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Utilizing acoustic measurements in equipment condition monitoring

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Condition based maintenance has become an increasingly popular maintenance strategy. According to the strategy, maintenance decisions are made in compliance with the actual condition of the equipment. The introduction of condition based maintenance strategy requires the establishment of a condition monitoring system that is used to determine the condition of the maintained equipment. One way to observe the condition of the equipment is to analyze the changes in its audio signature.

This study examines the feasibility of an audio based condition monitoring system for the condition monitoring of a certain type of equipment. First, the audio signatures are measured in several conditions, where the equipment operates normally, and in three fault situations. Obtained audio signatures are then analyzed by using statistical features in time and frequency domain as well as power spectral densities.

From the three fault cases, two can be accurately detected by using the selected methods. Different normal operational conditions do affect the sound signature, but notably not as much as the detected faults do.

Keywords:	maintenance, condition monitoring, audio
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Laitteen kunnonvalvontaan perustuva menetelmä on viime aikoina noussut suosituksi kunnossapitostrategiaksi. Kyseisessä strategiassa huollot ja korjaukset tehdään laitteen senhetkisen kunnon mukaan. Tästä syystä strategian käyttöönotto vaatii toimivan kunnonvalvontajärjestelmän. Eräs tapa havainnoida laitteen kuntoa on analysoida laitteen tuottamia ääniä ja niiden muutoksia.

Tässä työssä tutkitaan ääneen perustuvan kunnonvalvontajärjestelmän soveltuvuutta tietyn tyyppisen laitteen kunnonvalvontaan. Työssä mitataan laitteen tuottamia äänisignaaleja eri normaalin toiminnan olosuhteissa, sekä kolmessa eri vikatilanteessa. Äänisignaalien analysointiin käytetään aika- ja taajuustason tilastollisia parametreja, sekä äänisignaalin spektriä.

Valituilla menetelmillä pystytään selkeästi havaitsemaan kaksi kolmesta testatusta vikatilanteesta. Erilaiset normaalin toiminnan olosuhteet vaikuttavat myös laitteen tuottamiin ääniin, mutta vaikutukset ovat selvästi pienemmät kuin havaittujen vikojen aiheuttamat muutokset.

Asiasanat:	kunnossapito, kunnonvalvonta, ääni
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Thank you, and keep up the good work!

Espoo, May 23, 2016

Aleksi Seppänen

Contents

Chapter 1

Introduction

As in any field of business, also companies providing maintenance services try to constantly improve their operations. In the case of maintenance business, the improvements might be more efficient use of resources, reduced downtime of the maintained items or reduced number of failures. One way to improve is to use appropriate maintenance strategy in each circumstance. Condition based maintenance is one of the more recent widely used maintenance strategy, which can improve the mainenance operations by taking into account the actual condition of the maintained item.

Since condition based maintenance requires information on the condition of the maintained item, a condition monitoring system must be implemented before the condition based maintenance strategy can be adopted. Condition of an item can be observed through several manners. In case of electromechanic equipment, changes in the condition often result in changes in the audio signature of the equipment. Therefore observing the changes in equipment's audio signature is one possible way for determining the condition of the equipment.

In this study, applicability of audio based condition monitoring system for a specific type of electromechanic equipment is investigated. First, several techniques used in audio based, or similar, condition monitoring systems are searched from the literature. The number of different signal processing methods is vast. Based on the literature review, wavelet transformations are the most commonly used methods in audio based condition monitoring systems. However, condition monitoring system considered in this study requires the signal processing methods to be intuitive and computationally light. Therefore time and frequency domain statistical features and power spectral denstities are used in this study to analyze the audio measurements.

The applicability of the selected approach is tested by using data gathered from experiments performed on several pieces of equipment. In order to examine the stability of the audio signature of the equipment, measurements from different usage patterns are included in the experiments. The purpose of the condition monitoring system is to detect faults from the monitored equipment. To test this ability, three different faults are generated to one piece of equipment. Then k-nearest neighbours algorithm is used together with the selected signal processing methods to examine the diagnostic ability of the audio based condition monitoring system.

The rest of the thesis is structured as follows. Chapter 2 contains brief introduction to maintenance, condition monitoring and audio signals. In the condition monitoring introduction, the focus is on techniques applicable to audio based condition monitoring systems. In Chapter 3 the condition monitoring data obtained from the experiments are presented, as well as the methods, which are used to analyze the data. In Chapter 4 the results of the experiments are presented and analyzed and in Chapter 5 the findings are discussed. Finally Chapter 6 concludes the study.

Chapter 2

Background

2.1 Maintenance

The user of any electromechanical equipment wants that the equipment is able to perform the required tasks without interruptions due to malfunctions. Depending on the equipment, unpredicted failure might cause additional costs or even severe accident. Most pieces of equipment require maintenance in order to stay in operative condition.

There are several different maintenance strategies, which are suitable for different situations. One possible classification of the maintenance strategies is to divide them into these three categories: breakdown maintenance, preventive maintenance and condition based maintenance (CBM) [28]. When selecting the most appropriate maintenance strategy, several aspects of the maintained item should be considered. Influential aspects are for example spare part availability, mean time to repair, failure frequency, induced damage by failure and available resources [8].

In breakdown maintenance, the equipment is maintained only after malfunction has occured. This stategy is also known as run to failure maintenance or reactive maintenance. Obviously, this strategy is not suitable for safety critical items. It is also not a good strategy if a failure in one item might cause other failures in the same item or other items, which then amplifies the effect of the initial failure. This maintenance strategy is usually used for less expensive and noncritical items.

Preventive maintenance aims to prevent the malfunctions by maintaining the equipment periodically with a certain interval. The intervals could be based on historical data or prognostics about the life time of the equipment or some of its components. However, such interval is hardly optimal for all equipment, especially in the case, where the same maintenance plan is used for several equipment in various environments and usage profiles. Due to various environments, usage profiles and other aspects affecting the equipment, they tend to age and break down at various rates. Therefore, for some equipment, the pre-scheduled maintenance plan causes unnecessary downtime whereas other equipment break down before the next scheduled maintenance.

CBM is similar to preventive maintenance in the sense that ideally in both strategies, maintenance activities are always performed before actual problems occur. The idea of CBM is to monitor the condition of the equipment and conduct maintenance procedures only when required. When applied properly, CBM can decrease the maintenance costs and equipment failure occurrences [28]. The greatest drawbacks of CBM are the high development and implementation costs. Because CBM requires knowledge of the actual condition of the equipment, a condition monitoring system is a vital part of any CBM strategy. Therefore a condition monitoring system must be developed and implemented before CBM can be applied.

2.2 Condition monitoring

According to the definition by Williams et. al. [32], condition monitoring is comprised of continuous or periodic measurement and interpretation of data, indicating the condition of the monitored item and determining its need for maintenance. Some other authors use narrower definition by excluding the determination of the need for maintenance [11]. In this study, the latter definition is adopted, as the consideration of actual need for maintenance is not within the scope of this study. Condition monitoring system can be thus divided to three phases as presented in Figure 2.2.

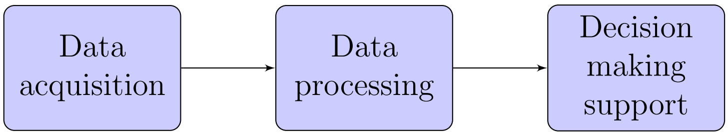

Figure 2.1: Phases of condition monitoring system. Modified from [1]

The first step is data acquisition. In order to tell something about the condition of an equipment, it must be observed. In modern condition monitoring systems, the observations are performed by sensors. The goal of the condition monitoring system is to identify the condition of the monitored equipment. Therefore the sensors should be selected so, that they measure signals which manifest changes in the condition of the equipment. In different types of machines, the faults occur differently. Often faults or other changes in equipment condition can be observed through changes for example in vibrations, sounds, temperature or electic current. Some commonly used sensor types are accelerometers, microphones, temperature sensors, current sensors and oil sensors [16].

The second step is data processing, or data analysis. In this step, the data acquired from the sensors is processed so that the most relevant information concerning the condition of the equipment is extracted from the vast amount of sensor data. First the data might require pre-processing, after which it is analyzed by using some of the many algorithms, models or tools developed for various circumstances. At the end of the data analysis, relevant information is extractred from the data and fed to the next step.

The last step of the condition monitoring system is decision making support. The role of condition monitoring system in maintenance decision making is to provide information on the condition of the equipment. Most of the condition monitoring systems provide information only on the current condition of the equipment. The analysis of the current condition is called diagnosis. Sometimes the future condition of the monitored equipment can be estimated as well. Prediction of time and type of potential upcoming faults is called prognosis.

2.2.1 Data acquisition

Data acquisition is in the basis of condition monitoring, because all the analysis and decision recommendations are essentially based on the data acquired from the equipment. The problem in data acquisition is to choose what kind of data is collected and how. The goal of condition monitoring is to gain insight on the condition of the equipment. Therefore it is intuitive that the acquired data should be such that it is affected by the changes in equipment condition. Sometimes also the environmental conditions have influence on the equipment. If that is the case, then the relevant environment parameters should be monitored as well. There are several possible variables to be measured and also several kind of sensors to measure them. Some of the sensors, e.g. accelerometers or microphones for measuring acoustic emission, must be attached to the monitored equipment, whereas other sensors, e.g. microphones for audio signature measurements, humidity sensor, etc., can be placed just close to the equipment, which makes them easier to install.

Since there are many different variables which can be measured, the type of the data varies as well. Jardine et al. [16] divided the condition monitoring data into three categories: value type, waveform type and multidimension type. Value type means the data, which is collected one value at time, e.g. temperature, humidity. Waveform type contains the data which is collected at high sample frequency, usually during a relatively short time period. Examples of waveform data are vibration and acoustic signals. Multidimension type contains the data which is collected as multidimensional variable, such as image data.

Condition monitoring systems may differ also in terms of sampling interval. Condition monitoring can be continuous or discrete. In continuous condition monitoring, the measurements are taken continuously or at short intervals with sensors permanently attached to the equipment, whereas in discrete case, the measurements are taken and analyzed in discrete points in time. Continuous sampling is more accurate solution, but it might be unnecessary or even simply not feasible. Appropriate sampling interval depend on the equipment, its requirements and its usage. Oil analysis is a typical example of discrete condition monitoring and vibration monitoring is an example of often continuous condition monitoring.

In many cases, the condition monitoring is done remotely, which requires the data acquisition hardware to contain also a communication interface for sending the data forward. Sometimes the equipment is in remote location, which poses challenges regarding the connectivity. Depending on the type of the connection, transfer capacity might be restrictive, if continuous online condition monitoring is performed remotely by using vast amount of data. In some cases the information security aspect of the data transmission must be taken into account as well.

In addition to condition monitoring data, i.e. vibrations, audio signals, environmental data, etc., also so called event data is collected. Event data contains information on what has happened, (e.g. what faults have occured and when, how the equipment has been used, etc.) and what has been made (e.g. maintenance, repairs, etc.). When this data is combined with the condition monitoring data, the deviations in condition monitoring data due to some specific fault can be identified and that information could be used in the future to predict the occurrence of a similar fault. This is important especially in the beginning of the condition monitoring system implementation, when there usually is not information available on the effects of all different fault situations. Another situation, where the event data is extremely useful is the identification of the reason of unexpected data. For example, if the equipment is modified, the condition monitoring data could change significantly. Without knowledge of the done modification, the changes in data could cause unnecessary troubleshooting. However, the event data is harder to collect automatically, so the implementation of the event data acquisition and integration to condition monitoring data can be complicated.

2.2.2 Data processing

The purpose of the data processing step is to extract the useful information from the vast amount of raw data obtained in the data acquisition step. Before the actual data processing, pre-processing of the data is often required.

Data pre-processing can be, for example, cleaning the data from corrupted measurements or selecting only a certain subset of the data. Methods used in data processing step depend on the type of the acquired data. As described in the previous section, condition monitoring data can be very versatile, which means that there are vast amount of different data processing methods as well. In this study focus is on acoustic signals. Because acoustic signals belong to the waveform data type, the data processing methods explained in this section are restricted to those for processing such data. The processing of waveform data is also known as signal processing. The most common signal processing methods can be categorized in three categories: time domain analysis, frequency domain analysis and time-frequency domain analysis.

Time domain analysis uses the original time series. Usually time domain analysis is done through statistical parameters calculated from the time series. Mean, standard deviation, maximum and kurtosis are examples of conventional statistical parameters. Features calculated from time domain signal can be used to get an overall impression of the signal. [20]

Frequency domain analysis is based on frequency domain transformation of the original signal. During operation, every mechanical component or process in a machine has characteristic frequency signature. If a fault or a defect changes the dynamics of the monitored system, the charachteristic frequency signature often changes as well. Fourier transform is the most common frequency domain representation of the time series data. Frequency domain representation of the signal shows the frequency content of the whole time series signal. Therefore the original time domain signal should be stationary. [20]

Time-frequency domain analysis is also based on a transformation, but as opposed to the transformations used for frequency domain analysis, the time-frequency transformations takes both time and frequency domains into account. Time-frequency domain analysis is especially useful for nonstationary signals. Short-time Fourier transform and wavelet transform are examples of signal's time-frequency representations.

Next, examples of various data processing methods utlizied in audio-based condition monitoring systems are presented.

Heng and Nor [13] used statistical time domain analysis to detect defects from rolling element bearings. Several statistical variables, e.g. kurtosis and crest factor, were calculated from sound pressure and vibration signals. The values of the variables were then compared in normal condition and several faulty conditions.

Ubhayaratne et al. [30] proposed a condition monitoring system for sheet metal stamping machine. The condition of the machine was determined by root meand square and maximum peak value of extracted audio signal.

Dai et. al. [5] proposed an audio feature based method for monitoring the progress of a bone drilling process. Dai et .al. [5] applied discrete wavelet transform to audio data. Products of standard deviations of the different scales of wavelet transform were used as features in condition diagnosis.

Rafezi et al. [26] used audio signals to detect the wear of a drilling tool. In their study, audio signal was first transformed by wavelet packet decomposition and then statistical features, i.e. root mean square, peak amplitude and variance were calculated from the selected wavelet packet components. Those features were then used to distinguish worn tools from the sharp ones.

