COMPARATIVE STUDY OF SEVERAL NOVEL ACOUSTIC FEATURES FOR SPEAKER RECOGNITION

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Abstract: Finding good features that represent speaker identity is an important problem in speaker recognition area. Recently a number of novel acoustic features have been proposed for speaker recognition. The researchers use different data sets and sometimes different classifiers to evaluate the features and compare them to the baselines such as MFCC or LPCC. However, due to different experimental conditions direct comparison of those features to each other is difficult or impossible. This paper presents a study of five new recently proposed acoustic features using the same data (NIST 2001 SRE), and the same UBM-GMM classifier. The results are presented as DET curves with equal error ratios indicated. Also, an SVM-based combination of GMM scores produced on different features has been made to determine if the new features carry any complimentary information. The results for different features as well as for their combinations are directly comparable to each other and to those obtained with the baseline MFCC features.

1 INTRODUCTION

Speaker recognition is the process of automatic identification or verification of a speaker using the information obtained from his/her speech. Verification permits access control by voice as well as facilitates in crime investigation if recordings of phone conversations are available. Speaker recognition systems includes speaker identification and speaker verification; however, studies usually focus on speaker verification only. Text-independent verification has gained much attention because does not require a user to speak any pre-defined phrases for the system to operate and thus is an attractive method of personal verification.

To represent a speaker features extracted from the audio file are used. It is supposed that different speakers can be represented differently in the feature space. Therefore by building statistical models that approximate the distribution of feature vectors for different speakers, the conditional probability of the speaker being who he claims can be estimated.

Finding good features with low intra-speaker variation and high inter-speaker variation, as well as not too sensitive to channel type, is an important problem in speaker recognition. Commonly used features are Linear Prediction (LP) based features such as Linear Predictive Cepstral Coefficients (LPCC) and Mel Frequency Cepstral Coefficients (MFCC) (Gish and Schmidt, 1994). Although recently research focus has been shifted mostly to developing methods of elimination of channel effects, a number of new and novel features have been proposed (Wang and Wang, 2005; Sant'Ana et al., 2006; Cordeiro and Ribeiro, 2006; Sri Rama Murty and Yegnanarayana, 2006). New classification method to be used with the new features has also been proposed in (Sant'Ana et al., 2006). Researchers use different data sets to compare performance of speaker verification systems with their features to that of the baseline systems. Therefore, it is often difficult or impossible to compare the effectiveness of the new features to each other and to baseline features (such as MFCC).

This paper presents a comparative study of five new features proposed in 2005–2006 publications. The features studied are *Mean Energy within Critical Bands (MECB)* and *Difference of Mean Energy within Critical Bands (DMECB)* (Wang and Wang, 2005), *pH* features based on Hurst parameter and fractional

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Brownian motion model (Sant'Ana et al., 2006), *Mel Line Spectrum Frequencies (MLSF)* (Cordeiro and Ribeiro, 2006), and *Residual Phase* (Sri Rama Murty and Yegnanarayana, 2006). The paper is organised as follows. Section 2 shortly describes the features and section 3 presents the feature combination scheme. Section 4 discusses the experimental setup and the results, and section 5 draws the conclusions.

2 FEATURES STUDIED

Mel Frequency Cepstral Coefficients. Commonly used MFCC features were taken as the baseline. The data set audio files were divided into frames of 30 ms length with 1/3 overlap using Hamming window. Twelve MFCC coefficients were calculated for each frame along with their first and second differences (ΔMFCC and $\Delta\Delta$MFCC) resulting in 36-dimensional feature vectors. The feature values were normalised by subtracting the mean and dividing by the standard deviation.

Mel Line Spectrum Frequencies. Mel Line Spectrum Frequencies (MLSF) are similar to Line Spectrum Frequencies calculated from Linear Prediction (LP) coefficients. The difference is in taking an advantage of mel frequency warping, emphasising the information in lower frequencies (Cordeiro and Ribeiro, 2006). To extract MLSF features, the signal was divided into 30 ms frames windowed using Hamming window with 1/3 frame overlap. Fast Fourier Transform (FFT) and mel filter bank were used to generate mel spectrum. Then the inverse Fourier transform was applied to get the mel autocorrelation of the signal. The MLSF features were then calculated via the Levinson-Durbin recursion. An LP filter of order 16 was used resulting in 16-dimensional feature vectors. The feature values were normalised by subtracting the mean and dividing by the standard deviation. Since addition of the first and second differences (ΔMLSF and $\Delta\Delta$MLSF) might increase the verification accuracy both differences were calculated. In the original paper MLSF features were evaluated on NIST 2002 SRE database.

