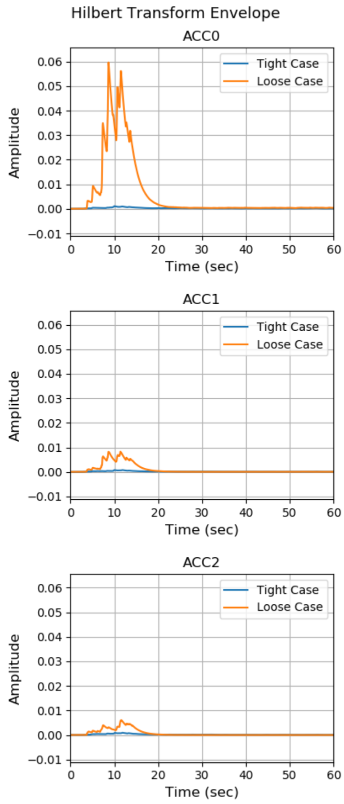

Figure 4.5: Features: Hilbert Envelope of the filtered signals

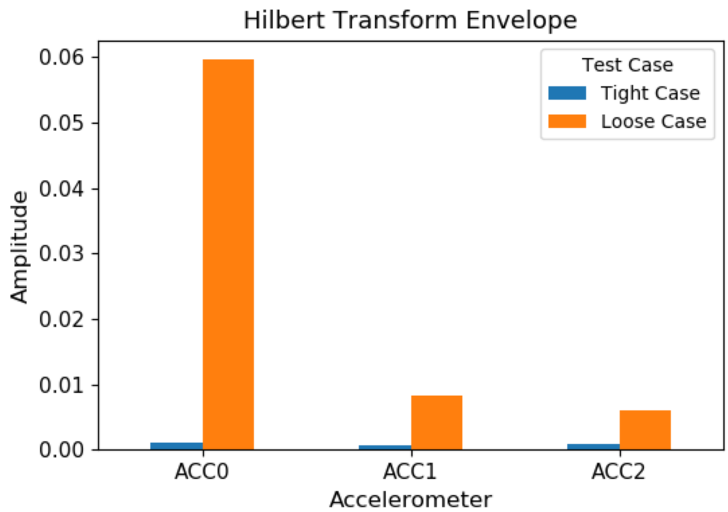

Figure 4.6: Peak tracking performed on the Hilbert envelope (Figure 4.5) of the filtered signal

4.2 Bearing Fault Early Detection

An enhanced SK-based algorithm was used to address missing gaps from explored literature findings in terms of fault alarm caused by spikes in signal, scalability of SK estimates and the high noise level. Referring to the pre-processed signal in Figure 3.11, the wavelet decomposition technique demonstrated how non-stationary patterns fused within raw vibration data can be extracted. The obtained data was then fed to the SK-based filtering function to compute the Spectral Kurtosis estimate.

This estimate can be calculated using Fast Fourier Transform (FFT) or time-frequency technique such as Short-Time Fourier Transform (STFT) alternatively. For instance, the STFT-based SK estimate has a better performance than the FFT-based approach in terms of filtering non-stationary signals due to the windows size variation. A part of the computed SK estimate is presented in Figure 4.7, and the two signals drew the comparison from the healthy and defect data sets. The feature estimate of all signals in the data set was presented in the following session.

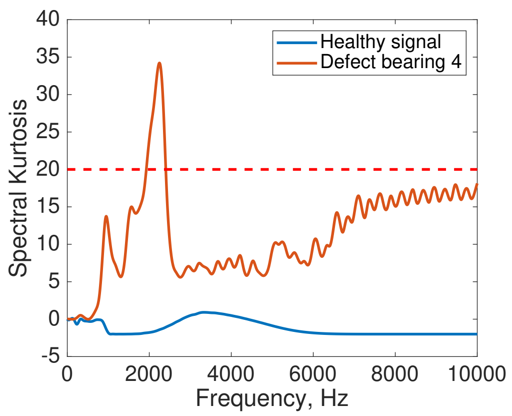

Figure 4.7: Spectral Kurtosis estimate of healthy and defect signal

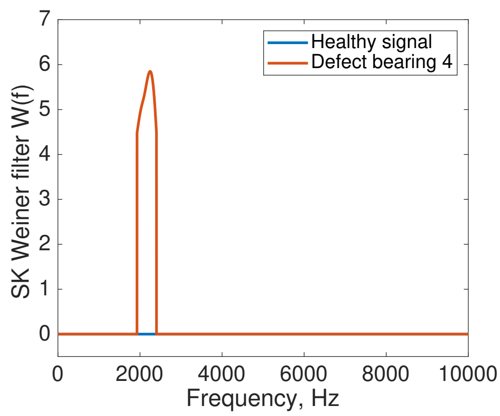

Figure 4.8: SK–based wiener filter extracted from SK curve through thresholding

An SK-based Wiener filter extracted by threshold filter is shown in Figure 4.8. It can be observed that a significant peak is detected from the defect bearing signal corresponds to the non-stationary behaviour in the signal. In contrast, no significant considerable peak was detected from the Wiener filter for the healthy bearing set data. Manual data processing was also implemented to cross-validate the results from part of the data set against the ground truth results published by the NASA authors [118].

