UNIVERSITY
OF GÄVLE

FACULTY OF ENGINEERING AND SUSTAINABLE DEVELOPMENT

Research and simulation on speech recognition by Matlab

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Dec 2013

Bachelor's Thesis in Electronics

Bachelor's Program in Electronics/Telecommunications
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Acknowledgements

I would like to express my gratitude to all those who helped me during the thesis work.
First, I'd like to thank my examiner, Niklas Rothpferffer who give me suggestions for new topics and outlines.
Then, I gratefully acknowledge the help with Doctor Wang, who has offered me really valuable advices and guidance with the literature screening and experimental Matlab simulation tutoring during the thesis work.
Last my thanks will go to my fellows that help me recording the simulations samples.

Abstract

With the development of multimedia technology, speech recognition technology has increasingly become a hotspot of research in recent years. It has a wide range of applications, which deals with recognizing the identity of the speakers that can be classified into speech identification and speech verification according to decision modes.

The main work of this thesis is to study and research the techniques, algorithms of speech recognition, thus to create a feasible system to simulate the speech recognition. The research work and achievements are as following: First: The author has done a lot of investigation in the field of speech recognition with the adequate research and study. There are many algorithms about speech recognition, to sum up, the algorithms can divided into two categories, one of them is the direct speech recognition, which means the method can recognize the words directly, and another prefer the second method that recognition based on the training model. Second: find a useable and reasonable algorithm and make research about this algorithm. Besides, the author has studied algorithms, which are used to extract the word's characteristic parameters based on MFCC(Mel frequency Cepstrum Coefficients) , and training the Characteristic parameters based on the GMM(Gaussian mixture mode) . Third: The author has used the MATLAB software and written a program to implement the speech recognition algorithm and also used the speech process toolbox in this program. Generally speaking, whole system includes the module of the signal process, MFCC characteristic parameter and GMM training. Forth: Simulation and analysis the results. The MATLAB system will read the wav file, play it first, and then calculate the characteristic parameters automatically. All content of the speech signal have been distinguished in the last step. In this paper, the author has recorded speech from different people to test the systems and the simulation results shown that when the testing environment is quiet enough and the speaker is the same person to record for 20 times, the performance of the algorithm is approach to 100% for pair of words in different and same syllable. But the result will be influenced when the testing signal is surrounded with certain noise level. The simulation system won’t work with a good output, when the speaker is not the same one for recording both reference and testing signal.

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1 Introduction

1.1 Background of Speech Recognition

Language is an important way of communication for human. The voice characteristic parameters of different people are almost different, such as the loudness, voice amplitude, all of them are different. As an emphasis of this report, speech recognition is a popular topic in nowadays life where the applications of it can be found everywhere, which make our life more effective. So it will be meaningful and significant to make an academic research with an adequate interpretation and comprehending for algorithms to recognize the speech characteristics.

Speech recognition technology is a process of extracting the speech characteristic information from people's voice, and then been operated through the computer and to recognize the content of the speech. It's interdisciplinary involving many fields, where modern speech recognition technology consist of many domains of technology, such as signal processing, theory of information, phonetics, linguistics, artificial intelligence, etc. Over the past few decades, scholars have done many research about speech recognition technology. With the development of computer, microelectronics and digital signal processing technology, speech recognition has acts an important role at present. Using the speech recognition system not only improves the efficiency of the daily life, but also makes people's life more diversified.

1.2 The history and status quo of Speech Recognition

The researching of speech recognition technology is started in 1950s. H . Dudley who had successfully developed the first speech coder, established the basic theory of speech recognition. And it followed by ,J . Rorgie began to research the computer voice recognition by using the English vowel and isolated words in in 1959. Meanwhile, the BELL labs invented language Spectrum instrument.

In 1960s, Many methods had been provided to research speech recognition , which have a significant impact for the development of speech recognition researching , one of the key research achievement is the time normalization method put forward by Doctor Martin which can solve the problem of detection of speech signal endpoint [1] .

And in 1965, Doctor Tukey invented a famous algorithm, FFT (Fast Fourier Transform) algorithm that can research the signal in the frequency domain, then In 1968, The most important speech recognition technology, dynamic programming technology and linear prediction analysis technology have been invented. [2]

There are many models didn't adopted in the article, which are also significant for speech recognition including: Hidden Markov Model (HMM), published by Doctor Baum in 70s that the speech sequence can been constructed based on Markov chain. The HMM method can well describe the time-varying and stationarity of speech signals, which can achieves a higher modeling precision and become the starting of continuous speech recognition research.

In the mean time, vector quantization (VQ) theory was invented, and linear prediction technology was developed more and more perfect. In 1980s, the artificial neural network (ANN) technology has been applied in the field of speech recognition successfully. The application of artificial neural network technology becomes a new way of researching voice recognition, which has the advantage of non-linearity, robustness, fault tolerance and learning characteristics. At the same time, the conjunctions speech recognition algorithms have been proposed, which makes the speech recognition research start from micro to macro. [3]

In this period, the most famous researching achievement is the continuous speech recognition system SPHINX, proposed by scholar Lee from Carnegie Mellon university of the United States in 1988. In the decade of the 21st century, the experts have researched many new methods of speech recognition in order to use it in the embedded devices. Although, there are also many problems in the real applications, but the Speech recognition technology is developing faster and faster. Recently, in the field of speech recognition, the direction of researching has focused on the spoken dialogue system and the embedded speech recognition system. Meantime, there are many projects of speech recognition, such as voice recognition, robust speech recognition, speaker adaptation technology, large vocabulary words recognition, speech recognition reliability evaluation algorithm and so on. The speaker adaptation technology has achieved a big improvement in the fields of voice channel normalization technology, maximum likelihood linear regression algorithm, bayesian adaptive value algorithm etc.

Speech recognition technology based on HMM is now developed mature , more and more people provided their own method based on it to get a better performance with various of speech recognition algorithms. In this field, Doctor Wang from Tsinghua University have put forward inhomogeneous improved hidden markov model of speech recognition. [4] In doctor Wang's theory , the traditional HMM model has some problems in the speech recognition

application , and give a long distribution based inhomogeneous hidden markov model (DDB-HMM) . Professor Zhao have put forward a hidden markov model by using even frame, which can improve the robust performance in a noise environment. [4] With decades optimization and evolution, speech recognition has developed with a quite mature extent that widely spread to various of application.

1.3 Thesis Outline

The main goal in this thesis is to use the chosen models for training and processing the signal, and select appropriate algorithms to analyze the computed data thus to simulate the speech recognition procedure with different variables based on the researched theory. And there are generally 4 sections composite of the report including:

Introduction section that describe the general background, history and status quo of Speech recognition technology.

Theories on models of speech recognition technology contains signal pre-processing , which describes a procedure to process signal with endpoint detection, pre-emphasis, framing and windowing; And then it's characteristic parameter extraction technology, author mainly used Mel Frequency Cepstral coefficient extraction and related speech recognition algorithm in the experiment. For analyzed the extracted parameter, Gaussian Mixture Model was utilized.

Then it will be the section detailed describing the process of the experiment based on the Matlab. And the testing samples are taken by 3 pairs of words and numbers with different variables to assume environmental difference, quantity of samples and syllable of words. Those speech samples were then written into MATLAB program with MFCC characteristic parameter extraction and GMM training model.

At last, it will be the discussion of the simulation result, and final conclusions about our algorithm will be conducted. The experiment of this algorithm shows that the method in this paper has relatively good performance. Simultaneously, author discussed the disadvantage of the algorithm and some recommendation were also proposed aiming at deficiency in the experiment.

1.4 Limitation in experiment

Several issues still exist in the practical application although GMM model has many advantages,

1) .The problem of selection of GMM order

The system recognition rate will be low if the GMM order is too small, and it also generates variety of problems such as increase the system computational complexity and the recognition time if the order is too large. When the order is bigger than a certain special value, its contribution to the performance of the system basic is negligible. In this case, it is very hard to select a suitable order. An appropriate GMM order should be selected to balance the performance and order, but it still may cause the experimental error of the accuracy.

2) .The length of training data

In most time, it is very difficult to obtain enough training data while the training data is insufficient, the components of covariance matrix will be small. Those small values may generate great influence on the performance of the system.

3) . The question of orthogonalization of GMM

The covariance matrix of gaussian mixture model is usually a full rank matrix which lead the calculation work complicated. In practical application, the author will use the diagonal matrix instead of the original covariance matrix to simplified computational complexity. But in fact, each dimension of Covariance matrix is correlation and conditionality. One solution of this problem is transforming the vector into the covariance matrix linearly, which can not only simplified the calculation, but also not ignored the characteristic vector of each dimension .

2 Theory

The process of speech signal can be divided into the following several stages: firstly, the language information produced in human's brain. Secondly, The human brain convert it into language coding. And then express the language coding with different volume, pitch, timbre and cycle. Once the last information coding completed, other people will hear the sound generated by the speakers. Listeners could receive speaker's speech information, and extract the parameter of speech and analysis the spectrum. And converting the spectrum signal into excitation signal of auditory nerve by Neural sensor, then transform the signal to the brain center by auditory nerve. At last, it's been converted into language coding. This is main process of speech generating and speech recognition in the physical phase. In this section, theories will be surrounded with how signal can be simulated and recognized in scientific method, they will explain the characteristics of speech signals, various pre-processing steps involved in feature extraction, how characteristics of speech were extracted and how to understand those characteristics when they are transformed to mathematical coefficient.

2.1 Signal sampling

A speech signal mainly contains two characteristics:

First, signal changes with the time where demonstrates short-time characteristics, which indicates that signal is stable in a very short period of time. Second, spectrum energy of the human's speech signal normally centralized in frequency between 0-4000Hz. [5]

It is an analog signal when speak out from human, and it will convert to a digital signal when input into computer, the conversion of this process introduce the most basic theory for signal processing- signal sampling. It provides principles that the time domain speech analog signal X(t) convert into the frequency domain discrete time signal X(n) while keeps characteristics of the original signal in the same time. [5]And to fulfill discretization of the sampling, another theory Nyquist theory is adopted. The theory requires sampling frequency Fs must equal and larger than two times of the highest frequency for sampling and rebuilding the signal, which can be represented as $F \geq 2*F_{max}$, it offers a way to extract the enough characteristics of the original analog signal in the condition of the least sampling frequency.in the process of signal sampling. Due to inappropriate high sampling frequency lead to sampling too much data （$N=T/\triangle t$）with a certain length of signal (T), it will increase unnecessary workload of computer and taken too much storage; On the contrary, the discrete

time signal won’t represent the characteristics of the original siganl if the sampling frequency is too low and the sampling point are insufficient. [5]

So we always utilize about 8000Hz as the sampling frequency according to Nyquist Theory that $F \geq 2*F_{max}$

2.2 Signal Pre-processing

Voice signal samples into the recognizer to recognize the speech directly, because of the non-stationary of the speech signal and high redundancy of the samples, thus it is very important to pre-process the speech signal for eliminating redundant information and extracting useful information. The speech signal pre-process step can improve the performance of speech recognition and enhance recognition robustness .

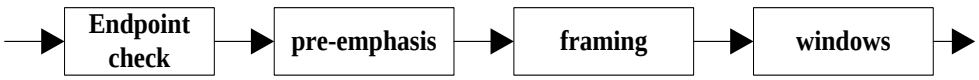


Figure 1 pre-processing structure [6] [7]

It shows that the pre-processing module includes the module of endpoint checking, pre-emphasis, framing, adding window. Endpoint checking can find the head and tail of useful signal, pre-emphasis can reduce the signal dynamic range, framing can divide the speech data into small chunks, Adding window can improve the frequency spectrum of the signal. [5]

2.2.1 Endpoint Detection

End point detection is one of a very significant technology in speech recognition and authors used it as speech signal pre-treatment in the experiment. It can be defined as a technology to detect the start and end point of the target signal so that the testing signal will be more efficiently utilized for training and analyzing with a rather precise recognition result. [8] An ideal end point detection contains the characteristics in reliability, accuracy, adaptability, simplification, real-time processing and no need for noise pre-testing. [6] Generally, it contains two methods in end point detection, one is based on entropy-spectral properties and another is according to double threshold method. The one based on spectral entropy means each frame signal is mainly divided into 16 sub-bands, and the selection will be those sub-bands where distributed in between 250-4000Hz and energy does not exceed 90% of the total in the frequency spectrum, then it will be the calculation of the energy after speech

enhancement and the signal-to-noise ratio of each sub-band. The evidence of the end-point detection will be based on weighted calculation of whole spectral entropy with different SNR adjustment. This method is effective for improving the detection rate in low SNR noisy environment. And the second one, also called double threshold comparison method, it's normally used for single words detection by comparing the short-time average magnitude of signal to short-time average threshold rate. The method is observed by the shape of average magnitude, comprehensively judged by short-time average magnitude which is been settled as a higher threshold T_1 and lower threshold T_2, in the mean while a lower threshold T_3 for short-time average threshold rate [6]

In practical experiment, end point detection will be a compiled program that system will accurately test the start and end point so that to collect the valid data for decreasing processing time and data for later use. After endpoint detection, the speech signal still contains a large number of redundant information, which need us to extract the useful characteristic parameters and remove the useless information. The model parameters, noise model parameters and the adaptive filter parameter are calculated by the corresponding signal segment. [8] Generally speaking, author will check the endpoint of speech voice by average energy or the product of average amplitude value and zero crossing rate with the following equation . [6]

Average energy can be defined as:

$$E_n = \sum_{m=0}^{N-1} \left[w(m) x(n-m) \right]^2, 0 \le m \le N-1 \qquad (1)\ [6]$$

where x(n) is the speech signal, N the length of frame, m is the frame shift, w (m) is the windows function which expressed as $w(m) = \begin{cases} 1, m = 0 \sim N-1 \\ 0, m = other \end{cases}$

Adding window for the signal is to avoid truncation effect when framing, so windowing is necessacery when extract every frames of signal. And it will be more detailed described in next section. [6]

Zero crossing rate is another equation been used during the detection, it indicates number of times that a frame of speech signal waveform cross throught the horizongtal axis. Zero crossing analysiss is one of the simplest method in time domain speech analysis. [9]

It can be defined as:

$$Z_n = \frac{1}{2} \sum_{m=0}^{N-1} \left| \mathrm{sgn}\left[x(m) \right] - \mathrm{sgn}\left[x(m-1) \right] \right| \cdot w(n-m) \qquad (2)\ [8]$$

The function here is to count the times that sign of signal x changes in the domain of 0 to N-1. Here sgn[ ] is the sign function, which defined as $\mathrm{sgn}[x] = \begin{cases} 1, x \geq 0 \\ -1, \ \mathrm{x} \leq 0 \end{cases}$ .Because of energy of the devoiced sound is more concentrated in the high frequency section which makes its zero crossing rate higher than the voiced sound, thus we can use zero crossing rate to distinguish voiced and devoiced sound. [6]

Author made an example of double threshold shown in figure2 :

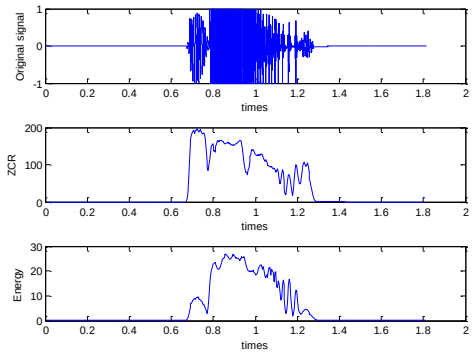


Figure 2 Double threshold detecting endpoints of speech signal, [11]

It manifests that the Double threshold detecting endpoints of speech signal, the first figure is the original signal and the second figure is the Zero crossing rate while the third figure is the Energy. And in the following technique can detect a speech voice or not, if Zn > ratio(ration is a pre setting Zero crossing rate) , then it's a speech signal , namely , it's been found the speech head . vice versa, if Zn < ratio, then the speech signal is over, which means speech tail will be found. The signal between head and tail is the useful signal and thus the threshold in a big noise environment is adjustable. [8] [9]

2.2.2 Pre emphasis

The speech generated from the mouth will loss the information at high frequency, thus it need the pre emphasis process in order to compensate the high frequency loss. Each frame need to be emphasized by a high frequency filter. And for speech signal spectrum, the higher the frequency is, the more serious the loss will be , where requires us do some operation for the high frequency information, namely the pre emphasis. In the speech signal model, the pre emphasis is a 1st order high pass filter. The speech will only remain the track section, it will be very simple to analysis the speech parameter. [10]

The transform function of pre emphasis can be defined as:

$$H(z) = 1 - \alpha z^{-1} \qquad (3)\ [10]$$

According to the pre-emphasis function $H(z) = 1 - \alpha z^{-1}$ we got from the literatures, it can then input the speech signal S(n) into the pre-emphasis module, thus we can got the signal and transform it:

$$\overline{S}(z) = S(z) H(z)$$

$$= S(z)\left(1-\alpha z^{-1}\right)$$

$$= S(z)-\alpha S\left(z^{-1}\right)$$

Parameter α is usually between 0 .94 and 0 .97 . [10]

Therefore, signal in time domain after pre emphasis can be defined as:

$$\overline{S}(n) = S(n)-\alpha S(n-1) \qquad (4)$$

Based on the theory, the author can make the speech signal spectrum more flat and reduce the signal dynamic range . Figure3 shows the simulation of pre emphasis.

