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Research Article

The Likelihood Ratio Decision Criterion for Nuisance Attribute Projection in GMM Speaker Verification

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We propose a way of integrating likelihood ratio (LR) decision criterion with nuisance attribute projection (NAP) for Gaussian mixture model- (GMM-) based speaker verification. The experiments on the core test of the NIST speaker recognition evaluation (SRE) 2005 data show that the performance of the proposed approach is comparable to that of the standard approach of NAP which uses support vector machines (SVMs) as a decision criterion. Furthermore, we demonstrate that the two criteria provide complementary information that can significantly improve the verification performance if a score-level fusion of both approaches is carried out.

1. INTRODUCTION

The basic problem in speaker recognition can be formulated like this. Given two speech recordings, decide whether they belong to the same speaker or they belong to two different speakers. Putting it another way, our task is to decide whether the differences between the recordings (i.e., the intersession variability) are better attributable to the interspeaker variability or to the intraspeaker variability. Intraspeaker variability refers to all the phenomena that cause different recordings of the same speaker to sound different from each other. Usually this can be attributed mostly to channel effects, although some other factors (e.g., the aging phenomenon, the state of health and mind as well as text dependency) can play an important role.

The problem of channel variability is especially apparent during telephone speech, where there are different transmission channels and different handset types involved. Performance degradation due to channel variability has been clearly demonstrated during a few previous NIST speaker recognition evaluations [1].

Many methods have been proposed to tackle the problem of channel variability. Based on their application domain, they can be categorized into three groups: feature-domain [2–5], model-domain [6–9], and score-domain [10, 11]. Since no individual method is capable of completely removing the channel effects, it is common practice to combine a number of different methods together.

Recently, eigenchannel analysis (or its more advanced counterpart, joint factor analysis) and nuisance attribute projection (NAP) have become especially popular among the model-based methods [12–15]. The main reason for their widespread adoption is that they are both unsupervised and they treat channel effects as continuous rather then discrete and thus do not require a special preprocessing step for channel detection, which is the case for other methods.

Although the key algorithm of both methods is formulated as an eigenvalue problem, their implementation and usage differ significantly. While the first one was designed to be used in combination with a decision criterion based on the likelihood ratio (LR) statistics, the other was originally designed to work with a criterion based on the support vector machines (SVMs). In this work, we point out that there is no real reason for such a distinction, since both methods can be used with both LR-based and SVM-based decision criteria. To prove our case, we propose three different variants of integrating the NAP approach with the LR-based decision criterion.

In this work, we do not deal with eigenchannel analysis, rather we focus exclusively on nuisance attribute projection.

Using the NIST 2005 data set, we compare the performance of discriminative (SVM-based) and generative (LR-based) decision criteria in combination with NAP-based channel variability compensation. We found that both criteria exhibit comparable performance, and more importantly that the overall performance can be further improved if we carry out the score-level fusion of both approaches.

The remainder of this paper is organized as follows. In Section 2, a brief introduction to GMM-based speaker verification is presented. In Section 3, a short review of NAP-based session variability modeling is given. In Section 4, the LR and SVM decision criteria are presented, and we describe how they give rise to different implementations of NAP. In Section 5, experimental results on the core test of the NIST SRE 2005 [16] are presented and analyzed. In the last section, conclusions are given and directions for further research are suggested.

2. GMM-BASED SPEAKER VERIFICATION

Although there has recently been some success reported with methods for text-independent speaker recognition that try to exploit the high-level information (e.g., prosody) embraced in the speech signal, their performance is still inferior to that of the methods which are based on the low-level acoustic properties of the speech signal [17–19]. Most of these acoustic-based methods that perform well are based on Gaussian mixture modeling (GMM) of the cepstral features. Here, we will give a brief overview of the main steps involved in GMM-based speaker verification.

The main assumption in GMM-based speaker verification is that each speaker can be represented as a weighted sum (mixture) of K multivariate diagonal covariance Gaussian densities, defined over a D-dimensional feature space (The number of Gaussians is typically 512 or 2048.):

$$p(\mathbf{x}) = \sum_{k=1}^{K} \pi_k \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}_\mathbf{k}, \boldsymbol{\Sigma}_\mathbf{k}). \tag{1}$$

Since only a limited amount of the target speaker's data is available in practice, the maximum likelihood (ML) estimation of the parameters of the speaker model would lead to overfitting. A better way would be to use a speaker-independent GMM—usually referred as a *universal background model* (UBM)—and estimate the parameters of the target speaker model by means of *maximum a posteriori* (MAP) adaptation [20].

Although, in general, all the parameters (i.e., weights, mean vectors, and covariance matrices) could be adapted, experiments show that it is better to adapt only the mean vectors, while keeping the weights and covariance matrices constant [21].

An important consequence of the UBM approach is that it induces a strict ordering of the Gaussian mixture components in the speaker models. This allows us to concatenate the components' mean vectors into one composite vector—*supervector*.

