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Symbolic Representation of Speech for Text Independent Speaker Recognition

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Abstract: ***Speaker recognition is an important branch of authenticating a speaker's identity automatically based on human biological feature. We present a novel method of representing a speech by interval valued symbolic features. A method of speaker identification based on the proposed representation is also presented. It is an ideal choice for biometric which can change the future of speaker authentication mechanism as it is computationally effective and efficient. We also adopted LBZ-Vector Quantization technique for the purpose of speaker modelling using MFCC features. MFCC takes human perception sensitivity into consideration with respect to frequencies and therefore are best for speaker recognition. The technique of VQ consists of extracting a small number of representative feature vectors as an efficient means of characterizing the speaker specific features. The newly proposed model significantly reduces the dimension of feature vectors and also the time taken to classify a given speech utterances. In this work we provide a brief overview of the area of speaker recognition, describing applications and some underlying techniques. We will discuss some of the strengths and weaknesses of current speaker recognition technologies. We outline some potential future trends in research, development and applications.***

Keywords: Speaker verification, Identification, Symbolic representation, VQ, MFCC.

1. Introduction

Tasks that are easily performed by humans, such as face or speech recognition, prove difficult to be performed with computers. In recent years, biometric-based authentication systems have been widely used in many applications. Various human characteristics such as the face, speech, fingerprint, iris, etc. have been considered as discriminative features for recognition systems. Voice is the most natural and economical biometric modality for person identification. Speaker recognition is to recognize persons from their voice. No two individuals sound identical because their vocal tract shapes, larynx sizes, other parts of their voice production organs. They also differ in manner of speaking including the use of a particular accent, rhythm, intonation style, pronunciation and choice of vocabulary. By establishing the factors that convey speaker-dependent information, researchers have been able to improve the naturalness of speech. Today, task-specific speaker-recognition systems are being deployed in large telecommunications applications. The general task of automatic speaker recognition is far from solved; however, many challenging problems and limitations remain to be overcome.

Speaker recognition involves two stages: identification and verification. In identification, the goal is to determine which voice in a known group of voices best matches the speaker. In verification, the goal is to determine if the speaker is who he or she claims to be. In speaker identification, the unknown voice is assumed to be from the predefined set of known speakers. Speaker-recognition tasks are further distinguished by the constraints placed on the text of the speech used in the system. In a text-dependent system, the spoken text used to train and test the system is constrained to be the same word or phrase. In a text-independent system, training and testing speech is completely unconstrained. This type of system is the most flexible and is required for applications such as voice mail retrieval, which lacks control over what a person says. In this paper, we propose a novel method for representing a speech signal based on the interval valued symbolic features. In addition, we also present the corresponding text independent speaker recognition method.

The paper is organized as follows. A brief literature survey and the limitations of the existing models are presented in section 2. The working principle of the proposed method is presented in section 3. Details of the dataset used, experimental settings and the obtained results are presented in section 4. The paper is concluded in section 5.

2. Related Work

The feature extraction module first transforms the raw signal into feature vectors in which speaker- specific properties are emphasized and statistical redundancies suppressed. In the enrolment process, a speaker model is trained using the feature vectors of the target speaker. In the recognition mode, the feature vectors extracted from the unknown person's utterance are compared against the model in the system database to give a similarity score. The decision module uses this similarity score to make the final decision. Virtually all state-of-the-art speaker recognition systems use a set of background speakers in one form or another to enhance the robustness and computational efficiency of the recognizer. (Campbell et.al., 2006) (Reynolds et.al., 2000). The typical process in most proposed speaker verification systems involves some form of pre-processing of the data (silence removal) and feature extraction, followed by some form of speaker modeling to estimate class dependent feature distributions. A comprehensive overview can be found in (Atal., 1974) Adopting this strategy the speaker

verification problem can be further divided into the two problem domains of:
(1) Pre-processing, feature generation and selection.
(2) Speaker modelling and matching.