Wu and Liu [33] used wavelet packet decomposition to extract features from audio signals in fault diagnosis system for internal combustion engines. In the study, audio signatures from a healthy motor as well as motors with five different faults were recorded. Wavelet packet decomposition was applied to those signals and entropies of the resulting components were calculated for each wavelet packet. The entropy levels corresponding to different motor conditions were then used to train a classifier for automatic fault diagnosis.

Also Olsson et al. [22] utilized wavelet packet decomposition technique to extract features from audio signals. In that study, peak values of wavelet packet coefficients from different scalings were used as features. The audio signals were recorded from industrial robot arm movements in three different conditions and the proposed condition monitoring system achieved 91% accuracy.

More examples of different data processing techniques can be found for example from the review article of Henriquez et al. [14]

2.2.3 Feature selection

Especially in the case of waveform data, such as vibration or acoustic data, the raw signals are usually so large, that it is not practical to use the whole raw signal in diagnosis step. Instead, the output of the data processing step is a set of features, which are supposed to appropriately represent the raw data acquired from the equipment.

What the features are and how many of them are needed varies from case to case. However, regardless of the occasion, there still are common requirements for the set of features. For example, the features should retain the information from the original data regarding the examined phenomena. Also the number of the features should not be unnecessarily large. If there are features which do not contain any useful information, the excessive amount of features just hinders the subsequent analysis and might also decrease accuracy of the condition diagnosis. The selection of the feature set is extremely important because the later analysis and diagnosis are based on these features.

The number of possible features is basically unlimited and the problem is to find the right set of features. It requires knowledge of the studied phenomena and the monitored system to decide the features which are calculated, i.e. features which are considered useful. Sometimes, if the studied system is simple enough, it might be easy to select one or two features which are affected the most by the condition changes. However, often it is not so clear how the measured signals behave in different conditions, so the set of extracted features might be huge.

The methods for selecting the appropriate subset of features can be divided into wrappers, filters and embedded methods [10]. Wrapper-based methods utilize the selected learning machine as a black box to evaluate the feature subsets based on their predictive power. Embedded methods are inherent to the training process of the learning machine. These methods are usually specific to given machine learning method. Unlike wrappers and embedded methods, filters are independent of the used machine learning methods. Usually the filters select the feature subset so that it maximizes some objective function.

A number of objective function alternatives have been proposed, such as Fisher's linear discriminant [7], Laplacian score [12] and ReliefF [27]. Fisher's method is widely used technique and it has been applied to condition monitoring systems as well [3, 34, 35]. The basic idea of Fisher's linear discriminant is to maximize the between class variance and minimize the within-class variance.

Based on the selected method, feature selection can be seen as a part of signal processing step or decision making support step of the condition monitoring system framework presented in Figure 2.2.

2.2.4 Decision making support

Decision making support is the last step of a condition monitoring system. In this step, the information extracted from the data in data processing step is used to evaluate the condition of the monitored equipment. The output of this step, and thus the whole condition monitoring system, is an estimation of the equipment's condition. There are two kind of estimations: diagnostics and prognostics [16]. Condition diagnostics focus on the current condition of the equipment and it aim to detect, identify and locate the present fault modes. Prognostics on the other hand attempt to predict faults and failures in advance, before they occur. In ideal situation all faults could be predicted through prognostics, because then there would be less failures and the maintenance planning would be much easier and more efficient. However, in practice that is not possible and therefore there is also need for diagnostics capabilities.

Prognostics is naturally much harder to implement than diagnostics. It also requires much more information, not only on the failure mechanisms, but also on the fault propagation process. The information can be obtained through historical data or by building models of the fault mechanisms. However, when the examined system is complex enough, modelling of the fault becomes infeasible. In that case, a condition monitoring system with diagnostic abilities is an exelent tool to collect the necessary data for prognostics development. In this study, the decision making support is restricted to diagnostics, leaving prognostics as a matter of future research.

In essence, diagnostics is a classification problem, where the features or the condition monitoring data are inputs and the output is the diagnosed state of the monitored system. As in the data processing step, the amount of possible techniques to solve this problem is huge. In this section, some of the most common methods are introduced.

One simple option is to set threshold values for certain features. If the value of the feature exceeds the threshold value, the equipment is diagnosed as faulty. The selection of the threshold levels manually may be difficult and time consuming. That causes problems especially then, if several pieces of equipment are being monitored and each of them has unique threshold levels. To overcome the problem of threshold setting, it can be automated. [15]

Statistical process control (SPC) is similar to using thresholds, as the idea of SPC is to measure the deviations of a signal or variable from a reference signal or value. Control limits are determined based on the deviations in normal condition. If the measured signal or variables drift outside the control limits, it indicates that something has changed. Although SPC was initially developed for quality control, it is also applied to fault detection in condition monitoring systems. [9]

Various machine learning methods are quite common tools for diagnostic purposes. Usually the selected machine learning algorithm is trained by labeled samples. This supervised learning requires data from each fault scenario. Some common machine learning methods are artificial neural networks and support vector machines.

Inspiration for artificial neural networks arise from biological nervous systems. Artificial neural networks consist of interconnected processing elements, i.e. neurons. In each neural network there are at least one input neuron and one output neuron. The connections between neurons, i.e. weights, are adjusted based on the training data. Artificial neural networks have been succesfully used for condition diagnosis for example by Wu and Liu [33], Yan and Gao [34] and Rad et. al. [25]. In addition to the requirement of vast training data, artificial neural networks have other drawbacks as well. One issue is that the neural networks are almost black boxes, as the network trains itself and after the training, the resulting weight matrix is hard to interpret. Artificial neural networks are also prone to overfitting. [29]

Support vector machines are essentially 2-class classifiers. They map the original input space to a high-dimensional feature space, where the two classes can be separated by a hyperplane. The mapping and the optimal separating hyperplane are determined by the training data. Despite the nature of 2-class classifier, support vector machine extensions to multi-class classification problems have been developed [24]. Support vector machines have been applied to condition diagnosis for example by Pöyhönen [24] and Yuan and Chu [36]. More examples can be found from a survey of support vector machine usage in machine condition monitoring and diagnosis compiled by Widodo and Yang [31].

K nearest neighbours algorithm is a simple and widely used nonparametric classification method. The algorithm compares a new observation to the training data and classifies the new sample to belong to the most frequent class among the k nearest training data samples. Although the algorithm requires training data as well, the amount of required training data is much smaller compared to the amount of data required by artificial neural networks and support vector machines. K nearest neighbour based algorithm have been used for condition diagnosis for example by Lei et. al. [18] and Olsson et. al. [22].

It is also possible to think the condition of the monitored machine to be a stochastic process, or more precisely, a Markov chain. Since the actual condition of the machine can not be observed, the state of the machine must be estimated based on the aquired sensor data, which is affected by the condition of the machine. Hidden Markov models can be used for analysis of such unobservable Markov chains. To define a hidden Markov model, the number of possible states, transition probabilities between states, probability distributions of observed variables in each state and probability distribution of initial state are required. Again, test data is required to estimate the model parameters. However, it is easier to incorporate new information to hidden Markov model than to artificial neural networks or support vector machines. Hidden Markov model based applications to condition diagnosis have been presented for example by Baruah and Chinnam [2], Bunks et. al. [4] and Dong et. al. [6].

All of the aforementioned condition diagnosis methods are data driven, because the observed training data is the only source of information on the observed system. Another way to perform condition diagnosis is to use model based methods. In model based methods, physics based models are constructed to predict how the system would behave in different situations and different conditions and how that behaviour would affect the measured values. The new measured data is then compared to the outputs of the different models. The condition of the system is then determined to be the same as the corresponding model, which provided the most accurate prediction. However, this method is difficult to implement, because it requires very deep knowledge of the examined system. Especially when the system is complex or when changes in environment affect the measurements as well, accurate models are even harder to build.

2.3 Sound

Sound is a pressure wave that propagates through an elastic medium, e.g. air. There are two fundamental mechanisms for generating sound waves. In the first mechanism, sound wave is caused by a vibrating solid body. Sound waves generated that way are also called structure-borne sounds. In the second mechanism, sound wave is caused by pressure fluctuations induced by turbulance and insteady flow. Those sound waves are also referred to as aerodynamic sound. Most of the sounds generated by mechanical machines are structure-borne sounds. When the machine is operating as intended, the audio signature stays usually the same, given the operation conditions and environment do not change. When the machine develops a defecct, it often changes the vibrations and sounds generated by the machine. For example a skilled technician can identify some faults from a car engine by just listening to it. [21]

Humans perceive sound waves through pressure changes incident on the eardrum. Humans can hear sound pressures ranging from 20μPa to 200Pa. As the range is so large, the sound pressure amplitude level is usually represented in decibels. When two variables differ by one decibel, the ratio of those numbers is $10^{1/10}(\approx 1.26)$. Thus the sound pressure level (SPL) is defined as

$$SPL = 10log_{10}\left(\frac{p^2}{p_{ref}^2}\right) = 20log_{10}\left(\frac{p}{p_{ref}}\right), \tag{2.1}$$

where p is the root mean square amplitude of the sound wave and p_{ref} is the reference sound pressure. Standardized reference pressure for sound waves in air is 20μPa [20].

Microphones are used to convert air pressure changes to electronic signals. Electronic signals are then converted to digital audio signals, which can be processed by computers. Because SPL value is relative to the reference sound pressure, the measurement instrumentation must be calibrated before it can be used for SPL measurements.

Humans do not hear sounds below 20Hz or over 20kHz. Within that range the perceived loudness of sounds with same amplitude depend on the frequency of the sound wave. As measurement instruments aim to achieve flat frequency response, the measured sound pressure levels must be filtered in order to get information on the perceived loudness of the sound. A-weighting is the most common method to obtain filtered sound pressure levels, which correspond to the human perception. The sound pressure levels after A-weighting are denoted as dBA. [20]

In audio measurements, the data acquisition device, i.e. microphone, do not have to be in contact with the monitored equipment. Therefore it is often easier to install compared to some other sensors such as accelerometers or acoustic emission microphones. One major drawback of audio measurements is the sensitivity to external noises and reflections of the original signal [20]. Therefore the ability of condition monitoring system to perform well in various environmental conditions is especially challenging when it is based on audio measurements. In some cases the unwanted noise could be filtered from the signal, but that requires knowledge of the properties of the actual signal and/or the external noise. For example, if it is known that the observed signal is limited to specific frequency range, other frequencies containing only noise could be ignored. On the other hand, if the external noise is known to be limited to certain frequency range, where the signal itself do not carry much relevant information, those frequencies could be filtered as well. There are also other, more sophisticated ways to remove unwanted noise from the signal, but they usually require more than one measurement of the signal. When the condition monitoring system is supposed to work in various environments, the external noise can be basically anything and for different equipments the audio signatures differ. As a result, there is basically no way to distinguish external noises from the noises generated by the examined equipment, which also makes signal de-noising extremely challenging.

Chapter 3

Materials and methods

The feasibility of audio based condition monitoring system is investigated through experiments performed on a specific type of equipment. In this chapter, the experiments, data gathered from them and the used analysis methods are explained in detail.

3.1 Materials

The methods described in this chapter are applied to data acquired from several similar type of equipment. The examined pieces of equipment are electromechanic systems consisting mainly of a container, which is sliding on metallic rails, an electric motor and its drive. All the measurements are conducted in an actual usage environment. In addition to audio signal, the measurement instrumentation provides information on the status of the equipment, i.e. whether the container is standing, accelerating, moving at constant speed or decelerating. In this study, only the constant speed phase of the movement is examined. The status information is used to extract the section of audio signal corresponding to the constant speed phase. Hereafter a sample refers to one such section of an audio signal acquired from one piece of equipment during one travel. Here travel is defined as the time interval, which starts when the equipment is preparing to move the container, and ends when the container has stopped again.

The data used in this study is acquired from five separate pieces of equipment. Samples of travels in normal condition are obtained from each piece of equipment. Those samples are used to analyze the variations between different sets of equipment as well as the effects of different start and end positions of travels. The amount of data used for the analysis of variations between different sets of equipment is 65, 56, 5, 7 and 40 samples from equipment #1 to equipment #5, respectively. To decrease other sources of variation, start and end positions are the same for all the samples from one piece of equipment and similar across all pieces of equipment.

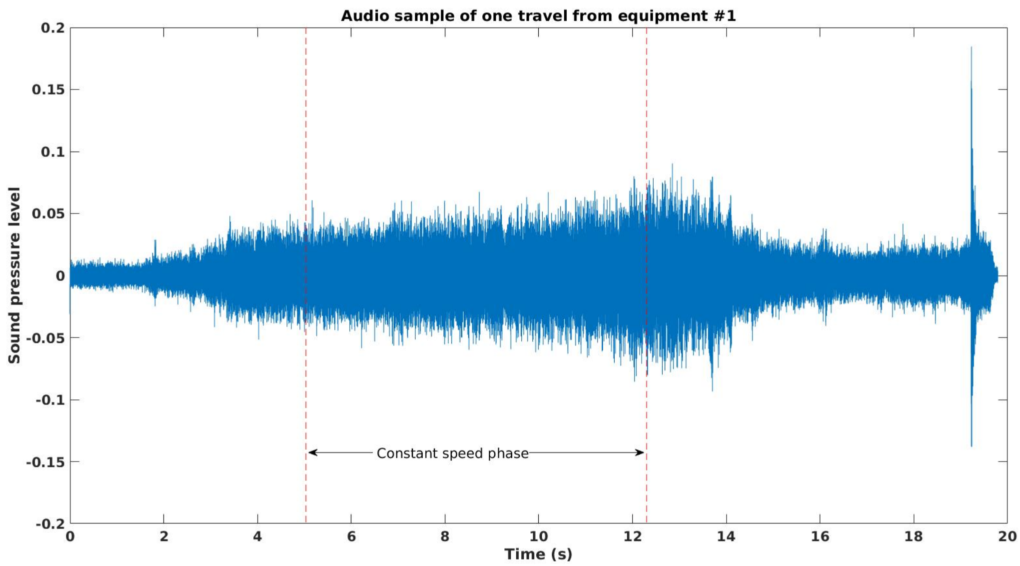

Figure 3.1: Example of one audio sample. This sample is taken from equipment #1 during normal operation. Start and end times of constant speed phase are marked by vertical dashed lines.