3. NUISANCE ATTRIBUTE PROJECTION APPROACH TO SESSION VARIABILITY COMPENSATION

3.1. Relevance maximum a posteriori

In order to explain the NAP approach to session variability compensation, it is worthwhile to look first at the MAP algorithm, which is used for deriving the speaker models from the UBM. Since we are not adapting weights and covariance matrices, it is sufficient to specify a prior distribution only for the mean vectors, which takes the following form:

$$\mathbf{m}_k(s) = \mathbf{m}_k + \mathbf{d}_k \mathbf{z}_k(s), \quad k = 1, \dots, K, \tag{2}$$

where $\mathbf{m}_k$ is a speaker-independent mean vector of the kth mixture component, $\mathbf{d}_k$ is a $D \times D$ diagonal matrix, and $\mathbf{z}_k(s)$ is a speaker-dependent random vector with a standard normal distribution, which implies that $\mathbf{m}_k(s)$ is distributed normally with a mean $\mathbf{m}_k$ and a diagonal covariance $\mathbf{d}_k^2$.

Given the training data $\mathbf{X}(s) = \{\mathbf{x}_1(s), \dots, \mathbf{x}_T(s)\}$ for the target speaker s, we are able to derive a MAP estimate of the vector $\mathbf{m}_k(s)$, which is given by

$$E[\mathbf{m}_k(s)] = \mathbf{m}_k + \left(\mathbf{I} + \mathbf{d}_k^2 \boldsymbol{\Sigma}_k^{-1} N_k\right)^{-1} \mathbf{d}_k^2 \boldsymbol{\Sigma}_k^{-1} (\mathbf{F}_k - N_k \mathbf{m}_k), \tag{3}$$

where the statistics N_k and $\mathbf{F}_k$ are computed in the E-step of the EM algorithm using the following relations:

$$\begin{aligned} N_k &= \sum_{t=1}^{T} \gamma_{k,t}, \\ \mathbf{F}_k &= \sum_{t=1}^{T} \gamma_{k,t} \mathbf{x}_t(s), \end{aligned} \tag{4}$$

where $\gamma_{k,t}$ is the responsibility of the mixture component k for generating the observation $\mathbf{x}_t(s)$.

Although matrix $\mathbf{d}_k$ can be estimated from the data [22] itself, it is usually assumed to be related to $\boldsymbol{\Sigma}_k^{-1}$ by an equation of the form $\mathbf{d}_k^2 = \tau^{-1} \boldsymbol{\Sigma}_k$. The constant τ is known as a relevance factor and is chosen empirically, typically in the range between 8 and 16 [21].

The MAP estimate of the vectors $\mathbf{m}_k(s)$ should ideally be identical (or sufficiently similar at least) for different recordings of the same speaker. Unfortunately, this is not the case, since we know that different channels cause the same speaker to sound different from one recording to another. Nevertheless, it turns out that it is possible to compensate (to some extent) for the channel effects if we make some minor assumptions about the channel.

3.2. Nuisance attribute projection

The problem that we want to address is, how to decompose, for a given recording, the speaker- and channel-dependent supervector $\mathbf{M}$, obtained by a MAP adaptation of the UBM (3), to the speaker-dependent supervector $\mathbf{S}$ and the channel-dependent supervector $\mathbf{C}$:

$$\mathbf{M} - \mathbf{M}_0 = \mathbf{S} + \mathbf{C}, \tag{5}$$

where the offset $\mathbf{M}_0$ corresponds to the supervector representation of the UBM.

The linear model of (5) states that perturbations of the background model can be split linearly into a speaker-dependent and a channel-dependent parts. Although this linear assumption plays the central role in most well-performing models of channel variability [5, 7, 9, 14], an explicit evidence for its validity has not yet been presented.

In order to present the arguments for the linearity in (5), it helps to consider the channel effects as noise, which is being convolutionally mixed with speech in the signal domain. Since convolution in the signal domain becomes addition in the cepstrum domain, the cepstral feature vectors consist of a sum of speech and noise (channel). If we further treat speech and channel as two independent random variables, each of them being distributed according to a (finite) mixture of Gaussians (MoGs), it follows (see the appendix) that their sum is also distributed as a MoG. Moreover, each mean of this MoG equals the sum of two means, one coming from the speech MoG and the other from the channel MoG.

Note, however, that although the number of Gaussian components in the sum will be $M \cdot N$, where M and N are numbers of components of the speech and channel GMM's, respectively, not all of the components will be observed—due to a finite duration—for a specific recording. Fortunately, this hindrance can be avoided by incorporating prior knowledge while inferring the parameters of the GMM (i.e., Bayesian learning, MAP adaptation).

To be able to carry out the decomposition, it turns out that we have to confine the channel-dependent supervector to lie in a low-dimensional subspace. This requirement seems reasonable, since the channel should not be able to transform one speaker into another, otherwise speaker recognition would be an ill-posed problem. In fact, some evidence has been presented [23] which indicates that the channel covariance matrix is indeed of low rank.

If we assume that the channel variability is constrained to a low-dimensional subspace (given by the matrix $\mathbf{U}$) of a supervector space and that the channel space and speaker space intersect only at the origin, then we are able to estimate the channel component $\mathbf{C}$ simply by centering the speaker- and channel-dependent supervector $\mathbf{M}$, projecting it onto the channel subspace, and finally projecting the resulting supervector from the channel subspace back to the original supervector space:

$$\mathbf{C} = \mathbf{U}\mathbf{U}^{*}\left(\mathbf{M} - \mathbf{M}_0\right). \tag{6}$$

By knowing the channel $\mathbf{C}$, retrieving the speaker component $\mathbf{S}$ is as simple as rearranging (5).

Since they were found in the cepstral domain, the projection of supervectors can be alternatively seen as a filtering operation—so, projecting the supervector into the speaker-subspace means that certain kinds of (speaker-dependent) filtering will be allowed, while other kinds of (channel-dependent) filtering will be suppressed.