The choice of features in any proposed speaker verification system is of primary concern, because if the feature set does not yield sufficient information then trying to estimate class dependent feature distributions is futile (Basiri., et.al 2008). Most feature extraction techniques in speaker verification were originally used in speech recognition. However, the focus in using these techniques was shifted to extract features with high variability among people. Most commonly used features extraction techniques, such as Mel-frequency cepstral coefficients (MFCCs) and linear prediction cepstral coefficients (LPCCs) have been particularly popular for speaker verification systems in recent years. This transforms give a highly compact representation of the spectral envelope of a sound (Cheung-chi., 2004). However, the delta-features can be used as a simplified way of exploiting inter-feature dependencies in sub-optimal schemes (Day 2007(a)., & Nandi., 2007(b)).

The speaker modeling stage of the process varies more in the literature. The purpose of speaker modeling is characterizing an individual that is enrolled into a speaker recognition system with the aim of defining a model (usually feature distribution values). The three most popular methods in previous works are Gaussian mixture models (GMM) (Cheung-chi., 2004) (Reynolds., 1995(a) & Rose., 1995(b)), Gaussian mixture models universal background model (GMM-UBM) (Basiri et.al., 2008) and vector quantization (VQ) (Linde et.al., 1980). Other techniques such as decision trees (Linde et.al.,1980), support vector machine (SVM) (Wan., 2003) and artificial neural network (ANN) (Wouhaybi.,1999(a) Al-Alaou., 1999(b)) have also applied.

In GMM a feature vector is not assigned to the nearest cluster but it has a nonzero probability of originating from each cluster. A GMM is composed of a finite mixture of multivariate Gaussian components. Template Matching is used almost exclusively for text-dependent applications. In nearest neighbour modelling technique no explicit model is used; instead all features vectors from the enrolment speech are retained to represent the speaker. To limit storage and computation, feature vector pruning techniques are usually applied. Neural Networks model can have many forms, such as multi-layer perceptions or radial basis functions. The main difference with the other approaches described is that these models are explicitly trained to discriminate between the speaker being modelled and some alternative speakers. Training can be computationally expensive and models are sometimes not generalizable. The main problem of using SVM for speaker classification is the effort needed to transfer the speech signal to numerical data. Thus this property of high dimensionality leads to the over fitting and hypothesis becomes too complicated to implement computationally. On the other hand, the SVM is too large to be used in a practical system with limited memory space. Vector quantization (VQ) model, also known as centroid model, is one of the simplest text- independent speaker models. It was introduced to speaker recognition in the 1980s and its roots are originally in data compression. For computational reasons, however, the number of vectors is usually reduced by a clustering method such as K-means. This gives a reduced set of vectors known as codebook. The choice of the clustering method is not as important as optimizing the codebook size.

3. Proposed Method

3.1 Mel frequency Cepstral Coefficients

The Mel-scaled Cepstrum is a signal representation scheme used in the analysis of speech signals. Due to its reported superior performance, especially under adverse conditions, it is a popular choice as feature extraction front end to spoken language systems. It is computationally efficient. In this section we clarify some of the issues regarding the Mel-scaled Cepstrum algorithm and its implementation as an approach to speech signal feature extraction. In this paper we are using Mel Frequency Cepstral Coefficient. Mel frequency Cepstral Coefficients are coefficients that represent audio based on human ear's' non-linear frequency characteristic perception. It is derived from the Fourier Transform of the audio clip. In this technique the frequency bands are positioned logarithmically, whereas in the Fourier Transform the frequency bands are not positioned logarithmically. As the frequency bands are positioned logarithmically in MFCC, it approximates the human system response more closely than any other system. These coefficients allow better processing of data. In the Mel Frequency Cepstral Coefficients the calculation of the Mel Cepstrum is same as the real Cepstrum except the Mel Cepstrum's frequency scale is warped to keep up a correspondence to the Mel scale. The Mel scale was projected by Stevens, Volkmann and Newman in 1937. The Mel scale is mainly based on the study of observing the pitch or frequency perceived by the human ear. The scale is divided into the unit called mel.

