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Text Independent Speaker Identification Model Using Finite Doubly Truncated Gaussian Distribution and Hierarchical Clustering

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ABSTRACT

In Speaker Identification the goal is to determine which one of a group of a known voice with best matches with the one of the input voices. Modelling the speaker voices is an important consideration for many applications. In developing the model, it is customary to consider that the voice of the individual speaker is characterized with finite component Gaussian mixture model. However, the Mel frequency-cepstral coefficient associated with the voice spectrum of the individual speaker is having the finite range and may be asymmetrically distributed. This motivated to generalise the Speaker Identification model with Finite Doubly Truncated Gaussian Mixture Model. The number of components in the mixture model is determined by using Hierarchical clustering algorithm. The model parameters are estimated using EM algorithm. The Speaker Identification is carried by maximizing the likelihood function of the individual speaker. The efficiency of the proposed model is studied through accuracy measures with experimentation on 100 speaker's database. This model performs much better than the existing earlier algorithms in Speaker Identification.
Keywords: Doubly Truncated GMM, EM Algorithm, Mel Frequency Cepstral Coefficients, Hierarchical Clustering Algorithm

1. INTRODUCTION

The development of efficient-speaker identification system has been a topic of active research during last two decades because they have a large number of potential applications in many fields that require accurate user identification such as shopping by telephone, bank transaction, accesses control, and voicemail etc.. In speaker identification since there is no identity claim, the system identifies the most likely speaker of the test speech signal. Speaker identification can be further classified into closed-set identification and open-set identification. The task of identifying a speaker who is known a priori to be a member of the set of *N* enrolled speakers is known as closed-set Speaker Identification. The limitation of this system is that the test speech signal from an unknown speaker will be identified to be one among the *N* enrolled speakers. Thus there is a risk of false identification. Therefore, closed-set mode should be employed in applications where it is surely to be used always by the set of enrolled speakers. On the other hand, speaker identification system which is able to identify the speaker who may be from outside the set of *N* enrolled speakers is known as open-set speaker identification. In this case, first the closed-set speaker identification system identifies the speaker closest to the test speech data. The speaker identification system is divided into two parts text independent speaker identification and text dependent speaker identification. Among these two, Text Independent Speaker Identification is more complicated in open test. In Text Independent speaker identification systems the model based methods are more efficient. Several authors have developed different Text Independent Speaker Identification systems based on Gaussian Mixture which fall into the implicit segmentation approach to speaker identification (Sadaoki Furi (1981), Douglas A.Reynolds and Richard C.Rose (1995) A.Kiran kurematsu, et al (2005)).

One of the widely used stochastic methods for Speaker Identification task is the Gaussian Mixture Model (GMM) which is similar to be Hidden Markov Model (HMM) with the difference that the GMM omits the temporal information implicit in HMM (K P Markov (1999) and Pool J et al (1999)). The Gaussian Mixture Model has only one state and does not meet the transition time from one state to another state as required in the HMM and also it does not impose Morkovian constrains. The Gaussian Mixture Model uses unique Gaussian Mixture distribution to represent each speaker. In addition in most cases it is not necessary to use all co-variance matrix components because all Gaussian components are acting together to model the overall probability density function. Then the full co-variance is not necessary even if the features are not statistically independent. This is because to take all components of the co-variance of the matrix is equivalent to take only the main diagonal of the co-variance matrix from each speaker model (A kira kurematsu(2005)). Thus the GMM has been widely used in text independent speaker recognition system because it decides its desirable features mentioned above. It has the capacity of representing broad acoustic classes with its individual Gaussian components. In Gaussian Mixture Model the performance strongly depends on the characterization of the feature vector that allows unambiguous representation of the pattern under analysis. Usually the speaker characteristic is estimated through linear prediction of the speech signal. The reason for this is the structure of the vocal tract can be satisfactorily represented by using these parameters. However, it has been reported that better performance can be obtained with cepstral analysis which allows to get a robust speaker characterization with low sensitivity to the distortion introduced in the signal transmitted through communication channel (D.A Reynolds (1995)).

