

## Towards an Optimal Speaker Modeling in Speaker Verification Systems using Personalized Background Models

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### Article Info

#### Article history:

Received Mar 19, 2017

Revised Jun 29, 2017

Accepted Jul 14, 2017

#### Keyword:

Speaker modeling

Speaker verification

Gaussian mixture models

Universal background model

Maximum a posteriori (MAP)

Personalized background models

### ABSTRACT

This paper presents a novel speaker modeling approach for speaker recognition systems. The basic idea of this approach consists of deriving the target speaker model from a personalized background model, composed only of the UBM Gaussian components which are really present in the speech of the target speaker. The motivation behind the derivation of speakers' models from personalized background models is to exploit the observed difference in some acoustic-classes between speakers, in order to improve the performance of speaker recognition systems.

The proposed approach was evaluated for speaker verification task using various amounts of training and testing speech data. The experimental results showed that the proposed approach is efficient in terms of both verification performance and computational cost during the testing phase of the system, compared to the traditional UBM based speaker recognition systems.

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## 1. INTRODUCTION

The GMM-UBM based speaker modeling approach was firstly introduced to the speaker recognition community by Reynolds, in 2000 [1]–[3]. Since then, it has become the predominant approach for speaker modeling in text-independent speaker recognition systems, and the basis of the most successful approaches that have been emerged in the last decade: the hybrid GMM-SVM approach [4], [5], the joint factor analysis approach [6]–[8], and the recently introduced i-vectors approach [9], [10]. The motivation behind the use of adapted Gaussian mixture models for speaker modeling is generally based on the assumption that Gaussian densities may model a set of hidden acoustical classes that reflect some general speaker dependent vocal tract characteristics.

The main idea of the UBM-based speaker recognition systems consist of deriving the target speaker model from a universal background model that represents the set of all human acoustic classes (e.g., gender dependent acoustic classes, age-dependent acoustic classes, accent dependent acoustic classes...). The target speaker model will therefore be composed of an adapted version of the various acoustic classes defined in the universal background model. However, as it sounds to the human ear, speakers don't share the same acoustic classes. For example, the acoustic classes of male speakers are different from those of female speakers and the acoustic classes of adult speakers are different from those of minor speakers, as well as, the acoustic classes of timid speakers are different from those of bold speakers, etc. Thereby, it seems that it is not logical to model a speaker by an adapted version of an acoustic class which may not exist in its voice. Furthermore, the difference of acoustic classes between speakers can be exploited to discriminate between them in speaker recognition systems.

In view of these observations, the present study attempts, firstly, to experimentally investigate the degree of acoustic-classes' difference between speakers, and secondly, to propose a speaker modeling approach that takes into account these observations and exploits the differences in acoustic classes between speakers to improve the performance of speaker recognition systems.

The remainder of this paper is organized as follows. The first section gives a brief overview of the traditional GMM-UBM based Speaker verification systems. Next, the proposed speaker modeling approach, based on personalized background models, is introduced. Afterward, experimental results and discussions are presented in the third section. Finally, conclusions and future research directions are drawn in the last section.

## 2. TRADITIONAL GMM-UBM BASED SPEAKER VERIFICATION SYSTEMS

The GMM-UBM based speaker verification system was originally proposed by Reynolds in 2000 [1], [11]. Since then, it has become the predominant approach for speaker modeling in text-independent speaker recognition systems and the basis of the most successful approaches that have been emerged in the last decade. The main idea of the GMM-UBM approach consists, as shown in Figure 1, of deriving speakers' models from a universal background model using maximum a posteriori (MAP) adaptation [1]. The Universal Background Model (UBM) is typically a Gaussian mixture model (GMM) that represents the distribution of the entire acoustic space of speech [2], [3].

