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Speaker Identification Using GMM with MFCC

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Abstract
Speaker identification comes under the field of digital signal processing. The earliest systems were based on acoustic phonetics built for Automatic Speech Recognition. For recognition part these systems used pattern matching and spectrum analysis. With recent advancement in technology voice recognition has become one of the efficient measure that is used to provide protection to human's computerized and electronic belongings. Voice recognition technology is the most potential technology that will make our daily lives more secure. It is one of the types of biometric that is used to identify and authenticate user on the basis of his/her voice. Voice recognition is divided into two types: text dependent and text independent. Text dependent recognition identifies user against a phrase while text independent recognition identifies the user irrespective of what he is saying. The success in both cases depends upon the various speaker characteristics which differentiate the one speaker from other. This paper targets the implementation of MFCC with GMM techniques in order to identify a speaker.

Index Terms: *Mel frequency Cepstral coefficient (MFCC), Gaussian Mixture Modeling, Expectation Maximization (EM) algorithm, Feature matching, Fast fourier Transform, Discrete fourier Transform, Clustering,window, Melfilter etc*

1. Introduction

With recent advancement in technology voice recognition has become one of the efficient measure that is used to provide protection to human's computerized and electronic belongings.[2] Voice recognition technology is the most potential technology that will make our daily lives more secure. It is one of the types of biometric that is used to identify and authenticate user on the basis of his/her voice. Voice recognition is divided into two types: text dependent and text independent. Text dependent recognition identifies user against a phrase while text independent recognition identifies the user irrespective of what he is saying. The success in both cases depends upon the various speaker characteristics which differentiate the one speaker from other. All voice recognition systems comprises of two modules feature extraction and feature matching. In feature extraction, data from the voice sample is extracted to represent the certain speaker and in feature matching the extracted features from the input voice sample is matched against a set known speaker.
The first step in any voice recognition system is for the user to give an input by speaking a word or a phrase into a microphone. Then an analog to digital converter converts the electrical signal into digitized form and stored it in the memory. The computer then attempts to determine the meaning of a voice sample by matching it with a template that has a known meaning. This is an analogy to the traditional inputs from a keyboard [1].
The greatest hurdles in Speaker-independent speech recognition systems are articulations and variety of accents used by the people having different nationalities. Other factors that present a challenge to voice recognition technology are acoustical noise and variations in recording environment which are beyond speaker variability.

The developed system is consisting of three processes:

- Features extracting
- Training
- Matching

In first process, the developed system will result as computed features of human voice. These features are voice features which are taken from the persons. These features are extracted by using MFCC (Mel frequency Cepstral coefficient) technique. MFCC is used as the acoustic features of human voice. It considers the human voice pitch in the form of frequencies and scale them on the Mel scale, these extracted feature are unique to others.
In training process, the extracted features are trained using the Gaussian Mixture Modeling. Expectation Maximization (EM) algorithm is used to train the extracted features of human voice in system and then finally used to store in database.

In matching process, the system authenticates the registered person by matching the real time voice sample to the stored voice samples in the database. This matching is done on by finding the log likelihood of voice sample.
The main purpose of doing this task is to describe and show that the voice recognition is efficient, reliable and inexpensive technique than other biometrics to secure our systems.

II. LITERATURE REVIEW

A Novel Method for Text-Independent Speaker Identification Using MFCC and GMM
M.S.Sinith, Anoop Salim, Gowri Sankar K, Sandeep Narayanan K V, and Vishnu Soman
M.S.Sinith, Anoop Salim, Gowri Sankar K, Sandeep Narayanan K V, and Vishnu Soman introduced the speaker identification model using Gaussian Mixture Model (GMM) technique. They have evaluated feature vector by using Mel-frequency cepstral coefficients (MFCC) on the pre-processed speech signal. In this study, they extract voice signal in the form of 10-15 features vectors and then convert it into frames. They use the technique of MFCC for extracting the feature vectors. Then the entire voice features are trained using GMM. To estimate the parameters of speaker model they have used Maximum Likelihood method. After training, the speaker is used to be identified in real time. They have used Maximum Likelihood Ratio Detector algorithm for the decision process.
Results have shown that recognition rate is maximum when speech is of 60 seconds duration and number of Gaussians is 16[11].