The NAP approach is illustrated in Figure 1.

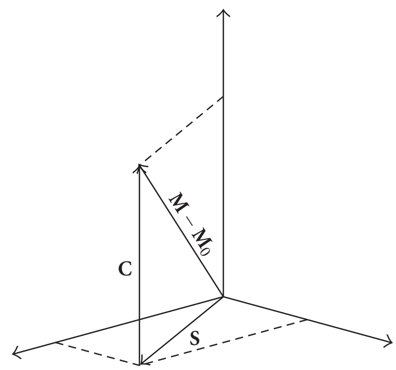


Figure 1: Schematic illustration of the NAP technique in a 3-dimensional supervector space. The speaker- and channel-dependent supervector $\mathbf{M}$ can be written as the sum of two supervectors, one of which ($\mathbf{S}$) lies in the speaker space and the other ($\mathbf{C}$) lies in the channel space.

3.3. Channel subspace estimation

In contrast to the diagonal matrix $\mathbf{d}_k$, the channel subspace matrix $\mathbf{U}$ has to be estimated from the data. The only requirement is that we have a sufficiently large database with multiple recordings available for each speaker. The steps needed to estimate the channel subspace matrix can be summarized with the following algorithm.

(i) For each recording, estimate a speaker- and channel-dependent supervector (see (3)).

(ii) Compute the mean supervector of each speaker by averaging the supervectors from all the recordings of that speaker. This averaging process will effectively filter out (at least if the number of recordings is sufficiently large) the channel component, since it is assumed to be zero-mean distributed.

(iii) Calculate the channel component of each recording by subtracting the corresponding mean supervector.

(iv) Use the principal component analysis (PCA) technique to estimate the first n largest eigenvalues and the corresponding eigenvectors from the covariance matrix of the channel supervectors.

Since the dimension of the supervectors can be very large, a straightforward PCA decomposition will not work in practice. A simple solution, popularized by Turk and Pentland [24], is based on the fact that the nonzero-valued eigenvalues of the matrix product AA^T are the same as those of the product A^TA. Yet another alternative would be to use the probabilistic variant of the PCA algorithm [25].

3.4. Relation to joint factor analysis

Although joint factor analysis and NAP are based on the same assumptions, there is an important difference between them. While NAP needs to explicitly calculate the channel- and speaker-dependent supervectors and uses a purely algebraic approach to derive the matrix $\mathbf{U}$, and later to project out the channel component, the joint factor analysis treats the channel and speaker supervectors as hidden variables and derives a special ML algorithm to estimate the matrix $\mathbf{U}$ (and possibly also other hyper-parameters) from their posterior distributions (instead of point estimates).

Although joint factor analysis is evidently theoretically more advanced than NAP, its drawback is that it is computationally more demanding and it is harder to implement. Since it is based on a probabilistic approach, it can only be applied to GMM-based speaker recognition. On the other hand, NAP is easier to implement and has a broader scope of applications, as demonstrated recently by the impressive performance of NAP in the context of the maximum likelihood linear regression (MLLR) approach to speaker recognition [14], and even in high-level speaker recognition [17].

4. DECISION CRITERIA

Many different classifiers can in principle be used for making the decision for or against the hypothesis that the speaker in the test utterance is the same as the speaker in the training utterance. However, the most common and successful for speaker verification have been LR and SVMs, which will be presented in the following subsections. Note that only the basic concepts of SVMs will be described; for a more general treatment see [26].

4.1. The LR-based decision criterion

If the decision criterion is based on the likelihood ratio, then the verification score is calculated as (In practice, the likelihood ratio is computed in the log domain for numerical reasons. Moreover, the score should be appropriately normalized to compensate for the different lengths T of the feature vector sequences.)

$$\frac{p(\mathbf{X}|\Lambda_s)}{p(\mathbf{X}|\Lambda_0)}, \tag{7}$$

where $\mathbf{X}$ is a feature vector sequence of length T, representing the test utterance, while Λ_s and Λ_0 denote the parameters (weights, mean vectors, and covariance matrices) of the speaker model (estimated from the training utterance) and UBM, respectively.

4.2. The SVM-based decision criterion

An SVM is a two-class classifier, based on the concept of the maximum margin. It can be expressed as a separating hyperplane given by

$$f(\mathbf{x}) = \sum_{i=1}^{N} \alpha_i y_i K(\mathbf{x}, \mathbf{x}_i) + b, \tag{8}$$

within the constraints $\sum_{i=1}^{N} \alpha_i y_i = 0$ and $\alpha_i > 0$. The y_i are target values (either -1 or 1, depending on which class the corresponding support vector $\mathbf{x}_i$ comes from). The function K is called the kernel, and it has to obey Mercer's condition. A class decision for vector $\mathbf{x}$ is based on whether the value $f(\mathbf{x})$ is above or below a given threshold.