The extracted Wiener filter was then applied to raw data to detect defect and computed using Hilbert Transform to extract the envelope of the signal components. The obtained envelope of a defective and unhealthy bearing data set was presented in Figure 4.9. It had indicated that the rolling element bearings were hitting the outer race periodically from the defected signal. In contrast, no non-stationary vibration components were detected from the healthy case. This comparison had showed that the diagnosis for finding bearing fault was successful.

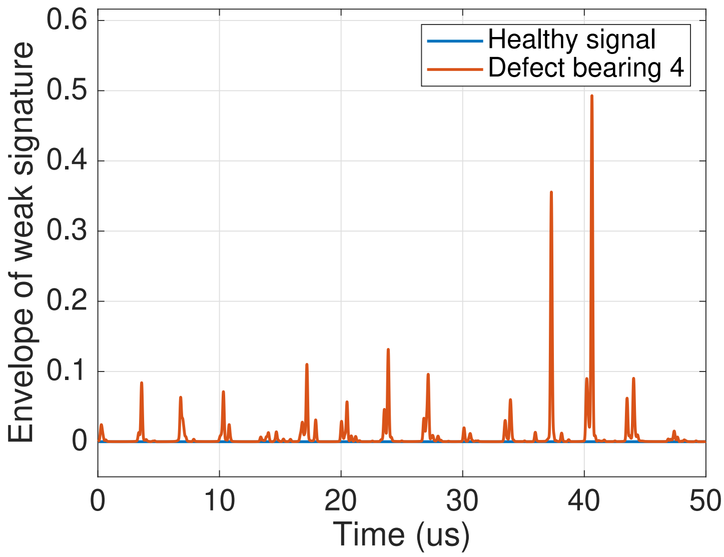

Figure 4.9: Envelope of the SK filtered signal

The SK feature estimate of the IMS bearing data set was presented in Figure 4.10; this had included a total of 2156 signal samples for 35 days' worth of data. The result had showed that the SK based feature extraction algorithm had successfully detected the faults detected after day 27 and other non-stationary behaviour in the data.

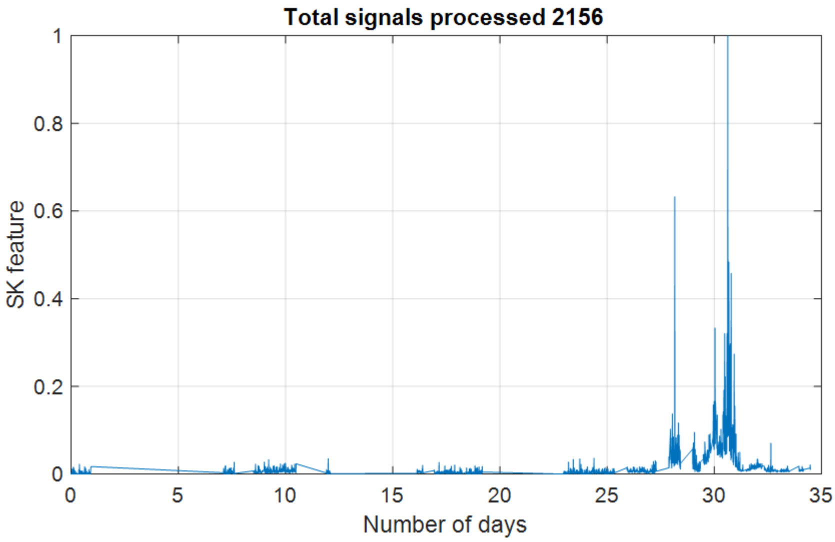

Figure 4.10: SK feature for all signals plotted against the number of days of testing

A change detection algorithm that involves detecting changes in SK estimates over time was implemented to address the missing piece of automated detection function from previously explored literature findings. This decision boundary helped to identify the sudden change in data and raise an alert of detected unique patterns as presented in Figure 4.11. The change algorithm had identified that bearing 4 was damaged on day 27 (highlighted in red), which is a week earlier than the final run to failure inspection day. This had proved that the proposed approach is capable to detect early fault characteristics.