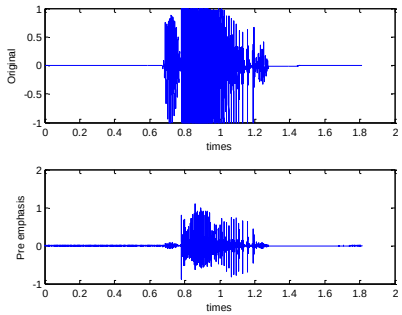


Figure 3 The pre emphasis of the original signal in time domain, [11]

And then do the FFT transform of Pre-emphasis speech signal as Figure 4 shows that after Pre-emphasis, the high frequency part of the speech signal is enhanced obviously. Which manifest the meaning of pre-emphasis process to enhance the high frequency section of speech signal so that compensate the loss of high frequency for lip eradiation and inherent decline of speech spectrum, and also eliminate impact of the lip eradiation. [12]

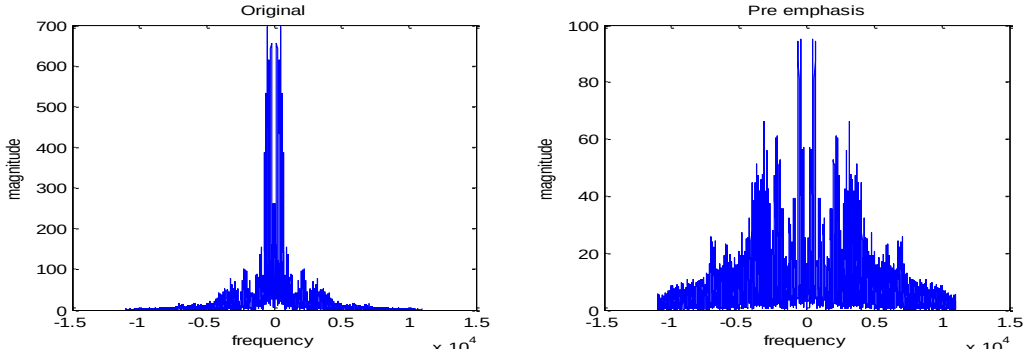


Figure 4 The pre-emphasis of the original signal in frequency domain, [11]

2.2.3 Frame Blocking

The speech voice belongs to time-varying signal, which means the speech signal is a no-linear signal with time changes. So we can't use the linear time invariant analysis method to observe the speech signal. In this case, the author cut the original signal into several small

pieces of continuous signal, because the speech signal has the characteristic parameters of short time smooth. Typically, a frame of 20 - 30 ms could be considered for the short time Time-Invariant property of speech signal. Framing can be classified as non-overlapping and overlapping frames. Based on the characteristics of short-time smooth, the voice signal is in the range of 20 - 30 ms is stable , which means the voice signal is stable in short time range, [13] hence linear time invariant method can be used to analysis the speech signal then.

It is commonly believed that it should be contained 1 ~ 7 pitch in a speech frame. But in most time, the pitch cycle of human is always different and changing . The pitch cycle of girl is nearly 2ms, an old man is nearly 14ms. So it is very hard to select a sure value of N. The range of N is always 100 ~ 200. if the sample frequency of speech is 10Khz, then the length of each frame is about 10 ~ 20ms .

2.2.4 Adding Windows

The window function is a sequence with finite length, which used to select a desired frame of the original signal and this process is a called windowing. Adding windows is a continuation of short time speech signal processing, which means the speech signal multiplied by a window function in time domain, simultaneously, it intercepted the signal part frequency components. [14] And author made simple comparison with three types of window function that most common to see as below including:

1) .Rectangular window:

$$w(n)=\begin{cases}1, 0\le n\le N-1\\ 0, n>N-1\end{cases} \quad (7)\ [14]$$

Rectangular windows function is a very simple window, which is replacing N values by zeros, and the waveform will be suddenly turned on and off

2) .Hanning window:

$$w(n)=\begin{cases}0.5-0.5\times\cos\left(\dfrac{2n\pi}{N-1}\right), 0\le n\le N-1\\ 0, n>N-1\end{cases} \quad (8)\ [14]$$

3) .Hamming window:

$$w(n)=\begin{cases}0.54-0.46\times\cos\left(\dfrac{2n\pi}{N-1}\right), 0\le n\le N-1\\ 0, n>N-1\end{cases} \quad (9)\ [14]$$

The selection of different windows will determine the nature of the speech signal short-time average energy. The shape of the window is different, but all of them are symmetric . And the length of window will play a very important role in the filter. If the length of window is too long, the pass band of filter will be narrow. Otherwise, if the length of window is too small , the pass band of filter will be wide, and the signal can be represented sufficiently equally distributed. [12] [14]

Author made the example of three windows in time and frequency domain respectively below:

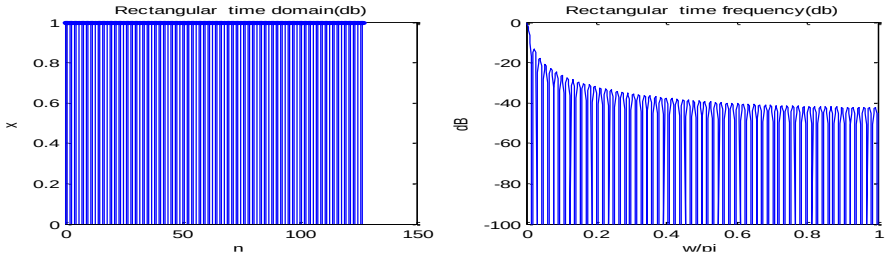


Figure 5 Rectangular window, [11]

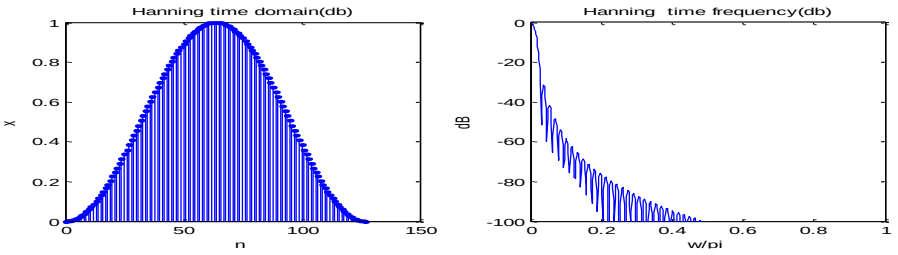


Figure 6 Hanning window, [11]

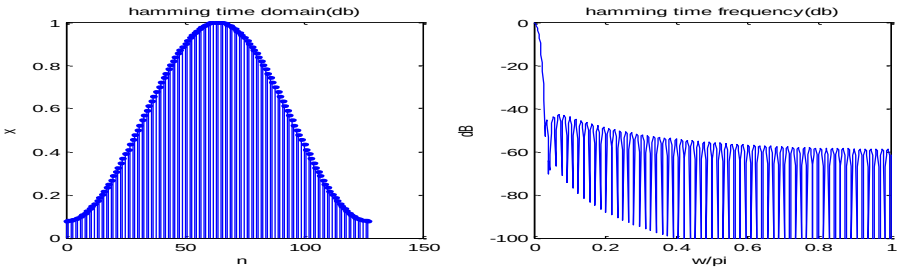


Figure 7 Hamming window, [11]

It's can been observed from the figures above that all three windows have common characteristics of low pass. The main lobe of Rectangular window is the smallest, while the highest side lobe level and frequency spectrum leakage phenomenon is obvious. The main lobe of hamming window is the widest, and it has the lowest side lobe level. The choice of the window is critical for analysis of speech signal, utilizing rectangular window is easily loss the details of the waveform, on the contrary, hamming window is more effective to decrease frequency spectrum leakage with the smoother low pass effect. Therefore, Rectangular window is more fit for processing signals in time domain and hamming window is more used

in frequency domain. [6] In the other hand, hamming window have relatively stable spectrum for speech signal, and it helps to enhance the characteristics of the central section of signal, which remains the better characteristics of original signal. [12] Besides, there's another purpose to use Hamming window for Gibbs phenomenon that relate to FFT that need to be used later in calculating MFCC section, it's a problem which caused by the truncation of Fourier series or DFT of data with finite length with discontinuities at end points. It means after FFT to the discrete periodic functions eg. rectangular pulses, and weight the data points. The more points are taken, the peak of the waveform will be closer to the discrete points of the original signals. When number of points are big enough, the value of the peak will be approximate to a constant. Utilizing windows Hamming windows therefore is the good way to force the end points to approximate to zero thus to ease the ripples of the Gibbs phenomenon. [15]

So author prefer hamming window to process the signal in the experiment by the code "hamming" function in Matlab.

w = hamming (L) ;

It returns an L point symmetric Hamming window in the column vector w. L should be a positive integer. The coefficients of a Hamming window are computed from the following equation .If the signal in a frame is denoted by s(n), n = 0,…N-1, then the signal will be s(n)*w(n) by adding Hamming windowing. And then the difference with different parameter α . w(n) is the Hamming window defined by, $w(n,\alpha)=(1-\alpha)-\alpha\cos(\frac{2\pi n}{N-1})$,which can be studied, as Figure 17 shows the influence of parameter α :

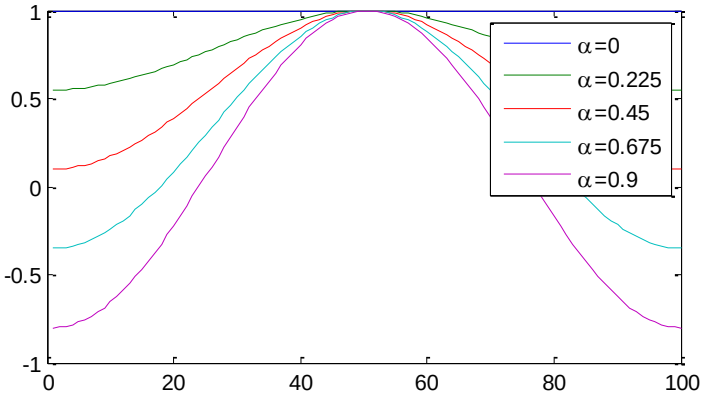


Figure 8 Generalized Hamming Window with different alpha, [11]

It shows a better observation when α is between 0.45 to 0.675 and in the experiment I set the value of α 0.46 and use the hamming window as the filter, The simulation results is shown in figure 18

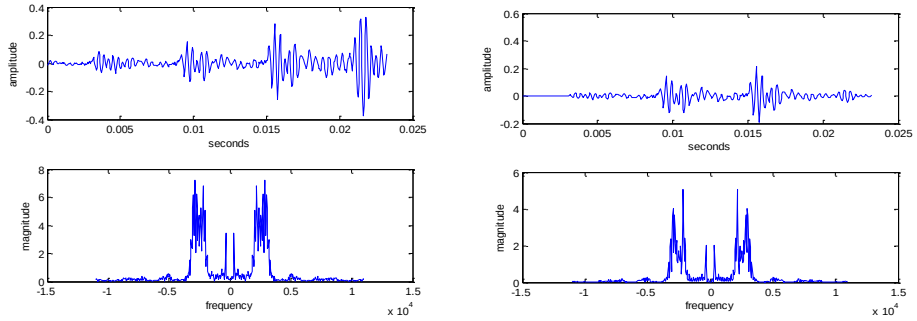


Figure 9 the result of Adding window, [11]

It can be observed that the signal will become smoother after the hamming window. As we know, In signal processing theory, The window function is a mathematical function that is zero-valued outside of some chosen interval. And as the results of pre process shown in the theory explanation, the speech signal will become smoother and low dynamic range, which manifest here we have get a relatively ideal signal to be processed. In summary, the hamming windows are weighting functions applied to data to reduce the spectrum leakage associated with finite observation intervals. It's better to use the window to truncate the long signal sequence into the short time sequence. In this way, the using of window in the pre-processing phase will not only reduce the leakage of the frequency component, but also make spectrum smoother.

2.3 The characteristic parameters of speech signal

Before the recognition of speech, characteristic parameters of the input speech signal is need to be extracted. The purpose of characteristic parameters extraction is to analyze speech signal processing and removes the redundant information which has nothing to do with speech recognition and obtain the important information .Generally speaking, there are two kinds of characteristic parameters, the first one is the characteristic parameters in time domain and the second is in transform domain. The advantage of characteristic parameters in time domain is simple calculation. However, it cannot be compressed and also not suitable for the characterization of amplitude spectrum characteristics. [16]

So far, the speech signal characteristic parameters are almost based on short-time spectrum estimation, the author learnt 2 related parameters that can be used in Matlab including Linear Predictive Coefficient, and the Mel frequency Cepstrum Coefficient in this research. The method of Linear predictive analysis is one of the most important and widely used speech analysis techniques. The importance of this method is grounded both in its ability to provide accurate estimates of the speech parameters and in its relative speed of computation. The method of Linear predictive analysis is based on the assumption that the speech can be characterized by a predictor model, which looks at past values of the output alone; hence it is an all pole model in the Z transform domain.