Recently the Mel Frequency Cepstral Coefficients (MFCC) used in speaker identification to describe the speech characteristics (vocal tract information). According to psychophysical studies (D.O' Shaughnessy, (1987)), human perception of the frequency content of sounds follows a subjectively defined nonlinear scale called the Mel scale (Ben Gold and Nelson Morgan (2002)). This is defined as,

$$f_{\text{mel}} = 2595\log_{10}\left(1+\frac{f}{700}\right)$$

where f_{mel} is the subjective pitch in Mels corresponding to f, the actual frequency in Hz.

D.A.Reynolds(1994),D.Hard and K.Feiibaum and Daniel j mashao(2006) have used Mel frequency cepstral coefficients as base line Acoustic feature for text independent Speaker Identification. The feature vectors computed by using MFCC are first applies discrete Fourier transform (DFT) on each frame and then weights the DFT spectrum by a Mel-scaled filter bank. The filter bank outputs are then converted to cepstral coefficients by applying the inverse discrete cosine transform (IDCT).

In all these methods they consider that the Mel Frequency Cepstral Co-efficient (MFCC) associated with each Speaker follows a Gaussian or finite Gaussian Mixture Model. These Speaker Identification models serve well when the Mel frequency cepstral co-efficient associated with the Speakers are having infinite range and symmetrically distributed miso kurtosis. But in some of the voice frames the elements in the feature lies between two finite values and in some cases the distribution of the feature vector may be asymmetric and skewed. Neglecting the realities of the finite range to the MFC coefficient leads to a serious falsification of the model estimation. So to have a robust model for the MFC coefficients. It is needed to consider a Finite doubly truncated Gaussian distribution which characterizes the features distribution for each speaker as Finite Doubly Truncated Gaussian Mixture Model (FDTGMM).

The FDTGMM includes the GMM also as a limiting case. It also includes the skewed nature of the component in the model. The effect of truncation in Gaussian distribution has been discussed by several researchers in other application areas (Cohen A.C. (1950) Johnson A.C.(1996) Matto R.S (2000)). But, no serious attempt is made to develop and analyse text independent speaker identification model with finite doubly truncated Gaussian Mixture Model. Using the Hierarchical Clustering algorithm the number of components in recognising the speech spectrum of the individual speaker is given. The model parameters are estimated using EM algorithm. The efficiency of the model is compared with that of the text independent speaker identification model with GMM given by (D A Reynold (2006)) through experimental results and rate of accuracy.

2. FINITE DOUBLY TRUNCATED GAUSSIAN SPEAKER MODEL

In this section we briefly describe the FDTGMM and motivate its use as a representative of the speaker identity for test independent Speaker identification. The choice of the probability density function is largely dependent on the features being used.

Here it is consider that the Mel frequency cepstral coefficients as the features for speaker identification. The Mel frequency cepstral coefficients are assumed to follow a FDTGMM. The motivation of this assumption is that the individual component densities of a multi model density, model the underlying set of acoustic process of the speaker. It is reasonable to assume the acoustic space corresponding to a speaker voice can be characterized by a acoustic classes representing some broad phonetic events such as vowels nasals or fricatives. These acoustic classes reflect some general speaker dependent vocal tract configurations that are useful for characterizing speaker identity. The spectral shape of the it's acoustic class can in turn be represented by the mean of the its component density and the variation of the average spectral shape can be represented by the co-variance matrix. Assuming the independent feature vectors, the observation density of the feature vectors drawn from these acoustic classes is a Doubly Truncated Gaussian Mixture. Also it is given that a linear combination of Gaussian basis function is capable of representing a large class of sample distributions. The FDTGMM is a generalization of the GMM and also as in the case of a Gaussian full co-variance is not necessary even is the features are not statistically independent.