Even when there is no fault present, the sound signature might change because of different type of usage. For example applied load, length of the travel and start and end positions of the travel may have an effect on the audio measurements. Different cases of normal usage should not be identified as a fault. Therefore it is necessary to take into account the effects these variations have on the equipment's sound signature. To test the effects of different loads, five different load situations are applied to one equipment. The effect of the microphone position is tested simultaneously by changing the microphone position during each load situation. The considered loads are: zero, low, high, unbalanced high and full. Usually the load is distributed evenly in the container, but in unbalanced high load case the load is applied only on one side of the container. High load only on one side of the container is not necessarily normal situation, but still possible scenario in normal usage. For each microphone and load combination, approximately ten samples with same travel length are collected from equipment #1.

Another source of variation in normal operation is the length of the movemement. When only constant speed phase is considered, the length of the movement must be at least so large that the container actually moves at constant speed between acceleration and deceleration. The effect of travel length is investigated by examining samples from one piece of equipment with different travel lengths. For that purpose 41, 31 and 14 samples with respective travel lengths of 0.33, 0.67 and 0.83 are collected from equipment #5. The aforementioned lengths are unitless, as they are relavite to the longest possible movement of the equipment in question. The starting positions are the same for every measurement, but the ending positions change according to the length of the movement. Similarly for investigation of effect of different start and end positions, samples with same travel lengths, but different start and end positions, are collected from equipment #5. The amount of data is 41, 38 and 21 samples for end positions 0.24, 0.40 and 0.57, respectively. Again, the positions are unitless, as they are relative to the length of the rails in the examined equipment.

To test the feasibility of audio measurements for condition monitoring in this particular case, also data from faulty equipment is required. For that purpose, three separate fault cases were examined in one equipment. The fault cases were selected based on the frequency of the fault occurence, so that some of the most frequent faults are considered. However, only such faults were selected, which supposedly generate audible noise. The analysis is restricted to the period, when the container is moving at constant speed. By doing so, the different speeds and accelerations cause less variations to

Table 3.1: The number of samples from each piece of equipment.

Experiment \ Equipment	#1	#2	#3	#4	#5
Normal operation	65	56	5	7	40
Different load	100	-	-	-	-
Different length	-	-	-	-	86
Different position	-	-	-	-	100
Fault cases	-	47	-	-	-

the measurements and thus it helps to detect the effects of the actual faults being tested. The restriction to only constant speed phase excludes the shortest measurements, as the container does not move at constant speed at all between acceleration and deceleration.

In the first fault test, the metallic rails were modified so that there were discontinuities in the rails. This would cause an additional noise each time the container slides past such a discontinuity. The second fault case is generated by removing lubricant from the sliding rails. The last case is also related to the rails. This time the sliding is hindered by placing dirt on the rails. In the last two cases, the friction between the container and rails is changed, which is expected to change the sound generated by the equipment across the whole period when the container is moving. The number of samples varies from five from fault #2 to 17 from the third fault case. From normal condition there are 13 samples and from the first fault case 12 samples. The samples in first fault case are measured from travels of fixed length, whereas for other cases the lengths of the signals vary.

The total number of samples from each piece of equipment for different experiments are presented in Table 3.1.

3.2 Data acquisition

In all of the aforementioned experiments, one microphone is used to measure the sounds generated by the monitored equipment. The placement of the microphone is determined by the surroundings of the equipment, so it is not possible to unify the position of the microphone across equipments. Audio measurements are generally sensitive to microphone position, as the distance to the sound sources and reflections from surrounding structures affect the measurements.

In addition to microphone, there are also other measurement instruments, which provide information on the status of the equipment. As the examined equipment contains a linearly moving object, it is natural to define the normal operation phases as: Standing, accelerating, moving at constant speed and decelerating. Through the data provided by those additional instruments, it is possible to link the audio measurements to different phases of the normal operation.

3.3 Signal processing

In this study, only conventional time and frequency domain methods are used. The main reasons for using only simple and conventional methods are the ease of interpretation of the results and small requirements for computational resources. Those reasons origin from the legislative restrictions for recording audio in public areas. Some of the possible locations of the examined pieces of equipment are within areas, where the recording of audio is forbidden. Therefore the audio measurements must be analyzed locally in real time, which poses demands for computatonally simple signal processing methods. Since the raw audio data can not be recorded, the measured audio signals are represented as a set of features calculated from the signals. If the measured feature values differ significantly from normal values for a given equipment, the reason for the deviations is often determined by comparing the feature values to previous fault situations. If some previously occured fault resulted in similar changes in the feature values, the same fault has possibly occured again. However, if there is no similar data, the ease of interpretation of the features might provide useful information for narrowing down the possible reason for the abnormal behaviour.

As described in Chapter 2, signal processing consist of signal pre-processing and actual signal processing methods. In the following sections, the used signal pre-processing procedures as well as used methods in time and frequency domains are presented.

3.3.1 Signal pre-processing

Before the actual signal processing methods are applied, the validity of aqcuired signals are checked. Signals may be invalid for example because of instrumentation malfunction. Because the audio data and equipment status information are used together in the analysis, measurement is discarded if either of those signals are missing or incomplete. The next step is to incorporate the equipment's status information to the audio signal. As each phase of the normal operation cycle has its own unique sound signature, the raw signal is divided into smaller bits corresponding to different phases. Different faults are present in different phases in different ways, so the analysis of the phases should be done separately and possibly by using different methods. In this study, the analysis is restricted to the constant speed phase. The faults considered in this case are such that they can be perceived by human ear. To bring forth the features audible to humans, the audio signals are A-weighted before the analysis.

3.3.2 Time domain analysis

The most straightforward way to gain information from the acquired audio signal is to examine the raw audio signal, which is in essence a time series of values corresponding to sound pressure levels at the location of the measurement microphone. The examined time series can be described through statistical features, i.e. parameters, calculated from it. Different features describe different aspects, so calculating several features from one signal can give comprehensive description of that signal. In this study, 11 statistical features are used to characterize a signal in time domain. The feature set is the same as the one used by Loutas et. al. [19] and some of those features are also used in condition monitoring by Lei et. al. [18], Pachaud et. al. [23] and Heng and Nor [13].

The 11 parameters, which are used as the features are presented below. Here $\{X_t\}$ is assumed to be a time series.

1. Expected value

$$\mu = E[X_t] \tag{3.1}$$

2. standard deviation

$$\sigma = \sqrt{E[(X_t - E[X_t])^2]} \tag{3.2}$$

3. square mean root

$$x_{smr} = (E[\sqrt{|X_t|}])^2 \tag{3.3}$$

4. Root mean square (RMS)

$$x_{rms} = \sqrt{\mu^2 + \sigma^2} \tag{3.4}$$

5. Peak value

$$x_{peak} = \max\{|X_t|\} \tag{3.5}$$

6. Skewness (Third moment)

$$x_{skew} = E[(\frac{X_t - \mu}{\sigma})^3] \tag{3.6}$$

7. Kurtosis (Fourth moment)

$$x_{kr} = \frac{E[(X_t - \mu)^4]}{(E[(X_t - \mu)^2])^2} \tag{3.7}$$

8. Crest factor

$$x_C = \frac{x_{peak}}{x_{rms}} \tag{3.8}$$

9. L factor

$$x_L = \frac{x_{peak}}{x_{smr}} \tag{3.9}$$

10. S factor

$$x_S = \frac{x_{rms}}{E[|X_t|]} \tag{3.10}$$

11. I factor

$$x_I = \frac{x_{peak}}{E[|X_t|]} \tag{3.11}$$

In the above mentioned functions, it is assumed that all the expected values $E[\cdot]$ do exist as finite quantities, that do not depend on the time point t.

In this case, the random variable X_t is the sound pressure level next to the observed equipment during the constant speed phase of one movement. Obviously, the real probability distribution of X is not known, but it must be estimated through the measurements. Parameter estimators calculated from the measurements converge in probability only if the observed values $\{x(1), x(2), x(3), \ldots, x(N)\}$ from one movement fulfill the corresponding stationarity assumptions (existence of finite expected values that do not depend on t). In essence, that means that the audio generating process should be stationary during the whole measurement period.

In practice those assumptions do not always hold exactly. However, as the audio signal is measured only during the constant speed phase, the process does not change too much during the measurements.

The measurement data is used to approximate the aforementioned parameters by using the the following estimators:

1. Mean

$$TD_1 = \bar{x} = \frac{\sum_{t=1}^{N} x(t)}{N} \tag{3.12}$$

where N is the number of data points in the signal and $x(t)$ is the t:th observed data point of the signal.

2. standard deviation

$$TD_2 = \hat{x}_{sd} = \sqrt{\frac{\sum_{t=1}^{N}(x(t) - \bar{x})^2}{N-1}} \tag{3.13}$$

3. square mean root

$$TD_3 = \hat{x}_{smr} = \left(\frac{\sum_{t=1}^{N} \sqrt{|x(t)|}}{N}\right)^2 \tag{3.14}$$

4. Root mean square (RMS)

$$TD_4 = \hat{x}_{rms} = \sqrt{\frac{\sum_{t=1}^{N} x(t)^2}{N}} \tag{3.15}$$

5. Peak amplitude

$$TD_5 = \hat{x}_{peak} = \max_t |x(t)| \tag{3.16}$$

6. Skewness (Third moment)

$$TD_6 = \hat{x}_{skew} = \frac{\sum_{t=1}^{N}(x(t) - \bar{x})^3}{(N-1)\hat{x}_{sd}^3} \tag{3.17}$$

7. Kurtosis (Fourth moment)

$$TD_7 = \hat{x}_{kr} = \frac{\sum_{t=1}^{N}(x(t) - \bar{x})^4}{(N-1)\hat{x}_{sd}^4} \tag{3.18}$$

8. Crest factor

$$TD_8 = \hat{x}_C = \frac{\hat{x}_{peak}}{\hat{x}_{rms}} \tag{3.19}$$

9. L factor

$$TD_9 = \hat{x}_L = \frac{\hat{x}_{peak}}{\hat{x}_{smr}} \tag{3.20}$$

10. S factor

$$TD_{10} = \hat{x}_S = \frac{\hat{x}_{rms}}{\frac{1}{N}\sum_{t=1}^{N}|x(t)|} \tag{3.21}$$

11. I factor

$$TD_{11} = \hat{x}_I = \frac{\hat{x}_{peak}}{\frac{1}{N}\sum_{t=1}^{N}|x(t)|} \tag{3.22}$$

Mean value of audio signals is always close to zero, so too high or too low values could indicate a failure in data acquisition device. RMS corresponds to the loudness of the measured sound signal. When mean is zero, RMS is equivalent to standard deviation. Skewness, kurtosis and crest factor as well as L, S and I factors describe the shape of distribution. Skewness measure the symmetry of the distribution; distribution which is symmetric about the mean has a skewness close to zero. Kurtosis measure the weight of tails of the distribution. Normal distribution has a kurtosis value close to three, whereas distributions with smaller tails have larger and flatter distributions have smaller values of kurtosis. Crest factor as well as L, S and I factors all describe in their own way, how much the extreme values differ from the rest of the population.

3.3.3 Frequency domain analysis

As described in Chapter 2, frequency domain analysis considers the frequency content of the signal. Power spectral density (PSD) describes how the power of the signal is distributed over frequency range and it is often used in frequency domain analysis. Before the PSD can be obtained, the signal must be converted from time domain to frequency domain. Discrete Fourier transform (DFT) is the most common way to perform the conversion. DFT of $x(k)$ on the interval $[0, N-1]$ is defined as

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-i\frac{2\pi kn}{N}} \tag{3.23}$$

where $0 \leq k \leq N-1$ and N is the number of points in the signal. The output of DFT is in general complex signal and contains information on both amplitudes and phases of the frequency componenets. PSD takes into account only the amplitudes of the frequency components, thus it is ignorant to the phase information. The simplest way to estimate PSD is periodogram and by using DFT it is calculated as

$$\tilde{P}_{per}(k) = \frac{\Delta t}{N} |X(k)|^2 \tag{3.24}$$

The main drawback of periodogram is high variance of the PSD estimator, which can also be seen from the example presented in Figure 3.2. Periodogram is also inconsistent estimator, because the variance does not approach zero as the sample size tends to infinity. One way to improve the estimate is to divide the signal into shorter, equally sized segments and then average the periodograms calculated for each segment. That is called

Bartlett's method and it reduces the variance of the PSD estimate. Welch's method improves the estimate further by applying a window function to each segment and allowing the segments to overlap. By doing so, the spectral leakage effect is reduced. Thus, PSD estimate obtained by Welch's method is

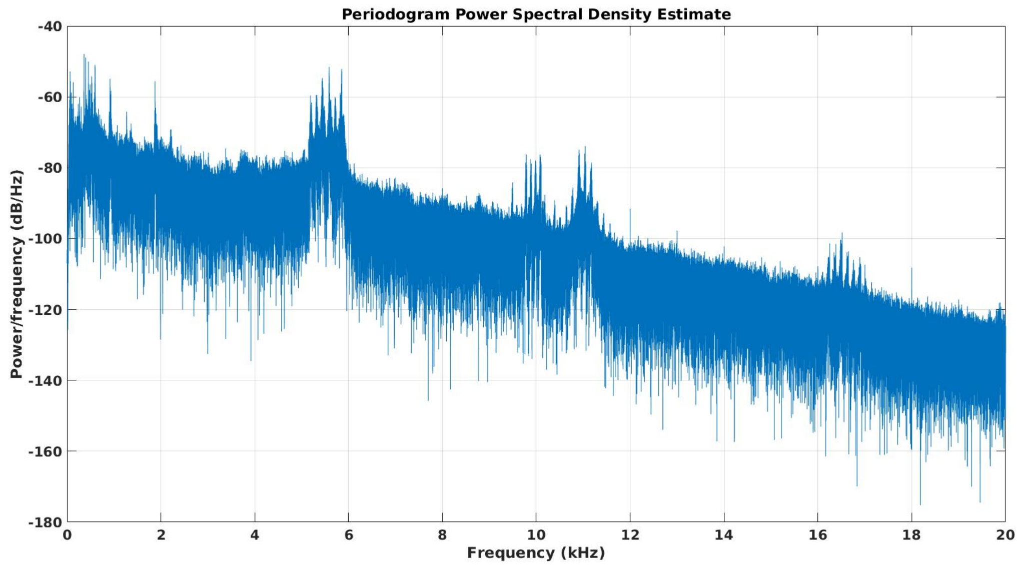

Figure 3.2: Example of periodogram PSD estimate calculated by 3.24. This sample is taken from equipment #1 during normal operation and it is the same as presented in Figure 3.1.

$$\tilde{P}_{Welch}(k) = \frac{\Delta t}{MU} \sum_{j=0}^{M-1} |\sum_{n=0}^{K-1} w(n)x(n+jD)e^{-i\frac{2\pi kn}{K}}|^2, \qquad (3.25)$$

where M is the number of averaged segments, K is the length of one segment and D is the offset between two consecutive segments. For example, for 50% overlap, $D = K/2$. U is a scaling coefficient, which compensates for the energy of the window function $w(n)$.

$$U = \frac{1}{K} \sum_{n=0}^{K-1} |w(n)|^2 \qquad (3.26)$$

Window functions which start and end at close to zero basically force the signal to be periodic. In this study, Hamming window is used and it is defined as

$$w(n) = 0.54 - 0.46\cos(2\pi\frac{n}{K}), \quad 0 \leq n \leq N \tag{3.27}$$

As the length of each segment is now $K < N$ insted of N in the periodogram, the frequency resolution of this estimate is worse than in periodogram. The range of index k is now $[0, K-1]$. In this study, Welch's method is used to estimate PSD. Therefore the notation P is used to denote PSD estimate calculated by using equation 3.25.

