Hindawi Publishing Corporation
EURASIP Journal on Advances in Signal Processing
Volume 2008, Article ID 258184, 10 pages
doi:10.1155/2008/258184

Research Article

On the Use of Complementary Spectral Features for Speaker Recognition

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Received 29 November 2006; Revised 7 May 2007; Accepted 29 September 2007

Recommended by Tan Lee

The most popular features for speaker recognition are Mel frequency cepstral coefficients (MFCCs) and linear prediction cepstral coefficients (LPCCs). These features are used extensively because they characterize the vocal tract configuration which is known to be highly speaker-dependent. In this work, several features are introduced that can characterize the vocal system in order to complement the traditional features and produce better speaker recognition models. The spectral centroid (SC), spectral bandwidth (SBW), spectral band energy (SBE), spectral crest factor (SCF), spectral flatness measure (SFM), Shannon entropy (SE), and Renyi entropy (RE) were utilized for this purpose. This work demonstrates that these features are robust in noisy conditions by simulating some common distortions that are found in the speakers' environment and a typical telephone channel. Babble noise, additive white Gaussian noise (AWGN), and a bandpass channel with 1 dB of ripple were used to simulate these noisy conditions. The results show significant improvements in classification performance for all noise conditions when these features were used to complement the MFCC and ΔMFCC features. In particular, the SC and SCF improved performance in almost all noise conditions within the examined SNR range (10–40 dB). For example, in cases where there was only one source of distortion, classification improvements of up to 8% and 10% were achieved under babble noise and AWGN, respectively, using the SCF feature.

1. INTRODUCTION

Speaker recognition has many potential applications as a biometric tool since there are many tasks that can be performed remotely using speech. Especially for telephone-based applications (i.e., banking or customer service), there are many costly crimes such as identity theft or fraud that can be prevented by enhanced security protocols. In these applications, the identity of users cannot be verified because there is no direct contact between the user and the service provider. Hence, speaker recognition is a viable and practical next step for enhanced security.

Speaker recognition is performed by extracting some speaker-dependent characteristics from speech signals. For this purpose, the speaker's vocal tract configuration has been recognized to be extremely speaker-dependent because of the anatomical and behavioral differences between subjects. Over the years, many techniques have been proposed for characterizing the vocal tract configuration from speech signals; a good review of these techniques is provided in [1]. In general, however, the Mel frequency cepstral coefficients (MFCCs) and linear prediction cepstral coefficients (LPCCs) have been the two most popular features used in previous works [2–5]. These features can characterize the highly speaker-dependent vocal tract transfer function from the convoluted speech signal ($s(t)$) by assuming a linear model of speech production as

$$s(t) = x(t) * h(t), \tag{1}$$

where $x(t)$ is a periodic excitation (for voiced speech) or white noise (for unvoiced speech) and $h(t)$ is a time-varying filter which constantly changes to produce different sounds. Although $h(t)$ is time-varying, it can be considered stable over short-time intervals of approximately 10–30 milliseconds [1]. This convenient short-time stationary behavior is exploited by many speaker recognition systems in order to characterize the vocal tract transfer function given by $h(t)$, which is known to be a unique speaker-dependent characteristic for a given sound. While assuming a linear model, this information can be easily extracted from speech signals using well-established deconvolution techniques such as homomorphic filtering or linear prediction methods.

Recent works have demonstrated that the linear model assumed in MFCC and LPCC is not entirely correct because there is some nonlinear coupling between the vocal source and the vocal tract [6, 7]. Therefore, when assuming a linear speech production model, the vocal tract and vocal source information is not completely separable. For example, MFCCs are calculated from the power spectrum of the speech signal and hence they is affected by the harmonic structure and the fundamental frequency of speech [8]. Similarly, the linear prediction (LP) residual is known to be an approximation of the vocal source signal [9], which implies that the LPCCs are influenced by the vocal source to some extent. NIST evaluations have also shown that the performance of speaker recognition systems is affected by changes in pitch [10], which indicates that vocal source information can be useful for speaker recognition.

These concerns motivated the use of features that can complement the traditional vocal tract features for a better characterization of the vocal system. This has been attempted before and it has been shown that the vocal source, for example, contains some speaker-dependent information. Plumpe et al. [7] combined MFCCs with features obtained by estimating glottal flow and obtained a 5% improvement in classification performance. Chan et al. [11] have shown that vocal source features derived from the LP residual can be more discriminative than MFCC features for short speech segments. Zheng and Ching [9] have reported improved performance by combining vocal source features derived from the LP residual with LPCC features.

This work attempts to extract several features from the speech spectrum that can complement the traditional vocal tract features. These features are the spectral centroid (SC), spectral bandwidth (SBW), spectral band energy (SBE), spectral crest factor (SCF), spectral flatness measure (SFM), Shannon entropy (SE), and Renyi entropy (RE). We have shown that these novel features can be used for speaker recognition in undistorted conditions [12]. This work examines the performance characteristics of these spectral features under noisy conditions. By combining several common distortions such as babble noise, additive white Gaussian noise (AWGN), and a nonlinear bandpass channel to simulate the telephone pathway, these features can be tested under more realistic conditions. In fact, these distortions can simulate the speakers' environment as well as a practical telephone channel. The proposed testing method will combine these spectral features with the traditional MFCC-based features in order to develop more robust speaker models for noisy conditions. To evaluate the performance of the feature set, a text-independent cohort Gaussian mixture model (GMM) classifier will be used since it has been extensively used in previous speaker recognition works, and therefore its characteristics and performance capabilities are well known.

