Robust Text-independent Speaker Identification in a Time-varying Noisy Environment

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Abstract—**Practical speaker recognition systems are often subject to noise or distortions within the input speech which degrades performance. In this paper, we proposed a new mel-frequency cepstral coefficients (MFCC) based speaker identification system with Vector Quantization (VQ) modeling technique. It integrates a hearing masking effect based masker and a group of dozen triflers into traditional MFCC feature extraction for robust speaker identification. The masker can decrease the influence of noise signal to the speech signal, and improve the recognition rate. The mixture of triflers can enhance high-frequency calculation accuracy. A purposeful voice samples database are collected under an unconstrained indoor environment for a month. The texts to be spoken are also unconstrained. The proposed method is evaluated with the voice samples database, and its recognition rates remain over 93% under different experiment condition. The experiments results show that the proposed speaker identification system has good accuracy and robustness to the unconstrained noisy condition and text-independent.**

Index Terms—**Speaker Identification, Improved MFCC, Vector Quantization (VQ), Voice Variation**

I. INTRODUCTION

Biometric recognition systems are increasingly being researched as a more "natural" means for the recognition of people. Biometric recognition is an identification technology using biological features including fingerprint, voice and face are specific to an individual. The simplest to acquire, most used and pervasive in society, and least obtrusive biometric measure is that of human speech. Consequently speech recognition becomes one of the key research areas in signal processing and pattern recognition [1, 2]. In security applications where a person has to be recognized there are two distinct modes of operation: identification and verification. In speaker identification human speech from an individual is used to identify who that individual is. In speaker verification human speech from an individual is used to verify the claimed identity of that individual. Speaker recognition can be text-dependent or text-independent. The former requires the speaker to issue an utterance on some predefined text, whereas the latter does not rely on a specific text being spoken.

Although the speaker identification technology has been developed very well, it is not the universal solution. The main strength of speaker verification technology is that it relies on a signal that is natural and unobtrusive to produce and can be obtained easily from almost anywhere using the familiar telephone network (or internet) with no special user equipment or training. This technology has prime utility for applications with remote users and applications already employing a speech interface. Additionally, speaker identification is easy to use, has low computation requirements (can be ported to cards and handhelds) and, given appropriate constraints, has high accuracy.

Some of the flexibility of speech actually lends to its weaknesses. First, speech is a behavioral signal that may not be consistently reproduced by a speaker and can be affected by a speaker's health (cold or laryngitis). Second, the varied microphones and channels that people use can cause difficulties since most speaker identification systems rely on low-level spectrum features susceptible to transducer/channel effects. Also, environmental effects such as background noise can stress speaker identification accuracy. Practical speaker recognition systems are often subject to noise or distortions within the input speech which degrades performance [3, 4].

Nowadays, researchers are trying their best to improve the speaker identification technology. In addition to the low-level spectrum features used by current systems, there are many other sources of speaker information in the speech signal that can be used. So exploitation of higher-levels of information become a focus in the area of speaker identification.

The main aim of the research paper is to design a speaker identification system, which should be reliable not only in normal conditions but also in time-varying noisy environment. In this paper, an improved MFCC [5] feature extraction front-end integrated with lateral inhibition masking, temporal integration and forward masking have been applied to speaker identification system. This paper collects the voice of 15 experimental individuals for 31 times lasting one month. The experimental result shows that the improved algorithm is able to effectively overcome the impact produced by the

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environment noise and the variation of speaker's voice with a higher recognition rate of voice signal to some extent.

