Speaker Recognition System Based on Wavelet Features and Gaussian Mixture Models

K. Sajeer, Paul Rodrigues

Abstract:. Identification of a person's voice from the different voices is known as speaker recognition. The speech signals of individuals are selected by means of speaker recognition or identification. In this work, an efficient method for speaker recognition is made by using Discrete Wavelet Transform (DWT) features and Gaussian Mixture Models (GMM) for classification is presented. The input speech signal features are decomposed by DWT into subband coefficients. The DWT subband coefficient features are the input for the classification. Classification is made by GMM classifier at 4, 8, 16 and 32 Gaussian component levels. Results show a better accuracy of 96.18% speaker signals using DWT features and GMM classifier.

Index Terms: Speaker recognition, DWT transform, subband coefficient features, GMM classifier.

I. INTRODUCTION

Speaker recognition is that the systems are created to identify, verify and differentiate the individual speaker. It was recognized by the frequency and flow of their voice in normal pronunciation. GMM and Convolutional Neural Network (CNN) hybrid method for speaker recognition in short utterance are discussed in [1]. The signal features are extracted by Mel-Frequency Cepstral Coefficients (MFCC) and classification is made by hybrid classifiers like CNN and GMM.

I-vector based speaker recognition for Discriminatively Learned Network (DLN) is discussed in [2]. The input signal features are extracted by MFCC with mean and variance. DLN with i-vector is used for classification. Speaker recognition using wavelet analysis and multimodal neural networks is discussed in [3]. The input speech signal features are extracted by DWT, wavelet packet transform, wavelet subband frequency and MFCC. The classification is made by radial basis function neural network models, probabilistic neural network and general regressive neural network.

Speaker verification with a combination of DWT and MFCC feature wrapping is discussed in [4]. Feature extraction and classification are made by DWT based MFCC features for enhanced forensic speaker verification. Automatic speaker recognition based on wavelet transform is discussed in [5]. The speech signal features are extracted by DWT based MFCC and linear predictive coding features are used for automatic speaker recognition.

Speaker recognition based on Stationary Wavelet Transform (SWT) and Principal Component Analysis (PCA) is discussed in [6]. The input speech signal features are decomposed by SWT and PCA. An artificial neural network is used for classification. Comparative analysis of MFCC and Bark Frequency Cepstral Coefficient (BFCC) for speaker recognition system is discussed in [7]. The feature extraction for speech signals features is made by MFCC and BFCC for speaker recognition system with vector quantization method.

Forensic speaker recognition in noise for mitigating effects is discussed in [8]. In preprocessing stage voice activity detector is used to achieve the robustness. The speech signal features are extracted by gammatone frequency cepstral coefficients. Classification is made by universal background model. Natural voice disguise technique for automatic speaker recognition is discussed in [9]. MFCC is used to extract the speech signal features and GMM is used for classification.

Speaker recognition based on MFCC and Back Propagation Neural Network (BPNN) is discussed in [10]. The input speech signal features are extracted by MFCC and the classification is made by BPNN. Speaker recognition using Butterworth Filter (BF) and wavelet cepstral coefficient is discussed in [11]. In the preprocessing stage, BF is applied to remove noise. Then the speech signals are decomposed into different frequency channels. The wavelet cepstral coefficient is applied for the individual speakers.

Automatic speaker recognition based on a machine learning algorithm is discussed in [12]. Initially, voice activity is detected. The speech signal features are extracted by time, frequency and cepstral domain. Finally, classification is made by support vector machine, k- nearest neighbor, multilayer perceptrons and random forest classifier. Speaker recognition using MFCC and Locality Sensitive Hashing (LSH) is discussed in [13]. At first, the speech signal features are extracted by MFCC. Then LSH classifier is used for classification.

Speaker recognition with MFCC application using Matlab is discussed in [14]. The speech signal features are extracted by MFCC. At last, the paper compares the rectangular window and hamming window technique based on the filters. In this paper, an efficient method for speaker recognition is presented based on DWT features and GMM classifier. The organization of this paper as follows: In section 2 the methods and materials of the speaker recognition are described. Section 3 gives the results of the

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speaker recognition at different Gaussian levels. The last section concludes the speaker recognition system..

II. METHODS AND MATERIALS

Figure 1 explains the workflow speaker recognition system. Implementation of this system is based on DWT features and GMM classifier.