The method of Mel Frequency Cepstral Coefficients is also a powerful technique, which is calculated based on the mel scale. Before calculating the MFCC coefficient, it is necessary framing the whole speech signal into multi sub frames, the Hamming windows and Fast Fourier transformation are computed for each frame. The power spectrum is segmented into a number of critical bands by means of a filter-bank typically consists of overlapping triangular filters which will adapt the frequency resolution to the properties of the human ear . The discrete cosine transformation applied to the logarithm of the filter-bank outputs results in the raw MFCC vector triangular filters. So the MFCC imitate the ear perception behavior and give, good identification than LPC. [17]

2.3.1 MFCC

Mel Frequency Cepstral Coefficient proposed by Dr Davis, is the characteristic parameter which widely used in speech recognition or speaker recognition. Before the Mel Frequency Cepstral Coefficients, the researchers always use the Linear Prediction Coefficients or Linear Prediction Cepstral Coefficients as the Characteristic parameters of speech signal. Mel Frequency Cepstral Coefficients is the representation of short time power spectrum of a speech signal, and it is calculated by DCT [1]to convert into time domain, based on a linear cosine transform of a log power spectrum on a nonlinear mel scale of frequency. Then the result will be set of the acoustic vectors. [7]

MFCC are commonly used as Characteristic parameters in speech recognition algorithm. In the theory of MFCC, the Critical Band is a very important concept which can solve problem of frequency division, it is also an important indicator of Mel frequency. The purpose of

[1] DCT: Abbreviated from discrete cosine transform, defined as a finite sequence of data points which establish a sum of cosine functions with different frequencies. [7]

introducing critical bandwidth is to describe the masking effect. When two similar or same pitches voiced in the same time, human ear can't distinguish the difference and only can receive one pitch. The condition that two pitches can be received is that the weight difference of two frequencies suppose two larger than certain bandwidth, and we called this as critical bandwidth. [14] In critical bandwidth, if the sound pressure of a speech signal with noise is constant, the loudness of speech signal with noise is constant then. But once the noise bandwidth beyond the critical bandwidth, the loudness will change obviously. And its expression defined as follows,

$$BW_c = 25 + 75 \times \left[1.4 \left(\frac{f_c}{1000} \right)^2 \right]^{0.69} \quad [2] \qquad (32)\ [14]$$

The characteristics of the ear receiving process is thus been simulated by establishing the critical bandwidth filter bank to achieving the recognition. The critical bandwidth filter bank is a set of filters where center frequency of every filters in mel frequency domain are distributed in linear and their bandwidth are always in the critical bandwidth range. [14] In practical use, critical bandwidth will change with the changing of frequency, and is proportional to the frequency growth. When the frequency is under 1000Hz, the Critical Band is almost linear, approximately 100Hz, when the frequency is more then 1000Hz , the Critical Band will growth exponently . Then it can divide the speech frequency into a series of triangular filter series. [18] [19]

The Mel scale relates perceived frequency or pitch of a pure tone to its actual measured frequency. Humans are much better at discerning small changes in pitch at low frequencies than they are at high frequencies. Incorporating this scale makes our Characteristic parameters match more closely what humans hear.

The formula for converting from normal frequency to Mel scale can be defined as:

$$M(f) = 1125 \times \ln\left(1 + \frac{f}{700} \right) \qquad (33)\ [14]$$

Then we can get $M^{-1}(m)$, the inverse function of above

$$M^{-1}(m) = 700\left(e^{(m/1125)} - 1 \right) \qquad (34)\ [14]$$

Then for implement and calculate MFCC:

Step1: Adding the hamming window to the input speech frame:

[2] f_c represent mel frequency.

$$\overline{x_l}(n) = x_l(n)w(n), 0 \le n \le N-1 \quad (35)\ [6]$$

where

$$w(n) = 0.54 - 0.46\cos\left(\frac{2\pi n}{N-1}\right), 0 \le n \le N-1 \quad (36)\ [14]$$

Step2: Do the calculation of FFT to get the signal in frequency domain.

Based on the equation 34, we can get the output of every filter thus to perform $S_i(k)$, the Discrete Fourier Transform of the frames of the signal in short time,

$$S_i(k) = \sum_{n=1}^{N} s_i(n)h(n)e^{-j2\pi kn/N}, 1 \le k \le K \quad (37)\ [14]$$

Where h(n) is an N sample long analysis window , K is the length of the DFT . The period gram based power spectral estimate for the speech frame Si(k) is given by function:

$$P_i(k) = \frac{1}{N}\left|S_i(k)\right|^2 \quad (38)\ [14]$$

This is called the Periodogram estimation of the power spectrum, it helps to take the absolute value of the complex fourier transform , and square the result .

The fast Fourier transform (FFT) is an algorithm which can calculate the discrete Fourier transform more quickly than the DCT itself. The signal can be transformed from the time domain to frequency domain, and vice versa. The most important advantage of the fast Fourier transform is its calculation speed. Nowadays, the FFT is widely used in many applications, such as signal process, science, communication and so on. The fast Fourier transform were first proposed by Cooley and Tukey in 1965. And then, doctor Danielson-Lanczos lemma have proposed the discrete Fourier transform, which can compute the fft by discrete time domain. Normally, the length of data will be calculated by FFT is always a power of two, when the length is not the power of two, we can add the points of zeros value until the length is power of two. An efficient real Fourier transform algorithm or a fast Hartley transform gives a further increase in speed by approximately a factor of two. [5]

The Fast Fourier transform algorithms can be divided into two classes, the first is decimation in time, the second is decimation in frequency. The famous algorithm of Cooley Tukey FFT, which first rearranges the input elements in bit-reversed order , then builds the output transform . [5]

$$\sum_{n=0}^{N-1} a_n e^{-2\pi ink/N} = \sum_{n=0}^{N/2-1} a_{2n} e^{-2\pi i(2n)k/N} + \sum_{n=0}^{N/2-1} a_{2n+1} e^{-2\pi i(2n+1)k/N}$$

$$= \sum_{n=0}^{N/2-1} a_n^{even} e^{-2\pi ink/(N/2)} + e^{-2\pi ik/N} \sum_{n=0}^{N/2-1} a_n^{odd} e^{-2\pi ink/(N/2)} \quad (39)\ [5]$$

Step3: Filter bank

To implement this filter bank, the window of speech data is transformed by using a Fourier transform and taking the magnitude. The magnitude coefficients are then binned by correlating them with each triangular filter. Here binning means that each FFT magnitude coefficient is multiplied by the corresponding filter gain and the results accumulated. Thus, each bin holds a weighted sum representing the spectral magnitude in that filter bank channel. Fig. 10 illustrates the general form of this filter bank:

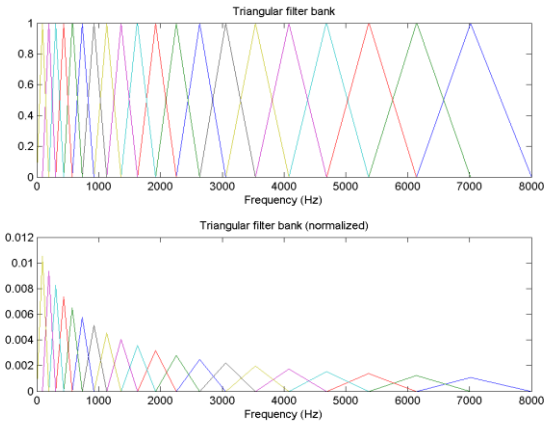


Figure 1 0 filter bank starts at 0Hz and ends at 8000Hz, [11]

This figure shows a set of triangular filters that are used to compute a weighted sum of filter spectral components so that the output of process approximates to a Mel scale. Each filter‘s magnitude frequency response is triangular in shape and equal to unity at the centre frequency and decrease linearly to zero at centre frequency of two adjacent filters. Normally the triangular filters are spread over the whole frequency range from zero up to the Nyquist frequency. However, band-limiting is often useful to reject unwanted frequencies or avoid allocating filters to frequency regions in which there is no useful signal energy. The main function of triangular band pass filters is smoothing the magnitude spectrum into to obtain the envelop of the spectrum which can indicate the pitch of a speech signal is usually not presented in MFCC.

This is a set of 20-40 (26 is standard) triangular filters that the author apply to the periodogram power spectral estimate from step 2. Our filter bank comes in the form of 26 vectors of length 257). Each vector is mostly zeros, but is non-zero for a certain section of the spectrum. To calculate filter bank energies it need to multiply each filter bank with the power spectrum, then add up the coefficients. Once this is performed there will left with 26 numbers that give us an indication of how much energy was in each filter bank. [5]For a detailed explanation of how to calculate the filter banks see below.

The main step of Computing the Mel filter bank：

Step1: Selecting a lower (300 ~ 600 Hz) and upper (6000 ~ 10000 Hz)frequency .

Step2: Converting the upper and lower frequencies to Mels .

Step3: Computing the filter bank, It is assumed that there are M filters, The output of triangle filter Y can be defined as:

$$Y_i = \sum_{k=F_{i-1}}^{F_i} \frac{k - F_{i-1}}{F_i - F_{i-1}} X_k + \sum_{k=F_i+1}^{F_{i+1}} \frac{F_{i+1} - k}{F_{i+1} - F_i} X_k, i = 1, 2, ..., M \quad (40)$$

[14]

Where M is the number of filter , Xk is the energy of k th frequency point , Yi is the output of i th filter , Fi is the centre frequency of i th filter .

Now the author create our filter banks. The first filter bank will start at the first point, reach its peak at the second point , then return to zero at the 3rd point . The second filter bank will start at the 2nd point, reach its max at the 3rd , then be zero at the 4th etc . A formula for calculating these is as follows:

$$H(k) = \begin{cases} 0, k < f(m-1) \\ \dfrac{k - f(m-1)}{f(m) - f(m-1)}, f(m-1) \le k \le f(m) \\ \dfrac{f(m+1) - k}{f(m+1) - f(m)}, f(m) \le k \le f(m+1) \\ 0, k > f(m+1) \end{cases} \quad (41)\ [14]$$

where M is the number of filters the author want , and f is the list of M+2 Mel-spaced frequencies . The centre frequency f(m) can be calculated by:

$$f(m) = \left(\frac{N}{F_s} \right) Mel^{(-1)} \left[Mel(f_l) + i \frac{Mel(f_h) - Mel(f_l)}{M + 1} \right] \quad (42)\ [14]$$

where fl is lower frequency, fh is the higher frequency . Fs is the sample frequency, Mel(-1) the inverse function of Mel .

Step4: Although MFCC alone can be used as the characteristic parameters for speech recognition, but here we can add up the log calculation to improve the performance in the process, and it can be simply programmed by the following code in Matlab to calculate the log of filter bank energies. So take the log of each of all the energies from step 3 and then we can get the MFCC after FFT translation.

Step5: DCT, the abbreviation of discrete cosine transform, which can express a finite sequence of data as a sum of cosine function value at different frequencies. Discrete cosine

transform is a very important technology in the applications of multimedia fields, such as the lossy compression of jpeg and audio. The reason why DCT transform is calculated based on the cosine function rather than sine functions is because of when calculate both of them, cos(-X) = cos(X) and sin(-X)=-sin(X), which indicates cosine function will save half of the storage cause it's one step less compared with the sine function, and cosine function is more flexible to get the value when it's in between 180-360° by taking the inversely value of 0-180° , while sine function can't. Thus cosine functions are much more efficient than the sine functions in compression, and the cosines functions can express a particular choice of boundary conditions in differential equations. In particular, a DCT is a Fourier-related transform similar to the discrete Fourier transform (DFT), but using only real numbers. There are eight standard DCT variants, of which four are common. The most common variant of discrete cosine transform is the type-II DCT, which is often called simply "the DCT". [5]The formula can be defined as:

$$X_k = \sum_{n=0}^{N-1} x_n \cos\left(\frac{\pi}{N}\left(n+\frac{1}{2}\right)k\right), k = 0,\ldots,N-1 \quad (43)\ [5]$$

where N is the triangular band pass filters numbers, is the number of mel scale cepstral coefficients. This transform is exactly equivalent to a DFT of real inputs of even symmetry where the even-indexed elements are zero.

Step6: In order to express the dynamic Characteristic parameters of speech signal , the author always add the 1-order cepstrum to the speech signal:

$$\Delta c_l(\tau) = \sum_{k=-2}^{2} k c_{l-k}(\tau), 1 \le \tau \le P \quad (44)\ [5]$$

2.4 Recognition

2.4.1 GMM (Gaussian Mixture Model)

GMM, the abbreviation of Gaussian Mixture Model, which can be seen as a probability density function. The method of GMM is widely used in many fields, such as recognition, prediction, clustering analysis. The parameters of GMM are estimated from the training data by Expectation-Maximization (EM) algorithm or Maximum A Posteriori (MAP) estimation.

Compared with many other model and method, the Gaussian Mixture Model has many advantages, hence it is widely used in the speech recognition field. As a fact, the GMM can be

seen as a CHMM with only one state, but yet it can not be simply regarded as a hidden markov model (HMM) due to GMM completely avoid the segmentation of the system state. When compared with the HMM model, the GMM mode will make the researching of speech recognition more simply, but the performance has no lossy. And the gaussian mixture model which is calculating the characteristic parameters space distribution by the weight sum of multi gaussian density function when compared with the VQ method, from this point of view, the GMM has more accuracy and superiority. [20] It is very hard to match the process of human's pronunciation organs, but we can simulate a model which express the process of sound, and it can be implemented by building a probability model for speech processing, while gaussian mixture model is the very probability model which can qualified the condition .

The definition of gaussian mixture model

The formula of M order gaussian mixture model can be defined as:

$$P(x_t) = \sum_{i=l}^{M} \alpha_i p_i(x_t) \quad (52)\ [14]$$

where xt is a D dimension Speech Characteristic parameters vector, $p_i(x_t)$ is the element of gaussian mixture model, namely the probability density function of each model. α_i is the weight coefficient of $p_i(x_t)$. M is the order of gaussian mixture model, namely the number of probability density function. the author can know that:

$$\sum_{i=1}^{M} \alpha_i = 1 \quad (53)\ [14]$$

$$p_i(x_t) = \frac{1}{\left(2\pi^{\frac{D}{2}}\right)\left|\sum_i\right|^{\frac{1}{2}}} \exp\left\{-\frac{(x_t - u_i)^T \sum_i^{-1} (x_t - u_i)}{2}\right\} \quad (54)\ [14]$$

Thus the element $p_i(x_t)$ of gaussian mixture model can be described the mean value and covariance. [21]

EM algorithm is the abbreviation of expectation maximization, which is an iterative method. The EM algorithm can search the maximum likelihood estimation of parameters in statistical models. The EM algorithm can be divided into two steps, the first step is the expectation (E) step, which can generate a function for the expectation of the log-likelihood. The second step is the maximization (M) step, which can compute the parameters and maximize the expected log-likelihood searched on the step E. In many research fields, the

Expectation maximization is the most popular technique, which is used to calculate the parameters of a parametric mixture model distribution. It is an iterative algorithm with Three steps: Initialization, the expectation step and the maximization step . [22]

Each class j of M clusters, which is constituted by a parameter vector (θ), composed by the mean (μ_j) and by the covariance matrix (P_j). On the initial time, the implementation can generate randomly the initial values of mean (μ_j) and of covariance matrix (P_j). The EM algorithm aims to approximate the parameter vector (θ) of the real distribution.

Expectation step is responsible to estimate the probability of each element belong to each cluster $P\left(C_j \mid x_k\right)$. Each element is composed by an attribute vector (x_k). With initial guesses for the parameters of our mixture model, The probability of hidden state i can be defined as [20]:

$$P\left(i_t = i \mid x_{t,\lambda}\right) = \frac{P_i P\left(x_t \mid i_t = i, \lambda\right)}{P\left(x_t \mid \lambda\right)} = \frac{P b_i\left(x_i\right)}{\sum_{m=1}^{M} P_m b_m\left(x_t\right)} \quad (55)\ [22]$$

Maximization step is responsible to estimate the parameters of the probability distribution of each class for the next step. First is computed the mean (μ_j) of class j obtained through the mean of all points in function of the relevance degree of each point.

The calculation of $\alpha_i\ \mu_i\ \sum_i$:

$$\alpha'_i = \frac{\sum_{t=1}^{T} r_t(i)}{\frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{M} r_t(i)} = \frac{1}{T}\sum_{t=1}^{T} P(i_t = i \mid x_t, \lambda) \quad (56)\ [22]$$

$$\mu_i = \frac{\sum_{t=1}^{T} r_t(i) x_t}{\sum_{t=1}^{T} r_t(i)} = \frac{\sum_{t=1}^{T} P\left(i_t = i \mid x_t, \lambda\right) x_t}{\sum_{t=1}^{T} P\left(i_t = i \mid x_t, \lambda\right)} \quad (57)\ [22]$$

$$\sum_i = \frac{\sum_{t=1}^{T} P\left(i_t = i \mid x_t, \lambda\right)\left(x_t - \mu_i\right)^2}{\sum_{t=1}^{T} P\left(i_t = i \mid x_t, \lambda\right)} \quad (58)\ [22]$$

The advantage of GMM is that the sample points after projection is not get a certain tags, but also get the probability of each class that is an important information. The calculation of

GMM in each steps is very large and the solving method of GMM is based on EM algorithm, where it is likely to fall into local extremum, which is related with the initial value. [21] [22]

2.5 Tools in the experiment.

The major tool to achieve the simulation experiment and analysis in this report is to utilize Matlab where I use the version 2010. MATLAB is a numerical computing environment and fourth-generation programming language which is Developed by MathWorks. MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms from elementary functions like sum , sine , cosine , and complex arithmetic, to more sophisticated functions like matrix inverse, matrix eigenvalues, Bessel functions, and fast Fourier transforms, creation of user interfaces , and interfacing with programs written in other languages , including C , C++ , Java , and Fortran .