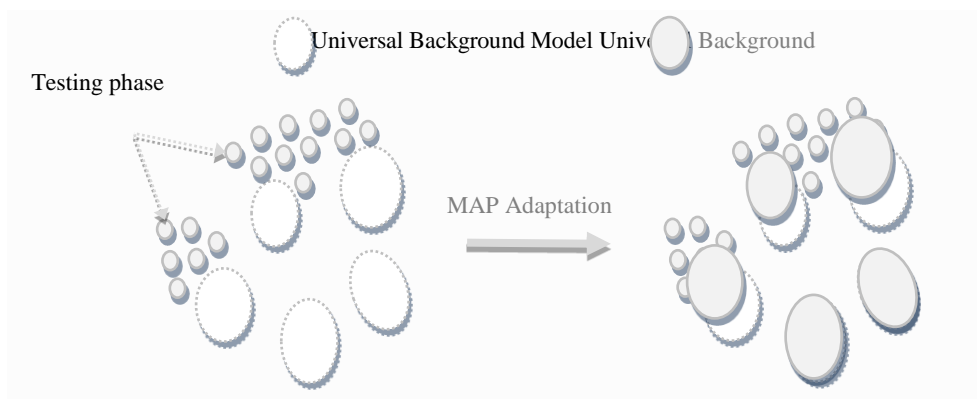


Figure 1. A MAP adaptation of a GMM comprises 5 Gaussian densities. Original Gaussian densities of the UBM are depicted as unfilled ellipses (dotted line), whereas the adapted Gaussian densities are denoted by filled ellipses, and the observed feature vectors are depicted as small circles

The MAP adaptation process is generally composed of two steps. First, the sufficient statistics estimates of the speaker's training data are computed for each mixture in the UBM. Next, the computed sufficient statistics estimates are combined with the old sufficient statistics from the UBM mixture parameters using a data-dependent mixing coefficient. The specifics of the adaptation are as follows. Given that the universal background model is composed of  $M$  Gaussian components, each of which is parameterized by a mean vector  $\mu_i$ , variance matrix  $\sigma_i^2$  and its weight  $w_i$  in the mixture model. Initially, the posteriori probability of each UBM component  $\{w_i, \sigma_i, w_i\}$  given the feature vector  $x_t$  is computed as follows:

$$Pr(i|x_t) = \frac{w_i p_i(x_t)}{\sum_{j=1}^L w_j p_j(x_t)} \quad (1)$$

where  $p_i(x_t)$  is the density of the probability, given by:

$$p_i(x_t) = \frac{1}{(2\pi)^{D/2} |\sigma_i|^{1/2}} \exp\left\{-\frac{1}{2}(x_t - \mu_i)^T \sigma_i^{-1} (x_t - \mu_i)\right\} \quad (2)$$

The sufficient statistics for the weight, mean, and variance parameters are then computed as follows:

$$n_i = \sum_{t=1}^T Pr(i|x_t); E_i(x) = \frac{1}{n_i} \sum_{t=1}^T Pr(i|x_t) x_t; E_i(x^2) = \frac{1}{n_i} \sum_{t=1}^T Pr(i|x_t) x_t^2 \quad (3)$$

Thereafter, the computed sufficient statistics are used for estimating the adapted mixture weights  $\widehat{w}_i$ , means  $\widehat{\mu}_i$  and variances  $\widehat{\sigma}_i^2$  of the given speaker:

$$\widehat{\mu}_i = [\beta_i^\mu E_i(x) + (1 - \beta_i^\mu) \mu_i] \quad (4)$$

$$\widehat{w}_i = [\beta_i^w n_i / T + (1 - \beta_i^w) w_i] \gamma \quad (4)$$

$$\widehat{\sigma}_i^2 = [\beta_i^{\sigma^2} E_i(x^2) + (1 - \beta_i^{\sigma^2})(\sigma_i^2 - \beta_i^{\sigma^2}) - \widehat{\mu}_i^2] \quad (5)$$

$$\text{with,} \quad \beta_i^\rho = n_i / (n_i + r^\rho), \quad \rho \in \{w, \mu, \sigma^2\} \quad (6)$$

Here,  $\gamma$  is a scale factor computed over all adapted mixture weights to ensure that they sum to unity,  $\beta_i^\rho, \rho \in \{w, \mu, \sigma^2\}$  are the adaptation coefficients that control how the adapted GMM parameters will be affected by the observed speaker data, and  $r^\rho$  is a fixed relevance factor for parameter  $\rho$ .