Comparison of different parameters used in GMM based automatic voice recognition
Archana Shende, Subhash Mishra, Shiv Kumar
The performance of voice recognition systems has improved due to recent advances in speech processing techniques but there is still need of improvement. This paper present the comparison of different parameters used in automatic speech recognition system for an increase in the system performance. The recognition of a human being through his voice is one of the simplest forms of automatic recognition because it uses biometric characteristics which come from a natural action, the speech. There are two types of voice recognition: Voice Identification (SI) and Voice Verification (SV) [11]. In voice identification, the goal is to determine that the input sample best matches to which known group of voices (closed set). Voice verification is a binary decision which means that the task of verifying if a speech signal belongs to a certain person or not. There are two tasks: text-dependent and text-independent voice identification. In text-dependent identification, the spoken phrase is known to the system whereas in the text-independent case, the spoken phrase is not known to the system. This paper provided a performance evaluation of the model Parameters used in a text independent voice recognition system with AUTOMATIC SEARCH REGOGNITION. Speech recognition is the process of recognizing who is speaking on the basis of distinctiveness in speech waves automatically. The three important components of voice Recognition are: Feature Extraction, Voice modeling or classification system.
From the simulation done in this paper it is clear that, the accuracy of the identification process can be prejudiced by certain factors i.e. MFCC technique should be applied for feature extraction. It has been found that combination of Mel frequency and Hamming window gives the best performance; as the number of voice's increases the number of centroids has to be increased in order to obtain the satisfactory result. In a GMM based text-independent voice identification system the identification rate increased as the amount of training data increased.
VQ is used to minimize the data of the extracted feature [12]. In This paper, the basic purpose is to improve the computation time, the approximation quality and the accuracy of the voice identification system by using the proposed method. Future work will be on investigation of the effectiveness of feature extraction techniques for more vigorous voice recognition. Investigation on a better revision function also will be done to ensure that the hybrid classifier get the better accuracy [12].

A Review on Voice Recognition Technique
Santosh K.Gaikwad, Bharti W.Gawali, Pravin Yannawar
The Voice is most prominent & primary mode of Communication among the human being. Voice is important mode of interaction with computer .This paper gives an overview of major technological perspective and appreciation of the fundamental progress of voice recognition and also gives overview in each stage of voice recognition which techniques are developed. This paper helps in choosing the technique along with their relative merits & demerits. A comparative study of different technique is done as per stages. The voice is primary mode of communication among human being and also the most natural and efficient form of exchanging information among human is voice. Voice or voice Recognition can be defined as the process of

converting voice signal to a sequence of words by means Algorithm implemented as a computer program. Voice processing is one of the exciting areas of signal processing. Since the 1960s computer scientists have been researching ways and means to make computers able to record interpret and understand human voice. Throughout the decades this has been a daunting task. Even the most rudimentary problem such as digitalizing (sampling) voice was a huge challenge in the early years. Off course these early systems were very limited in scope and power. Communication among the human being is dominated by spoken language, therefore it is natural for people to expect voice interfaces with computer. Different types of voice are discussed in this paper Voice Recognition is a special case of pattern recognition. The voice recognition system may be viewed as working in a four stages

1) Analysis 2) Feature extraction 3) Modeling 4) Testing

In this paper, the technique developed in each stage of voice recognition system is discussed. Also the list of technique with their properties for Feature extraction is presented. Through this review it is found that MFCC is used widely for feature extraction of voice and GMM and HMM is best among all.

Voice Identification Using Mel Frequency Cepstral Coefficients by Md. Rashidul Hasan, Mustafa Jamil, Md. Golam Rabbani Md. Saifur Rahman

This paper presents a security system based on voice identification. Mel frequency Cepstral Coefficients (MFCCs) have been used for feature extraction and vector quantization technique is used to minimize the amount of data to be handled.

