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Non-intrusive monitoring of milling process

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Abstract

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Fault diagnosis of industrial equipments is more and more important for improving the quality of products and avoiding a waste of money and resources, especially for expensive precision machines, like the milling machine used in Berg Propulsion. If the milling process is continued when the cutting tool is worn out, one may have a failure product. This will cost the company a lot of money. And what's more, with the time going on, the worn out tool may cause the damage to the milling machine. So developing a fast and reliable diagnosis system is necessary for these industrial equipments. In this thesis, we will analyze the working conditions of cutting tools by collecting the sound signals from the machine using Wavelab and using signal processing and case based reasoning methods to detect the faults during the milling process. Analyses in the time and frequency domains are conducted first on the collected sound signals in order to illustrate their main features and then extraction of features is made. Features extracted can be built as a case library for case-based reasoning (CBR) to give a recommendation later on when the machine should stop when the tool damage is just beyond the specified tolerance of damaging degree. This recommendation is based on the previously identified and classified cases in a case library. However, as there are some limitations, such as the precision of microphone used to collect the data, the exact features are difficult to find and thus not given in this thesis, and building the case library will be one of the future researches. This thesis is mainly focused on analysis of signals, extraction of features for a few cases using signal processing and establishing a few simple cases, e.g. analyzing the features of each sound signal detected during the process, illustrating a few examples and some ideas, and making a few suggestions on improvement in the future research.

Key Words: signal processing, feature extraction, case-based reasoning

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1. Introduction

1.1. Outline of the thesis work

In this thesis, we will discuss the sound signal processing which can be applied to the cutting tool condition monitoring of the milling machine in Berg Propulsion according to the status of the cutting tool monitoring technique nowadays. The thesis is organized in the following manner.

In this chapter, the background of the problem will be bought in front of us to demonstrate the signification and necessity to carry out this project. Via the overview of both the advantages and disadvantages of state of the art in the cutting tool monitoring, and also status in quo of digital signal processing and case-based reasoning, the sound signal processing is conducted to best monitor the status of the cutting tool which is used as the first step to abstract the main features we want to use when building a case library later. Then the artificial intelligence method- case-based reasoning could be used over this case library to judge whether the tool is worn out or not. In the end, the arrangement of this thesis is presented.

The second chapter will present the theories in signal processing. For examples, basic concepts related to the signals we use in the analysis, and fast Fourier transform and so on. Also the concept related to the filters.

In the third chapter, the technique in artificial intelligence area named case-based reasoning will be presented. Here an outline of case-based reasoning is given to readers, presenting what is case-based reasoning, what are the processes during applying case-based reasoning method, and also what are the advantages of this technique in artificial intelligence, and telling us why more and more attention has been put on case-based reasoning and why we would like to apply the method in our project later.

The fourth chapter is about the setup of the measurement, and the details of the data collection are also displayed here.

The fifth part will be the most important part in this thesis. The fifth part is about the signal analysis which reflects how we analyze the mixed signals full of the unwanted noises and signals (interferences) apart from the sound of the working machine, such as the human sound, water sound and so on. Analyzing and good understanding nose and signals is the basis of filter design in order to filter out all the unwanted noises while needed, sequentially obtain the machine sound which is easy for us to analyze from time to time to find the regulation from when the cutting tool is new to the cutting tool needed to be changed. The final sensor data we get will be quite useful for building case library later which can make the case-based reasoning into practice.

After analyzing all the data and design the filters we want to use during the process, here comes the sixth part in which the feature will be identified according to the previous analysis, and also how it could be associated with case-based reasoning which will be done in the coming research.

In the seventh part, according to the analysis above, we will give out the conclusion of this thesis work, and make some discussions where necessary.

Suggestions of improvements and expectation will be given for the future work in the eighth section.

1.2. Background

Manufacturing industry is one of the basic industries which promote the development of our society and the progress of the technologies. It could have relationship with all aspect in our life. Taking Berg Propulsion for example, Gothenburg is surrounded by the sea, water transportation is certainly extremely important in this city. So the main product propellers, an important component of ships produced by the milling machine used in this company play an important role in the transportation industry. Precise machines that are often expensive are coming into use during the producing processes. And with the development of the high technology, automation becomes increasingly important and less people should be put onto the working place. During the large-scale producing process, in order to guarantee the smoothly producing steps, it is important to monitor the condition of a cutting tool, e.g., whether it has worn out or not. If it is worn out, the alarm should arise and the machine should be stopped automatically immediately. This not only can improve work efficiency and product quality, but also can avoid the damage of the machine itself and save a large amount of money.

With the high manufacturing level nowadays, machine cutting process is growing rapidly with high speed, high precision and high automation. Thus, on one hand, it benefits companies a lot by increasing the accuracy and reducing the intervention of human beings during the working process. On the other hand, if the cutting process system can not monitor the condition of the cutting tool automatically, then there will be no stability during the cutting process, namely the extent of the automation will be affected increasingly.

In Berg Propulsion, they use a very expensive milling machine to produce the hub body for the boat. If the cutting tool has been worn out but it continues working in that terrible situation, it will cost a lot of money, and also the quality of hub bodies produced afterwards could also affected seriously. Since the milling machine has a fully-enclosed protection structure, the operator has difficulty in observing the status of the cutting tool just in time. In Berg Propulsion, the existing way to monitor the condition of the cutting tool is listening. The workers need to stand on the working stage all the time when the milling machine is running and listen to the cutting sound emitting from within the enclosed cabin carefully. When the sound seems to be abnormal, the worker will stop the machine, open the cabin, step inside to get the cutting tool out and change a new one. So it is obvious that, though they use a high-tech milling machine in the factory, they still need a lot of people to stand by to make sure the machine is running in the right condition. And what’s more, those people should be the expert in hearing the sound, they should quite familiar with which kind of sound is normal and which kind of sound is abnormal. So in order to make sure the working efficiency, there are shift from early morning to the midnight to ensure the machine working properly. That’s really a big demand on human resources.

The advanced processing equipment such as the milling machine used in Berg Propulsion usually costs the company a huge amount of money. So this incredibly large input inevitably requires the company to best use the machine to make sure its utilization as much as possible. However, the unavoidable wear and tear of the cutting tool could impact the machine utilization and work piece quality directly. If it is not so severe, it would cause the quality decline of the work piece. And if it is severe, the work piece could be rejected. And more important, in the extremely terrible situation, it might damage some accessories of the milling machine. So the method and algorithm for monitoring the status of the cutting machine whether it is worn out needing to be changed or not is necessary during the machining process. In our project, analyzing the sensor data and trying to monitor the cutting status automatically by computer but not by the experience of a human brain are obviously quite important during the milling process to release the working load of human beings, increase the accurate of the cutting tool identification and improving the quality of the final product-hub body.

All in all, the significances for the cutting tool monitoring are presented as follows:

1) First, it improves the efficiency for the milling machine.
2) Second, it ensures the quality of the hub body.
3) Third, it saves the human resources and makes sure that the machine can be working normally and stopped immediately when the fault arises without workers standing beside, which can also avoid the accident happening.

4) Fourth, it could reduce the chance of unnecessary cutting tool changing which also leads to a waste of lots of money. Because there is error inherently when people try to listen to the sound and make the decision whether the cutting tool should be changed or not, it is quite possible that workers think the cutting tool should be changed, but in fact the cutting tool could still be used for a moment longer. In that case, it could cost big waste because of insufficient use of the cutting tools.

1.3. State of the art

1.3.1. State of the art of cutting tool monitoring

A great progress in cutting tool monitoring has been made in the recent decades. But some of the monitoring methods are just suitable in a special area, and some of them are still in the test session, thus it is far away to be put into practical use. So it is reasonable for us to say there will be long way to go in the cutting tool monitoring field.

Now, there are two main ways in the automatic monitor of cutting tools. One is directly monitoring the parameters of the cutting tools, such as the shape, the position and so on, which could only be monitored off-line. This contains several regular methods, such as contact resistance, optical method, optical fiber, pick-up of TV signal and so on. The other one is indirectly monitoring some of the parameters by measuring them during the cutting process, and then comparing with the normal values, which can give out whether or not the cutting tool is worn out. This can also reach our goal of monitoring the status of the cutting tool. There are also several different methods in the second way, for example, measuring cutting resistance, torsional moment, cutting vibration, acoustic emission, cutting temperature, workpiece dimension, workpiece surface roughness, cutting sound method, etc.

Here are some conventional methods for monitoring cutting tools[1].

1) Ray Measurement

If some radical materials are mixed in the cutting tool, then we can imagine, with the wearing and tearing of the cutting tool itself, the microparticle of the radical material will go through a previously designed ray measurer together with the cutting chip. The microparticle in the ray measurer will be closely related to the cutting tool wear extent. The amount of the ray reflects the abrasion loss of the cutting tool. But the biggest disadvantage of this method is the radical material pollutes the air a lot, and it is quite bad for people’s health. Besides, it is not so easy to make all radical microparticles into the ray meter. Thus, although the ray measurement is one kind of the cutting tool monitor methods, it is just useful in some special situation and can not be put into use widely.

2) Optical Fiber Measurement

This method makes use of the reflection capacity changes of the edge after the cutting tool is worn out. This method is good to use when the diameter of the cutting tool is big. So in our project, since the cutting tool is the small, this is not the best method to be considered.

3) Computer image processing

The camera is used to receive the images of the edge of the cutting tool. The images will be digitalization and image processing by the computer, then the shape and dimension of the worn out cutting tool will appear on the computer screen. This method sounds good, but still can not make broad use in the real world, since it demand high requirement in the optical equipment. Also, in the actual production process, the working environment for the cutting tool is quite abominable, for example, there are hot chips everywhere and cold water sprinkling out for the workpieces cooling down, so it is impossible to use in the factory environment. For now it is just suitable for the automatic monitor in the laboratory.

4) Cutting Resistance Measurement

Cutting resistance is the most obvious and related physical feature to the worn extent during the cutting process. There are several main parameters as cutting force and its differential coefficient, the ratio of cutting resistance, time series analysis, spectrum analysis and correlation function of the dynamic cutting resistance. However, this method also has some shortcomings. For it is quite complicated during the cutting process, there are lots of factors which could affect the changing of cutting resistance. Thus, it is difficult to say whether the cutting tool is worn out or not.

5) Workpiece Dimension Measurement

With the cutting tool worn out during the process, the size of the workpiece will change. So by measuring the dimension changes on the surface of the work piece, it is possible to estimate the status of the cutting tool indirectly. There are two ways to do this kind of measurement from the measuring mode point of view. They are contact-based workpiece measurement and distance meterage between the cutting tool and the workpiece, which we say as contactless measurement. The advantage of this kind of method is the radial attrition value of the cutting tool is able to be given directly, and also can be combined with the on-line and real time compensation of processing precision, which can make sure the quality of workpieces and make the cutting tool monitor in finish machining come true. But the disadvantages are also distinct. For example, the real time measurement can be easily disturbed by the environment, and the cutting compound and chips could influence the measured result. During the processing cycle, the thermal expansion, run-out and vibration and some other aspects of the workpiece and cutting tool could also affect measurement accuracy. Apart from all above, when cross section workpieces are processed, it requires the exact positioning tracking of the sensor, which could also make errors and increase the difficulty of implement.

6) Cutting Temperature Measurement

Cutting temperature is also an crucial physical phenomenon. With the increasing abrasion of the cutting tool, the temperature could ascend promptly. There are three kinds of ways to measure the cutting temperature. The first one is cutting tool and workpiece thermocouple. It can measure out the average temperature in the cutting area with different standards among different cutting tools and workpieces. The second one is thermocouple using two kinds of metal filaments which are fixed on a specific point inside the cutting tool. This can measure out the temperature on this point of the cutting tool. But it has some problems when using this method. For example, the response is slow when the temperature has changed, and also it wastes of time for the preparation at the beginning. The last one is setting the infrared camera operation system, which can tell the cutting temperature field distribution. It has high sensitivity and short response time, but the instrument itself is quite complicated and expensive and quite hard to focus which is certainly difficult to diagnose the cutting tool temperature in the cutting field.

7) Vibration Frequency Measurement

During the cutting process, the different vibration frequencies can be emerged when the friction exists between the workpiece and the edge of the cutting tool. Two techniques are used in the vibration monitor. The first one is dividing the amplitude into high and low parts, and then compared those two parts during the cutting process. The second one is separating the amplitude into several independent spectrum bands, and then using computers to record and analyze these bands continuously during the cutting process, which could monitor wear extent of the cutting tool as well.

8) Workpieces Surface Roughness Measurement

With the increasing of the cutting tool attrition rate, the surface roughness of the workpiece could also augment rapidly. From this point of view, it is possible to evaluate the wear extent of the cutting tool indirectly. This technique has a high efficiency, but sample demarcation is needed in advance. However, this kind of method is affected apparently by cutting emulsion, chips, work piece textures, vibration and other cutting factors, it still can not put into use in practice.

To sum up, because of the terrible working environment of the cutting process, usually the cutting process is carried into a hermetic cabin, which is difficult to monitor the cutting tool straightly. In allusion to some important and correlative physical features, a lot of indirect cutting tool monitor techniques are proposed, which have both pros and cons and are suitable in a particular situation. Although there are different precisions between different methods, still as a whole they are not really good ways for the cutting tool monitor. A lot of them can be just carried out in the laboratory, and still have a long way to go into the industrial application.

1.3.2. State of the art of digital signal processing

In some sense, the origin of digital signal processing techniques can be traced back to the seventeenth century. The more recent interest in digital signal processing arose in the 1950s with the availability of large digital computers. Initial applications were primarily concerned with the simulation of analog signal processing methods. Around the beginning of the 1960s, researchers began to consider digital signal processing as a separate field by itself. Since then, there have been significant and numerous developments and breakthroughs in both theory and applications of digital signal processing[2].

Digital signal processing develops very fast in modern electronics which could be used in any field where information is handled in a digital format or operated by a digital processor. The following shows the areas where digital signal processing is applied[3].

1) Image processing
2) Instrumentation/control
3) Speech/audio
4) Military
5) Telecommunication
6) Biomedical

7) Consumer application

Digital signal processing is at the core of many new and emerging digital information products and applications which hold the information society nowadays. It impacts the way we live, work and play. So digital signal processing plays an important way in our society.

1.3.3. State of the art of case-based reasoning

Case-based reasoning (CBR) is a mature subfield of artificial intelligence[4]. There have already been fundamental principles in the case-based reasoning area. A lot of successful applications, such as CLAVIER system at Lockheed Missiles and Space Company in Sunnyvale, California, Wayland system which advises on the setup of aluminum pressure die-casting machines, and CASELine which is a first-generation technology demonstrator used by British Airways to assess the potential of CBR, also demonstrate the usefulness of this technology. CBR is also put into use in the customer service area. As we know customer service is a multimillion-dollar industry, CBR which is put into the Help-Desk architecture seems more and more important and useful nowadays. It not only saves the time to solve one problem for a customer, but also save experts who have to work in the first line before.

Over these years, case-based reasoning has attracted much attention to knowledge-based systems. It solves new problems by adapting previously successful solutions to similar problems. It does not require an explicit domain model, the implementation is reduced to identifying significant features that describe a case not create an explicit model, by applying database techniques largely volumes of information can be managed, and also CBR systems can learn by acquiring new knowledge as cases which could make maintenance easier. Because of all the convenience shown above, CBR is more and more welcome.

1.4. Developmental Trend of cutting tool monitor

The existing cutting tool monitor methods still can not satisfy all the practical needs for quick response, reliability, robustness and some other performances. So it is necessary for us to find some other research techniques to improve the result. We will present some trends in development as follows.

1) The first is techniques that are based on information fusion of cutting tool monitor. For example, multi-sensor fusion, decision-making on signal processing and sensor integration.
2) The second is methods which are based on the signal processing of cutting tool monitor. The final purpose when using signal processing is to abstract the feature information related to the status of the cutting tools. Usually wavelet technique is used to monitor the condition of the cutting tool.
3) The third is means that are based on intellectual technology of cutting tool monitor. The conventional methods are fuzzy inference, neural network, genetic algorithm and expert system.
4) The last one is the integration of the cutting tool monitor system, numerical control machining transmission system, cutting tool management system and ERP system, which requires that the cutting tool monitor system is able to send the status of the cutting tool to the cutting tool information management system just in time. This is the main development trend of cutting tool monitoring.

1.5. Monitoring methods based on sound signals

The monitoring technique based on sound signals has been broadly used in practice. It can be used in the area of early warning, target recognition, target preliminary orientation and condition monitoring which is mainly discussed in this project that monitor the condition of the cutting tool of a milling machine used in Berg Propulsion.

There are lots of advantages when using sound signal for the cutting tool monitoring.

For examples, it is not easy to be interfered during the sound signal collection if we use a precise microphone to gather the sound files. The equipments for collecting the sound signal are just a microphone and a laptop, and thus they are simple and easy to use.

Usually, during the machining process, experienced operators can roughly judge whether the tool should be changed or not by listening to the sound coming out from the manufacturing process. When the tool is worn out severely or in the situation that the cutting tool is damaged, the variation of the sound from the working machine is quite obvious. So they can, according to the sound change, decide whether to change the cutting tool or whether to adjust some manufacturing parameters on the working stage. From this point of view, the cutting tool monitoring using the sound signal is considered to be put into use in our project. Later in this thesis, the detail of sound signal processing will be discussed.

Since the experienced workers usually judge the cutting tool conditions by listening to the sound coming out from the milling machine, the monitoring system should also reach this level. So how to abstract and discriminate the features of the cutting tool status from the sound signals collected from the milling machine in Berg Propulsion is the main issue to be investigated in this thesis. Sound signals from cutting process will be analyzed in both the time and frequency domains to identify the features related to the conditions of the cutting tools. Then the features will be used to decide whether to stop the milling machine or not.

1.6. Methods for diagnose and classification of tool conditions

After the signal processing at the first stage, the features extracted from different sounds using signal processing could be finally used to build a case library required for case-based reasoning (CBR) which is an advanced technique in Artificial Intelligence (AI).

Considering that supporting tools used in the milling process are so important to the company even to the skilled operator, constructing automatic diagnosis systems based on AI techniques received increasing attention for widening the eyes and capability of the expert and also reducing the machine maintenance fee while using the AI diagnosis system. Expert systems really provide a convenient way to recognize and classify the tool problem arising during the milling process according to transforming operators' expertise into production rules. However, there are still a few major disadvantages in the conventional expert systems:

1) Knowledge elicitation is acknowledged to be very difficult and time consuming. Many experts know how to manage the problems themselves but do not know how to express them explicitly and accurately.
2) Expert systems can be very complex and can take many years to develop.
3) Expert systems are frequently slow because of complex inferencing processes.
4) Expert systems are often poor at managing large volumes of information.
5) Once developed, they are notoriously difficult to maintain.

For the above discussion, it can be drawn the conclusion that the traditional expert systems are not very suitable to the practice today. But how about the rule induction and neural network models? As we know, though they are quite strong in discovering crucial knowledge from previous data, rule induction need people who use the systems have expertise on the problem which need to be solved, and neural network requires a large training set of historic data to make sure the result using for the current samples is satisfied. But one thing we have to know very well is that in most situations only a small number of samples could be collected for the use of data training.

CBR has come into being in this situation, and provides another choice to develop intelligent diagnosis systems for real-world applications. It is different from the way computing has worked from the first days of computer. It will not repeat the computing again and again which certainly wastes time and resources. Case-based reasoning just remembers the previous failed or successful cases, namely stores the cases in a database, and next time when you encounter a similar problem as the cases placed in the database, CBR will fit well to identify and classify the issues based on experiences of past categories in the database. Therefore, CBR encourages computers to stop wasting time resolving problems of which they have known the results. Of course it will solve a similar situation much more quickly. CBR not only enables the use of the insufficient number of historic examples, but also eases the knowledge acquisition bottleneck. It skips the data training process, but still quite easy to learn the former experience through the similarity fit algorithm which I mean the nearest neighbor case retrieval. And also CBR has learning abilities itself by adding the new case which can not find the similarity with the existing cases to the database to make it grow stronger and more precise in identification and classification later on.

In this thesis, CBR will be used for non-intrusive monitoring of milling process in Berg Propulsion. To be able to use CBR, the features related to milling tool conditions need to be found using signal processing, and the case base need to be built.

2. Theories of signal processing

Signal processing is a cutting-edge discipline which is fast developed and widely used. So there are both lots of methodologies and practices in this subject. In order to make good use of the signal processing into practice to analyze the sound signals we have got from Berg Propulsion, several important theories should be understood first.

2.1. Basic concepts

Signals

In a broad sense, signal is some kind like the physical quantity or physical phenomenon while the time and space are varying. For example in communication area, languages, characters, images and data can be classified as messages which contain the special information. And communication is sending messages from one end to another to inform the other end something. However, this kind of transportation should have the aid of some special signals which can help to carry the messages and process the message to the form that can be transmitted and read later. In this point of view, we could see signal is a kind of presentation media of information, and information is the content of the signal[5].

1) Analog signals

An analog signal is any continuous signal for which the time varying feature (variable) of the signal is representation of some other time varying quantity, for examples, analogous to another time varying signal[6]. Analog is usually thought of in an electrical context, e.g. telephone voice signal is analog. The intensity of the voice causes electric current variations. At the receiving end, the signal is reproduced in the same proportion. Hence the electric current is a 'MODEL' but not one's voice since it is an electrical representation or analog of one's voice. Apart from this, mechanical, pneumatic, hydraulic, and other systems may also convey analog signals.

And analog signal uses some property of the medium to convey the signal's information, i.e., an aneroid barometer uses rotary position as the signal to convey pressure information. Electrically, the property most commonly used is voltage followed closely by frequency, current, and charge.

The analog signal is shown in figure 2-1. But not all analog signals vary as smoothly as the waveform shown in this figure. Analog signals represent some physical quantity and they are a 'MODEL' of the real quantity.

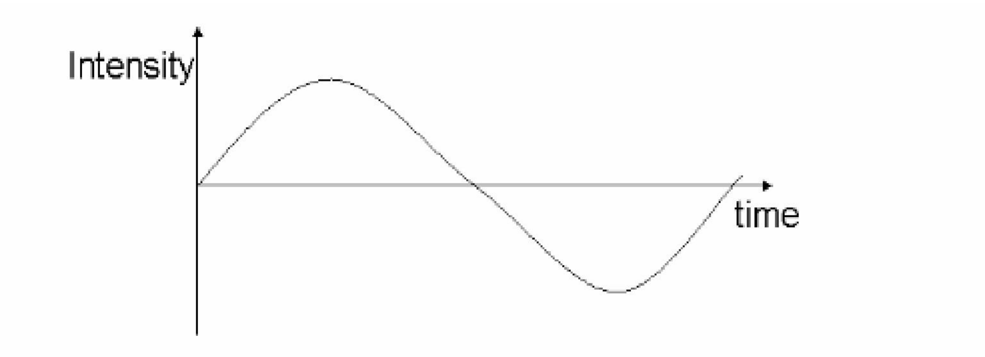


Figure 2-1. Analog Signal

There are both advantages and disadvantages by using analog signals.

Advantages:

First, the fine definition of the analog signal has the potential for an infinite amount of signal resolution[7]. Compared to digital signals, analog signals are of higher density[8].

Second, the processing of analog signals may be achieved more simply than with the digital equivalent. An analog signal may be processed directly by analog components[9], though some processes are not available except in digital form.

Disadvantages:

Any system of analog signaling has noise, for example random unwanted variation. As the signal is copied and re-copied, or transmitted over long distances, these apparently random variations become dominant. Electrically, these losses can be diminished by shielding, good connections, and several cable types such as coaxial or twisted pair. And the effects of noise create signal loss and distortion. This is impossible to recover, since amplifying the signal to recover attenuated parts of the signal amplifies the noise as well. Even if the resolution of an analog signal is higher than a comparable digital signal, the difference can be overshadowed by the noise in the signal. Most of the analog systems also suffer from generation loss.

2) Digital signals

Digital signals are non-continuous, they change in individual steps. They consist of pulses or digits with discrete levels or values. The value of each pulse is constant, but there is an abrupt change from one digit to the next. Digital signals have two amplitude levels called nodes. The value of which are specified as one of two possibilities such as 1 or 0, HIGH or LOW, TRUE or FALSE and so on. In reality, the values are anywhere within specific ranges and we define values within a given range[10]. Figure 2-2 shows the digital signal.

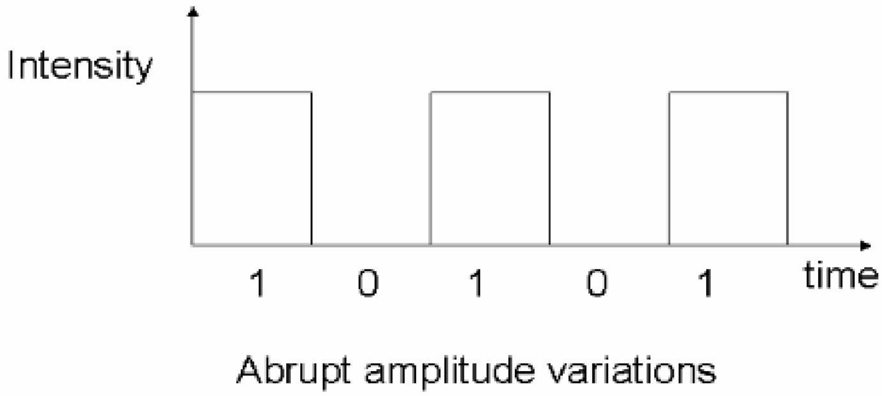


Figure 2-2. Digital Signal

Digital signals consist of patterns of bits of information. These patterns can be generated in many ways, each producing a specific code. Modern digital computers store and process all kinds of information as binary patterns. All the pictures, text, sound and video stored in this computer are held and manipulated as patterns of binary values.

The main advantage of digital signals over analog signals is that the precise signal level of the digital signal is not vital. This means that digital signals are fairly immune to the imperfections of real electronic systems which tend to spoil analog signals. As a result, digital CD's are much more robust than analog LP's[11].

2.2. Fast Fourier Transform

A fast Fourier Transform which is short for FFT is an efficient algorithm to compute the discrete Fourier transform which is used as DFT for short and its inverse.

An FFT computes the DFT and produces exactly the same result as evaluating the DFT definition directly; the only difference is that an FFT is much faster. In the presence of round-off error, many FFT algorithms are also much more accurate than evaluating the DFT definition directly, as discussed below[12].

Let x_0, ..., x_{N-1} be complex numbers. The DFT is defined by the formula

$$X_k = \sum_{n=0}^{N-1} x_n e^{-i2\pi k \frac{n}{N}} \qquad k = 0, \dots, N-1.$$

Evaluating this definition directly requires $O(N^2)$ operations: there are N outputs X_k, and each output requires a sum of N terms. An FFT is any method to compute the same results in $O(N \log N)$ operations. So we could say that the fast Fourier transform (FFT) is a discrete Fourier transform algorithm which reduces the number of computations needed for N points from $2N^2$ to $2N \lg N$, where lg is the base-2 logarithm.

2.3. Filters

In signal processing, a filter is a device or process that removes from a signal some unwanted component or feature. It is essentially a system or network that selectively changes the wave shape, amplitude-frequency and/ or phase-frequency characteristics of a signal in a desired manner. Filtering is a class of signal processing, the defining feature of filters being the complete or partial suppression of some aspect of the signal. Most often, this means removing some frequencies and not others in order to suppress interfering signals and reduce background noise. Common filtering objectives are to improve the quality of a signal(for example, to remove or reduce noise), to abstract information from signals or to separate two or more signals previously combined to make, for example, efficient use of an available communication channel. However, filters do not exclusively act in the frequency domain; especially in the field of image processing many other targets for filtering exist[13].

One of the most important functions of filters is to allow signals in some specific part of the frequencies getting through while signals in other part of the frequency intervals are being limited[14]. Essentially the filter is a frequency selection unit, and it an be of different types, e.g., low-pass, high-pass filters, band-pass, and band-stop in terms of frequency characteristics, analog and digital filters in terms of signal type, etc.

Classified by signal processing mode:

1) Analog Filter

Analogue filters are a basic building block of signal processing much used in electronics. Amongst their many applications are the separation of an audio signal before application to bass, mid-range and tweeter loudspeakers; the combining and later separation of multiple telephone conversations onto a signal channel; the selection of a chosen radio station in a radio receiver and rejection of others[15].

2) Digital Filter

In electronics, computer science and mathematics, a digital filter is a system that perform mathematical operations on a sampled, discrete-time signal to reduce or enhance certain aspects of that signal. This is in contrast to the other major type of electronic filter, the analog filter, which is an electronic circuit operating on continuous-time analog signals. An analog signal may be processed by a digital filter by first being digitized and represented as a sequence of numbers, then manipulated mathematically, and then reconstructed as a new analog signal. In an analog filter, the input signal is “directly” manipulated by the circuit[16].

A digital filter system usually consists of an analog-to-digital converter and a microprocessor. Digital filters may be more expensive than an equivalent analog filter due to their increased complexity, but they make practical many designs that are impractical or impossible as analog filters. So normally, we prefer to use digital filters over analogue filters. Here are the four main reasons[17]:

i. It is very difficult to implement RLC filters with low cut-off frequencies. But in digital filters, cut-off frequency is determined by the clock frequency and the filter coefficient values. So it will be possible to realize digital filters with very low cut-off frequencies which achieve high filter performance as providing good stop-band rejection.

ii. Digital filters are programmable. They may be multiplexed with different coefficient values to realize distinct characteristics. For instance, one signal can experience a low-pass filter response and another signal a band-pass response, simply by time-division multiplexing the input signal and accessing the stored frequency characteristics using sets of coefficients stored in random access memory (RAM). Alternatively, a desired filter design can be split into stages and the input signal progressively filtered in these multiplexed stages within a single filter structure.

iii. Digital filters do not suffer from the aging distortion of analogue filters.

iv. There is also no need for impedance matching with digital filters.

There are two types of digital filters. One is FIR filters, the other one is IIR filters. Either type of filter, in its basic form, can be represented by its impulse response sequence, h (k) (k = 0, 1,...). These two classes of filters are defined as follows.

FIR Filters

The FIR filter is short for finite impulse response filter. The basic FIR filter is characterized by the following two equations[18]:

$$y(n) = \sum_{k=0}^{N-1} h(k)x(n-k) \qquad (2.3a)$$

$$H(z) = \sum_{k=0}^{N-1} h(k)z^{-k} \qquad (2.3b)$$

where $h(k)$, k=0,1,…,N-1, are the impulse response coefficients of the filter, $H(z)$ is the transfer function of the filter and N is the filter length, that is the number of filter coefficients. Equation 2.3a is the FIR difference equation. It is a time domain equation and describes the FIR filter in its non-recursive form: the current output sample, $y(n)$, is a function only of past and present values of the input, $x(n)$. When FIR filters are implemented in this form, which is by direct evaluation of Equation 2.3a, they are always stable. Equation 2.3b is the transfer function of the filter. It provides a means of analyzing the filter, for example evaluating the frequency response.

IIR Filters

The IIR filter is short for infinite impulse response filter. Realizable IIR digital filters are characterized by the following recursive equation[19]:

$$y(n) = \sum_{k=0}^{\infty} h(k)x(n-k) = \sum_{k=0}^{N} b_k x(n-k) - \sum_{k=1}^{M} a_k y(n-k) \qquad (2.3c)$$

where $h(k)$ is the impulse response of the filter which is theoretically infinite in duration, b_k and a_k are the coefficients of the filter, and $x(n)$ and $y(n)$ are the input and output to the filter. The transfer function for the IIR filter is given by

$$H(z) = \frac{b_0 + b_1 z^{-1} + ... + b_N z^{-N}}{1 + a_1 z^{-1} + ... + a_M z^{-M}} = \frac{\sum_{k=0}^{N} b_k z^{-k}}{1 + \sum_{k=1}^{M} a_k z^{-k}} \qquad (2.3d)$$

An important part of the IIR filter design process is to find suitable values for the coefficients b_k and a_k such that some aspect of the filter characteristic, such as frequency response, behaves in a desired manner. Equations 2.3c and 2.3d are the characteristic equations for IIR filters.

In practice, choosing FIR or IIR depends largely on the relative advantages of the two filter types[20].

i. FIR filters can have an exactly linear phase response. The implication of this is that no phase distortion is introduced into the signal by the filter which is an important requirement in many applications, such as data transmission, biomedicine, digital audio and image processing and so on. The phase responses of IIR filters are nonlinear, especially at the band edges.

ii. FIR filters realized non-recursively which are always stable. The stability of IIR filters cannot always be guaranteed.

iii. The effects of using a limited number of bits to implement filters such as round-off noise and coefficient quantization errors are much less severe in FIR than in IIR.

iv. FIR filters requires more coefficients for sharp cutoff filters than IIR. So for a given amplitude response specification, more processing time and storage will be required for FIR implementation. But one can readily take advantage of the computational speed of the FFT and multi-rate techniques to improve significantly the efficiency of FIR implementations.

v. Analog filters can be readily transformed into equivalent IIR digital filters meeting similar specifications. This is impossible with FIR filters, for they do not have analog counterpart. However, it is easier to synthesize filters of arbitrary frequency responses with FIR.

vi. In general, FIR is algebraically more difficult to synthesize, if CAD support is not available.

To summarize from above, a broad guideline on when to use FIR filters or IIR filters could be described as follows.

i. Use IIR when the only important requirements are sharp cutoff filters and high throughput, as IIR filters, especially those using elliptic characteristics, will give fewer coefficients that FIR.
ii. Use FIR if the number of filter coefficients is not too large and ,in particular, if little or no phase distortion is desired. One might also add that newer DSP processors have architectures that are tailored to FIR filtering, and indeed some are designed specifically for FIRs.

Since it is very simple to implement FIR filters and all DSP processors available have architectures which are suited to FIR filtering, here we use FIR filter in my thesis.

Assorted by transmission bands:

1) Low-pass Filter[21]

A low-pass filter as shown in figure 2-3 is a filter that passes low-frequency signals but reduces the amplitude of signals with frequencies higher than the cutoff frequency. The actual amount of attenuation for each frequency varies from filter to filter. It is sometimes called a high-cut filter, or treble cut filter when used in audio application. A low-pass filter is the opposite of a high-pass filter, and a band-pass filter is a combination of a low-pass and a high-pass.

The concept of a low-pass filter exists in many different forms, including electronic circuit, digital algorithms for smoothing sets of data, acoustic barriers, blurring of images, and so on. Low-pass filters play the same role in signal processing that moving averages do in some other field, such as finance; both provide a smoother form of a signal which removes the short-term oscillations, leaving only the long-term trend.