The Doubly truncated D variate Gaussian density is

$$b_i(\vec{x}) = \frac{1}{(B-A)(2\pi)^{D/2}|\Sigma_i|^{1/2}} \exp\left\{-\frac{1}{2}(\vec{x}_i - \vec{\mu}_i)\sum_i^{-1}(\vec{x}_i - \vec{\mu}_i)\right\} \quad (1)$$

$$A = \int_{-\infty}^{x_L} \ldots \int_{-\infty}^{x_L} b_i(\vec{x}_t) d\vec{x}_t \qquad B = \int_{-\infty}^{x_M} \ldots \int_{-\infty}^{x_M} b_i(\vec{x}_t) d\vec{x}_t$$

$\vec{x}_t = (x_1, x_2, \ldots\ldots x_t)$ is the future vector, $\vec{\mu}_i$ is the i^{th} component feature mean vector, Σ_i is the i$^{\text{th}}$ component of variance co- variance matrix.

The probabilities density functions of the finite M component doubly truncated Gaussian mixture distribution is

$$p(\vec{x}/\lambda) = \sum_{i=1}^{M} \alpha_i b_i(\vec{x}) \quad (2)$$

where, $\vec{x}$ is a D dimensional random vector, $b_i(\vec{x})$, i = 1 ……. M are the component densities and $\alpha_i(\vec{x})$, $i = 1$ ……. M is the mixer weights, with mean vector

$$E(\vec{x}) = \mu_i + \sigma_i^2 \left[\frac{f(\vec{x}_L) - f(\vec{x}_M)}{\varnothing(\vec{x}_L) - \varnothing(\vec{x}_M)}\right] \quad (3)$$

where, $\varnothing(\vec{x}_L)$ and $\varnothing(\vec{x}_M)$ are the standard normal areas and $\vec{x}_L, \vec{x}_M$ are the lower and upper truncated points of the feature vectors.

The variance of each feature vector (Mel frequency cepstral coefficients) is

$$V(x_i) = \left[\frac{\left(\frac{\vec{x}_L - \vec{\mu}_i}{\sigma_i}\right)\vec{x}_L - \left(\left(\frac{\vec{x}_L - \vec{\mu}_i}{\sigma_i}\right)\vec{x}_M\right)}{B-A}\right] \quad (4)$$

The mixture weights satisfy the constraints $\sum_{i=1}^{M} \alpha_i = 1$

Then the FDTGMM is parameterized by the mean vector, Co-variance matrix and mixture weights from all components densities. The parameters are collectively represented by $\lambda_i = \{\alpha_i, \mu_i, \Sigma_i\}$ $\quad i = 1, 2, \ldots .M$

For speaker identification each speaker is represented by FDTGMM and is referred to by his /her model parameter λ. The FDTGMM can represent different forms depending on the choice of the co-variance matrices and truncation parameters. One co-variance matrix for all Gaussian components (grand co-variance) or a single co-variance matrix shared by all speakers models (global covariance) used in FDTGMM. The covariance matrix can also be full or diagonal. In the present work the diagonal covariance matrix as primarily used for speaker model. This choice is based on the works given by (D.A Renold, Richard rose (1995)) and initial experimental results indicating better identification performance and hence Σ can be represented as

$$\Sigma = \begin{bmatrix} \sigma_1^2 & 0 & 0 & 0 \\ 0 & \sigma_2^2 & 0 & 0 \\ - & - & - & - \\ 0 & 0 & 0 & \sigma_M^2 \end{bmatrix} \quad (5)$$

This simplifies the computational complexities.

3. ESTIMATION OF THE MODEL PARAMETERS

For developing the speaker identification model it is needed to estimate the parameters of the speaker model. For estimating the parameters in the model we consider the EM algorithm which maximizes the likelihood function of the model for a sequence of i training vectors $\vec{x}_t = (x_1, x_2, \ldots\ldots x_t)$.