Although SVMs were originally applicable only to fixed-length data (i.e., vectors), they were later extended to work also with variable-length data in a straightforward way through the use of sequence kernels. The sequence kernel can be defined as

$$K(\mathbf{X}, \mathbf{Y}) = \Phi(\mathbf{X})^* \mathbf{R}^{-1} \Phi(\mathbf{Y}), \tag{9}$$

where $\Phi(\mathbf{X})$ and $\Phi(\mathbf{Y})$ are high-dimensional vector representations of the sequences $\mathbf{X}$ and $\mathbf{Y}$, respectively, and $\mathbf{R}$ is a diagonal matrix. Note that the "kernel trick" is redundant, since the sequence expansion is done explicitly. Moreover, if each vector $\Phi(\mathbf{X})$ is multiplied by $\mathbf{R}^{-1/2}$, a linear SVM is obtained. As a consequence, an SVM model can be represented in a compact form [27], which enables a rapid evaluation of the value $f(\mathbf{X})$.

Two popular sequence kernels for speaker verification are the generalized linear discriminant sequence kernel [27] and the GMM supervector kernel [28]. We will focus on the latter.

The GMM training described in the previous section can be seen as an expansion of a sequence of cepstral vectors into a GMM. A natural choice for a distance between GMMs would be the Kullback-Leibler (KL) divergence. Unfortunately, the KL divergence does not obey the Mercer's condition and there exists no closed-form solution for calculating the KL divergence between GMMs. So instead of using the KL divergence directly, we consider its upper bound [29], which satisfies the Mercer's condition. The diagonal entries of the matrix $\mathbf{R}^{-1}$ are, in this case, given by $\pi_k \mathbf{\Sigma}_k^{-1}$, where π_k are the mixture weights and $\mathbf{\Sigma}_k$ are the covariance matrices of the UBM.

4.3. Combining NAP with LR and SVMs

While there have been different variants of LR-based classification strategies proposed, which naturally arise from the joint factor analysis model [23] for speaker verification, the NAP approach has been limited to the SVM-based decision criterion [9, 30]. The reason for this discrepancy comes from the fact that the LR criterion is asymmetric in the sense that only the training utterance is used to estimate the speaker model (supervector), while the SVM criterion is symmetric since both the training and the test utterance are "expanded" to supervectors.

We see that NAP suits well the SVM criterion, since both the training and the test supervectors can be compensated in the same way by simply projecting out the channel component of each supervector (see (7)).

However, the same approach is not feasible in the case of the LR criterion. Although the channel compensation can be made for the training model by first converting the GMM to a supervector, projecting out the channel component in the supervector space, and converting the resulting supervector back to a (channel-independent) GMM, this would only be a partial solution, since the test utterance would, in this case, remain uncompensated. Therefore, a different strategy is needed if we want to perform the compensation for both the training and the test utterances. We will now describe three methods for doing this.

4.3.1. *Feature space channel compensation*

The solution of transforming features to compensate for the channel mismatch between the training and test utterances (in the context of GMM-based speaker recognition) became known as feature mapping [5]. Recently, a very similar approach has been proposed by Castaldo et al. [15] for the eigenchannels, which can be adapted to the NAP approach in a straightforward way.

In the first step, the channel component $\mathbf{C}$ of the utterance is detected by projecting the centered supervector $\mathbf{M}$ to the channel subspace (see (6)). In the second step, this channel supervector is used to transform each feature vector $\mathbf{x}_t$ using the following formula:

$$\hat{\mathbf{x}}_t = \mathbf{x}_t - \sum_{k=1}^{K} \gamma_{k,t}\mathbf{c}_k, \qquad (10)$$

where $\gamma_{k,t}$ is the posterior probability (responsibility) that the observation $\mathbf{x}_t$ was generated by the kth mixture component and $\mathbf{c}_k$ is part of the supervector $\mathbf{C}$ that corresponds to the kth mixture component.

In this way, we are able to compensate for both the training and test utterances prior to training the target speaker model and calculating the LR score.

An important property of the feature space channel compensation is that it can be regarded as a (front-end) preprocessing step and is therefore independent of the application and the classifier. For example, a similar feature space compensation method was recently used in a speech recognition task [31].

4.3.2. *Asymmetric channel compensation*

Another possibility is to normalize the training utterance in the same way as in the SVM case, and to normalize the test utterance in the feature space. A similar strategy was proposed recently for the eigenchannel approach [13].

4.3.3. *Model space channel compensation*

We propose another alternative where both the training and test utterances are normalized in the model space. The idea is to transform the channel component of the training supervector $\mathbf{M}$ from the training channel $\mathbf{C}$ to the test channel $\mathbf{C}_t$, using the following equation:

$$\mathbf{M}' = \mathbf{M} - (\mathbf{C} - \mathbf{C}_t) = \mathbf{M}_0 + \mathbf{S} + \mathbf{C}_t. \qquad (11)$$

The resulting supervector $\mathbf{M}'$ is converted back to GMM space and then used for calculating the nominator of the LR (see (8)).

Since the UBM, which is used for calculating the denominator of the LR, is inherently channel-neutral, (The channel component has been averaged out in the training process because the UBM is trained from a large number of different speakers recorded in many different channel conditions.) it is important to adapt the UBM in a similar fashion in order to avoid any bias towards positive LR scores. Note, however, that the normalization of the UBM is not necessary when a t-norm score normalization is applied, since the denominator of (7), in this case, effectively drops out.

Observe that only the speaker component of the training signal is required, while the channel component is discarded. On the other hand, the speaker component of the test signal is discarded, while the channel component is needed to adapt the training speaker supervector to the test conditions. Since this is very similar to the idea of the standard eigenchannel approach and is also more straightforward to implement than the other two alternatives, we have decided to use the model-space variant of the channel compensation algorithm in our experiments.