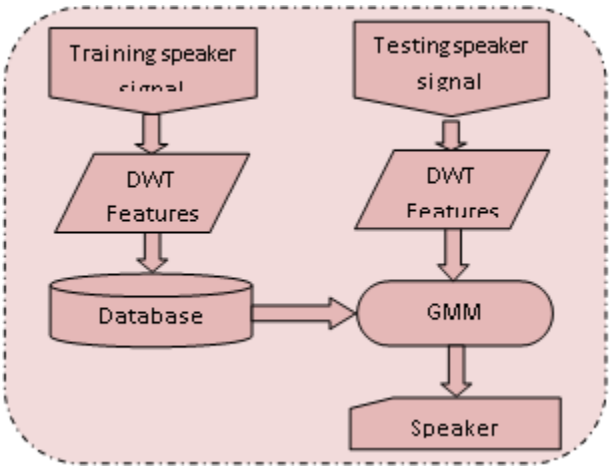


Figure 1 Speaker recognition system

A. *Wavelet Decomposition*

The speaker signals features are decomposed by DWT features. It produces higher and lower frequency subbands and also it is familiar. The discrete set of rules and translation scales are implemented by wavelet transform. In the set of input signal features the discrete set of shrinking signal features are decomposed. The DWT decomposition is defined as,

$$\Phi(K)=\sum_{v=-\infty}^{\infty}(-1)^{v}L_{T-1-v}\Phi(2K-v) \tag{1}$$

where T is even integer and it decomposes the set of wavelets and forms the decomposition signal. The input speech signal features are extracted by DWT. DWT is also widely used in other fields like epileptic seizure detection [15] and video steganography method for secure video transaction [16].

B. *GMM Classifier*

GMM is a supervised learning classifier algorithm and it classifies the wide variety of signals. GMM is a superior algorithm to use for classification in pattern recognition. It is a probabilistic model and generates the data point from the overall finite Gaussian distributions with their parameters. Parameters in the GMM are derived from the well trained earlier model. GMM is used for modelling data from several groups.

Let us consider N clusters, and is estimated for each n. It has only one estimation and it is estimated by the maximum-likelihood method. The n clusters have the probability density and it is defined by a linear function of densities of all the n distributions,

$$q(Y)=\sum_{n=1}^{N}\gamma_n H(Y|\delta_n,\lambda_n) \tag{2}$$

where γ_n is the coefficient of n.

The parameter estimation of the maximum log-likelihood method is $q(Y|\delta,\lambda,\gamma)$.

$$\ln q(Y|\delta,\lambda,\gamma)=\sum_{j=1}^{K}q(Y_j) \tag{3}$$

$$=\sum_{j=1}^{K}\ln\sum_{n=1}^{N}\gamma_n H(Y_j|\delta_n,\lambda_k) \tag{4}$$

The random variable is defined as $\psi_n(Y)$ such that $\psi_n(Y)=q(n|Y)$.

Baye's theorem, $\psi_n(Y)$

$$=\frac{q(Y|n)q(n)}{\sum_{n}^{N}q(n)q(Y|n)} \tag{5}$$

$$=\frac{q(Y|n)\gamma_n}{\sum_{n=1}^{N}\gamma_n q(Y|n)} \tag{6}$$

The maximum derivative function is $q(Y|\delta,\lambda,\gamma)$ with respect to δ,λ and δ should be zero. The derivative of q is equalled by $q(Y|\delta,\lambda,\gamma)$ with respect δ to zero and rearranged by the terms is,

$$\delta_n=\frac{\sum_{j=1}^{J}\psi_j(y_j)y_j}{\sum_{j=1}^{J}\psi_j(y_j)} \tag{7}$$

The derivative is taken with respect to λ and γ respectively, the obtained expressions are,

$$\lambda_n=\frac{\sum_{j=1}^{J}\psi_j(y_j)(y_j-\delta_j)(y_j-\delta_j)^{M}}{\sum j=1^{J}\psi_n(y_j)} \tag{8}$$

$$\gamma_n=\frac{1}{J}\sum_{j=1}^{J}\psi_n(y_j) \tag{9}$$

where $\sum_{j=1}^{J}\psi_n(y_j)$ denotes the sample points in the nth cluster. The total K number of samples and each sample contains g features are denoted by y_j. The classification is made by GMM classifier at 4, 8, 16 and 32 Gaussian component levels. GMM classifier is also used for texture image classification [17], single image super-resolution method [18] and in online signature verification method [19].

