Using Kernel Discriminant Analysis to Improve the Characterization of the Alternative Hypothesis for Speaker Verification

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***Abstract*—Speaker verification can be viewed as a task of modeling and testing two hypotheses: the null hypothesis and the alternative hypothesis. Since the alternative hypothesis involves unknown impostors, it is usually hard to characterize *a priori*. In this paper, we propose improving the characterization of the alternative hypothesis by designing two decision functions based, respectively, on a weighted arithmetic combination and a weighted geometric combination of discriminative information derived from a set of pretrained background models. The parameters associated with the combinations are then optimized using two kernel discriminant analysis techniques, namely, the kernel Fisher discriminant (KFD) and support vector machine (SVM). The proposed approaches have two advantages over existing methods. The first is that they embed a trainable mechanism in the decision functions. The second is that they convert variable-length utterances into fixed-dimension characteristic vectors, which are easily processed by kernel discriminant analysis. The results of speaker-verification experiments conducted on two speech corpora show that the proposed methods outperform conventional likelihood ratio-based approaches.**

***Index Terms*—Kernel Fisher Discriminant (KFD), likelihood ratio, speaker verification, support vector machine (SVM).**

I. Introduction

SPEAKER verification is usually formulated as a hypothesis testing problem and solved using a likelihood ratio (LR)-based decision function [1]. Given an input utterance U, the goal is to determine whether or not U was spoken by the target (hypothesized) speaker. Let us consider the following hypotheses:

$$\begin{aligned} H_0 &: \quad U \text{ is from the target speaker} \\ H_1 &: \quad U \text{ is not from the target speaker.} \end{aligned} \tag{1}$$

The LR-based decision function can be expressed as

$$L(U) = \frac{p(U|H_0)}{p(U|H_1)} \begin{cases} \geq \theta, & \text{accept } H_0 \\ < \theta, & \text{accept } H_1 \text{ (reject } H_0) \end{cases} \tag{2}$$

where $p(U|H_i)$, $i = 0, 1$, is the likelihood that hypothesis H_i gives the utterance U, and θ is a decision threshold. H_0 and H_1 are called the null hypothesis and the alternative hypothesis, respectively. Although H_0 can be modeled straightforwardly using speech utterances from the target speaker, H_1 does not involve any specific speaker, and thus lacks explicit data for modeling. As a result, various approaches have placed special emphasis on better characterization of H_1. One simple approach involves pooling all the speech data from a large number of background speakers, and training a single speaker-independent model Ω, called the world model or the universal background model (UBM) [1]. During a test, the logarithmic LR measure that an unknown utterance U was spoken by the claimed speaker can be evaluated by

$$L_{\mathrm{UBM}}(U) = \log p(U|\lambda) - \log p(U|\Omega) \tag{3}$$

where λ is a target speaker model trained using speech from the claimed speaker. The larger the score of $L_{\mathrm{UBM}}(U)$, the more likely it is that U was spoken by the claimed speaker.

Instead of using a single model, an alternative approach is to train a set of models $\{\lambda_1, \lambda_2, \ldots, \lambda_B\}$ using speech from several representative speakers, called a cohort [2], which simulates potential impostors. This leads to the following logarithmic LRs, where the alternative hypothesis can be characterized as follows.

1) The likelihood of the most competitive cohort model [3], i.e.,

$$L_{\mathrm{Max}}(U) = \log p(U|\lambda) - \max_{1 \leq i \leq B} \log p(U|\lambda_i). \tag{4}$$

2) The arithmetic mean of the likelihoods of the B cohort models [4], i.e.,

$$L_{\mathrm{Ari}}(U) = \log p(U|\lambda) - \log \left\{ \frac{1}{B} \sum_{i=1}^{B} p(U|\lambda_i) \right\}. \tag{5}$$

3) The geometric mean of the likelihoods of the B cohort models [3], i.e.,

$$L_{\mathrm{Geo}}(U) = \log p(U|\lambda) - \frac{1}{B} \sum_{i=1}^{B} \log p(U|\lambda_i). \tag{6}$$

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In a well-known score normalization method called T-norm [6], $L_{\mathrm{Geo}}(U)$ is divided by the standard deviation of the log-likelihoods of the B cohort models.