And another toolbox which called VOICEBOX is used for speech processing, it consists of MATLAB routines that are maintained by and mostly written by Mike Brookes [23]

The speech processing toolbox contains many speech process function, in this project, the author has used the following functions.

frq2mel .m : Convert Hertz to mel scale;
mel2frq .m : Convert mel scale to Hertz;
rfft .m : FFT of real data;
rdct .m : DCT of real data;
enframe .m : Divide a speech signal into frames;
Lpc .m : Convert between alternative LPC representation;
kmeans .m : Vector quantisation, k-means algorithm;
melbankm .m : Mel filterbank transformation matrix;
melcepst .m : Mel cepstrum frontend for recogniser;
gaussmix .m : Fit a gaussian mixture model to data values;

3 Process and results

3.1 Process

3.1.1 Flow chart of the experiment

From the literature review, Pre-processing, MFCC Characteristic parameters extraction, GMM recognition is the most important module in this the whole structure of algorithm. it can be learnt that the new module of the speech recognition can be sort out into sequence of pre-processing-MFCC-GMM implementation which gives relatively higher accuracy on diverse conditions and in presence of noise, as well as for a wide variety of speech words and hence this paper will be focusing on this particular area .

The whole algorithm flow chart can be described in figure 11 with the sequence of the theory author introduced,

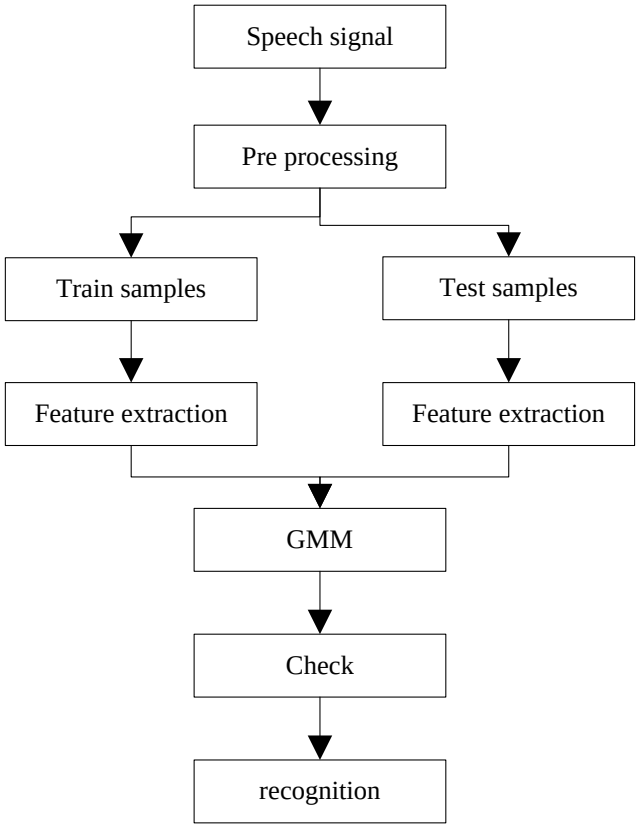


Figure 1 1 main flow of algorithm, [11]

The flow of the experiment will start with the recorded reference signal simples, which will be first pre-process by the characteristic parameters extraction and then go through GMM recognition and realized as the sound reference library, and then it will be the testing signal

simples that implemented by the same algorithms and routines where the output will be extracted to compare with the reference therefore to achieving the recognition.

3.1.2 Speech recognition system evaluation criterion

After the signal processing and simulated recognition, the result requires a criteria to represent and analysis. Normally for the isolated word recognition system, whole word recognition rate to evaluate and identify accuracy will be defined as:

$$R = \frac{N_{right}}{N_{total}}$$

(58)

where R is recognition rate, N_{right} is the number of right recognition words, N_{total} is the total number of words .

For the continuous speech recognition system, sentence recognition rate can be achieved by assessing the system recognition accuracy where quantity of the sentence recognition rate is often affected by the number of sentence and the influence of language model information utilization .

$$R_{word} = \frac{N_{right-word}}{N_{total-word}}$$

(59)

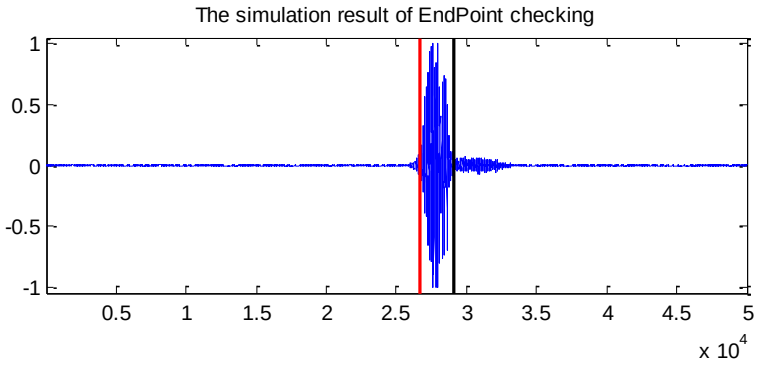
R_{word} is the identification accuracy, $N_{right-word}$ is the number of right recognition words , $N_{total-word}$ is the total number of words .

In this project, the first method will be used in the analysis due to the focus in this project is the recognition of isolated word recognition system and some simple words as samples like “Yes and No”, ”on and off” will be utilized.

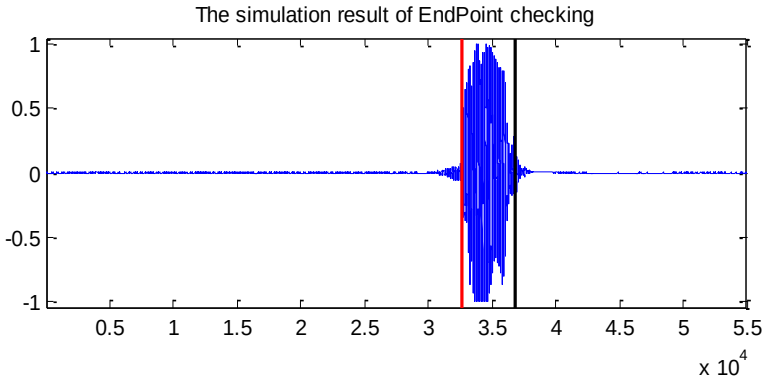
3.2 Result

3.2.1 Pre Process

As introduction mentioned, the first model of our algorithm is the Pre Process Steps, which includes the module of endpoint checking, pre-emphasis , framing , adding window , etc. The function of Endpoint checking will get the useful segment of speech signal and remove the useless segment of speech signal. In this project, the author use the theory based on zero crossing rate .



a). **The Endpoint of test samples "Yes"** [11]



b). **The Endpoint of test samples "No"** [11]

Figure 1 2 The Endpoint of two test samples

Based on the theory, if Zn > ratio, the speech head is been found. Vice versa, if Zn < ratio, then the speech signal is over and we have found the speech tail. The signal between head and tail is the useful signal. In figure 12, the speech signal can be detected by the Endpoint checking module, The red line means the start line of the speech signal, the black line mean the end of the speech signal. If there is noise in the speech signal, the author can also use this method to find the head and tail of the speech signal. Thus we can generate the useful signal from a whole speech signal, which establish a great start for the follow process steps. On the

other hand, if the speech signal is a continuous sequence, the signal can be divided into the continuous sequence in some isolated words.

Pre emphasis is widely used in the field of telecommunications, digital speech recording and so on. In a high speed digital transmission, the process of Pre emphasis is always used to improve signal quality at the output of the system. In the process of signal transmission that the signal may be distorted so that the pre emphasis is used to distort the transmitted signal to correct for this distortion. In a whole speech process system, the Pre emphasis is the first part of noise reduction technique, higher frequencies are boosted before they are transmitted or recorded onto a storage medium.

In this project, the parameter α of pre-emphasis function is 0 .95, which make 95% of any one sample is presumed to originate from previous sample. Pre emphasis can be expressed as the following formula:

$$H(z) = 1 - 0.95z^{-1} \quad (1)$$

$$\bar{s}(n) = s(n) - 0.95s(n-1) \quad (2)$$

In MATLAB , the code author has written is:

yPreEmp = filter ([1 , -0 .95] , 1 , y);

Then by using filter function directly it comes a filtered data sequence using a digital filter where works for both real and complex inputs. The filter is a direct form II transposed implementation of the standard difference equation and this make Pre-emphasis a filter .

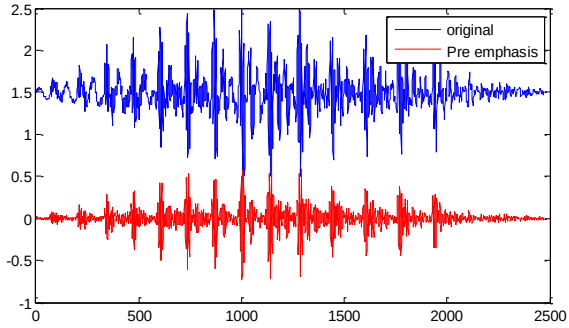


Figure 1 3 The signal after pre emphasis [11]

Figure above shows that the original speech signal becomes more stable after Pre-emphasis , and this conduct reducing the dynamic range which makes the signal become suitable for processing .

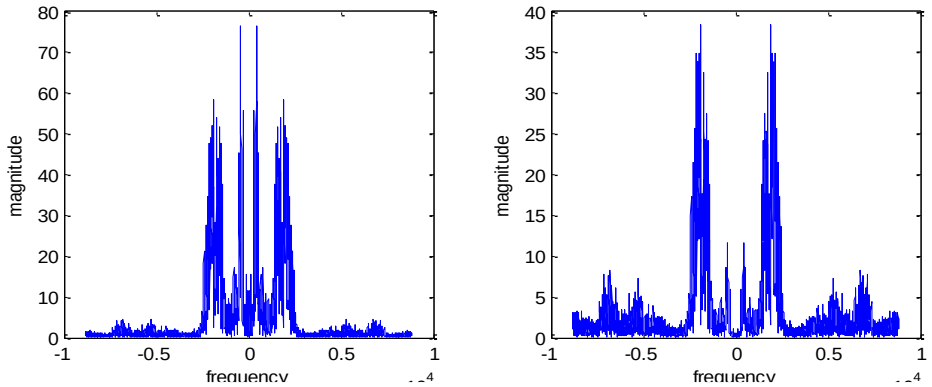


Figure 1 4 The signal after pre emphasis, [11]

And the spectrum shows that the system can compensate the high-frequency part which was suppressed during the sound production process by pre emphasis. And then it's been the framing part to sampling the signal and framing operation can convert the whole frame into N short frame from short frame 1 to N, and it followed by the main code as follows:

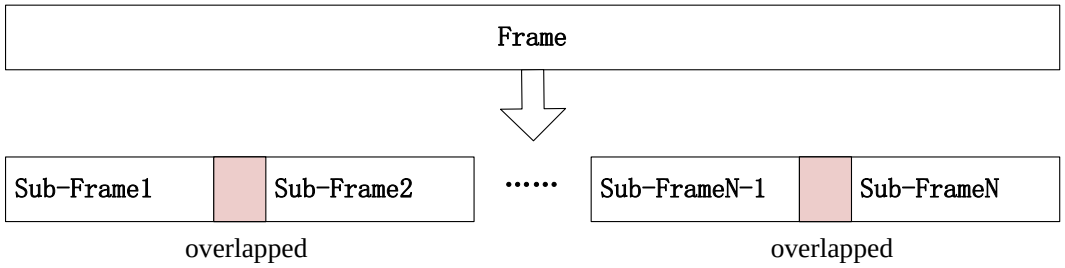


Figure 1 5 framing, [13]

Length of each frame is recorded 256 samples points as 22.8ms. The overlap of frame is 12 samples. Then, the speech signal can be analysis by Linear time invariant method.

As the theory introduced, the purpose of utilizing hamming windows is to ease the ripples of the Gibbs phenomenon, which are the result of the Fourier series approximation, a series of continuous functions, over the discontinuous desired magnitude response.

3.2.2 MFCC

Now computation of MFCC will be discussed step by step. The main stage for calculating the MFCC coefficients is taking the log spectrum of the windowed waveform which will then be smoothened out by triangular filters and then compute the DCT of the waveform to generate the MFCC coefficients. In programming, experiment procedure for this part was followed by the following steps based on the literature reviews,

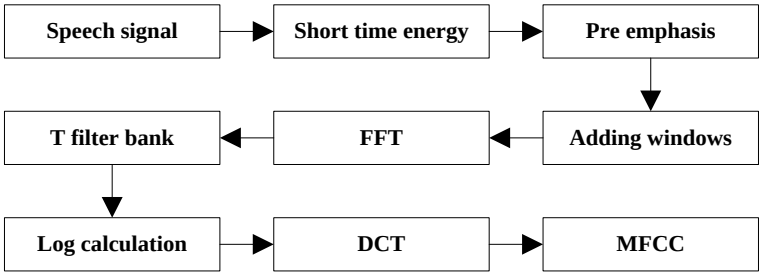


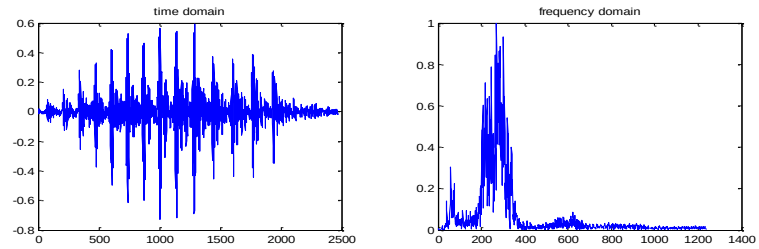
Figure 1 6 the extraction step of MFCC [7]

It's total 9 steps of MFCC extraction where the first four steps are the signal pre-process including signal input, short time energy, pre emphasis, adding windows as we mentioned before. And the following five steps are the extraction process , including the FFT , filter bank ,Log , DCT and MFCC .

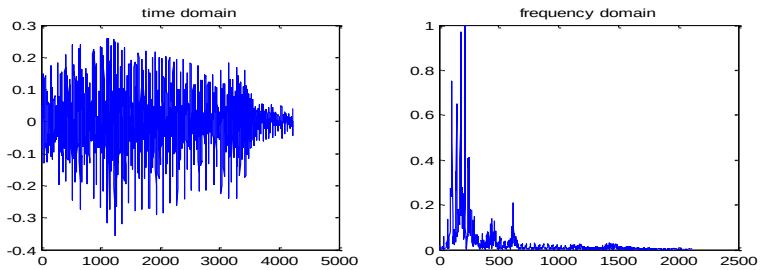
FFT , the abbreviation of the Fast Fourier Transform, is essentially transformed from the discrete-time signal from time domain into its frequency domain. Algorithm is the Radix-2 FFT Algorithm where we can directly use the MATLAB code

y=fft(x,n);

Here, the "FFT" function is used to get the frequency domain signal. The following spectrum are respectively represent time domain and frequency domain, where the spectrum in frequency domain only display the right section from 0. So the frequency domain spectrum are always about half of the length compared with the time domain spectrum. The word of "YES" is disyllable, which means the total range of it will be longer that other monosyllable words.

