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Performance Analysis Of Speaker Identification System Using MFCC And DWT Under Various Noise Levels

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Abstract

This paper presents an effective method for speaker identification system. Our aim is to implement text dependent speaker identification system that is insensitive to noise. This method is based on the combination of MFCC and DWT for feature extraction. In this paper, a novel family of windowing technique is used to compute Mel Frequency Cepstral Coefficient (MFCC). Here,classical windowing scheme such as hamming window is modified to obtain derivatives of discrete time Fourier transform coefficients. This paper, presents an effective approach to improve the accuracy of speaker recognition even at low SNR.

1. Introduction

Voice comes under the category of biometric identity. Anatomical structure of the vocal tract is unique for every person .So the voice information available in the speech signal can be used for speaker recognition. Speaker recognition classified in to speaker verification and speaker identification. Speaker identification is the process of determining which registered speaker provides a given utterance. Speaker verification, on the other hand, is the process of accepting or rejecting the identity claim of a speaker. Speaker identification is a broad subject, but the commercial and personal use implementations are rare. One of the main problems of speaker recognition in general is the impact of noise [1].

In case of speaker identification the similarity is computed only between the input signal and the stored patterns of the other recorded speakers. Speaker recognition is a popular biometric identification technique used for authenticating and monitoring human subjects using their speech signal. The objective of this work is to design an efficient system for human speech recognition that is able to identify human speech more accurately. This work presents a technique of text-dependent speaker identification system. The combined MFCC and discrete wavelet coefficients are used as the features, which will be inputs to the GMM classifier.GMMs have unique advantages compared to other modeling approaches because their training is relatively fast and the models can be scaled and updated to add new speakers with relative ease[2].

2. Related Works

Many researchers have been done on the feature extraction of speech. The linear predictive cepstral coefficients (LPCC) were used because of their simplicity and effectiveness in speaker/speech recognition [3, 4]. Other widely used feature parameters, namely, the mel-scale frequency cepstral coefficients [5] are the most popular acoustic features used in speaker recognition. The use of MFCCs for speaker identification provides a good performance in clean environments, but they are not robust enough in noisy environments. Recently, a lot of research has been directed towards the use of wavelet based features [6-8]. The discrete wavelet transform (DWT) has a good time and frequency resolution and hence it can be used for extracting the localized contributions of the signal of interest. Wavelet denoising can also be used to suppress noise from the speech signal and it can lead to a good representation of stationary as well as non-stationary segments of the speech signal.

In this paper, a new method for speaker identification is presented. This method is based on the extraction of the MFCCs from the original speech signal and its wavelet transform. Then, a new set of features can be generated by concatenating both features. The objective of this method is to enhance the performance of the MFCCs based method in the presence of noise by introducing more features from the signal wavelet transform. Speaker identification systems have been developed for a wide range of applications. Although many new techniques were invented and developed, there are still a number of practical limitations because of which widespread deployment of applications and services is not possible. Still it is very true that humans can recognize speech and speaker more efficiently than machines.There is now an increasing interest in finding ways to reduce this performance gap.

We have organized this paper as follows: First, in section 3, briefly explain the proposed system. In section 4, we explained the experimental set up and result and finally, the paper is concluded in Section 5.

3. Proposed system

After an extensive study of various features of human speech and the model of speech production, we have decided to use following techniques to develop a robust, credible speaker identification system.

- Estimation of MFCC
- Spectral analyses using discrete wavelet transform.

3.1. Estimation of MFCC

Feature extraction algorithm steps are:

1) Speech signal converted to windowed frames.The size of window depends on the input speech signal frequency.Thus the system becomes insensitive to speaking rate.

2) In this work, we apply a simple time domain processing of speech after it is multiplied with a hamming window. The processing is based on well-known difference in frequency property of discrete time Fourier transform [9], and it can be easily integrated with standard window during DFT computation [10].Let x(n) be a windowed speech frame of length N and its DTFT is given by, $X(e^{j\omega})$. From differentiation in frequency property that DTFT of nx(n) can be written as,