An estimation of a characteristic PSD $P_{eq,i}$ of equipment i is obtained by taking a median of all the measurements from that equipment separately for each frequency component, i.e.

$$P_{eq,i}(k) = \operatorname*{median}_{j \in J_i}\{P_j(k)\}, \quad \forall k \in \{0, 1, 2, ..., K-1\} \tag{3.28}$$

where P_j is the PSD estimate of measurement j. J_i is the set of measurements from equipment i.

Traditionally the frequency domain analysis concerns a few selected frequency bands, which are known to be associated with certain fault modes. However, in this case the frequencies affected by the faults are not known beforehand. Therefore the whole PSD estimate is used in fault detection.

In addition to the PSD estimate itself, some statistical features are also used to describe the frequency content of the signal. Some of the used parameters, and the corresponding estimates, are similar to the parameters used in time domain. However, some additional estimates, based on applied literature [19], are also considered. For those features, it is difficult to find exact population quantities from the literature. One could say, however, that if the corresponding expected values exist as finite quantities and they do not depend on k, then by weak law of large numbers, estimates based on averages do converge in probability to the corresponding expected values.

The used frequency domain features are: 1. Mean

$$FD_1 = \bar{P} = \frac{\sum_{k=0}^{K-1} P(k)}{K} \tag{3.29}$$

where K is the number of data points in the PSD and $s(k)$ is the k:th data point of the PSD.

2. Standard deviation

$$FD_2 = P_{sd} = \sqrt{\frac{\sum_{k=0}^{K-1}(P(k) - \bar{P})^2}{K-1}} \tag{3.30}$$

3. Skewness (Third moment)

$$FD_3 = P_{skew} = \frac{\sum_{k=0}^{K-1}(P(k) - \bar{P})^3}{KP_{sd}^3} \tag{3.31}$$

4. Kurtosis (Fourth moment)

$$FD_4 = P_{kr} = \frac{\sum_{k=0}^{K-1}(P(k) - \bar{P})^4}{KP_{sd}^4} \tag{3.32}$$

5. Spectral centroid

$$FD_5 = P_{sc} = \frac{\sum_{k=0}^{K-1} f(k)P(k)}{\sum_{k=0}^{K-1} P(k)} \tag{3.33}$$

where $f(k)$ is the frequency corresponding to k:th data poin of the PSD.

6. Spectral standard deviation

$$FD_6 = P_{ssd} = \sqrt{\frac{\sum_{k=0}^{K-1}(f(k) - P_{sc})^2 P(k)}{K-1}} \tag{3.34}$$

7. Spectral RMS

$$FD_7 = P_{sRMS} = \sqrt{\frac{\sum_{k=0}^{K-1} f(k)^2 P(k)}{\sum_{k=0}^{K-1} P(k)}} \tag{3.35}$$

8. Spectral shape parameter 1

$$FD_8 = P_{ss1} = \sqrt{\frac{\sum_{k=0}^{K-1} f(k)^4 P(k)}{\sum_{k=0}^{K-1} f(k)^2 P(k)}} \tag{3.36}$$

9. Spectral shape parameter 2

$$FD_9 = P_{ss2} = \frac{\sum_{k=0}^{K-1} f(k)^2 P(k)}{\sqrt{\sum_{k=0}^{K-1} P(k) \sum_{k=0}^{K-1} f(k)^4 P(k)}} \tag{3.37}$$

10. Spectral shape parameter 3

$$FD_{10} = P_{ss3} = \frac{P_{ssd}}{P_{sc}} \tag{3.38}$$

11. Third moment of spectrum

$$FD_{11} = P_{sskew} = \frac{\sum_{k=0}^{K-1} (f(k) - P_{sc})^3 P(k)}{K P_{ssd}^3} \tag{3.39}$$

12. Fourth moment of spectrum

$$FD_{12} = P_{skurt} = \frac{\sum_{k=0}^{K-1} (f(k) - P_{sc})^4 P(k)}{K P_{ssd}^4} \tag{3.40}$$

13. 0.5. moment of spectrum

$$FD_{13} = P_{skurt} = \frac{\sum_{k=0}^{K-1} (f(k) - P_{sc})^{1/2} P(k)}{K P_{ssd}^{1/2}} \tag{3.41}$$

3.4 Condition diagnosis

In this study, the amount of data from fault situations is not sufficient for training a sophisticated machine learning algorithm, e.g. artificial neural network or support vector machine. As the condition monitoring system should be applicable to various machines, model-based methods are also inapplicable.

For condition diagnosis, a simple k nearest neighbor (k-NN) method is used. As described in Chapter 2, the idea of k-NN is to assign a label to a new sample based on the k nearest, i.e. most similar training samples. Euclidean distance is used as a measure of similarity between two samples. Let y_1 and y_2 be the feature vectors of samples x_1 and x_2, respectively. Euclidean distance between samples x_1 and x_2 is then

$$d(y_1, y_2) = \sqrt{(y_1 - y_2)'(y_1 - y_2)} \tag{3.42}$$

The class label for new sample is then obtained by first finding the k training samples with smallest euclidean distances to the new sample. Then the most frequent class label in the set of k nearest neigbors is assigned to the new sample. If there is no single most frequent class label, then the class is selected, which has the nearest training sample. Before the classification, the features are scaled to similar scale so that each feature has the same importance when the distances are calculated. In this case, the features' variations in the normal operation samples are utilized for scaling. The features of each sample are scaled linearly so that -1 and 1 correspond to the smallest and largest values of each feature in the normal operation samples. Formally

$$\tilde{y} = 2\frac{y - y_{Nmin}}{y_{Nmax} - y_{Nmin}} - 1 \tag{3.43}$$

where $\tilde{y}$ is the scaled feature vector, y_{Nmin} and y_{Nmax} are vectors of minimum and maximum values of each feature in the normal condition samples, respectively. All of the calculated features do not necessarily contain any useful information. Therefore only a subset of the original features are used for classification. The feature subset selection is performed by filtering the best features based on Fisher discriminants. Let $\mathcal{T}$ be the set of all features, $\mathcal{S} \subseteq \mathcal{T}$ the set of selected features and z the feature vector containing only the selected features. Then define class means μ_i, total means μ, within-class scatter matrix S_W and between-class scatter matrix S_W as follows

$$\mu_i = \frac{1}{n_i}\sum_{j=1}^{n_i} \tilde{z}_j \quad i = 1, \ldots, C \tag{3.44}$$

$$\mu = \frac{1}{n}\sum_{i=1}^{C} n_i \mu_i \tag{3.45}$$

$$S_W = \sum_{i=1}^{C}\sum_{j=1}^{n_i}(z_j - \mu_i)(z_j - \mu_i)' \tag{3.46}$$

$$S_B = \sum_{i \in \mathcal{S}}(\mu_i - \mu)(\mu_i - \mu)' \tag{3.47}$$

where C is the number of classes. Based on Fisher discriminant, the best feature set consisting of m features is obtained by solving the following optimization problem

$$\begin{aligned} \underset{\mathcal{S}\subseteq\mathcal{T}}{\text{maximize}} \quad & F(\mathcal{S}) = \frac{|S_B|}{|S_W|} \\ \text{subject to} \quad & |\mathcal{S}| = m, \end{aligned} \tag{3.48}$$

where $|\mathcal{S}|$ is the cardinatlity of $\mathcal{S}$. Unfortunately finding the optimal subset is NP hard problem. Therefore the selected subset is determined by heuristic greedy algorithm. In greedy algoritm, Fisher discriminant ratio is calculated intependently for each feature and then m features with largest values are selected to form the set $\mathcal{S}$. When only one feature is considered, Fisher discriminant is calculated as

$$F(y^k) = \frac{\sum_{i=1}^{C} n_i(\mu_i^k - \mu^k)^2}{\sum_{i=1}^{C}\sum_{j=1}^{n_i}(y_j^k - \mu_i^k)^2}, \quad k = 1, \ldots, M \tag{3.49}$$

where M is the total number of original features.

To decrease the bias of the k-NN algorithm, the classification is done by using leave-one-out method. The features used for classification are thus selected separately for each sample by using the whole data set except the sample being classified.

The k-NN algorithm is then tested for different combinations of k and m. Because the sample size is so small, some combination of k and m can give very good results by chance. To obtain a more robust assessment of the classification accuracy, the most frequent classification result is used to analyze the accuracy of the k-NN method.

Chapter 4

Results

In this chapter are presented the results of the analysis, when methods described in Chapter 3 are applied to data obtained from the experiments.

4.1 Normal audio signature

The starting point of analyzing the audio signatures of the examined pieces of equipment is to examine several audio measurements from one piece of equipment. In Figure 4.1 are presented PSD estimates of 56 measurements from equipment #1. The measurements are collected from travels with same length, while the equipment was being used normally in actual usage environment. Due to the authentic environment, there are a few abnormal measurements, which are caused by external noises.

The sound signatures of different pieces of equipment can be compared in frequency domain by comparing the PSDs of the measured audio signals. PSD estimates for each of the five pieces of equipent are constructed from individual samples from that equipment by using equation 3.28.

From Figure 4.2 it can be seen that the frequency contents, and thereby the audio signals as well, are clearly different for different pieces of equipment. Also the distributions of the statistical features calculated from both time and frequency domain signals differ between the pieces of equipment. Four examples of those variations are presented in Figure 4.3.

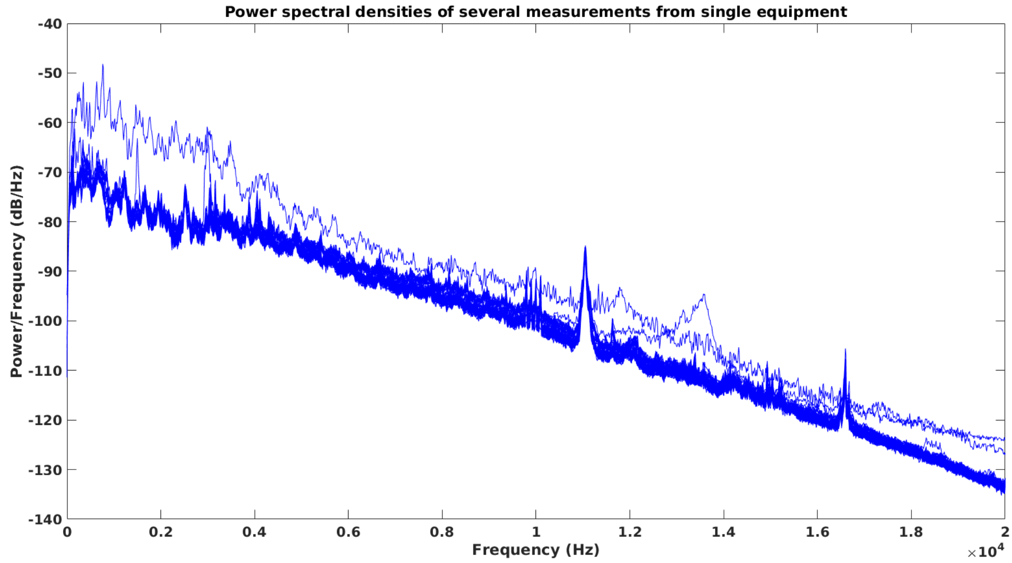

Figure 4.1: PSD estimates of 56 measurements from equipment #1. All the measurements are taken from travels with same start and end positions.

4.2 Variations in normal operation

During normal operation, equipment can be used in many ways. Different usage patterns may change the audio signature and condition monitoring system should not mistake those variations as faults. First analyzed source of variation is load. All the feature values from the load test can be found from appendix A, but the most notable results are presented in this chapter.