II. Principle of System Design

Speaker identification is the problem of pattern classification which recognizes a correct result after classifying the features of different speakers' speech. Fig. 1 shows the flow chart of a complete speaker

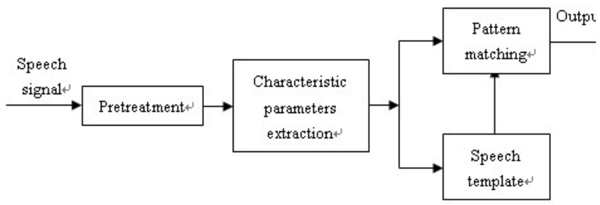

Fig. 1. Speaker identification system flowchart

identification system, it consists of the following steps:

(1) Pretreatment/Feature extraction: This step generally consists of three sub-processes. First, some form of speech activity detection is performed to remove non-speech portions from the signal. Next, features conveying speaker information are extracted from the speech. From the source-filter theory of speech production, it is known that the speech spectrum shape encodes information about the speaker's vocal tract shape via resonances. So some form of spectral based features is used in most speaker identification systems. Short-term analysis, typically with 20 ms frames generated every 10 ms, is used to compute a sequence of magnitude spectra using either LPC or FFT analysis. Most commonly the magnitude spectra are then converted to cepstral features after passing through a mel-frequency filterbank and time-differential (delta) cepstra are appended. The final process in pretreatment/feature extraction is some form of channel compensation. It is well known that different input devices will impose different spectral characteristics on the speech signal, such as bandlimiting and shaping. Channel compensation aims at removing these channel effects. Most commonly some form of linear channel compensation, such as long- and short-term cepstral mean subtraction, are applied to features.

(2) Speech template: The speech from each known, verified speaker, for all speakers that need to identified, is acquired to build (train) the speech template for that speaker. Usually this is carried out off-line as part of the system configuration and before the system is deployed. Speech from a speaker is passed through the pretreatment/feature extraction steps described above and the feature vectors are used to create a speaker speech template. Desirable attributes of a speaker speech template are: (a) a theoretical underpinning so one can understand model behavior and mathematically approach extensions and improvements; (b) generalizable to new data so that model does not over fit the enrollment data and can match new data; (c) parsimonious representation in both size and computation.

(3) Speaker classification: Speaker classification operation of the system is carried out where the speech from an unknown utterance is compared against each of the trained speech template in order to achieve speaker identification.It acts as a normalization to help minimize non-speaker related variability (e.g., text, microphone, noise) in the likelihood ratio score. There are two dominant approaches used for representing speaker classification in the likelihood ratio test. The first approach, known as likelihood sets, cohorts or background sets, use a collection of other speaker models to compute the imposter match score. The imposter match score is usually computed as a function, such as the max or average, of the match scores from a set of non-claimant speaker models. The non-claimant speaker models can come from other enrolled speakers or as fixed models from a different corpus. The second approach, known as general, world or universal background modeling, uses a single speaker-independent model trained on speech from a large number of speakers to represent speaker-independent speech.

There are many techniques, such as, dynamic time-warping (DTW), hidden Markov models (HMMs), neural networks (NNs), and vector quantization (VQ), have some or all of these attributes and have been used in speaker verification/identification systems.

In the training mode of the DTW approach [6,7], the speaker templates, which are the sequences of feature vectors obtained from the text-dependent speech waveforms, are created. In the testing mode, matching scores are produced by using DTW to align and measure the similarities between the test waveform and the speaker templates.

In the HMMs approach [8-10], the sequences of feature vectors, which are extracted from the speech waveforms, are assumed to be a Markov process and can be modeled with an HMM. During the training mode, HMMs' parameters are estimated from the speech waveforms. In the testing mode, the likelihood of the test feature sequence is computed based on the speaker's HMMs.

In the neural networks-based method [11-12], each speaker has a personalized neural network that is trained to be activated only by that speaker's utterances. The testing waveforms are tested by the speakers' personalized neural networks to make Speaker Identification decisions.

In the VQ Speaker Identification approach [13-14], in the training mode, a codebook for each speaker is obtained as a reference template for the speaker. In the testing mode, Speaker Identification is usually performed by finding the codebook and its corresponding speaker that gives the smallest average VQ distortion to represent the unknown speaker's waveform. The average VQ distortion here shows the similarity between the unknown speaker's speech and the reference template. The smaller average VQ distortion, the better match between testing speech and reference template is. The lack of time warping in the VQ approach greatly simplifies the system. However, some speaker-dependent temporal information, which is present in the waveforms, is neglected in VQ Speaker Identification.