The likelihood function of the DTGMM is

$$p(\vec{x};\lambda_i) = \Pi_{i=1}^{T} p_i(\vec{x};\lambda_i) \quad (6)$$

where, $p(\vec{x};\lambda_i)$ is given in equation (2)

The likelihood function contains the number of components M which can be determined from Hierarchical algorithm. The Hierarchical algorithm does not requires the initial number of components. Once M-is assigned the EM algorithm can be applied for refining the parameters with up dated equations.

The updated equations of the parameters for each Mel frequency cepstral coefficients are as follows

$$\alpha_k^{l+1} = \frac{1}{T}\sum_{i=1}^{T} p(i \mid \vec{x}_t, \lambda^l) \quad (7)$$

$$\mu_k^{l+1} = \frac{\Sigma_{i=1}^{T}\vec{x}_t p(i \mid \vec{x}_t, \lambda^l) + \Sigma_{i=1}^{T} \frac{f(x_M) - f(x_L)}{B-A} \sigma_k^2 p(i \mid \vec{x}_t, \lambda^l)}{\Sigma_{i=1}^{T} p(i \mid \vec{x}_t, \lambda^l)} \quad (8)$$

$$\sigma_k^{l+1} = \frac{\Sigma_{i=1}^{T} p(i \mid \vec{x}_t, \lambda^l)(\vec{x}_t - \mu_i^{(l+1)})^2}{c\Sigma_{i=1}^{T} p(i \mid \vec{x}_t, \lambda^l)} \quad (9)$$

where C is given by

$$C = \frac{1}{(B-A)}\left(1 + \mu_k^{l+1}\right)[(f(\vec{x}_{M}) - f(\vec{x}_L)) + (x_M(f(\vec{x}_L) - x_L f(\vec{x}_M))]$$

and $f(x_{M,}) = \int_{-\infty}^{x_M} b_i(x_t) dx_t$, $f(x_{L,}) = \int_{-\infty}^{x_L} b_i(x_t) dx_t$

The a posterior probability for acoustic class i is given by

$$p(i \mid \vec{x}_t, \lambda^l) = \frac{a_i b_i(\vec{x}_t)}{\Sigma_{i=1}^{k} a_i b_i(\vec{x}_t)} \quad (10)$$

4. INITIALIZATION OF THE MODEL PARAMETERS

To utilize the EM algorithm we have to initialize the parameters μ_i, σ_i and α_i $i = (1 \ldots.. M)$ X_M and X_L obtained can be estimated with the values of the maximum and the minimum values of each feature vector respectively. The initial estimates of μ_i, σ_i and α_i of the i^{th} component is obtained using the method given by A.C.Cohen (1950).

Hierarchical Clustering Algorithm: In this section we develop the Hierarchical clustering Algorithm for clustering the speech data. Based on the physical assumption we propose the following procedure for determining the number of clusters:

Step 1: Start by assigning each item to a component. Each of the N items, are associated with N components, each containing just one item. Let the distance (similarities) between the components be the same as the distance (similarities) between the items they contain.

Step 2: Find the closest (most similar) pair of components and merge them into a single class. The number of classes is now reduced by one. Compute distance (similarities) between the new class and old classes.

Step: 3 repeat the step 2 and 3 until all items are grouped.

5. SPEAKER IDENTIFICATION ALGORITHM:

Once the speech spectrum of a speaker is observed the main purpose is to identify the speaker from the group of S speakers. The following algorithm can be adopted for speaker identification using Doubly Truncated Gaussian Mixture Model.