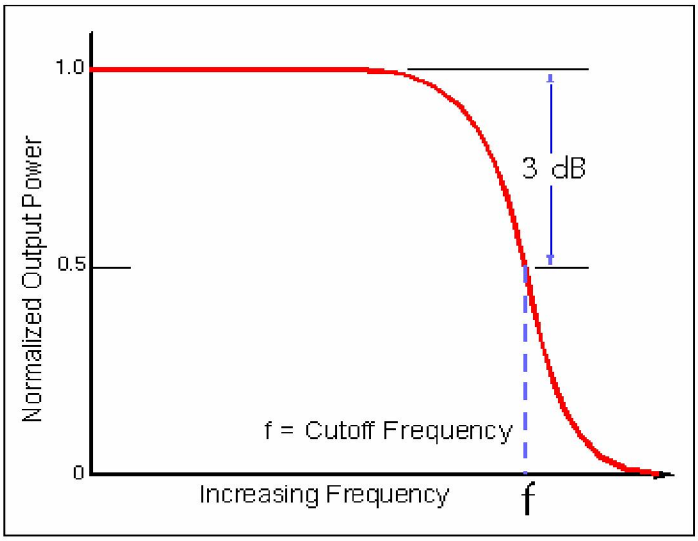


Figure 2-3. Low-pass Filter

2) High-pass Filter

A high-pass filter shown in figure 2-4 is an LTI (Linear time-invariant) filter that passes high frequencies well but attenuates frequencies lower than the cutoff frequency. The actual amount of attenuation for each frequency is a design parameter of the filter. It is sometimes called a low-cut filter; the terms bass-cut filter or rumble filter are also used in audio applications[22].

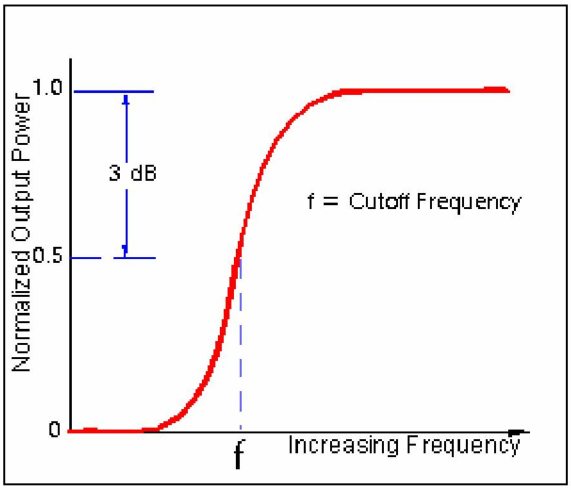


Figure 2-4. High-pass Filter

3) Band-pass Filter[23]

A band-pass filter shown in Figure 2-5 is a device that passes frequencies within a certain range and rejects frequencies outside that range. An example of an analogue electronic band-pass filter is an RLC circuit (a resistor-inductor-capacitor circuit). These filters can also be created by combining a low-pass filter with a high-pass filter.

An ideal bandpass filter would have a completely flat passband, e.g. with no gain/attenuation throughout, and would completely attenuate all frequencies outside the passband. Additionally, the transition out of the passband would be instantaneous in frequency. However, in practice, no bandpass filter is ideal. The filter does not attenuate all frequencies outside the desired frequency range completely; in particular, there is a region just outside the intended passband where frequencies are attenuated, but not rejected. This is known as the filter roll-off, and it is usually expressed in dB of attenuation per octave or decade of frequency. Generally, the design of a filter seeks to make the roll-off as narrow as possible, thus allowing the filter to perform as close as possible to its intended design. Normally, this is achieved at the expense of pass-band or stop-band ripple.

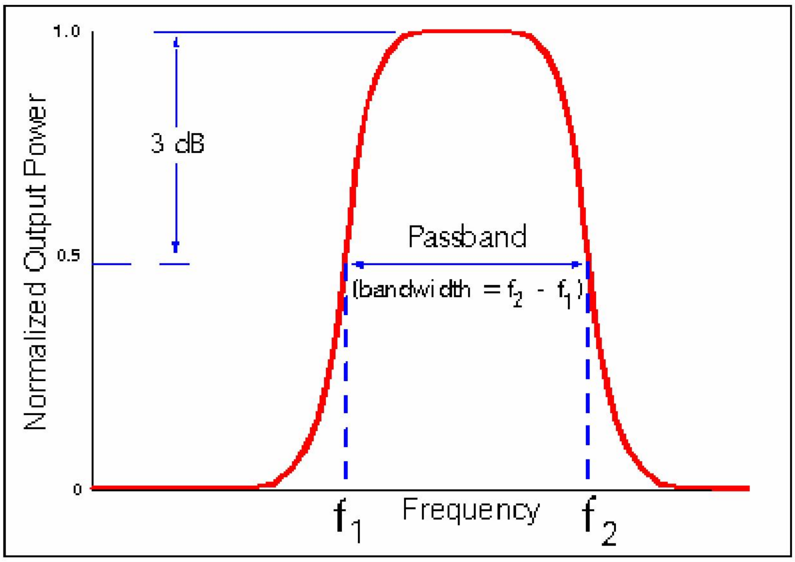


Figure 2-5. Band-pass Filter

4) Band-stop Filter

In signal processing, a band-stop filter or band-rejection filter shown in figure 2-6 is a filter that passes most frequencies unaltered, but attenuates those in a specific range to very low levels[24]. It is the opposite of a band-pass filter. A band-stop filter may be designed to stop the specified band of frequencies but usually only attenuates them below some specified level.

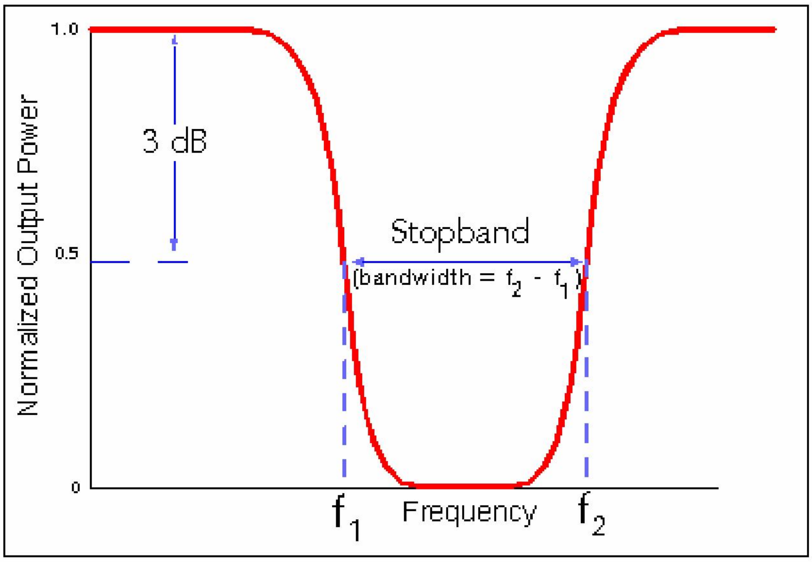


Figure 2-6. Band-stop Filter

3. Case-based Reasoning

Case-based reasoning (CBR) is the process of solving new problems based on the solutions of similar past problems[25]. CBR is a four-step process[26]:

1) Retrieve: Give a target problem and retrieve cases from memory relevant to solving it. A case includes a problem, as well its solution, annotations about how the solution was derived.
2) Reuse: Map the solution from the previous case to the target problem. This might involve adapting the solution as needed to fit the new case.
3) Revise: Having mapped the previous solution to the target case, testing of the new case in the real world or a simulation will be implemented. If necessary, the solution in the new case will be revised.
4) Retain: After the solution has been successfully adapted to the target problem, the resulting experience should be stored as a new case in the memory.

The four steps consists a CBR cycle. So we can simplify this mental process to describe CBR typically as a cyclical process comprising the four REs: REtriecve the most similar cases, Reuse the cases to attempt to solve the problem, Revise the proposed solution if necessary, and Retain the new solution as a part of a new case. This cycle currently rarely occurs without human intervention. For example, many CBR tools just play a role in case retrieval and reuse systems. Case revision, namely adaptation, is usually undertaken by managers of the case base. But it is not a weakness of CBR. It encourages human collaboration in decision support. Here is the demonstration of how each step in the cycle is handled[27].

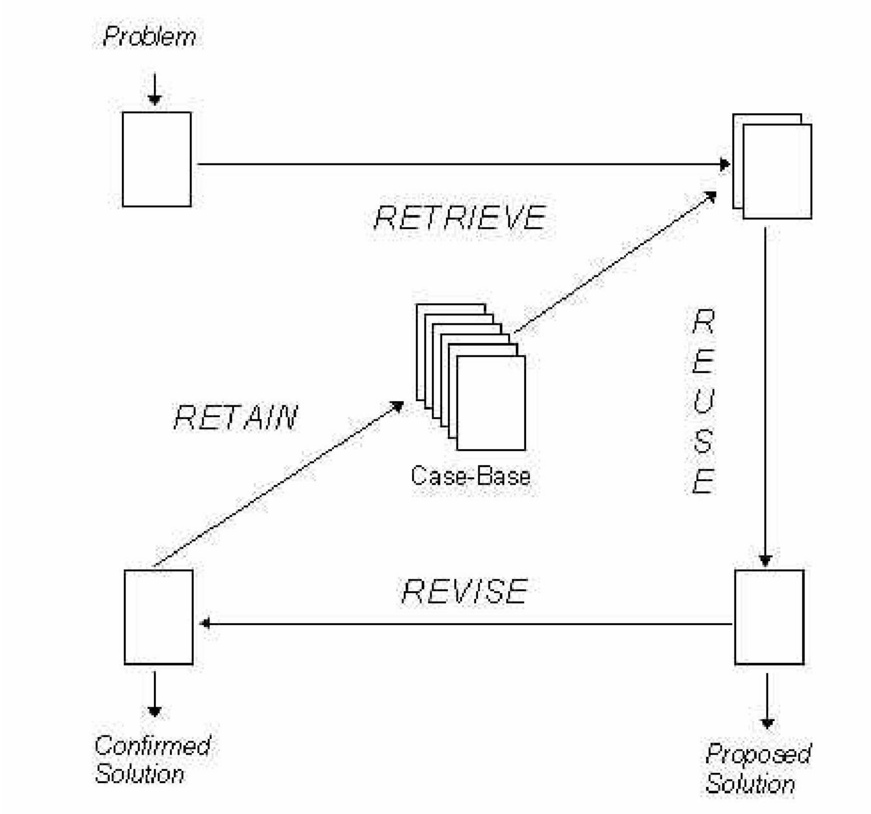


Figure 3-1. The CBR Cycle

Case-based reasoning is the method in Artificial Intelligence that we will use in the upper-layer in building this project. It not only save the time of working out a problem just looking into the case library and find out the most similar case to the current case and give out the solving methods of the new case, but also release the expert from all the trivial problem to deal with some big and important problem, which means it is very good for companies just hiring some low-cost and inexperienced workers to be in the front desk to solve some problems just searching up in the case library, and it certainly save a lot of money for the company to employ so many experts everywhere.

There are several advantages of CBR over rule-based reasoning through which we can see the perspective of this new kind of method[28]:

1) CBR systems can be built without passing through the knowledge elicitation bottleneck, since elicitation becomes a simpler task of acquiring past cases.

2) CBR systems can be built where a model does not exist.
3) Implementation becomes a simpler task of identifying relevant case features.
4) A CBR system can be rolled out with only a partial case-base which means using CBR, a system need never be complete, since it will continually growing. This removes one of the troubles of rule-based systems how to tell when a system is complete.
5) CBR systems can propose a solution quickly.
6) Individual or generalized cases can be used to provide explanations that are sometimes more satisfactory than explanations generated by chains of rules.
7) CBR systems can learn by acquiring new cases, making maintenance easier.
8) Finally, by acquiring new cases, CBR systems grow to reflect their organization's experience which rule-based systems can not.

So there will be no doubt that this kind of expert system can be very successful in the future. And that’s why we choose case-based reasoning in the upper-layer of this project.

4. Measurement setup and data collection

The setup for the sound signal collection is simple in this project. It contains of a laptop and a microphone. The microphone is placed outside but close to the enclosure cabin, for there are quite hot cutting chips and cold cutting compound using for cooling down the hub body inside the cabin. This might cause damage to the microphone if it is put inside the cabin. So the microphone is just beside the cabin and about 1 to 2 meters to the cutting tool. And also the microphone is just the normal microphone used for audible frequencies. But it is good enough to record the sound frequencies from 0 Hz to 22 kHz. Software used to record the sound signals is named Wavelab which is installed on the computer. The sampling rate used was 44.1 KHz.

With this setup, we collected more than 8 hours long sound signals which contain the whole process of milling a hub body from the beginning to the end in Berg Propulsion. So it is enough for our project.

However, all the sounds from all directions will be heard by the microphone. Thus, in addition to desired sound from milling and cutting process in the measurements there are unwanted sounds from different sources (e.g., from human beings, cooling water, other machines in surroundings) and noises, which need to be filtered out before we can abstract the features we want in those sound signals.

We choose to record a process of manufacturing a mid-size hub body. Since the Wavelab can pause and stop the collection during the data gathering process, the recording can be easily split into a set of small-sized data files. Thus, the whole eight-hour data was split into 29 separated sound files according to the different cutting stages.

The process of milling a hub body can be divided into mainly two stages. The first stage is called first cut, during which the processed surface of the hub body is coarse. The rough cut will be done by the cutting tool first. The second stage is called final cut, which means the cut (after the first cut) that can make the surface more smooth.

However, it is not like this that the first cut is all done then the second cut is started. The first cut is separated into two big parts also- the top half parts of the hub body and the rest half of hub body. And the top half parts can also be divided into three small parts during the cutting process- top surface of the hub body, inside of the hub body and the side of the hub body. After finish the first cut of the top half parts of the hub body, the tool was changed to do the final cut of the finished first cut part.

We will take sound file of the top half part of the hub body for example to analyze here. File 2 is the starting file which saves the cutting sound of the top surface cut of the hub body in the first cutting stage. File 3 stores the inside cutting which cut inside the three big circles in the first cutting stage. And file 4 is the sound of the first side cutting. File 5 here is useless, for in during this period of time, the operator just went into the cabin and changed the edge of the cutting tool. Then file 6 recorded the sound of the final cut of top surface, inside and side cutting of the top half parts of the hub body.

5. Signal analysis and filter design

During the data collection, a large amount of cutting signal is gathered from the beginning to the end. However, while recording the sound from the milling machine, there are other sounds from surrounding, e.g., sounds from people talking all the time, water cooling cutting tool, sharp noise outside the cutting cabin and so on. Here, through listening to all the sound files and picking out the sound intervals I want to analyze, I use the software named “Audacity” to abstract the useful sound intervals from the original sound files which makes the analysis of the useful signals much easier. The following shows the process of the analysis throughout this thesis work.

5.1. Investigation of time window size

During the analysis of the sound files we collected from Berg Propulsion, first the Fast Fourier Transform is used to draw the frequency domain figures to see how the frequencies have been changed during the cutting process.

So in order to draw the useful pictures which could help us to abstract the proper features in the later work, a suitable window size should be decided in this situation.

As we know, one of the features for sound signal is chronotropic character. But for human voices, it could be stable relatively in a short period of time. In general, we could say 10ms to 30ms. Thus it could be considered as a quasi-stationary process during this short period, namely human sound signal has the short-time stationarity, which also illustrated that any kind of sound signals should be analyzed and disposed within a short period of time. So the proper window size for human voices is 10ms to 30ms. We could choose any proper window size in Fast Fourier Transform according to the speed or other parameters we need.

However, there are some differences in the machine sound compared with the human voices. It will be much more stable when a machine is working, so the sound from the machine will also be more stable than the sound from a human being. The tests have been used when we try to fix the proper window size. The window sizes of 100ms, 200ms and 500ms are chosen and tested on the same sound fragment. So here we take one of the collected sound fragment file2 as an example. We will abstract the sound from 30 second to 36 second in this file to analyze. Here are the figures to show the differences as follows. The first figure shows the 100ms window size when we do the Fast Fourier Transform to draw amplitude spectrum figures. Here I choose the second 100ms figure to demonstrate, namely the analyzed sound from 30.1s to 30.2s in file two. The second figure demonstrates the 200ms window size in the same sound period. The figure is the first 200ms frequency-amplitude figure for the sound, namely the sound from 30s to 30.2s in file2. The last one displays the 500ms window size of the sound file. Here the first 500ms figure is chosen to show, which is the sound from 30s to 30.5s in the same sound file- file2.

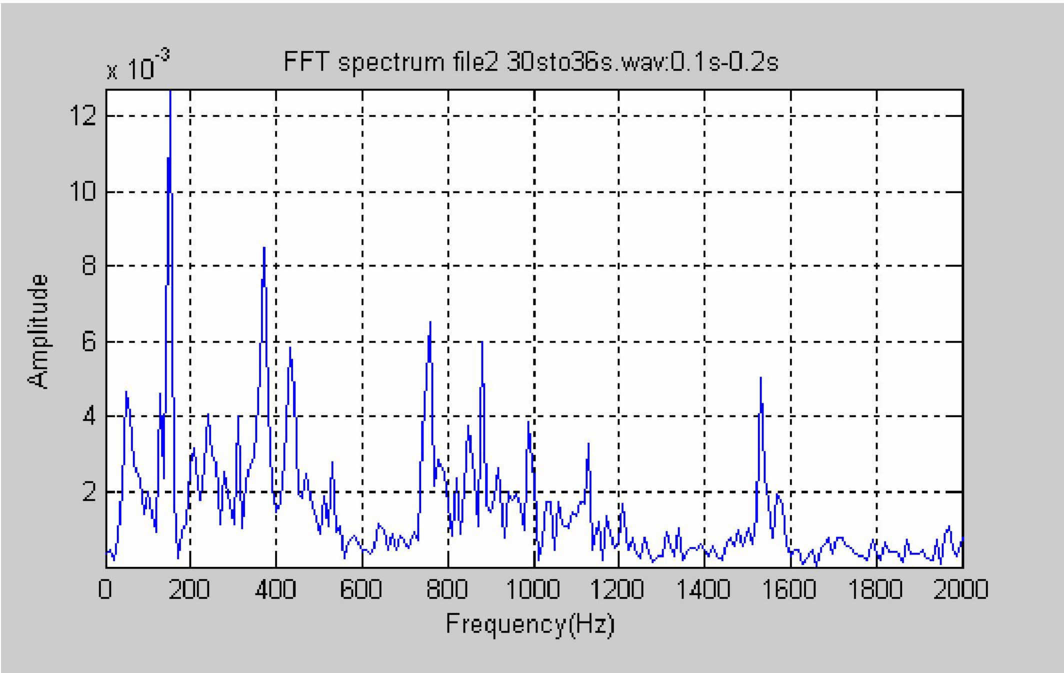


Figure 5-1a. 100ms window size

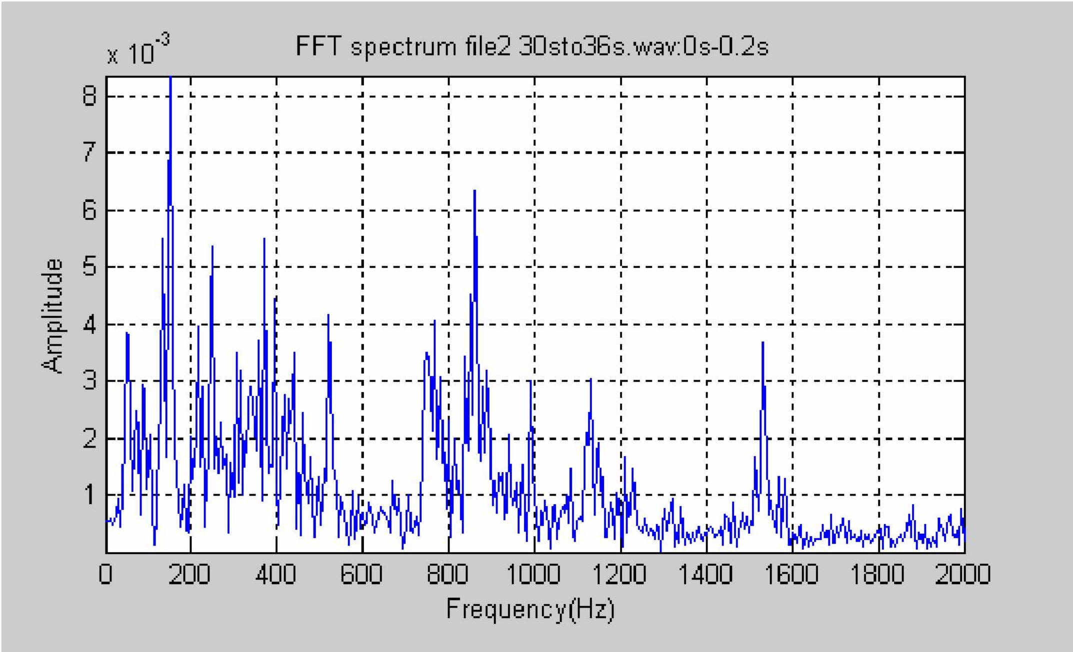


Figure 5-1b. 200ms window size

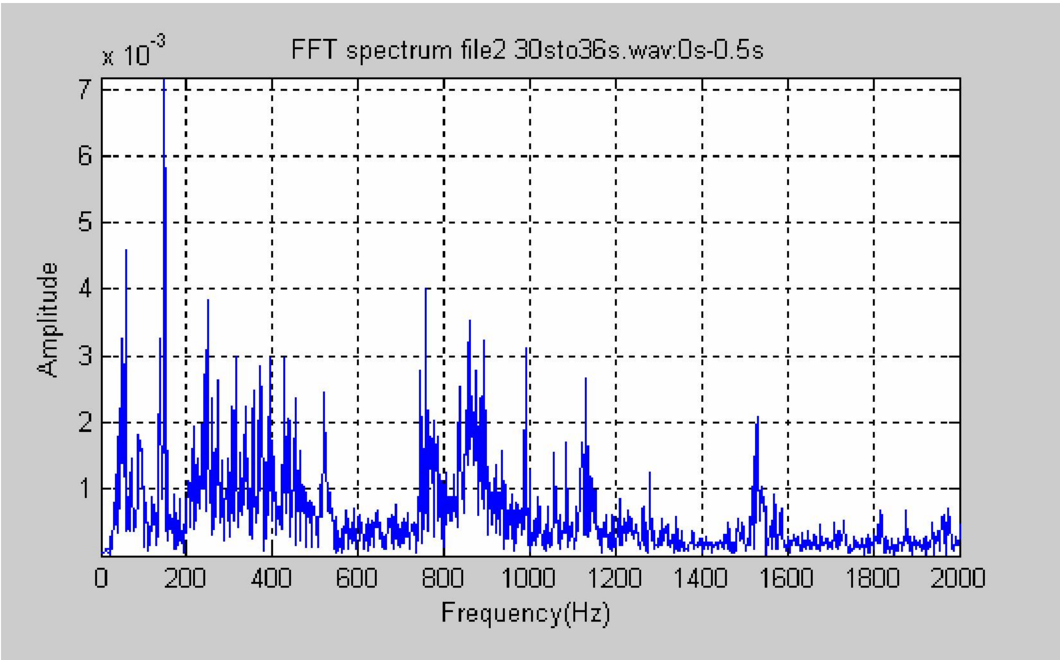


Figure 5-1c. 500ms window size

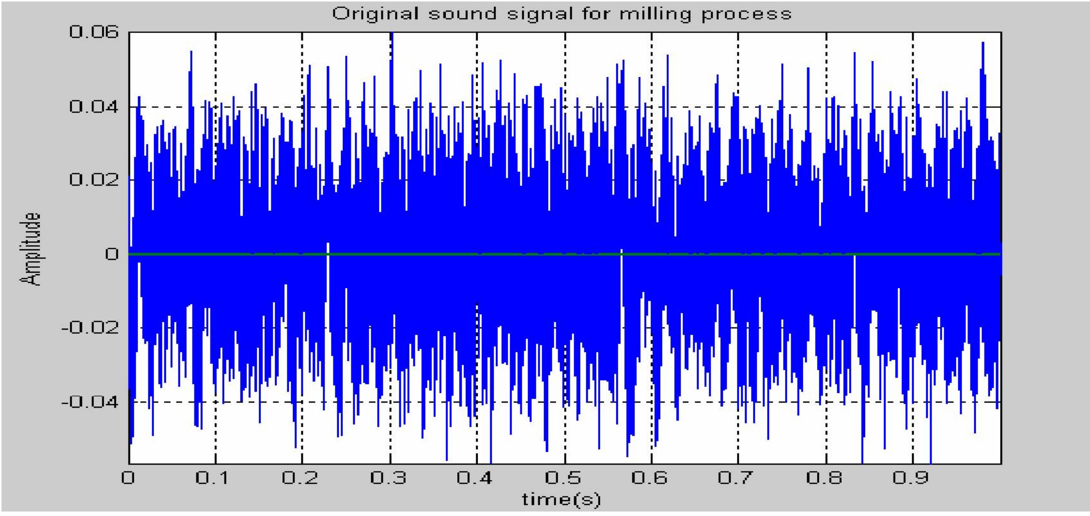
From the three figures above, we could see the main peak frequencies look similar. We can take spectral segment around 800Hz as an example. The frequency peaks emerging around 800Hz look similar for the three window sizes. At the beginning of this experiment, the 100ms window size is chosen. So now we can say that the 100ms is good enough for analyzing the sound from the machine in this situation for sure, which we could make sure the precision of the result coming from the sound analysis. Since the figures from 200ms and 500ms window size are not changed significantly, we could fix the window size as 100ms which is not too small as we analyze the human voice or too big as 500ms window size which might affect the processing speed when we deal with some larger data.

5.2. Characteristics of sound from milling process

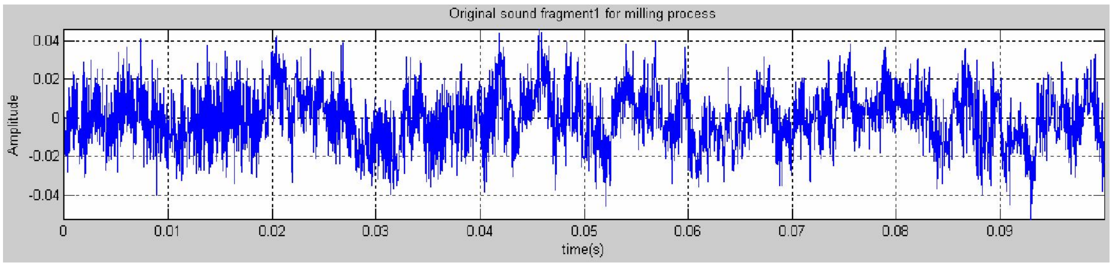
The aim of this project is to find some features which we could monitor whether the cutting tool is worn out or not during the milling process of the milling machine. So this part of the sound is the main sound which we should analyze.

5.2.1. Analysis of characteristics

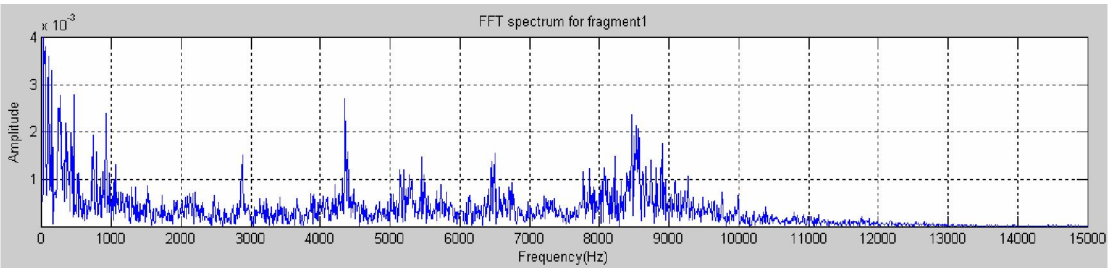
The sound we analyze here is abstracted from the sound files I collected. Through listening to the gathered file, this abstracted sound period is only cutting sound without other noise from outside. Figure 5-2(a) below is 1 second time domain analysis of the milling sound. Figures 5-2(b-1), (c-1), (d-1), (e-1) and (f-1) are abstracted from this 1 second time domain analysis, and each of them has 4410 samples, which means the time domain analysis in 100ms. And Figure 5-2(b-2), (c-2), (d-2), (e-2) and (f-2) are the frequency analysis in each 100ms time window size of the five time domain figures above respectively. From both time domain and frequency domain figures in Figure 5-2, a conclusion is able to be made as the sound coming from the milling is stationary, for the figures in each domain all look similar to each other. So for analyzing sound from the milling machine, we can abstract any intervals from the milling sound to analyze in the frequency domain without problems. It also proves here 100ms time window size is perfect according to what we have analyzed above in part 5.1.


Original sound signal for milling process
Amplitude
time(s)

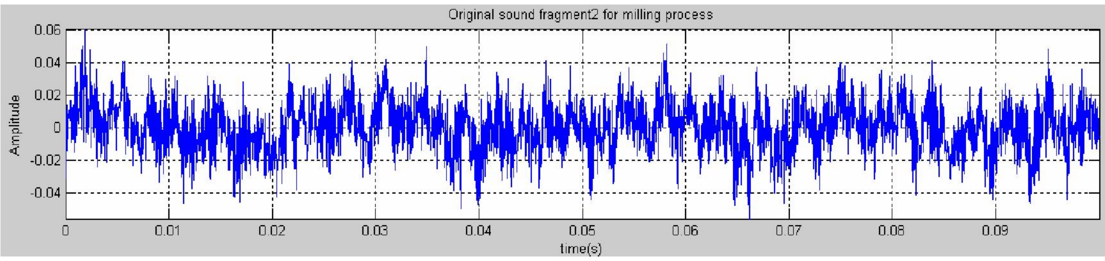
(a)


Original sound fragment1 for milling process
Amplitude
time(s)

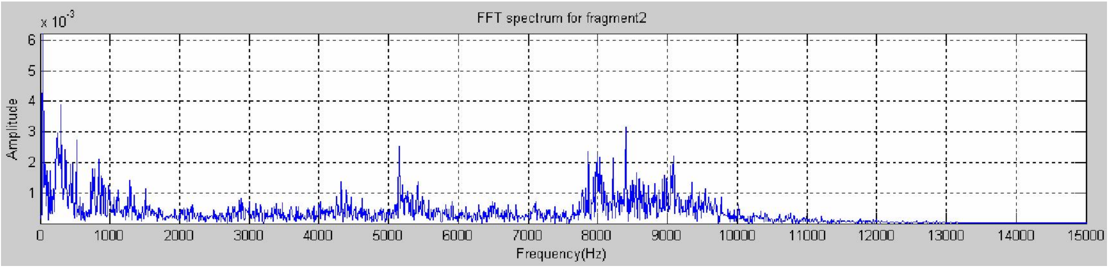
(b-1)


FFT spectrum for fragment1
Amplitude
Frequency(Hz)

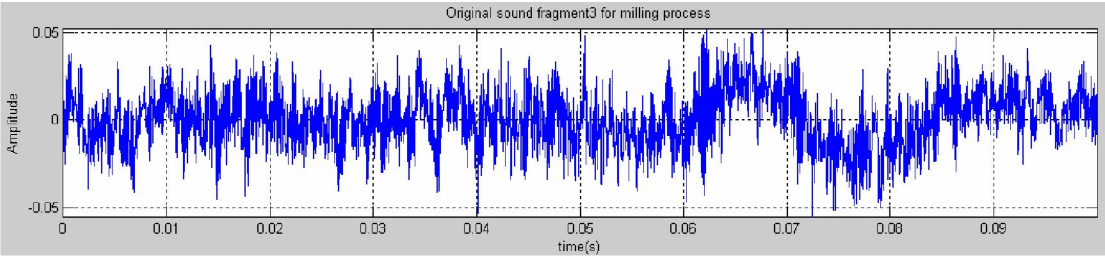
(b-2)


Original sound fragment2 for milling process
Amplitude
time(s)

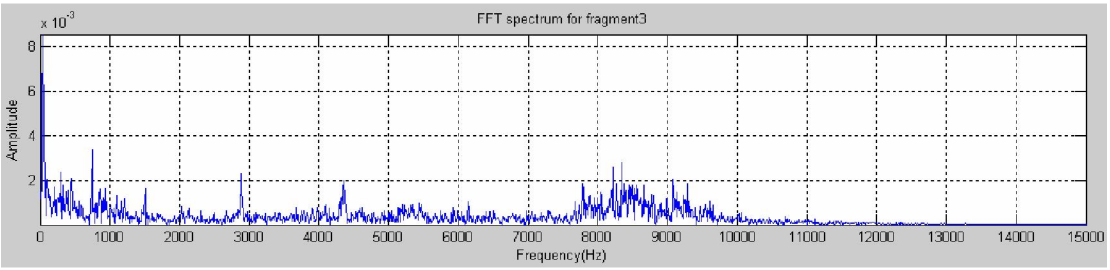
(c-1)


FFT spectrum for fragment2
x 10-3
Amplitude
Frequency(Hz)
0 1000 2000 3000 4000 5000 6000 7000 8000 9000 10000 11000 12000 13000 14000 15000

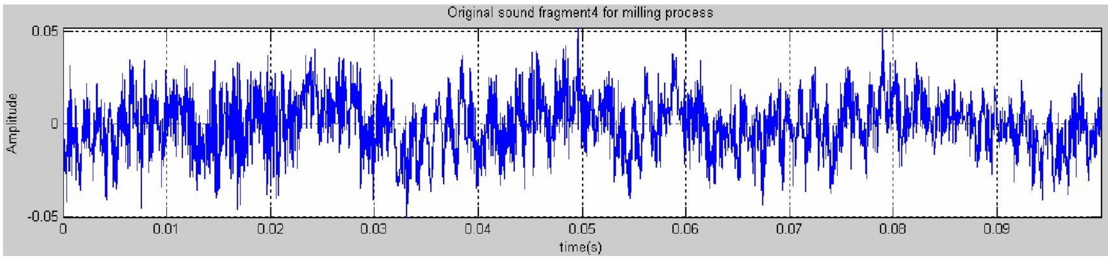
(c-2)


Original sound fragment3 for milling process
Amplitude
0.05
0
-0.05
time(s)
0 0.01 0.02 0.03 0.04 0.05 0.06 0.07 0.08 0.09