The paper is organized as follows. Section 2 describes in detail the proposed features and Section 3 describes the classification scheme used. Section 4 presents the experimental conditions, results, and discussions, and lastly Section 5 concludes the paper.

2. SPECTRAL FEATURES

The information embedded in the speech spectrum contains speaker-dependent information such as pitch frequency, harmonic structure, spectral energy distribution, and aspiration [7, 13, 14]. Therefore, this section proposes several spectral features that can quantify some of these characteristics from the convoluted speech signal. These features are expected to provide additional speaker-dependent information which can complement the vocal tract information for better speaker models.

Similar to MFCCs, spectral features should be calculated from short-time frames so that they can add information to the vocal tract features. Frame synchronization is expected to be important for achieving enhanced performance with the spectral features. In addition, for a given frame, the spectral features should be extracted from multiple subbands in order to better discriminate between speakers. Capturing the spectral trend, via subbands, for a given frame will provide more information than obtaining one global value from the speech spectrum. The latter option is not likely to show significant speaker-dependent characteristics.

Spectral features are extracted from framed speech segments as follows. Let $s_i[n]$, for $n \in [0, N]$, represent the ith speech frame and let $S_i[f]$ represent the spectrum of this frame. Then, $S_i[f]$ can be divided into M nonoverlapping subbands, where each subband (b) is defined by a lower frequency edge (l_b) and an upper frequency edge (u_b). Now, each of the seven proposed spectral features can be calculated from $S_i[f]$ as shown below.

(1) *Spectral centroid* (SC) as given below is the weighted average frequency for a given subband, where the weights are the normalized energy of each frequency component in that subband. Since this measure captures the center of gravity of each subband, it can detect the approximate location of formants which are large peaks in a subband [15]. However, the center of gravity of a subband is effected by the harmonic structure and pitch frequencies produced by the vocal source. Hence, the SC feature is effected by changes in pitch and harmonic structure:

$$\mathrm{SC}_{i,b} = \frac{\sum_{f=l_b}^{u_b} f \left| S_i[f] \right|^2}{\sum_{f=l_b}^{u_b} \left| S_i[f] \right|^2}. \tag{2}$$

(2) *Spectral bandwidth* (SBW) as given below is the weighted average distance from each frequency component in a subband to the spectral centroid of that subband. Here, the weights are the normalized energy of each frequency component in that subband. This measure quantifies the relative spread of each subband for a given sound. This measure is a good indication of

the range of frequencies that are produced by the vocal system in a subband for a given sound:

$$\mathrm{SBW}_{i,b} = \frac{\sum_{f=l_b}^{u_b} \left(f - \mathrm{SC}_{i,b}\right)^2 \left|S_i[f]\right|^2}{\sum_{f=l_b}^{u_b} \left|S_i[f]\right|^2}. \tag{3}$$

(3) *Spectral band energy* (SBE) as given below is the energy of each subband normalized with the combined energy of the spectrum. The SBE gives the trend of energy distribution for a given sound, and therefore it describes the dominant subband (or the frequency range) that is emphasized by the speaker for a given sound. Since the SBE is energy normalized, it is insensitive to the intensity or loudness of the vocal source:

$$\mathrm{SBE}_{i,b} = \frac{\sum_{f=l_b}^{u_b} \left|S_i[f]\right|^2}{\sum_{f} \left|S_i[f]\right|^2}. \tag{4}$$

(4) *Spectral flatness measure* (SFM) as given below is a measure of the flatness of the spectrum, where white noise has a perfectly flat spectrum. This measure is useful for discriminating between voiced and unvoiced components of speech [16]. This is also intuitive since structured speech (voiced components) will have a narrower bandwidth than nonstructured speech (unvoiced components) which can be modeled with AWGN, and therefore it will have a larger bandwidth:

$$\mathrm{SFM}_{i,b} = \frac{\left[\prod_{f=l_b}^{u_b} \left|S_i[f]\right|^2\right]^{1/(u_b-l_b+1)}}{\left(1/\left(u_b - l_b + 1\right)\right) \sum_{f=l_b}^{u_b} \left|S_i[f]\right|^2}. \tag{5}$$

(5) *Spectral crest factor* (SCF) as given below provides a measure for quantifying the tonality of the signal. This measure is useful for discriminating between wideband and narrowband signals by indicating the normalized strength of the dominant peak in each subband. These peaks correspond to the dominant pitch frequency harmonic in each subband:

$$\mathrm{SCF}_{i,b} = \frac{\max\left(\left|S_i[f]\right|^2\right)}{\left(1/\left(u_b - l_b + 1\right)\right) \sum_{f=l_b}^{u_b} \left|S_i[f]\right|^2}. \tag{6}$$