In time domain features, the effects of load changes are small, except for the unevenly distributed load. For example maximum and rms values are generally higher in unevenly distributed load compared to other load conditions. The differences between different evenly distributed loads are visible in frequency domain features. For example, the value of spectral fourth moment (FD_{12}) is much higher in high and maximum loads compared to low and zero load situations, respectively. The corresponding values are listed in Table 4.1. Again, the values of unevenly distibuted load are clearly distinguishable in several features, e.g. mean of PSD (FD_1), spectral standard

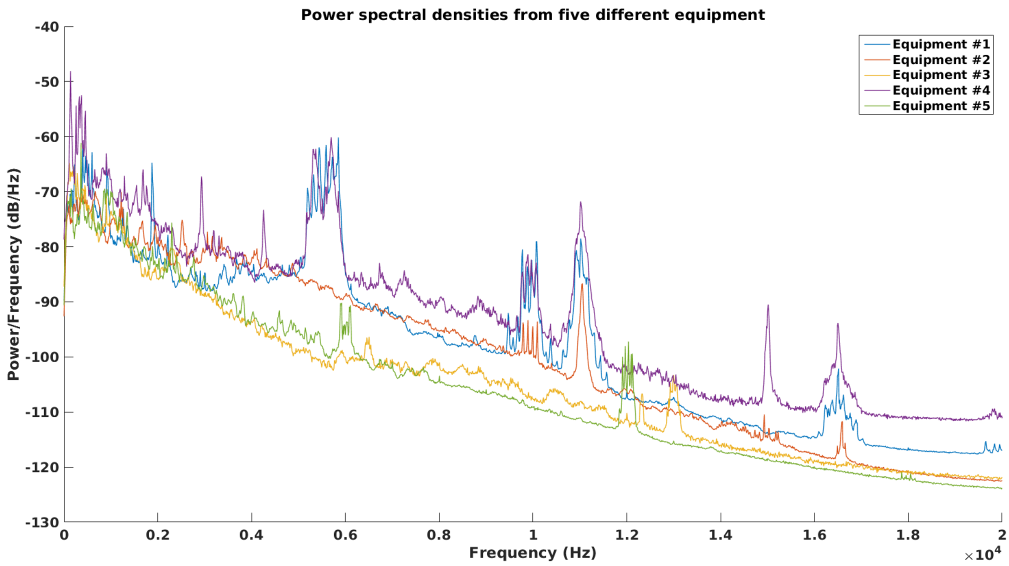

Figure 4.2: Averaged PSD estimates from five different pieces of equipment.

deviation (FD_6) and spectral shape parameter (FD_8).

Table 4.1: Examples of frequency domain features, which are different for different evenly distributed loads.

	Mic position #2		Mic position #5	
Load / FD_{12}	**Low**	**High**	**Zero**	**Full**
$Min * 10^{-8}$	0.857	1.311	0.925	1.846
$Median * 10^{-8}$	0.883	1.657	0.972	1.880
$Max * 10^{-8}$	1.071	1.692	1.013	1.909

In Figure 4.4 are presented two examples how different loads change the PSD estimates. In both Figures 4.4a and 4.4b, median PSD estimates as well as upper and lower limits of PSD estimates of given set of samples. Number of samples considered in Figure 4.4a is 10 for low load case and 9 for high load case. In Figure 4.4b, the corresponding sample sizes are 10 and 7 for evenly distributed high load and unevenly distributed high load, respectively. From Figure 4.4a it can be seen that the PSD remains approximately the same

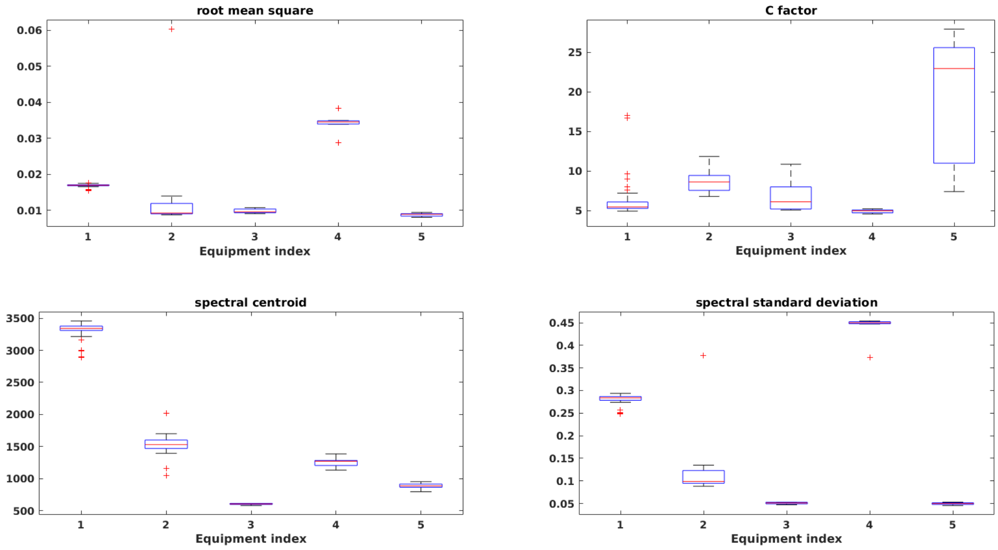

Figure 4.3: Four examples of statistical features, which differ among the different pieces of equipment.

for most of the frequencies. However, the spikes at frequencies around 5.5 Hz and its harmonics are higher when there is no load applied compared to the maximum load. The PSD estimates for evenly and unevenly distributed high loads are shown in Figure 4.4b. The additional noise caused by unevenly distributed load changes the PSD significantly for almost the whole frequency range. Also the variance of PSD estimates is clearly larger when the load is unevenly distributed.

Another source of variation in normal operation is the length of the movemement. All time and frequency domain feature values as well as the PSD estimates for the measurements are presented in appendix B. There are two main results from the length test. First is that the two longest movements are very similar to each other according to the features and PSD estimates. And the other is that the values of the shortest movements differ significantly from the two other sets in many features. Differences between the shortest and other travels are most apparent in features rms (TD_4), C factor (TD_8) and mean of PSD (FD_1). The differences in values of the aforementioned

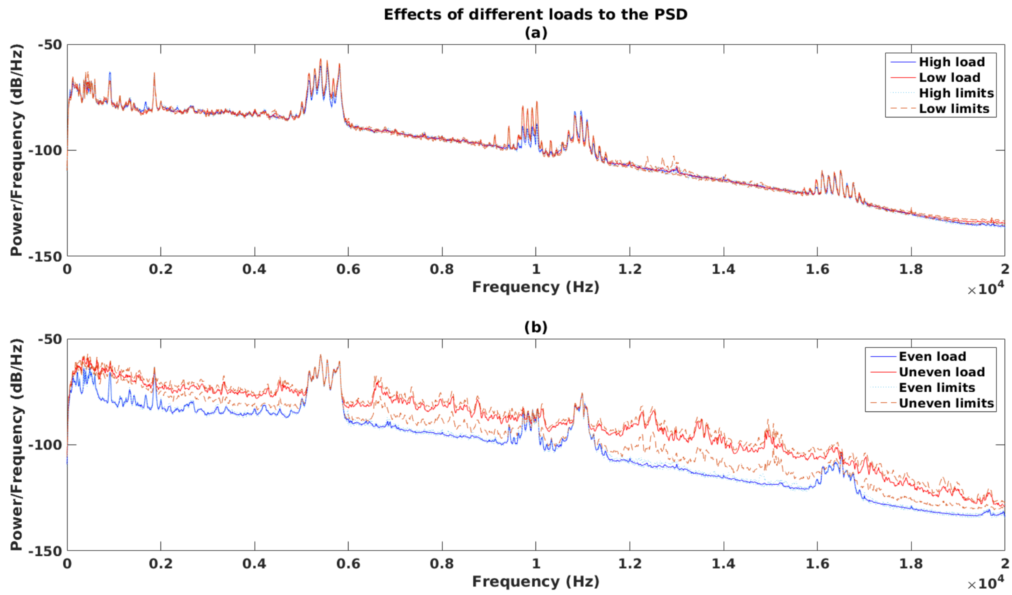

Figure 4.4: Changes in PSDs when load changes. (a) differences between zero load and full load. (b) differences between high, evenly distributed load and high, unevenly distributed load. In (a), the microphone is positioned at location #5, whereas in (b), the microphone is located at #3.

featuers between the two shortest travels are presented in Table 4.2.

The position of the container might also affect the sound signature of the equipment. That is the case especially if there is some stationary sound source in proximity of the container route. For example the motor's drive can be loud, if not soundproofed. In Figure 4.5 the rms values of several measurements from equipment #5 with same length are plotted against the end positions. The rms values are clearly increasing as the end position increases. However, this phenomena does not occur in every equipment. Rest of the results from container position test are presented in appendix C.

4.3 Fault situations

To test the audio measurements as a condition indicator, three separate faults were generated to one piece of equipment. The changes in time and frequency

Table 4.2: Examples of time and frequency domain features, which are different for samples from short and long travels. The feature values in this table are median values from the measurements. P-values are results from Wilcoxon rank sum test for same medians against alternative hypothesis of different medians.

Feature \ **Travel length**	**0.33**	**0.67**	**P-value**
TD_4	$1.886 * 10^{-3}$	$3.702 * 10^{-3}$	$2.78 * 10^{-3}$
TD_8	1.279	1.349	$1.01 * 10^{-11}$
FD_1	12.773	18.497	$6.63 * 10^{-9}$

domain features caused by the three tested fault cases are visualized in Figure 4.6. From the figure it can be noticed that the third fault has the highest variance in the values, especially for mean (FD_1), standard deviation of PSD (FD_2) and spectral standard deviation (FD_6). Most of the values of those features are also clearly above the maximum values of normal condition. The variations are not so large in the second fault, but still slightly larger than during the normal condition. However, the values are mostly within the normal extremes except for spectral standard deviation (FD_6). The first fault scenario show much less variation compared to other measurements. Most of the features are between the normal minimum and maximum, but the maximum value of the signal (FD_5) and other features derived from it, i.e. crest factor (FD_8), L factor (FD_9) and I factor (FD_{11}) are slightly larger than the corresponding values in normal condition.

In Figure 4.7 are the PSD estimates from the three fault cases as well as from operation in normal condition. The PSD estimates for each case are calculated by using equation (3.28). From the figure it can be seen that the PSD of the first fault case is almost identical compared to the PSD of normal condition. The PSDs of the last two fault cases differ from the normal case in frequency ranges 7-12 kHz and 3-9kHz for second and third fault cases, respectively.

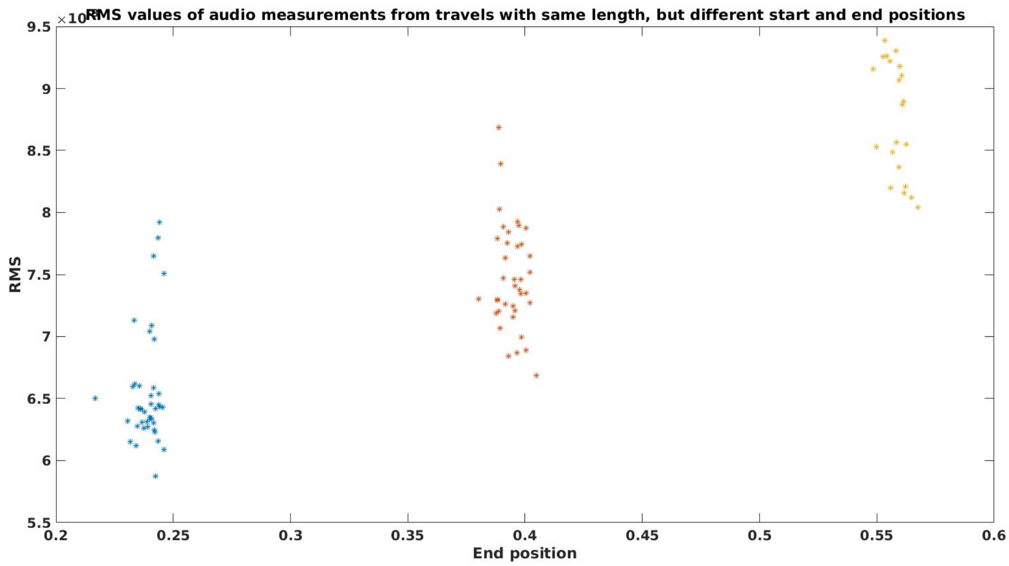

Figure 4.5: Audio signal rms values plotted against travel end position. Data is acquired from equipment #5.

4.3.1 Classification results

Before the actual classification, the Fisher discriminant is used to identify the best variables for the classification task from the time and frequency domain features as well as power density estimates at different frequencies. The values of Fisher discriminant for all time and frequency domain parameters and 13 PSD estimate indices with the greatest values are presented in Table 4.3. The discriminant values are much higher for selected PSD estimate indices compared to the discriminant values of other features. The distributions of five variables, which have the highest discriminative information based on Fisher discriminant are illustrated in Figure 4.8. The variables in the figure are scaled by using (3.43).

To demonstrate the disctiminative properties of the audio data, each sample is assigned to one of the four classes, i.e. normal, fault #1, fault #2 or fault #3 by using k-NN algorithm. The classification results for different number of considered variables m and nearest neighbors k are presented in

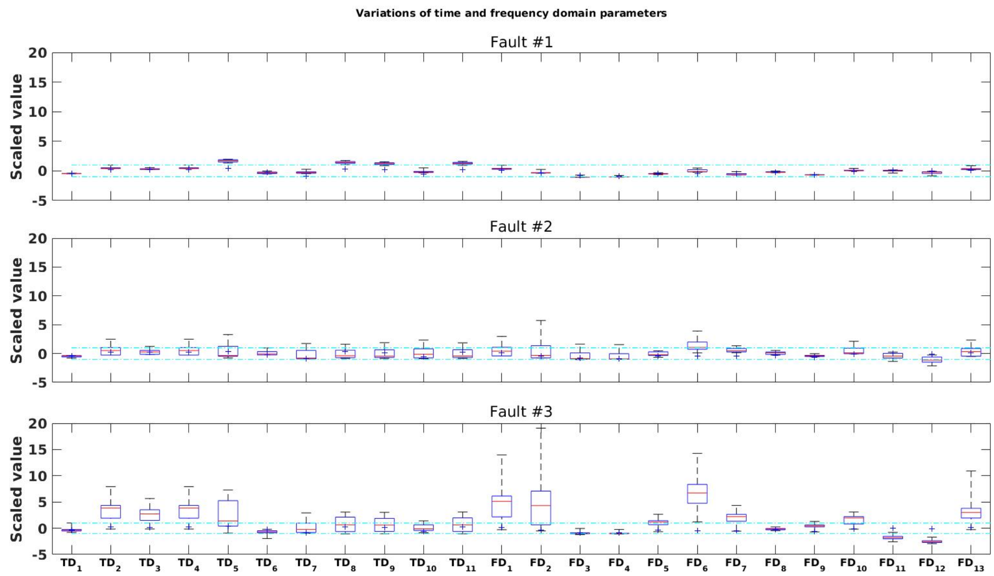

Figure 4.6: Scaled values of the time and frequency domain parameters in all three fault cases. The plus signs and horizontal lines at -1 and 1 correspond the median, minimum and maximum values of the features in normal condition, respectively. The boxes span from first to third quantile, the horizontal line within the box denotes median and the whiskers indicate the minimum and maximum values.