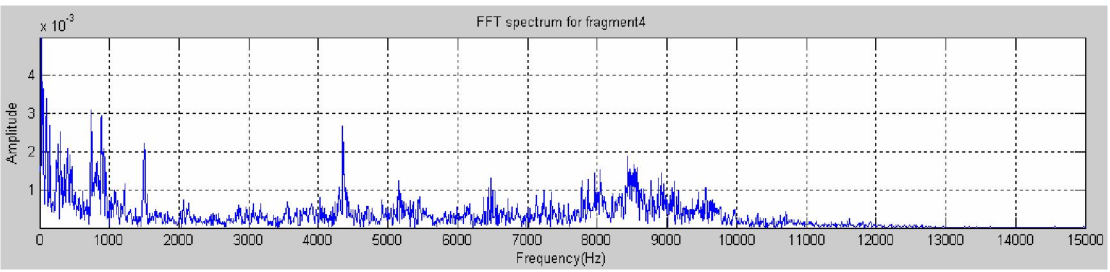
(d-1)


FFT spectrum for fragment3
x 10-3
Amplitude
Frequency(Hz)
0 1000 2000 3000 4000 5000 6000 7000 8000 9000 10000 11000 12000 13000 14000 15000

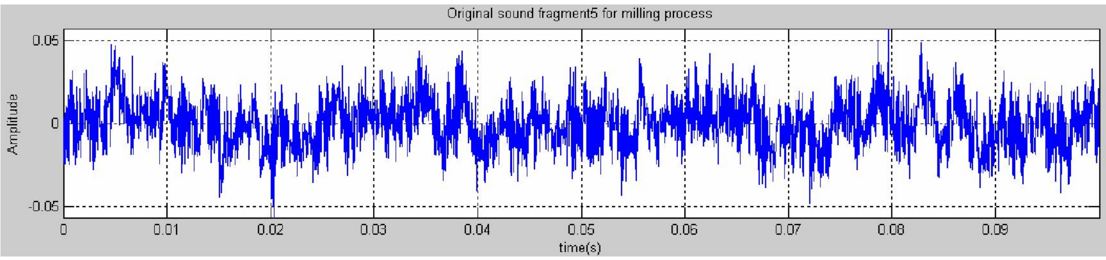
(d-2)


Original sound fragment4 for milling process
Amplitude
0.05
0
-0.05
time(s)
0 0.01 0.02 0.03 0.04 0.05 0.06 0.07 0.08 0.09

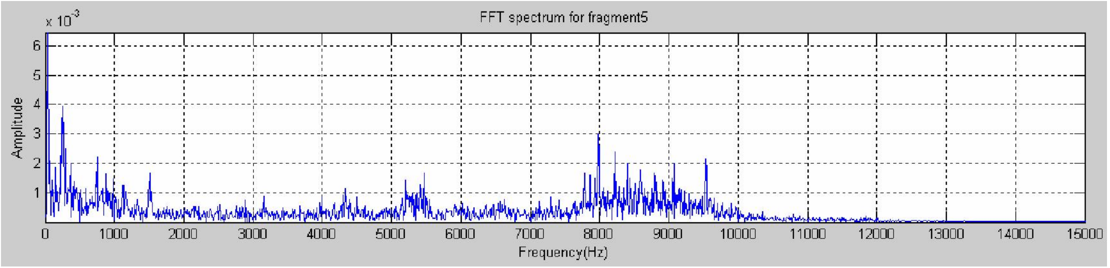
(e-1)


FFT spectrum for fragment4
x 10-3
Amplitude
Frequency(Hz)
0 1000 2000 3000 4000 5000 6000 7000 8000 9000 10000 11000 12000 13000 14000 15000

(e-2)



(f-1)



(f-2)

Figure 5-2. Time domain analysis of milling sound

(a) 1 second time domain analysis of milling sound

(b-1)-(f-1) 100ms time domain analysis abstracted from (a)

(b-2)-(f-2) 100ms frequency domain analysis of (b-1)-(f-1) respectively

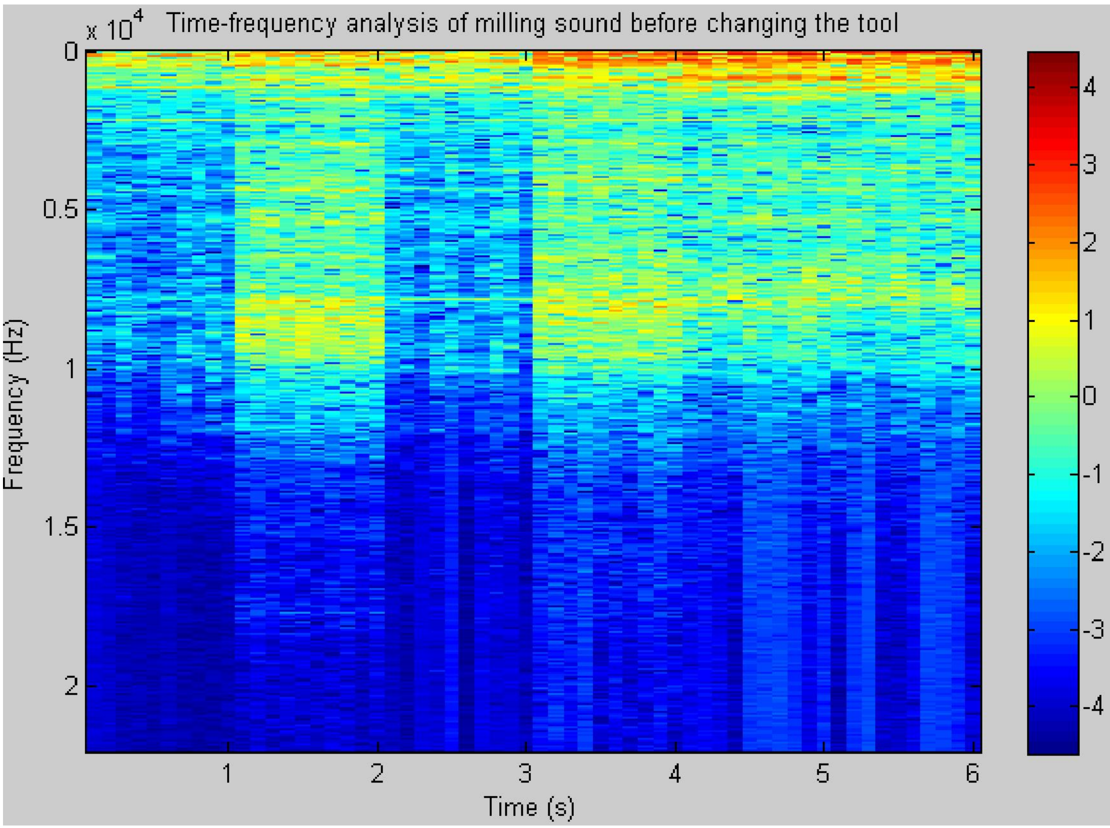
It is clear to see from Figure 5-2 that the energy of the milling sound is accumulated in 0Hz to 2000Hz, 4000Hz to 6000Hz as well as 8000Hz to 10000Hz.

In order to show more clearly features of the milling sound, we abstract totally 6 seconds (100ms by 100ms) milling sound to analyze from the beginning to the end in file4 which records the sound before the tool was changed. The analyzed result is displayed as Figure 5-3(a) below. We can see that the energy of the milling sound in low frequency is increasing until the cutting tool was changed. And also the energy of the milling sound is high in low frequency below 2000Hz. So we will also do some analysis in the low frequency interval in the coming part.

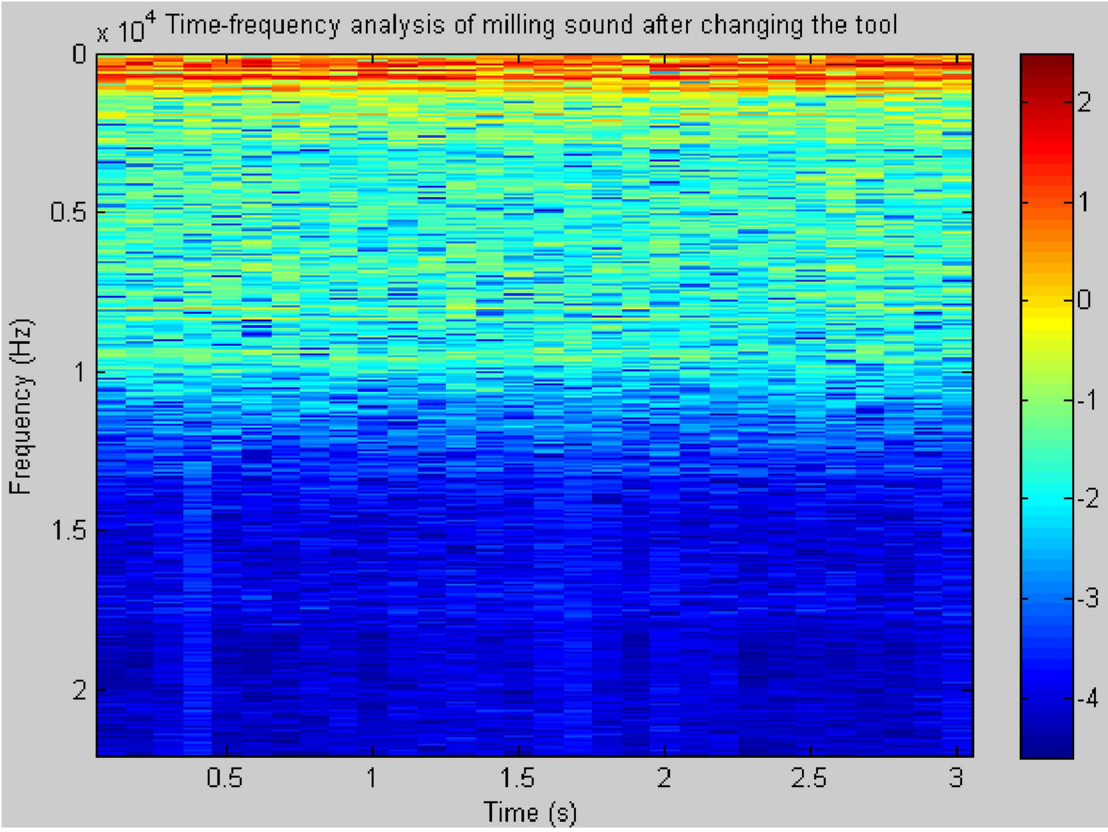
Apart from what we discussed above, we can see energy of the milling sound also appears in high frequency areas from 5000Hz to 10000Hz, which might be quite useful if the data is well collected at the beginning. So this is also important information and feature which we cannot simply ignore.

Figure 5-3(b) shows the time-frequency analysis of the milling sound after the tool is changed, which is in the final cutting stage. The energy is more in the lower frequency, like below 2000Hz as well.

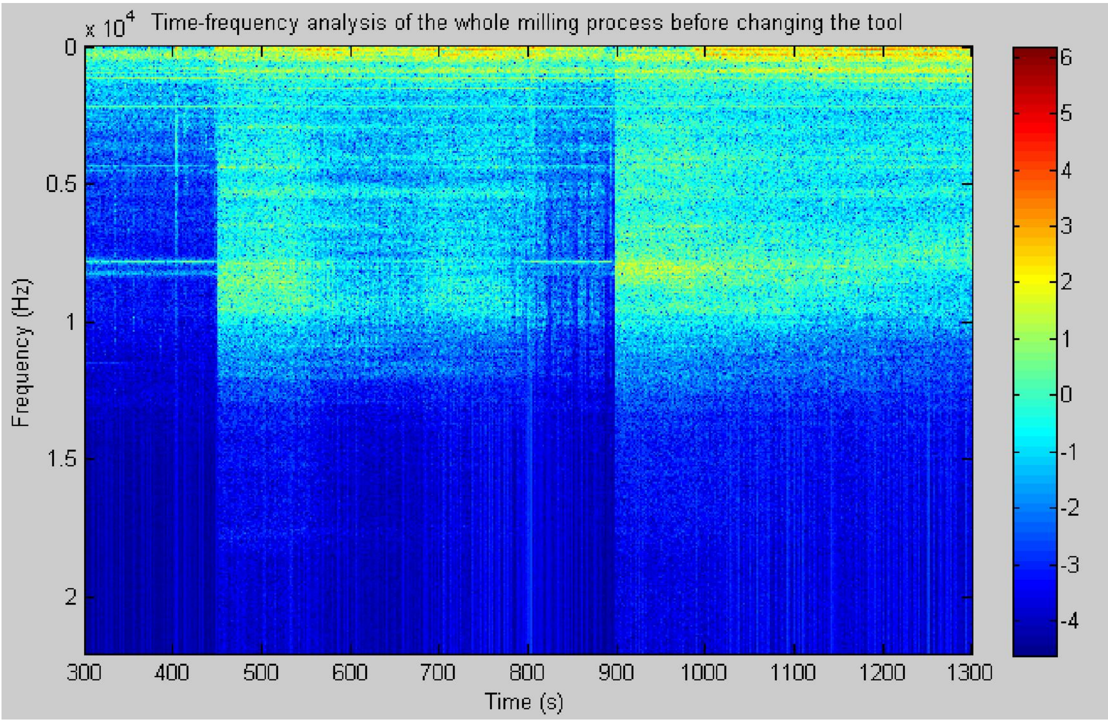
Figure 5-3(c) below is the time-frequency analysis throughout the whole process before the cutting tool was changed. It reflects the information in file4 starting from the 300th seconds to almost the end of this file. We gathered the sample in this figure every 0.5 second. It has milling sound signal all through this process, but contains other kinds of noises, like human voices, cooling water sound signal, as well.



(a)



(b)



(c)

Figure 5-3. Time-frequency analysis of milling sound before changing the tool

(a) Time-frequency analysis of milling sound

(b) Time-frequency analysis of milling sound after changing the tool

(c) Time-frequency analysis of milling sound during which it contains all kinds of noise as well

5.2.2. Low frequency analysis

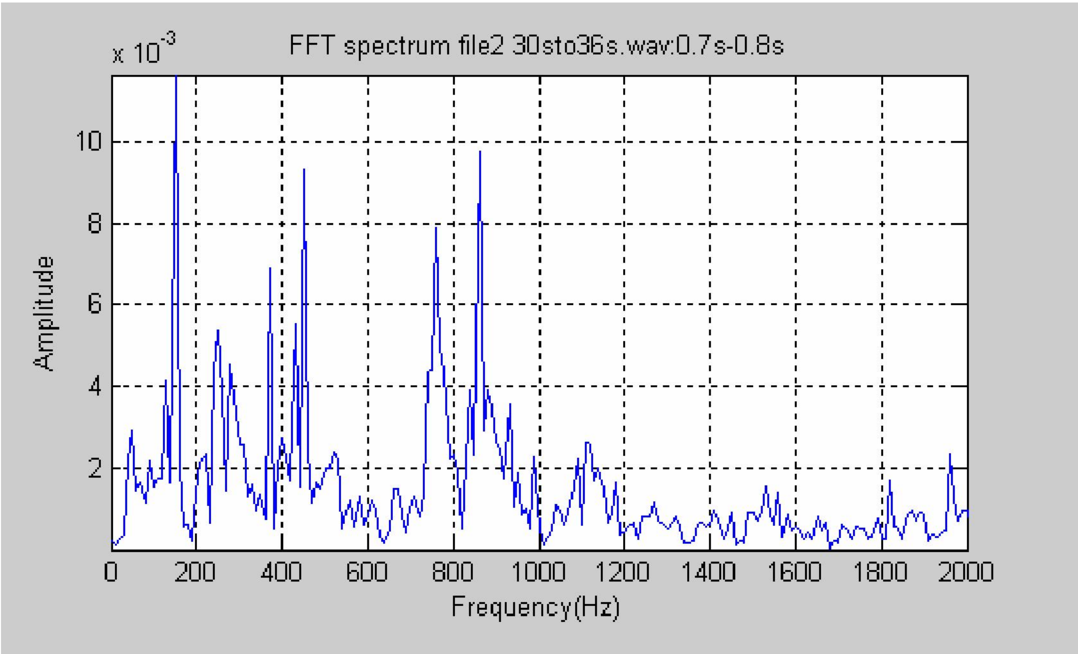
1) Before the tool is changed

As I described before, in file5 we changed the cutting tool, and in file2, file3 and file4, the same cutting tool is used to cut the different places of the hub body. And all the cutting sounds in these three files are the first cut of the hub body, namely the rough cut, since the rough surface will be cut in the first stage and then the final cut which can smooth the surface of the hub body will be done. File2 displays the sound of top surface cutting. File3 demonstrated the sound of inside cutting. File4 shows the sound of side cutting. We abstract the pure cutting sound, namely without human sound and obvious water sound and sharp nose outside. And also we will pick the pure sound fragments from the beginning to the end in each sound file, so that we could compare them to find the rules. Since different cutting place will have different cutting frequencies which we consider of, we will analyze the sound from one cutting place to another, which means we will look for the changing regulations from file2, file3 and file4 separately. And file4 should be the key consideration, since after file4 the cutting tool was changed to do the final cut. So the boarder frequency line could be found in file4 if we could find some rules during the analysis.

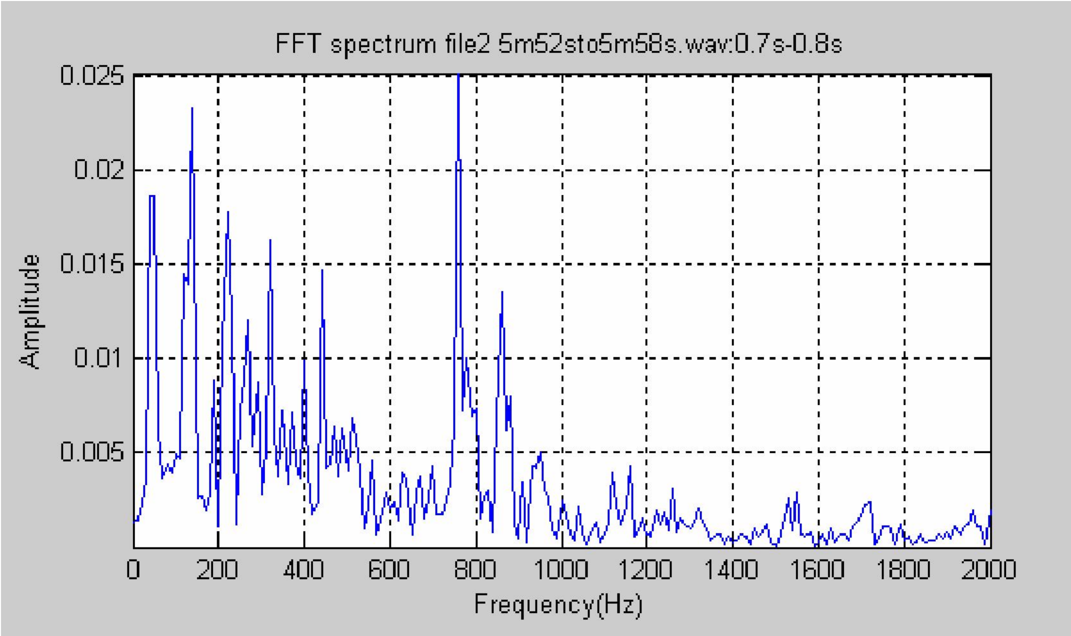
Figure 5-4 shows the sound analyzing results in file2 which did the top surface cutting of the hub body. We choose three different time period during the first top surface cutting in file2, which illustrates here as Figure 5-4 (a), Figure 5-4 (b) and Figure 5-4 (c) respectively. Figure 5-4 (a) shows the frequency- amplitude figure of top surface cutting at the very beginning started from 30 second to 36 second. Figure 5-4 (b) is abstracted out from 5 min 52 sec to 5 min 58 sec. And Figure 5-4 (c) is separated out from the end of the top surface cutting file- file2 which is from 8 min 30 sec to 8 min

34 sec. Since they are all from the same cutting place and same cutting stage, the analyzing results are comparable.

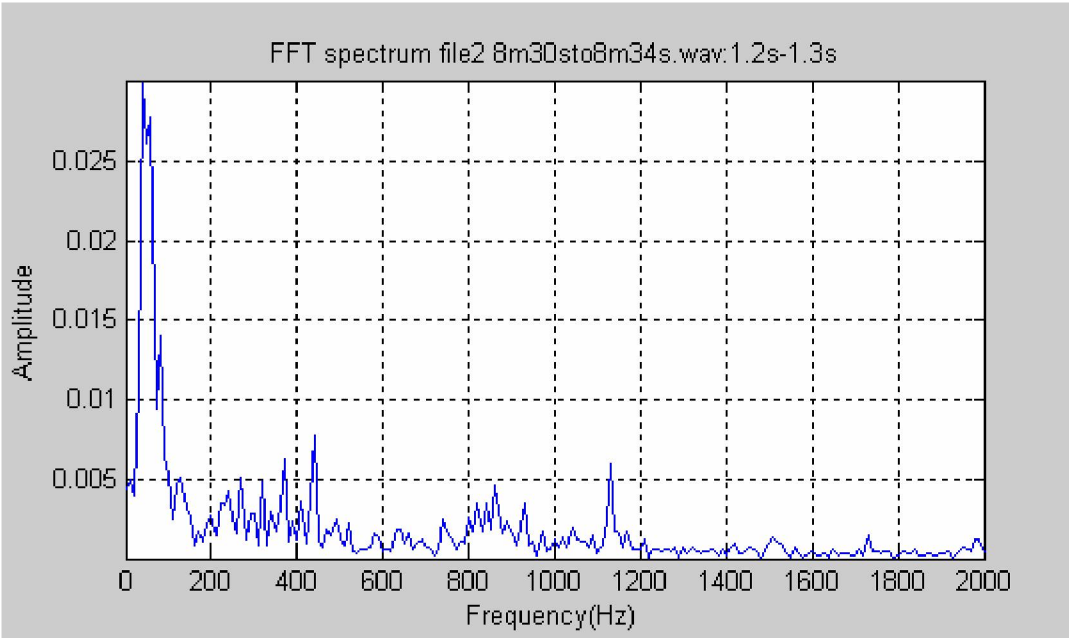
From all the three figures which displays as follows, we could see some slice relevances here. We could focus on the frequency interval in 1-200 Hz. The relevance is that from the beginning to the end of the top surface cutting in the rough cutting stage, trend of the frequency peaks are ascendant. We can see very clearly from the three figures that the frequency peaks are much more in the Figure 5-4 (a) than the Figure 5-4 (b). The second relevance is that from Figure 5-4 (a) to Figure 5-4 (b) the width of each frequency peak is widened. It is obvious that the band width in figure 5-4 (c) is much broader than it in Figure 5-4 (a).



(a)



(b)



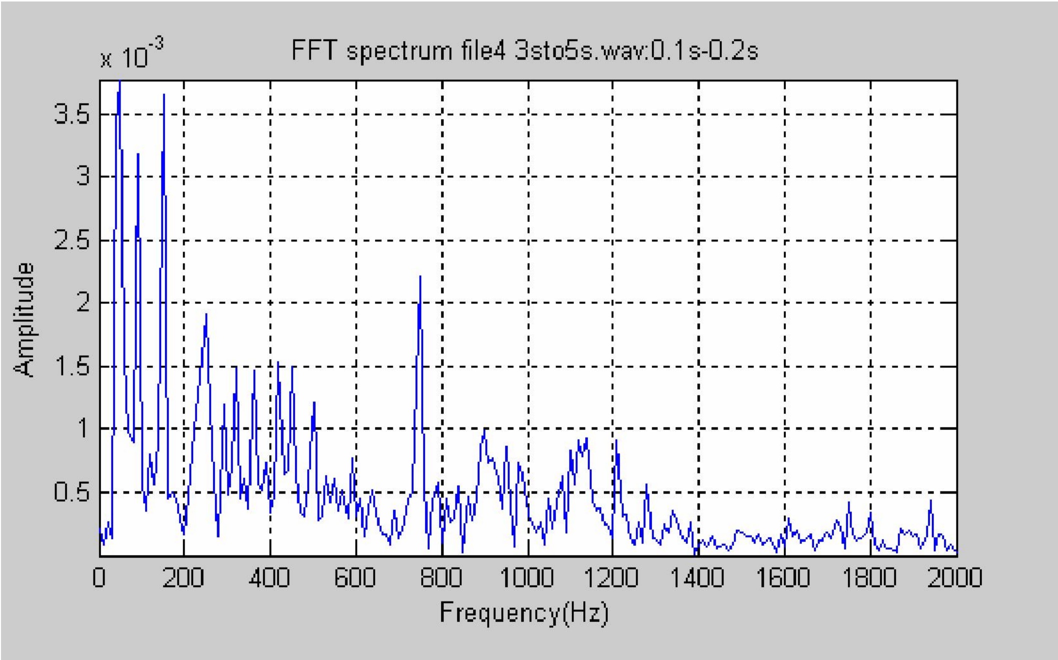
(c)

Figure 5-4. Cutting frequencies of the top surface cutting in the first cutting stage

And these relevances are also quite clear in file4 which recorded the sound of the side cutting of the hub body. The figures abstracted from the beginning to the end in file4 are shown as the following from Figure 5-5 (a) to Figure 5-5 (f). I choose the sound period during 3 sec to 5 sec, 8 min to 8 min 5 sec, 14 min 20 sec to 14 min 25 sec, 16 min 55 sec to 17 min, 20 min to 20 min 5 sec, and 22 min 5 sec to 22min 10 sec separately.

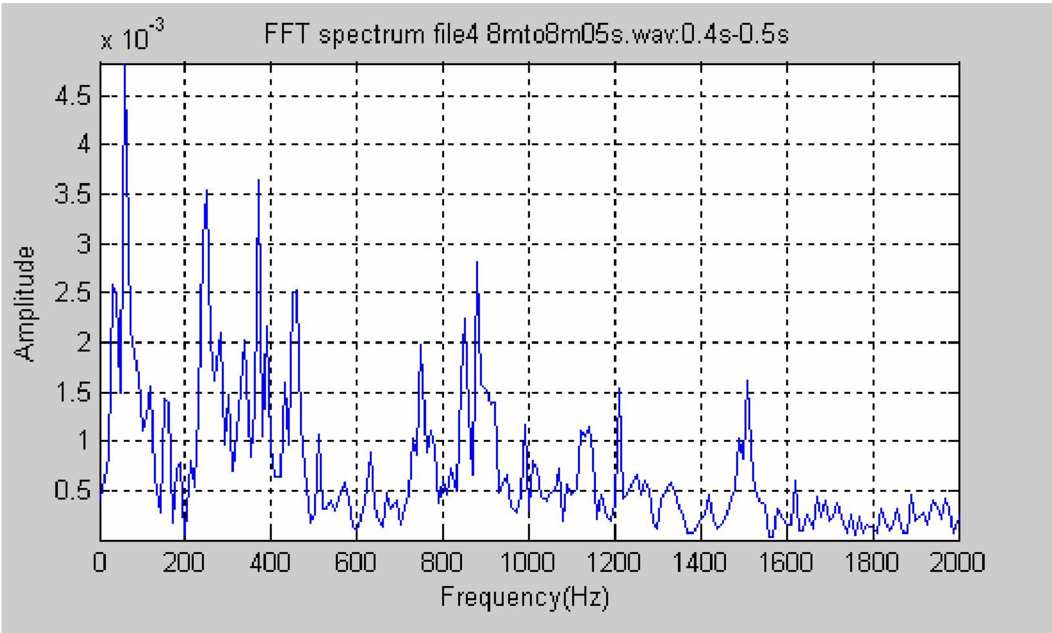
And also since the cutting tool will be changed after the first cut of the side cutting on the hub body is finished, file 4 would be the very important sound data to analyze. File4 recorded the whole cutting sound while doing the first cut on the side of the hub body. Thus we could focus on this file and analyze the regular patterns of the sound changing while doing the first cut on the side of hub body. As it will be different cutting frequencies and also cutting amplitudes among different cutting part on the hub body, we can not just simply analyze file2 (which recorded the first cut sound on the top surface of the hub body), file 3 (which recorded the first cut sound inside the hub body) and file4 (which recorded the first cut sound on the side of the hub body) together to find the laws during the cutting process. So in this article I would rather like to take file4 which recorded the whole process of the first cut on the side of the hub body before the cutting tool was changed which will be quite important for our project. In the end of the file4 the sound coming from the cutting process could be considered to be the abnormal sound already. I remembered quite clear when the operator took out the cutting tool while the first cut on the side of the hub body was finished, I noticed that the cutting edge of the cutting tool has already worn out. That’s why I said the sound recorded in file4 would be quite important to analyze.

During analyzing the sound stored in file4, I began to find some regular patterns. If you look at the figures in different time periods abstracted from file4 below, one rule which is quite easy to observe is that the amplitudes of the frequencies in 0 to 100 Hz is increasing rapidly from the beginning to the end.



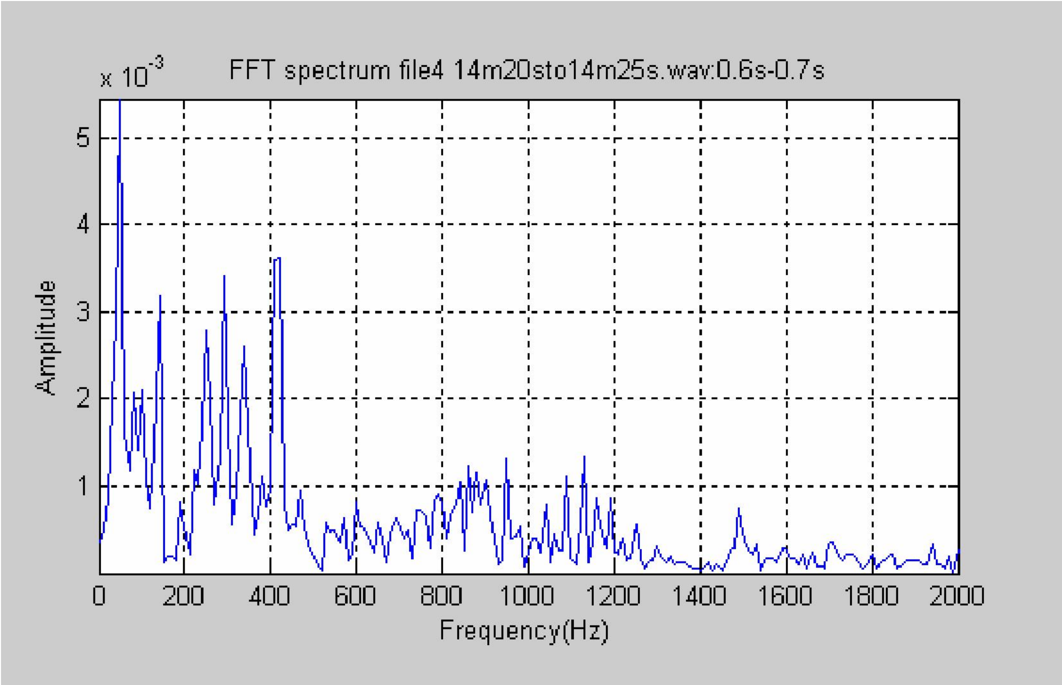
x 10^-3
FFT spectrum file4 3sto5s.wav:0.1s-0.2s
Amplitude
Frequency(Hz)
0
200
400
600
800
1000
1200
1400
1600
1800
2000
0.5
1
1.5
2
2.5
3
3.5

(a)

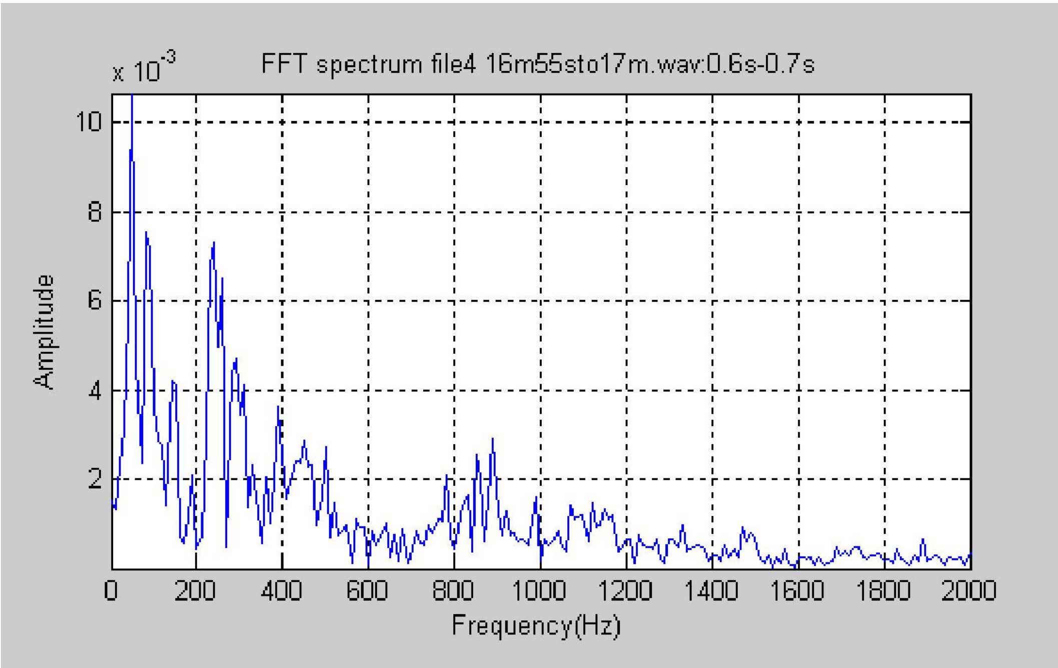


x 10^-3
FFT spectrum file4 8mto8m05s.wav:0.4s-0.5s
Amplitude
Frequency(Hz)
0
200
400
600
800
1000
1200
1400
1600
1800
2000
0.5
1
1.5
2
2.5
3
3.5
4
4.5