Speech is one of the natural forms of communication. Recent development has made it possible to use this in the security system. In voice identification, the task is to use a speech sample or voice sample to select the identity of the person that produced the speech from among a population of voices. In voice verification, the task is to use a speech sample to test whether a person who claims to have produced the speech has in fact done so [4].This technique makes it possible to use the voices' voice to verify their identity and control access to services such as voice dialing, banking by telephone, telephone shopping, database access services, information services, voice mail, security control for confidential information areas, and remote access to computers.

The MFCC technique has been applied for voice identification. VQ is used to minimize the data of the extracted feature. The study reveals that as number of centroids increases, identification rate of the system increases. It has been found that combination of Mel frequency and Hamming window gives the best performance. It also suggests that in order to obtain satisfactory result, the number of centroids has to be increased as the number of voice's increases. The study shows that the linear scale can also have a reasonable identification rate if a comparatively higher number of centroids are used. However, the recognition rate using a linear scale would be much lower if the number of voices increases. Mel scale is also less vulnerable to the changes of voice's vocal cord in course of time. The present study is still ongoing, which may include following further works. HMM may be used to improve the efficiency and precision of the segmentation to deal with crosstalk, laughter and uncharacteristic speech sounds. A more effective normalization algorithm can be adopted on extracted parametric representations of the acoustic signal, which would improve the identification rate further. Finally, a combination of features (MFCC, LPC, LPCC, Formant etc.) may be used to implement a robust parametric representation for voice identification.

Efficient Speaker Identification and Retrieval Hagai Aronowit1, David Burshtein

Hagai and David [12] presented an algorithm for efficient and accurate speaker recognition. The algorithm is based on the GMM-simulation algorithm and is useful for both identification of a large population of speakers and for speaker retrieval. For example, assuming a false acceptance rate of 1%, speedup factor of 3.3 for identification of 1,000 speakers is achieved and a speedup factor 23 for 10,000 speakers. For the speaker retrieval task, speedup factor of 160,000.

The authors also verified that techniques are also suitable when testing on short test sessions.

III.METHODOLOGY

The proposed system was designed using methodology of incremental model

Incremental model

Incremental model is used for designing, implementing, integrating and testing the system.

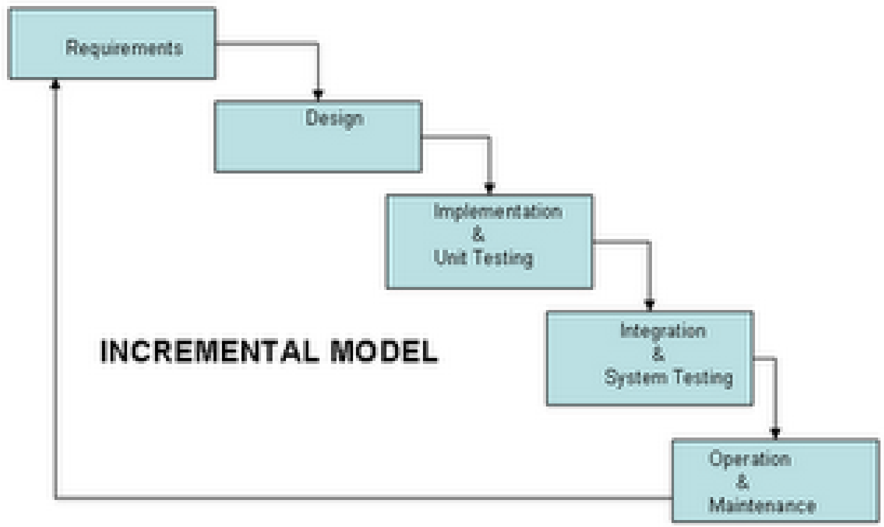

Figure 1: Incremental Model

The proposed system has four phases and each phase is developed under incremental model. Incremental system is chosen for this system because system can be developed and delivered in increments, accomod--ate changes evolved with time, are easy to test and debug and easier to manage risks involved.