We know that human ears, for frequencies lower than 1 kHz, hears tones with a linear scale instead of logarithmic scale for the frequencies higher that 1 kHz. The mel-frequency scale is linear frequency spacing below 1000 Hz and a logarithmic spacing above 1000 Hz. The voice signals have most of their energy in the low frequencies. It is also very natural to use a mel spaced filter bank showing the above characteristics. For each tone with an actual frequency, f, measured in Hz, a subjective pitch is measured on a scale called the 'mel' scale. The pitch of a 1 kHz tone, 40 dB above the perceptual hearing threshold, is defined as 1000 mels.

$$mel(f) = 2595 * \log_{10}(1 + f/700)$$

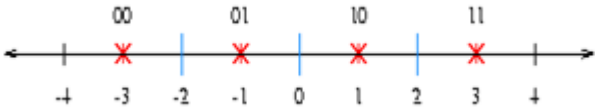
The equation above shows the mapping the normal frequency into the Mel frequency.

3.2 Vector Quantization

Vector quantization (VQ) is a lossy data compression method based on the principle of block coding. It is a fixed-to-fixed length algorithm. In the earlier days, the design of a vector quantizer (VQ) is considered to be a challenging

problem due to the need for multi-dimensional integration. In 1980, Linde, Buzo, and Gray (LBG) proposed a VQ design algorithm based on a training sequence. The use of a training sequence bypasses the need for multi-dimensional integration. A VQ that is designed using this algorithm are referred to in the literature as an LBG-VQ.

A VQ is nothing more than an approximator. The idea is similar to that of ``rounding-off" (say to the nearest integer). An example of a 1-dimensional VQ is shown below:



Here, every number less than -2 is approximated by -3. Every number between -2 and 0 are approximated by -1. Every number between 0 and 2 are approximated by +1. Every number greater than 2 is approximated by +3. Note that the approximate values are uniquely represented by 2 bits. This is a 1-dimensional, 2-bit VQ. It has a rate of 2 bits/dimension.

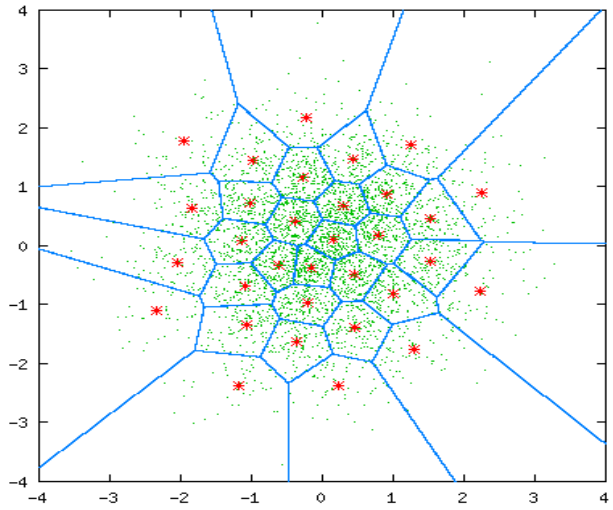


Figure 1: 2-dimensional VQ

In the above two examples, the red stars are called code vectors and the regions defined by the blue borders are called encoding regions. The set of all code vectors is called the codebook and the set of all encoding regions is called the partition of the space.

By using these training data features are clustered to form a codebook for each speaker. In the recognition stage, the data from the tested speaker is compared to the codebook of each speaker and measure the difference. These differences are then use to make the recognition decision.