(6) *Renyi entropy* (RE) as given below is an information theoretic measure that quantifies the randomness of the subband. Here, the normalized energy of the subband can be treated as a probability distribution for calculating entropy and α is set to 3, as commonly found in literature [17, 18]. This RE trend is useful for detecting the voiced and unvoiced components of speech since it can detect the degree of randomness in the signal (i.e., structured speech corresponds to voiced speech and has a lower entropy compared to nonstructured speech which corresponds to unvoiced speech with a higher entropy value):

$$\mathrm{RE}_{i,b} = \frac{1}{1-\alpha} \log_2\left(\sum_{f=l_b}^{u_b} \left|\frac{S_i[f]}{\sum_{f=l_b}^{u_b} S_i[f]}\right|^{\alpha}\right). \tag{7}$$

(7) *Shannon entropy* (SE) as given below is also an information theoretic measure that quantifies the randomness of the subband. Here, the normalized energy of the subband can be treated as a probability distribution for calculating entropy. Similar to the RE trend, the SE trend is also useful for detecting the voiced and unvoiced components of speech:

$$\mathrm{SE}_{i,b} = -\sum_{f=l_b}^{u_b} \left|\frac{S_i[f]}{\sum_{f=l_b}^{u_b} S_i[f]}\right| \cdot \log_2 \left|\frac{S_i[f]}{\sum_{f=l_b}^{u_b} S_i[f]}\right|. \tag{8}$$

Although these features are novel for speaker recognition, they have been used in other fields such as multimedia fingerprinting [19]. For speaker recognition, these features may enhance recognition performance when used to complement the vocal tract transfer function since the vocal tract transfer function significantly alters the spectral shape of the speech signal, and hence it is the dominant feature.

Among the spectral features, there may be some correlation between the SC and the SCF features because they both quantify information about the peaks (locations of energy concentration) of each subband. The difference is that the SCF feature describes the normalized strength of the largest peak in each subband, while the SC feature describes the center of gravity of each subband. Therefore, these features will perform well if the largest peak in a given subband is much larger than all other peaks in that subband. The RE and SE features are also correlated since they are both entropy measures. However, the RE feature is much more sensitive to small changes in the spectrum because of the exponent term α. Therefore, although these features quantify the same type of information, their performance may be different for speech signals.

2.1. Subband allocation

Features derived from the speech spectrum (i.e., Fourier domain) are more discriminative than those derived from several distinct subbands. Due to the effects of averaging and normalization, the proposed spectral features are not likely to perform well if they are calculated from the entire spectrum. Furthermore, by adopting nonoverlapping subbands, the spectral trend can be obtained for each of the proposed features.

In order to calculate the subband boundaries, several factors were considered: incorporation of the human auditory perception model (Mel scale), the frequency resolution of the spectrum, and the bandwidth of typical telephone channel. In order to let the experiments simulate practical conditions, all of the features are extracted from a typical telephone channel bandwidth (300 Hz–3.4 kHz). With this consideration in mind, the 5 subbands were defined according to the Mel scale, which is consistent with the nonlinearities of human auditory perception. The boundaries for the 5 subbands are shown in Table 1.

The number of subbands was governed by the frequency resolution of the spectrum. With a 30-millisecond speech

Table 1: The subband allocation used to obtain spectral features.

Subband	Lower edge (Hz)	Upper edge (Hz)
1	300	627
2	628	1060
3	1061	1633
4	1634	2393
5	2394	3400

frame, sampled at 8 kHz, a maximum frequency resolution of approximately 33.3 Hz can be obtained. Therefore, the first subband (i.e., the narrowest subband), which contributes to the intelligibility and contains a significant percentage of the speech signals' energy, should contain sufficient frequency samples for calculating the proposed features. Therefore, the first subband was set to have 10 frequency samples starting at 300 Hz. This condition determines the bandwidth of the first subband. The remainder of the boundaries were linearly allocated on the Mel scale with equal bandwidth as the first subband, as shown in Table 1. Using the proposed subband allocation, each spectral feature will generate a 5-dimensional feature vector from each speech frame.

3. PROPOSED METHOD

To compare the effectiveness of the proposed spectral features with the that of commonly used MFCC-based features, a cohort GMM identification scheme will be used. The proposed method is a speaker identification system since it uses the log-likelihood function to find the best speaker model for a given utterance.

GMMs are the most popular statistical tool for speaker recognition because of their ability to accurately capture speech phenomena [2, 13, 21]. In fact, some GMM clusters have been found to be highly correlated with particular phonemes [22]. And the overall GMM can capture a broad range of phonetic events or acoustic classes within a speaker's utterances [2] when used with MFCC features. These are very useful characteristics that can lead to very good speaker recognition models if a comprehensive training set is used. A good training set would include multiple instances of a wide range of phonemes and phoneme combinations.

Since GMMs characterize acoustic classes of speech and not specific words or phrases, they can be effectively used for text-independent identification. Text-independent systems are much more secure than text-dependent systems because text-independent systems can prompt the user to say any phrase during identification. Conversely, a major drawback of text-dependent speaker recognition systems is that they use predetermined phrases for authentication; so it is possible to use a recorded utterance of a valid user to "fool" the system. This issue is particularly important for telephone-based applications since there is no physical contact with the person requesting access, and therefore text-independent systems are required.