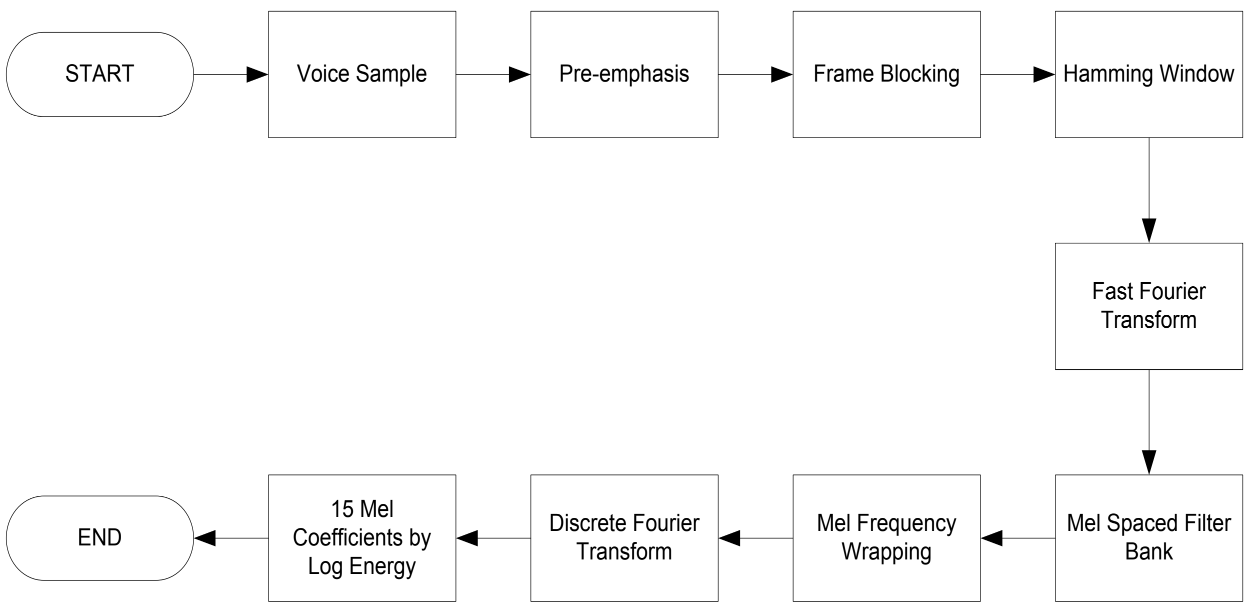

Figure 2: Block diagram of feature extraction

Voice Sample: The first step in any voice recognition system is to take the voice sample. When a user speaks, his voice is recorded for duration of 2 seconds using a sampling rate of 8 KHz. And then this sample is saved as a wav file to use in further steps.

Feature Extraction

After taking voice sample the next step is to extract the required features from the voice. Mel Frequency Cepstral Coefficients technique is used to extract features. The steps involved in MFCC are:

1. Pre emphasizing
2. Framing
3. Windowing
4. Fast Fourier Transform

5. Mel filter
6. Frequency wrapping
7. Discrete cosine transform

Pre Emphasizing

The main purpose of pre-emphasis is to recompense the high-frequency part that was suppressed when user produce sound. It can also use to increase the importance of high-frequency formants. The speech signal is passed to the high pass filter. **Equation 1: X2(n) = X(n) - a*X(n-1)**

Where the value of a is between 0.9 and 1. z transform of the filter is computed by

Equation 2: H(z)=1-a*z-1

Framing

Aim of framing is to divide the speech signal into frames of 30~20 ms with optional overlap of 1/3~1/2 of frame size. To make signal feasible for fft the frame size is usually taken as power of two. But if it is not the case zero padding is done to the nearest length of power of two. Zero padding consists of extending a signal with zeros and by increasing its length N to M where M>N. In this proposed system, the sampling frequency of 8 KHz is used and 256 sample points and 156 overlap frames are defined. The frame duration is calculated as

Sample rate=8 KHz = 8000 Hz
Frame size=256 sample points
Frame duration=256/8000= 0.03~ 30 ms
Overlapping frame= 156 sample points=156/ 8000= 0.019~ 20 ms
Frame rate= 8000/ (256-156) = 80 frames/sec

Windowing

Framed speech signal is facilitate with the hamming window in order to remove the discontinuities in the signal.

Equation 3: w(n, α) = (1 - α) - α cos(2 α n/(N-1)), 0≦n≦N-1

Value of α is usually 0~ 0.5 and it shows different curves of hamming window.