1. Find feature vectors using front end process explained in section 1.
2. Divide the T samples into M groups by Hierarchical clustering algorithm.
3. Find mean vector (μ_i) and variance vector (σ_i) for each group.
4. Take $\alpha_i = 1/6$, $I = 1,2,3,4,5,6$.
5. Use EM algorithm for obtaining the refined estimates of μ_i, α_i, and σ_i for each component of the i^{th} speaker.
6. Write the speaker Model as $p(x/\lambda) =$

   $\Sigma_{i=1}^{M} \alpha_i p_i((x \mid \lambda_s)$ where $\lambda_i = \{\mu_i, \sigma_i, \alpha_i\}$ put $\lambda = \lambda_1, \lambda_2, \ldots \lambda_6$. from each speaker.
7. For Speaker identification, from a group of S Speakers $S = \{1,2,\ldots..S\}$ each represented by FDTGMM's with parameters, $\lambda_1, \lambda_2, \lambda_{3,\ldots} \lambda_s$ we find the speaker model which has the maximum a posterior probability for a given observation sequence that is

$$\hat{s} = \max_{1<k<s} p_r(\lambda_k \mid x) = \arg\max_{1<k<s}[p_r((\lambda_k \mid x) p_r(\lambda_k)]$$

where the second equation is due to bye's rule assuming equally likely speakers (that is $P_r(\lambda_k) = 1/S$ and noting that $p(X)$ is the same for all speaker models, the classification rule simplifies to $\hat{s} = \arg\max_{1<k<s} p_r(\lambda_k)$.

Using logarithms and the independent between observations, the speaker identification system computes $\hat{s} = \arg\max_{1<k<s} \sum_{i=1}^{T} \log p_r(\vec{x}_t \mid \lambda_k)$ in which is given in equation (2).

6. EXPERIMENTAL RESULTS

To demonstrate the ability of the developed model it is trained and evaluated by using a database of 100 speakers. For each speaker there are 10 conversations of approximately 2sec. each recorded in 10 separate sessions under different environmental conditions locally by using high quality Microphone.

The test speech was first processed by front end analysis to produce a sequence of feature vectors (MFCCs) which are obtained for test sequence length 2 seconds, with the procedure given by D.A Reynolds (1995).

The data set $\{(\vec{x})_1, \vec{x}_2, \vec{x}_3, \vec{x}_4, \ldots, \vec{x}_\tau\}$ is divided into a training set and a test set. Using the Hierarchical clustering algorithm for each speaker the sampled speech data is classified and using the moment estimators the initial estimate of the parameters are obtained.

With these initial estimates and the updated equations of the parameters given in section (3), the refined estimates of the parameters are obtained using these estimates. The global model for each speech spectrum is estimated. The efficiency of the developed model is studied by identifying the speaker with the Speaker identification algorithm given in section (5) with the test data set.

The percentage of correct identification is computed as

PCI = % correct identification =

$$\frac{\text{\#correctly identified speakers}}{\text{total\#of speakers}} \times 100$$

It is observed that this algorithm identifies the speaker with 97.1%±1.6 correctly. The variation of PCI is also computed by repeating the experiment over 10 sessions in different environmental conditions and using binomial distribution the confidence interval for the correct identification is computed as

$$APCI \pm z_{\alpha}\sqrt{\frac{\frac{APCI}{100}(1-\frac{APCI}{100})}{n}}$$

Where, APCI represents average percentage of correctness $\frac{\Sigma_{i=1}^{n} APCI}{n}$ and n is the number of sessions z_{α} is the significant value computed from the binominal probabilities for the given level of significance α.

A comparative study of the Performance of FDTMGMM is carried with reference to the speaker modeling techniques. The other techniques are the uni modal Gaussian classifier given by H.Gish (1985), Tied Gaussian Mixture model given by J. Oglesby and J. Mason, (1985) and the Gaussian Douglas A Reynolds (1995) with Gaussian Mixture Model using nodal variance (GMM_{nv}) and Gaussian Mixture Model using global variance (GMM_{gv}) using Mel frequency cepstral co-efficient as feature vectors. The average percentage of correct identification for 100 speakers utterances of the models are computed with their confidence intervals and are presented in Table 1.