III. FEATURE EXTRACTION

The most fundamental process common to all forms of speaker and speech recognition systems is that of extracting vectors of features uniformly spaced across time from the time-domain sampled acoustic waveform. Mel-frequency Cepstral Coefficients (MFCC) [15-16], based on short-time spectral analysis, are commonly used feature vectors for speaker identification. Fig. 2 illustrates the computation of MFCC feature extraction flowchart:

PRE-ENHANCEMENT: A high-pass filter is applied to the waveform. This emphasizes the higher frequencies and compensates for the human speech production process which tends to attenuate high frequencies. Let the

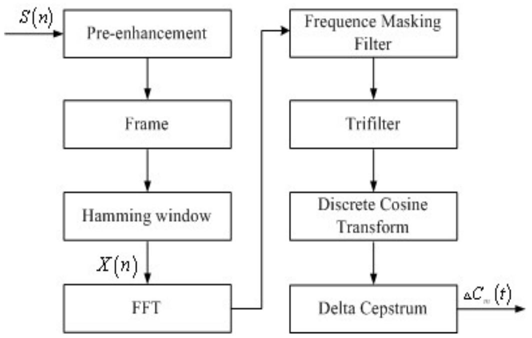

Fig. 2. MFCC flow chart

input speech signal $s(n)$ pass through 1^{st} order high-pass filter

$$H(z) = 1 - a \times z^{-1} \quad 0.1 \le a \le 0.9 \tag{1}$$

The filtered signal function is:

$$s_1(n) = s(n) - a \times s(n-1) \tag{2}$$

FRAMING: Combine N sample spots to a conservative unit called frame(we set N 256).To prevent the drastic change of neighboring two frames for a smooth short-time voice features and sequence spectral, we make some overlaps which includes M sample spots(here we set M=N/2)between the neighboring two frames.

WINDOWING: Each frame is multiplied by a window function such as hamming window. The window function is needed to smooth the effect of using a finite-sized segment for the subsequent feature extraction by tapering each frame at the beginning and end edges. Supposing the signal after frame process is $s(n), n = 0,1,...,N-1$, after multiplied with hamming window is $x(n) = s(n) \times w(n)$, the form of $w(n)$ as follow:

$$W(n,\alpha) = (1-\alpha) - \alpha\cos\left(2\pi n / (N-1)\right), 0 \le n \le N-1 \tag{3}$$

Different α will produce different hamming window. The hamming window offers the familiar bell-shaped weighting function but does not bring the signal to zero at the edges of the window. It minimizes the spectral distortion.

FOURIER TRANSFORM AND HEARING MASKING: A Fast Fourier Transform (FFT) operation is applied to each frame to yield complex spectral values. Here, the phase information is ignored and only the FFT magnitude spectrum is considered. Human can exactly identify the speech which has low signal noise ratio even with jamming voice. This mainly depends on the input function of both ears. To decrease the influence of noise signal to speech signal, a hearing masking effect based masker is applied in the frequency domain to speech signals [16].

TRIFLER: Multiply spectrum energy by a group of dozen triflers(1-7 order using low-frequency MFCC,8-13 order using MidMFCC,14-20 order using IMFCC[17]) in order to find out the logarithmic energy of each filter's output. The frequency of triangle's two down points in the each filter equals to the center frequency of the neighboring two filters which means the transition belt of every two neighboring filters overlap. The correspondence of Hz-Mel frequency as follows:

$$f_{MFCC} = 2595 \times \log_{10}(1 + f / 700)$$

$$f_{IMFCC} = 2146.1 - 1127 \times \ln\left(1 + \frac{4000 - f}{700}\right) \tag{4}$$

$$f_{MIDMFCC} = \begin{cases} 1073.05 - 527 \times \ln\left(1 + \dfrac{2000 - f}{300}\right), 0 < f \le 2000 \\ 1073.05 + 527 \times \ln\left(1 + \dfrac{f - 2000}{300}\right), 2000 < f \le 4000 \end{cases}$$