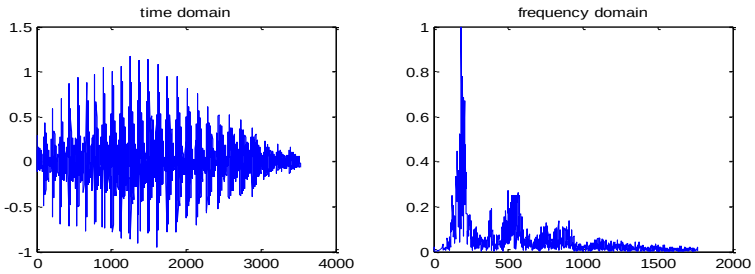


a). **The frequency signal of speech word "Yes"** [11]

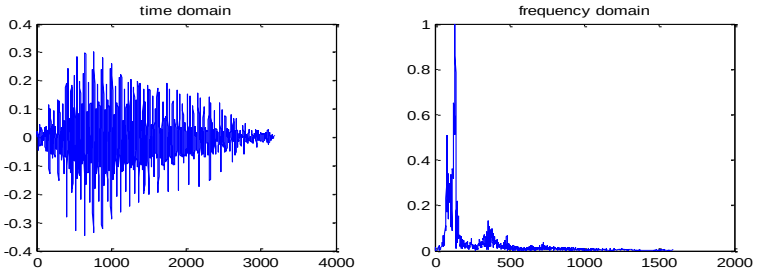


b). **The frequency signal of speech word "No"** [11]

Figure 1 7 The frequency signal after fft



a). **The frequency signal of speech word "on"** [11]



b). **The frequency signal of speech word "off"**

Figure 1 8 The frequency signal after FFT [11]

After doing DFT and FFT transform, The signal will be changed from the discrete time signals x(n) to the frequency domain signal X(ω) . The spectrum of the X(ω) is the whole integral or the summation of the all frequency components. When talking about the speech signal frequency for different words, each word has its frequency bandwidth, For examples, Speech "Yes" has the frequency range between 200 and 400, while speech "No" has the frequency range between 50 and 300, and speech "On" has the frequency range between 100 and 200 , speech "off" has the frequency range between 50 and 200, all of them are not just a single frequency. And the max value of frequency spectrum is 1, where is the result of normalization after FFT. The normalization can reduce the error when comparing the spectrums, which is good for the speech recognition. On the other hand, the result of FFT transform is always a complex value, which is not suitable for other operation, so here adopt absolute values of the FFT and lead it to be a real value like the figure 20 and 21 shown. The frequency analysis shows that that different timbre in speech signals corresponds to the different energy frequency distribution.

It's the filter bank followed by the normalization of the signal, I multiple the magnitude frequency response by a set of 20 band pass filters to get the log energy of each triangular band pass filter. As we know, the filters used are triangular band pass filter. The positions of

these filters are equally spaced along the Mel frequency, which is related to the linear frequency. They are equally spaced along the mel scale which is defined by

$$Mel(f) = 2595 \times \log_{10}\left(1 + \frac{f}{700}\right)$$

As theory mentioned, the goal of computing the discrete cosine transform (DCT) of log filter-bank is to get the uncorrelated MFCC. In this project, With our MFCC computation, the DCT is applied to the output of 40 mel scale filters. The following value of the output of the filters.

-2.586 , -2.627 , -2.086 , -2.100 , -2.319 , -1.975 , -2.178 , -2.195 , -1.953 , -2.231 ,
-2.021 , -1.933 , -1.966 , -1.514 , -1.646 , -1.530 , -1.488 , -2.062 , -2.286 , -2.348 ,
-2.538 , -2.696 , -2.764 , -2.852 , -2.950 , -2.843 , -2.454 , -2.438 , -2.655 , -2.318 ,
-2.457 , -3.171 , -3.413 , -2.628 , -2.558 , -3.296 , -3.576 , -3.560 , -3.462 , -3.396 ;

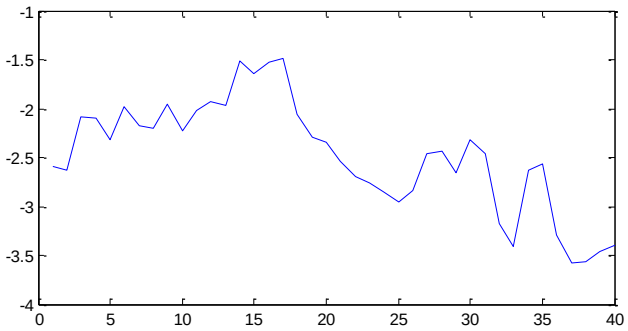
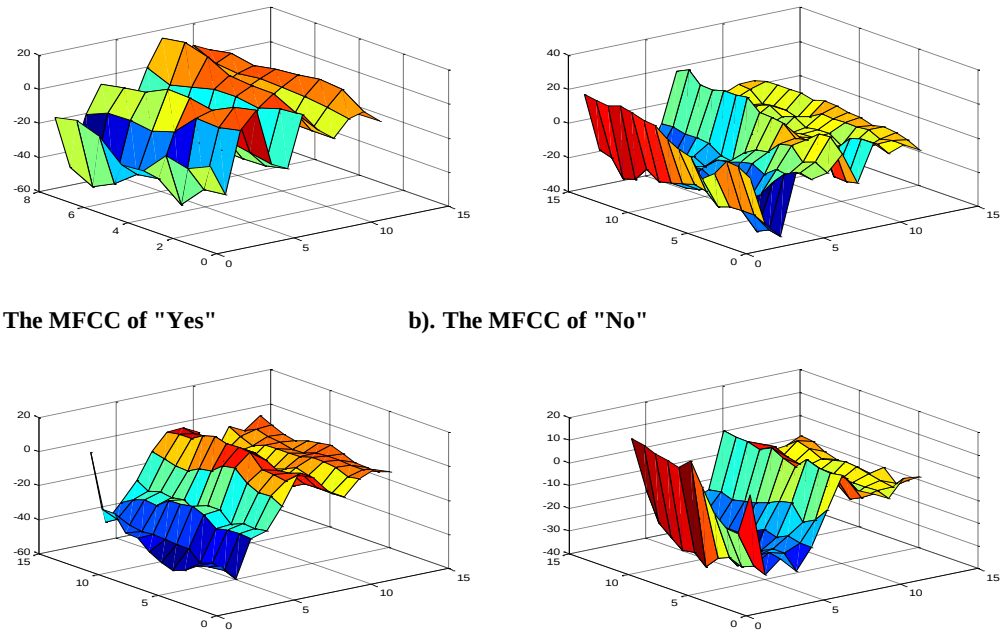


Figure 1 9 The results of discrete cosine transform [11]

Figure 20 is the waveform of the output of 40 mel scale filters, all the value of mel scale filters is negative. Since the author has calculated the FFT, DCT which can transform the frequency domain into a time like domain. Obtained Characteristic parameters are similar to cepstrum, thus it is referred to the mel scale cepstral coefficients, or MFCC. MFCC can be used as the Characteristic parameters for speech recognition. Compared with the MFCC coefficient before DCT, The data size is compressed obviously, so the function of the DCT transform is a compression step. Typically with MFCCs, you will take the DCT and then keep only the first few coefficients, which is the same theory of DCT used in JPEG compression. So, When you take the DCT, you will discard the higher coefficients, and only keeping the parts that are more important for representing a smooth shape. The higher-order coefficients that you discard are more noise-like and are not important to train. To sum up, DCT transform can remove the higher-order coefficients and enhance the training performance.

And then it flows to the main steps of generating a set of MFCC coefficient, these are obtained from a band-based frequency representation, and then with a discrete cosine

transform. The DCT is an efficient approximation for principal components analysis, and it allows a compression, or reduction of dimensionality, of the data, thus to reduce some band readings to a smaller set of MFCCs. A small number of Characteristic parameters end up describing the spectrum. The MFCCs are commonly used as timbral descriptors.



a). The MFCC of "Yes" **b). The MFCC of "No"**

c). The MFCC of "ON" **d). The MFCC of "OFF"**

Figure 2 0 MFCC 3-D view plot (MFCC are result in sets of parameters without any unit) [11]

The value of MFCC is given in MFCC result of Appendix B.

MFCC is a very robust parameter for modelling the speech as it can be modelled as MFCC kind of models the human auditory system and hence makes the reduction of the frame of a speech into the MFCC coefficients a very useful transformation as now we have an even more accurate transform to deal with for the recognition of the speakers. The other thing is that MFCC is the tool that produces very high level of accuracy when used as a parameter model for modelling the speech and hence for my study I have given focus in this area.

3.2.3 GMM

A Gaussian mixture model is a probabilistic model that assumes all the data points are generated from a mixture of a finite number of Gaussian distributions with unknown parameters. One can think of mixture models as generalizing k-means clustering to incorporate information about the covariance structure of the data as well as the center of the latent Gaussians.

The main steps of GMM is "ESTIMATION STEP" and "MAXIMIZATION STEP". Expectation Maximisation (EM) is a well established maximum likelihood algorithm for fitting a mixture model to a set of training data. It should be noted that EM requires an a priori selection of model order, simultaneously, the number of M components to be incorporated into the model. Often a suitable number may be selected by a user, roughly corresponding to the number of distinct colors appearing in an object to be modelled. The problem of fully automating this process, known as Automatic Model Order Selection, has been addressed in. Now, the author will introduce the most important step:

·ESTIMATION STEP which suppose to represent the model, but not the assignment of individual points,

```
[ lBM , lB ] = func_multi_gauss( X , mu , sigm , c );
LLH          = mean( lB );
lgam_m   = lBM - repmat ( lB , [ 1, M ] );
gam_m    = exp ( lgam_m );
```

·MAXIMIZATION STEP that we can learn the assignment of individual points, but not the model.

```
sgam_m = sum ( gam_m ) ;
new_c    = mean ( gam_m ) ' ;
 .....
new_sigm        = max (new_sigm , min_sigm ) ;
```

After simulation, the author will get the new parameter of Gaussian mixture model, The Results of Expectation Maximisation (EM) is given in GMM result of Appendix B.

3.3 Simulation and Analysis

3.3.1 Algorithm flow chart

We have introduced the designing of the speech recognition in the methodology chapter that the final module is the recognition module and the system will output the speech content based on MFCC extraction and GMM training, where the logic of the main flows is shown below according to all steps introduced in previous chapter:

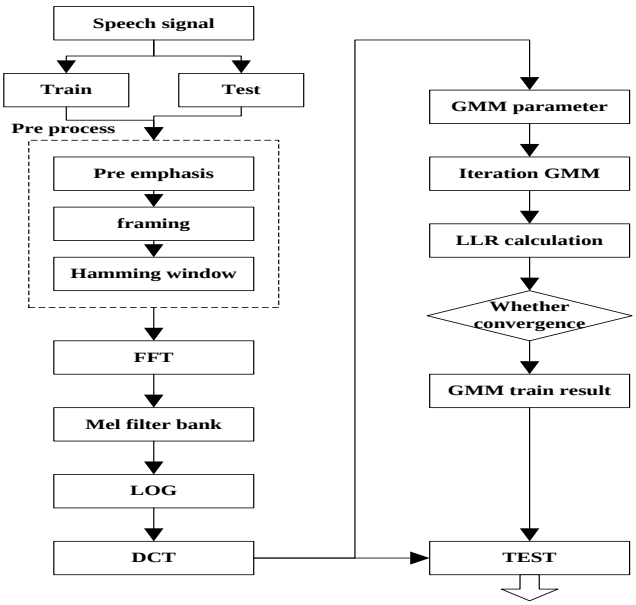


Figure 2 1 flow of algorithm [11]

Generally Speaking, The function of each steps is:

1) . Step " Speech signal ": Recording some samples of English words, " Yes "," No "," On "," Off ", from different person in different environment, In this project, the author will record the signal both in a very quiet environment and the noisy environment. And also recording the digital number from " 0 " to " 9 " in a quiet environment.

2) . Step " Train & Test ": Dividing the samples into training set and testing set. Training set is a standard sample, and the testing set is the samples from different person in different environment. The author will train the GMM model based on the training sample set and test the system based on the testing set.

3) . Step " Pre process ": Doing the pre process of pre emphasis, framing, adding windows. In this step, the author will program the matlab code to realize the function.

4) . Step " FFT ": Converting the signal in time domain into linear spectrum, and calculating the square of the absolute value. In this step, the system will calculate the result in the frequency domain.

5) . Step " Mel filter bank ": Calculating the Mel spectrum by Mel filter bank. The MFCC coefficient will be the Characteristic parameters of the system.

6) . Step " Log ": Calculating the Log of Mel spectrum. $S(m) = \ln\left[\sum_{k=0}^{N-1}|X(k)|^2 H_m(k)\right], 0 \le m \le M$.

7) . Step " DCT ": Getting the MFCC parameter by calculating DCT after LOG,

$$c(n) = \sum_{M=0}^{M-1} S(m)\cos\left[\frac{\pi n(m+1/2)}{M}\right], 0 \le m \le M$$

8) . Step " GMM ": Setting the initial parameter randomly, and Starting iterative calculation, until meet the convergence conditions. the convergence condition is:

if $100 \times \frac{\log L(X \mid \lambda_t) - \log L(X \mid \lambda_{t-1})}{\log L(X \mid \lambda_{t-1})} < \varepsilon$ then the result is meeting the convergence conditions.

9) . Step " TEST ": Using different samples to test the performance.

The algorithm can make every gaussian distribution of the GMM model as one kind, The parameter of Mean is the position in Characteristic parameters space of different sample Characteristic parameters, which is the most important parameter in GMM, The variance is the density of data distribution, the weight is the number of data.

3.3.2 Simulation result Analysis

In this chapter, author simulated the designed systems and the only task of operator is to run the program and record speech signals. Two sets of train speech signal and ten set of test speech signal recorded. In the first experiments, speech signals will record from the three different people both in quiet environment and noisy environment, and author has also recorded a standard as the training samples. The content of first speech is "YES" and "NO" is the pair of word different syllable, and the second one is "ON" and "OFF" with the similar pronunciation. In the testing, the author will play "YES" and "NO" or "ON" and "OFF" 10 times respectively, in both quiet environment and noisy environment. In the second experiments, number 0~9 from one person have been recorded. The goal of this experiment is checking the performance of the algorithm in a real application. Author tested the number 10

times. The statistical simulation results of environment 1 and environment 2 will be put in tables and will also be plotted and been discussed in next chapter.

And the following result are 3 groups of simulation where tested in the quiet lab room in Arhus University by 3 different people with the content of speech is " Yes " and " No " with different pronunciation basis and each of the group have taken 10 times testing samples respectively to ensure the validity and accuracy of the experiment;

The speech signal from People 1.