An overall diagram of the GMM-UBM based speaker verification system is shown in Figure 2. The basic operating structure of the system, as shown in Figure 2, is composed of three phases: the training phase, the enrollment phase and the testing phase. During the first phase, i.e. the training phase, a large collection of speech utterances is collected from a background population of speakers, their corresponding feature vectors are extracted and used to train the universal background model. The training process of the UBM is done generally using maximum likelihood estimation via the EM algorithm. In the second phase, i.e. the enrollment phase, speaker models of new client speakers are derived from the universal background model through MAP adaptation using the speakers' training feature vectors [13]. While in the testing phase, the extracted feature vectors of the unknown speaker's utterance  $X^u = \{x^u_1, x^u_2, \dots, x^u_N\}$  are compared against both the claimed target speaker model and the background model. The log likelihood ratio  $LLR(X^u; \lambda_{spk}, \lambda_{UBM})$  between the claimed speaker model and the universal background model is then calculated and used to make a decision about the acceptance/rejection of the claimed identity. The log likelihood ratio (LLR) of the test utterance  $X^u$  between the speaker model  $\lambda_j$  and the UBM model  $\lambda_{UBM}$ :

$$LR(X^u; \lambda_{spk}, \lambda_{UBM}) = \frac{1}{N} \left[ \sum_{i=1}^N \log p(x^u_i | \lambda_{spk}) - \sum_{i=1}^N \log P(x^u_i | \lambda_{UBM}) \right] \quad (7)$$

$$\text{With,} \quad p(x_t | \lambda) = \sum_{i=1}^M w_i b_i(x_t) \quad (8)$$

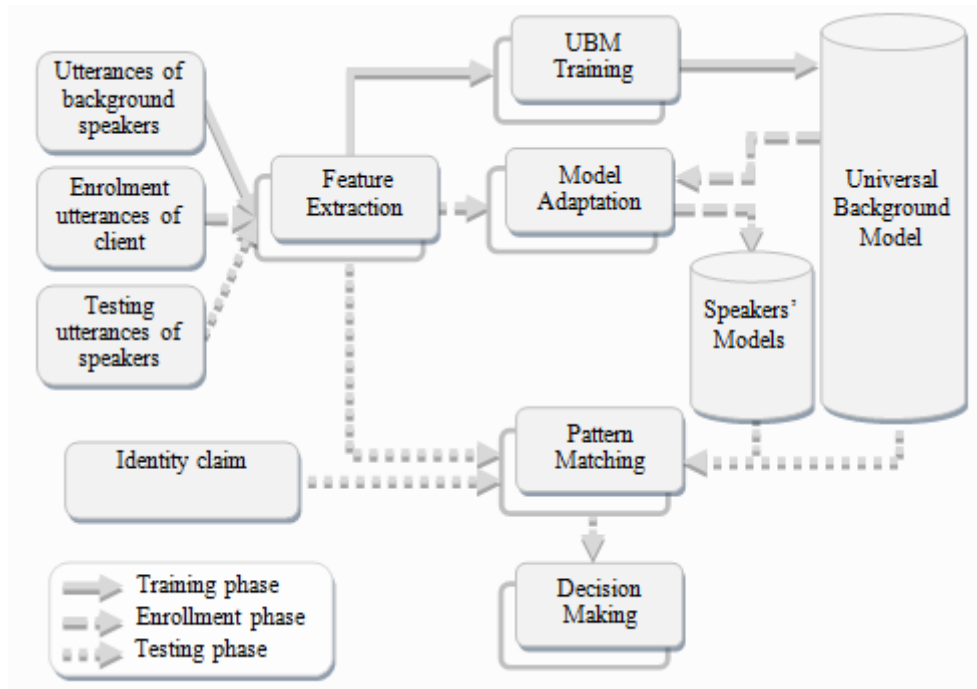


Figure 2. Block diagram of the GMM-UBM based speaker verification system

**3. SPEAKER RECOGNITION USING PERSONALIZED BACKGROUND MODELS (PBMS)**

The main idea of the proposed PBM-based speaker modeling approach consists of adapting the target speaker model from a personalized background model (PBM), composed only of the UBM Gaussian components which are actually present in the speaker’s speech. The MAP adaptation step of traditional UBM based systems will, therefore, be preceded by a selection step that selects the background Gaussian component which reflect the general form of the acoustic classes characterizing the speaker, see Figure 3.