3.1. *Training and GMM estimation*

The expectation maximization (EM) algorithm [23] was used to estimate the parameters of the GMM. Although the EM algorithm is an unsupervised clustering algorithm, it cannot estimate the model order and it also requires an initial estimate for each cluster. In previous speaker recognition works, models of orders 8–32 have been commonly used for cohort GMM systems. In many cases, good results have been obtained with as few as 16 clusters [2, 8, 24]. In these experiments, however, a higher model order can be used because of the larger feature set. Preliminary experimental results indicated that a model order of 24 was the optimal order for the proposed feature set given models of orders 16, 20, 24, 28, and 32. It has also been shown that the initial grouping of data does not significantly affect the performance of GMM-based recognition systems [2]. Hence, the k-means algorithm was used for the initial parameter estimates.

A diagonal covariance matrix was used to estimate the variances of each cluster in the models since they are much more computationally efficient than full covariance matrices. In fact, diagonal covariance matrices can provide the same level of performance as full covariance matrices because they can capture the correlation between the features if a larger model order is used [2, 21]. For these reasons, diagonal covariance matrices have almost been exclusively used in previous speaker recognition works. Each element of these matrices is limited to a minimum value of 0.01 during the EM estimation process to prevent singularities in the matrix, as recommended by [2].

3.2. *Feature set*

The spectral features along with the MFCC and ΔMFCC features will be extracted from each speech frame and appended together to form a combined feature vector for each speech frame. Equation (9) shows the feature matrix that can be extracted based on only one spectral feature, say, the SC feature, from i frames, where the bracketed number is the length of the feature. It should be noted that any other spectral feature can be substituted for the SC feature in the feature matrix. Furthermore, all features will be extracted from the bandwidth of a typical telephone channel, which is 300 HZ–3.4 kHz [2]:

$$\vec{\mathcal{F}} = \begin{bmatrix} \mathrm{MFCC}_1(14) & \Delta\mathrm{MFCC}_1(14) & \mathrm{SC}_1(5) \\ \vdots & \vdots & \vdots \\ \mathrm{MFCC}_i(14) & \Delta\mathrm{MFCC}_i(14) & \mathrm{SC}_i(5) \end{bmatrix}. \tag{9}$$

MFCC coefficients are calculated from the speech signal after it has been transmitted through a channel. It has been shown that linear time-invariant channels, such as telephone channels, result in additive distortion on the output cepstral coefficients. To reduce this additive distortion, cepstral mean normalization (CMN) was used [1, 24]. CMN also minimizes intraspeaker biases introduced over different sessions from the intensity (i.e., loudness) of speech [2].

Cepstral difference coefficients such as ΔMFCC are less affected by time-invariant channel distortions because they rely on the difference between samples and not on the absolute value of the samples [2]. Furthermore, the ΔMFCC feature has been shown to improve the performance of the MFCC feature in speaker recognition. As a result, the MFCC and ΔMFCC features have been extensively used in previous works with good results. Here, these two features will be used to train the baseline system which is then used to judge the effectiveness of the proposed spectral features.

4. EXPERIMENTAL RESULTS

This section will present the experimental conditions as well as the results. Section 4.1 explains the details of the experimental procedures and the data collection procedures, while Section 4.2 provides a detailed discussion about the results.

4.1. Experimental conditions

All speech samples used in these experiments were obtained from the well-known TIMIT speech corpus [25]. 623 speakers (438 males and 192 females) from the corpus were used, which include speakers from 8 different dialect regions in the United States. Each user provided 10 recordings with a wide range of phonetic sounds suitable for training the classifier. However, the recordings are made in an acoustically quiet environment using a high-quality microphone, and therefore some distortions were added to simulate a practical telephone channel. These distortions included bandpass filtering (300 Hz–3.4 kHz) to simulate the characteristics of a telephone channel, babble noise to simulate background speakers that might be found in some environments, and AWGN to simulate normal background noise found in many environments. The simulation model is shown in Figure 1.

Each GMM was trained with 20 seconds of silence-removed clean speech. The remaining speech was segmented into 7 s utterances and used to test the speaker models under noisy and noise-free conditions. A total of 298 test samples was available since some of the speakers only had enough data for training. The sampling frequency of the recordings was reduced from 16 kHz to 8 kHz which is the standard for telephone applications. Features were then extracted from 30-millisecond long frames with 15 milliseconds of overlap with the previous frames, and a Hamming window was applied to each frame to ensure a smooth frequency transition between frames. From each frame, the feature matrix ($\vec{\mathcal{F}}$) extracted was a concatenation of a 14-dimensional MFCC vector, 14-dimensional ΔMFCC, and 5-dimensional spectral feature vector as shown in (9). In cases where multiple spectral features are used, all features are appended together to form the feature matrix as shown in the example below:

$$\vec{\mathcal{F}} = \begin{bmatrix} \mathrm{MFCC}_1(14) & \Delta\mathrm{MFCC}_1(14) & \mathrm{SC}_1(5) & \mathrm{SCF}_1(5) & \mathrm{SBE}_1(5) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \mathrm{MFCC}_i(14) & \Delta\mathrm{MFCC}_i(14) & \mathrm{SC}_i(5) & \mathrm{SCF}_i(5) & \mathrm{SBE}_i(5) \end{bmatrix}, \tag{10}$$

where i represents the frame number and the bracketed number represents the length of the feature. The MFCC features were processed with the CMN technique to remove the effects of additive distortion caused by the bandpass channel (i.e., the telephone channel).