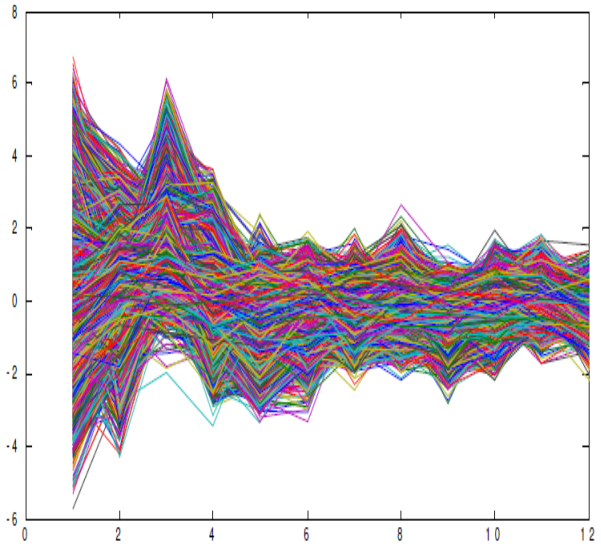


Figure 2: The vectors generated from training speech file before VQ

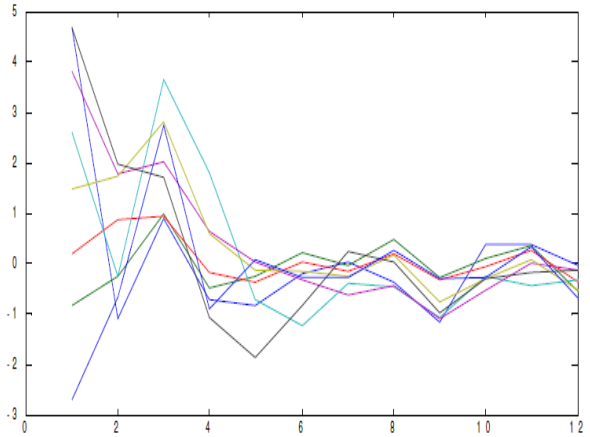


Figure 3: The representative feature vectors from speech file resulted after VQ

3.3 Algorithmic module:

Step1: Read input train file.
Step2: Calculate MFCC for train file.
Step3: Calculate code book for the train file using Vector Quantization with code book size 16.
Step4: Repeat Step 1, 2, 3 for all train files and calculate the code book representing each train file.
Step5: Read input test file.
Step6: Calculate MFCC for test file.
Step7: Calculate code book for the test file using Vector Quantization with code book size 16.
Step8: Calculate the distortion (Euclidean Distance) between the training vector codebook and testing vector.
Step9: Check if the distortion is minimum. If yes go to Step 10 else go to Step 12.
Step10: Print that the test file belong to train file and Update the minimum distortion.
Step 11: Take up the next test file go to Step 5.
Step12: If the distortion is not minimum then take up the next train file code book and repeat Step 8.

3.4 Symbolic Represe ntation based Speaker Identification

Let [D1, D2, D3……Dn] be a set of 'n' training speech files of a class Cj:j=1,2,3….p (p denotes the number of categories) and let Xm={xm,1,xm,2,……xm,k} be k-dimensional code vectors (vector quantized) characterizing the speech file Dn of the class Cj. We have computed the mean and standard deviation of the code vectors in each category. Then we add mean and standard deviation to obtain the maximum interval and we subtracted the mean and standard deviation to obtain the minimum interval. The obtained intervals of all speech files with respect to each category are combined to form a feature vector of length k. This process is repeated for all the speech files present in the class Cj and also for all other trained speech files of all other classes. These minimum and maximum class intervals of each class i.e., interval valued type of class Cj are represented as Cj = { Cj+ , Cj-}.The Cj = { Cj+ , Cj-} represents the upper and lower limits of feature value of a class in the knowledge base.
Now the representative vector for the class Cj, is formed by representing each 'm' feature in the form of an interval and is given by,

Sj={ [fj1- , fj1+],[fj2- , fj2+],
[fj3- , fj3+],……..,[fjm- , fjm+]}

This is a vector of interval-valued features and this symbolic feature vector is stored in the knowledge base as a representative of the jth class. Similarly we compute symbolic feature vectors for all the classes (j = 1, 2, 3 ,…, p) and store them in the knowledge base for classification. Thus, the knowledge base has 'p' number of symbolic vectors each corresponding to a class instead of p × n vectors in case of conventional representation.
Given a test speech, which is described by a set of 'm' feature values that is code vectors derived from the vector quantization compare it with the corresponding interval type feature values of the respective class that is stored in the knowledge base. Let Ft = [ft1 , ft2 , ft3……. ftm] be a 'm' dimensional feature vector describing a test document. Let Sj be the interval valued symbolic feature vector of jth class. Now, each mth feature value of the test speech is compared with the corresponding interval in Sj to examine whether the feature value of the test speech lies within the corresponding interval. The number of features of a test speech, which fall inside the corresponding interval, is defined to be the degree of belongingness. We make use of Belongingness Count Bc as a measure of degree of belongingness for the test speech to decide whether it belongs to the correct class or not

$$B_c = \sum_{m=1}^{k} C\left(f_{tm}, \left[f_{jm}^{-}, f_{jm}^{+}\right]\right), \text{where}$$

$$C\left(f_{tm}, \left[f_{jm}^{-}, f_{jm}^{+}\right]\right) = \begin{cases} 1 \text{ if } \left(f_{tm} \geq f_{jm}^{-}, f_{tm} \leq f_{jm}^{-}\right) \\ 0 \text{ otherwise} \end{cases}$$

The value of a test speech that falls into its respective feature interval of the reference class contributes a value '1' towards belongingness count and there will be no contribution from other features which fall outside the interval. The time required to classify each test speech is less as we consider interval features for all the train files belonging to each class.