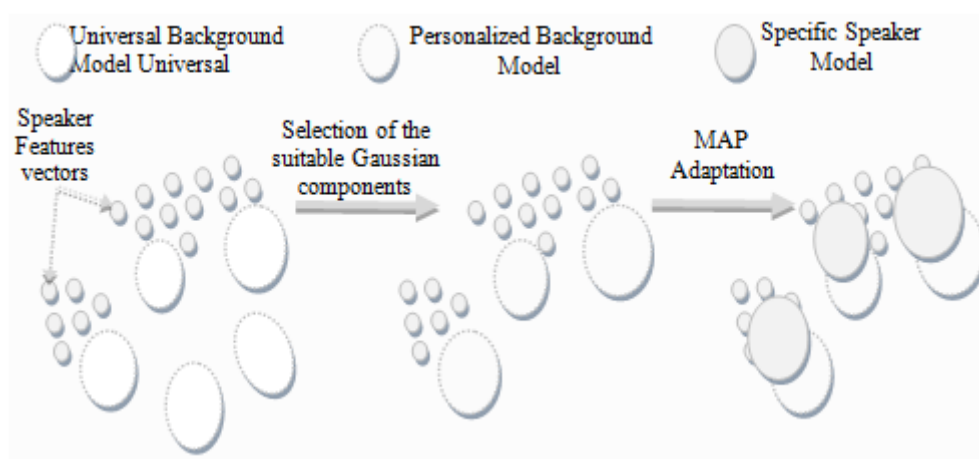


Figure 3. A MAP adaptation of a GMM comprises 5 Gaussian densities. Original Gaussian densities of the UBM are depicted as unfilled ellipses (dotted line), whereas the adapted Gaussian densities are denoted by filled ellipses, and the observed feature vectors are depicted as small circles.

Given a UBM of  $M$  Gaussian component  $\lambda_{UBM} = \{\mu_{UBM_i}, \sigma_{UBM_i}, w_{UBM_i}\} / i \in \{1, 2, \dots, N\}$ , and  $M$  training feature vectors  $X = \{x_1, x_2, \dots, x_N\}$ , extracted from the target speaker’s speech. The PBM Gaussian components are generally chosen from the UBM using a winner-take-all based strategy. A UBM Gaussian

component  $\theta_{UBM_i} = (\mu_{UBM_i}, \sigma_{UBM_i}, w_{UBM_i})$  is selected to belong to the personalized background model  $\lambda_{PBM}$  of the target speaker, if there is at least one feature vector  $x_n \in X$ , where the UBM Gaussian component  $\theta_{UBM_i}$  achieves the maximum posterior probability of  $x_n$  belongingness:

$$Pr(\theta_{UBM_i} | x_n) \geq Pr(\theta_{UBM_l} | x_n), \forall l \in \{1, 2, \dots, N\} \quad (9)$$

Once the PBM Gaussian components are selected, the weights  $w_{UBM_j}$  of the selected components are divided by their sum so that the total weight is equal to unity.

A block diagram of the speaker modeling process using personalized background models is shown in Figure 4. Firstly, the training feature vectors of the target speaker are extracted from its enrollment utterances. Next, the extracted feature vectors are used to select the UBM Gaussian components which will compose the speaker's personalized background model. Afterwards, the composed personalized background model is utilized to derive the speaker model using the MAP adaptation procedure. Finally, the adapted model is stored together with the corresponding indices of the PBM Gaussian components in the UBM.

An example of a two-dimensional projection of two speakers' features and the means of their corresponding UBM and PBM adapted models is shown in Figure 5. As it can be seen from this figure, the means of the PBM adapted models fit the speakers' features better than the means of the traditional UBM adapted models. Moreover, it seems that the adaptation of the UBM Gaussian components which haven't any relationship with the target speaker influence on the feature vectors belongingness to the appropriate Gaussian components, which therefore affect negatively the adapted model.