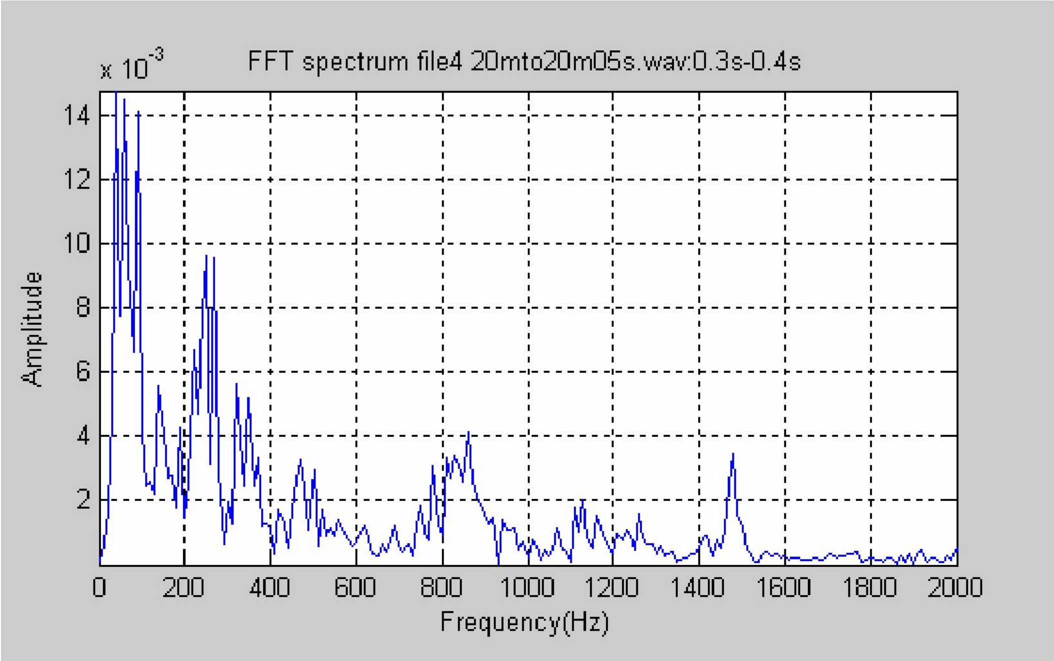
(b)


FFT spectrum file4 14m20sto14m25s.wav:0.6s-0.7s
x 10^-3
Amplitude
Frequency(Hz)
0
200
400
600
800
1000
1200
1400
1600
1800
2000
1
2
3
4
5

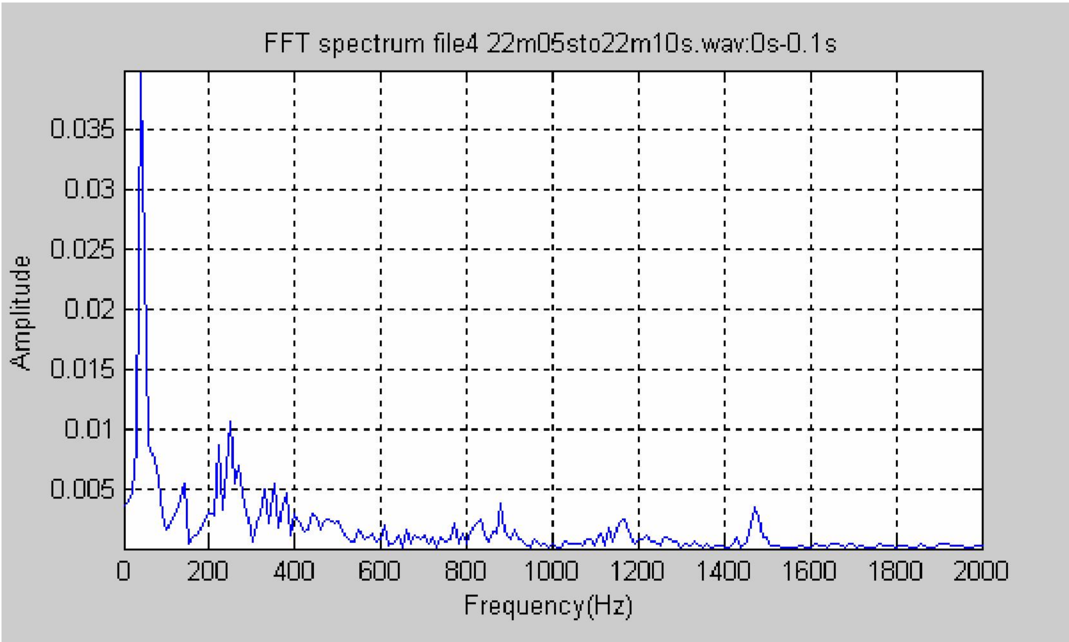
(c)


FFT spectrum file4 16m55sto17m.wav:0.6s-0.7s
x 10^-3
Amplitude
Frequency(Hz)
0
200
400
600
800
1000
1200
1400
1600
1800
2000
2
4
6
8
10

(d)



(e)

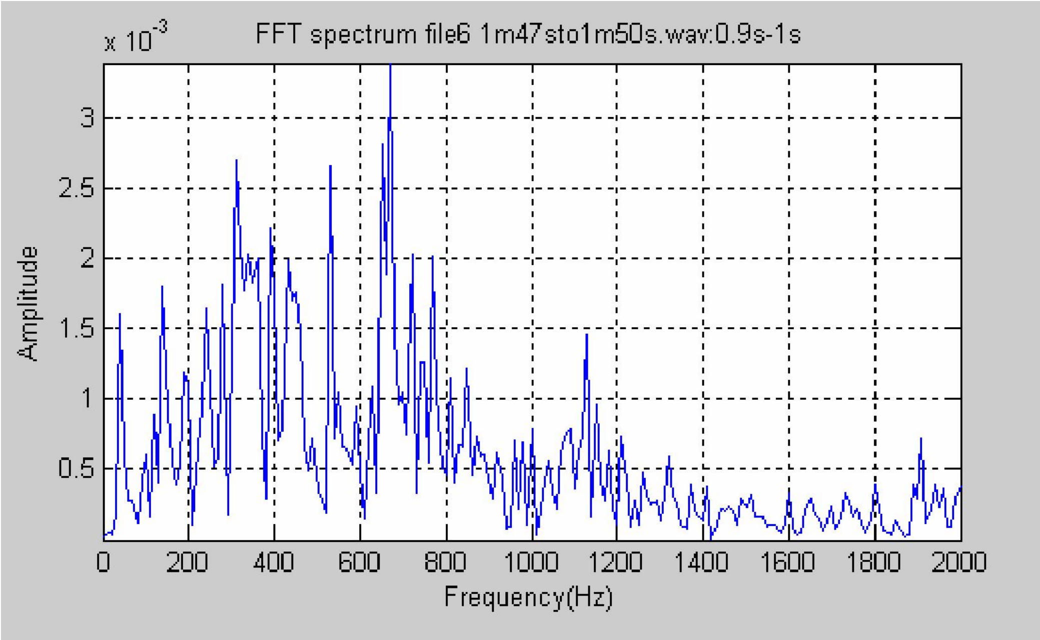


(f)

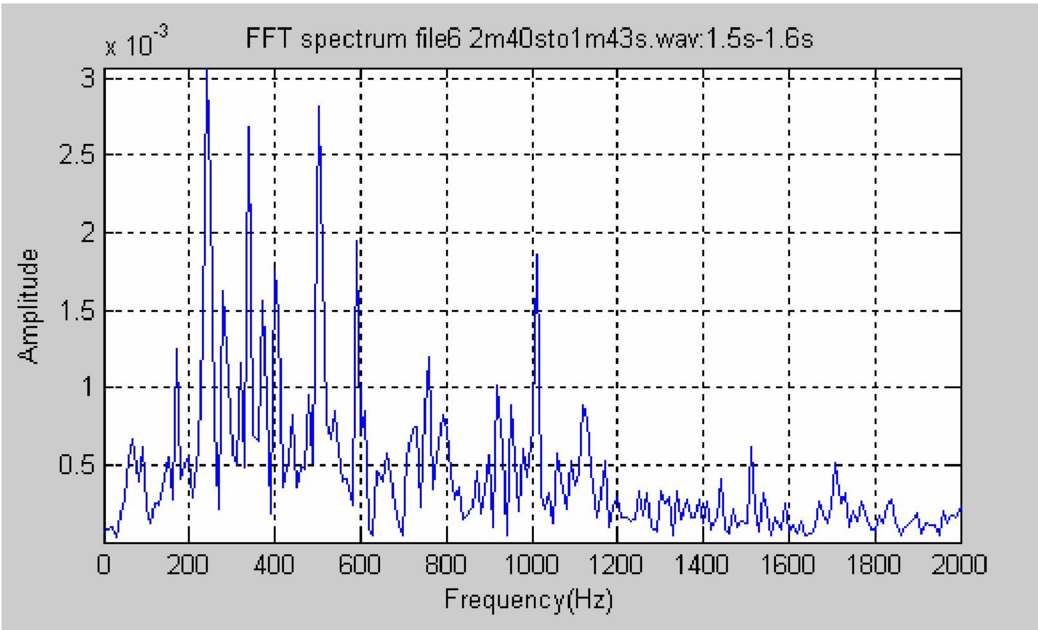
Figure 5-5. Cutting frequencies of the side cutting in the first cutting stage

2) After the tool is changed

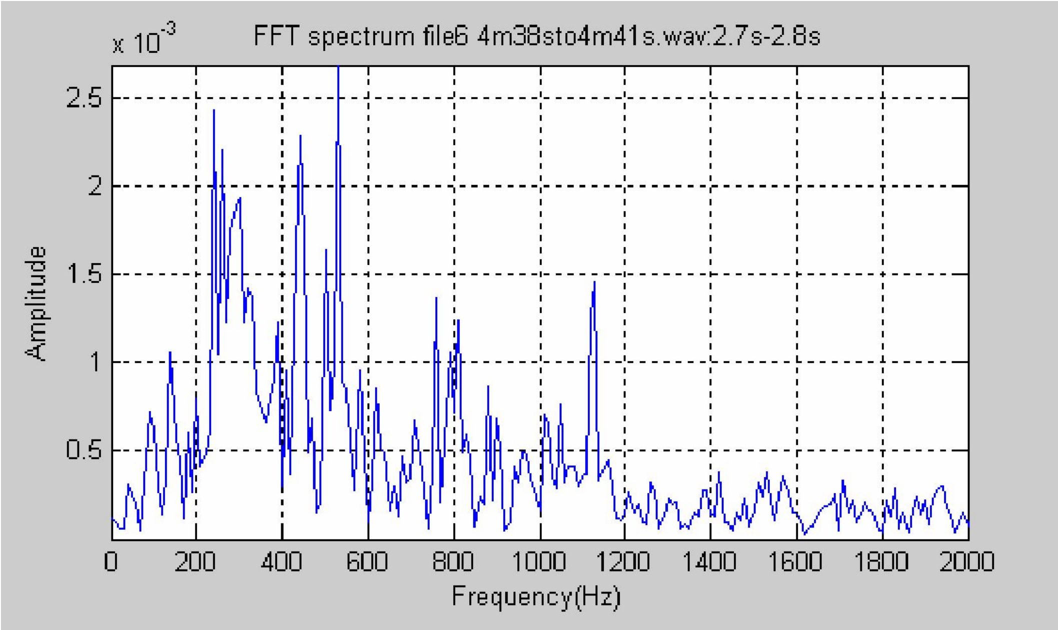
After the tool is changed in file5, file6 recorded the sound signals of the final cut done in the first half parts of the hub body. Since the tool is totally new while doing this final cut, the signals here are all quite good and normal sound. The following figures show the frequency spectrums of the cutting sound abstracted in the lower frequency part the same as we did above, namely from 0Hz to 2000Hz.



(a)



(b)



(c)

Figure 5-6. Cutting frequencies of the final cutting stage

From the figures shown in Figure5-6, I can not see some regular patterns among the signals with the time moving on, since they are all quite normal data. So in order to get some more useful information, I think maybe the boundary data as shown in file4 could help us a lot by collecting it using a nearly worn out tool which still could work as doing the first cut on the side of the hub body shown in file4.

5.3. Characteristics of sound of human beings

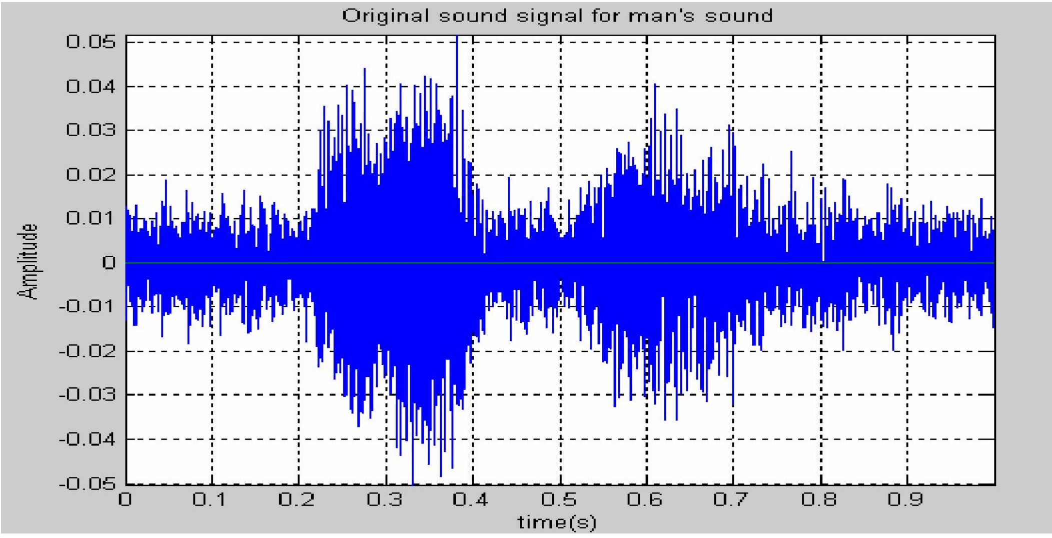
While collecting the sound file from the milling machine, there are people talking all the time. Since the microphone was put just outside the milling cabin, the sound from people is also quite loud and significant. Thus it interferes the quality of the data we got a lot. Here we will analyze human voices in both time domain and frequency domain. The voice will be divided into two categories: man’s voice and woman’s voice. Through the whole process, we could find the man’s or woman’s sound while the machine did not work, so it will be easier for us to focus on the human sound analysis.

5.3.1. Analysis of characteristics

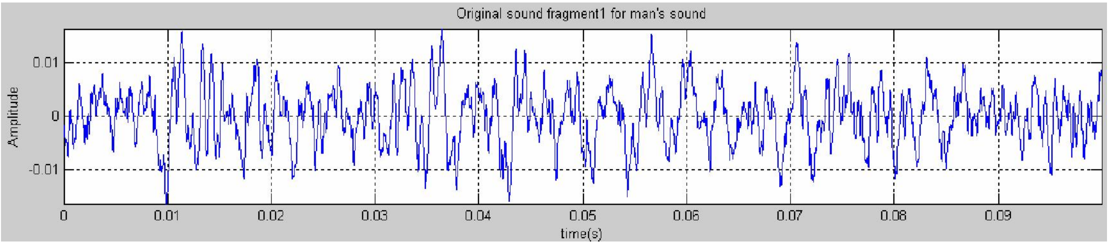
This kind of analysis can show us whether the sound is stationary during a specific period, which could help us to test time window size we suggested above and also fix another window size for the minority situation.

1) Characteristics analysis of men's sound

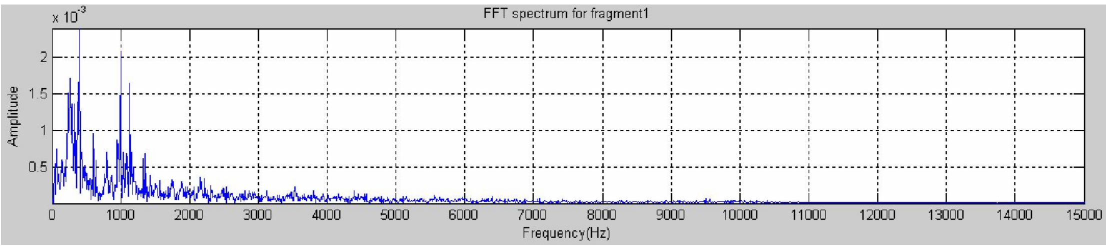
We can see the typical human voice in the time-amplitude figures in Figure 5-7. It is not stationary through 1 second that is analyzed here. This time region is abstracted from sound file 6. The man spoke "quite long" in the 913th second. It is very clear to see in which time regions the man's voice is. Since when we are talking we speak word by word, the voice is not continuous all through. According to Figure 5-7(a), it is between 0.2 second and 0.4 second as well as from 0.5 second to 0.7 second during 1 second time here. Thus, we can focus on these two time intervals in this figure to analyze frequencies of men's sound in the frequency domain correspondingly (show as Figure 5-11), but not waste the time on the time intervals where there is no human sound. Because human voice is non-stationary signal, which is very clear from the Figures 5-7(b-1), (c-1), (d-1), (e-1) and (f-1) (all these figures in Figure 5-7 are 100ms in time domain) that they look quite different from one to another in 100ms time window size both in time domain analysis and frequency domain analysis which is corresponding to the time domain analysis, we cannot simply use the 100ms window size for human voice like the stationary signal from milling machine discussed above. As mentioned before, human's voice is stationary among 10ms to 30ms, it would be better if we fix time window size to 20ms when we analyze men's sound. This kind of analysis is shown in Figure 5-11 below, which reflects the frequencies of man's voice well.


Original sound signal for man's sound
Amplitude
time(s)

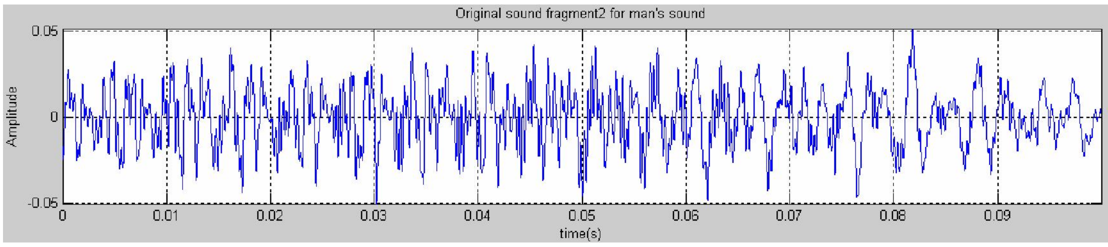
(a)


Original sound fragment1 for man's sound
Amplitude
time(s)

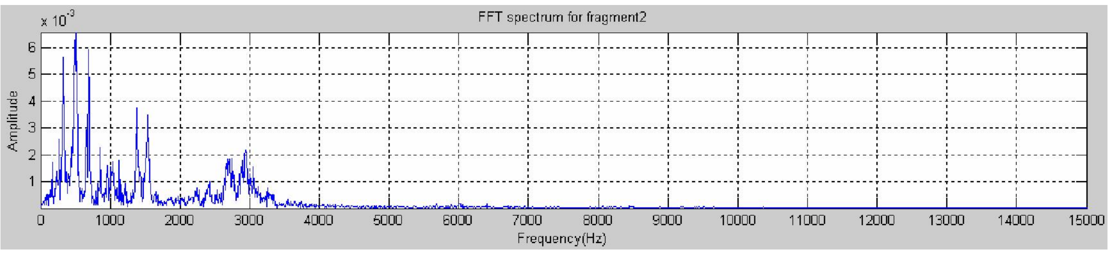
(b-1)


FFT spectrum for fragment1
Amplitude
Frequency(Hz)

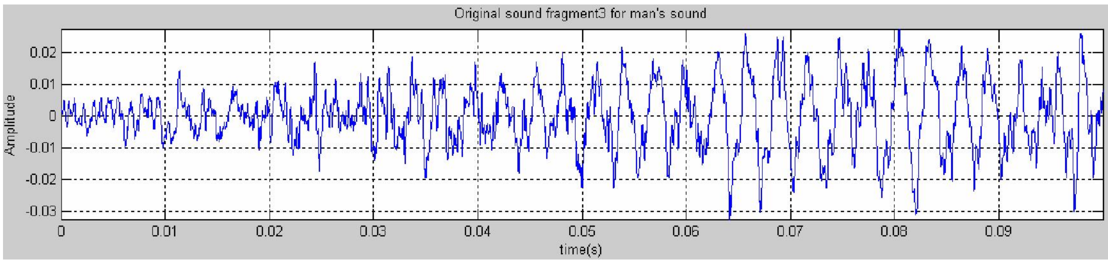
(b-2)


Original sound fragment2 for man's sound
Amplitude
time(s)

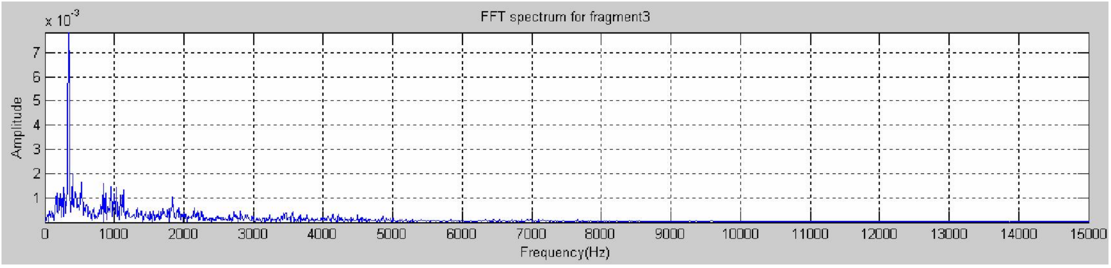
(c-1)


FFT spectrum for fragment2
Amplitude
Frequency(Hz)

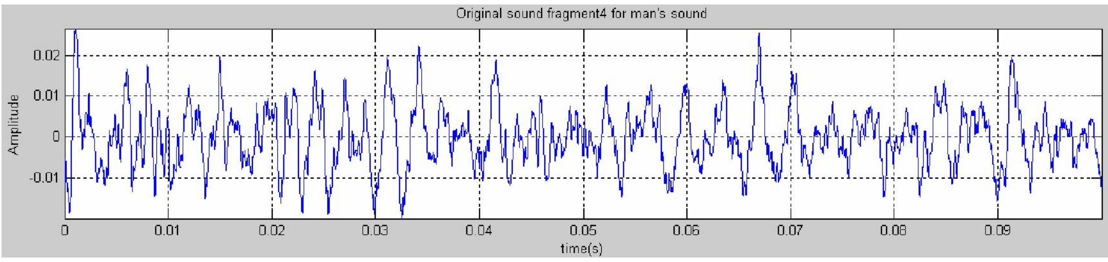
(c-2)


Original sound fragment3 for man's sound
Amplitude
time(s)

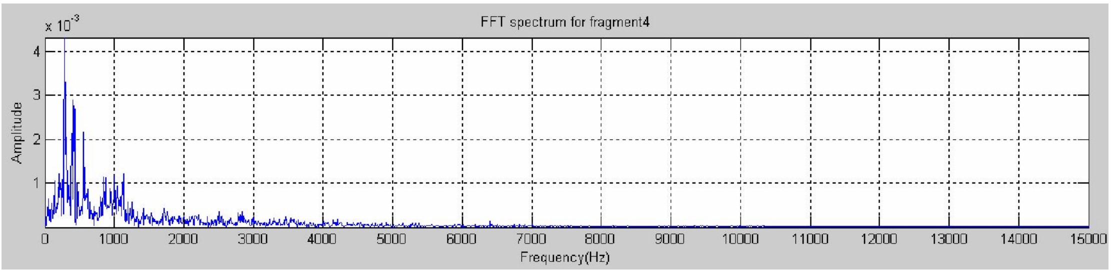
(d-1)


FFT spectrum for fragment3
Amplitude
Frequency(Hz)

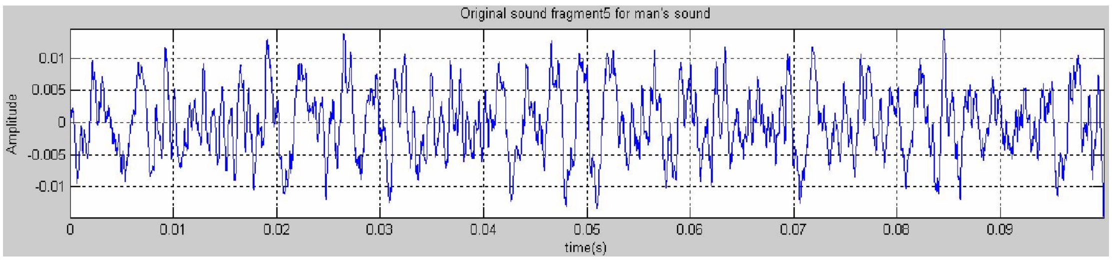
(d-2)


Original sound fragment4 for man's sound
Amplitude
time(s)

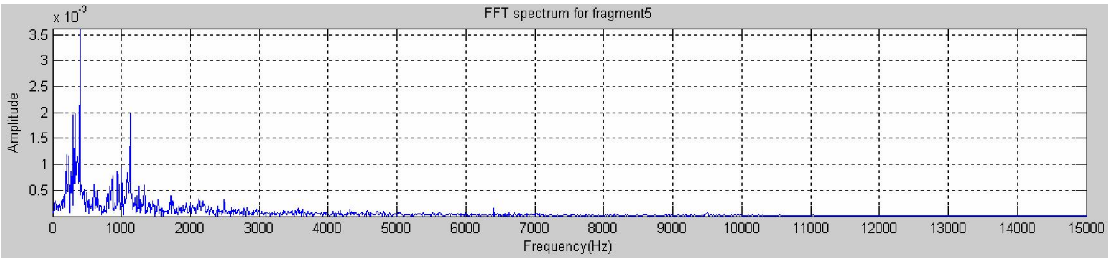
(e-1)


FFT spectrum for fragment4
Amplitude
Frequency(Hz)

(e-2)


Original sound fragment5 for man's sound
Amplitude
time(s)

(f-1)



(f-2)

Figure 5-7. Time domain analysis of man's voice

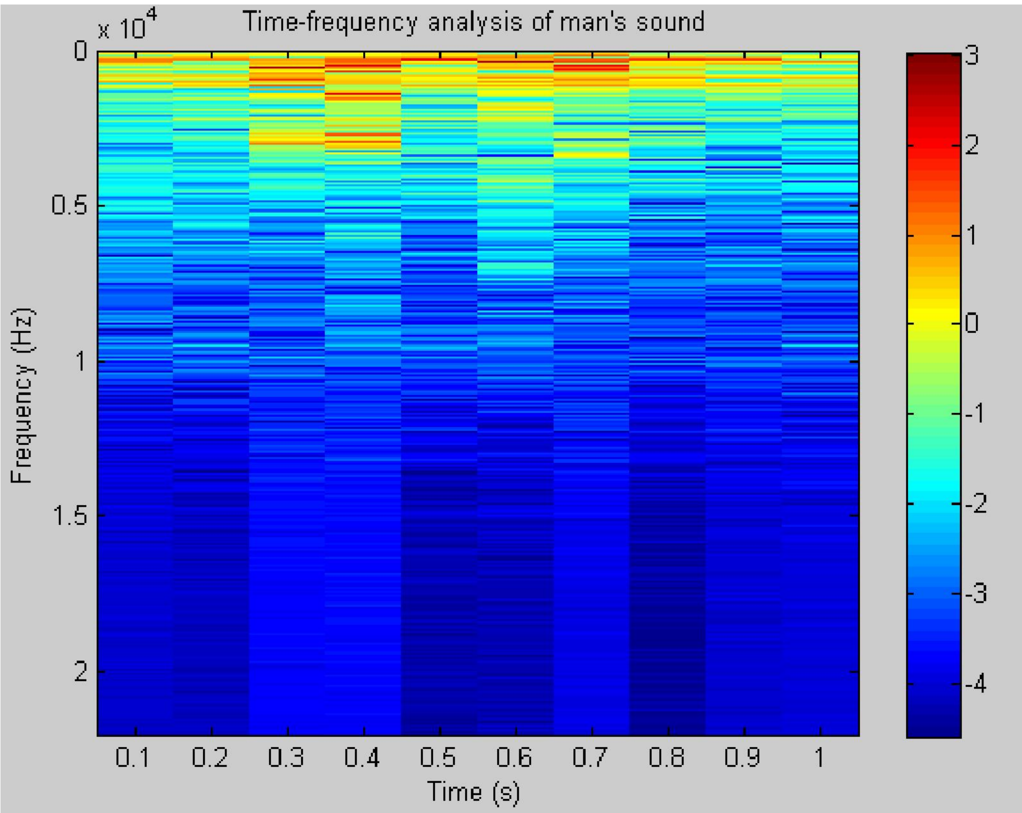
(a) 1 second time domain analysis of man's sound

(b-1)-(f-1) 100ms time domain analysis abstracted from (a)

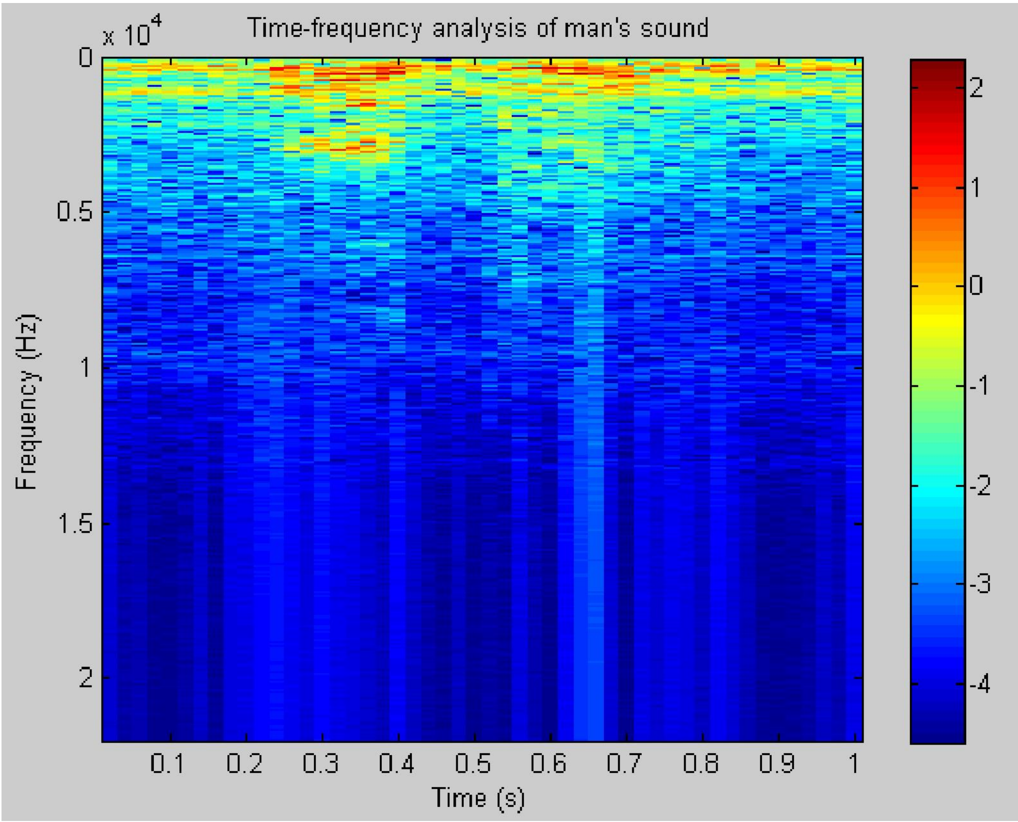
(b-2)-(f-2) 100ms frequency domain analysis of (b-1)-(f-1) respectively

Figure 5-8 below shows the two dimension time-frequency figure of man's voice. It is quite different from Figure 5-8(a) to Figure 5-8(b). From these two figures, we can see how important a proper time window size is. So if we choose 100ms window size as the stationary milling sound when analyzing human's voice, it is possible the result in human sound analysis would be incorrect.

We can see from Figure 5-8(b) that the energy of man's voice is gathered in the low frequency areas below 2000Hz in most of the situation. Thus, we could do some further research in the low frequency intervals to analyze man's voice in the coming part 5.3.2.



(a)



(b)

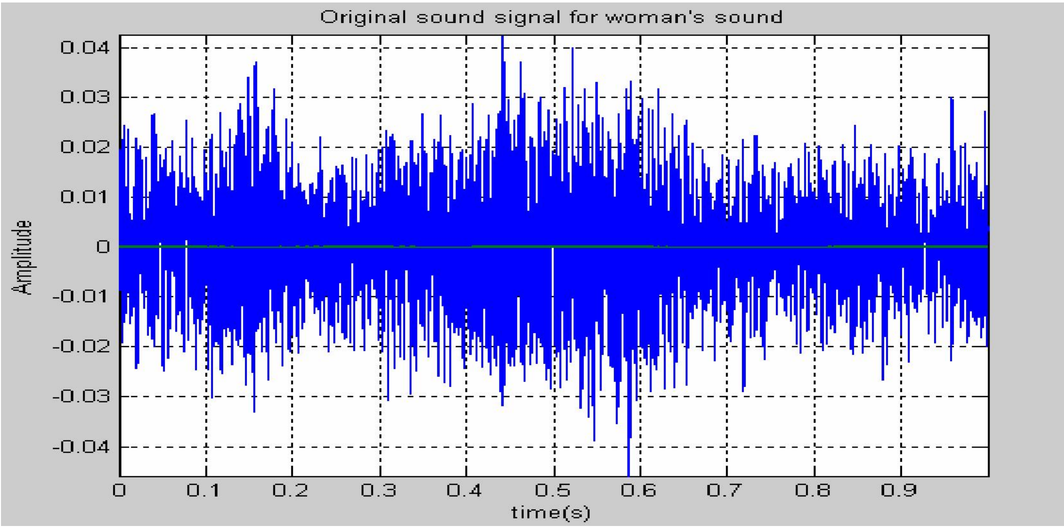
Figure 5-8. Time-frequency analysis of man's sound

(a) Time window size 100ms

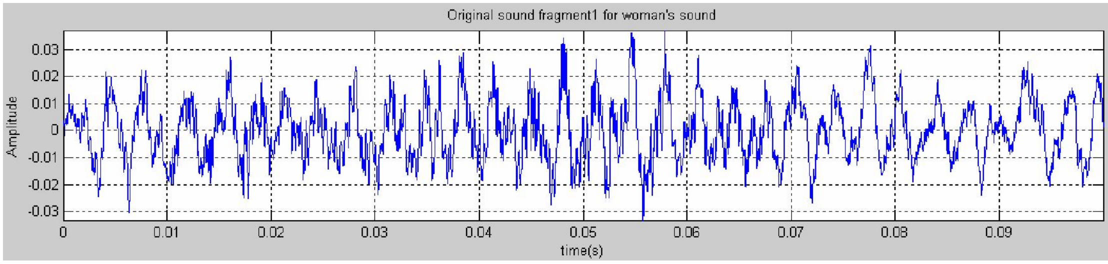
(b) Time window size 20ms

2) Characteristics analysis of women’s sound

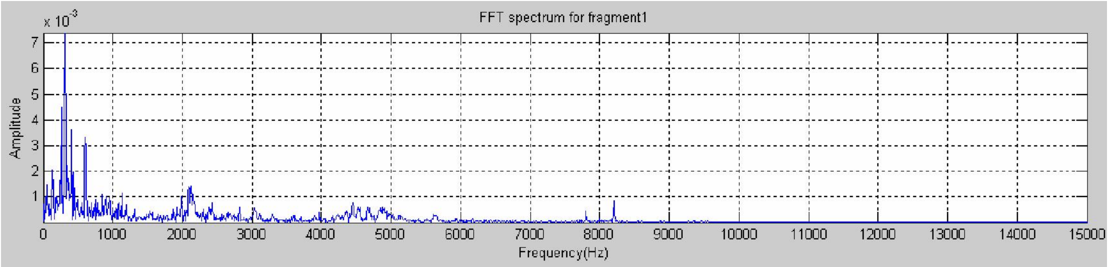
Like men’s sound, women’s sound is also not stationary in 1 second time period, which has several peak intervals. Here, we abstract this 1 second woman’s voice from file21 in the 836th second. By using Audacity, the word said during this second can be identified as “they stop”. So here it is probably two voice peaks in Figure 5-9(a). This difference can also be detected through time domain analysis as well as corresponding frequency domain analysis using 100ms window size shown from all the 10 figures from Figure 5-9(b-1) to Figure 5-9(f-2). Thus, it is improper to analyze woman’s voice by using 100ms time window size just like milling machine sound as well. While analyzing women’s sound, time window size should be adjusted to 20ms as well, but not 100ms as we suggested above in part 5.1.