Fast Fourier Transform

FFT is used to convert the signal into frequency domain from time domain and also used to obtain the magnitude frequency response of each frame. In doing so it is assumed that the signal in frames in periodic and continuous when wrapping around. In the opposite case of this, there are some discontinuities at the frames start and end points that causes detrimental effects in frequency response. The FFT is obtained by the simple MATLAB function **Equation 4: y=fft (b)**

Mel Filter

In Mel filter the magnitude of frequency response is multiplied with the 40 number of triangular band pass filters in order to obtain the log energy of triangular band pass filter on Mel scale.

These filters are equally spaced on the Mel scale and use to calculate the linear frequency by using following formula

Equation 5: m=2595 log10 (1+f/ 700)

Frequency Wrapping

The Mel Frequency wrapping allows keeping only the part of useful information.

Discrete Cosine Transform

DCT transforms the log Mel scale cepstrum from frequency domain into time domain. The obtained features are known as mel-frequency cepstral coefficients.

Equation 6:

$$y(k) = w(k)\sum_{n=1}^{N} x(n)\cos\left(\frac{\pi(2n-1)(k-1)}{2N}\right) \quad k = 1,2,\dots N$$

N=length of the computed Mel frequencies

GMM Training

In this phase extracted features from MFCC are trained into GMM. The steps involved in GMM training are

1. Clustering 2.Expectation and Maximization

Clustering

In this part cluster number specific to each observation vector is obtained by applying K-mean algorithm. It is used to set centroids of the observation vector. . By clustering the model, it returns the centroids, one for each of the cluster k and refers to the cluster number closest to it. K-mean algorithm minimizes the distortion that is defined as the sum of squared distances between each observation vector and its dominating centroids. Squared Euclidean distance is between two points which one can measure easily from ruler. In this proposed system, Euclidean distance is used to find the distance between observation vector and its cluster centroids by using formula

Equation7: ||Y-Yc|| = sqrt (|| Y ||^2 + || Yc ||^2 - 2* Y. Yc)

GMM Training by Expectation-Maximization

Algorithm

Given training data, the parameters of GMM model are estimated by using maximum likelihood (ML) estimation. ML parameters estimates are obtained iteratively using expectation-maximization algorithm.it returns the mean M, variance V, weight W and log probability.[6]

GMM Recognition

GMM recognition recognizes the speaker on the basis

of log probability. It recalculates the log probability of voice vector and compares it to previously stored value. The log probability equal to the stored value provides access to the entire speaker.[7][8] .The implementation source code and results have been provided in Annexure-A.

IV.RESULTS

The results are tested against the specified objectives of proposed system. The developed system is tested by taking 2 speech samples from each speaker with the sampling frequency of 8 KHz. Voice features were extracted from 30 ms frame duration and 20 ms overlapping with the previous frame. The speech sample of 2 sec with noise is used to extract features and then trained using GMM. [5] The proposed MFCC features are used to expect the high accuracy in extracting the vocal features of voice. The GMM algorithm is anticipated getting best results in identification system. Accuracy rate shows the percentage of correctly identified test samples by the system. It is obtained by:
Total error of verification system= false accepted+ false rejected= 1+1= 2/16*100=12.5%. The error rate of total test samples that are being false rejected or accepted is 12.5 as indicated in Table-I provided in Annexue-B.

Accuracy= number of correctly identified test samples/ total number of test samples
= 14/ 16*100= 87.5%

V. CONCLUSIONS

Proposed system is concluded in this chapter. A real time voice recognition system is proposed. It depends on MFCC for feature extraction and on GMM for training.[9] Firstly the voice is taken through microphone and voice features are extracted by dividing by dividing voice sample into 30 ms frame duration with 20 ms frame overlapping to the previous frame. Hamming window is applied to minimize the discontinuities at the edge of each frame i.e. to get the smooth frequency transmission in voice signal. 15 MFCC coefficients are obtained by using 40 Mel filters in Mel Frequency Cepstral Coefficients. These coefficients are then passed to GMM for training part. Vector quantization with K-means is used to find the clusters. A special case of ML (Maximum Likelihood) is used for estimation parameters. It resulted in the log probability of training sequence, which is further used to define the threshold and for verification of speaker. The speaker is recognized by comparing the log probability to the defined threshold in the system.