Table 2: Experimental results using 7 s test utterances (298 tests).

Feature	Accuracy (%)
MFCC & ΔMFCC (baseline system)	95.30
MFCC & ΔMFCC & SC	97.32
MFCC & ΔMFCC & SBE	97.32
MFCC & ΔMFCC & SBW	96.98
MFCC & ΔMFCC & SCF	96.31
MFCC & ΔMFCC & SFM	81.55
MFCC & ΔMFCC & SE	90.27
MFCC & ΔMFCC & RE	98.32
MFCC & ΔMFCC & SBE & SC	96.98
MFCC & ΔMFCC & SBE & RE	96.98
MFCC & ΔMFCC & SC & RE	99.33

4.2. Results and discussions

MFCC-based features are well suited for characterizing the vocal tract transfer function. Although this is the main reason for their success, MFCCs do not provide a complete description of the speaker's speech production system. By complementing the MFCC features with additional information, the proposed spectral features are expected to increase identification accuracy of MFCC-based systems. Furthermore, these experiments aim to demonstrate the effectiveness of the proposed features under noisy and noise-free conditions.

(1) Results with undistorted speech

Table 2 demonstrates the identification accuracy of the system when using spectral features in addition to MFCC-based features with undistorted speech sampled at 8 kHz. The reported accuracy represents the percentage of tests that were correctly identified by the system, as shown below:

$$\text{Accuracy (\%)} = \frac{\text{Utterances Correctly Identified}}{\text{Total Number of Utterances}} \times 100. \tag{11}$$

It is evident from these results that there is some speaker-dependent information captured by the SC, SBE, SBW, SCF, SBE, and RE features as they improved identification rates when combined with the standard MFCC-based features. In fact, when two of the best performing spectral features (SC and RE) were simultaneously combined with the MFCC-based features, an identification error of 99.33% was achieved, which represents a 4.03% improvement over the baseline system. These results suggest that the spectral features provide enough speaker-dependent information about the speaker's vocal system to enhance the performance of the baseline system which is based on the MFCC and ΔMFCC features.

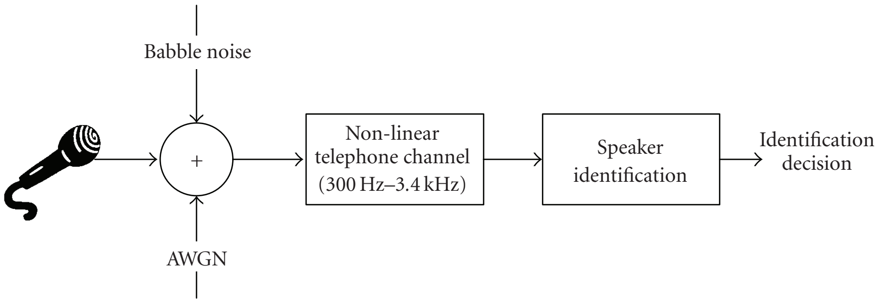
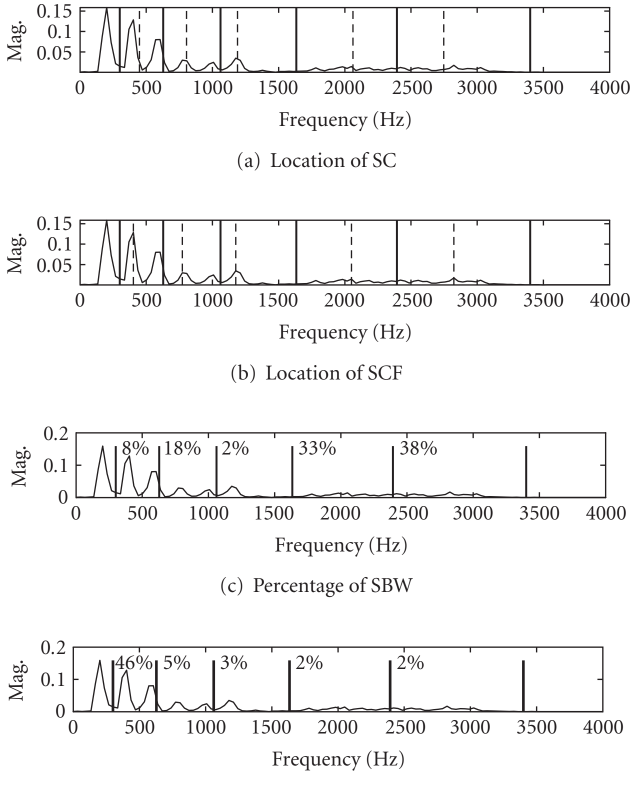


Figure 1: Simulation model.

The best performing features set was the combination of the MFCC-based features and the RE feature. The RE feature is very effective at quantifying voiced speech which is quasi-periodic (relatively low entropy) and unvoiced speech which is often represented by AWGN (relatively high entropy). However, we suspect that the RE feature may also be characterizing another phenomenon other than voiced and unvoiced speeches. This is likely since the SE feature did not show any performance benefits, and it is too an entropy measure capable of discriminating between voiced and unvoiced speeches. One possibility is that the exponential term α in the RE definition is contributing to this performance improvement. Since the spectrum is normalized in the range of $[0, 1]$ before calculating these features, the exponent term α has the effect of significantly reducing the contributions of the low-energy components relative to the high-energy components. Therefore, the RE feature is likely to produce a more reliable measure since it heavily relies on the high-energy components of each subband. However, we show later that this improvement is not sustainable under noisy conditions.