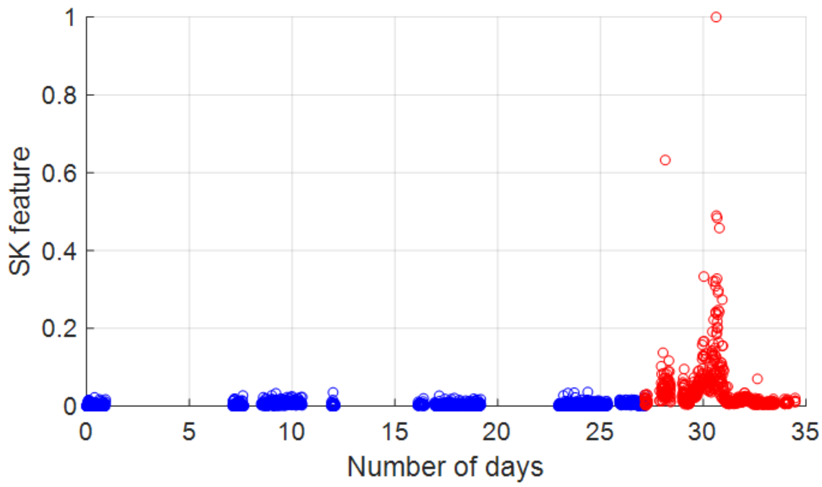

Figure 4.11: SK features vector after application of change detection algorithm

Summary

This chapter had presented the result of the designed experiments to showcase the feasibility of the proposed technique to detect damage in the two applications. The experiment result was first investigated in time series data and processed by PSD that indicated conventional signal processing technique was not suitable to detect small damage that were non-stationary signal. The proposed technique was then applied to the signal to extract the weak signatures buried in noisy transient data. The investigated result in the bolt looseness application had validated Spectral Kurtosis was capable in detecting loosened bolt from extracting non-stationary components buried in time-series signals in three stages of processing. A peak tracking operation was applied on the Hilbert envelope to indicate the feature to localise defect by distinguishing the corresponding sensor channel.

The proposed technique is further enhanced to address the current missing gaps from the explored literature findings on detecting early bearing faults in terms of adaptability and scalability. It was validated using an open-source data published by NASA that the SK-based filtering algorithm successfully detected the bearing fault a week earlier than the run-to-failure inspection day.

Chapter 5

Conclusion and Recommendations for Future Work

Early fault detection was crucial in asset health monitoring applications as it improves engineering maintenance efficiency; for instance, scheduled inspection and maintenance work can be planned ahead to prevent severe damage to save cost and preserve quality of industrial process.

This study had proposed an advanced digital signal processing technique to detect small defects that were difficult to diagnose in early stage inspection. An overall review was delivered to discuss the introduction of need in asset health monitoring and the relevant literature review of the current state-of-the-art in health monitoring techniques as well as the cause of damages. A comparison was drawn to outline the limitation of conventional signal processing techniques such as time series analysis, wavelet transfer and Hilbert-Huang transform cannot be used to extract non-stationary signal buried in noisy transient data. Therefore, the author has proposed the use of Spectral Kurtosis to detect bolt looseness due to its outstanding performance in identifying non-stationary components induced by damage. The methodology of the proposed technique Spectral Kurtosis was presented as a three stages processing algorithm; firstly, a SK-based Wiener filter was applied to raw vibration data to extract the SK residual, secondly, a statistical threshold was applied to the SK estimates to eliminate the non-linear components fused in the signal, lastly, the extracted features were presented using a Hilbert envelope to indicate the detected damage.

The proposed technique was validated using two applications of bolt looseness detection and bearing fault detection to show its feasibility and capability in detecting non-stationary component induced by damage. The obtained experimental results presented that Spectral Kurtosis was capable in detecting non-linear and non-stationary buried in time-series data that were induced by small defects. Further enhancement was implemented to address missing gaps of explored literature findings in existing SK-based techniques for bearing fault detection. This study had made contribution of knowledge to propose an advanced signal processing technique to develop a vibration-based method using optimal filtering approach to detect bolt looseness in bolted structure and an enhanced methodology to address missing gaps of current asset monitoring applications in regards to spikes subtraction, scalability of the data analysis pipeline and SNR ratio.

Given the promising result of the proposed technique, this was confident that the technique can be further improved to provide meaningful damage sensitive features. For instance, different signal processing techniques such as wavelet transform, Hilbert-Huang transform, time-frequency analysis and principal component analysis can be combined to form a multiple stages of processing; this can also further enhance the SNR ratio of data, noise subtraction as well as data compression to reduce storage required. The enhanced extracted features could be used to improve the accuracy of data to localise damages precisely, capable to detect multiple bolts looseness and possibly quantify the looseness.

These features shows a meaningful insight into how they can be used as input for machine learning models for both supervised and unsupervised learning methods. The automated change detection algorithm developed in the bearing fault detection algorithm can be used to label data to diagnose if damage is detected; which can be used to train different models such as random forest, Bayesian decision tree and SVM. On the other hand, unlabelled data can be fed to neural network model such as LSTM (Long-short term memory) in which the model learns from the data to detect damage.

The benefit of data provides a way to detect damage sensitive signal with a better understanding to small defects that are difficult to detect using conventional signal processing techniques. These models could be used to develop automated early fault detection for asset health monitoring applications such as Industrial IoT digital twin to enable smart remote monitoring. The mentioned future works could be contributed to other papers focusing on the development of combination of signal processing techniques and benchmark the performance amongst existing techniques and using the extracted features for training machine learning model.

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