Proposed system shows the best efficiency up to 87.5% with the error rate of 12.5% on the basis of 16 test samples of 8 speakers (2 test samples per speaker). The proposed system is developed under MATLAB R2009b environment with the user friendly interface.[10][11]

Instead of using k-means algorithm for clustering, Distribution based clustering can also be used. Maximum A Posteriori (MAP) estimation can also be used to estimate parameters instead of estimating GMM parameters via the EM algorithm. In MAP a GMM-UBM (universal background model) can be used derive speaker model. Future work leads to reduce error rate.

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ANNEXURE –A

Voice Sample

```
fs=8000;
Nseconds=2;
fprintf('Say your name after enter');
input('');
x=wavrecord(Nseconds*fs,fs,'int16');
wavwrite(x,fs,16,'audio');
t=(0:length(x)-1)/fs;
figure(1);
plot(t,x);
wavplay(x,fs);
title('Original Wave');
xlabel('Time(x)');
ylabel('Amplitude');
```

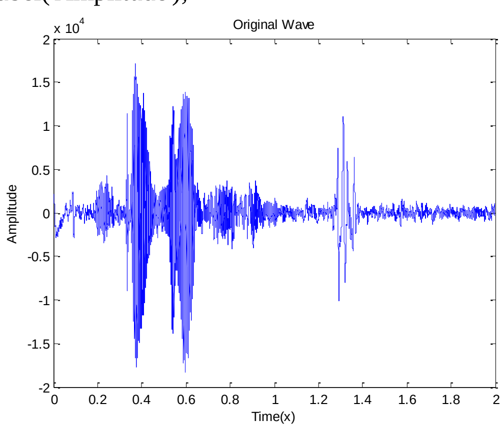

Figure 3: Original Voice Sample

MFCC Feature Extraction
Pre Emphasizing

```
audio=double(x);
audio_normalized=audio/32768;
a=0.95;voice = filter([1, -a], 1, audio_normalized);
```

Identification Using MFCC and GMM”, 2010 IEEE.

```
time=(1:length(voice))/fs;          %times of sampling instants after pre-emphasis
wavplay(voice,fs);                  % Playing the recorded sound
figure(2);
plot(time, voice);
title(sprintf('Voice signal after pre-emphasis', a));
xlabel('Time (voice)');
ylabel('Amplitude');
```

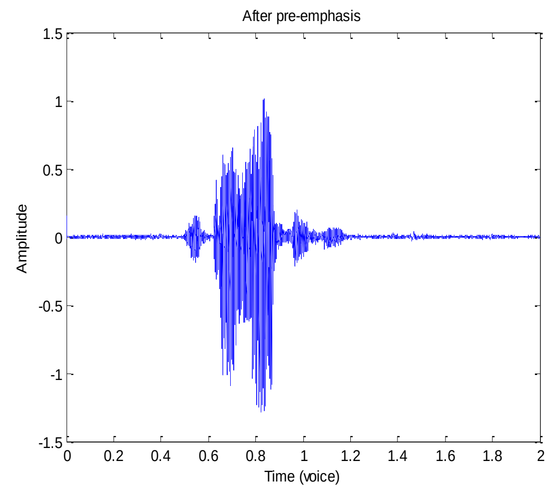

Figure 4: Pre-emphasized Voice Signal

Frame Blocking

```
function CepCoeff =
gmmfeatures(voice,N,deltaN,fs,Q)
N=256;              %number of frames
M=156;              %number of overlapping frame
a(1:256,1:82)=0;a(:,1)= voice (1:256,1);
for j=2:82;a(:,j)= voice ((N-M)*j+1:(N-
M)*j+N,1);end;figure(3); plot(a(:));title('Frame
blocking of the Voice
Signal');
```