Figure 2(a) shows that the SC feature can capture the center of gravity of each subband. Since the subband's center of gravity is related to the spectral shape of the speech signal, it implies that the SC feature can also detect changes in pitch and harmonic structure since they fundamentally affect the spectrum. Pitch and harmonic structure are well known to be speaker-dependent and complementary to the vocal tract transfer function for speaker recognition. In addition, the SC feature can also locate the approximate location of the dominant formant in each of the subbands since formants will tend towards the subband's center of gravity in some cases. These properties of the SC feature provide complementary information and lead to the improved performance of the MFCC-based classifier.

The SCF feature shown in Figure 2(b) quantifies the normalized strength of the dominant peak in each subband. The fact that the dominant peak in each subband corresponds to a particular pitch frequency harmonic shows that the SCF feature is pitch-dependent, and therefore it is also speaker-dependent for a given sound. This dependence on pitch frequency is useful when the vocal tract configuration (i.e., MFCC) is known as seen by the enhanced performance. Moreover, the SCF feature is a normalized measure and should not be significantly affected by the intensity of speech from different sessions.



(a) Location of SC

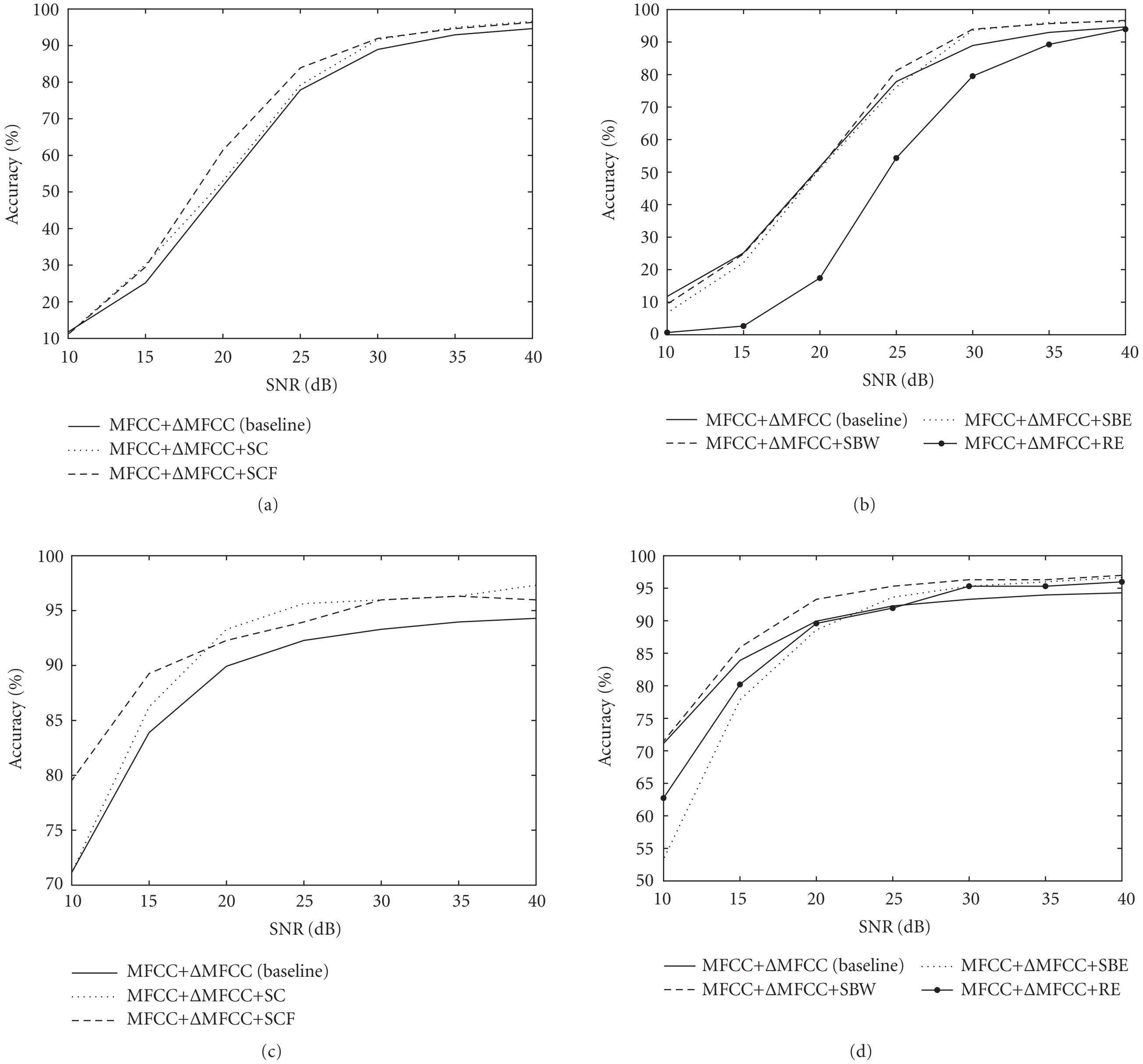
(b) Location of SCF

(c) Percentage of SBW

(d) Percentage of SBE

Figure 2: Plot of the spectral features. Subband boundaries are indicated with dark solid lines and feature location is indicated with dashed lines. (a) Location of the SC, (b) location of the SCF, (c) SBW as a percentage of the five subbands, (d) SBE as a percentage of the whole spectrum.