$$\hat{X}(e^{j\omega}) = j\frac{dX(e^{j\omega})}{d\omega} \qquad (1)$$

As DFT coefficients X(k) are samples of DTFT at $\omega = \frac{2\pi k}{N}$, DFT of nx(n) are discrete samples of $\hat{X}(e^{j\omega})$ at $\omega = \frac{2\pi k}{N}$. Therefore, $\hat{X}(k) = \hat{X}(e^{j\omega})$ are the DFT coefficients of nx(n).Since x(n) is a windowed speech frame, it can be represented as w(n)s(n), where s(n) is raw speech frame and w(n) is window function. Proposing a new window function as $\hat{w}(n)$ = nw(n). The windowed speech frame is then represented as $\hat{x}(n) = \hat{w}(n)$ s(n). From generalization of differentiation in frequency property, for an integer τ, DTFT of n^{τ}x(n) is $j^{\tau}\frac{d^{\tau}X(e^{jw})}{d^{\tau}w}$. Therefore, the window function of τ – th order window can be written as n^{τ}w(n). The window functions are shown in fig.3.1 for first and second order along with hamming window. Assume that power spectrum of Hamming windowed signal is given by P(ω), and power spectrum of the modified window is $\hat{P}(\omega)$. Therefore, $P(\omega) = H^2(\omega) = \left|X(e^{j\omega})\right|^2$ and $\hat{P}(\omega) = \hat{H}^2(\omega) = \left|\frac{dX(e^{j\omega})}{d\omega}\right|^2$, where H(ω) and $\hat{H}(\omega)$ magnitude spectrum of two signals respectively. The mathematical connection between power spectrum of new windowed speech frame and power spectrum of original Hamming windowed speech frame[10].

$$\hat{H}^2(\omega) = \frac{1}{4P(\omega)}\left[\frac{dp(\omega)}{d\omega}\right]^2 \times sec^2[\Phi(\omega) - \varphi(\omega)] \qquad (2)$$

The term $\frac{dp(\omega)}{d\omega}$ in (2) corresponds to the slope of the power spectrum of the Hamming windowed speech at frequency ω .Hence, as a consequence of power spectrum computation from derivative of fourier transform,obtain a modified power spectrum which is related to the slope of original power spectrum. Apart from it, the newly formulated power spectrum is also related to phase spectrum of the signal $\Phi(\omega)$.

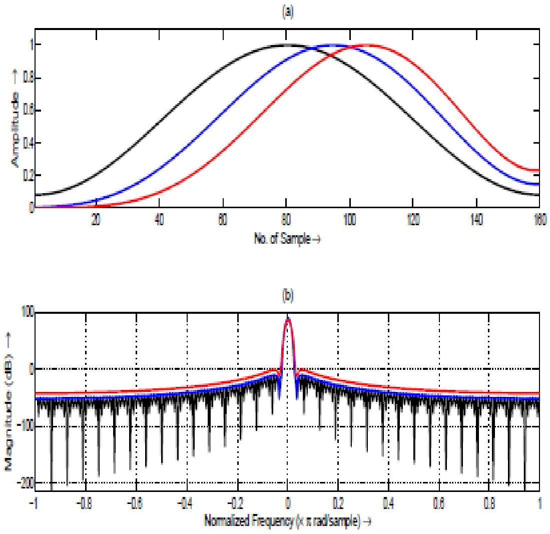

Figure.3.1 Comparison of hamming window (black) with first (blue) and second (red) order differentiation based window in (a)time domain and (b)frequencydomain for a window of size 160 samples

There are evidences that speaker discriminating attribute is present in slope of power spectrum [11] as well as in phase information [12]. The modified DFT magnitude coefficients are nothing but the samples of $\hat{H}(\omega)$ at $\omega = \frac{2\pi k}{N}$. Therefore, mel cepstrum computation using proposed window integrates the slope of power spectrum, phase, and of course, power spectrum of the signal. It is expected that the speech feature will be more efficient compared to the standard cepstrum which is solely based on power spectrum [10].

3) We used (3) to compute the mels for a given frequency f in Hz. After that taking log and DCT to get MFCC

$$Mel(f) = 2595*\log10(1 + f/700) \quad (3)$$

3.2. Spectral analysis using DWT

The recorded speech signal contains background noise.This noise badly affects the accuracy of speaker verification.DWT reduces the noise present in input speech signal. Speech signals have a very complex waveform because of the superposition of various frequency components.By using the multi-resolution decomposing technique; one can decompose the speech signal into different resolution levels. The characteristics of multiple frequency channels and any change in the smoothness of the signal can then be detected to perfectly represent the signals [13].