Table 4.4. $k = 1$ and $k = 2$ are equivalent, so $k = 2$ is omitted and because the sample sizes are so small, maximum value of k is set to five. The number of variables used for classification ranges from one to ten. The number of missclassifications is smallest for combination $(k, m) = (5, 6)$ with two misses and largest for $(k, m) = (5, 1)$ with 10 misses. The mode of missclassification rate is four samples out of 47 and it is achieved 13 times.

The most frequent result is presented as a confusion matrix in Figure 4.9. This result was obtained ten times in 40 different combinations of m and k. The ten parameter combinations are written in *italic* in Table 4.4. Even if the misclassification rate changes with different k and m, the accuracy between groups {*Normal, Fault #1*} and {*Fault #2, Fault #3*} remains good. When $k > 1$, only once a sample from fault #1 is classified as fault #2 and otherwise there are no misclassifications between those two groups.

Table 4.3: Fisher discriminant values of all time and frequency domain features as well as top 13 PSD estimate indices.

Feature	Value	Feature	Value	Feature	Value
TD_2	1.24	FD_6	5.68	$P(626)$	893
TD_4	1.24	FD_2	3.50	$P(667)$	568
TD_3	0.77	FD_1	2.67	$P(669)$	556
TD_5	0.69	FD_{13}	1.08	$P(670)$	555
TD_8	0.16	FD_7	0.75	$P(662)$	453
TD_{11}	0.14	FD_{12}	0.68	$P(677)$	451
TD_9	0.13	FD_{11}	0.41	$P(573)$	434
TD_6	0.06	FD_{10}	0.33	$P(570)$	432
TD_7	0.04	FD_5	0.30	$P(575)$	410
TD_{10}	0.02	FD_9	0.14	$P(657)$	394
TD_1	0.00	FD_3	0.03	$P(625)$	390
		FD_4	0.02	$P(672)$	385
		FD_8	0.00	$P(526)$	377

Table 4.4: The number of misclassified samples for different number of considered variables m and nearest neighbors k. The smallest value is bolded and the values corresponding to combinations resulting in the most frequent result are written in italic.

k \ **m**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	9	7	8	9	7	8	8	6	7	8
3	6	8	5	5	4	*4*	*4*	*4*	*4*	5
4	9	7	6	6	4	*4*	*4*	*4*	5	6
5	10	7	5	6	4	**2**	*4*	*4*	*4*	6

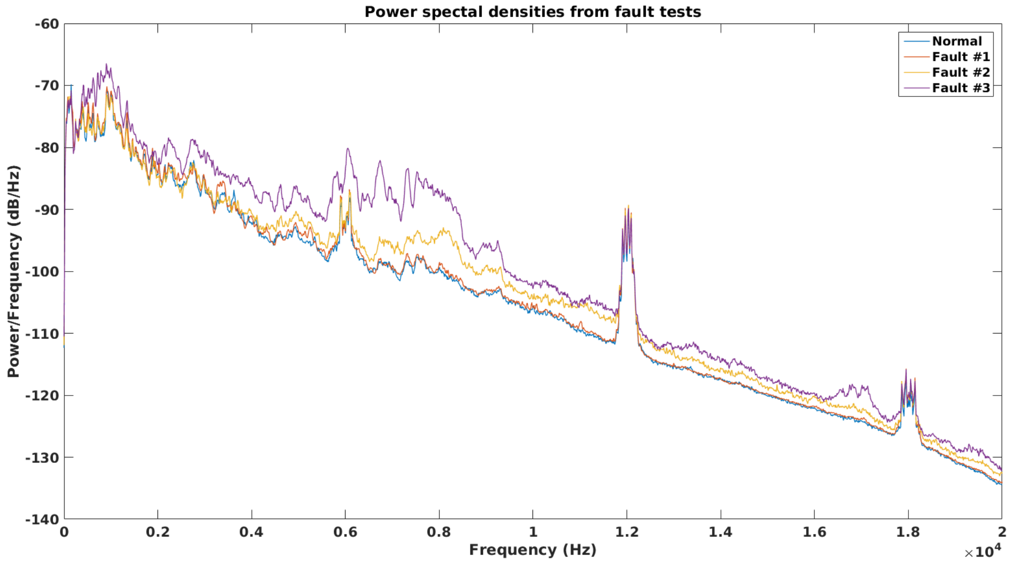

Figure 4.7: PSD estimates of normal operation and three fault cases.

Because the size of the test data is so small, it is also interesting to examine how much the set of selected variables changes when one sample is left out. The selections of the most common variables within top five are presented in 4.10. The first variable is the same for each iteration. Also four of the five variables are almost always among the top five and most of the time they consist the top four variables. There are some variations especially in the selection of the fifth variable, but also the second, third and fourth variables are occasionally different from the usual top five variables.

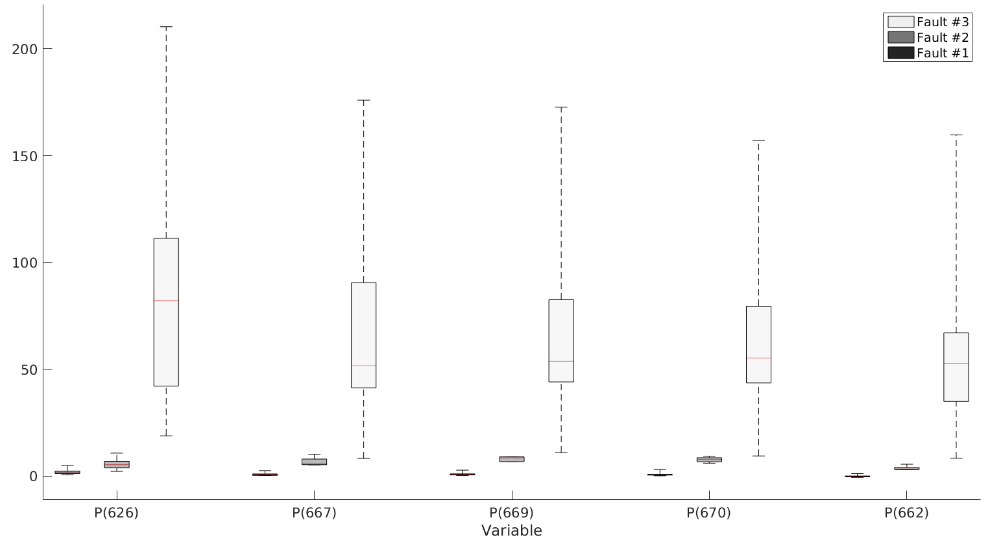

Figure 4.8: The variations of the variables with highest Fisher discriminant value in each fault case. The scaling and interpretation of boxes are the same as in Figure 4.6

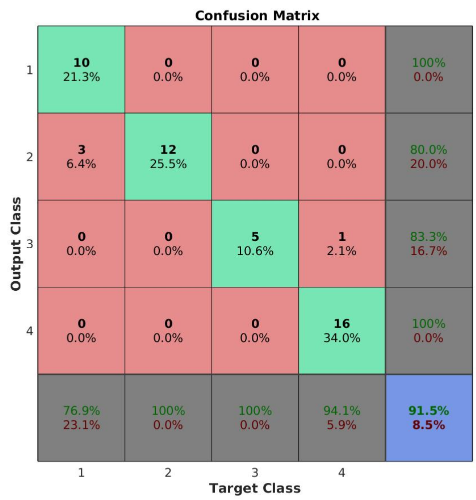

Figure 4.9: Confusion matrix of the most frequent classification result.

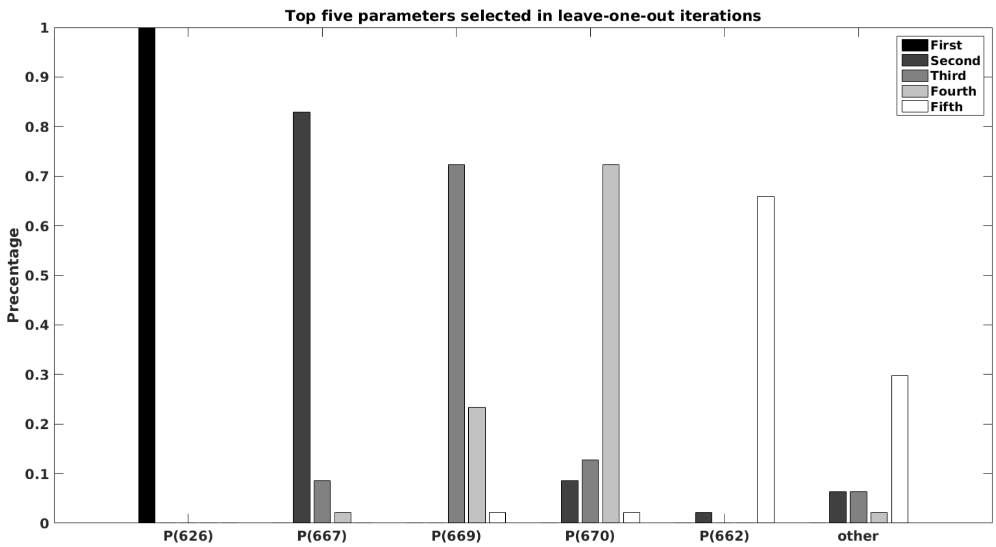

Figure 4.10: The appearance of the five most frequent parameters in 47 leave-one-out iterations.

Chapter 5

Discussion

The audio based condition monitoring often rely on the assumption that the equipment has a characteristic sound signature, which stays fairly constant when the condition of the equipment and its environment stay the same. Based on the measurements presented in Figure 4.1, it seems that the assumption of repeatability is valid also in this case. There are clearly some outliers due to external noises. However, the number of abnormal samples is so small, that the external noises do not prevent the condition monitoring through audio measurements in similar environments. On the other hand, the few outliers show that excessive external noise change the audio signature remarkably. Therefore, in noisier environments, it is possible that condition monitoring through audio measurements is not possible.

The comparisons between different pieces of equipment reinforce the assumption that different pieces of equipment have different sound signatures. The differences are caused not only by some adjustable design parameters, e.g. size or speed etc., but also by different technical implementations. Therefore it is not feasible to construct a model based condition monitoring system for these equipment, as new model should be developed individually for almost every equipment.

In the load test, the unevenly distibuted high load differs the most from the other load situations. As there is high load only on one side of the container, the container is tilted, which causes additional parts of the container to be in contact with the rails. That results in an excessive noise, which can be seen through the changes in the values of several features. That kind of load is, however, rarely applied in actual usage.

Among the other load situatons, the changes in audio signatures are not so large. Most notably, the changes seem to be smaller than the changes caused by most of the tested faults. In frequency domain the changes occur at the frequency ranges corresponding to the characteristic frequencies of the motor. If condition diagnosis is done by comparing current measurements to previous results, the various loads increase the variance of some features. Because the different normal loads do not change the audio signature as much as some faults do, those faults should be distinguishable even if information on load is not available or taken into account.

As expected, the position of the microphone changes the acquired sound signature, as the reflections and distances to sound sources are different. For example, in Figure 4.4 the effect of microphone position can be seen through the peaks at around frequencies 11 kHz and 16.5 kHz, which are clearly more prominent and have different shapes in 4.4b than 4.4a. Based on this test it is not possible to say which position is the best. However, it can be said that if the microphone positions are not the same, comparison between two similar equipment even in similar environments based on the features considered in this study is not feasible.

Also the start and end positions of the travel as well as travel length have effect on the audio signature of the equipment. Since travels with different lengths can not have same start and end positions, part of the changes associated with different travel lengths are caused by differences in start and end positions.

Due to changes caused by start and end positions of the travel, a condition monitoring system can detect faults and other anomalies more accurately if only travels with same start and end positions are used as normal reference. The main drawback of that approach is that it requires normal reference for every different combinations of travel start and end positions. Frist problem arising from that is the increased need for storage space, as the number of differenct combinations can be large. Another and more significant problem is the numer of normal reference samples. Some travel positions might be rarely used, so condition monitoring system might be unable to detect faults during such travels due to lack of normal reference data.

The similarities between spectrums of fault case #1, i.e. discontinuity in the sliding rails, and normal operation were expected, because the PSD averages the frequency content of the whole signal and the phenomenom caused by the first fault, i.e. the sound when the container passes the discontinuity, is localized in short timeframe. It is also difficult to distinguish the sound caused by the fault from the time domain signal, because in the audio signal there are often similar and even louder noises even when there is no fault present. Still the accuracy of the k-NN classifier is very good also for that fault, even though it only uses power densities at various frequencies as features. The reason for this lies in the difference between the type of samples from normal operation and the first fault case: the samples of normal operation are measured from travels with random length, whereas the samples of the first fault are all measured from travels with fixed length and same start and end positions. The results described in Chapter 4 also show that the sound signature slightly changes when the position and length of the travel changes. Because of the similarities of the first fault case's samples, k-NN algorithm likely finds another sample from the same fault to be the nearest neighbour, even though samples from normal operation might be just as close, if the start and end positions were the same.

From the features calculated from the samples, only maximum value and a few other features derivatived from the maximum seem to display difference between normal situation and the first fault case. However, the difference in the values of those features are not very large and any external noise can easily cause large variations in maximum value. Maximum value on its own does not reveal much about the fault. Considering all that, it seems that there is no adequate way to detect faults similar to the fault #1 by using the methods presented in Chapter 3.