The LR measures in (3)–(6) can be collectively expressed in the following general form [1]:

$$L(U) = \frac{p(U|\lambda)}{\Psi\left(p(U|\lambda_1), p(U|\lambda_2), \ldots, p(U|\lambda_N)\right)} \tag{7}$$

where $\Psi(\cdot)$ represents a certain function that combines the likelihoods of a set of so-called background models $\{\lambda_1, \lambda_2, \ldots, \lambda_N\}$. For example, if the background model set is generated from a cohort, letting $\Psi(\cdot)$ be the maximum function gives $L_{\mathrm{Max}}(U)$, while the arithmetic mean gives $L_{\mathrm{Ari}}(U)$, and the geometric mean gives $L_{\mathrm{Geo}}(U)$. When $\Psi(\cdot)$ is an identity function, $N = 1$, and $\lambda_1 = \Omega$, (7) becomes $L_{\mathrm{UBM}}(U)$.

In essence, there is no theoretical evidence to indicate what sort of $\Psi(\cdot)$ is optimal, so the selection of $\Psi(\cdot)$ is usually application and training data dependent. Simple functions, such as the arithmetic mean, the maximum, and the geometric mean, are heuristics that do not involve an optimization process. Thus, the resulting system is far from optimal in terms of verification accuracy. To handle the speaker-verification problem more effectively, it is necessary to devise a decision function with a trainable mechanism, such that one hypothesis can be optimally separated from another. To this end, we formulate the characterization of the alternative hypothesis as a problem of optimally combining the discriminative information derived from a set of pretrained background models, and design the decision function based on two perspectives: a weighted geometric combination (WGC) and a weighted arithmetic combination (WAC) of the likelihoods of the background models. In contrast to the geometric mean in $L_{\mathrm{Geo}}(U)$ and the arithmetic mean in $L_{\mathrm{Ari}}(U)$, both of which are independent of the system training, our combination scheme treats the background models unequally according to how close each model is to the target model. The unequal nature of the background models is quantified by a set of weights optimized in the training phase. Since the optimization is related to the verification accuracy, the resulting decision function is expected to be more effective and robust than those of conventional methods. Thus, the task is to determine the associated weights. To obtain a reliable set of weights, we regard the WGC- and WAC-based decision functions as nonlinear discriminant classifiers. Then, we apply kernel-based techniques, namely the kernel Fisher discriminant (KFD) [7], [8] and support vector machine (SVM) [9], to solve the weights, by virtue of their good discrimination ability.

In recent years, a number of SVM-based speaker verification techniques have been developed [10]–[14]. One of the main issues with using SVMs for speaker verification is that the number of training samples represented by frames is usually too large to handle efficiently. For this reason, the concept of a sequence kernel [10]–[14] was proposed to compare speech utterances at the sequence level instead of the frame level. However, constructing a proper sequence kernel for utterance-based SVMs is an issue that requires further investigation. In this paper, as the proposed WGC and WAC methods convert variable-length utterances into fixed-dimension characteristic vectors, the derived kernel processes play the same role as the sequence kernel method, but they have the advantage of not having to specifically design the kernel functions.

In addition, most existing SVM-based speaker verification approaches only use a single background model, i.e., the world model, instead of multiple background models, to characterize the alternative hypothesis. For example, Bengio *et al.* [13] proposed the following decision function:

$$L_{\mathrm{Bengio}}(U) = a_1 \log p(U|\lambda) - a_2 \log p(U|\Omega) + b \tag{8}$$

where a_1, a_2, and b are adjustable parameters estimated using SVM. The input to SVM comprises the two-dimensional vector $[\log p(U|\lambda) \;\; -\log p(U|\Omega)]^T$. An extended version of (8) using the Fisher kernel and the LR score-space kernel for SVM was investigated in [14]. In contrast, our framework integrates more available information from multiple background models into a characteristic vector as the input to SVM, which makes it easier to distinguish one hypothesis from another. The results of speaker verification experiments conducted on both the XM2VTS database and the ISCSLP2006-SRE database show that the proposed methods outperform all of the above-mentioned approaches.