The SBE feature, shown in Figure 2(d), also performed well in the experiments. This feature provides the distribution of energy in each subband as a percentage of the entire spectrum. The SBE is therefore related to the harmonic structure of the signal as well as the formant locations. Therefore, the SBE trend can detect changes in the harmonic structure for a given vocal tract configuration. This is useful because the SBE trend, when used in conjunction with the vocal tract information (i.e., the MFCCs), can provide complementary information. The SBE feature is also a normalized energy



(a)

(b)

(c)

(d)

Figure 3: Performance of spectral features with noise, (a)-(b) with AWGN, (c)-(d) with babble noise.

measure and should not be significantly affected by the intensity (or relative loudness) of speech from different sessions. The results in Table 2 suggest that for a given vocal tract configuration the SBE trend is predictable and complementary for speaker recognition.

The SBW feature is largely dependent on the SC feature and the energy distribution of each subband; therefore it has also performed well for the reasons mentioned above. Figure 2(c) shows the SBW for each subband as a percentage of all subbands.

The SFM feature did not perform well because it quantifies characteristics that are not well defined in speech signals. For example, the SFM feature measures the tonality of the subband—a characteristic that is difficult to define in the speech spectrum since its energy is distributed across many frequencies.

(2) Robustness to distortions

Figure 3 shows the performance of the spectral features with AWGN and babble noise. It can be seen that most of the proposed features are robust to these types of noise since they outperform the baseline system. In fact, many of the spectral features that showed good performance in undistorted conditions also outperformed the baseline system in noisy conditions with the exception of the RE feature. The RE feature does not perform well under noisy conditions because the the entropy of noise tends to be greater than the entropy of