III. RESULTS AND DISCUSSION

A set of 36 speakers in the Chain corpus [20] database is used to estimate the performance of DWT-GMM based speaker recognition system. Performance of DWT-GMM is implemented by the DWT features with Gaussian

components like 4,8,16 and 32. The speech signal features are extracted by DWT at 5 levels for all speech signals of the speaker. GMM classifier is used for the classification of 8, 16 and 32 speakers set respectively. Figure 2 shows some of the speech signals in the database. Figure 3 shows the DWT feature extraction at 4 levels and approximate subband. Table 1, 2 and 3 shows the accuracies obtained by DWT-GMM system for 8, 16 and 32 speaker.

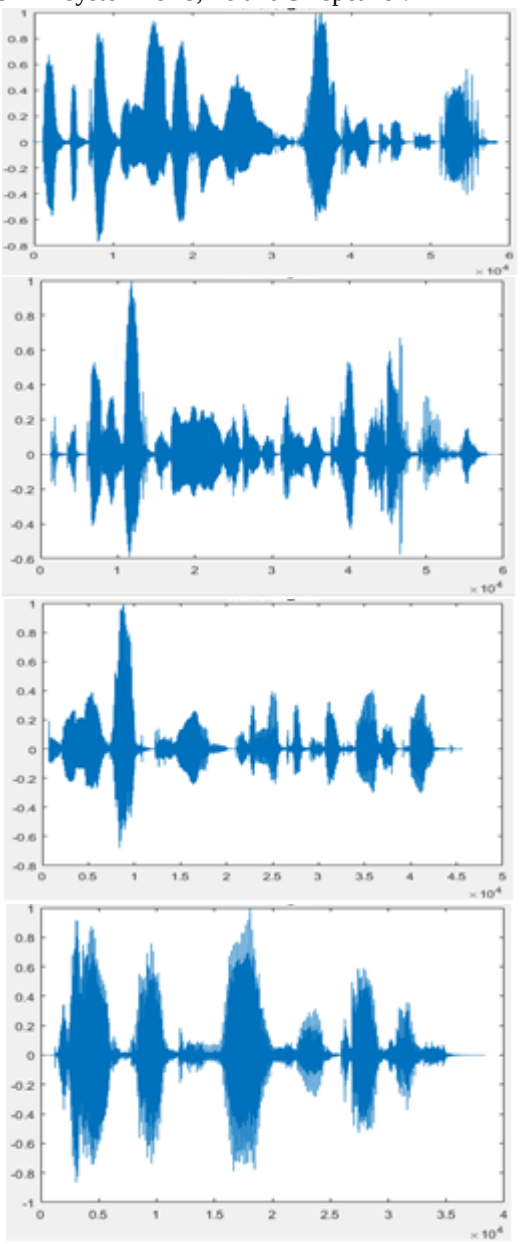
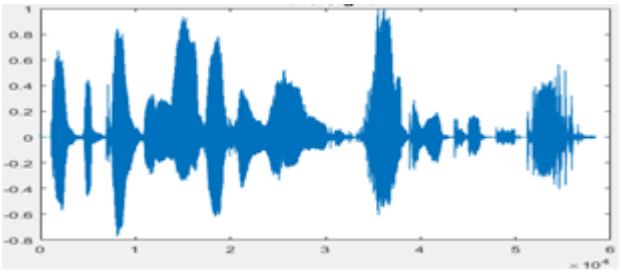
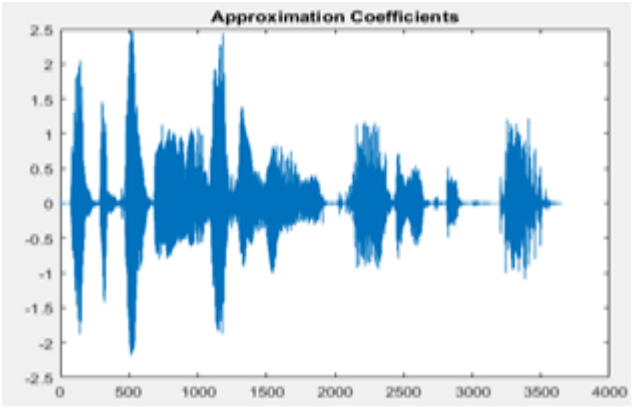