DISCRETE COSIN TRANSFORM: Put the above-mentioned 20 logarithmic energy into the discrete cosine transform formula in order to get the L-order Mel-Scale Cesptral parameter. Here, L is usually set 12, N adopts 20. Discrete cosine transforms formula as follow:

$$y(k) = \alpha(k)\sum_{n=0}^{N-1} x(n)\cos\left(\frac{\pi(2n+1)k}{2N}\right), k = 0,1,...,L-1 \tag{5}$$

Where $\alpha(k) = \begin{cases} \sqrt{\dfrac{1}{N}} & k = 0 \\ \sqrt{\dfrac{2}{N}} & k \ne 0 \end{cases}$.

DELTA CEPSTRUM: Although we've got 12 feature parameters, we usually alternatively add Delta cepstrum parameter in practical application of voice recognition to show the variations of Delta cepstrum parameter with respect to the time which means the differentiation of Delta cepstrum parameter with respect to the time. In other words, it represents the dynamic change of Delta cepstrum in time. Formula as follows:

$$\Delta C_m(t) = \left[\sum_{j=-M}^{M} C_m(t+\tau)\right] \Big/ \left[\sum_{j=-M}^{M} \tau^2\right] \tag{6}$$

So far, the MFCC feature extraction is finished. From the point of overall frame, actually we first process the voice signal by STFT (Short-time Fourier Transform), then process the energy spectrum by Bandpass filter using group filters, finally make Delta cepstrum calculation. In the practical application, we can show the feature vector in different dimension according to the test as required.

IV. Speech Pattern Recognition

For speaker identification system, after feature extraction we need to build speech template for the speaker recognize which one is the speaker through the feature classification. The so-called speech template is a recognition model for presenting the speaker's speech characteristics' distribution in feature space. Gaussian Mixture Model (GMM), Hidden Markov Model (HMM), Dynamic Time warping (DTW) and Vector Quantization (VQ) are prevalent techniques for patterns matching in speaker identification systems[18,19]. The VQ technique includes two steps: training and testing. In the training phase, required number of highly representative code vectors for each speaker is achieved by using VQ. Vector quantization is implemented through Binary-Splitting Linde-Buzo-Gray algorithm. The collection of these code vectors is called a codebook. A codebook (acoustic model) for each speaker is constructed in the same way. In the testing phase, an unknown voice after extracting voice feature vectors will be compared with the codebook of each speaker in the speaker database and distortion will be computed in order to identify who is the speaker.

A. Lbg Algorithm

LBG algorithm is a codebook training recursive algorithm with the principle of nearest algorithm and minimize average distortion algorithm, which generates the codebook whose performance has much to do with the original codebook [20]. The codebook is clustered from the MFCC feature vector of speaker's training series. LBG algorithm as follows:

(1) Give all reference vectors X required in tainting VQ codebook. Let S represent the class of X; Set quantitative series, distortion control threshold (here we adopts 0.01), maximum iteration times L and original codebook $\left\{Y_1^{(0)},\ Y_2^{(0)},...,Y_N^{(0)}\right\}$; Set overall distortion $D^{(0)}=\infty$; Initialize the iteration time m=1

(2) In terms of nearest principle we divide S into N subsets

$$\left\{S_1^{(m)},S_2^{(m)},...,S_n^{(m)}\right\}\quad d\left(X,Y_l^{(m-1)}\right)\le d\left(X,Y_i^{(m-1)}\right),\forall i,i=l\quad \left(x\in S_1^{(m)}\right) \tag{7}$$

(3) Calculate distortion:

$$D^{(m)}=\sum_{i=1}^{N}\sum_{X\in S_i^{(m)}} d(X,Y_l^{(m-1)}) \tag{8}$$

(4) Calculate new code:

$$Y_1^{(m)},Y_2^{(m)},...,Y_N^{(m)}.\qquad Y_i^{(m)}=\frac{1}{N_i}\sum_{X\in S_i^{(m)}} X \tag{9}$$