5. EXPERIMENTS

We carried out the verification experiments on the core condition (1conv4w-1conv4w) of the NIST 2005 speaker recognition evaluation (SRE) [16]. This evaluation set consists of 636 target speakers (372 females, 264 males) and 31418 test trials (2771 target trials, 28647 impostor trials). For each target speaker, there is a 5-minute-long recording available, containing roughly 2 minutes of speech. Note that in order to obey the rules of the NIST protocol, each trial must be processed independently of all the others.

5.1. *System configuration*

We used a (gender-dependent) UBM that contained 512 Gaussians, trained on the data collected from different data sets (Switchboard-II Phase 3, Switchboard Cellular I, Switchboard Cellular II, NIST SRE 2004, and NIST SRE 2005). The amount of data used from the individual databases is summarized in Table 1. The features were standard MFCCs (12 + log-energy, appended with their deltas), extracted every 10 milliseconds from a 25-millisecond-long windowed speech signal, using the HTK toolkit [32]. Feature warping [2] with a 3-second-long sliding window was also applied, as suggested in [7], where a strong synergy between feature warping and channel compensation was reported, although a mean-variance normalization would probably have a similar impact on the system's performance. To remove the silence (nonspeech) frames, a simple three-Gaussians energy-based speech detector was employed [33], retaining, on average, around one-third of the frames per recording.

The channel matrix $\mathbf{U}$ was estimated using the algorithm described in Section 3.3. The training data was extracted from the NIST 2004 SRE collection. It consisted of all the recordings of those speakers that were recorded in at least eight different sessions. Altogether, there were 184-female and 121-male speakers present in 4551 recordings (see Table 1). The rank of the channel matrix was chosen empirically and remained fixed (at 40) throughout the experiments.

Note that in contrast to the LR-based verification another data set is needed for training the target speaker models in the case of the SVM-based approach. This background data set was selected as a subset of the data used for training the UBM and the channel subspace. As a consequence, a fair comparison between the SVM-based and LR-based systems was possible since the same data was used for training both systems.

Table 1: Development data sets used in the experiments. The figures in the table correspond to the number of conversation sides from the data sets that were used in different tasks.

Task/data set	SWB2P3	SWBCELL1	SWBCELL2	SRE-04	Overall
UBM	2324/2631	1165/1023	1635/2013	1895/2656	7019/8323
Channel subspace				1895/2656	1895/2656
Background				1895/2656	1895/2656
z-norm	100/100	100/100	100/100		300/300
t-norm	100/100	100/100	100/100		300/300

5.2. Score normalization

The main idea of many score-normalization methods (see [10] for an overview) is to linearly transform each score s (produced by comparing the client model with the test recording) according to the following equation:

$$s_n = \frac{s - \mu}{\sigma}, \tag{12}$$

where the parameters μ and σ can be estimated either from the client model (z-norm) or the test recording (t-norm).

Since both techniques can be easily combined by successively applying z-norm and t-norm (in that order), we considered also zt-norm in our experiments.

5.3. Performance metrics

Speaker-verification systems are susceptible to two type of errors—rejection of the true speaker (false rejection; miss) and acceptance of the impostor speaker (false acceptance; false alarm). The two errors are coupled in a way such that if one wants to achieve low false rejection rate, this inevitably increases the false acceptance rate (and vice versa). To see the relation between the two errors explicitly, we usually draw either receiver operating characteristic (ROC) curve or its variant, detection error tradeoff (DET) curve [34].

Accuracy of speaker-verification systems is usually measured in terms of equal error rate (EER), which is the point on the DET curve where the two errors are equal. An additional performance metric, preferred by NIST, is detection cost function (DCF), which is the (minimal) weighted sum of the two errors [16].

5.4. Results and analysis

We present the results for the core condition (all trials) of the NIST SRE 2005 for the "uncompensated" baseline system and for the system where NAP-based channel compensation was performed. Two different decision criteria (SVM-based and LR-based) were applied to each of the systems. While the standard (symmetric) NAP algorithm was used for the channel compensation of the SVM-based system, the model-space variant (Section 4.3.3) of the NAP algorithm was used in the case of LR-based system. The reasons for choosing the latter are discussed in the last paragraph of Section 4.3.3.

The impact of the channel compensation on the two-decision criteria was analyzed, and the effect of different types of score normalization (namely, z-norm, t-norm, and zt-norm) on systems' performance was compared.