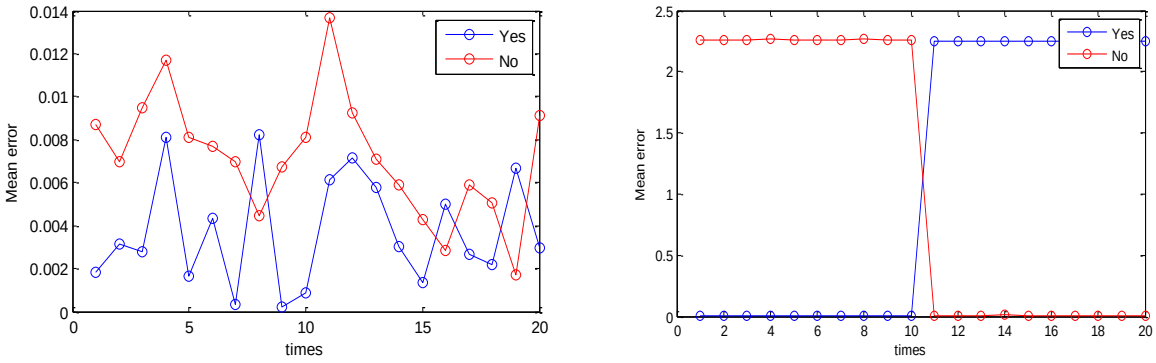


Figure 2 2 [3]mean errors for the train signals with test signals, people 1 [11]

Here the definitions of error is $Err = abs(mean(MFCC_1) - mean(MFCC_2))$, Table 1 shows the result of this test:

Table 1indicates the results for train signals "Yes" and "No" as the information given at the test Results, people 1 [11]

times	error	Final output	Times	error	Final output
1	0. 0018	Yes	11	2. 2490	No
2	0. 0032	Yes	12	2. 2508	No
3	0. 0028	Yes	13	2. 2483	No
4	0. 0081	Yes	14	2. 2461	No
5	0. 0017	Yes	15	2. 2496	No
6	0. 0043	Yes	16	2. 2250	No
7	0. 0003	Yes	17	2. 2508	No
8	0. 0082	Yes	18	2. 2532	No
9	0. 0002	Yes	19	2. 2510	No
10	0. 0009	Yes	20	2. 2496	No

[3] Right figure means in total 20 times simulating result, the input for 1-10th times are recognized as "NO" cause the algorithm calculate that the value of redline "No" is bigger than the blueline "YES". Similarly, 11-20th times are recognized as "YES". And figure behind for other simulating result has same meaning to observe the recognition result precisely.

Total successful probability(Yes)	100%	Total successful probability(NO)	100%

The speech signal from People 2

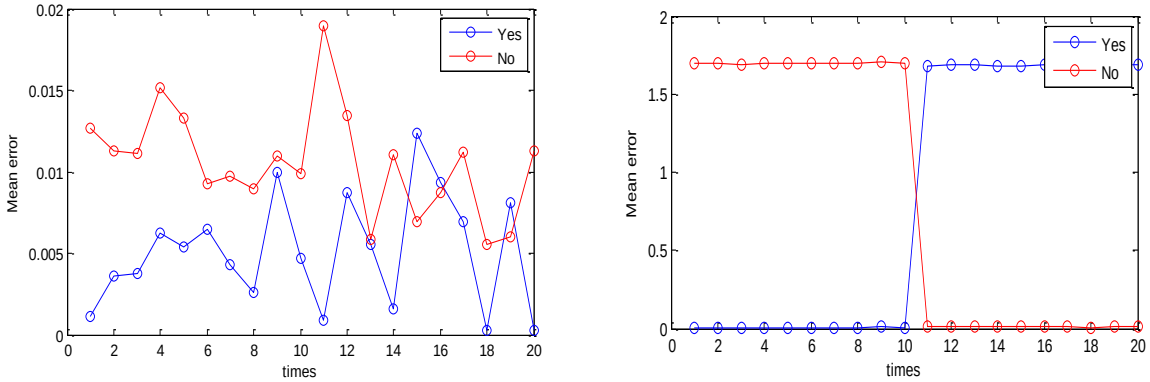


Figure 2 3 mean errors for the train signals with test signals, people 2 [11]

Table 2the results for train signals "Yes" and "No" as the information given at the test Results, people 2 [11]

times	error	Final output	Times	error	Final output
1	0. 0011	Yes	11	1. 6819	No
2	0. 0036	Yes	12	1. 6833	No
3	0. 0038	Yes	13	1. 6834	No
4	0. 0062	Yes	14	1. 6794	No
5	0. 0054	Yes	15	1. 6812	No
6	0. 0065	Yes	16	1. 6853	No
7	0. 0043	Yes	17	1. 6849	No
8	0. 0026	Yes	18	1. 6856	No
9	0. 0100	Yes	19	1. 6836	No
10	0. 0047	Yes	20	1. 6846	No
Total successful probability(Yes)		100%	Total successful probability(NO)		100%

The speech signal from People3.

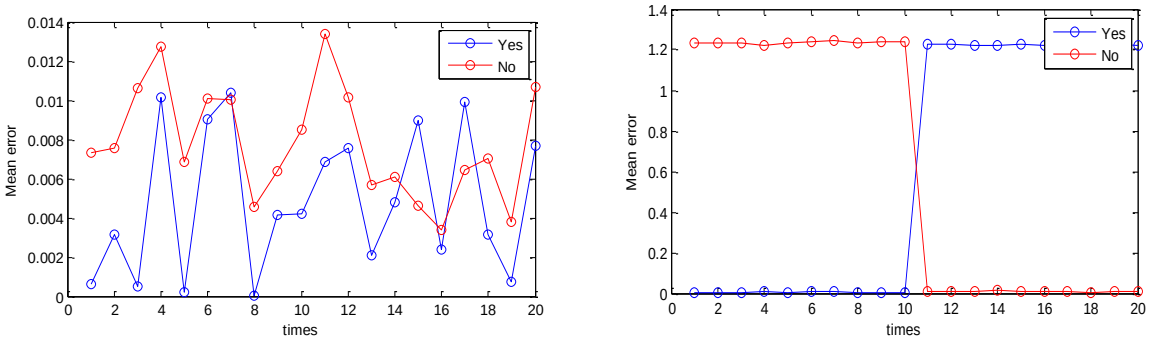


Figure 2 4 mean errors for the train signals with test signals, people 3 [11]

Table 3mean errors for the train signals with test signals, people 3 [11]

times	error	Final output	Times	error	Final output
1	0. 0006	Yes	11	1. 2252	No
2	0. 0005	Yes	12	1. 2249	No
3	0. 0101	Yes	13	1. 2219	No
4	0. 0002	Yes	14	1. 2197	No
5	0. 0091	Yes	15	1. 2257	No
6	0. 0104	Yes	16	1. 2224	No
7	0. 0000	Yes	17	1. 2225	No
8	0. 0032	Yes	18	1. 2279	No
9	0. 0042	Yes	19	1. 2261	No
10	0. 0042	Yes	20	1. 2240	No
Total successful probability(Yes)		100%	Total successful probability(NO)		100%

We can observe from three groups of testing of the word “Yes” and “No” reveals the excellent with all 3 testing has 100 successful probability to recognition.

And then, the simulation goes other round of test with 3 groups of testing in the quiet lab room in Arhus University by 3 different people with the content of speech is " On " and " Off " in same pronunciation, and each of the group have taken 10 times testing samples respectively to ensure the validity and accuracy of the experiment;

The speech signal from People1.

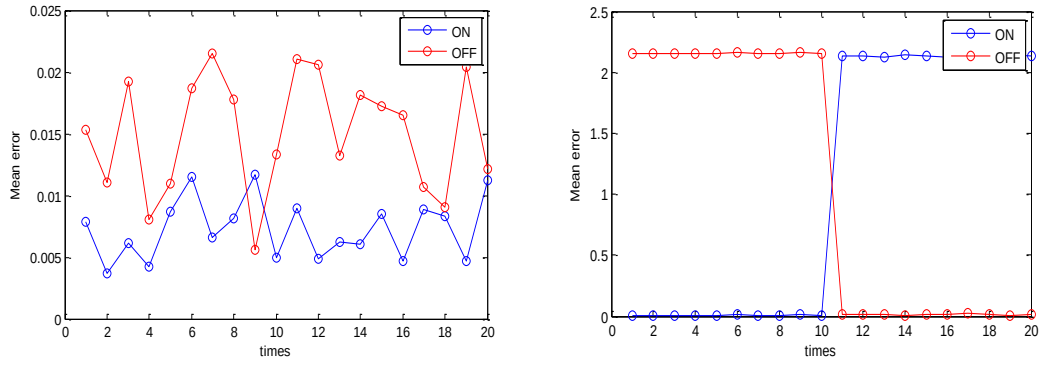


Figure 2 5 , mean errors for the train signals with test signals , people 1 [11]

Table 4the results for train signals “On” and “Off” as the information given at the test Results, people 1 [11]

times	error	Final output	Times	error	Final output
1	0. 0078	On	11	2. 1320	Off

2	0. 0037	On	12	2. 1362	Off
3	0. 0062	On	13	2. 1280	Off
4	0. 0042	On	14	2. 1392	Off
5	0. 0087	On	15	2. 1364	Off
6	0. 0115	On	16	2. 1286	Off
7	0. 0066	On	17	2. 1258	Off
8	0. 0082	On	18	2. 1296	Off
9	0. 0117	On	19	2. 1417	Off
10	0. 0049	On	20	2. 1340	Off
Total successful probability(On)		100%	Total successful probability(Off)		100%

The speech signal from People2.

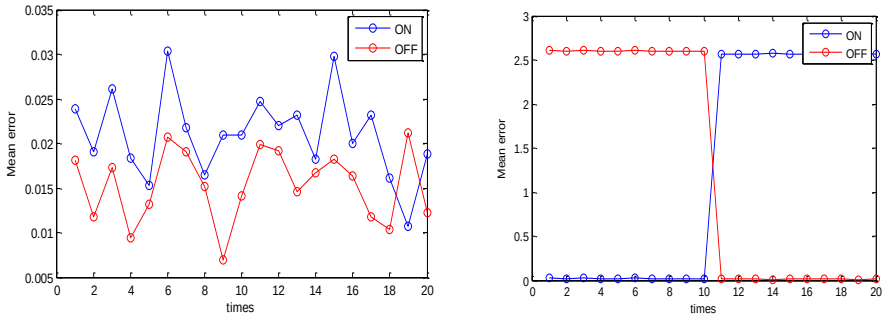


Figure 2 6 mean errors for the train signals with test signals,people 2 [11]

Table 5results for train signals “On” and “Off” as the information given at the test Results, people 2 [11]

times	error	Final output	Times	error	Final output
1	0. 0239	On	11	2. 5630	Off
2	0. 0191	On	12	2. 5694	Off
3	0. 0261	On	13	2. 5639	Off
4	0. 0184	On	14	2. 5718	Off
5	0. 0153	On	15	2. 5680	Off
6	0. 0304	On	16	2. 5605	Off
7	0. 0218	On	17	2. 5621	Off
8	0. 0164	On	18	2. 5660	Off
9	0. 0209	On	19	2. 5742	Off
10	0. 0210	On	20	2. 5670	Off
Total successful probability(On)		100%	Total successful probability(Off)		100%

The speech signal is from People3.

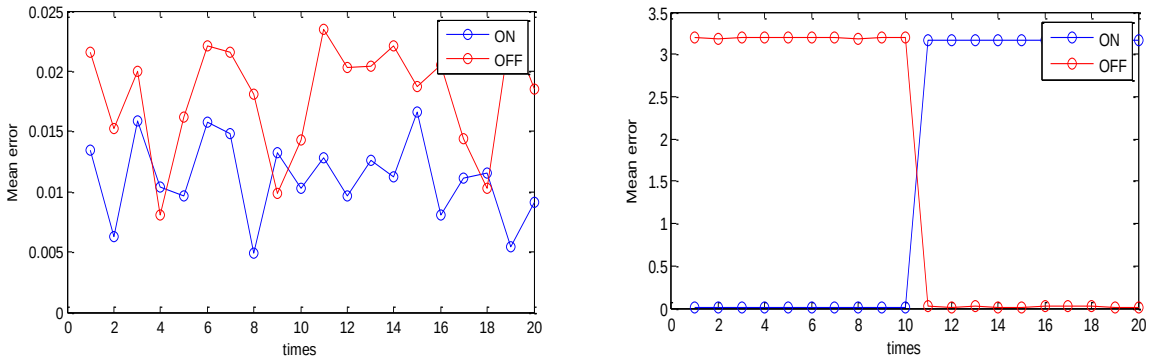


Figure 2 7 mean errors for the train signals with test signals, people 3 [11]

Table 6the results for train signals "On" and "Off" as the information given at the test Results, people 3 [11]

times	error	Final output	Times	error	Final output
1	0. 0135	On	11	3. 1598	Off
2	0. 0062	On	12	3. 1660	Off
3	0. 0158	On	13	3. 1613	Off
4	0. 0104	On	14	3. 1733	Off
5	0. 0096	On	15	3. 1652	Off
6	0. 0158	On	16	3. 1592	Off
7	0. 0149	On	17	3. 1597	Off
8	0. 0049	On	18	3. 1633	Off
9	0. 0132	On	19	3. 1715	Off
10	0. 0103	On	20	3. 1670	Off
Total successful probability(On)		100%	Total successful probability(Off)		100%

The results of speech "on" and "off" in the quiet environment with similar pronunciation shows that the performance is perfect and the total successful probability is 100%. And the experiment proceed in the next step to test how the simulation could be outcome when the environment is more close to the reality with different level of the noise, and the test will take same indicator, with speech of "on" and "off", "Yes" and "No" and each of the groups will sampling 10 times, where the only variable changed is that we will add the noise with different SNR level,

First is the output of the content of speech is " On " and " Off " , the author have added the noise before recognition module. So the reference signal here is the overlapped sound with clear speech and noise in different SNR in 9,7,5,3 and 1dB to analysis the performance in the test, operation module is as follows,

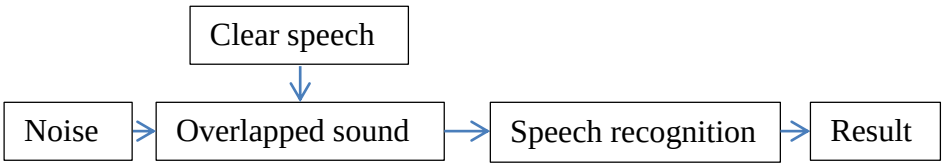


Figure 2 8 Add noise flow chart [5]

Table 7the results for train signals "On" and "Off" with different noise [11]

Times	SNR=9	SNR=7	SNR=5	SNR=3	SNR=1
1	off	off	Off	off	On
2	off	off	Off	off	Off
3	off	off	Off	on	On
4	off	off	Off	off	On
5	off	off	Off	off	On
6	off	off	Off	off	On
7	off	off	Off	off	On
8	off	off	Off	off	On
9	off	off	Off	on	On
10	off	off	Off	off	On
11	off	off	Off	off	Off
12	off	off	Off	off	On
13	off	off	Off	off	On
14	off	off	Off	off	On
15	off	off	Off	off	Off
16	off	off	Off	off	On
17	off	off	Off	off	Off
18	off	off	Off	off	Off
19	off	off	Off	off	On
20	off	off	Off	off	On
Performance	100%	100%	100%	90%	25%

The table indicates that SNR level can be adjusted to 5 and the system can still recognize the right testing word "off" with 100% accuracy, but when the SNR is lower than that level the trained signal appears error with match the reference signal and the performance begins to weaken, and the performance is really poor that only matches 25% recognition probability when SNR level is 1. The poor result when SNR equal 1 also reveal the limitation for the

algorithms I choose, it can be assumed here that when the noise in the certain degree, in between 1dB-3dB in our case, this conjected recognition won't work well anymore.

And it followed by the testing of "Yes and No" that added the noise with different level of SNR 9,7,5,3,1dB to analysis the performance as table 8 shown,

Table 8the results for train signals "Yes" and "No" with different noise [11]

Times	SNR=9	SNR=7	SNR=5	SNR=3	SNR=1
1	no	No	No	no	No
2	no	No	No	yes	Yes
3	no	No	No	no	No
4	no	Yes	Yes	yes	Yes
5	no	Yes	Yes	yes	Yes
6	no	No	No	no	No
7	no	No	No	no	Yes
8	no	No	No	no	No
9	no	No	No	no	No
10	no	No	No	no	No
11	no	No	No	yes	Yes
12	no	No	No	yes	Yes
13	no	No	No	no	No
14	no	No	No	yes	No
15	no	No	No	no	No
16	no	No	No	no	No
17	no	No	No	no	No
18	no	No	No	no	No
19	no	No	No	yes	Yes
20	no	No	No	no	No
Performance	100%	90%	90%	65%	65%

It can be observed that noise impact is different compared with word "Yes and No" and "On and off". When testing the word "No", it describes that the performance will be decrease after taken SNR 7 or below, and become weak when SNR is less than 3. The recognition of the word "Yes and No" is relatively stable and gradually drop off as the noise level is stronger, while the word "On and off" performs good when SNR is 5 or larger but will dramatically drop the accuracy when SNR level is lower than 3 from 90% to 25%. In summary, the current simulation system is more appropriate to use the word "On and Off" which is the

monosyllable when the recognition environment is relatively quiet and the noise is small, and part for recognizing the disyllable or more complex words need to be implemented more technique to improve but it will be more easier to recognize when the paring words with different syllable in more noisy environment.