(5) Calculate relative distortion:

$$\delta^{(m)}=\frac{\left|D^{(m-1)}-D^{(m)}\right|}{D^{(m)}} \tag{10}$$

Compare $\delta^{(m)}$ with distortion threshold δ. If $\delta^{(m)}\le\delta$, it turns to step (4), else turns to step (3). Fig 3. Shows some sample of speech VQ feature vectors calculated by LBG algorithm.

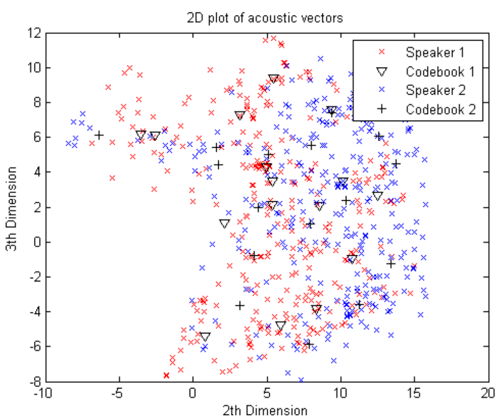

Fig. 3. Speech VQ vectors

B. Vq Voice Recognition

In this phase, an unknown voice after extracting voice feature vectors will be compared with the codebook of each speaker in the speaker database and distortion will be computed. Unknown voice will have minimum distortion with the true speaker. By the following method, system will provide the identity of the speaker.

Given $X=\{x_1,x_2,...,x_T\}$ is an uncertain speaker's feature vector of T frames, $\left\{B^1,B^2,...,B^N\right\}$ is the codebook in training phase (N is the number of speakers).Specific step of recognition as follows:

(1)Find out $\min_{m\in M} d\left(x_j,B_m^i\right)$, thereby, x_j is the feature

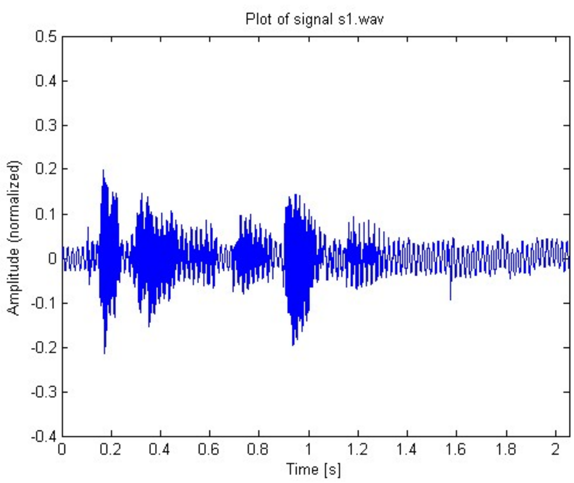

Fig. 4. Voice of "Zhejiang Sci-tech University " time domain waveform figure

vector in j th frame, B_m^i represents the m th code of the ith speaker, with the overall M codes, here d is the Euclidean distance measure.

(2)Calculate average quantitative distortion

$$D_i = \frac{1}{T}\sum_j \min_{1\le m\le n}\left[d\left(x_j, B_m^i\right)\right]. \qquad (11)$$

(3)The index i of minimum distortion in $\{D_1, D_2, ..., D_N\}$ corresponds to the speaker.

V. Experimental Results

The voice samples are recorded in a room (window and door open) contains about 12 people, one people recorded a random sentence for several seconds, and the others doing work on themselves. The voice signals are acquired by a PC sound card at sampling frequency 11025 Hz and resolution 16 bit. There are some uncertain noisy generated by the activities of the other people in the room and indoor and outdoor environment acoustic noisy. Fig. 4 shows the speech signal collected by the system when one speaker utters the name of Zhejiang Sci-Tech University in Chinese.