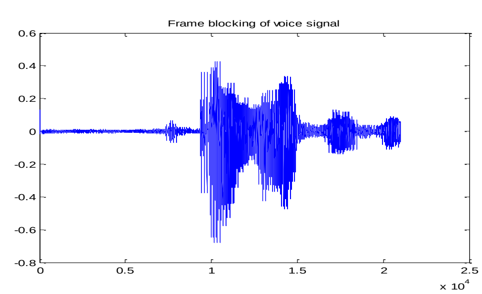

Figure 5: Frame Blocking after Pre-Emphasizing

Frame Energy

C1=sum(a(:,j).^2); %Frame energy
C2=max(C1,2e-22); %floors to 2 X 10 raised to power -22
C=log(C2);

Hamming Window

h=hamming(256); %hamming window of total frame
figure(4);
plot(h(:));
title('Hamming Window');

for j=1:82
b(:,j)=a(:,j).*h; %hamming window of each frame
end;
figure(5);
plot(b(:));
title('Hamming Window applied to each frame');

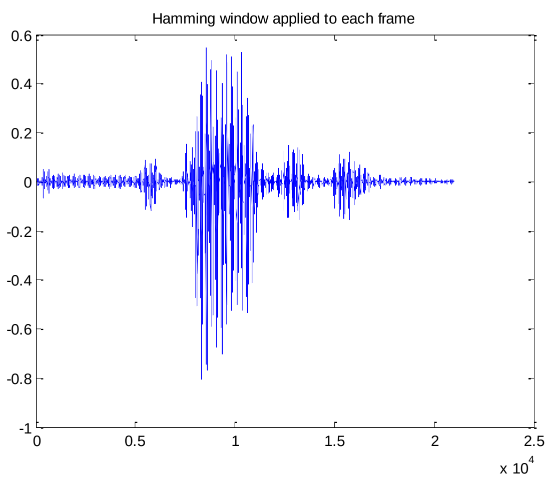

Figure 6: Hamming Window of each Frame

Fast Fourier Transform

for j=1:82
y(1:256,j)=fft(b(1:256,j));
n=length(y(:,j));
figure(6);
plot(y);title('Fast fourier transform');
end;

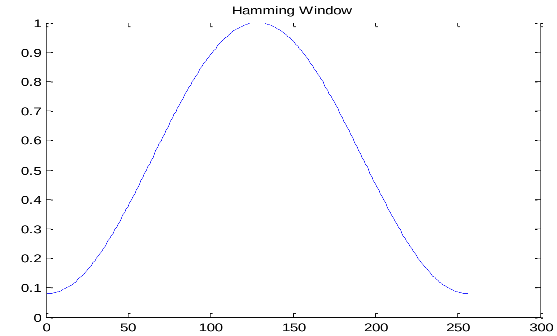

Figure 7: Hamming Window of Total Frame

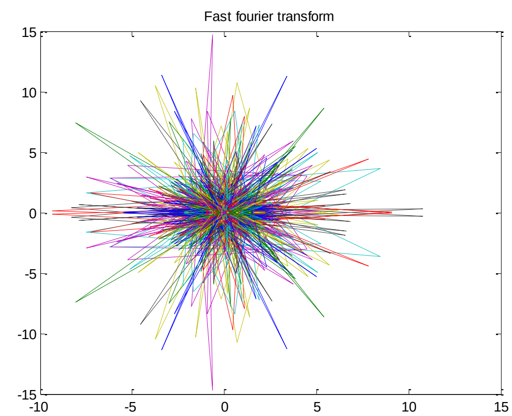

Figure 8: Fast Fourier Transform of each Frame

Mel Spaced Filter Bank

p=40; %number of Mel filters in filter bank
m = melfb(p,n,fs);figure(7);plot(linspace(0, (8000/2), 129), melfb(40, n, 8000)');title('Mel-spaced filterbank'), xlabel('Frequency (Hz)'), ylabel('Mel Scale');

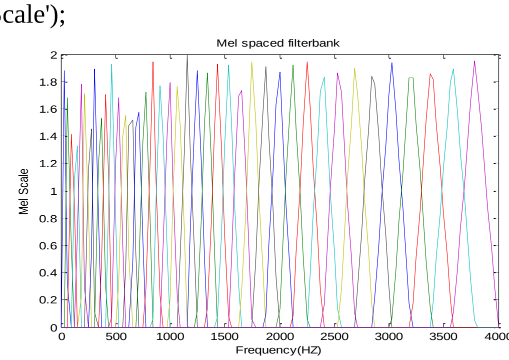

Figure 91: Mel Scale Filter Bank

Frequency Wrapping

```
for j=1:82
n2=1+floor(N/2);
ms=m*abs(y(1:n2,j)).^2;
figure(8);
plot(ms(:));
title('speech signal after frequency wrapping');
```