The remainder of this paper is organized as follows. Section II introduces the design of the decision function used in our methods. Section III presents the kernel discriminant analysis techniques that we use to find the weight vector. Sections IV and V describe the concepts related to the characteristic vector and the background model selection methods, respectively. Section VI details the experiment results. Then, in Section VII, we present our conclusions.

II. Proposed Decision Functions

To characterize the alternative hypothesis, we generate a set of background models using data that does not belong to the null hypothesis. Instead of the arithmetic mean or the geometric mean mentioned earlier, our goal is to design a function $\Psi(\cdot)$ that can optimally exploit the information available from background models. In this section, we present our design approach, which characterizes the alternative hypothesis in two ways: by a weighted geometric combination (WGC) and by a weighted arithmetic combination (WAC). Each combination can be viewed as a generalized and trainable version of conventional approaches.

A. Weighted Geometric Combination (WGC)

We begin by defining the function $\Psi(\cdot)$ in (7) in terms of a weighted geometric combination as

$$\Psi(p(U|\lambda_1), \ldots, p(U|\lambda_N)) = \left(\prod_{i=1}^{N} p(U|\lambda_i)^{w_i}\right)^{1/(w_1+w_2+\cdots+w_N)} \tag{9}$$

where w_i is the weight of the likelihood $p(U|\lambda_i)$, $i = 1, 2, \ldots, N$. This function assigns different weights to N background models according to their individual contribution to the alternative hypothesis. It is clear that (9) is equivalent to the simple geometric mean when $w_i = 1$, $i = 1, 2, \ldots, N$; i.e., it is assumed that all the background models contribute equally. One additional advantage of WGC is that it avoids the problem of $\Psi(p(U|\lambda_1),\ldots,p(U|\lambda_N)) \rightarrow 0$. This problem can arise with the simple geometric mean because some values of the likelihood may be rather small when the background models λ_i are irrelevant to an input utterance U, i.e., $p(U|\lambda_i) \rightarrow 0$. However, if a weight is attached to each background model, $\Psi(\cdot)$ defined in (9) may be less sensitive to very small likelihood values, and hence should be more robust than the simple geometric mean. It is also clear that (9) will reduce to a maximum function if $w_{i^*} = 1$, $i^* = \arg\max_{1\le i\le N} p(U|\lambda_i)$ and $w_i = 0, \forall\, i \neq i^*$.

By substituting (9) into (7), and taking the logarithmic form, we obtain

$$\begin{aligned} L_{\mathrm{WGC}}(U) &= \log\left(\prod_{i=1}^{N}\left(\frac{p(U|\lambda)}{p(U|\lambda_i)}\right)^{w_i}\right)^{1/(w_1+w_2+\cdots+w_N)} \\ &= \frac{\sum_{i=1}^{N} w_1 \log\frac{p(U|\lambda)}{p(U|\lambda_i)}}{\sum_{i=1}^{N} w_1} \begin{cases} \ge \log\theta, & \text{accept} \\ < \log\theta, & \text{reject} \end{cases} \\ &= \mathbf{w}^T\mathbf{x} \begin{cases} \ge \theta', & \text{accept} \\ < \theta', & \text{reject} \end{cases} \end{aligned} \tag{10}$$

where $\mathbf{w} = [w_1 \quad w_2 \quad \ldots \quad w_N]^T$ is an $N \times 1$ weight vector, the new threshold $\theta' = (w_1 + w_2 + \cdots + w_N)\log\theta$, and $\mathbf{x}$ is an $N \times 1$ vector in the space R^N expressed as

$$\mathbf{x} = \left[\log\frac{p(U|\lambda)}{p(U|\lambda_1)} \log\frac{p(U|\lambda)}{p(U|\lambda_2)} \ldots \log\frac{p(U|\lambda)}{p(U|\lambda_N)}\right]^T. \tag{11}$$

The implicit idea in (11) is that the input utterance U can be represented by a characteristic vector $\mathbf{x}$.