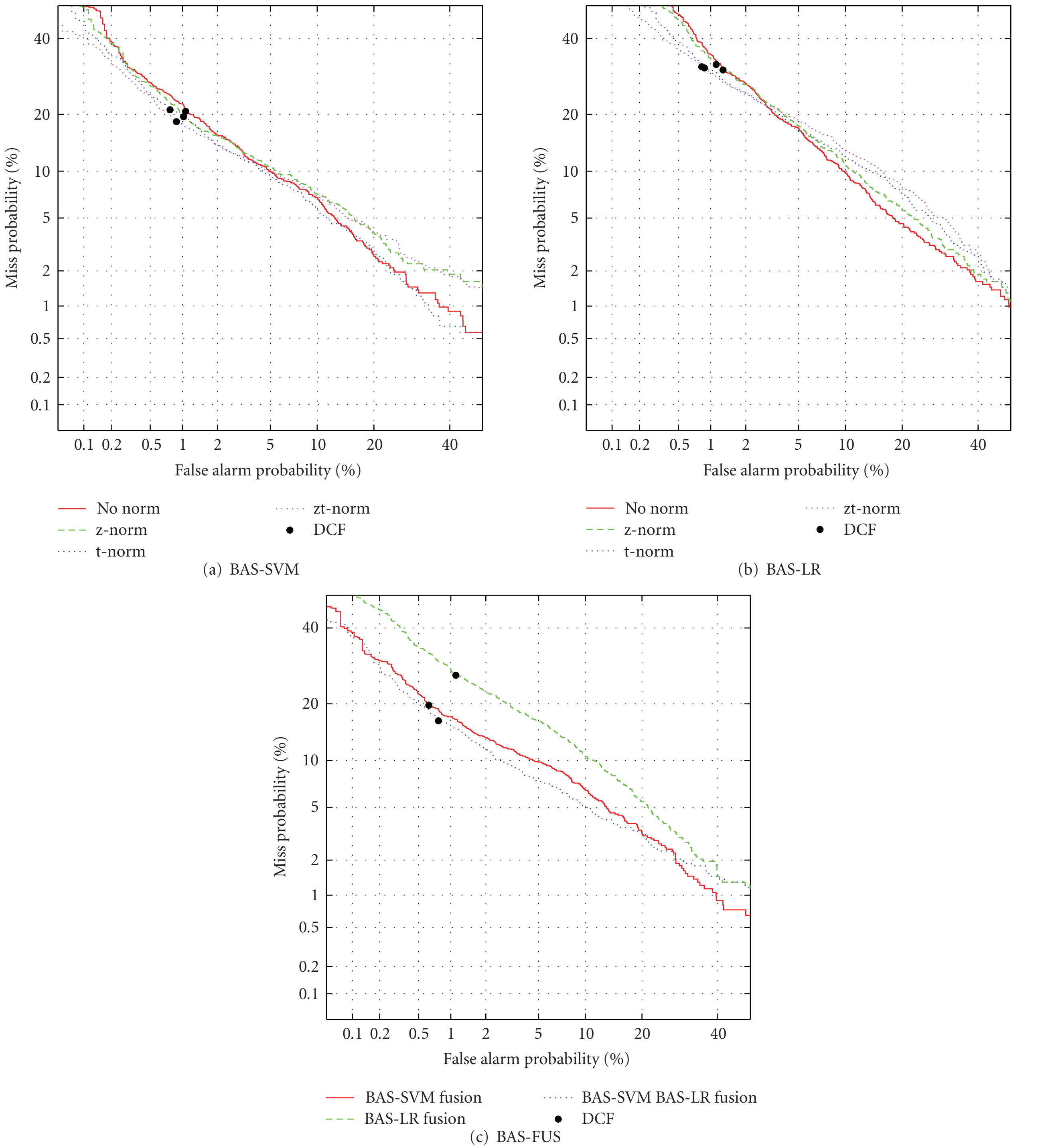
5.4.1. Effect of score normalization

The most evident observation from the DET curves in Figures 2 and 3 is that score normalization rotates the DET curve counterclockwise. This effectively means that normalization is always beneficial for the DCF point, but it can be detrimental for the EER point. However, the rotation is more evident for the LR-based systems, especially if they are combined with channel compensation (see Figure 3(b)). This could lead to the conclusion that channel normalization tends to produce scores that are more diverse (comparing to the scores produced by systems that do not use channel normalization). This agrees with the findings presented in [7], where a similar synergy between the joint factor analysis and the zt-norm was observed.

On the other hand, the different sensitivity to score-normalization for LR- and SVM-based systems (compare Figures 3(a) and 3(b)) could be explained by hypothesizing that the SVMs are inherently capable of performing score-normalization to some degree already by themselves.

5.4.2. Effect of channel compensation

By comparing the performance of the BAS (see Figure 2, Table 2) and NAP (see Figure 3, Table 3) systems, it is evident that the channel compensation is crucial for achieving high performance. However, the impact of channel compensation is not the same for the LR and SVM systems. We can see that in the case of the SVM decision criterion, the EER drops from 7.5% (t-norm) to 6.1% (t-norm, zt-norm) and DCF drops from 0.027 (zt-norm) to 0.021 (t-norm, zt-norm), while on the other hand, in the case of the LR criterion, the EER drops from 9.9% (no score normalization) to 6.4% (no score normalization, z-norm) and the DCF drops from 0.040 (t-norm, zt-norm) to 0.021 (zt-norm). The reason for greater impact of channel compensation on the performance of the LR-based systems can be due to the discriminative nature of the SVMs, which enables them to perform channel compensation (as previously hypothesized also for score-normalization) to some extent by themselves. This can be seen by noting that SVMs tend to orient the separating hyperplane approximately perpendicular to the subspace spanned by the background supervectors. Since background supervectors contain speaker variability as well as channel variability, this effectively means that projecting the test supervector to the hyperplane helps to "filter" out the channel effects.