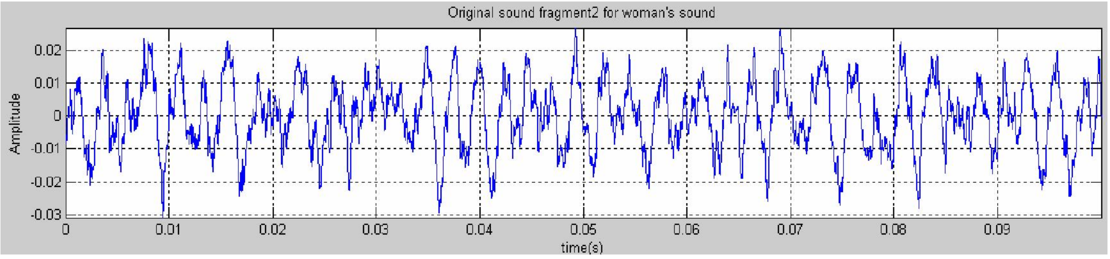
(a)



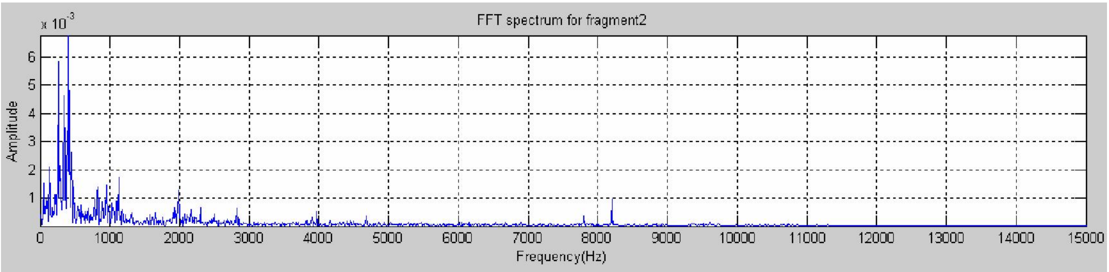
(b-1)


FFT spectrum for fragment1
x 10^-3
Amplitude
Frequency(Hz)

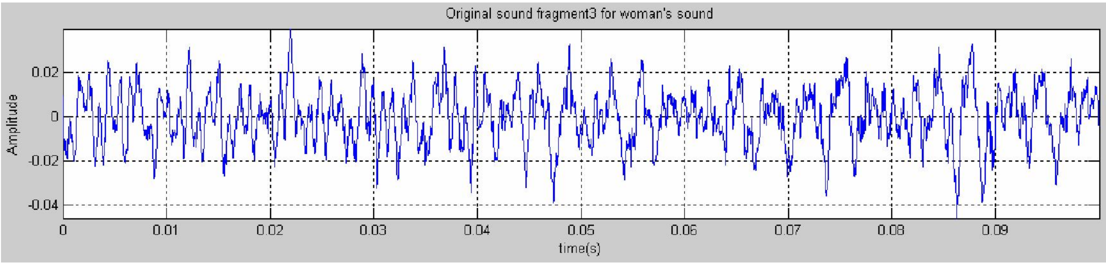
(b-2)


Original sound fragment2 for woman's sound
Amplitude
time(s)

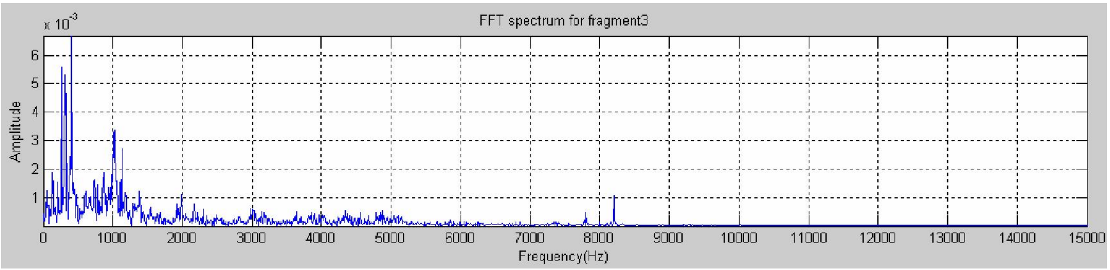
(c-1)


FFT spectrum for fragment2
x 10^-3
Amplitude
Frequency(Hz)

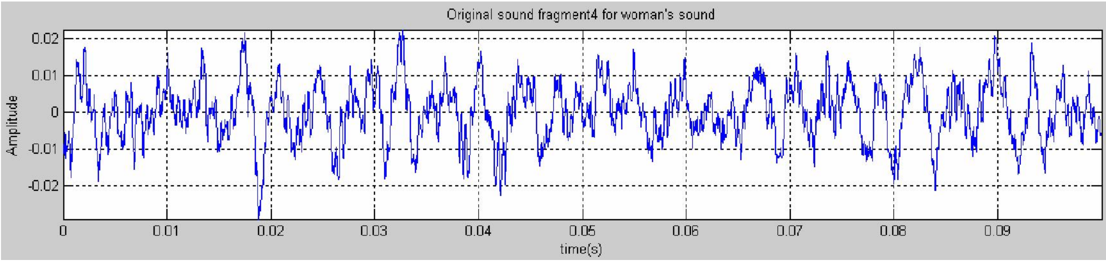
(c-2)


Original sound fragment3 for woman's sound
Amplitude
time(s)

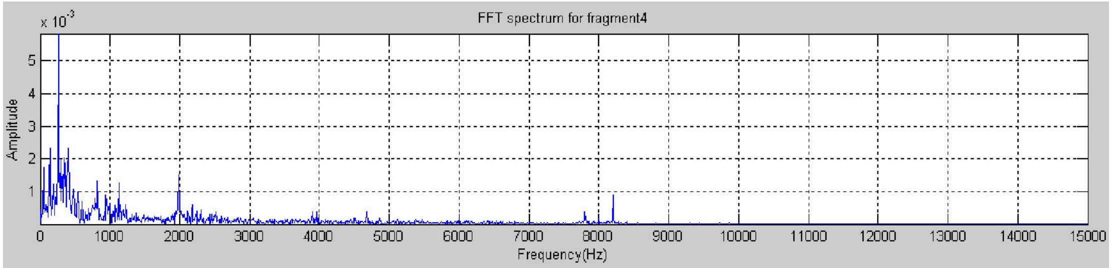
(d-1)


FFT spectrum for fragment3
x 10^-3
Amplitude
Frequency(Hz)

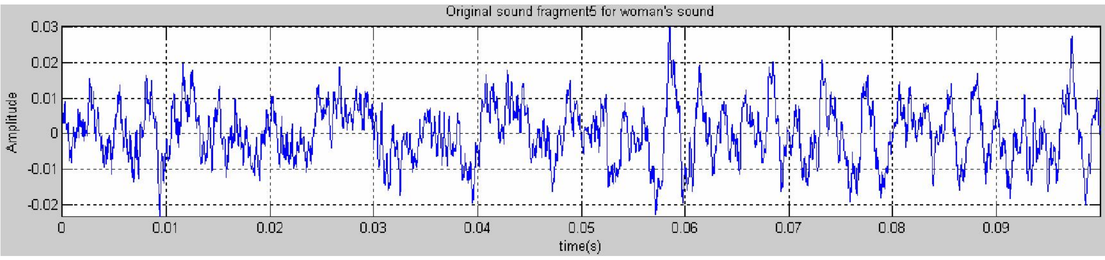
(d-2)



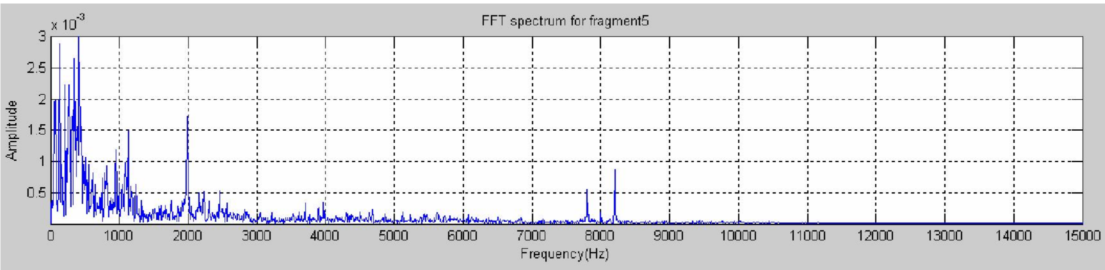
(e-1)



(e-2)



(f-1)



(f-2)

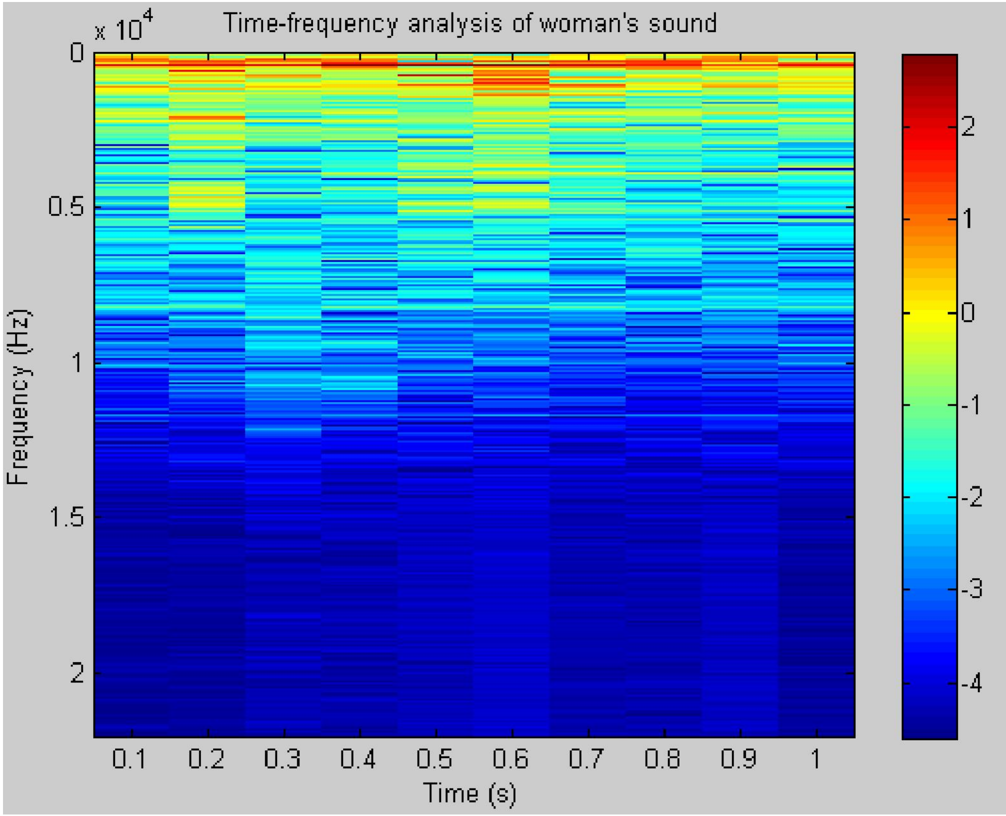
Figure 5-9. Analysis of woman's voice. (a)

(a) 1 second time domain analysis of woman's sound

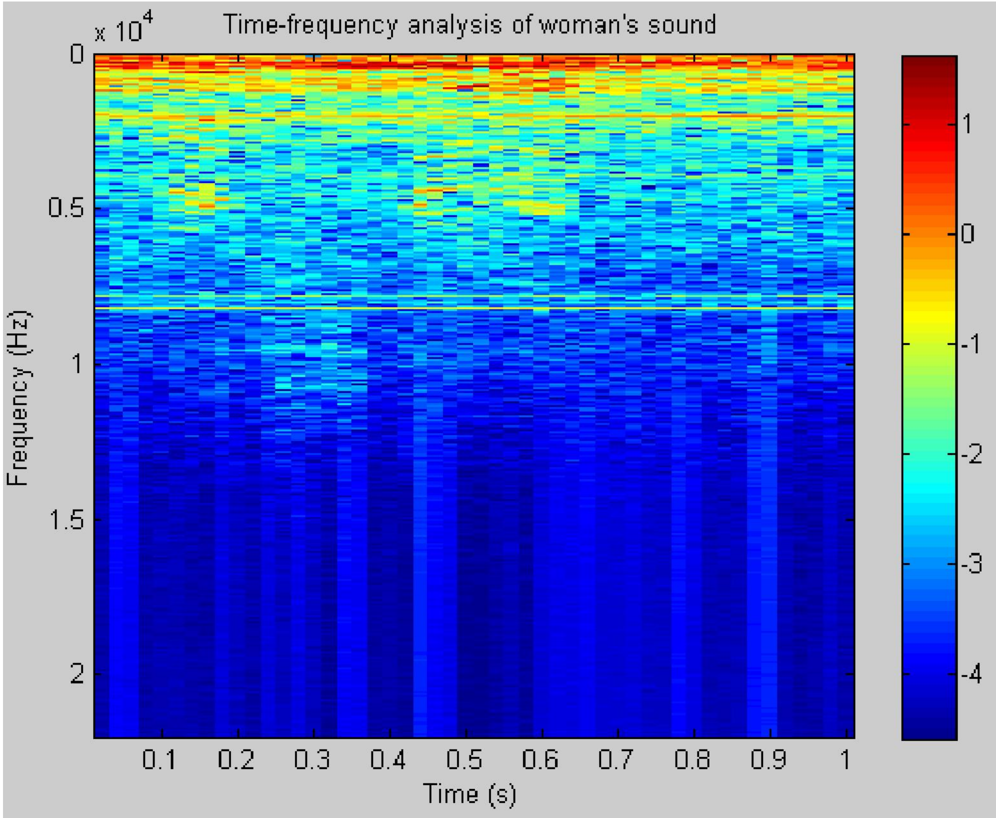
(b-1)-(f-1) 100ms time domain analysis abstracted from (a)

(b-2)-(f-2) 100ms frequency domain analysis of (b-1)-(f-1) respectively

Figure 5-10 is the two dimension time-frequency analysis of woman's sound. Like man's voice, it is different to analyze it from using 100ms time window size to 20ms time window size. So as we discussed above, a suitable time window size is important in analyzing. And the energy of woman's voice is also high in low frequencies below 2000Hz, which we will do the further analysis in part 5.3.2.



(a)



(b)

Figure 5-10. Time-frequency analysis of woman's sound

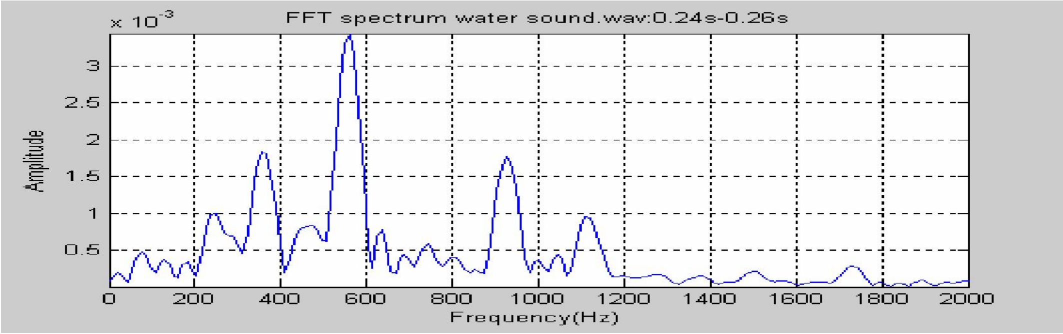
(a) Time window size 100ms

(b) Time window size 20ms

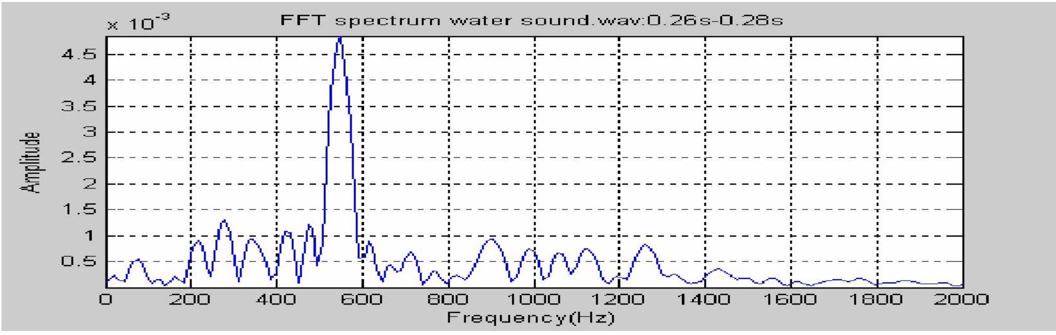
5.3.2. Low Frequency analysis of human sound

1) Frequency domain analysis of men's sound

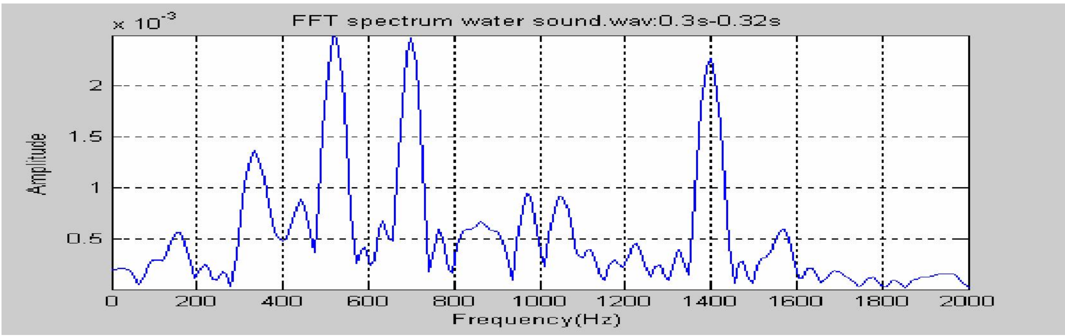
The following figures just show the frequency intervals of men. We abstract several of the figures in a special time period to see how it is. And from all these figures, we could include man's sound frequency interval to 400-600 Hz, 600-800 Hz and somehow around 1400Hz.


FFT spectrum water sound.wav:0.24s-0.26s
x 10^-3
Amplitude
Frequency(Hz)

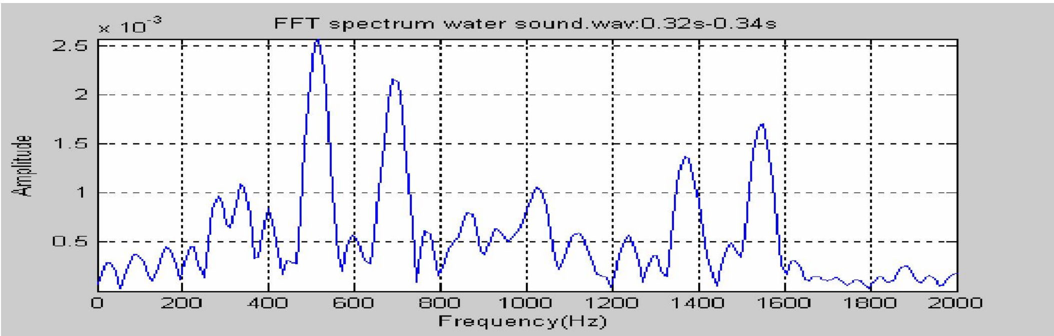
(a)


FFT spectrum water sound.wav:0.26s-0.28s
x 10^-3
Amplitude
Frequency(Hz)

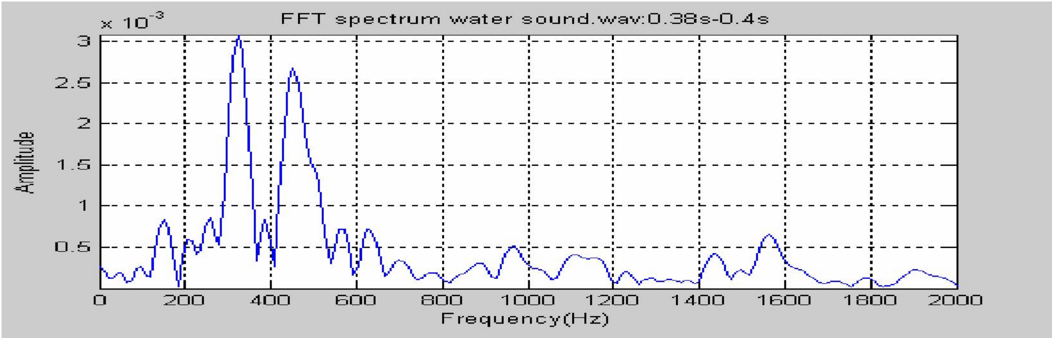
(b)


FFT spectrum water sound.wav:0.3s-0.32s
x 10^-3
Amplitude
Frequency(Hz)

(c)


FFT spectrum water sound.wav:0.32s-0.34s
x 10^-3
Amplitude
Frequency(Hz)

(d)

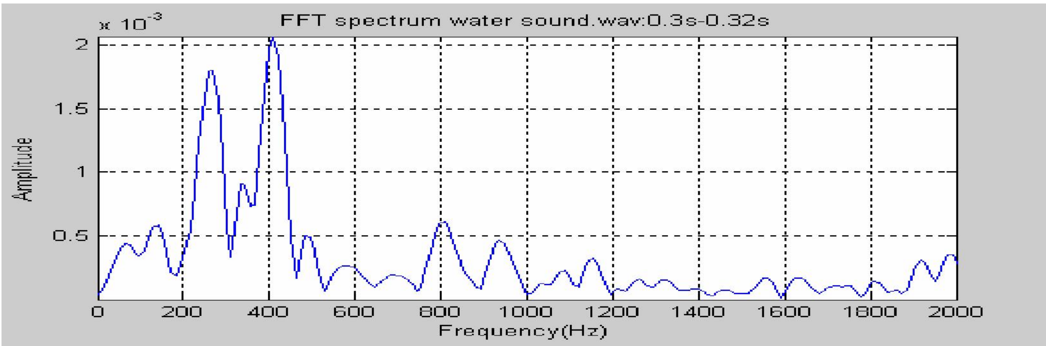


(e)

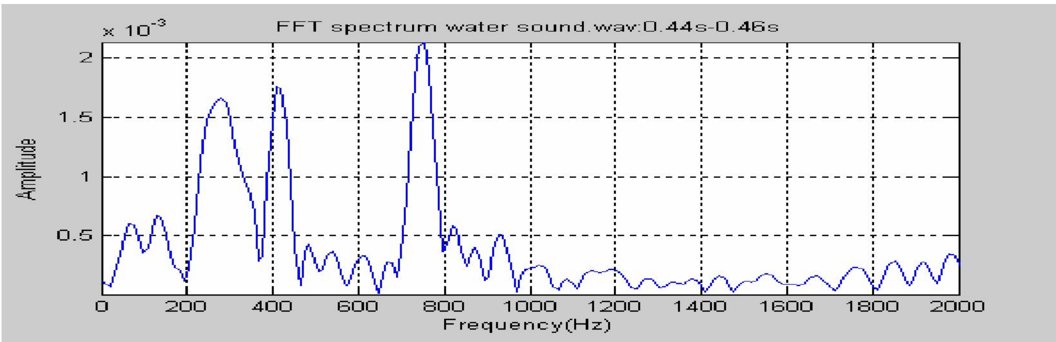
Figure 5-11. Man’s sound frequencies

2) Frequency domain analysis of women’s sound

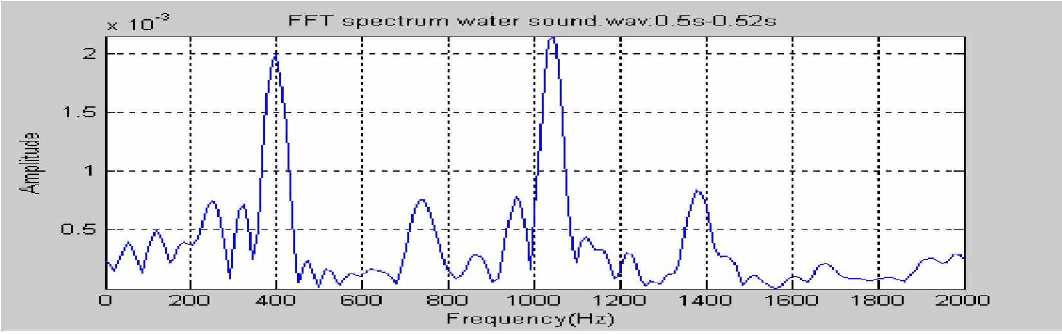
The figures below illustrate the features of women’s voice. The human voice frequencies are changed from time to time, so we could see from the figures that women’s voice frequencies are mainly in 200-400Hz, 400-600Hz, 600-800Hz, and also the frequency peak is changed a lot in 1000-1200Hz in Figure 5-12. It is wider than the frequency bands in man’s voice.



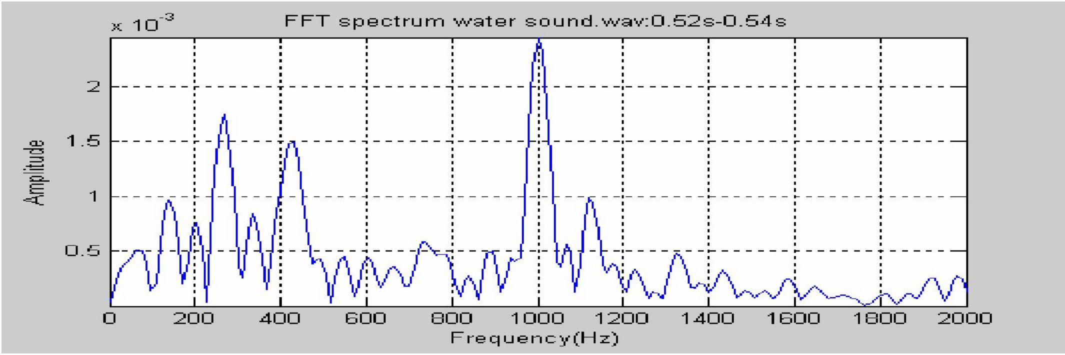
(a)



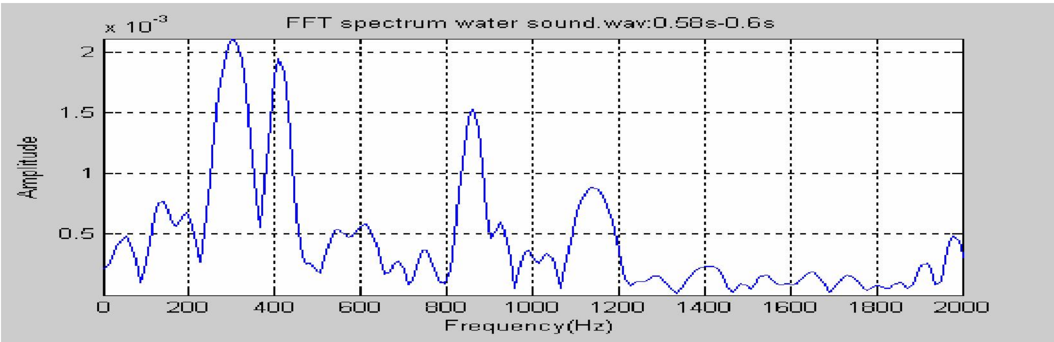
(b)



(c)



(d)



(e)

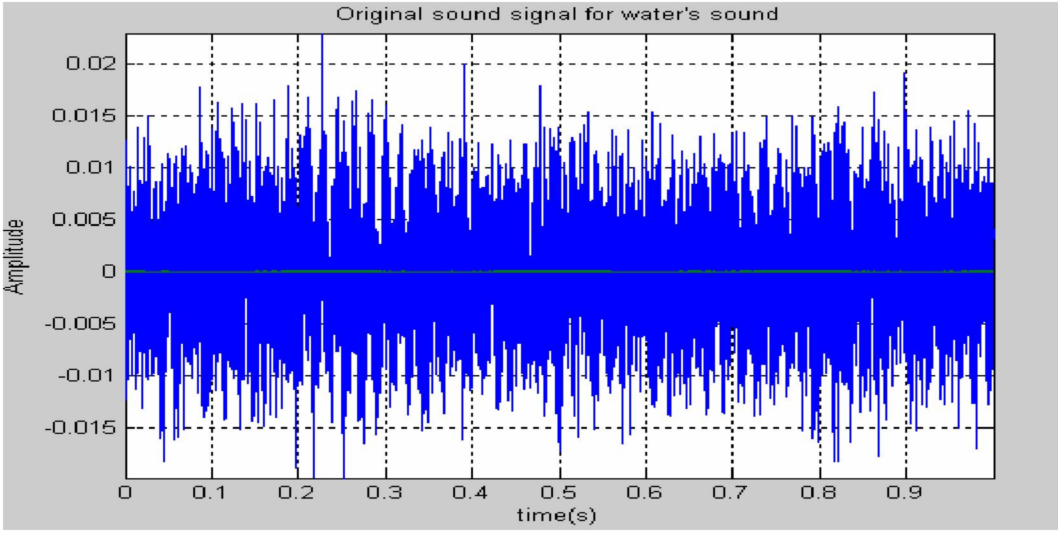
Figure 5-12. Woman's sound frequencies

5.4. Characteristics of sound of cooling water

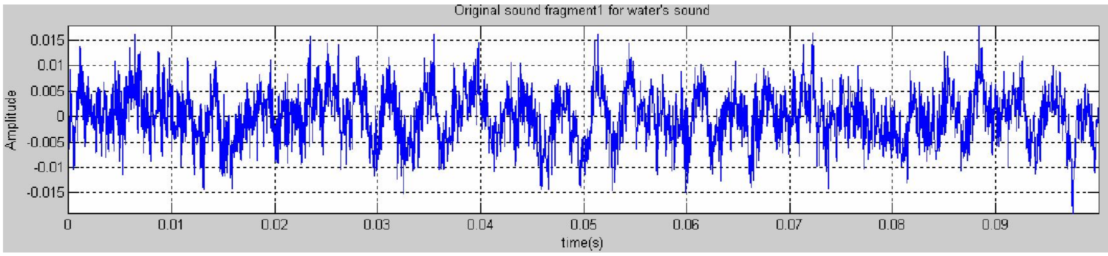
For there is water sound all through the milling process which is needed to cool down hot work piece, the water sound should also be analyzed here so that we could not mistake the frequencies of the water as the indication of the cutting tool has been worn out. And also we should design the corresponding filters to filter out the interference and focus on the sound of the milling machine itself.

5.4.1. Analysis of characteristics

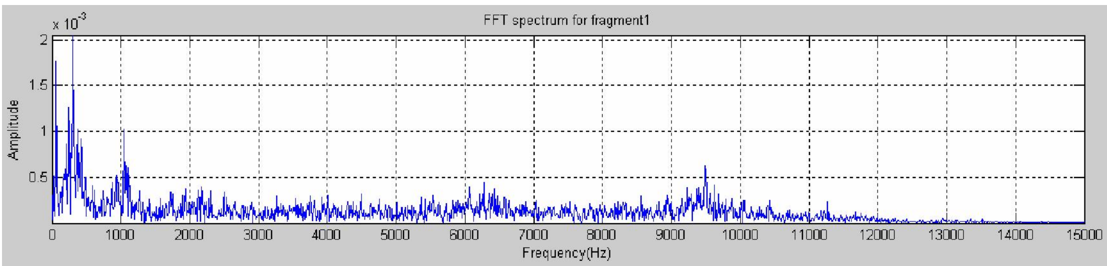
From Figure 5-13 we can see the sound from the sprinkling water used to cool down the work piece is stationary in 1 second time domain. The five different 100ms time window size figures look all similar to each other, which can be considered that the sound signal of the cooling water is stationary sound signal. So 100ms time window size for frequency domain analysis of the water is definitely ok here.