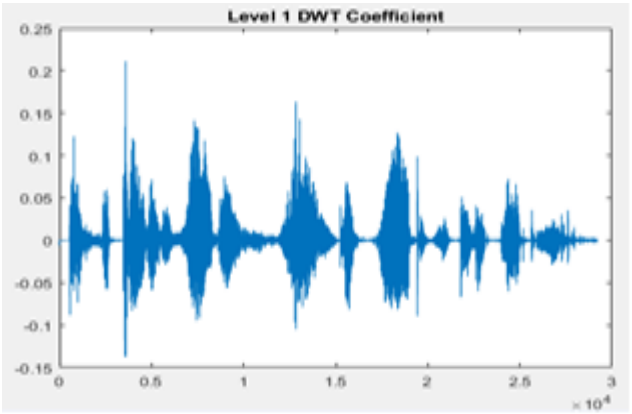
Figure 2 Speech signals in the chain corpus database



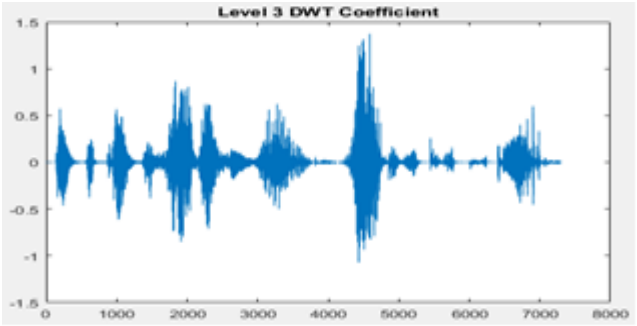
(a) Original speech signal



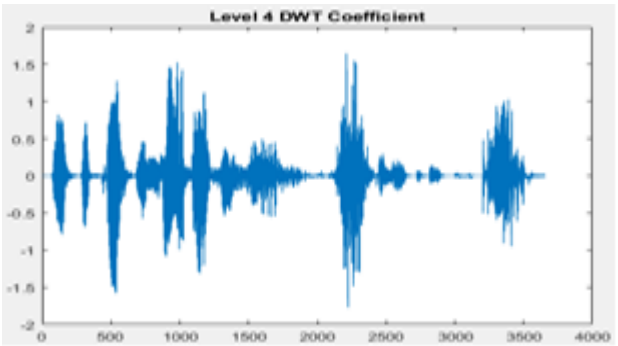
(b) Approximate coefficient



(c) DWT decomposition at 1st level



(e) DWT decomposition at 3rd level



(f) DWT decomposition at 4th level

Figure 3 DWT feature extraction stage at 4 levels with approximate subband

DWT Levels	Speaker recognition accuracy (%)			
	Gaussian levels for 8 Speaker			
	G4	G8	G16	G32
1	56.94	58.33	66.66	63.88
2	65.27	73.61	76.38	70.83
3	86.11	90.27	95.83	83.33
4	73.61	80.55	87.5	81.94

Table 1 Accuracies of DWT based GMM system on 8-speaker set

DWT Levels	Speaker recognition accuracy (%)			
	Gaussian levels for 16 Speaker			
	G4	G8	G16	G32
1	56.94	59.02	67.36	64.58
2	65.97	77.01	77.08	71.52
3	86.11	90.97	95.83	84.02
4	74.30	79.86	86.80	81.94

Table 2 Accuracies of DWT based GMM system on 16-speaker set

DWT Levels	Speaker recognition accuracy (%)			
	Gaussian levels for 32 Speaker			
	G4	G8	G16	G32
1	57.29	57.63	65.27	62.84
2	64.23	75.34	76.04	70.13
3	84.72	88.88	96.18	82.98
4	72.56	77.77	84.02	79.16

Table 3 Accuracies of DWT based GMM system on 32-speaker set

From table 1 to 3 it is observed that DWT-GMM system provides 95.83% accuracy at 8-speaker set, 95.83% accuracy at 16-speaker set and 96.18% for 32-speaker set and these accuracies are obtained at 3rd level of DWT-GMM system for 8, 16 and 32 sets of the speaker. Also, it is observed that the 32-speaker set produces a higher accuracy when compared to the 8 and 16 speaker set.

IV. CONCLUSION

An efficient method for speaker recognition based on DWT-GMM is presented. The speech signal features are extracted by DWT. The extracted signal features are the input for the classification of GMM with different Gaussian components for 8, 16 and 32 speaker sets. The higher classification accuracy is produced by 3rd level of DWT decomposition in 32 speaker set. CHAINS corpus speech signal database is used for implementation. Results show better classification accuracy.

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