(a) BAS-SVM

(b) BAS-LR

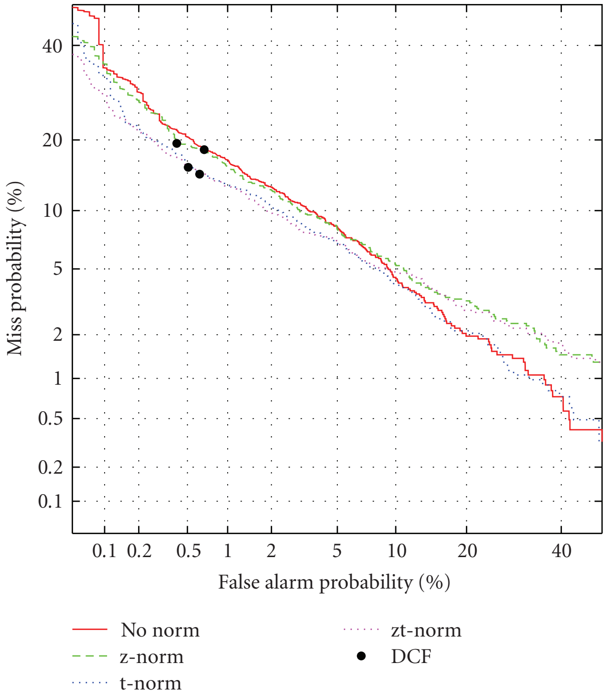
(c) BAS-FUS

Figure 2: Speaker verification results of the baseline (BAS) systems. The DET curves for (a) the SVM and (b) LR decision criteria as well as (c) their fusion are shown. The black circle on each DET curve represents the DCF point.

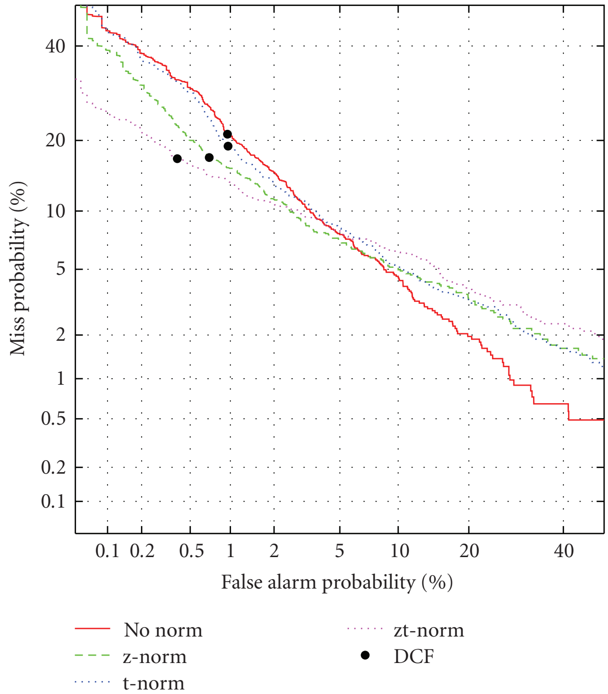
5.4.3. Fusion of LR and SVM systems

Although the idea of fusing similar classifiers into a better one is not new (see, e.g., [35]), it has not been extensively used for speaker-verification. Most of speaker-verification systems that make use of score-level fusion rely on combining scores from highly heterogeneous systems [36]. Therefor, we found it interesting to explore to what extent can we improve the results by fusing scores that come from almost identical systems, trained on the same data, which differ only in one detail, that is, the decision criterion.

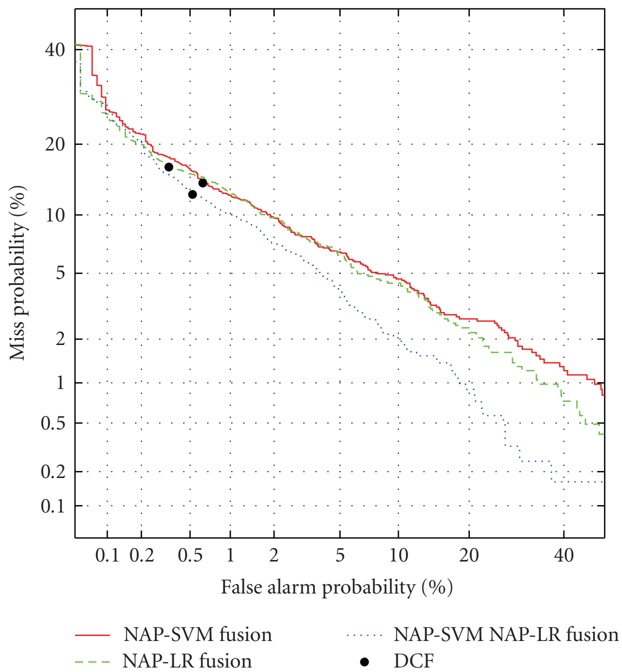
To answer this question, we carried out a score-level fusion of the LR- and SVM-based systems. (We included all the scores produced by different score-normalization



(a) NAP-SVM



(b) NAP-LR



(c) NAP-FUS

FIGURE 3: Speaker verification results of the NAP-based systems. The DET curves for (a) the SVM and (b) LR decision criteria as well as (c) their fusion are shown. The black circle on each DET curve represents the DCF point.

methods in the fusion.) We performed a weighted linear fusion using linear logistic regression [37], as implemented in the FoCal toolkit [38]. Although it can be seen (see Figures 2(c), 3(c)) that the fusion of different score normalization methods helps on its own, the results clearly show that the generative and discriminative decision criteria indeed introduce complementary information that significantly improves the verification performance in terms of the DCF and especially in terms of the EER, which (for the fusion of NAP systems) drops from 0.020 to 0.018 (10% relatively) and from 5.6% to 4.5% (20% relatively) in terms of the EER and DCF, respectively.