B. Weighted Arithmetic Combination (WAC)

We can also define the function $\Psi(\cdot)$ in (7) in terms of a weighted arithmetic combination as

$$\begin{aligned} &\Psi(p(U|\lambda_1),\ldots,p(U|\lambda_N)) \\ &\qquad = \frac{1}{w_1 + w_2 + \cdots + w_N}\sum_{i=1}^{N} w_i p(U|\lambda_i) \end{aligned} \tag{12}$$

where w_i is the weight of $p(U|\lambda_i)$, $i = 1, 2, \ldots, N$. Similar to the weighted geometric combination, (12) considers the individual contribution of background models to the alternative hypothesis by assigning a weight to each likelihood value. It is clear that (12) is equivalent to the arithmetic mean when $w_i = 1$, $i = 1, 2, \ldots, N$. It is also clear that (12) will reduce to a maximum function if $w_{i^*} = 1$, $i^* = \arg\max_{1\le i\le N} p(U|\lambda_i)$ and $w_i = 0, \forall\, i \neq i^*$. Suppose that all the N background models are Gaussian mixture models (GMMs) [4]. Then, (12) constitutes a two-layer GMM, in which one layer represents each background model and the other layer represents the combination of background models.

By substituting (12) into (7) and reversing (7), we obtain

$$\begin{aligned} L_{\mathrm{WAC}}(U) &= \frac{1}{L(U)} \\ &= \frac{\sum_{i=1}^{N} w_i \frac{p(U|\lambda_i)}{p(U|\lambda)}}{\sum_{i=1}^{N} w_i} \begin{cases} \le \frac{1}{\theta}, & \text{accept} \\ > \frac{1}{\theta}, & \text{reject} \end{cases} \\ &= \mathbf{w}^T\mathbf{x} \begin{cases} \le \theta'', & \text{accept} \\ > \theta'', & \text{reject} \end{cases} \end{aligned} \tag{13}$$

where $\mathbf{w} = [w_1 \quad w_2 \quad \ldots \quad w_N]^T$ is an $N \times 1$ weight vector, the new threshold $\theta'' = (w_1 + w_2 + \cdots + w_N)/\theta$, and $\mathbf{x}$ is an $N\times$ 1 characteristic vector in the space R^N, expressed by

$$\mathbf{x} = \left[\frac{p(U|\lambda_1)}{p(U|\lambda)} \frac{p(U|\lambda_2)}{p(U|\lambda)} \ldots \frac{p(U|\lambda_N)}{p(U|\lambda)}\right]^T. \tag{14}$$

III. Kernel Discriminant Analysis

The process of representing an utterance U as a characteristic vector $\mathbf{x}$ in (11) or (14) can be regarded as $x = \Phi(U)$, where $\Phi(\cdot)$[1] is a nonlinear mapping function. If we replace the threshold θ' in (10) or θ'' in (13) with a bias b, the decision functions in (10) and (13) can be rewritten as

$$L(U) = \mathbf{w}^T\Phi(U) + b \tag{15}$$

where $L(U)$ forms a nonlinear discriminant classifier for U. The classifier translates the goal of solving an LR test problem into one of optimizing $\mathbf{w}$ and b, such that the utterances of target speakers and nontarget speakers can be separated. To realize this classifier, we need three distinct data sets: one for generating each target speaker's model, one for generating the background models, and one for optimizing $\mathbf{w}$ and b. Since the bias b plays the same role as the decision threshold θ of the LR test defined in (2), which can be determined through a tradeoff between the false acceptance and the false rejection rates, our main goal here is to find $\mathbf{w}$.

To solve the weight vector $\mathbf{w}$, we propose using two kernel-based discriminant techniques, namely the KFD [7], [8] and SVM [9], because of their ability to separate samples of target speakers from those of nontarget speakers efficiently.