Residual Phase. A person's vocal tract can be modelled as an excitation source and a set of filters that characterise the vocal tract shape. While LP coefficients approximate the vocal tract shape, the excitation source can be evaluated from the residual signal:

$$e_n = s_n + \sum_{k=1}^{p} a_k s_{n-k} \tag{1}$$

where s_k is the signal, a_k are the LP coefficients. Examples of features calculated from the residual signal include Haar Octave Coefficients of Residue (HOCOR) (Zheng and Ching, 2004) and Residual Phase (Sri Rama Murty and Yegnanarayana, 2006). The latter was evaluated on NIST 2003 SRE database. To extract the residual phase, the analytic signal $R_n = r_n + jh_n$ is calculated from the residual signal r_n, where h_n is the Hilbert transform h_n of r_n. The phase is then calculated from the analytic signal as:

$$\theta_n = \arccos\left(r_n / \sqrt{r_n^2 + R_n^2}\right) \tag{2}$$

Authors (Sri Rama Murty and Yegnanarayana, 2006) recommend to calculate the residual phase from short segments of speech of around 5 ms, which is justified by the period of the bursts in the excitation source. In the our study the signal was divided into 6 ms frames with 1/3 overlap. LP of orders 6 and 10 were tried.

Hurst Parameter Features. Hurst parameter features were proposed for speaker recognition (Sant'Ana et al., 2006) and evaluated on BaseIME database developed in the Instituto Militar de Engenharia. The feature vector is a vector of Hurst parameters calculated for frames of a speech signal via Abry-Veitch Estimator using discrete wavelet transform. To extract the features the speech signal was divided into 80 ms frames with 1/2 overlap, which were chosen to make the extraction similar to that presented in the original paper. Daubechies wavelets with 4, 6, and 12 coefficients were used, thus resulting in pH_4, pH_6, and pH_{12} features. The depth of wavelet decomposition was to be 5, 4, and 3 for pH_4, pH_6, and pH_{12} respectively.

Mean Energy within Critical Bands. Fractional Fourier transform (FrFT) is a generalisation of the ordinary (integer) Fourier transform. Mean Energy within Critical Bands (MECB) features based on the fractional Fourier transform were proposed in (Wang and Wang, 2005) and evaluated on a custom data set. The critical bands are formed by warping frequency according to the mel or bark scale. MECB_p are calculated by taking the fractional Fourier transform of order p of each frame of the signal. For i-th critical band $f_i \dots f_{i+1}$ the log of mean energy is

$$E_i = \log \frac{\int_{f_i}^{f_{i+1}} |F(f)|^2 \, df}{f_{i+1} - f_i} \tag{3}$$

For two MECB features of orders p_1 and p_2 the difference MECB (DMECB) features are calculated as:

$$\mathrm{DMECB}_{p_1 - p_2} = \mathrm{MECB}_{p_1} - \mathrm{MECB}_{p_2} \tag{4}$$

In our study the signal was divided into 30 ms long frames with 1/3 overlap. MECB of orders $p = 0.5, 0.6, \ldots, 1.0$ were extracted. DMECB were calculated for a fixed p_1 of 1.0 and p_2 $0.5 \ldots 0.9$.

3 COMBINATION OF FEATURES

Combining different acoustic features can be performed in a number of ways. One way is to concatenate the feature vectors of the corresponding frames. However, this leads to feature vectors of very high dimensionality, which means much more data is required for reliable training of a classifier. Thus the concatenation was only done for low-dimensional feature vectors pH, while for the high-dimensional features another method was used. A GMM enables modelling the conditional probability density functions in the feature space for each class. A GMM classifier returns a score for each given pattern, which is an estimation of the log likelihood ratio for the hypothesis that the speaker is who he claims to be (Reynolds and Rose, 1995). These scores from GMM classifiers for each of the acoustic features were used as features. The resulting score feature vectors were used with an SVM classifier.

4 EXPERIMENTS AND RESULTS

All experiments were conducted on NIST 2001 Speaker Recognition Evaluation (SRE) database, single-speaker files. The audio files sampled at 8 kHz were pre-emphasised with filter coefficient of 0.97 and divided into frames as described above. For all features a Gaussian Mixture Model (GMM) classifier of 512 multivariate normal distributions with diagonal covariance matrices was used (Reynolds and Rose, 1995). The Universal Background Models (UBM) were trained on samples from 82 male and 56 female speakers. The resulting Detection Error Tradeoff (DET) curves and the Equal Error Ratios (EER) are shown in Fig. 1(a)–(g).

Individual Features. The results achieved with MFCC features with the first and second differences were taken as the baseline (Fig. 1(a)). As seen from the DET curves in Fig. 1(b), adding the first difference to MLSF improves the speaker verification accuracy, which is in agreement with the results in (Cordeiro and Ribeiro, 2006). Adding the second difference improves the accuracy further. Because of high dimensionality of the resulting feature vectors (48) more training data may lead to better system performance.

Fig. 1(c) shows the DET curves for Residual Phase features and two different order LP filters. The difference in the LP filter order does not result in a significant difference in the speaker verification accuracy. It was also found that adding the first difference features does not change the system performance either, so the second difference was not tried.

Features pH_{4+6+12} were obtained by concatenating feature vectors pH_4, pH_6, and pH_{12} for each frame. It was found that performance of the speaker verification system is similar when either one of pH_4, pH_6, pH_{12} are used. Concatenating them into 12-dimensional pH_{4+6+12} vectors leads to a dramatic improvement in the accuracy with EER dropping from 29.0% to 20.8% (Fig. 1(d)).