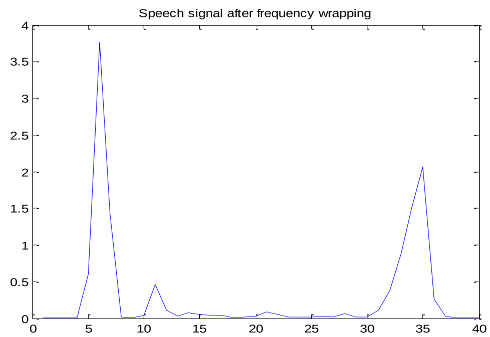

Figure 10: Voice Signal after Frequency Wrapping

Discrete Cosine Transform

```
v(:,j)=dct(log(ms+0.1));
figure(9);
plot(v(:));
title('mfc coefficients in time domain(after dct)');
```

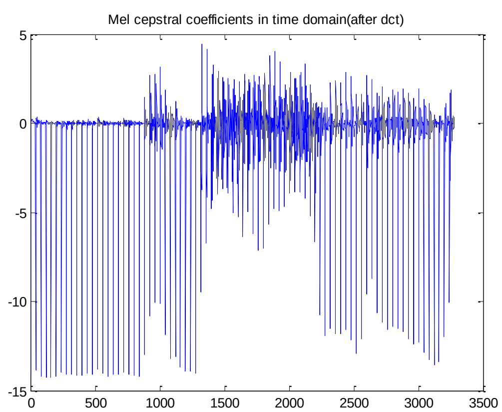

Figure 21: Mel Cepstral Coefficients after DCT

```
fprintf('Iteration count = %d, log prob. = %f\n',i, logProb(i));
```

Mel Cepstral Coefficients

```
c(1,:)=v(:,j);
c(1)=Ce;            %replaces first coefficient
coeffs=c(1:num);            %retains first num coefficients
CepCoeff=coeffs;enddistance=vecdist(M');
   distance(1:(gaussianNum+1):gaussianNum^2)=inf;
% Diagonal elements are inf
   [minDistance, index]=min(distance);
   V=minDistance.^2;    % Initial variance for each Gaussian
end
% Set initial W
W = ones(1, gaussianNum)/gaussianNum;   % Weight for each Gaussian
 for i = 1:maxLoopCount
   % Expectation step:
   % P(i,j) is the probability of data(:,j) to the i-th Gaussian
   [prob, P]=gmmEval(data, M, V, W);
   logProb(i)=sum(log(prob));
   if dispOpt, fprintf('i = %d, log prob. = %f\n',i-1, logProb(i)); end
   PW = diag(W)*P;
   BETA=PW./(ones(gaussianNum,1)*sum(PW));   % BETA(i,j) is beta_i(x_j)
   sumBETA=sum(BETA,2);

   % Maximization step:
   M = (data*BETA')./(ones(dim,1)*sumBETA');
   DISTSQ = vecdist(M', data').^2;          % Distance of M to data
   V = max((sum(BETA.*DISTSQ, 2)./sumBETA)/dim, minVariance);  % (2.97)
   W = (1/dataNum)*sumBETA;           % (2.98)
  if dispOpt & dim==2, displayGmm(M, V, data); end
if i>1, if logProb(i)-logProb(i-1)<minImprove, break; end; end
end
[prob, P]=gmmEval(data, M, V, W);
logProb(i)=sum(log(prob));
logProb(i+1:maxLoopCount) = [];
```

ANNEXURE-B

TABLE I. TESTING RESULTS OF SPEAKER IDENTIFICATION

Number of speakers	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**
Correct acceptance **(with noise)**	√ √	√	√	√	√ √		√	√
Correct rejection **(with noise)**		√		√		√	√	√
False acceptance **(with noise)**			√					
False rejection **(with noise)**						√		