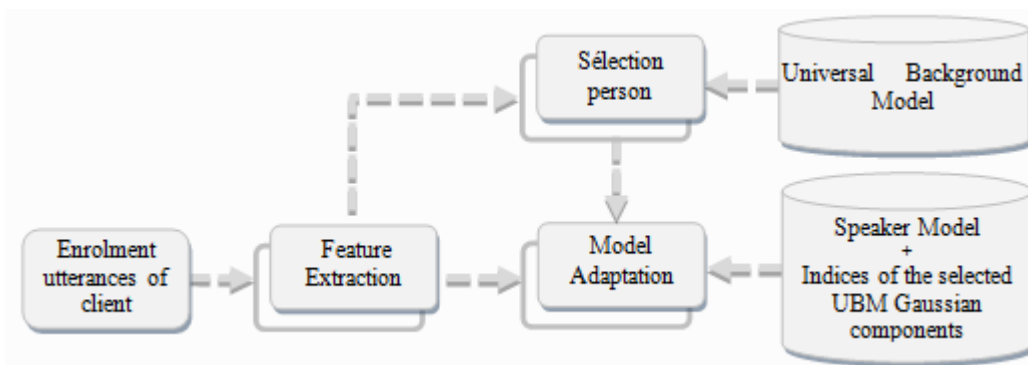
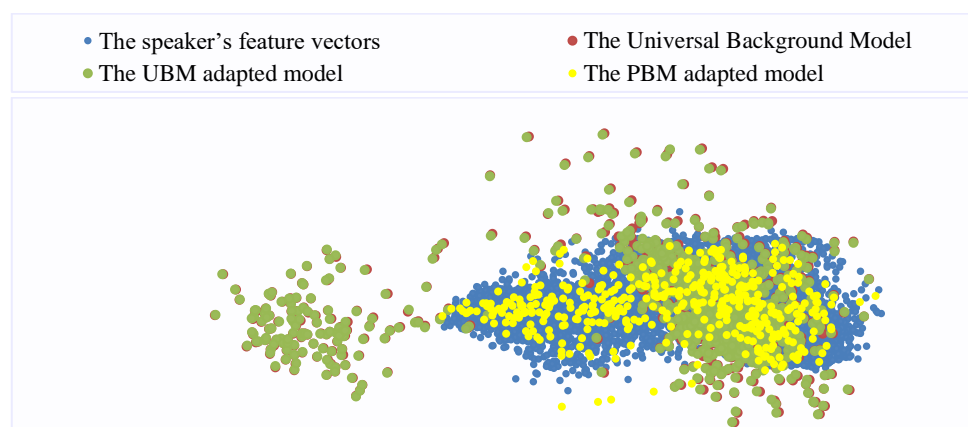


Figure 4. Block diagram of speaker modeling process using personalized background models



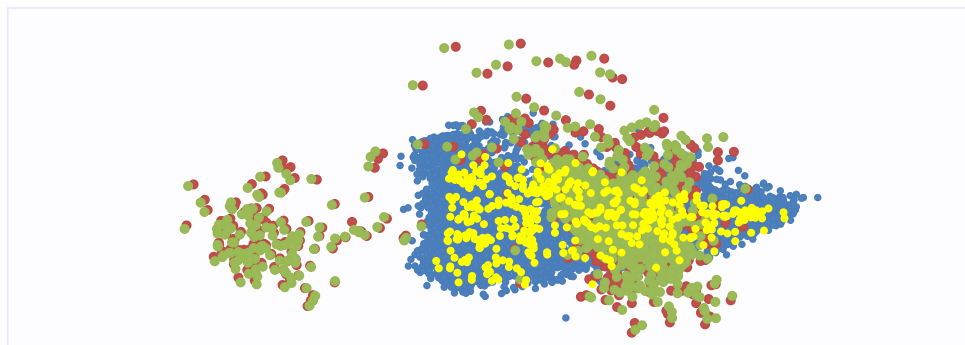


Figure 5. A two-dimensional projection of two speakers' features (blue points), the means of their corresponding UBM and PBM adapted models (in green and yellow points, respectively) and the means of the UBM model (red points)

During the test phase, the log-likelihood ratio  $LLR(X^u; \lambda_{spk}, \lambda_{PBM})$  between the claimed speaker model and the personalized background model is used to make a decision about the acceptance or the rejection of the claimed identity:

$$LLR(X^u; \lambda_{spk}, \lambda_{PBM}) = \frac{1}{N} \left[ \sum_{i=1}^N \log p(x_i^u | \lambda_{spk}) - \sum_{i=1}^N \log P(x_i^u | \lambda_{PBM}) \right] \quad (10)$$

$$\text{With,} \quad p(x_t | \lambda) = \sum_{i=1}^M w_i b_i(x_t) \quad (11)$$

The motivation behind the use of the personalized background model instead of the universal background model is to penalize the decision score of impostor speakers who don't share the same acoustic classes with the target speaker.

## 4. EXPERIMENTS, RESULTS AND DISCUSSION

### 4.1. The Experimental Protocol

The performed experiments in this study were conducted on the THUYG-20 SRE database [14]. This database is generally composed of 353 speakers, collected in a controlled environment (silent office by the same carbon Microphone). The entire speech corpus was divided into three data sets: the first dataset consists of 200 gender-balanced speakers (100 Male and 100 Female) and devoted to train the Universal Background Model (UBM), the second and the third data sets are composed of the same set of 153 client speakers. The first dataset comprises the training speech data, whereas the second comprises the testing speech data of the 153 speakers. During the testing phase of the system, the client speakers were tested against each other, resulting in total of 896,886 trials of 4 seconds and 441,558 trials of 8 seconds.