Table 2: Speaker verification results of the baseline (BAS) systems. The EER and DCF figures for (a) the SVM and (b) LR decision criteria as well as (c) their fusion are given.

(a) BAS-SVM

Norm. type	EER	DCF
—	7.8	0.031
t-norm	7.5	0.029
z-norm	8.3	0.030
zt-norm	8.1	0.027

(b) BAS-LR

Norm. type	EER	DCF
—	9.9	0.044
t-norm	11.2	0.040
z-norm	10.4	0.043
zt-norm	12.0	0.040

(c) BAS-FUS

Fusion	EER	DCF
LR	10.3	0.038
SVM	8.0	0.026
LR + SVM	6.7	0.024

Table 3: Speaker verification results of the NAP-based systems. The EER and DCF figures for (a) the SVM and (b) LR decision criteria as well as (c) their fusion are given.

(a) NAP-SVM

Norm. type	EER	DCF
—	6.7	0.025
t-norm	6.1	0.021
z-norm	6.8	0.023
zt-norm	6.1	0.021

(b) NAP-LR

Norm. type	EER	DCF
—	6.4	0.031
t-norm	6.8	0.029
z-norm	6.4	0.024
zt-norm	7.1	0.021

(c) NAP-FUS

Fusion	EER	DCF
LR	5.6	0.020
SVM	5.9	0.020
LR + SVM	4.5	0.018

6. CONCLUSION

We have proposed a novel way of integrating the NAP approach to channel compensation, which was previously limited to an SVM-based decision criterion, with a LR decision criterion for the speaker verification task.

Experimental results on the core test of the NIST 2005 SRE have shown that the performance of the proposed approach is comparable to the standard approach that uses SVM-based decision criterion. However, we have found out that both approaches respond differently to score normalization. It turns out that score normalization (especially zt-norm) is much more effective for LR than for SVM decision criterion. The apparent reasons for this discrepancy have been presented in Section 5.4.

The proposed approach provides an attractive alternative to the more general approach of joint factor analysis [22], which is computationally more expensive and harder to implement. Additionally, the PCA-based NAP algorithm, described in Section 3.3, can be easily substituted with some other method for subspace estimation, for example, independent component analysis (ICA), linear discriminant analysis (LDA), or even their nonlinear variants [39, 40]. However, the effectiveness of those methods is yet to be explored.

A further important contribution of this paper is that we confirmed that generative (LR) and discriminative (SVM) decision criteria introduce complementary information, which can significantly improve the performance of speaker verification by fusing the scores from both criteria.

APPENDIX

A. SUM OF TWO INDEPENDENT RANDOM VARIABLES

Lemma 1. *If the p.d.f. of the multivariate random variable X is given by $f_X(x) = \sum_{n=1}^{N}\sigma_n\mathcal{N}(x|\mu_n,\Sigma_n)$, then its characteristic function equals $\varphi_X(t) = \sum_{n=1}^{N}\sigma_n\exp(i\mu_n^T t - (1/2)t^T\Sigma_n t)$.*

Proof. The characteristic function of a multivariate random variable is defined by $\varphi_X(t) = E[\exp(it^T X)]$, thus

$$\varphi_X(t) = \int_{x\in\mathcal{R}^d}\left(\sum_{n=1}^{N}\sigma_n\mathcal{N}(x|\mu_n,\Sigma_n)\right)\exp\left(it^T x\right)\mathrm{d}x. \tag{A.1}$$

By linearity, we are allowed to change the order of summation and integration:

$$\varphi_X(t) = \sum_{n=1}^{N}\sigma_n\int_{x\in\mathcal{R}^d}\mathcal{N}(x|\mu_n,\Sigma_n)\exp\left(it^T x\right)\mathrm{d}x. \tag{A.2}$$

Solving the integral, we get the required result. □

Theorem 1. *Let X and Y be d-variate independent r.v.'s. If their p.d.f.'s are given by $f_X(x) = \sum_{n=1}^{N}\sigma_n\mathcal{N}(x|\mu_n,\Sigma_n)$ and $f_Y(y) = \sum_{m=1}^{M}\omega_m\mathcal{N}(y|\nu_m,\Omega_m)$, respectively, then the distribution of the sum $Z = X + Y$ is given by*

$$f_Z(z) = \sum_{n=1}^{N}\sum_{m=1}^{M}\sigma_n\omega_m\mathcal{N}(z|\mu_n+\nu_m,\Sigma_n+\Omega_m). \tag{A.3}$$

Proof. The characteristic function of the sum of two independent (multivariate) random variables is given by the product of their characteristic functions. Therefore,

$$\varphi_Z(t) = \left(\sum_{n=1}^{N} \sigma_n \exp\left(i\mu_n^T t - \frac{1}{2} t^T \Sigma_n t\right)\right) \cdot \left(\sum_{m=1}^{M} \omega_m \exp\left(i\nu_m^T t - \frac{1}{2} t^T \Omega_m t\right)\right). \tag{A.4}$$

After rearranging, we get

$$\varphi_Z(t) = \sum_{n=1}^{N} \sum_{m=1}^{M} \sigma_n \omega_m \exp\left(i(\mu_n + \nu_m)^T t - \frac{1}{2} t^T (\Sigma_n + \Omega_m) t\right). \tag{A.5}$$

By Lemma 1, this is exactly the characteristic function of $f_Z(z)$. Since for any characteristic function there is exactly one probability distribution, the theorem is proved. □

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