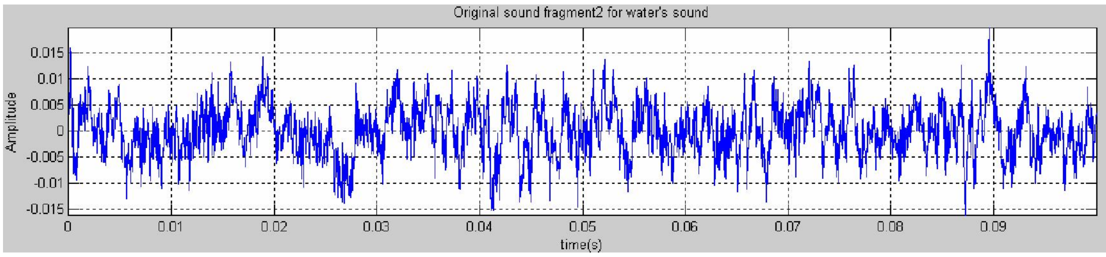
(a)



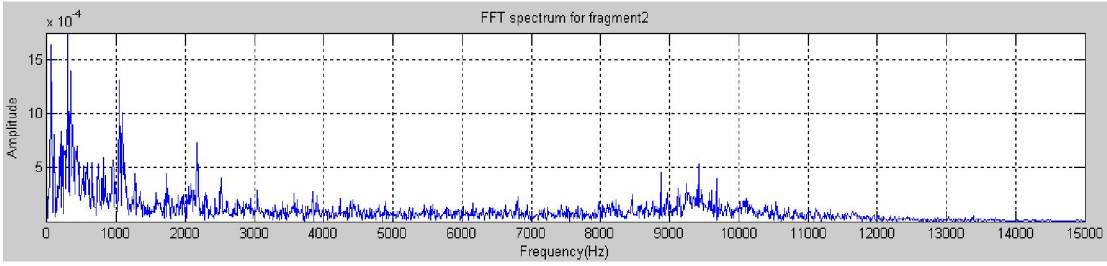
(b-1)



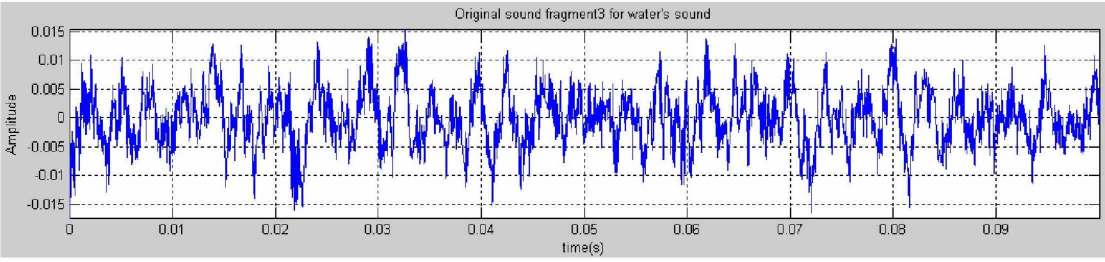
(b-2)


Original sound fragment2 for water's sound
Amplitude
time(s)

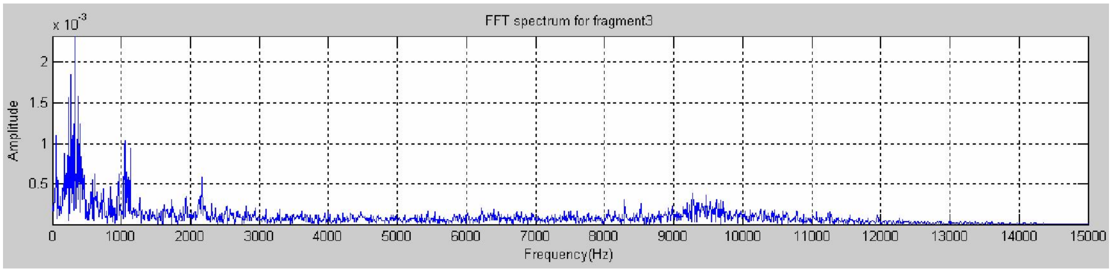
(c-1)


FFT spectrum for fragment2
x 10^-4
Amplitude
Frequency(Hz)

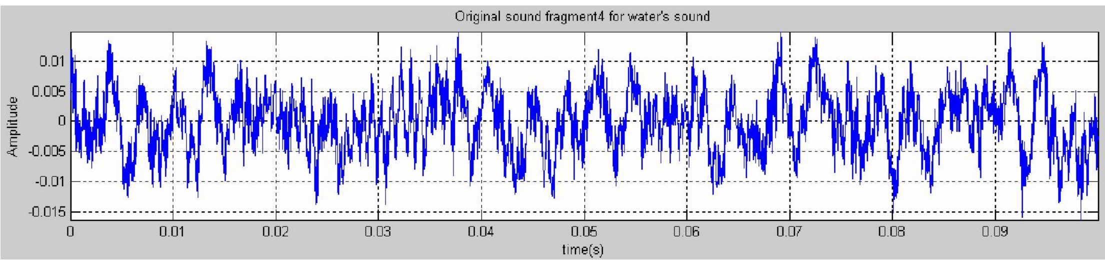
(c-2)


Original sound fragment3 for water's sound
Amplitude
time(s)

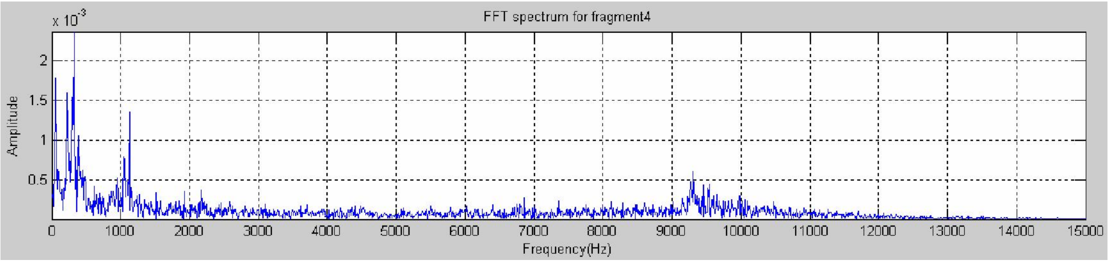
(d-1)


FFT spectrum for fragment3
x 10^-3
Amplitude
Frequency(Hz)

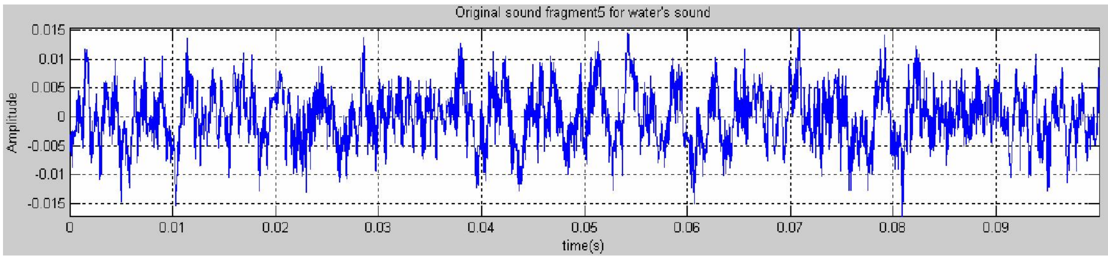
(d-2)


Original sound fragment4 for water's sound
Amplitude
time(s)

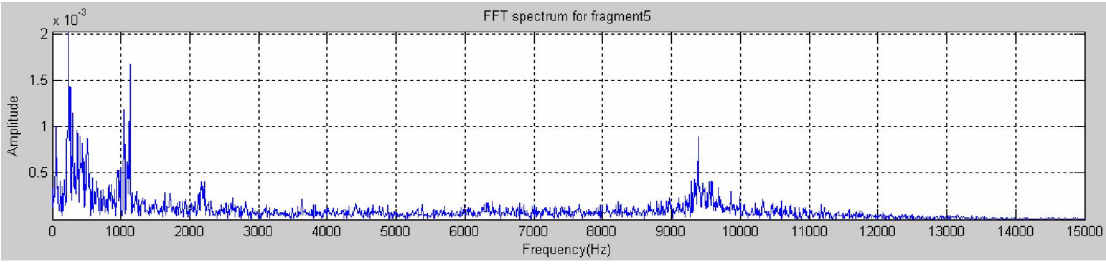
(e-1)



(e-2)



(f-1)



(f-2)

Figure 5-13. Time domain analysis of cooling water

(a) 1 second time domain analysis of water's sound

(b-1)-(f-1) 100ms time domain analysis abstracted from (a)

(b-2)-(f-2) 100ms frequency domain analysis of (b-1)-(f-1) respectively

From Figure 5-13(b-2), (c-2), (d-2), (e-2) and (f-2), we can see that the energy of the cooling water sound appears mainly from 0Hz to 1500Hz as well as 9000Hz to 10000Hz. Compared with the milling sound, they are both stationary sound signals, and both sound energy appear in high frequencies, though there are some overlaps of frequency regions from these two sound signals, there are still existing different frequency regions between these two signals, which are good for us to filter out the interferences and picking out the useful signal of milling process itself to analyze.

Still, in order to show more clearly features of the cooling water sound signal, the two dimension time-frequency figure is done to show more information. The analyzed result is shown as following in Figure 5-14. We can see from Figure 5-14 that though there is some energy appearing in the high frequency, the main energy is still accumulating in low frequencies below 2000Hz. So it is necessary to pick out the low frequency intervals to do the further analysis in the coming part 5.4.2.

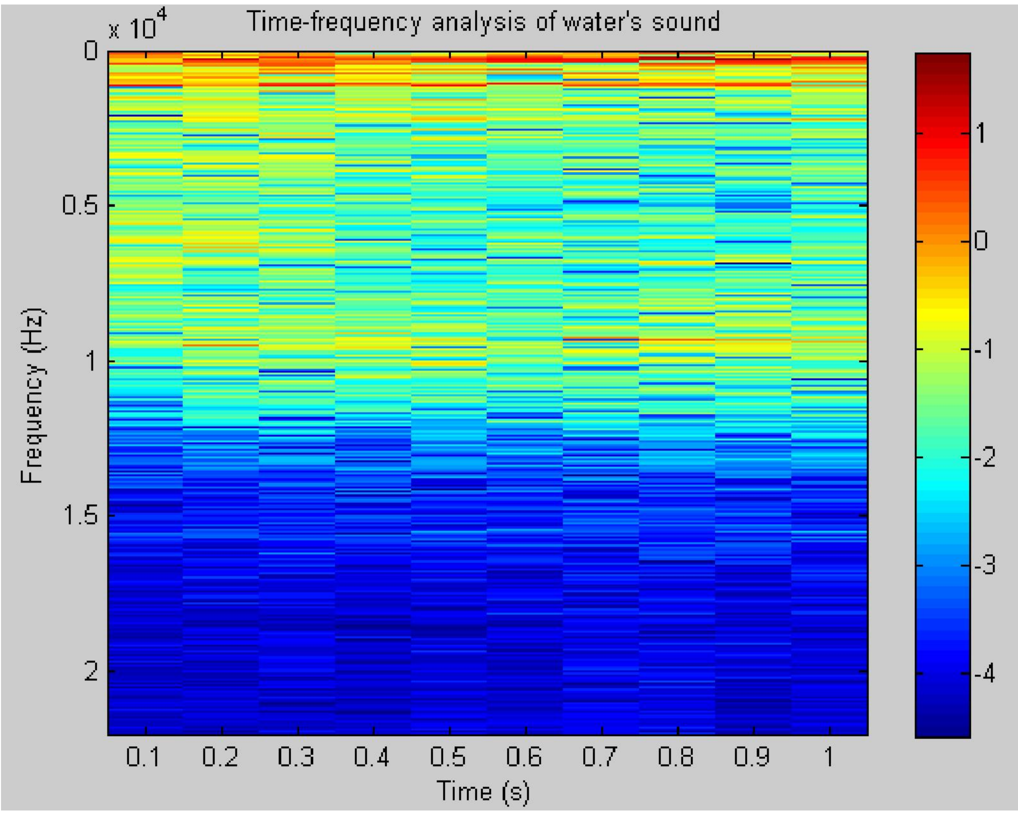
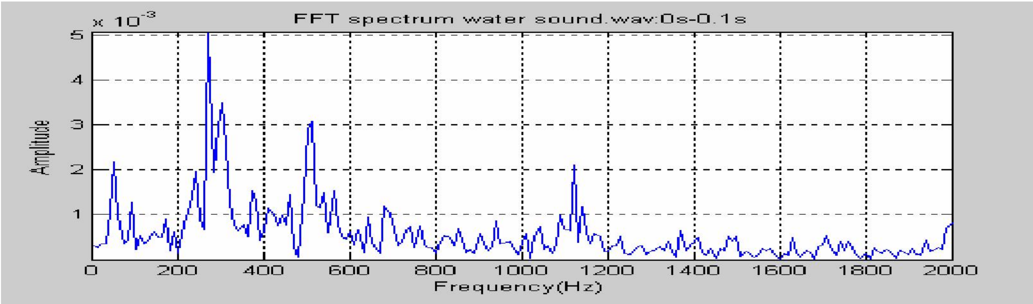


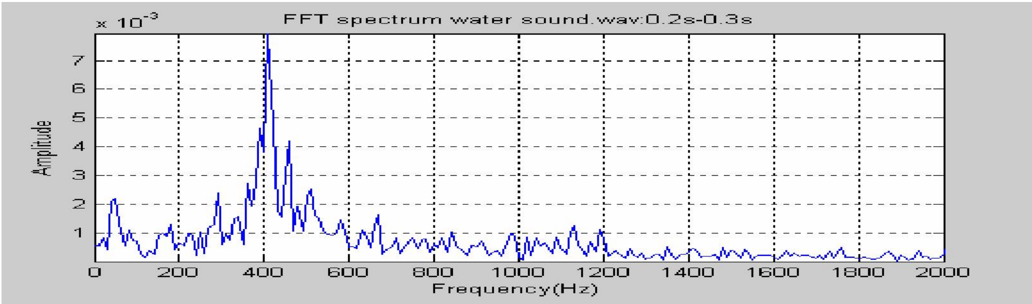
Figure 5-14. Time-frequency analysis of water's sound

5.4.2. Low frequency analysis

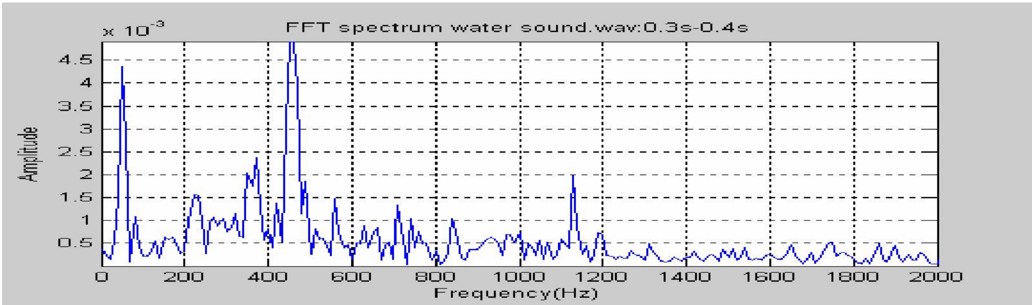
The following is the figures which demonstrate the frequency intervals of the water sound. From the figures picked, we could see that the frequencies of the water are mainly in 0 -200 Hz, 200 -400 Hz, 400 -600 Hz which are also somehow overlapped with the human's sound.


FFT spectrum water sound.wav:0s-0.1s
x 10^-3
Amplitude
Frequency(Hz)

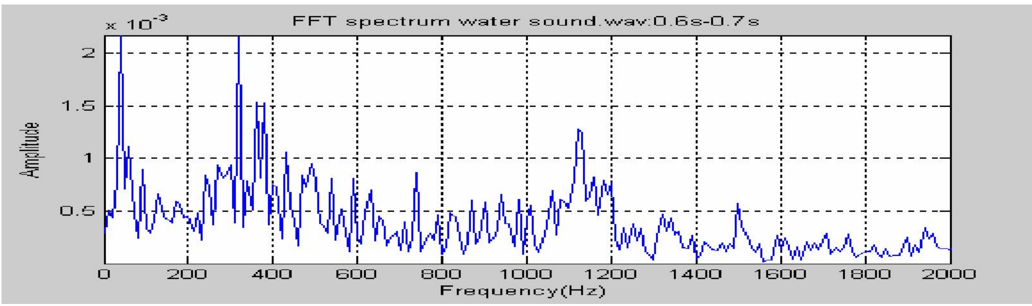
(a)


FFT spectrum water sound.wav:0.2s-0.3s
x 10^-3
Amplitude
Frequency(Hz)

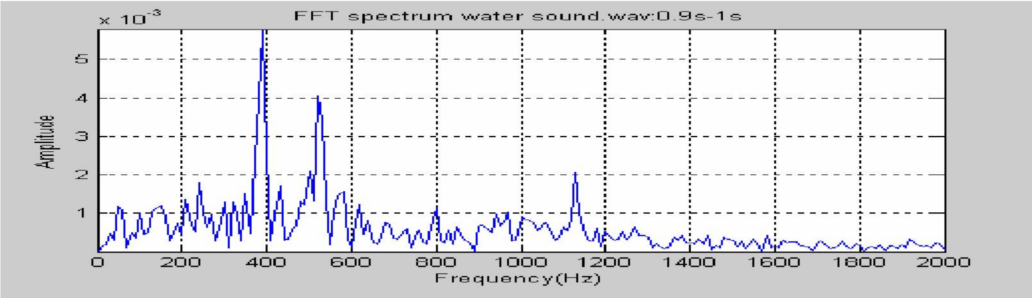
(b)


FFT spectrum water sound.wav:0.3s-0.4s
x 10^-3
Amplitude
Frequency(Hz)

(c)


FFT spectrum water sound.wav:0.6s-0.7s
x 10^-3
Amplitude
Frequency(Hz)

(d)



(e)

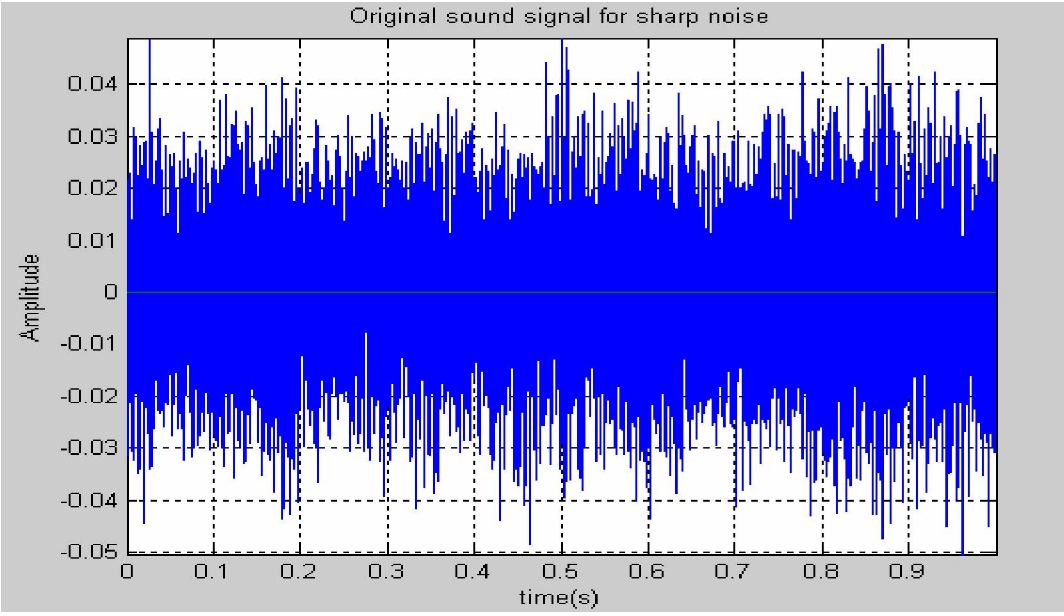
Figure 5-15. Sound frequencies of water

5.5. Characteristics of sound of the sharp noise from outside

The milling machine is put in the factory which produces the whole propeller, and hub body is a part of the propeller of the ship. So we can image that there would be a lot of working interference during the hub body is processed. And since the microphone was just put outside the working cabin, the sharp cutting metal noises from the factory will be also collected into the sound files. Thus, we have to separate the sharp noises out to analyze it and see what its time and frequency figures look like. Then we could fix it with some kind of filters to filter out this kind of interference from the factory.

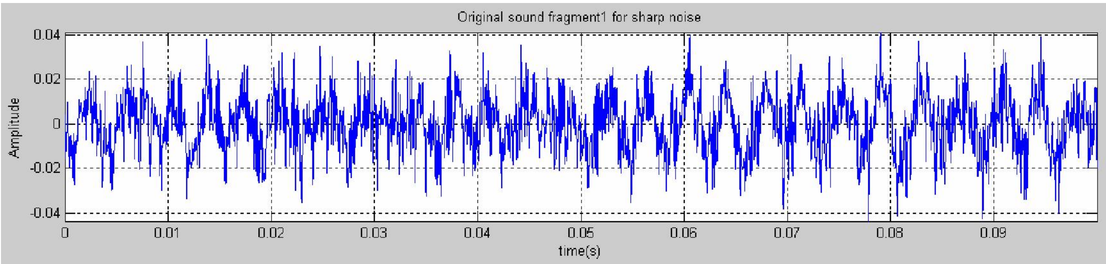
5.5.1. Analysis of characteristics

It is same when looking at the time domain analyzing figures of the sharp noise outside the milling cabin, which shows as Figure 5-16 below. It can be found that sound from the sharp noise is also stationary in both time domain and frequency analysis, which proves that 100ms time window size is good enough for analyzing sound of the sharp noise in the frequency domain as well.



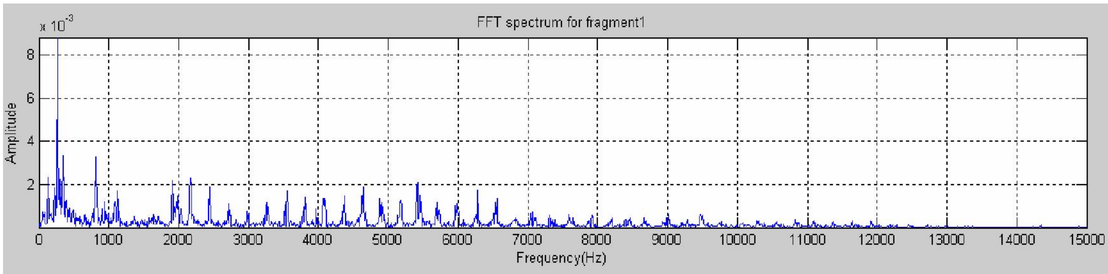
Original sound signal for sharp noise
Amplitude
time(s)

(a)



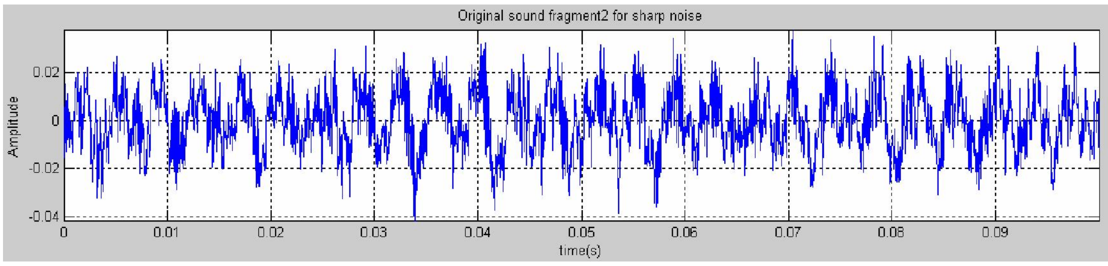
Original sound fragment1 for sharp noise
Amplitude
time(s)

(b-1)



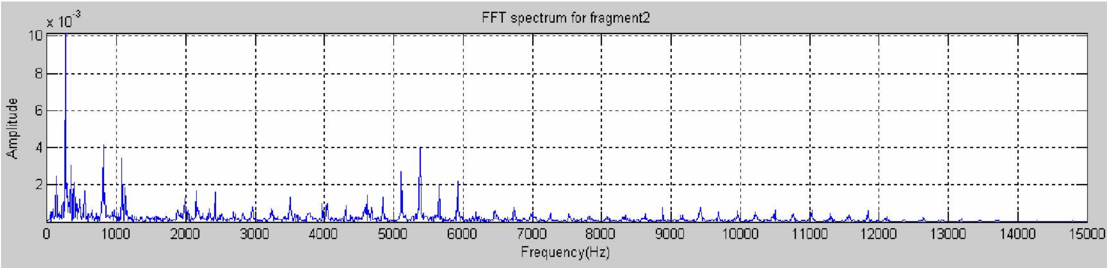
FFT spectrum for fragment1
Amplitude
Frequency(Hz)

(b-2)

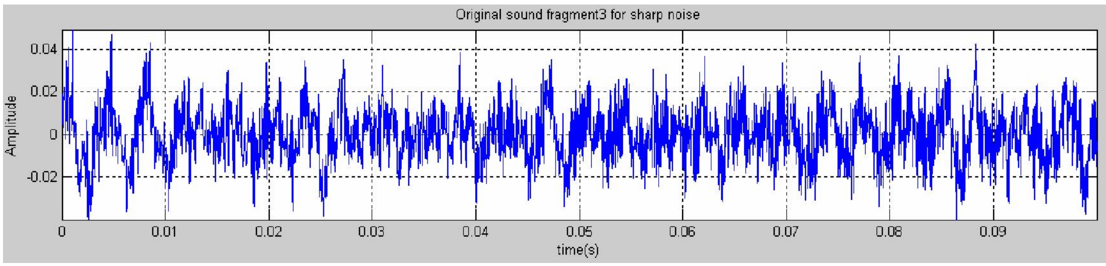


Original sound fragment2 for sharp noise
Amplitude
time(s)

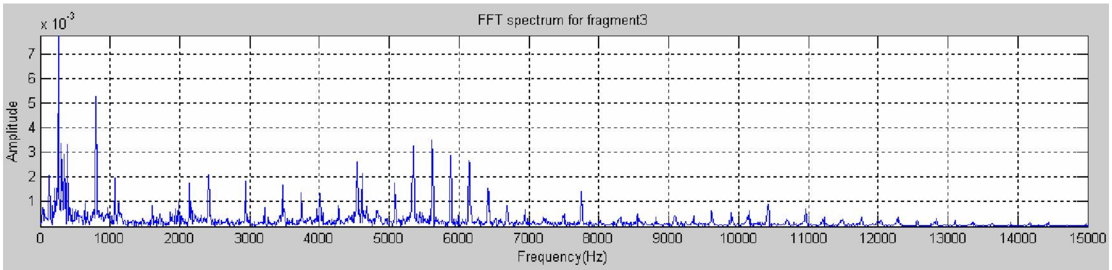
(c-1)


FFT spectrum for fragment2
x 10-3
Amplitude
Frequency(Hz)

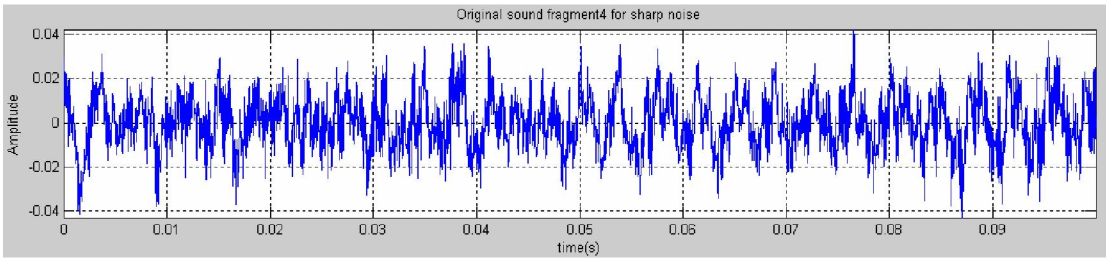
(c-2)


Original sound fragment3 for sharp noise
Amplitude
time(s)

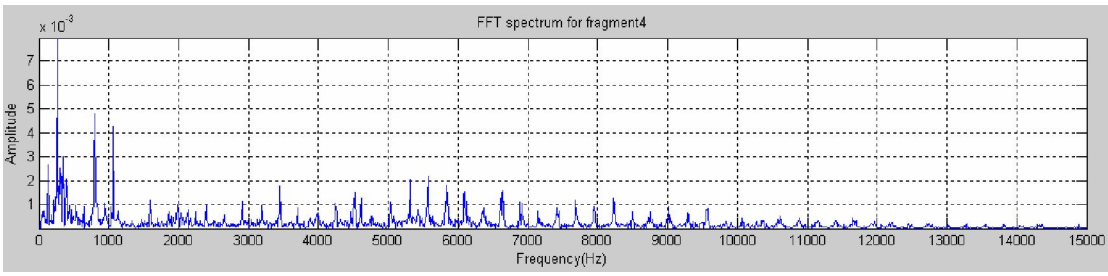
(d-1)


FFT spectrum for fragment3
x 10-3
Amplitude
Frequency(Hz)

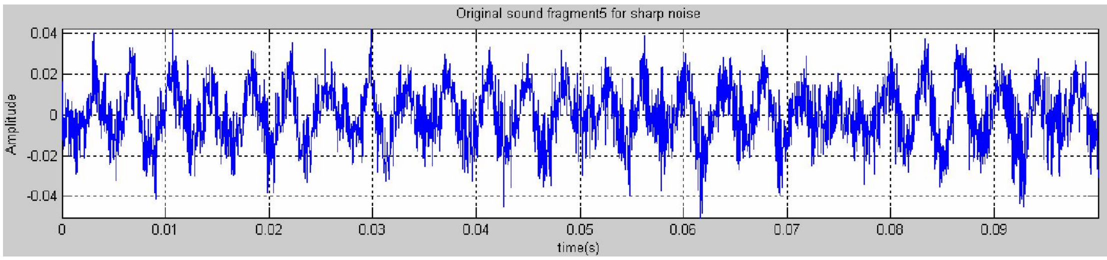
(d-2)


Original sound fragment4 for sharp noise
Amplitude
time(s)

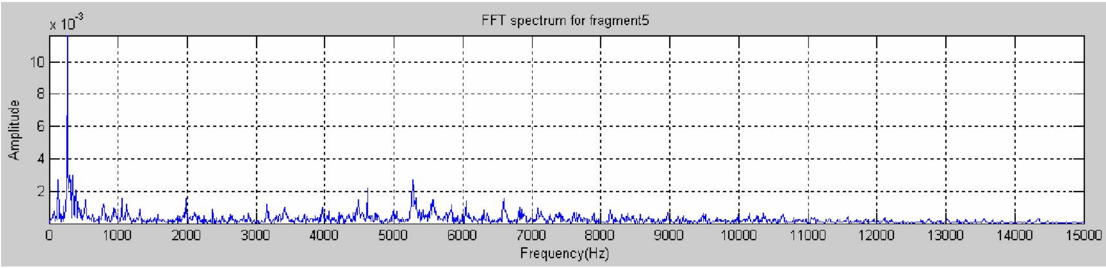
(e-1)


FFT spectrum for fragment4
x 10-3
Amplitude
Frequency(Hz)

(e-2)



(f-1)



(f-2)

Figure 5-16. Time domain analysis of sharp noise

(a) 1 second time domain analysis of sharp noise

(b-1)-(f-1) 100ms time domain analysis abstracted from (a)

(b-2)-(f-2) 100ms frequency domain analysis of (b-1)-(f-1) respectively

It is obvious from Figure 5-16(b-2), (c-2), (d-2), (e-2) and (f-2) that energy distribution of the sharp noise is quite special and different from both milling sound signal and cooling water sound signal discussed above, though they are all stationary sound signals. Energy of the sharp noise is spread all over the frequency domain to around 10000Hz. It is significant from 0Hz to 1200Hz and 5000Hz to 6000Hz. In the high frequency areas, the main frequency intervals for the sharp noise are still a bit different from both milling sound signal and cooling water signal.

Figure 5-17 below gives us an overview of the sharp noise in the two-dimension time frequency figure, from which we can see energy of the sharp noise is all over the frequency area till around 10000Hz. This feature here is different from the signals analyzed above, though energy in low frequencies is still a little stronger than it in high frequencies.

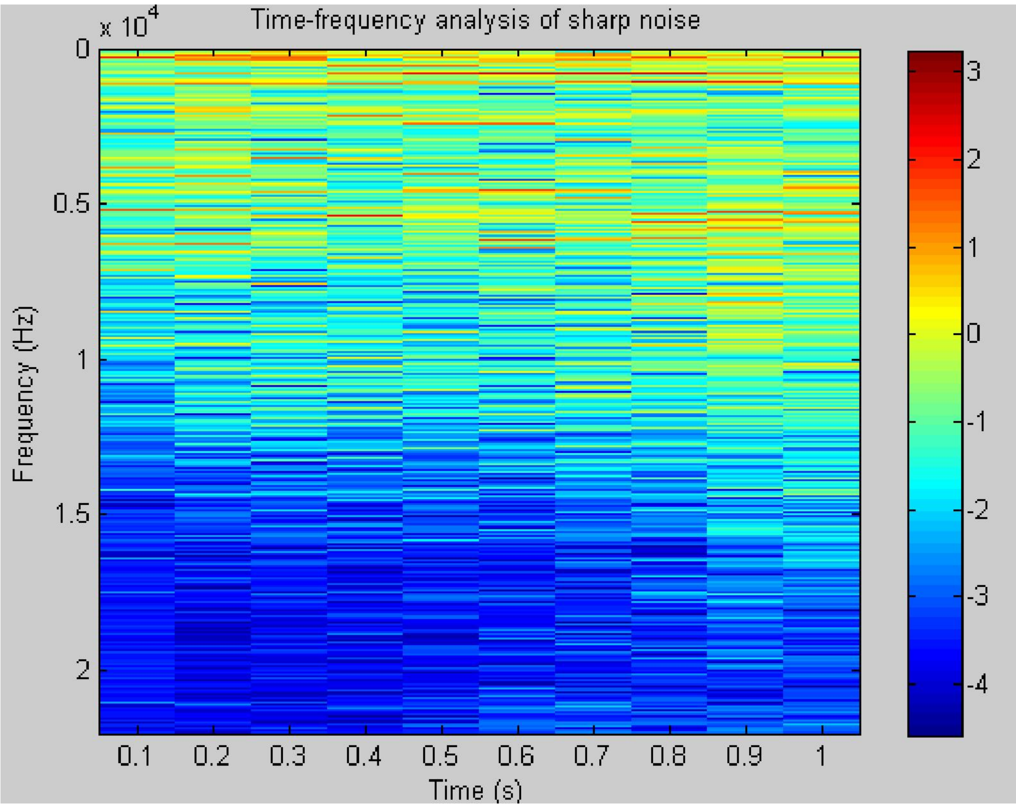
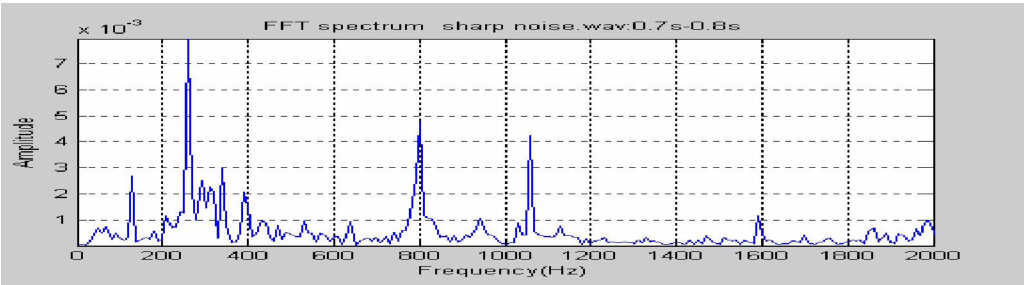


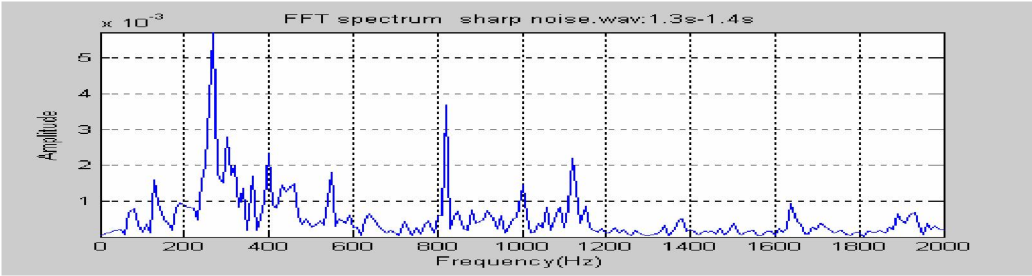
Figure 5-17. Time-frequency analysis of sharp noise

5.5.2. Low frequency analysis

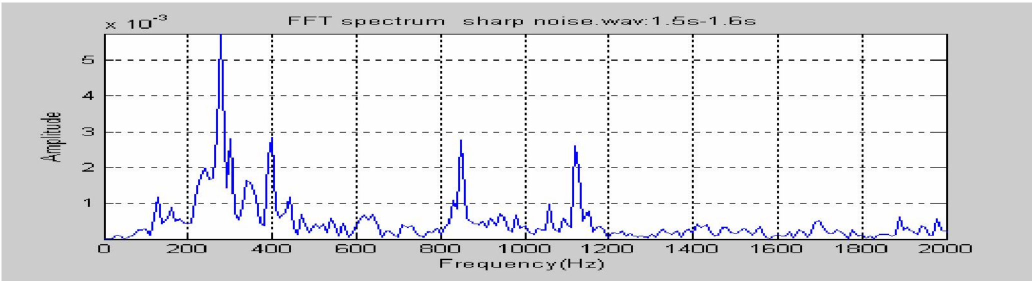
From the figures we abstract out from the analysis, we could see that the main frequency interval is in 200-400 Hz, 400-600 Hz, 800-1000Hz, and also the frequency changes significantly during 1800-2000Hz in the last two figures as we can see.