In the experimental stage, I also utilize the simulation of the speech of simple numbers from "0" to "9" to verify and ensure the feasibility and validity of the simulation system, and the test of numbers is also in the environment of the quite lab room with my own pronunciation, In this test, I will analysis the performance of the MFCC-GMM simulation system in multi testing samples from zero to nine, and the result is shown in below,

Table 9 the results for train signals "0" "9" as the information given at the test Results [11]

times	1	2	3	4	5	6	7	8	9	10	Accuracy
0	0	0	0	0	0	0	9	9	9	9	60 %
Error	0.6635	0.6579	0.6191	0.5880	0.5811	0.5677	0.5231	0.5058	0.5560	0.5099	
1	1	1	1	1	1	1	1	1	1	1	100 %
Error	0.2341	0.3043	0.4127	0.4511	0.4685	0.5410	0.5531	0.6403	0.6563	0.7202	
2	2	2	2	2	2	2	2	2	2	2	100 %
Error	0.1629	0.1274	0.0484	0.0798	0.0761	0.0833	0.0595	0.0333	0.0052	0.0646	
3	3	3	3	3	3	3	3	3	3	3	100 %
Error	0.5211	0.4148	0.4232	0.3781	0.2464	0.3113	0.2751	0.2560	0.2091	0.2141	
4	4	4	4	4	4	4	4	4	4	4	100 %
Error	0.2255	0.1856	0.1123	0.1985	0.0305	0.2245	0.0359	0.0539	0.0314	0.0779	
5	5	5	5	5	5	5	5	5	5	5	100 %
Error	0.9158	1.1218	1.2795	1.4027	1.5248	1.5946	1.5572	1.6183	1.8048	1.8291	
6	6	6	6	6	6	6	6	6	6	6	100 %
Error	0.1160	0.0996	0.1020	0.0844	0.0855	0.0455	0.0423	0.0380	0.0451	0.0387	
7	7	7	7	7	7	7	7	7	7	7	100 %
Error	0.1741	0.0965	0.0268	0.0221	0.0973	0.1474	0.0917	0.2241	0.1639	0.2217	
8	8	8	8	8	8	8	8	8	8	6	90 %
Error	0.1469	0.1641	0.1207	0.0899	0.1294	0.0615	0.0900	0.0904	0.0606	0.0464	
9	9	9	9	9	9	9	9	9	9	9	100 %
Error	0.5794	0.5088	0.4672	0.4262	0.3911	0.3739	0.3021	0.3847	0.3620	0.3117	
Total successful probability											95%

The simulation result of numbers from "0" to "9" manifest the system is very stable and recognized in the quiet environment with similar result of testing of "Yes and No" ,"On and

Off", we can told that system can be perfectly used on very simple monosyllable that they can almost achieve with the 100% accuracy, but when the word becomes complex to pronounce , for example the word "zero" and word " eight" which the system recognized with the output "nine" and "six" in some times, the simulation system will have problem to recognizing and accuracy will drop off even in the ideal environment. And another variable as this chapter mentioned earlier that the noise level will have very significant impact with the recognition accuracy, and the best scenario for use the system is that the SNR level of signal should be higher that 5 at least and the word for recognition should be simple monosyllable to ensure the efficient accuracy.

4 Discussion

In this project, author has recorded three different speech samples. The first set is " YES " and " NO " from 3 person which has the different pronunciations while the second set is" ON " and " OFF " from 3 person which has the same pronunciations, and the third set of numbers from zero to nine is also been utilized for testing.

With a MATLAB code which achieved the GMM and MFCC algorithm in the experiment where generated 7 tables to analyze. Table 1, 2 and table 3 are simulated based on the first sample set for word “Yes and No”, where the algorithm works for the different isolated words. The first sample set was recorded from three people and there are also 20 different samples from each person which gathered the total of 60 samples. And the output figures of each person’s speech in the left column indicates the error between the training sample and testing samples is very small, it reveals the algorithm will have the better performance to recognize the first word, while the right columns are the errors of different test samples in one files, we still can discern the content of the speech quickly when the speech content is changing. The simulation results show that the utilization of algorithm can reach almost successful probability on 100% when two words with the different pronunciations without the noise.

Table 4, 5 and 6 are simulated based on the Second sample set for testing word “ On and Off” which also recorded from three people, and by taking 20 different samples from each person respectively with 60 different samples of the total . And three output figures are corresponding error between the trained signal and the reference signal, as we know, The pronunciations of " ON " and " OFF " are almost the same, which make it very hard to recognize by common methods. And the left column shows similarities as the experiment on “Yes and No”, that the error between the training sample and testing samples is also quite small, in this case it can be concluded that whether the words pair has similar pronunciations or not have no influence on the algorithm. Meanwhile, the right column of the figure are the errors of different test samples in one files, we can also discern the content of the speech quickly when the speech content is changing and the result of it is also 100% success probability .

And when accretion of the noise in the signal as the Table 7 and 8 shown, the performance of the recognition will change with different SNR level, it’s can be observed that the performance of the word pair with the similar pronunciation monosyllable like " ON " and "

OFF " will be so poor in large noise environment that the total successful probability is only 25% when SNR is equal to 1, but it behaves very stable when the SNR level equal or larger than 5. And if the case is for the word pair that has obviously different pronunciations syllable like " Yes " and " No ", the performance will be relatively stable in quite noise environment and it still can kept 65% recognition when the SNR is terribly equal to 1 , and there's slightly difference here that the performance of "Yes and No" is not good as "On and Off" when SNR is in between 5-7dB. In summary, the algorithm based on GMM and MFCC has good performance both in the words pair with different syllable and in the words pair with similar pronunciations in the silent environment, but algorithm will be greatly impacted by loud noise when the words pair with similar pronunciations. In this case, the result suggest that the testing signal should have the good quality as the basis of simulation, simultaneously, it will be better use the pair of words that has distinctly pronunciation difference if the noise level is relatively large.

Table 9 are simulated based on the third sample set for 10 numbers from "0" to "9", where are still isolated words that some of them have slight similar pronunciations with monosyllable, while the others have different pronunciations in disyllable like "Zero, six and eight". Strictly, adoption of this multiple samples is to test and verify the accuracy of the simulation in the quiet environment with more complex files that makes it difficult to recognize. And compared with the 2 pairs words, it can be found that some errors happened in the disyllable word that no as accurate as the experiment before with 10 times samples of each words, based on our simulation results the average successful probability can also reach to about 95%. This manifest that the system is still fit for the simple pair and word recognition instead of complicated word, and the accuracy will decrease if the using more complex words and language. And variables of noise is always surrounded in our environment no matter how quiet the testing place is located, and it might be one critical fact to take count in when error occurred.

According to the experimental result, it's been found some disadvantage in my method.

When person who provide the trained signal and the person who provide the reference signal is the same, the speech recognition algorithm can work well for distinguishing different words. Vice versa, the system will not work well during the simulation while the training speech and testing speech from different people or from the same people with different intonation. So here should be research more techniques to generate more feature for different people and different intonation is necessary in order to improve the system performance in the future work.

And it happened in the experiment that when the environment noise is big enough, especially the SNR smaller certain level, the performance will reduce quickly performs really bad. As we concluded that the noise is the biggest variable that may drive the result of simulation, so designing of a high performance filter to reduce the noise frequency and improve the training process is considerable in future work for enhancing the system performance,

From the aspect of the reality, a real speech recognition module should be available embedded in the system with the related algorithm, thus it will requires a large size of train database which will lead the memory and equipment cost to a big issue. Hence some techniques like artificial intelligence is contemplable to reduce the database size in order to get a common used algorithm in the complex environment in the future.

5 Conclusions

Generally speaking, feature extraction is the first step for speech recognition, In this paper, the author has introduced many algorithms for feature extraction, and the Mel Frequency Cepstrum Coefficient (MFCC) feature has been used for the speech recognition system. The second step is training and GMM which used for speech recognition system.

Based on the discussions, the designed systems for speech recognition have a better performance for different pronunciations and similar pronunciations word on both monosyllable and disyllable, the total successful probability can reach 100% if the testing word is simple enough and signal been recorded in a relatively ideal environment with very low noise, and multi-speech signal also have very impressive simulation result with 95% successful probability, when the system used in the reality, a large of training database should be established due to the larger the database size is ,the better performance the algorithm is. On the other hand, the speech signal from different people have no influence for the performance of speech recognition system which is been proved by testing set “On and Off” , “Yes and No” in first phase. And the experiment implies that the performance will reduced quickly if the variable noise is unstable and quite large.

Finally, the conclusion can be proposed that the system can work with both different pronunciations and similar pronunciations word in the quiet environment, and the system will also work well when the words' pair with the different pronunciations and syllable word in the noise environment, and the process for similar syllable and pronunciation words recognition should be improved in the loud noise. When the sets of words for recognized are larger, the system will have deficiency on the disyllable or more complicated word.

Although the speech recognition technology has achieved many research achievements in the past ten years, many applications has surrounded in people’s daily life and speech recognition systems have been researched over several decades and have numerous applications, they still cannot match the perfect performance of a human recognition system and as well as not reliable sufficiently to be considered as a standalone security system. The methods of speech recognition technology based on HMM model and characteristic parameters catching based on MFCC coefficient is very difficult to recognize the natural speech or the speech with big noise environment, generally there are four key problems including 2 problems shown in my experiment and 2 thoughts that need to be resolved in the future.

a) . The Speech recognition performance in a real world noisy scenario cannot provide a high level of confidence. The adaptability of speech recognition system is poor, all the testing speech samples are standard "reading voice", it is very hard to recognize the natural speech. When there's a little difference between the training voice and user's speech patterns, the speech recognition system performance will be greatly reduced. Especially under high noise environment, for example when we adjust the SNR from 3 to 1dB, the speech recognition performance will reduce faster. Thus the influence of environment fact will be one variable that been tested in our experiment that may affect the simulation result in this project.

b) .The theory of continuous speech recognition is not very mature, the search algorithm efficiency is not high and the vocabulary is limited. The number of vocabulary the system can identify is the most important indicators of the performance of speech recognition system, But it becomes harder to select and build the model when vocabulary becomes bigger and bigger, which we can see from the test for 10 groups of numbers, the system has problem to recognize word "Zero" and output "Nine" instead which are two words that pronounce very differently. And it's also can be assumed here when the speech word is not in the vocabulary, the output of the speech recognition system will be wrong. So the size of vocabulary will also be a factor in the experimental stage.

c).When the speech recognition technology used in the embedded products, it must with a bigger vocabulary database so that the product achieve a high performance. Therefore the conflict between performance and recognition speed, memory consumption will limit the embedded product performance and it maybe bottleneck to resolve the experiment .

d).Speech recognition is a technology which contains phonetics, linguistics, physiology and psychology is a body comprehensive disciplines, how to put these knowledge into speech recognition are also issues to conquer.

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Appendix A

A1.Signal Training

```
clc;
clear;
close all;
addpath 'func\'
addpath 'func\func_pregross\'
addpath 'Speech_Processing_Toolbox\'
Num_Gauss               = 64;
 [Speech_Train10,Fs,nbits] = wavread('Train_Samples\yes_no\yes.wav');
[Speech_Train20,Fs,nbits] = wavread('Train_Samples\yes_no\no.wav');
Index_use     = func_cut(Speech_Train10,Fs,nbits);
Speech_Train1 = Speech_Train10(Index_use(1):Index_use(2));
Index_use     = func_cut(Speech_Train20,Fs,nbits);
Speech_Train2 = Speech_Train20(Index_use(1):Index_use(2));
Speech_Train1 = filter([1, -0.95], 1, Speech_Train1);
Speech_Train2 = filter([1, -0.95], 1, Speech_Train2);
global Show_Wind;
Show_Wind = 0;
global Show_FFT;
Show_FFT  = 0;
Train_features1=melcepst(Speech_Train1,Fs);
Train_features2=melcepst(Speech_Train2,Fs);
 [mu_train1,sigma_train1,c_train1]=fun_GMM_EM(Train_features1',Num_Gauss);
[mu_train2,sigma_train2,c_train2]=fun_GMM_EM(Train_features2',Num_Gauss);
mu_train{1}    = mu_train1;
mu_train{2}    = mu_train2;
sigma_train{1} = sigma_train1;
sigma_train{2} = sigma_train2;
c_train{1}     = c_train1;
c_train{2}     = c_train2;
```

```
save GMM_MFCC.mat mu_train sigma_train c_train
 [RR,CC] = size(sigma_train1);
for i = 1:RR
   for j = 1:8
      fprintf('%2.6f',sigma_train1(i,j));
      fprintf(' , ');
   end
   fprintf(' \n ');
end
```

A2.Signal Testing

```
clc;
clear;
close all;
addpath 'func\'
addpath 'func\func_pregross\'
addpath 'Speech_Processing_Toolbox\'
Num_Gauss=64;
 [Speech_Test0,Fs,nbits]=wavread('Test_Samples\test5\yes_no\yes.wav');
Index_use    = func_cut(Speech_Test0,Fs,nbits);
Speech_Test  = Speech_Test0(Index_use(1):Index_use(2));
figure;
plot(Speech_Test0);
hold on;
Len = [-1.05:0.01:1.05];
plot(Index_use(1)*ones(length(Len),1),Len,'r','linewidth',2);
hold on;
plot(Index_use(2)*ones(length(Len),1),Len,'k','linewidth',2);
hold off
axis([1,length(Speech_Test0),-1.05,1.05]);
title('The simulation result of EndPoint checking');
figure;
```

```
plot(Speech_Test+1.5,'b');
Speech_Test = filter([1, -0.95], 1, Speech_Test);
hold on
plot(Speech_Test,'r');
legend('original','Pre emphasis');
global Show_Wind;
Show_Wind = 1;
global Show_FFT;
Show_FFT  = 1;
Test_features= melcepst(Speech_Test,Fs);
figure;
surf(Test_features);
load GMM_MFCC.mat
A=[0,0];
for i = 1:2
    [lYM,lY]=func_multi_gauss(Test_features', mu_train{i},sigma_train{i},c_train{i});
    A(i)=mean(lY);
end
[V,I] = max(A);
if I == 1
  disp('The speech is: YES');
else
  disp('The speech is: NO');
end
```