The feature vectors of the overall speech utterances were extracted using the MFCC approach: the digitized speech is firstly emphasized using a simple first order digital filter with transfer function  $H(z) = 1 - 0.95z$ . Next, the emphasized speech signal is blocked into Hamming-windowed frames of 25 ms (400 samples) in length with 10 ms (160 samples) overlap between any two adjacent frames. Finally, 19 Mel-Frequency Cepstral Coefficients were extracted from each frame [15]. During the training phase, a universal background model (UBM) of 1024 Gaussian components was trained on the overall training data (7.5 hours of speech) using the EM algorithm.

### 4.2. Investigation on the Degree of Difference in Acoustic Classes between Speakers

The aim of the performed experiments in this section is to investigate the degree of difference in acoustic classes between speakers. For this purpose, we have carried out several speaker verification experiments in which we have based only on the difference between the acoustic classes present in the target speaker's speech and those present in the claimed speaker's speech. To proceed, we have represented the training speech utterance(s) of the target speaker and the test speech utterance of the claimed speaker by histograms. Each histogram is composed of 1024 bins, where each bin represents a UBM Gaussian component.

The value of each bin is defined as the number of times that the corresponding UBM Gaussian component has the maximum posterior probability over the feature vectors of the speaker. The specifics of the histogram construction process are shown in Algorithm 1.

**Algorithm 1** The histogram construction process

**Input:** The feature vectors  $X = \{x_1, x_2, \dots, x_N\}$  of the speech utterance,  
The universal background model  $\lambda_{UBM} = \{\mu_{UBM_i}, \sigma_{UBM_i}, w_{UBM_i}\} / i \in \{1, 2, \dots, N\}$ .  
**Output:** The corresponding histogram  $\mathcal{H}$  of the speech utterance.  
 $\mathcal{H} = \text{zeros}(1, 1024)$   
**FOR EACH**  $x_i$  **IN**  $X$   
 $j = \arg \max_i Pr(i|x_t)$   
 $\mathcal{H}(j) = \mathcal{H}(j) + 1$   
**END**

Once the histogram of the target and the claimed speakers are constructed,  $\mathcal{H}_T$  and  $\mathcal{H}_C$  respectively, the comparison between them is done using the Bhattacharyya distance:

$$D(\mathcal{H}_T, \mathcal{H}_C) = -\log \sum_{i=1}^{1024} \sqrt{\mathcal{H}_T(i) \cdot \mathcal{H}_C(i)} \quad (12)$$

The computed distance  $D(\mathcal{H}_T, \mathcal{H}_C)$  is then used to make a decision about the acceptance or the rejection of the claimed speaker. The obtained results of the performed experiments, while varying the amount of training and testing speech data, are shown in Table 1.

Table 1. The obtained EERs using several amount of training and testing speech data.

		Amount of Enrollment Speech Data		
		20 seconds	40 seconds	60 seconds
Amount of Testing Speech Data	4 seconds	6.38	5.90	4.64
	8 seconds	5.86	5.31	3.98

First and foremost, as it can be seen from Table 1, the obtained results are highly encouraging. The lower obtained equal error rates, based only on the difference in hidden acoustic classes between speakers, reflect a great difference in those hidden acoustic classes between speakers. Additionally, it appears that each increase in the amount of training or testing speech data is translated into better verification performance. This proportional relationship between the amounts of speech data and the performance of the system reflects the fact that the overall acoustic classes of a speaker cannot be assembled in its pronunciation of one or two utterances.

#### 4.3. Assessment of the Proposed GMM-PBM Approach Compared to the Traditional GMM-UBM Approach

The performed experiments in this section attempt to assess the performance of the proposed GMM-PBM based speaker modeling approach, compared to the traditional GMM-UBM based approach. Hence, various experiments were carried out using the two approaches while varying the amount of training and testing speech data. The obtained results are illustrated in Figure 6.