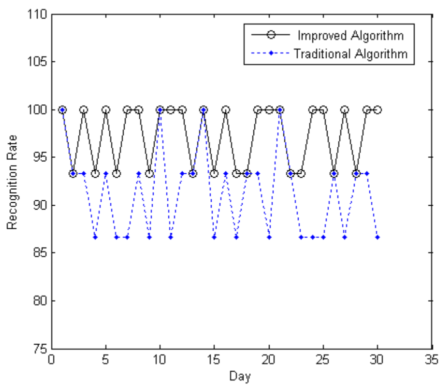

Fig. 5. Comparison of two speaker identification algorithm recognition rate variation over time.

TABLE 1.
INDIVIDUAL RECOGNITION ACCURACY RATES OF TRADITIONAL METHOD AND OUR PROPOSED METHOD.

Speaker ID	Recognition Accuracy Rate (%)		Speaker ID	Recognition Accuracy Rate (%)	
	Traditional	Proposed		Traditional	Proposed
1	96.7	100	2	86.7	100
3	96.7	96.7	4	83.3	93.3
5	93.3	100	6	90	100
7	100	96.7	8	90	100
9	83.3	96.7	10	93.3	100
11	96.7	96.7	12	90	93.3
13	93.3	93.3	14	90	96.7
15	90	96.7			

In a month, every speaker reordered one different sentence everyday. The environment during sound recording is detected with some noises (No 4 sample environment with stronger noise). Thus, we collect a voice database includes more than 450 voice samples of 15 (13 males and 2 females) different speakers. The digitized speech signals are blocked into consecutive overlapping frames, during of each frames is 23 ms and a new frame contains the last 11.5ms of the previous frame's data. In other words, a frame has 256 samples and every new frame has 128 samples of previous frame. The performance of the proposed speaker identification is evaluated by performing two experiments on this voice database. Following are the voice samples for the both experiments.

In the first experiments, the voice samples collected on first day are used as training data, and the other data are used to testing. The performance of the proposed method is compared with traditional speaker identification system using MFCC Features with VQ Technique. Here, we set $\alpha = 0.46$ to produce hamming window

TABLE 2.
RECOGNITION ACCURACY RATES USING SAMPLES COLLECTED ON DIFFERENT DAY AS TRAINING DATA

Training Data	Recognition Accuracy Rate (%)	Training Data	Recognition Accuracy Rate (%)
1st day	97.8	2nd day	97.3
3rd day	97.6	4th day	97.1
5th day	98.0	10th day	96.7
15th day	97.3	20th day	97.8
25th day	98.0	30th day	96.7

In the second experiments, we selected the voice samples collected on different one day as training data, and the other voice samples used as testing data. It is clearly that the noisy contained in the voice samples on different day and the physical states of the speakers are not same. In other word, there time-varying noisy in the collected voice sample. Results of Experiment 1 are shown in Fig. 5 and Table 1. The comparison results show that the accuracy and robustness of speaker identification are improved by introducing a hearing masking effect based masker and a group of dozen triflers during the MFCC features extraction process. Results of Experiment 2 as illustrated in Table 2, which show that the recognition accuracy rates are unrelated to the training data selects.

VI. Conclusion

In this paper, we proposed a new MFCC based speaker identification system with VQ modeling technique. Its performances are investigated under an unconstrained situation, includes variable noise condition and text-independent speech. Results show that the proposed speaker identification system has very good identification accuracy and therefore, it is robust against time varying noise.

In addition to the low-level spectrum features used by current systems, there are many other sources of speaker information in the speech signal that can be used. High-level features not only offer the potential to improve accuracy, they may also help improve robustness since they should be less susceptible to noise. In future, we will focus on exploitation higher-level of information to the identification accuracy and effort to overcome the more difficult issues in unconstrained situations.

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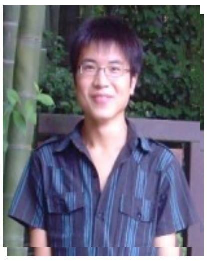

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