Table 1
Speaker Identification Performance for Various Speaker Models

Speaker Model	*% Correct Identification (2 Sec test length)*
GMM-nv	94.6±1.8
GMM-gv	89.7±2.4
TGMM	80.2±3.1
GC	67.3±3.7
FDTMGMM(K-means)	96.4±1.7
FDTMGMM(Hierarchical clustering)	97.1±1.6

From Table 1 it is observed that the unimodal Gaussian classifier has PCI of 67.7%±3.7. Where as the average percentage of correct identification for the developed model is 97.1%±1.6. The percentage correctness for the Gaussian Mixture Model with nodal variance is 94.1% ±1.8. The average percentage of correct identification for Finite Doubly Truncated multivariate Gaussian Mixture Model with K-means is 96.4%±1.7. This clearly shows that the average percentage of correct identification for Finite Doubly Truncated multivariate Gaussian Mixture Distribution and Hierarchical clustering model is having higher rate of correct identification with the other models.

The experiment is also conducted with respect to the size of the speakers population by considering the speaker size as S=20, S=40, S=60, S=80, S=100 and S=120 with the same experimental set up of locally recorded speakers speech data base consisting of 10 conservation of each with approximately 2 seconds duration with 10 sessions. The average percentage of correctness of identification is computed and given in Table 2. The relationship between the speaker population size and average percentage of correct identification is shown in Fig 1.

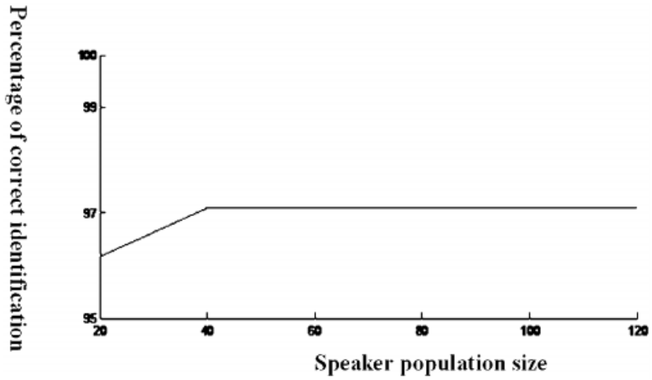

Fig 1: Speaker Population Size Versus Average Percentage of Correct Identification

Table 2
Speaker Population Size Versus Average Percentage of Correct Identification

Speaker population size	*% Correct Identification (2 Sec text length)*
20	96.2±1.8
40	97.1±2.4
60	97.1±3.1
80	97.1±3.7
100	97.1±1.7
120	97.1±1.7

From the Table 2 it is observed that the size of speaker population has an effect on average percentage of correct identification. As the population size increases the average percentage of correctness is also increases and stabilizes after certain size. It is observed that the percentage of correctness for the developed is stabilizes when the speaker size is approximately 40. The proposed model is suitable for both homogeneous and heterogeneous speaker's population as it model each individual speaker uniquely.

The developed model can be applied for speaker identification like voice dialing, banking by telephone, telephone shopping, Forensic investigations, database access services, information services, voice mail, security control for confidential information areas, and remote access to computers etc,. This model outperforms the earlier models even with heterogeneous population with large speaker population size.

7. CONCLUSION

In this paper the proposed a text independent speaker identification model based on Finite Doubly truncated GMM with EM and Hierarchical clustering algorithm. The model parameters are estimated through EM algorithm after identifying the number of component densities in each speaker voice spectrum using mel frequency cepstral co-efficient as feature vectors with the component maximum likelihood. The speaker identification algorithm is developed.

The FDTGM feature vector components are a generalization of the Finite Gaussian Mixture Model. This also includes the Gaussian mixture model as limiting case when the truncated points tend to infinite. Experimental results shown that the proposed model as better identification capabilities compared to the finite Gaussian mixture speaker model. This is also validated through a comparative study using speaker identification quality metrics, % of correct identification and its confidence interval. The developed model is much useful for robust text independent speaker identification in at places like banking by telephone, telephone shopping, Data Base access services, information services, voice interactive system, Security Control for confidential information areas and Remote access etc,..

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