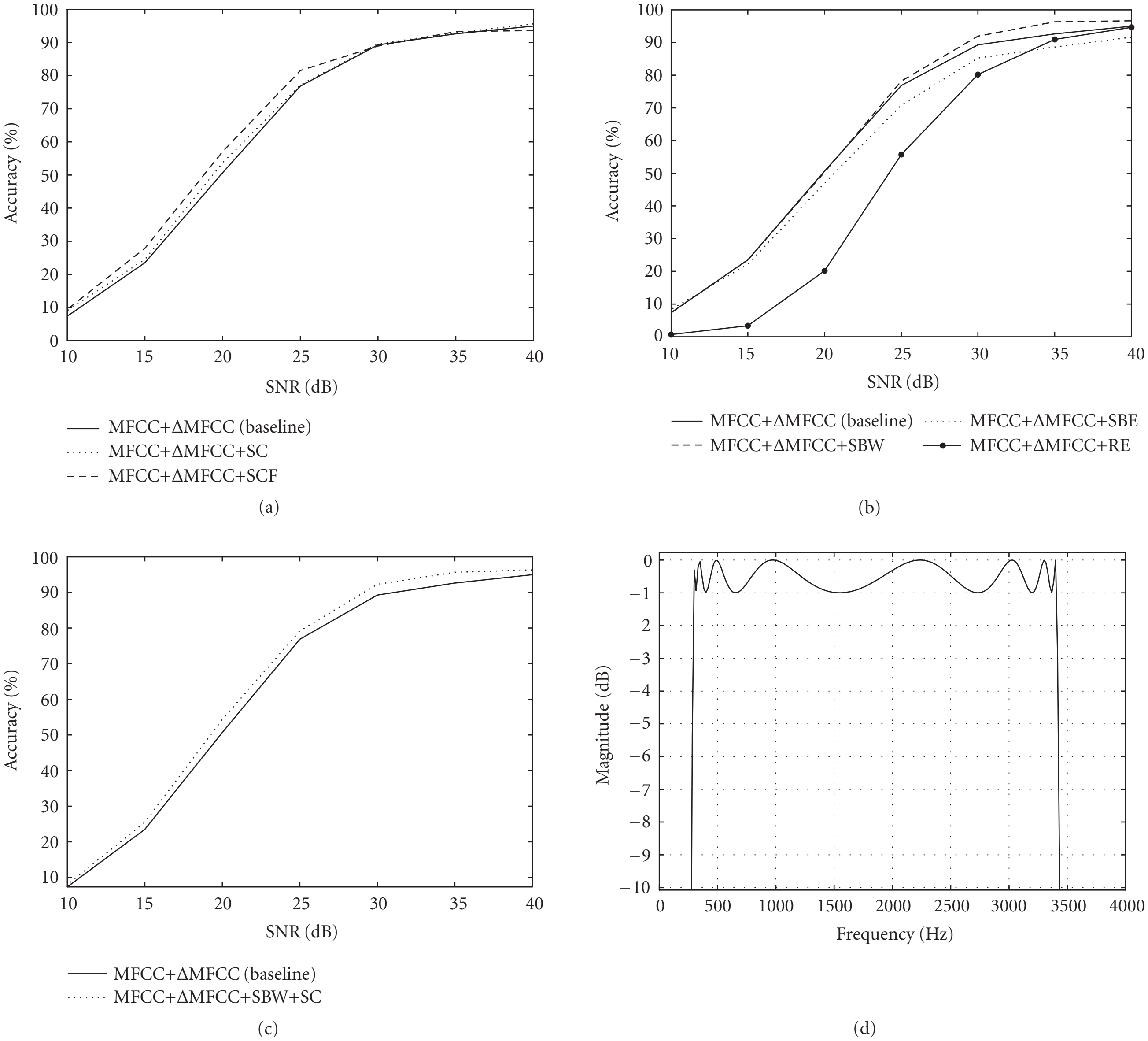


Figure 4: (a), (b), (c) Performance of spectral features in a bandpass channel with AWGN and babble noise (see Figure 1). (d) shows the frequency response of channel used with 1 dB ripple in the passband (300 Hz–3.4 kHz).

speech signals. Particularly in the case of AWGN, which has a relatively high entropy, the RE feature effectively characterizes the amount of noise rather than vocal source activity due to increased signal variability. Therefore, entropy measures become less discriminative and lead to poorer performance under these conditions. Under babble noise, the RE feature outperformed the baseline system only at high SNR values, which also indicates that the RE feature is sensitive to the effects of other speakers.

The best performing feature under both AWGN and babble noise was the SCF feature which significantly improved performance under all SNR conditions tested. Since the SCF feature relies on the peak of each subband, it is very robust to low SNR conditions. Under babble noise, the SCF shows an 8.4% improvement over the baseline system at an SNR of 10 dB. A significant improvement can also be seen at other SNR levels for both babble noise and AWGN.

The SC also improved performance under all of the SNR conditions tested, while the SBW feature provided improved performance under most conditions. The SC and SBW features rely on the center of gravity of each subband, and therefore they are not severely affected by wideband noise such as AWGN and babble noise. The SC feature showed maximum improvements of 5.1% (@15 dB) and 3.2% (@20 dB) for AWGN and babble noise, respectively. The SBW feature also performed significantly better than the baseline system under babble noise and generally better than the baseline system under AWGN as shown in Figure 3.

As expected, the SBE feature tends to perform better than the baseline system only at higher SNR cases. The SBE feature does not perform well at low SNR conditions because the energy trend of the spectrum is significantly disturbed at low SNR conditions.

(3) Robustness to channel effects

Figure 4 shows the system performance when bandpass distortion has been used to simulate the telephone channel, and babble noise and AWGN have also been added in equal amounts to the test utterances. Figure 4(d) shows the frequency response of the channel used, which has a bandpass range of 300 Hz–3.4 kHz with 1 dB of ripple in the passband. These conditions result in significant amounts of nonlinear distortion in the test utterances which are not found in the training data. Therefore, these results are the most convincing because three of the most common distortions have been simultaneously added in order to simulate a typical telephone channel and the speaker's environment. As can be seen from Figure 4, the same feature sets (SCF, SBW, SC) still outperform the baseline system. The SCF feature is still the best performing feature, providing improved results of up to 4.6%. It should be noted that the MFCC features were adjusted for the channel effects using the CMN technique, while the spectral features were used in their distorted form.

5. CONCLUSION

Speaker identification has been traditionally performed by extracting MFCC or LPCC features from speech. These features characterize the anatomical configuration of the vocal tract, and therefore they are highly speaker-dependent. However, these features do not provide a complete description of the vocal system. Capturing additional speaker-dependent information such as pitch, harmonic structure, and energy distribution can complement the traditional features and lead to better speaker models.

To capture additional speaker-dependent information, several novel spectral features were used. These features include SC, SCF, SBW, SBE, SFM, RE, and SE. A text-independent cohort GMM-based speaker identification method was used to compare the performance of the proposed spectral features with the baseline system in noisy and noise-free conditions.

To show the robustness of the proposed spectral features in practical conditions, three different distortions were used. More specifically, AWGN, babble noise, and bandpass filtering (300 Hz–3.4 kHz with a 1 dB bandpass ripple) were individually and simultaneously applied to the speech signals to simulate the identification rate of the proposed features for a practical telephone channel. Experimental results show that the spectral features improve the performance of MFCC-based features. In particular, the SCF feature combined with the MFCC and the ΔMFCC features significantly outperformed all other feature combinations in almost all conditions and SNR levels. Other spectral features such as SC and SBW also performed better than the baseline system in many of the simulated conditions.

These features improved the overall identification performance because they complement the MFCC-based features with additional vocal system characteristics not found in MFCC or LPCC features. As a result, these features led to better speaker models. The spectral features are also energy normalized measures, and hence they are robust to intraspeaker biases stemming from the effort or intensity of speech in different sessions.

The good performance of spectral features for speaker recognition in this simple speaker identification system is very promising. These features should also produce good results if used with more sophisticated speaker recognition techniques such as universal background model- (UBM-) based approaches. Furthermore, in this work, the identification tests were limited to 7 s utterances due to the size of the database. Preliminary results show that the identification performance may be improved significantly for lengthier utterances.

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