The experimental results show, across the various amounts of training and testing speech data that our proposed approach has achieved a better verification performance compared to the traditional UBM based approach. Even in little amounts of training speech data, where the speaker's acoustic classes may not be all present, our proposed approach demonstrates its enhanced verification performance as compared with the UBM based approach. Furthermore, we can see that the obtained performance under the UBM based system using test utterances of 8 seconds was obtained under our proposed PBM based system using test utterances of only 4 seconds. Moreover, it can be seen that the relative error reduction was doubled when we have doubled the amount of testing utterances.

In addition to its performance advantage, the proposed approach can significantly reduce the CPU time required for speaker verification during the testing phase of the system compared to the traditional system, see Figure 7. In fact, the derivation of speakers' models from personalized background models reduces the order of their adapted models, which consequently, reduces their storage and computational costs.

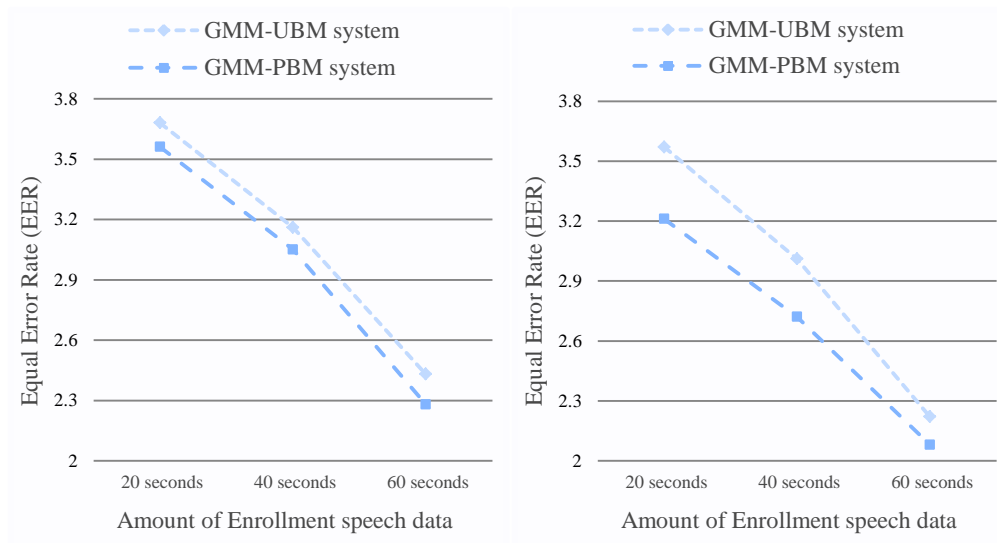


Figure 6. The obtained Equal Error Rates using test utterances of 4 seconds (left figure) and 8 seconds (right figure)

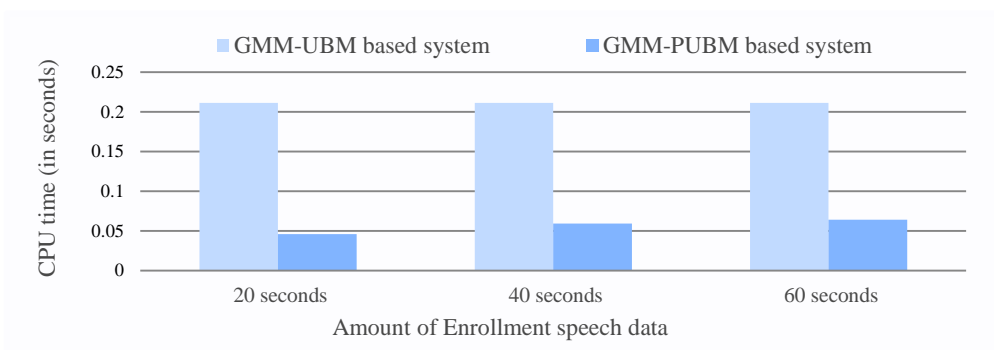


Figure 7. CPU time required for speaker verification using the UBM based approach and the PBM based approach

## 5. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

The aim of the present study was two-fold. The first aim was to investigate the degree of difference in hidden acoustic-classes between speakers. The second aim was to propose a novel speaker modeling approach that exploits this difference to improve the performance of speaker recognition systems. The findings of the study revealed that there is a great difference in hidden acoustic classes between speakers. Additionally, the evaluation of the proposed approach demonstrates its efficiency in terms of both verification performance and computational cost during the verification phase of the system, compared to the traditional approach. Future research will concentrate on applying the proposed approach within the hybrid GMM-SVM and the i-vectors based systems.

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