The accuracy of speaker verification for $MECB_p$ features declines with p of FrFT (Fig. 1(e)). This is in accordance with the results reported in (Wang and Wang, 2005), while the results for $DMECB_{1.0-p_2}$ features with various p_2 (Fig. 1(f)) are different from that reported in the paper: the highest speaker verification accuracy was achieved for $p_2 = 0.5$ and for $p_2 = 0.6 \ldots 0.9$ the accuracy decreased with increase of p_2. Adding the difference features to MECB and DMECB did not lead to accuracy improvement.

Table 1: Equal error rates for MECB features of different orders.

$MECB_p$, p	1.0	0.9	0.8	0.7	0.6	0.5
EER, %	17.6	18.7	21.2	24.2	27.5	31.4

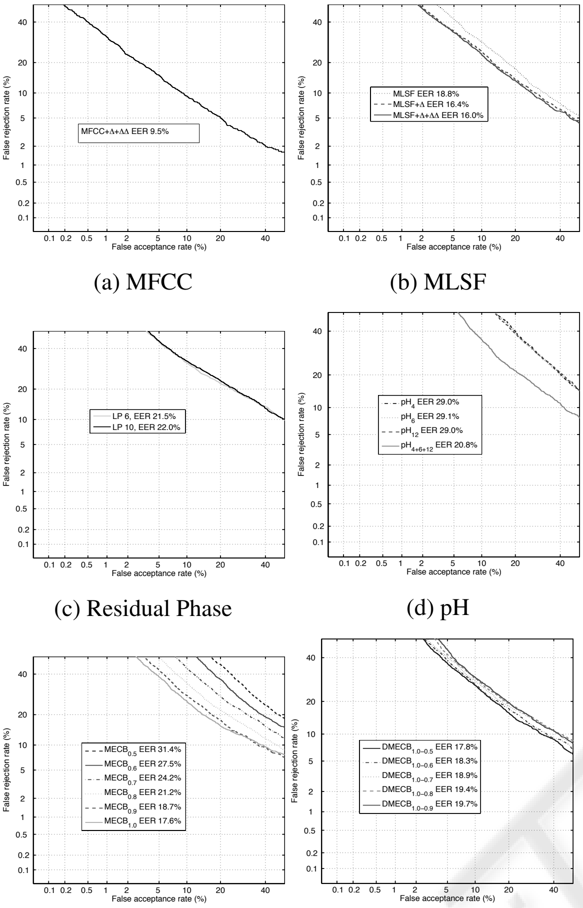
Table 2: Equal error rates for DMECB features of different orders.

$DMECB_{1.0-p_2}$, p_2	0.9	0.8	0.7	0.6	0.5
EER, %	19.7	19.4	18.9	18.3	17.8

Table 3: Summary of equal error rates for different feature types and their SVM combination.

Feature type	EER, %	Feature type	EER, %
MFCC+Δ+$\Delta\Delta$	9.5	Residual phase	21.5
MLSF+Δ+$\Delta\Delta$	16.0	pH_{4+6+12}	20.8
$MECB_{1.0}$	17.6	$DMECB_{1.0-0.5}$	17.8
Combined	8.7		

Combination of Features. To make the results comparable to those of acoustic features alone a 5-fold cross-validation scheme was applied. The test set of speakers was divided into 5 approximately equal parts. Every time one different part was left for testing and four others were used for training the SVM, resulting in 5 experiments in total. The SVM was designed to produce a soft decision, which



(a) MFCC (b) MLSF

(c) Residual Phase (d) pH

(e) MECB (f) DMECB

Figure 1: DET curves for different feature types.

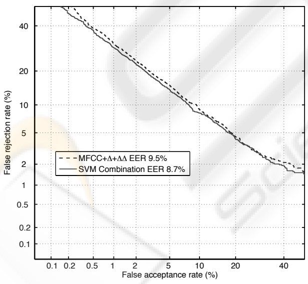


Figure 2: DET curve for combination of acoustic features.

was then treated as a score for plotting the DET curve and calculating the EER. It was decided to combine MFCC+$\Delta + \Delta\Delta$, MLSF+$\Delta + \Delta\Delta$, Residual Phase with LP of order 6, pH_{4+6+12}, $MECB_{1.0}$, and $DMECB_{1.0-0.5}$, choosing one feature from each group with the best performance. The results of the combination are shown in Fig. 2 with the EER in Table 3 with the DET curve for the MFCC+$\Delta+\Delta\Delta$ plotted for comparison.

5 CONCLUSIONS

As assessed on NIST 2001 SRE database, none of the novel acoustic features considered in this study outperformed the MFCC features. MLSF and MECB features have performance that is comparable to that of MFCC. Features pH showed a high accuracy of speaker verification taking into account their low dimensionality (5, 4, and 3 for pH_4, pH_6, and pH_{12} respectively), hence they may be attractive when limited training data is available. Combination of several different acoustic features resulted in significantly higher accuracy of speaker verification. We can conclude that the studied features carry additional information about speakers. How big is the contribution of each of the features into the speaker verification accuracy, however, needs to be established. To determine this either all possible feature combinations have to be tried, or feature selection methods have to be used.

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