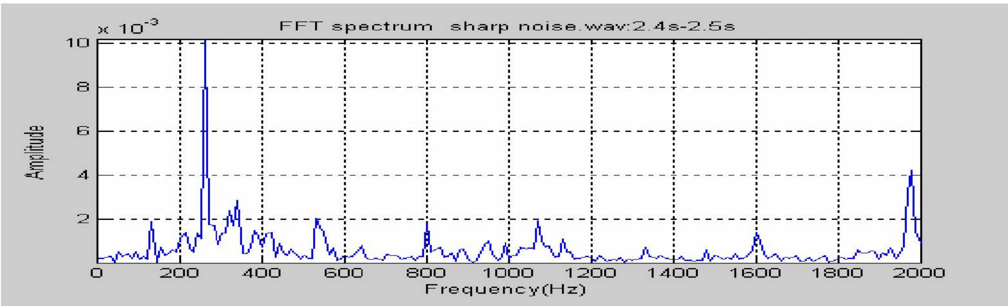
(a)



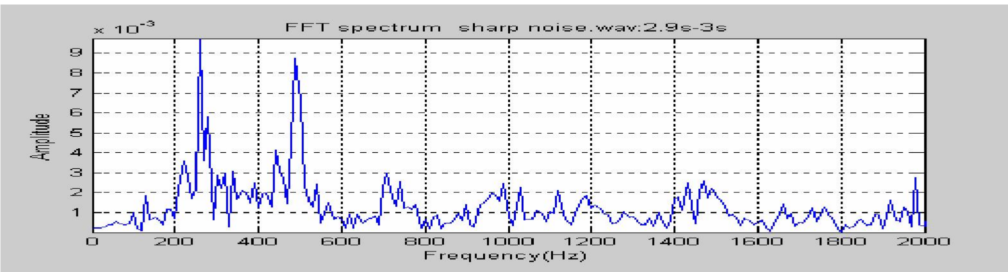
(b)



(c)



(d)



(e)

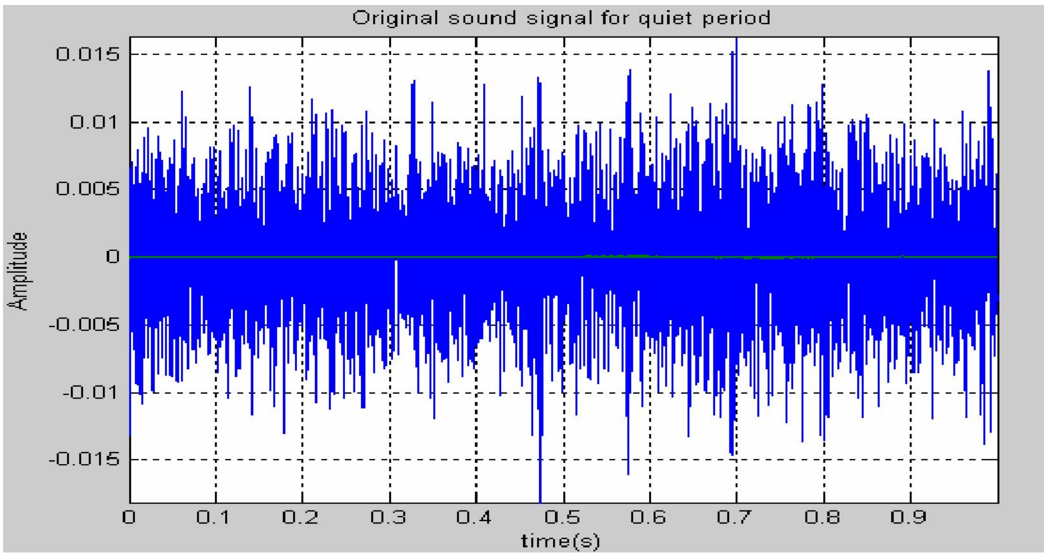
Figure 5-18. Sound frequencies of sharp noise

5.6. Noise coming from the microphone itself

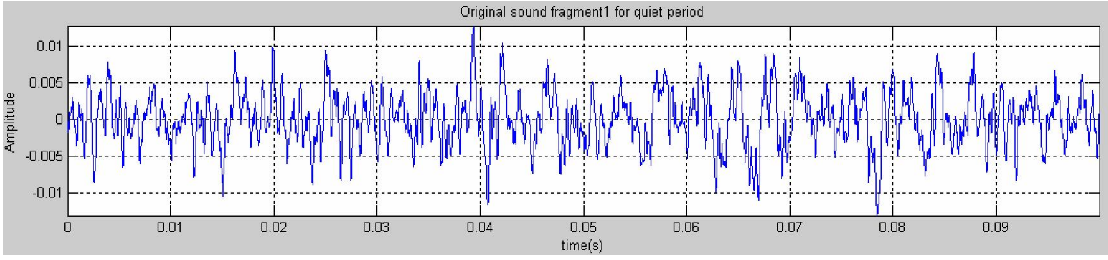
Since we just gathered the data using a normal microphone, the precision of microphone itself should also be considered. And I just tested the microphone by picking out the period in the sound files that have collected when the machine didn't work, for example during the lunch break, and there are no water sound, no human voices, no sharp noises and other kind of noises. In this case, we will see more clearly how the interference looks like in the microphone itself while it was working from both time and frequency domains.

5.6.1. Analysis of characteristics

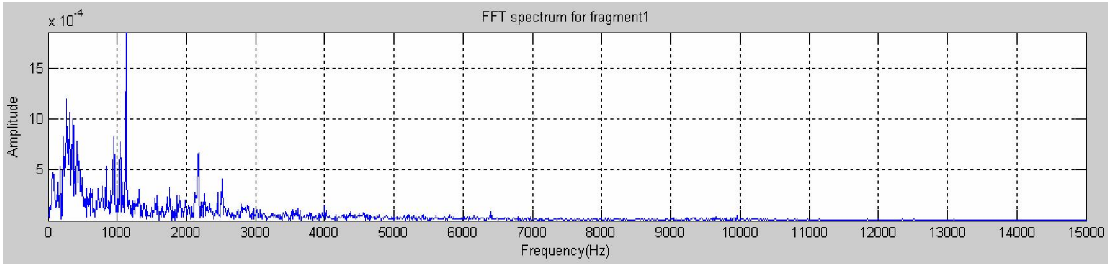
What comes next is the time domain analysis of the interference noise coming from the microphone which we used to collect all the data. From Figure 5-19, we can see the interference sound coming from the microphone is stationary. The five figures of 100ms time window size of time domain analysis are similar to each other, and the five figures of frequency domain analysis which are corresponding to the five ones of time domain analysis look similar as well. Thus 100ms is also suitable while analyzing in the frequency domain. Energy of this kind of noise appears mainly in low frequency areas below and around 1200Hz, which can be found in the frequency-amplitude figures below.



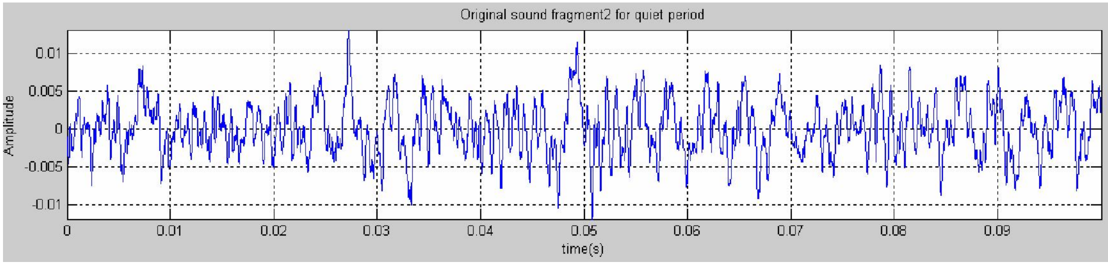
(a)


Original sound fragment1 for quiet period
Amplitude
time(s)

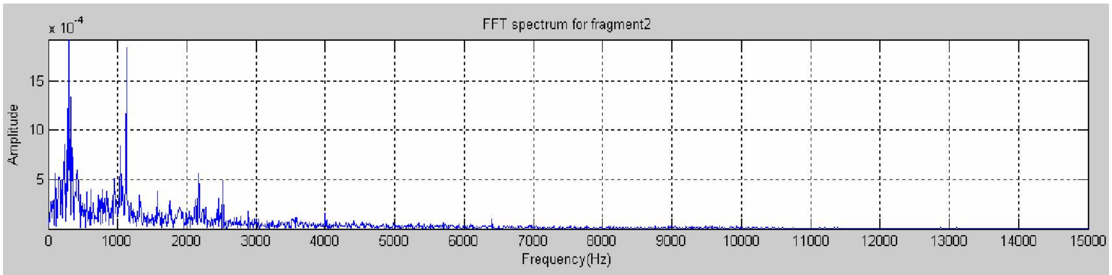
(b-1)


FFT spectrum for fragment1
Amplitude
Frequency(Hz)

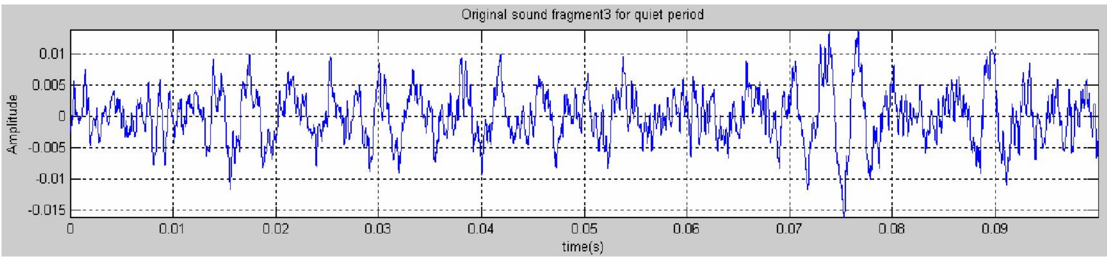
(b-2)


Original sound fragment2 for quiet period
Amplitude
time(s)

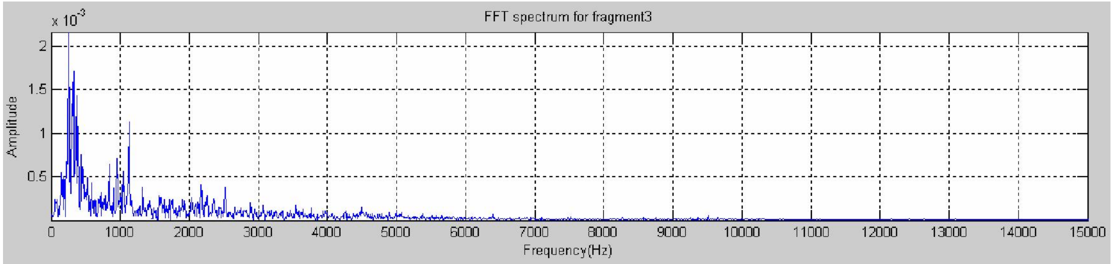
(c-1)


FFT spectrum for fragment2
Amplitude
Frequency(Hz)

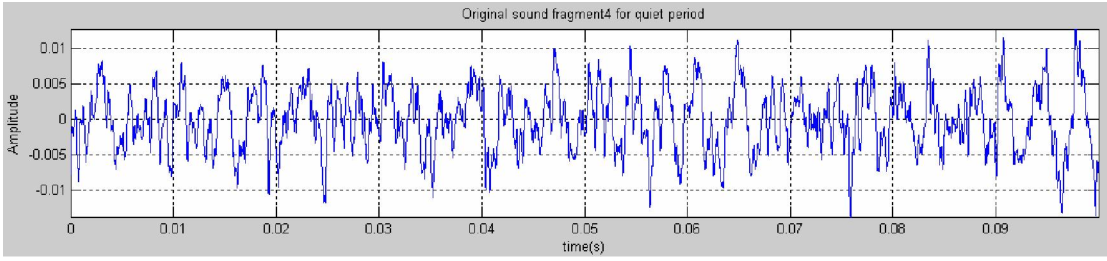
(c-2)


Original sound fragment3 for quiet period
Amplitude
time(s)

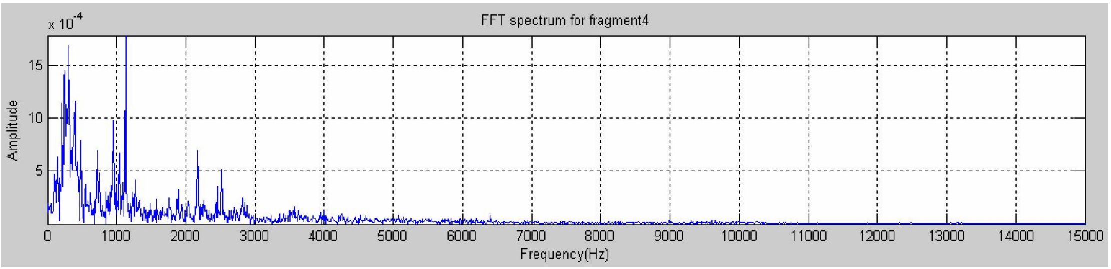
(d-1)



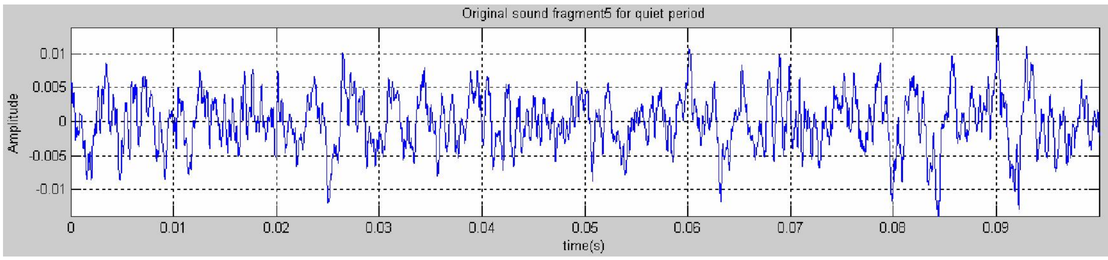
(d-2)



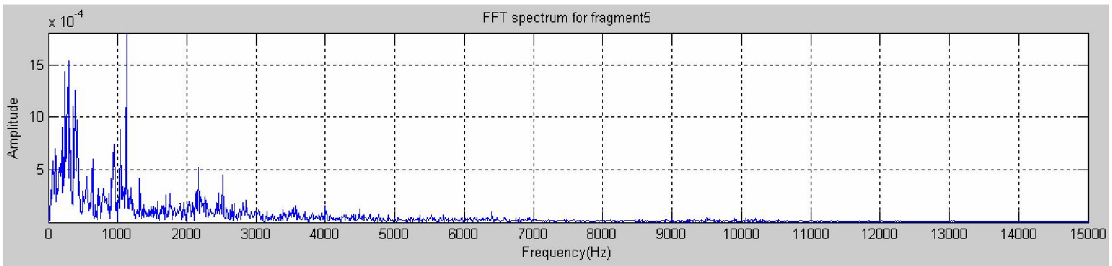
(e-1)



(e-2)



(f-1)



(f-2)

Figure 5-19. Time domain analysis of noise in the microphone

(a) 1 second time domain analysis of noise existing in the microphone

(b-1)-(f-1) 100ms time domain analysis abstracted from (a)

(b-2)-(f-2) 100ms frequency domain analysis of (b-1)-(f-1) respectively

Figure 5-20 shows time-frequency analysis result of noise coming from the microphone itself which used to gather all the sound signals. We can find that energy of this kind of noise accumulates mainly in low frequencies below 2000, which we will discuss in the following part.

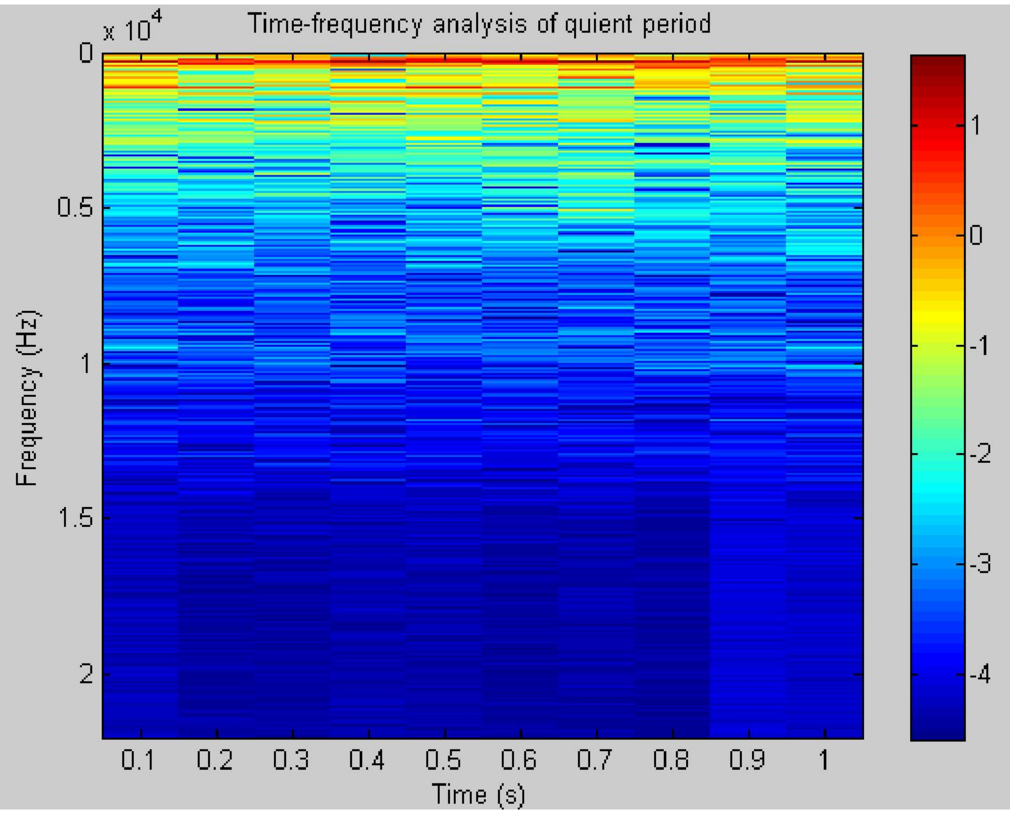


Figure 5-20. Time-frequency analysis of noise coming from the microphone

5.6.2. Low frequency analysis

From the figure that I picked out below, we could see very clear that there are interference frequencies indeed during the microphone was working. There are obvious frequency peaks during 200-400 Hz as well as 1000-1200 Hz. So when we try to analyze other kind of sounds, we should consider this kind of interference existed in the microphone itself and identify whether or not the frequency peak in this sound file is the peak that we need to abstract.

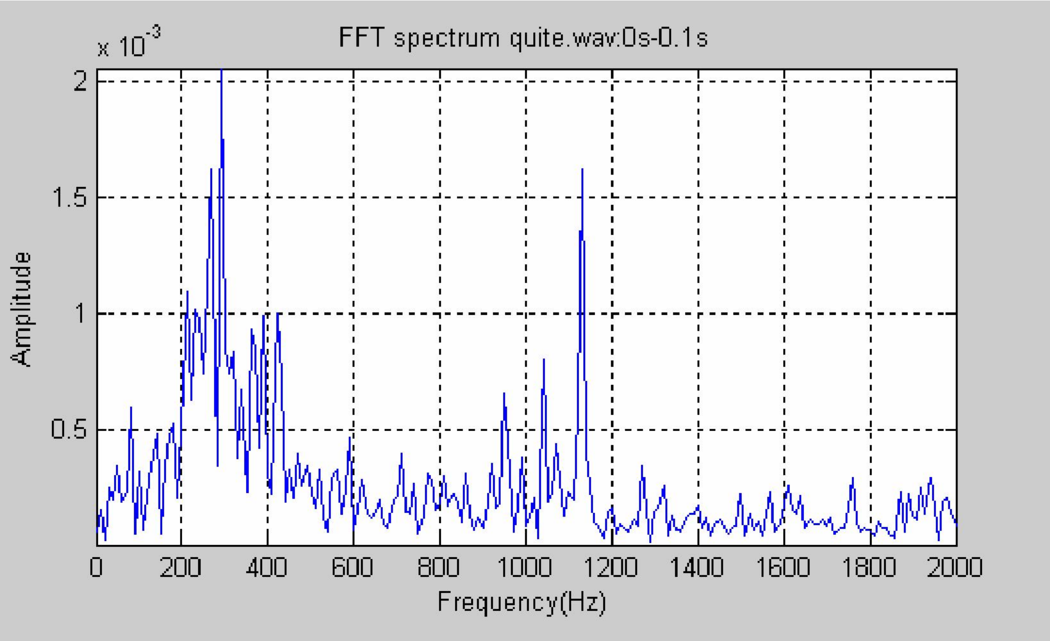


Figure 5-21. Sound frequencies of interference noise

5.7. Filter design

5.7.1. Low-pass Filter

I use FDATOOL to design the low-pass filter. It is quite easy and convenient to design the filter. Just press "Lowpass", then you can set the "Fs", "Fpass", "Fstop" according to the requirements you need.

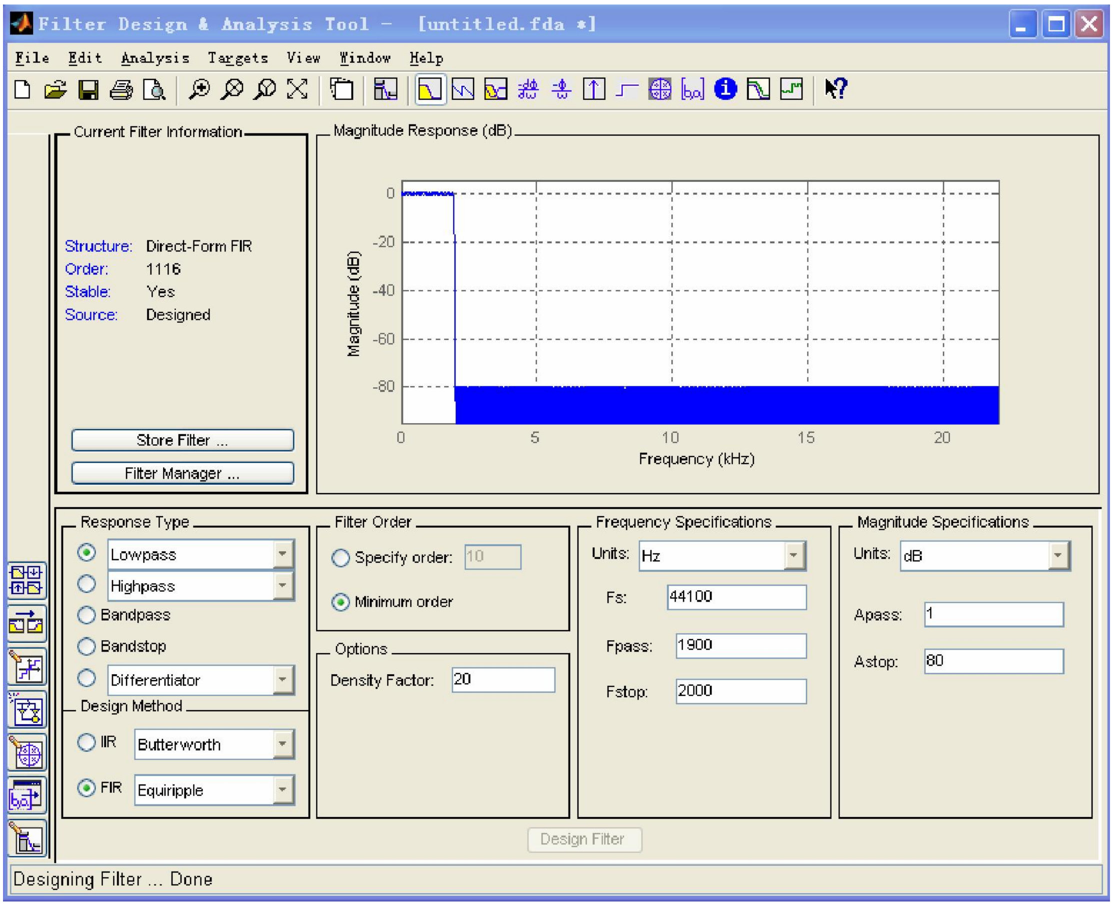
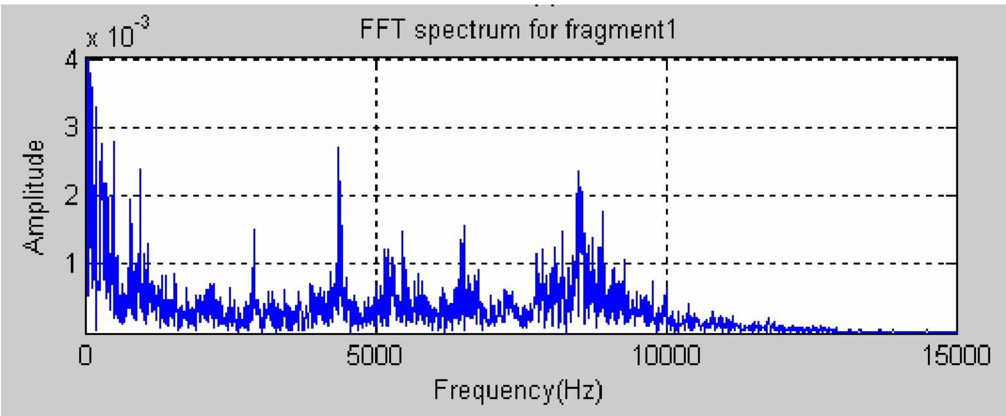


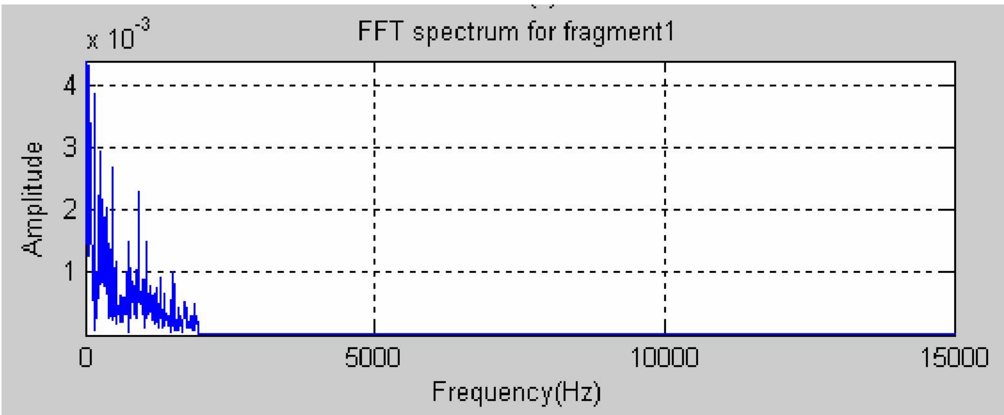
Figure 5-22. Low-pass Filter

The sample rate here is 44100Hz, and we set pass band is 1900Hz in the low-pass filter. After finish setting all the parameters, press "Design Filter", then the filter will be designed automatically for you. This designed filter can be saved as a M-file named "lowpass2000.m'. You can use the function directly afterward to deal with the sound files.

We take the first cut sound on the side of the hub body in file 4 for example. The result (spectrum before and after the sound is passing the low pass filter designed above) is presented in Figure 5-23.



(a)



(b)

Figure 5-23. Frequency spectrums of the milling sound

(a) The frequency spectrum before passing the low-pass filter

(b) The frequency spectrum after passing the low-pass filter

After the original milling sound is passing the low-pass filter, a new milling sound is created by using “wavwrite” command in Matlab. But when I listen to the new milling sound file created, there is nearly no milling sound inside, which means the main features of the pure milling process is not in the low frequency, and again proved the data we collected is not good enough to do an accurate analysis. For it could mislead us to consider the low-frequency more, since there is really high energy in the low frequency area when looking at the spectrum figures.

But for human sound, using the low-pass filter can gain the exactly human sound as before, which means human’s voices is mainly in the low-frequency area.

However, water's sound as well as sharp noises from other machine cutting are also in the high frequency areas which could overlap with milling sound. This is a big problem for us to abstract the pure milling sound to analyze.

5.7.2. High-pass Filter

As discussed in part 5.7.1, the main feature of milling machine is not in the low frequency area. After analyzing spectrums of milling sound, we also find that there is obvious energy after 4000Hz in the higher frequency intervals as well. So the high-pass filter for filtering out the interference noise below 4000Hz is designed as follows shown in Figure 5-24.

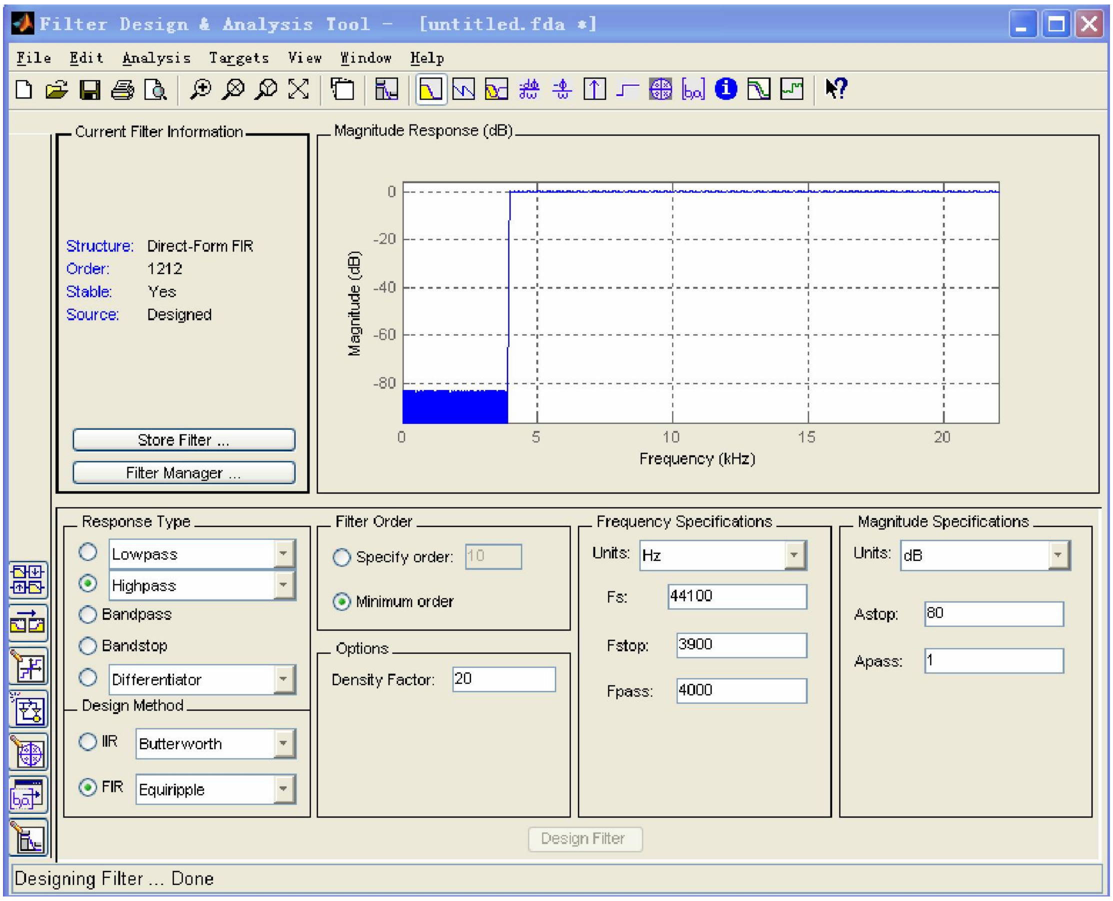
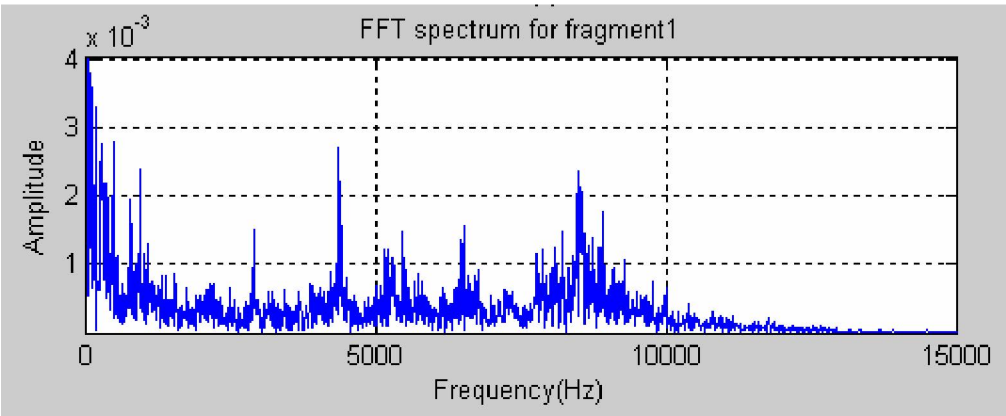
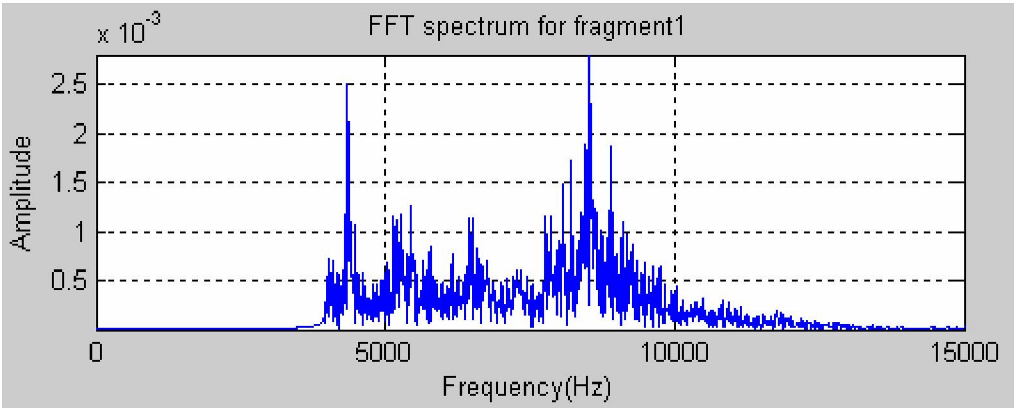


Figure 5-24. High-pass Filter

We also take the same example as above to show the result in spectrum form after the sound has been filtered using the high-pass filter in Figure 5-25 as the following.