The DWT is computed by successive lowpass and highpass filtering of the discrete time-domain signal .This is called the Mallat algorithm or Mallat-tree decomposition. Its significance is in the manner it connects the continuous-time mutiresolution to discrete-time filters[14]. In the figure, the signal is denoted by the sequence x[n], where n is an integer. The low pass filter is denoted by G_0while the high pass filter is denoted by H_0. At each level, the high pass filter produces detail information, D[n], while the low pass filter associated with scaling function produces coarse approximations, A[n].

An important consideration in implementing the discrete wavelet transform is the choice of the wavelet and its associated scaling function. Once this choice is made, the implementation is a straightforward digital filtering scheme, which can be easily achieved on a general-purpose digital computer. The Haar wavelet is the simplest and is efficient in terms of computation, as the filters involved have just two taps. However, the Haar wavelet causes significant leakage of frequency components and is not well suited to spectral analysis of speech. The Daubechies family of wavelets has the advantage of having low spectral leakage and generally produces good results. There are several wavelets in this family, and we have chosen the D4 member for our application. We use three levels DWT to split the input speech into 0-1 kHz , 1-2 kHz, 2-4 kHz, 4-8 kHz ,this improves the result as shown in fig 3.2.

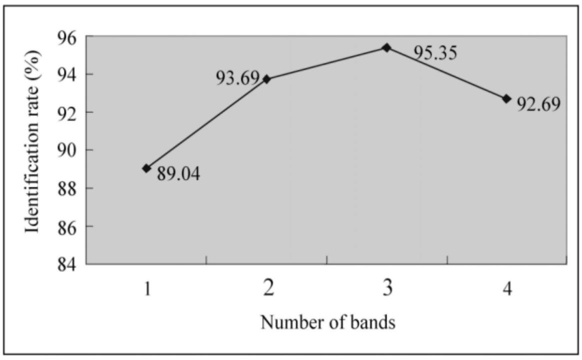

Figure 3.2 Effect of number of bands on the identification performance

4. Experimental set up and result

Here, we consider 2 different speakers saying 4 different words. The samples are saved in Matlab work folder .Total 8 of the samples were taken.We have two folders, TRAIN and TEST.Train folder contains 2 speech samples ie,S1_01.WAV and S2_01.Wav. Here,S1 and S2 are the two different speakers.Test folder contains 8 files, named: p1_01.WAV, p1_02.WAV, …, p1_04.WAV (samples from the speaker1) and p2_01.WAV, p2_02.WAV, …, p2_04.WAV(samples from the speaker 2); each is labeled after the ID of the speaker. These files were recorded in Microsoft WAV format. The task is to train a voice model for each speaker S1 ,S2 using the corresponding sound file in the TRAIN folder. After this training step, the system would have knowledge of the voice characteristic of each (known) speaker. Next, in the testing phase, the system will be able to identify the (assumed unknown) speakers of each sound file in the TEST folder.Here, only one GMM is used to classify the two speakers.Noise is added to the speech samples.and for this particular recognition,analysed the system performance under various noise levels .

The average identification rate was computed as follows:

Identification rate= $N_{correct} / N_{total}$

where *Ncorrect* is the number of correctly identified segments, and *Ntotal* is the total number of test segments.

The speaker Identification results are shown in fig. 4.1. The average speaker identification performance with modified MFCC and combination of MFCC and DWT features in the clean environment are 100%.

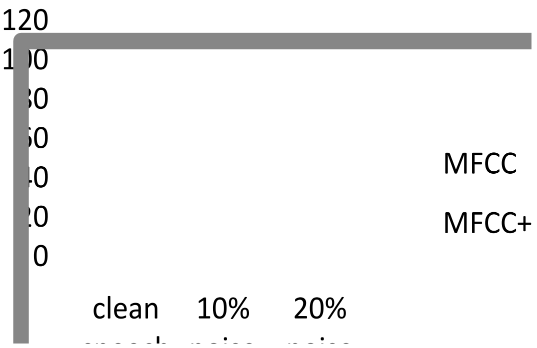

Figure 4.1: Comparative performance of speaker verification system

5. Conclusion

There are considerable amount of researches going on the field of speech and speaker recognition. The results of shorter test sessions with limited users showed impressive performance in noisy and clean conditions.Here we use MFCCs because they follow the human ear's response to the sound signals and DWT reduces the noise present in input speech signal. Proposed system takes advantages of both wavelet and MFCC features and gives satisfactory results for speaker identification .Under various noise levels also,we could check the accuracy of the system. Speech may vary over a period of 2-3 years. So the training sessions have to be repeated so as to update the speaker specific database. In the future work, the proposed features can be used for text independent speaker verification and identification purpose.

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