However, sound measurements can still be used to identify and even localize those faults, at least if information on the position of the container is available. Then the fact that the sounds caused by the fault occur only in specific location can be used to distinguish such a fault from other similar noises appearing randomly. The position information can be used to identify the fault by examining the sound pressure levels, i.e. short term rms values of the audio signal, against the position of the container, if such information is available. By comparing the rms against position plots presented in Figure 5.1, it can be seen that in the measurements of faulty equipment, there are peaks at positions 0.44 and 0.53, which are not present in normal condition. In addition to noise, the discontinuity in rails most likely causes also abnormal vibrations to the sliding object. If vibrations of the sliding object are measured, the first fault would probably be much easier to detect through the vibration data.

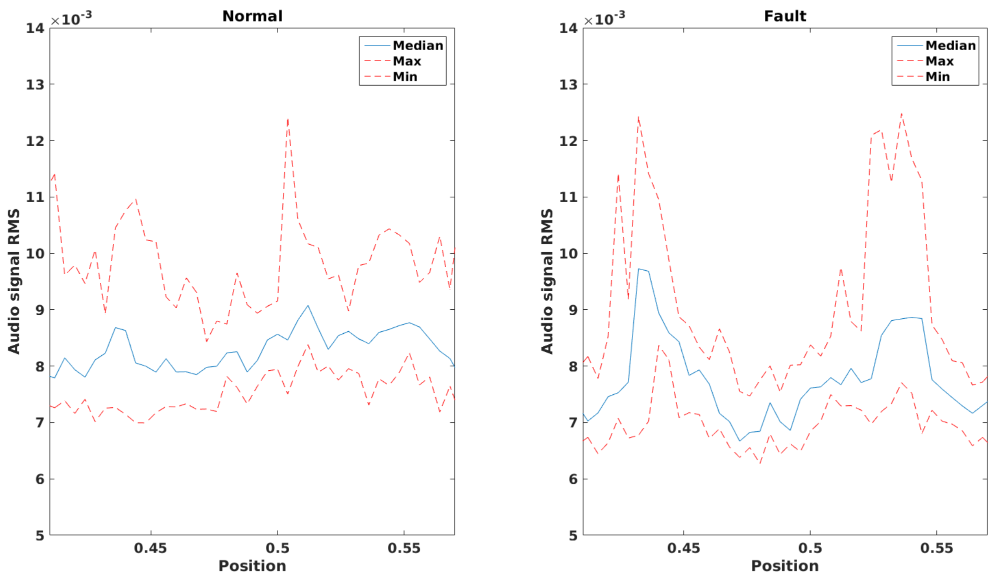

Figure 5.1: Audio signal rms levels against position of the sliding object. Left figure is from normal operation and right figure is from fault case #1.

The two other fault cases were quite similar, so they also caused similar changes to the measured features. In both faults, the friction between the rails and the container is increased, which changes the resulting sound when the container is moving.

Friction noises can be classified in two types based on the contact pressure.

In this case, the contact is weak without any apparent stick-slip. In such situations, the noise is caused by the surface roughness. That kind of noise is called roughness noise and its characteristics are rather low amplitude and broad frequency band. [17]

The theory of friction induced noise agrees with the experiments, as the power increases in wide frequency band due to increased friction. The friction increased more in the third fault case. Therefore the friction noise has higher amplitude and wider frequency band. The grater changes in the third fault case enabled to distinguish the last two faults from each other. However, in the test cases the faults were generated manually in an instant, whereas in actual usage the severity of the faults vary and most likely progress gradually through time. Therefore it might be a troublesome task to distinguish the two faults from each other if they were to occur naturally during normal usage.

In the fault test, only three possible fault cases were tested. In reality the number of faults is much higher. Different faults require different analysis methods, which can be seen for example in the first teted fault case. Based on this study, some faults can be detected through simple time and frequency domain analysis, but many other faults require more advanced analysis techniques, e.g. those introduced in Chapter 2.

With one microphone in an arbitrary environment, the fault identification is very challenging. In the monitored equipment there are several possible sound sources and with one microphone it is practically impossible to deremine the source of the abnormal sound. If there are other data available as well, such as vibration data, position data and operational data, i.e. what is supposedly happening at each time, it would be possible to combine these data sources and thus deduce the possible location and/or the cause of the abnormal noise. An example of this is presented above in the case of the first fault, where the locations of the rail discontinuities were found out by combining the audio data to position information.

The min-max scaling used in this study is not suggested to be used in actual condition monitoring system because of its sensibility to outliers. When sample size is large enough, more robust way to scale the features is to use for example 5th and 95th percentiles of the observed normal condition feature values. In this study the sample size is so small, that the use of quantiles is not reasonable. The changes in selected parameters during leave-one-out cross validation demonstrate the sensibility of the min-max scaling and effects of small sample size.

As the condition of the whole equipment is being considered, the number of possible faults is vast. Therefore it is not possible to test each of them and to obtain training data for the classifier. That is why the classifier demonstrated in Chapter 3 can not be used in actual online condition monitoring system. Shin and Jun [28] discuss the issue of condition monitoring system without or very scarce prior data. They suggest that in such situation, a physics-based model might be suitable solution. In this particular application, physics-based models are not applicable because of diversity of the considered faults and equipment/enviroment types. Another proposed solution is to use machine learning techniques with unsupervised learning properties in the beginning of the condition monitoring system implementation. As the amount of observed data from several conditions increases, supervised machine learning thechniques can be applied.

One simple alternative for condition diagnosis technique is to establish limits for normal operation right after the data acquisition system is installed. By doing so, it is assumed that the equipment is in normal condition for a while after the data acquisition system is installed. When the system is installed, the technician who installs the data acquisition hardware can also check the condition of the monitored equipment and fix it if necessary. Of course, it is possible that the equipment break right after the installation, but since there is no other way to remotely check the condition of the equipment, the aforementioned assumption is the best bet for obtaining reference data of normal condition.

Then if some parameter value drifts outside the normal limits for a longer period of time, something has most likely changed in the equipment or its environment. If the reason for abnormal signals is found to be a fault in the equipment, the latest measurements can be later used as reference for identifying similar faults.

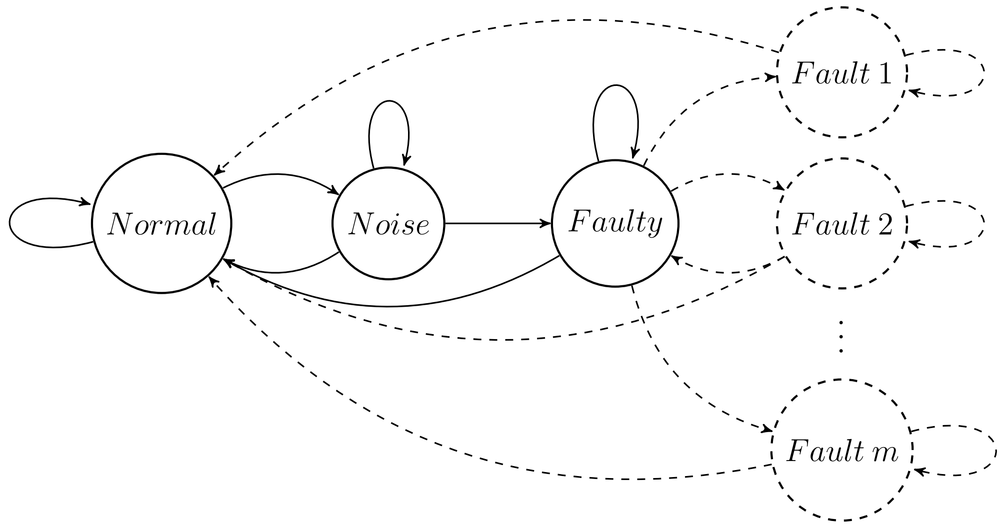

Figure 5.2: Possible structure of hidden Markov model used for condition diagnosis. Dashed lines and nodes represent components, which are not always present in the model.

Similar approach might be possible to automate by using adaptive hidden Markov models. The basic idea of hidden markov models is presented in Chapter 2. In this case the number of states in the model could be three plus m, where m is the number of fault cases, where reference data is available. Out of the three first states, one would be normal state, one would be noise state and the last one would be faulty state. In Figure 5 a possible structure of the model is illustrated.

Initially the equipment is always in normal state, as described earlier. If the values of the monitored parameters are not normal enough, the state changes to *"Noise"*. When the state changes to *"Noise"*, the *"Faulty"* state is being updated based on the observations in *"Noise"* state. If the anomality has occured due to external noises, the following samples are most likely normal, which change the state back to *"Normal"*. However, if the changes in the observed data originate from a fault, the audio signature characteristic to the fault are most likely present also in the following samples. If the equipment stays in the *"Noise"* state and the sound signatures exhibit similar abnormal characteristics long enough, *"Faulty"* state will adapt to the fault and the state of the equipment changes to *"Faulty"*.

If the newly constructed *"Faulty"* state is similar to some earlier observations of a certain fault, the state of the equipment would move to the node corresponding to that fault. If the fault is observed the first time, the current *"Faulty"* node is added to the model as a new fault reference.

The issues regarding this method include the estimation of transition probabilities, determining the learning rate of *"Faulty"* node and selecting which features to use for determining the states. In practice the only way to estimate the transition probabilities is through observed data, which is usually not available in the beginning of the condition monitoring system implementation. Therefore this method is not suitable as the initial diagnosis system.

The estimation of the model parameters belong to one of the possible directions of future research, i.e. investigating the actual implementation of condition monitoring system and its integration to maintenance strategy. Some of the interesting topics in that area are the propagation of the faults and condition prognostic possibilities as well as the maintenance decision making based on the condition monitoring data. Regarding the propagation of the fault, it is challenging to select the correct tolerance for abnormal observations before the equipment is classified as faulty.

Another area of future research is the performance of different analysis methods in detecting different type of faults. Especially interesting would be to investigate how many faults can be found by using the simple methods used in this study or how the condition diagnostics can be improved by integrating several sources of information. A third direction to future research is the audio measurement aspect of the study, e.g. how much a condition monitoring system might improve if there are two or more microphones. Supposedly with several microphones, the information gained from the audio signals can be greatly increased. For example it might be possible to better identify the source and location of the sound and separate sounds from different sources.

Chapter 6

Conclusions

In this study, feasibility of utilizing audio measurements for equipment condition monitoring is examined. The experiments show that audio signature of single equipment is fairly repetative, given certain usage pattern. Audio signatures are also unique for each equipment. The uniqueness makes data driven approach the only feasible option for condition diagnosis.

Variations in load, length of the travel as well as start and end position of the travel affect the sound signature of the equipment. The changes due to variations in normal usage patterns are smaller than the changes caused by several faults. Thus the audio based condition monitoring system can be used even if the changes in usage patterns are not taken into account. However, for the condition monitoring system to be as accurate as possible, only samples with similar usage pattern, i.e. load and travel, should be compared to each other.

There are plethora of methods for analyzing audio data, but even simple time and frequency domain analysis methods are capable to distinguish and detect faults from the equipment. Especially those faults are clearly detected, which cause constant noise during the travel. However, not all faults can be found, which generate additional noises. Faults which cause shorter and quieter noises at certain location are hard to distinguish by using the proposed methods.

On its own, audio based monitoring is not comprehensive enough to form a condition monitoring system for the examined equipment. However, audio measurements can be a useful addition to a condition monitoring system, when used in conjunction with other data sources. The implementation to actual condition monitoring system requires still some work, especially regarding the propagation of faults and decision making support, i.e. when to define the monitored equipment as faulty.

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Appendix A

Appendix A

Results of the load test. On x axis are the different load and microphone position combinations. There are five load situations: zero, low, high, uneven and full and five microphone positions: #1 to #5.

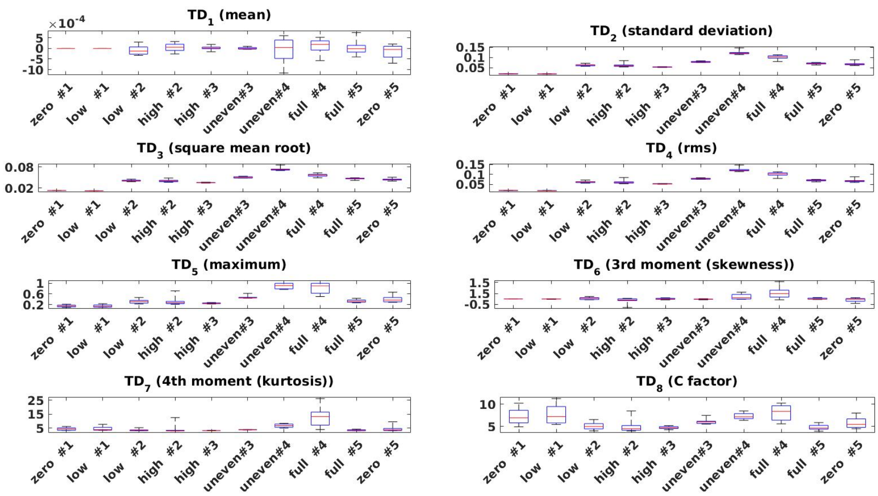

Figure A.1: The values of first eight time domain features in load experiments.

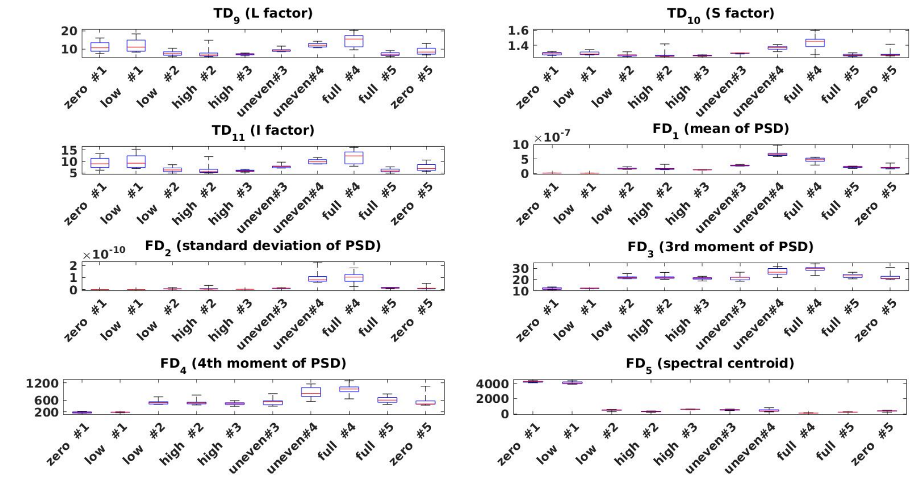

Figure A.2: The values of rest of the time domain features as well as first five frequency domain features in load experiments.