(a)



(b)

Figure 5-25. Frequency spectrums of the milling sound

(a) The frequency spectrum before passing the high-pass filter

(b) The frequency spectrum after passing the high-pass filter

The milling sound passed through the high-pass filter is saved in file "m1-highpass4000.wac". When listening to this sound file, we can detect much purer milling sound.

As we discussed in last part, the sharp main features of cooling water and sharp noise can also be saved after both original sounds are passed through this designed high-pass filter. This is true, for we also can see this in the signal analysis part above. Milling sound, cooling water sound, as well as sharp noise are all not quiet during high frequency intervals, although they all have higher energy in low frequency intervals below 2000Hz than in high frequency intervals above 4000Hz, after the these two kinds of filters – both low-pass filter and high-pass filter are designed to put into use, it is quite clear to detect the main features of each sound, which proves the features shown in the high frequencies above 4000Hz are significant, which is important for the coming research.

6. Feature identification and case-based reasoning

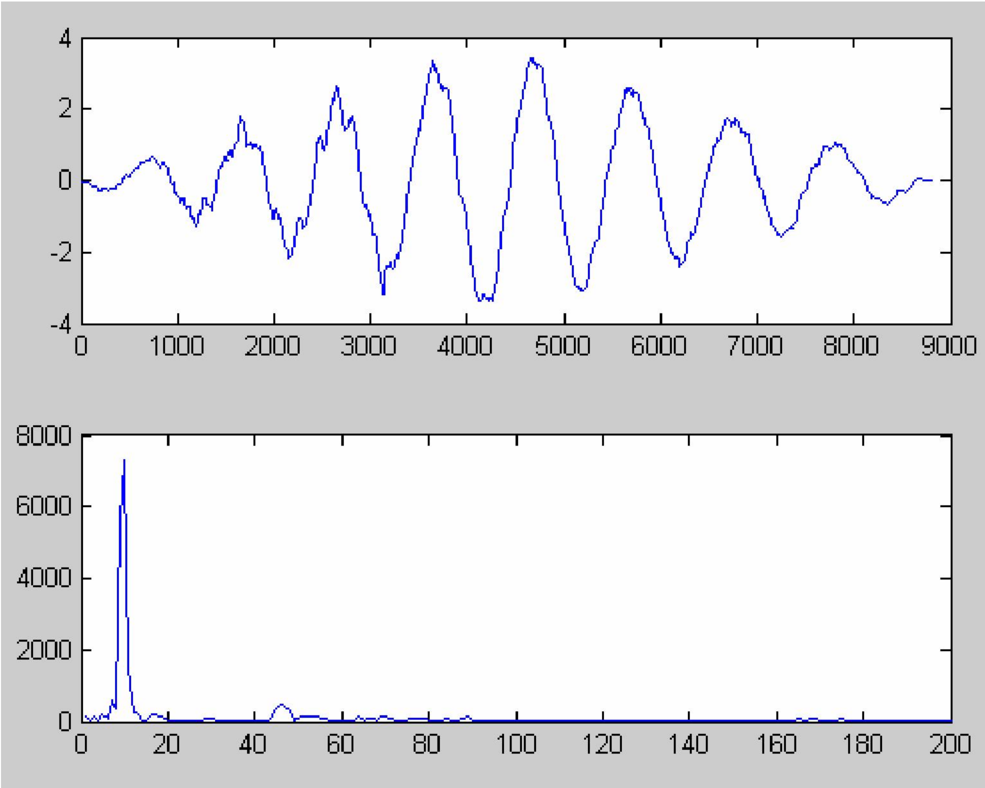
6.1. Feature identification

As we talked in section5 part 5.2 when analyzing the sound frequencies of milling process, there is a quite obvious feature in file4 which recorded the first cut sound on the side of the hub body exactly before the cutting tool was changed. The feature is with the first cut on the side of the hub body going on the amplitude of the frequencies between 0Hz to 100Hz is increasing gradually. When the cutting steal has to be changed, the energy of the frequency interval will increase up to 0.035. Thus, we could use this feature to build the boundary case library. However, I cannot say this is the accurate feature to be identified. Because, we I used the 2000Hz low-pass filter designed above to filter the milling sound, there is not significant milling sound in the filtered milling sound file, the main milling features are probably not below 2000Hz. So I have to say, more samples have to be collected from Berg Propulsion to test this feature identified here.

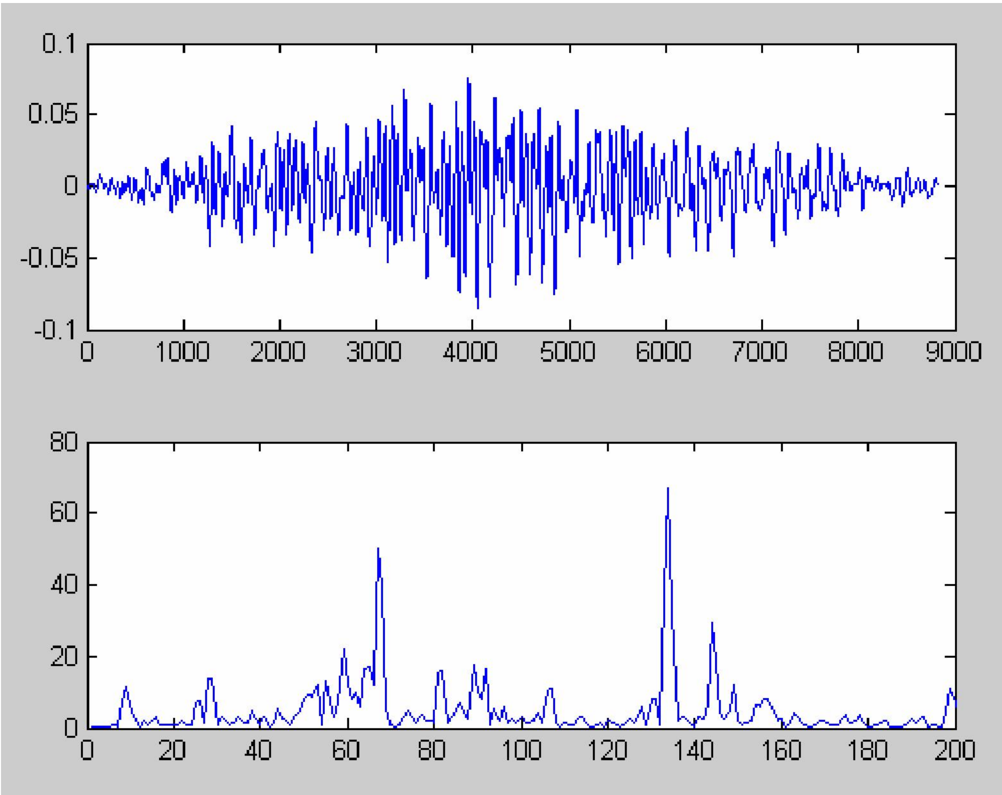
Since the data is not so well collected, we cannot say some features in these signals for sure, the information on what we can get from all those signals has been stated above.

However, in this part we try to find some useful information and features in someway in order to give examples of the cases. Since there are not significant features during the signal analysis (what we have done during the analysis part is just stating what we have got from those kinds of sound signals), we have to find another efficient way to try to build up cases by using the sound data before the tool was changed as well as after the tool was changed. In this situation, we are trying to use correlation in signal processing to find further information contained in the sound signal. We did the cross correlation of each neighbor 100ms time window size sound signal, and then did the Fast Fourier Transform of each cross correlation. According to the spectrum figures we got, we could see quite obvious features from before changing the cutting tool and after changing the cutting tool.

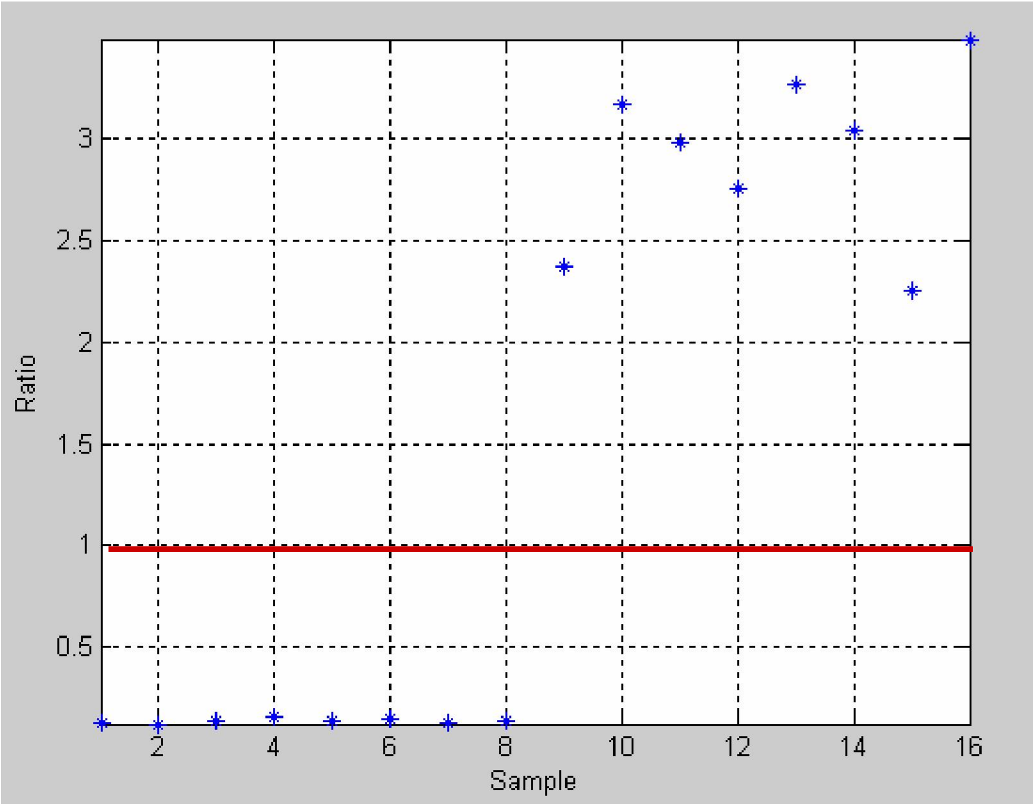
We abstract eight samples respectively from the milling sound signal before the cutting tool was changed and after it was changed. Figure 6-1(a) shows one of the sample figures before the cutting tool was changed. The upper figure shows the cross correlation of the neighbor 100ms time window size milling sound signal, and the lower figure in Figure 6-1(a) is the corresponding FFT figure for the upper cross correlation figure. Relatively, Figure 6-1(b) shows the same information after the cutting tool was changed. We could see a very clear feature in the spectrum figures that there are significant peaks before 60 before changing the cutting tool, and there are significant spectrum peaks after 60 after changing the cutting tool. So it is easy for us to think about that 60 could be the division in these two different cutting conditions and cutting stages (Figure 6-1(a) is in the condition before changing the tool and in the first cut stage, Figure 6-1(b) is in the condition after changing the tool and in the final cut stage). So the summary of all peak values before 60 (high frequency energy) can be calculated out saved in variable a, and the values after 60 (low frequency energy) saved in variable b. So here coming out Figure 6-1(c) which shows the changing trend of "ρ =b/a". The first eight sample shown in Figure 6-1(c) are the samples in the milling sound signal before the tool was changed, the next right samples are from the milling sound signal after the tool was changed. The feature we could abstracted is before changing the tool, ρ is far less than 1, but after changing the cutting tool, ρ is more than 1, which could be used in building case library to probably determine the cutting conditions and cutting stages of the milling machine, and further more, when good data is collected once more which could come out more useful features (such as in frequency domain detection), the further cases could be created in those conditions and stages to monitor whether the tool is worn out or not.



(a)



(b)



(c)

Figure 6-1. Feature identification

(a) Correlation and corresponding FFT results of the milling sound signal before the cutting tool was changed

(b) Correlation and corresponding FFT results of the milling sound signal after the cutting tool was changed

(c) Changing trend of ρ before and after the cutting tool was changed

6.2. Case-based reasoning

Since one of the features discussed in part 6.1 is just before the cutting tool is changed. So this feature could be used in building up the case library later. The case could be classified into the category described as the cutting stage is first cut, namely rough cut of the hub body, and the cutting part is the side of the hub body. After this the amplitude value correspondingly to the frequency interval 0Hz to 100Hz close to the end of the file4 can be saved in the case. This boundary value could be considered as the abnormal value here to monitoring the cutting tool condition in the first cut stage cutting on the side of the hub body. So according to this feature detected, a boundary case library could be built. Here is one example according to the changing relationship during 0Hz to 100Hz before the cutting tool is changed on side cut of the hub body in the first cutting stage.

Table 6-1. A case example of feature abstracted of the milling sound

Case1
Cutting part: side cutting of the hub body
Cutting stage: first cut of the hub body
Frequency interval: from 0Hz to 100Hz
Energy (Amplitude): > 0.035
Result
Changing the cutting tool

Since I only have one boundary case here, so more data should be collected to abstract more cases. For example, file2 saves the sound signals while doing the first cut on the top surface of the hub body, but since after this cutting stage on this part of the hub was done, the tool was still used. None of the values in this cutting stage on the top part of the hub body is the boundary value, so it is hard to find a regular pattern in this file. We could say afterward that if the cutting sound in the new case in the same stage and in the same cutting part is like the signal here, it could be the normal condition, but still we cannot monitor the cutting tool status using this normal sound files. If the tool is worn out here, we could not tell the sound coming from the new case is surely an abnormal one.

So it seems more important to gather more useful signal data to build the boundary case library. Then the nearest neighbor method in case-based reasoning could be used to identify whether the tool is worn out or not by testing whether the amplitude value in the relative frequency interval in the current case is around the boundary value in the cases saved in the case library.

However, since the data is not so well collected, the ideal case library cannot be built right now. I will also give two simple examples of the cases to decide on which stage and in which condition of the cutting steel of the milling machine according to the features we identified above in part 6.1.

Table 6-2. A case example of feature abstracted of each cutting stage

Case1	Case2
ρ <1	ρ >1
Result	Result
First cutting stage	Final cutting stage

The two cases are just simple examples given out to show how they look like. In order to put case-based reasoning into practice, more accurate sound data has to be collected to abstract more features. Figure 6-2 shows how those cases could be used in the decision tree while combining table 6-1 as well as table 6-2 above. After we use ρ to decide which stage and condition the cutting steel is right now, more features have to come up for the decision tree to go on to show which ones could be classified to the normal status of the cutting steel, and which ones could be classified as the abnormal ones that have to stop the machine from working right now. This part will be the huge future work which needs us to put more effort on.

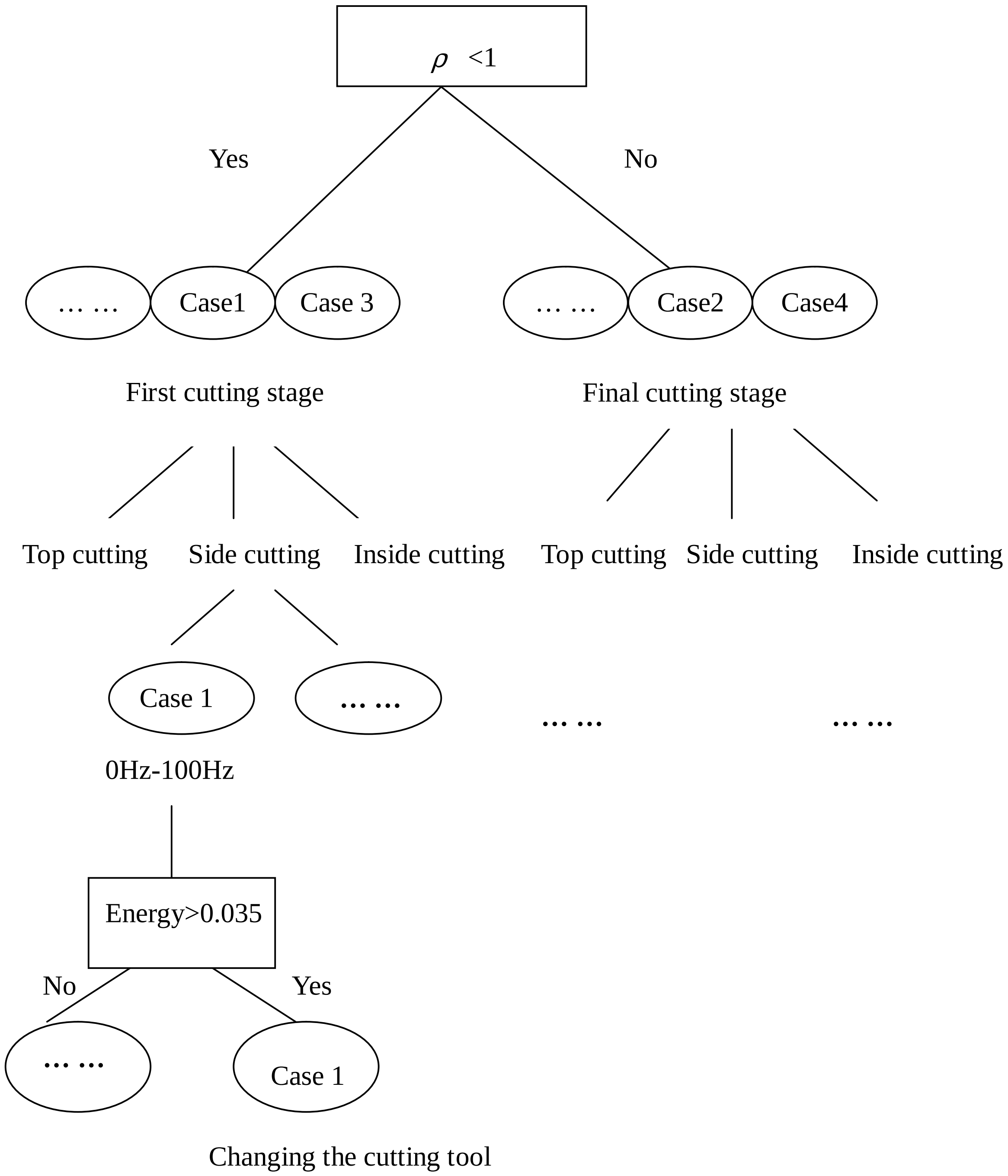


Figure 6-2. One node showed in decision tree

7. Conclusion and discussion

In this thesis work, the main purposes are to analyze the sound data collected from the milling machine, and identify the features in the sound signal so that it might help in building the case library later using one of the methods called case-based reasoning in Artificial Intelligence to monitor the condition of the cutting tool to free the experts from the milling machine.

The tasks which have been done in this thesis present as follows.
Firstly, trying to give readers an outline of what has been done in this cutting tool monitoring area, namely the state of the art in cutting tool monitoring, digital signal processing, as well as in case-based reasoning.

Secondly, classifying the sound signals I collected in Berg Propulsion into milling sound (the main sound that has to be analyzed), noises which contain human voices (man’s voice and woman’s voice), cooling water sound signals, sharp noises coming from other machines outside the milling cabin, and noise coming from the microphone itself as well.

Thirdly, after classifying all the sound signals, more details have to be found from all these signals which would help us to build up the case library later which could focus on the milling sound only to monitor whether the cutting tool is worn out or not. So both time domain and frequency domain analysis have been done to find more features of all those sound signals, especially the milling sound signals. From the analyzed figures shown above, the frequency intervals in which energy of each sound signals appears will be figured out, which might help to design related filters afterward and also could help to find some regular patterns from these frequency intervals, especially for the milling sound before the cutting tool was changed.

Fourthly, the two dimension time-frequency figures of each sound signals which can give us an overview of each sound signals are created for us to try to find more features and information, and also try to pick out features through all frequency area from 0Hz to 22050Hz.

Fifthly, after analyzing for a while, we found that the low frequency areas seem important. Energy of each sound signal all appears high in the frequency area below 2000Hz. So analysis focusing on the low frequency from 0Hz to 2000Hz is done for each sound signal, which I hope it could help in the coming research for this project in Berg Propulsion.

Sixthly, for there existing some kinds of noises, in order to get the useful milling sound signal, filters for filtering out noises have to be designed as well.

Finally, according to the features that we could identify, case examples are given to illustrate how the cases look like and how to create cases in a case library. And at last part of the decision tree is shown to make the CBR process more clearly.

Because the microphone which used to collect the data is not good enough, the sound gathered here contain so many noises, and we can not find significant features of the milling sound signal. However, the analyzing methods using here would provide a good way to see how are these signals and could help people who will do the coming research a lot if they can using more precise microphone to collect more accurate data as I suggest in the coming chapter.

I think it would be better and easier to build up an abnormal case library by collecting all the abnormal data in different stages. For example, we use the worn out tool to do the first cut on the top surface of the hub body, analyze the signal collected and save the cases which could be the frequencies of this kind of abnormal signals. Then we use the worn out tool to make the first cut on the side of the hub body, analyze the collected cutting sound signal and save the cases from this time period. Next the cases might be produced from the signal while doing the final cut on the top surface of the hub body, or the final cut on the side of the hub body and so on. After we collect all the cases to build up the case library, later while monitoring the milling machine, we could just simply compare the new case (the signal collected during the milling process in real time) with the abnormal cases stored in the case library using one method called nearest neighbor in case-based reasoning. If the comparing result is quite similar to the case stored in the case library, then we could say the milling tool has to be changed, the milling machine will be stopped in this situation.

But this proposal seems so difficult to take into practice, since it will take a great risk while collecting the abnormal data from the milling machine. The deeply worn out tool might cause damage to the milling machine and waste a lot of money afterwards, so we still have to consider about that. However, this method could be the convenient and precise way to monitor the status of the cutting tool using in the milling machine. So if this can not realize now, we still could consider the boundary values as abnormal data to build up the case library which also need us to collect data in different stage and different cutting part using nearly worn out tool.

Apart from the feature extracted, some kinds of filters are also designed in this thesis work. The filters designed for filtering out the man's voice, woman's voice, sprinkling water sound using for cooling down the hot chips and hub body itself during the cutting process, as well as the sharp noises coming from other sides of the big factory will all be quite useful later if more accurate data signals are collected to put into analysis. The noises among the cutting signals could be filtered out using these designed filters, since all the noise frequency intervals have been analyzed.

Since the data samples are limited, the analysis done in this thesis is based on the data existed currently. The sound frequencies in different parts of the hub body as well as in different cutting stages during the cutting process are all different, so we have to separate them to analyze and identify all the features to build up the case library using all the normal signals cases. In this thesis, we just mainly take the first cutting stage while cutting the side of the hub body for example to abstract the feature which can be identified from the data collected in file4 before the cutting tool was changed. The other kind of sound signals which we classify them as noises, such as human voices, cooling water sound signal, sharp noise signal and so on, are also analyzed in the thesis. This kind of analysis is good for us to understand the sound signal I collected from the milling machine in Berg Propulsion from the overall situation, and also might illustrate some idea in the coming research.

8. Future work

8.1. Further work

The basic work of this project has been down to abstract the sensor data using sound signal processing. Then it has to combine with the Artificial Intelligence method case-based reasoning to build up the whole diagnosis system. This is quite crucial. In this thesis work, a lot of work has been done in signal process. In order to perfect the whole system, the above work which need to use the artificial intelligence method case-based reasoning should be forwarded, which also need a big workload.

8.2. Suggestions after doing this thesis work

1) For the sensor data gathering at the beginning, we just use the normal microphone to collect the sound signals. So the sounds from all directions have been collected into the sound file. It brings us a large amount of workload to design the filters for the unpleasant sounds, such as the human voices, water sound and the sharp noised coming from the outside in the factory. However, if we use another kind of microphone, say multi-dimension microphone in this situation, it would save us a lot of energy to design the complex filter. We could receive the machine sound directly in this case and go to analyze and discriminate the main features quickly which would save us a lot of time and make us put more energy on the system perfection. That will be good.

2) In one conference held in the field of signal process, some one just proposed one kind microphone which we could say “highly directional microphone”. It is highly focused on the sound from one direction. For example, if we just want one person’s voice, so we just fixed this kind of microphone to the direction of the person’s mouth. Then other voices from other directions will be automatically

declined to zero in this situation. If this highly directional microphone could be used in our project, it would be quite good and convenient for us to analyze the sound and abstract more useful features to build the cases later. What could be proposed is that we use this highly directional microphone, fix it directly beside the cutting tool (since it is not so big), and then in order to protect the microphone from the hot chips and water, we could cover it with a thin and fire, water-protected box or some other stuff, which could of course makes the voice get through easily. In this case, since the microphone has both been put into the milling cabin and also been changed to the highly directional one, the precision will be improved a lot, and there will be little noise from the sound file we collected. So the sound could be used directly to see the fluctuation relationship in the figures from the tool is new to the tool is nearly worn out. And in the end the new cases can also be collected using this kind of microphone and compared with the cases we built in the case library, which is absolutely make the work much more easier.

3) As I introduced before, I collected data using wavelab last time. This software is quite good for us to gather the data. Because there are ‘split’, ‘stop’, ‘pause’ and some other functions like this. So it is quite easy for me to split the sound files I collected whenever I want but not interrupt the collecting process. So in the end the files I got are continuous in the totally eight hours but separated files formally by different stages and categories. For example, file 2 saves the sound when the first cut is processed on the top of the hub body. File 3 stores the sound when the first cut of the inside cut of the hub body is carried on. File 4 is the data for the side cut of the first cut. Then during the time in file 5 the cutting tool was changed, namely another new edge of the cutting tool was used for the following cut. And file 6 is the data recorded the final cut of the cutting place during file 2 to file4. I collected all these final cut process into the same file. As it is the first time I went to Berg Propulsion to get the data and before that there was no useful data to analyze, I am not so confident about what kind of data I would use later.

However, after analyzing the data I collected for a while, I became to realize which kind of data I want to use in the analysis. Since I have already had the separated data in the first cut stage to cut the top, the inside and the side of the hub body, it would be much better we also had the divided data in the second cut stage, namely final cut stage correspondingly to the files in the first cut stage. It would be much easier for us to find the regular pattern of the sound frequencies between the first cut and final cut in different parts of the hub body which would help us a lot later to abstract the whole features to build the relatively case library and find out the abnormal cases while the milling machine is working without any operator standing besides. What's more, when collecting all the data in Berg Propulsion, it is important to have some operator who is the expert in this milling machine to introduce some basic knowledge to you. Do not think it is not so important since you are not in this area. When you have the background of this machine and the working conditions of the milling machine, then you could start to collect the data from the beginning to the end while the milling machine is working. During the data collection, it is better to keep quiet than talking a lot with each other, and watch the milling machine carefully which stage it is in right now, and which part the machine is working on now. That information is all quite important and would help us a lot while analyzing the data afterward. So you could have one worker to show you and explain the detail of the blueprint before the starting collecting the data- which part will cut in the first time, after the first cut of some part on the hub body is done, when will the final cut of this part be done, in the next step, or after some first cut of other parts on the hub body. That information is all quite critical to listen to and record them down if you can not remember all of them by mind. Then I think you would collect a much better data than I did last time to do the analysis and give out much more precise even more perfect result.

4) It is important to gather the abnormal data in different cutting stage. For example, the abnormal data while doing the first cut on the top surface of the hub body, the

abnormal data while doing the first cut on the inside as well as on the side of the hub body, and also the abnormal data while doing the final cut in different parts of the hub body and so on. Those abnormal data will help us a lot to build up the abnormal case library to monitor the working condition of the cutting tool later. The result coming from this kind of data collected will be much more accurate and useful. But it will take a long time to gather all these data. So it seems gathering a good data at the first step is much more important to serve the system development later.

5) The result given out in this thesis is only based on the data I collected in the first time. But I have to say the data is not so sufficient. In order to test whether the feature found in this thesis is correct or not, more data samples should be collected, which means the data coming from one hub body milling process is not enough. We have to collect more samples at the same cutting period while doing the cutting process on other hub bodies. For example, here we find some feature during the first cut on the side of the hub body exactly in the time before the cutting tool was changed, so in order to test whether this feature we abstracted is right or not, the same data samples should also be collected to analyze. If the results are also like this, then this feature could be used into practice, otherwise some other method should be found as well, like the method I recommended above to focus on the abnormal data collection.

6) Collect the boundary data in different stage as well as in different cutting part of the hub body, which need the operator to change the tool very often using the nearly worn out tool to do the cut in each stage and each part. This really needs time and patience to do so. However, this movement will help us a lot to find more useful features.

Acknowledgements

I should say this project bring me a quite interesting topic to research during the past 7 months. Thanks a lot to Peter Funk and Erik Olsson in Mälardalen University to give me this opportunity to work on this project. I really learned a lot during doing this thesis. I never know there is a method called case-based reasoning in Artificial Intelligence. But now after reading the books and a lot of material concerning about this method, I start to have an overview in my mind about this case-based reasoning. Also, for signal processing, I never did that before. Since the data I got is the '.wav' files, I have to use signal processing to analyze the data. It really made me a big headache at the beginning. Gradually, when I tried to learn the basic concepts of signal processing and use it into practice, I found it is quite interesting subject.

Here, I will give my great thanks to my reviewer Ping Wu. During this thesis, he helps me a lot and lights a lot of brilliant ideas to me, so that I could move on step by step. At the beginning when I tried to manage signal processing, it proves so difficult to me. However, after I found Professor Wu, we talked a lot about this thesis and I received a lot of useful information from our conversation. Then I started to know how to do it in the regular way, and I do not feel confused any more. When I felt difficult during the process and wanted to give up, it is Professor Wu who always encourage me to move on and on. So thank you very much.

I want to say thank you to my friend Amanj Sherwany who tutorialed me a lot at the beginning when I had no idea about the thesis stuff. It was him companies me to step it over, and taught me a lot during those days.

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Also, I want to give my warm thanks to my parents who really gave much courage and love during those seven months. I will love you both forever.

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References

[1] Dong Quancheng. Acoustic spectrum feature abstraction and discrimination of cutting tool working condition.

[2] Sanjit K. Mitra. Digital Signal Processing- A Computer-Based Approach.

[3] Emmanuel C. Ifeachor, Barrie W. Jervis. Digital Signal Processing- A Practical Approach. Second Edition. Page 3-4.

[4] David B. Leake. CASE-BASED REASONING: EXPERIENCES, LESSONS, AND FUTURE DIRECTIONS. Indiana University. Editor 1996, second printing 2000.

[5] http://jpkc.nwpu.edu.cn/jp2005/06/xinhaoxitong/ch1/kejian/1-1.htm

[6] http://en.wikipedia.org/wiki/Analog_signal

[7] "Digital Signal Processing: Instant access." Butterworth-Heinemann - Page 3

[8] "Concise Dictionary of Computing." Penguin Reference - Penguin Books - pages 11-12.

[9] "Digital Signal Processing: Instant access." Butterworth-Heinemann - pages 2-3.

[10] http://cbdd.wsu.edu/kewlcontent/cdoutput/TR502/page8.htm

[11] http://cbdd.wsu.edu/kewlcontent/cdoutput/TR502/page8.htm

[12] http://en.wikipedia.org/wiki/Fast_Fourier_transform.

[13] http://en.wikipedia.org/wiki/Filter_(signal_processing).

[14] http://www.avrw.com/article/art_109_2762.htm.

[15] http://en.wikipedia.org/wiki/Analogue_filter.

[16] http://en.wikipedia.org/wiki/Digital_filter.

[17] Bernard Mulgrew, Peter Grant, John Thompson. Digital signal processing – concepts and applications. Second Edition. Page 126.

[18] Emmanuel C. Ifeachor, Barrie W. Jervis. Digital Signal Processing- A Practical Approach. Second Edition. Page 343.

[19] Emmanuel C. Ifeachor, Barrie W. Jervis. Digital Signal Processing- A Practical Approach. Second Edition. Page 455.

[20] Emmanuel C. Ifeachor, Barrie W. Jervis. Digital Signal Processing- A Practical Approach. Second Edition. Page 321.

[21] http://en.wikipedia.org/wiki/Low-pass_filter.

[22] http://en.wikipedia.org/wiki/High-pass_filter.

[23] http://en.wikipedia.org/wiki/Band-pass_filter.

[24] http://en.wikipedia.org/wiki/Band-stop_filter.

[25] http://en.wikipedia.org/wiki/Case-based_reasoning

[26] Aamodt, Agnar, and Enric Plaza. "Case-Based Reasoning: Foundational Issues, Methodological Variations, and System Approaches" *Artificial Intelligence Communications* 7, no. 1 (1994): 39-52.

[27] Ian Watson, Farhi Marir. Case-Based Reasoning: A Review. AI -CBR. Dept. of Computer Science, University of Auckland, New Zealand.

[28] Ian Watson. Applying Case-Based Reasoning- Techniques for Enterprise Systems. AI-CBR, University of Salford, U.K..