3.5 Algorithmic Module

Step1: Input train file belonging to class Cj: j=1,2,3,…p.
Step 2: Find MFCC feature for each train file in Cj.
Step 3: Calculate code vectors for each train file using Vector Quantization in Cj.
Step 4: Calculate the Mean of code vectors representing each training file of class Cj.
Step 5: Calculate the Standard Deviation of code vectors representing each training file of class Cj.
Step 6: Calculate minimum interval for class Cj by Subtracting standard deviation from mean.
Step 7: Calculate Maximum interval for class Cj by Adding standard deviation to mean.
Step 8: Repeat the Steps 1,2,3,4,5,6,7 for all j=1,2,3,4,…p classes and find out the interval features representing each class Cj.
Step 9: Input test file.
Step 10: Find MFCC feature for test file.
Step 11: Calculate code vectors for test file using Vector Quantization.
Step 12: Calculate the degree of belongingness count Bc for the test code vectors in class Cj for all j=1,2,3,….p.
Step 13: Identify the class Cj with j for which highest belongingness count for the test file is recorded.
Step 14: Output test file belongs to the class Cj with j for which Bc is maximum.

4. Experimental Settings

During experimentation, we conducted three sets of experiments; where each set contain three different trails. In the first set of experiment we used 40% for training and remaining 60% for testing purpose. For the second set of experimentation we used 60% for training and remaining 40% for testing. For third set we used 50% for training and remaining 50% for testing. Each set of experiments contain three different trials. In each trails documents are shuffled between training and testing set.

We have used a database of 29 speakers taken from TIMIT database with 9 samples for each speaker. All the 9 samples are different utterances with different sentences for each speaker. We considered our own dataset of ten speakers also. To evaluate any system we use Precision, Recall and F-Measure as metrics to find the efficiency and robustness of the adopted method.

In order to check the robustness and to study the behavior of the LBG-vector quantization method on different speakers, we have conducted experiments on datasets viz., 29 class dataset, 10 class dataset. We analyzed the results obtained from different datasets. The maximum F-measure values are stated in the table 4.

5. Conclusion

The method works well on dataset 1. In 40% training and 60% testing trail we got highest F-measure for 1st dataset. It

shows that the method works well on standard dataset. The two sets of experiments show the efficiency of the methods.

Table 1: Maximum F – Measure table obtained from the method

Datasets	Max F-Measure		
	Training / Testing Ratio		
	40 : 60	60 : 40	50:50
Dataset 1	85.93	85.87	84.87
Dataset 2	60.92	67.07	66.09

To study the behaviour of the speaker identification method using symbolic interval valued representation for speech, extensive experiments were carried out on the dataset 1. The maximum F-measure values obtained for the proposed method are stated in table 5.3. The method works well on the dataset 1. In 60% training and 40% testing trail we got highest F-measure for dataset 1.

A brief introduction to various feature extraction techniques, a study of speaker recognition techniques are addressed in this paper. In addition to this, considering distance as a proximity measure a MFCC and LBG-Vector Quantization method is adopted to classify the speakers. A novel symbolic representation for speech is presented. A technique to use symbolic speech data for speaker recognition is also explored. To check the efficiency and robustness of the proposed models, an extensive experiment is carried out on speech datasets, the details of the results are presented in respective chapter. The result evaluations of all the experiments are carried out by considering precision, recall and F-measure as metrics.

The proposed method is efficient on bench mark dataset and there by indicates that the proposed speaker recognition method is an effective tool for authentication that can be adopted in near future.

6. Future Work

The vector quantized data can be represented in a better way as a tree to make the matching faster. A similar kind of an attempt can also be made on interval valued data representation. Indexing and hashing can be used to improve the results. These methods may be implemented for speech related research.

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