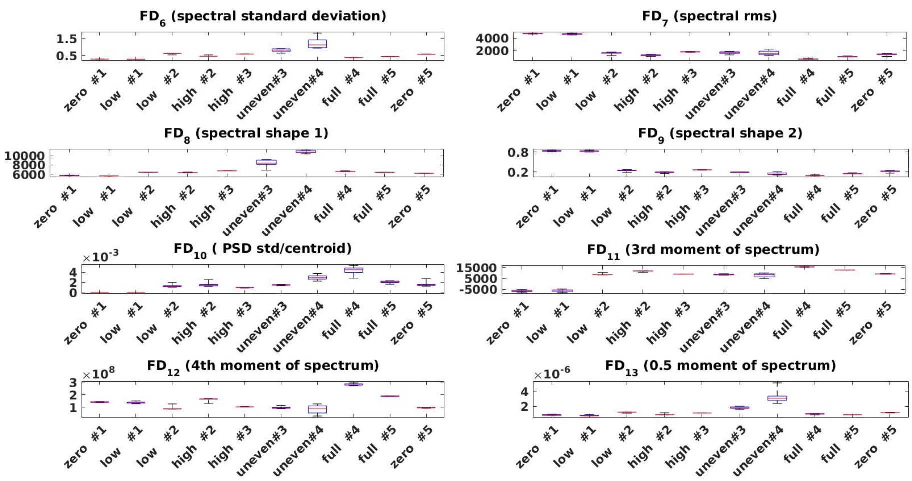

Figure A.3: The values of rest of the frequency domain features in load experiments.

Appendix B

Appendix B

Comparison of travels with different lengths. On x axis, smaller number correspond to shorter travel.

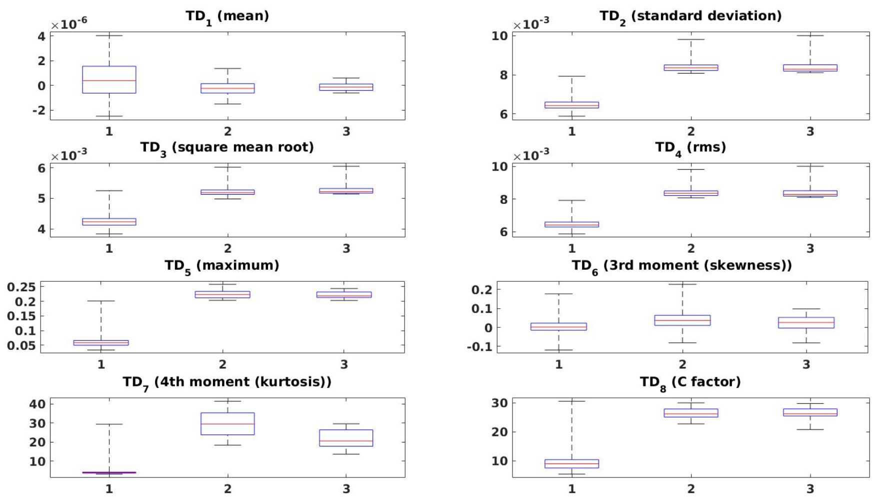

Figure B.1: The values of first eight time domain features in travel length experiments.

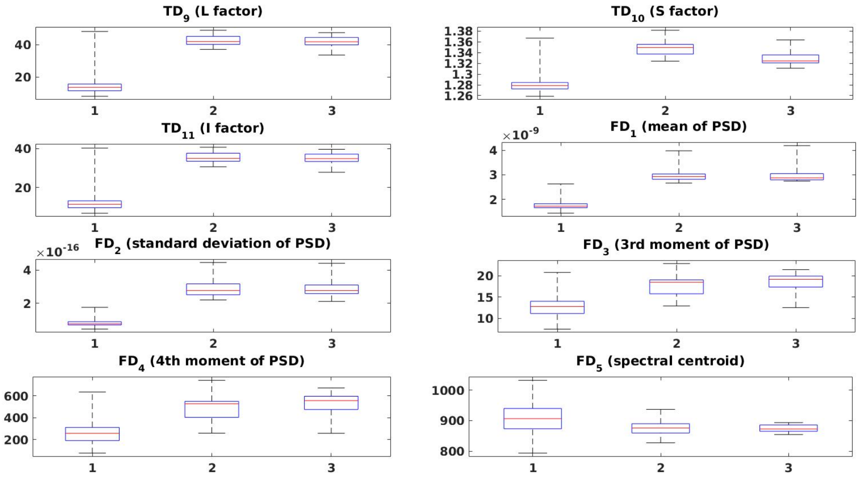

Figure B.2: The values of rest of the time domain features as well as first five frequency domain features in travel length experiments.

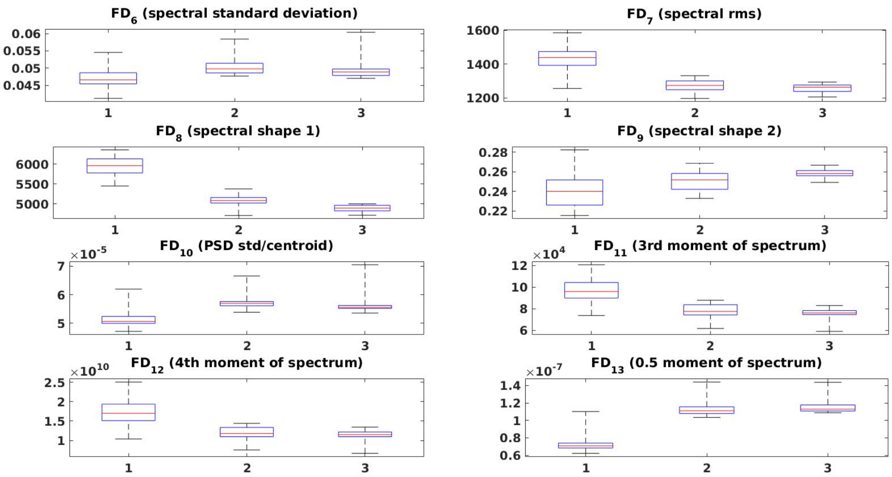

Figure B.3: The values of rest of the frequency domain features in travel length experiments.

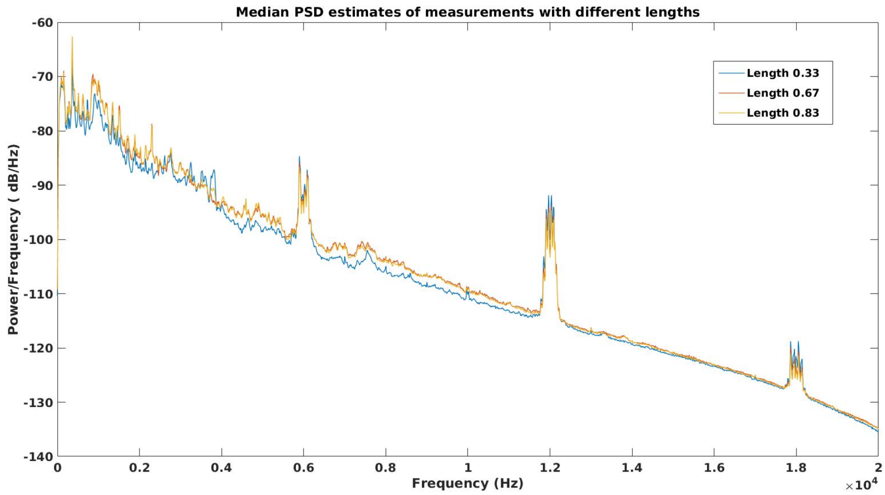

Figure B.4: Averaged PSD estimates of travels with different lengths.

Appendix C

Appendix C

Comparison of travels with different start and end positions. On x axis, smaller number correspond to travels with smaller end position.

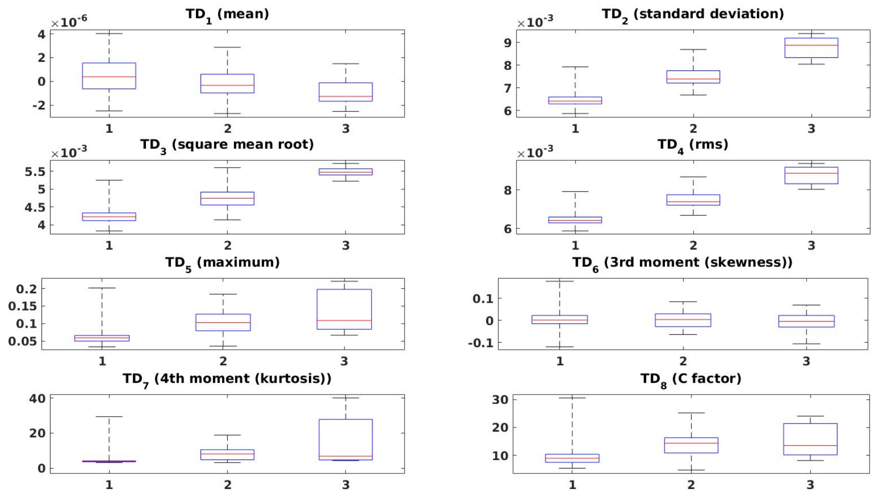

Figure C.1: The values of first eight time domain features in travel position experiments.

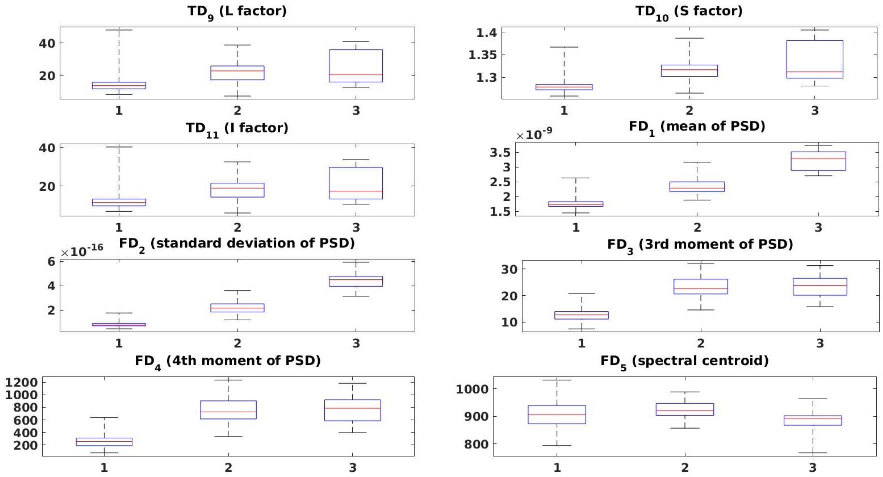

Figure C.2: The values of rest of the time domain features as well as first five frequency domain features in travel position experiments.

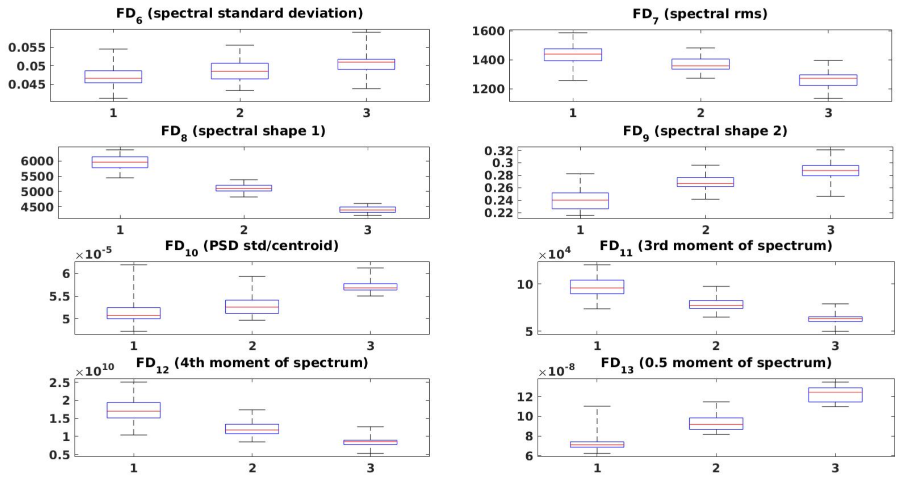

Figure C.3: The values of rest of the frequency domain features in travel position experiments.

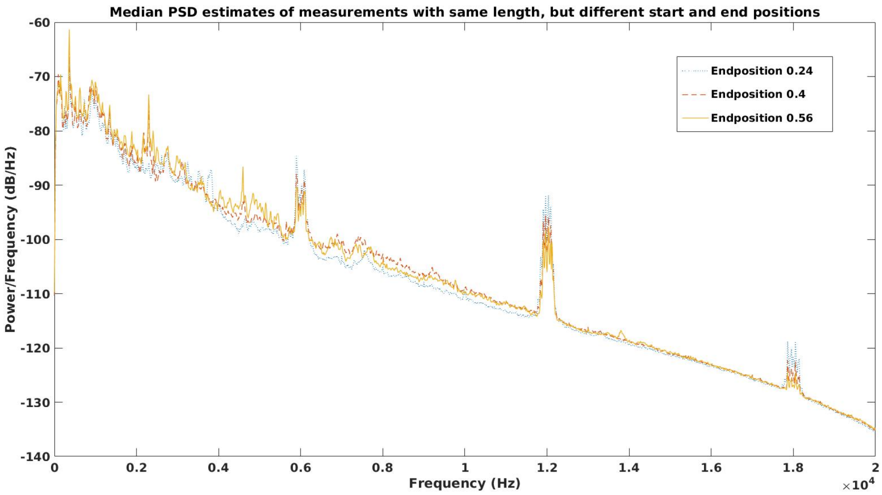

Figure C.4: Averaged PSD estimates of travels with different start and end positions, but same lengths.