A3.fun_GMM_EM.m

```
function [mu,sigm,c]=fun_GMM_EM(X,M,iT,mu,sigm,c,Vm)
GRAPH       = 1;
[L,T]       = size(X);   % data length
varL        = var(X')';  % variance for each row data;
min_diff_LLH = 0.001;     % convergence criteria
%DEFAULTS
```

```
if nargin<3  iT=10; end
if nargin<4  mu=X(:,[fix((T-1).*rand(1,M))+1]); end
if nargin<5  sigm=repmat(varL./(M.^2),[1,M]); end
if nargin<6  c=ones(M,1)./M; end
if nargin<7  Vm=4; end
min_sigm=repmat(varL./(Vm.^2*M.^2),[1,M]);
% VARIABLES
lgam_m=zeros(T,M);    % prob of each (X:,t) to belong to the kth mixture
lB=zeros(T,1);        % log-likelihood
lBM=zeros(T,M);       % log-likelihhod for separate mixtures
old_LLH=-9e99;        % initial log-likelihood
mus      = [];
sigms    = [];
cs       = [];
for iter=1:iT
   %ESTIMATION STEP
   [lBM,lB] = func_multi_gauss(X,mu,sigm,c);
   LLH      = mean(lB);
   disp(sprintf('log-likelihood :  %f',LLH));
   lgam_m   = lBM-repmat(lB,[1,M]);  %logarithmic version
   gam_m    = exp(lgam_m);           %linear version
   %MAXIMIZATION STEP
   sgam_m=sum(gam_m);
   %gaussian weights
   new_c=mean(gam_m)';
   mu_numerator =
sum(permute(repmat(gam_m,[1,1,L]),[3,2,1]).*permute(repmat(X,[1,1,M]),[1,3,2]),3);
   new_mu       = mu_numerator./repmat(sgam_m,[L,1]);
   %variances
   sig_numerator=
sum(permute(repmat(gam_m,[1,1,L]),[3,2,1]).*permute(repmat(X.*X,[1,1,M]),[1,3,2]),3);
   new_sigm     = sig_numerator./repmat(sgam_m,[L,1])-new_mu.^2;
   new_sigm     = max(new_sigm,min_sigm);
   if old_LLH>=LLH-min_diff_LLH
```

```
      break;
    else
      old_LLH = LLH;
      mu      = new_mu;
      sigm    = new_sigm;
      c       = new_c;
    end
end
```

A4.func_multi_gauss.m

```
function [YM,Y]=func_multi_gauss(x,mus,sigm,c)
 [L,T] = size(x);
M     = size(c,1);
X     = permute(repmat(x',[1,1,M]),[1,3,2]);
Sigm  = permute(repmat(sigm,[1,1,T]),[3,2,1]);
Mu    = permute(repmat(mus,[1,1,T]),[3,2,1]);
lY    =-0.5.*dot(X-Mu,(X-Mu)./Sigm,3);
lcoi  = log(2.*pi).*(L./2)+0.5.*sum(log(sigm),1);
lcoef = repmat(log(c')-lcoi,[T,1]);
YM    = lcoef+lY;
Y     = lsum(YM,2);
```

A5.lsum.m

```
function lz=lsum(X,DIM);
if nargin==1
  DIM = 1;
end
s = size(X);
if DIM == 1
  X=sort(X,1);
  lz=X(end,:,:,:,:)+log(1+sum(exp(X(1:end-1,:,:,:,:)-repmat(X(end,:,:,:,:),[size(X,1)-
```

```
1,1,1,1,1])),1));
else
  X  = permute(X,[ DIM, 1:DIM-1 , DIM+1:length(s)]);
  X  = sort(X,1);
  lz = X(end,:,:,:,:)+log(1+sum(exp(X(1:end-1,:,:,:,:)-repmat(X(end,:,:,:,:),[size(X,1)-
1,1,1,1,1])),1));
  lz = permute(lz,[2:DIM, 1, DIM+1:length(s)]);
end
```

A6.plotspec.m

```
function plotspec(x,Ts)
N=length(x);                    % length of the signal x
t=Ts*(1:N);                     % define a time vector
ssf=(-N/2:N/2-1)/(Ts*N);            % frequency vector
fx=fft(x(1:N));                 % do DFT/FFT
fxs=fftshift(fx);               % shift it for plotting
subplot(2,1,1), plot(t,x)           % plot the waveform
xlabel('seconds'); ylabel('amplitude')    % label the axes
subplot(2,1,2), plot(ssf,abs(fxs))      % plot magnitude spectrum
xlabel('frequency'); ylabel('magnitude')  % label the axes
```

Appendix B

B1.MFCC result

The MFCC value of sample is in table 1 ~ table 4:

Table 3 The data of MFCC,"ON"

-35.07 , -44.56 , -22.71 , -19.85 , -7.46 , 8.86 , 6.03 , -4.16 , -9.17 , -0.57 , 3.21 , 0.12 ,
-37.64 , -41.67 , -22.18 , -20.96 , -3.64 , 3.10 , 5.84 , -4.26 , -9.69 , -1.57 , 0.56 , -2.67 ,
-39.59 , -40.08 , -22.37 , -20.39 , -4.12 , 4.79 , 3.42 , -4.48 , -7.82 , 1.29 , 0.67 , -2.45 ,
-44.75 , -42.58 , -24.17 , -23.30 , -1.24 , 5.01 , 2.80 , -8.27 , -3.98 , 2.15 , 1.09 , -1.94 ,
-47.04 , -36.47 , -18.49 , -17.27 , 5.57 , 12.72 , 6.30 , -7.38 , -1.48 , 2.50 , 1.28 , 0.91 ,
-45.12 , -36.11 , -15.64 , -17.27 , 4.40 , 13.25 , 8.58 , -7.69 , -4.95 , 0.26 , 0.48 , 3.35 ,
-41.00 , -35.72 , -16.89 , -23.18 , -1.09 , 12.95 , 7.52 , -6.91 , -7.20 , 0.20 , -1.91 , 2.23 ,
-35.52 , -35.28 , -17.37 , -18.52 , -2.17 , 14.83 , 6.56 , -7.24 , -7.68 , 0.28 , -2.02 , 1.09 ,
-34.85 , -35.81 , -22.54 , -19.80 , -5.92 , 12.93 , 6.60 , -9.23 , -7.60 , -0.12 , -0.54 , -1.52 ,
-26.07 , -34.74 , -21.59 , -18.78 , -5.68 , 8.78 , 7.90 , -8.21 , -4.53 , -3.27 , 0.75 , -0.23 ,
-25.74 , -33.88 , -24.08 , -21.06 , -3.68 , 8.91 , 7.52 , -5.72 , -6.88 , -0.06 , 2.20 , 2.97 ,
5.08 , -38.01 , -28.28 , -17.06 , -1.97 , 7.65 , 8.43 , 3.73 , -11.56 , 3.28 , -0.84 , 6.02 ,

Table 4 The data of MFCC,"OFF"

10.36 , -26.27 , -20.91 , -27.71 , -18.53 , -3.45 , 10.39 , 2.29 , -0.62 , -4.14 , 3.44 , 2.71 ,
-8.68 , -24.43 , -19.87 , -21.57 , -18.36 , -9.64 , 9.63 , 5.91 , -4.07 , -2.31 , -1.99 , -0.73 ,
-8.40 , -26.66 , -23.19 , -21.45 , -17.23 , -12.65 , 10.00 , 5.89 , -6.48 , -2.46 , -1.21 , -3.88 ,
-3.48 , -24.37 , -17.45 , -24.31 , -19.53 , -5.81 , 11.83 , 5.63 , -2.03 , -2.34 , -0.10 , 1.36 ,
6.32 , -26.31 , -19.76 , -32.87 , -17.80 , -6.87 , 6.98 , 5.51 , -4.58 , -2.70 , 1.33 , -3.73 ,
16.10 , -31.94 , -18.18 , -34.34 , -20.87 , -9.48 , 8.92 , 4.95 , -5.99 , -4.19 , 1.55 , -5.14 ,
11.25 , -27.41 , -16.68 , -30.75 , -23.21 , -11.28 , 11.53 , 6.10 , -5.04 , -3.10 , 0.33 , -3.10 ,
12.72 , -28.30 , -15.95 , -32.44 , -23.10 , -12.47 , 9.05 , 8.76 , -4.10 , -2.89 , -0.63 , -2.47 ,
13.58 , -24.50 , -17.46 , -29.57 , -22.70 , -13.74 , 10.72 , 7.85 , -5.01 , -2.64 , 1.76 , -0.80 ,
15.82 , -19.96 , -16.47 , -27.98 , -19.97 , -12.10 , 10.65 , 4.76 , -6.25 , -2.22 , 3.61 , 1.68 ,
16.84 , -7.46 , -16.01 , -24.52 , -15.57 , -12.94 , 11.73 , 6.62 , -8.14 , -1.28 , -0.66 , 2.56 ,

Table 2 The data of MFCC,"YES"

-15.10 , -33.59 , 2.28 , 12.35 , -21.33 , -25.52 , 4.04 , -6.68 , -13.41 , -4.00 , -1.56 , -9.05 ,
-20.84 , -35.23 , -0.35 , 9.27 , -19.12 , -28.60 , 3.10 , -1.30 , -13.30 , -1.96 , 6.82 , -9.31 ,
-17.66 , -48.30 , 0.26 , 3.13 , -16.61 , -28.96 , -1.03 , 5.58 , -13.36 , -0.15 , 8.11 , -6.83 ,
-31.19 , -37.97 , -12.10 , 5.61 , -17.68 , -28.35 , 1.01 , 5.73 , -4.67 , 0.79 , 6.09 ,

0.98 ,
-32.45 , -40.03 , -16.16 , 6.33 , -15.08 , -28.72 , 0.54 , 6.73 , -2.80 , 1.35 , 5.22 , 0.04 ,
-20.13 , -49.97 , -14.80 , -0.10 , -8.24 , -27.04 , -2.44 , 13.29 , -5.29 , -0.22 , 2.51 , -5.77 ,
-15.39 , -56.09 , -15.13 , -2.01 , -9.36 , -24.75 , -5.95 , 17.21 , -3.14 , 1.28 , 5.20 , -6.00 ,
-18.34 , -49.51 , -20.28 , -4.37 , -11.58 , -21.18 , -0.27 , 14.95 , -1.16 , 7.26 , 2.93 , -1.53 ,

Table 1 The data of MFCC,"NO"

0.33 , -28.67 , -37.69 , -1.99 , -7.80 , -5.92 , 3.09 , -15.80 , 5.79 , -2.05 , 0.86 , -3.61 ,
4.77 , -25.63 , -36.15 , -5.73 , -6.83 , -2.06 , 10.56 , -17.55 , 5.72 , 0.97 , 1.04 , -0.34 ,
5.13 , -25.58 , -39.78 , -12.56 , -10.19 , -4.44 , 10.18 , -16.79 , 3.58 , -4.22 , -0.30 , 1.46 ,
-4.31 , -25.92 , -24.38 , -22.39 , -9.38 , 2.48 , 4.11 , -1.42 , -4.38 , -3.83 , 2.82 , 2.51 ,
-9.65 , -28.04 , -23.92 , -27.36 , -14.95 , 1.25 , 2.55 , -1.30 , -6.15 , -7.09 , 2.07 , 0.81 ,
0.58 , -21.18 , -25.62 , -25.55 , -10.92 , -5.87 , 9.26 , -1.02 , -3.30 , -2.60 , 1.79 , 3.21 ,
2.77 , -20.10 , -24.92 , -26.90 , -12.44 , -7.39 , 10.05 , -0.31 , -3.38 , -2.66 , 1.44 , 3.56 ,
6.30 , -21.93 , -27.14 , -23.31 , -15.06 , -11.17 , 10.54 , 0.97 , -5.36 , -4.21 , 1.98 , 4.83 ,
11.90 , -24.19 , -28.84 , -19.34 , -16.07 , -18.74 , 17.01 , -3.86 , -7.50 , -0.02 , -2.03 , 5.28 ,
12.22 , -25.61 , -27.73 , -20.30 , -22.18 , -18.08 , 15.90 , -8.83 , -5.99 , -2.33 , -4.89 , 3.41 ,
14.51 , -20.76 , -24.23 , -18.04 , -19.02 , -13.05 , 15.90 , -5.96 , -3.62 , 1.68 , -3.14 , 5.27 ,
15.77 , -29.42 , -21.91 , -19.67 , -26.34 , -12.04 , 13.95 , -5.77 , -6.01 , -0.69 , -3.05 , 4.90 ,
13.30 , -31.28 , -22.56 , -20.10 , -28.26 , -12.60 , 14.43 , -4.53 , -6.59 , -3.00 , -4.25 , 4.93 ,
14.35 , -21.65 , -21.75 , -16.71 , -24.83 , -10.88 , 20.89 , -2.97 , -8.74 , -1.83 , 1.84 , 4.77 ,

5.23 -19.30 , -18.68 , -13.75 , -27.94 , -11.49 , 17.46 , -3.73 , -4.24 , -1.51 , 2.25 , 2.57 ,

B2.GMM result

The parameter of α'_i is

0.015625 ,
0.015625 ,
.....
0.031250 ,
0.031250 ,

The parameter of μ_i is :

-16.8625 , -17.6629 , -16.8625 , -20.8420 , -15.0972 , -31.1946 , -17.6629 , -17.6629 ,
-52.8000 , -48.3020 , -52.8000 , -35.2325 , -33.5934 , -37.9716 , -48.3020 , -48.3020 ,
-17.7025 , 0.2625 , -17.7025 , -0.3480 , 2.2799 , -12.0968 , 0.2625 , 0.2625 ,
-3.1888 , 3.1329 , -3.1888 , 9.2735 , 12.3539 , 5.6101 , 3.1329 , 3.1329 ,
-10.4739 , -16.6126 , -10.4739 , -19.1198 , -21.3347 , -17.6842 , -16.6126 , -16.6126 ,
-22.9639 , -28.9601 , -22.9639 , -28.5964 , -25.5170 , -28.3512 , -28.9601 , -28.9601 ,
-3.1071 , -1.0266 , -3.1071 , 3.0993 , 4.0357 , 1.0106 , -1.0266 , -1.0266 ,
16.0803 , 5.5788 , 16.0803 , -1.3006 , -6.6809 , 5.7252 , 5.5788 , 5.5788 ,
-2.1509 , -13.3627 , -2.1509 , -13.3010 , -13.4150 , -4.6732 , -13.3627 , -13.3627 ,
4.2685 , -0.1455 , 4.2685 , -1.9615 , -3.9980 , 0.7948 , -0.1455 , -0.1455 ,
4.0670 , 8.1091 , 4.0670 , 6.8187 , -1.5599 , 6.0897 , 8.1091 , 8.1091 ,
-3.7610 , -6.8311 , -3.7610 , -9.3142 , -9.0478 , 0.9843 , -6.8311 , -6.8311 ,

The parameter of $\sum_i$ is :

0.000696 , 0.000696 , 0.000696 , 2.169289 , 0.000696 , 0.000696 , 0.000696 , 0.000696 ,
0.001020 , 0.001020 , 0.001020 , 10.832914 , 0.001020 , 0.001020 , 0.001020 , 0.001020 ,
0.001188 , 0.001188 , 0.001188 , 6.629924 , 0.001188 , 0.001188 , 0.001188 , 0.001188 ,
0.000499 , 0.000499 , 0.000499 , 1.388701 , 0.000499 , 0.000499 , 0.000499 , 0.000499 ,
0.000340 , 0.000340 , 0.000340 , 1.231727 , 0.000340 , 0.000340 , 0.000340 , 0.000340 ,

0.000112 , 0.000112 , 0.000112 , 3.195049 , 0.000112 , 0.000112 , 0.000112 , 0.000112 ,

0.000152 , 0.000152 , 0.000152 , 8.061221 , 0.000152 , 0.000152 , 0.000152 , 0.000152 ,

0.001017 , 0.001017 , 0.001017 , 1.278013 , 0.001017 , 0.001017 , 0.001017 , 0.001017 ,

0.000428 , 0.000428 , 0.000428 , 0.984487 , 0.000428 , 0.000428 , 0.000428 , 0.000428 ,

0.000162 , 0.000162 , 0.000162 , 8.946041 , 0.000162 , 0.000162 , 0.000162 , 0.000162 ,

0.000142 , 0.000142 , 0.000142 , 1.286680 , 0.000142 , 0.000142 , 0.000142 , 0.000142 ,

0.000245 , 0.000245 , 0.000245 , 4.999355 , 0.000245 , 0.000245 , 0.000245 , 0.000245 ,