A. Kernel Fisher Discriminant (KFD)

Suppose that we have n_i training utterances $\{U_1^i,\ldots,U_{n_1}^i\}$ for hypothesis H_i, $i = 0$, or 1. The goal of KFD is to locate the weight vector $\mathbf{w}$ that maximizes the between-class scatter, while minimizing the within-class scatter. According to [7], the solution of $\mathbf{w}$ must lie in the span of all mapped training utterances; therefore, we can represent $\mathbf{w}$ as

$$\mathbf{w} = \sum_{j=1}^{J} \alpha_j \Phi(U_j) \tag{16}$$

[1]More precisely, $\Phi(U)$ should be denoted by $\Phi(U;\lambda;\lambda_1,\lambda_2,\ldots,\lambda_N)$.

where $\{U_j, 1 \leq j \leq J\} = \{U_1^0, U_2^0, \ldots, U_{n_0}^0\} \cup \{U_1^1, U_2^1, \ldots, U_{n_1}^1\}$, $J = n_0 + n_1$, and α_j is the combination coefficient. Substituting (16) into (15), we obtain

$$L(U) = \sum_{j=1}^{J} \alpha_j \Phi^T(U_j)\Phi(U) + b = \sum_{j=1}^{J} \alpha_j k(U_j, U) + b \quad (17)$$

where the inner product of two vectors $\Phi(U_j)$ and $\Phi(U)$ is expressed by a kernel function $k(U_j, U)$. Such a kernel function is also called the sequence kernel [10], because it takes two utterance sequences, U_j and U, as inputs. The goal therefore changes from finding $\mathbf{w}$ to finding $\boldsymbol{\alpha} = [\alpha_1 \quad \alpha_2 \quad \ldots \quad \alpha_J]^T$, which maximizes

$$\Gamma(\boldsymbol{\alpha}) = \frac{\boldsymbol{\alpha}^T \mathbf{M} \boldsymbol{\alpha}}{\boldsymbol{\alpha}^T \mathbf{N} \boldsymbol{\alpha}}. \quad (18)$$

$\mathbf{M}$ and $\mathbf{N}$ are computed by

$$\mathbf{M} = (\boldsymbol{\eta}_0 - \boldsymbol{\eta}_1)(\boldsymbol{\eta}_0 - \boldsymbol{\eta}_1)^T \quad (19)$$

and

$$\mathbf{N} = \sum_{i=0,1} \mathbf{K}_i(\mathbf{I}_{n_i} - \mathbf{1}_{n_i})\mathbf{K}_i^T \quad (20)$$

respectively, where $\boldsymbol{\eta}_i$ is an $J \times 1$ vector with element $(\boldsymbol{\eta}_i)_s$; $\mathbf{K}_i$ is an $J \times n_i$ matrix with element $(\boldsymbol{\eta}_i)_s = (\mathbf{1}/n_i)\sum_{j=1}^{n_i} k\left(U_s, U_j^i\right)$; $\mathbf{I}_{n_i}$ is an $n_i \times n_i$ identity matrix; and $\mathbf{1}_{n_i}$ is an $n_i \times n_i$ matrix in which all elements are equal to $1/n_i$. Following [8], the solution to $\boldsymbol{\alpha}$, which maximizes $\boldsymbol{\Gamma}(\boldsymbol{\alpha})$ defined in (18), is taken as the leading eigenvector of $\mathbf{N}^{-1}\mathbf{M}$.

B. Support Vector Machine (SVM)

The weight vector $\mathbf{w}$ can also be solved with SVM. In this case, the goal is to find a separating hyperplane that maximizes the margin between the classes. Following [9], $\mathbf{w}$ can be expressed as

$$\mathbf{w} = \sum_{j=1}^{J} y_j \beta_j \Phi(U_j) \quad (21)$$

which yields

$$L(U) = \sum_{j=1}^{J} y_j \beta_j k(U_j, U) + b \quad (22)$$

where each training utterance $U_j, j = 1, 2, \ldots, J$, is labeled by either $y_j = 1$ (a null hypothesis) or $y_j = -1$ (an alternative hypothesis). The optimal coefficients $\boldsymbol{\beta} = [\beta_1 \quad \beta_2 \quad \ldots \quad \beta_J]^T$ can be determined by maximizing the objective function

$$Q(\boldsymbol{\beta}) = \sum_{j=1}^{J} \beta_j - \frac{1}{2}\sum_{i=1}^{J}\sum_{j=1}^{J} y_i y_j \beta_i \beta_j k(U_i, U_j) \quad (23)$$

subject to the constraints $\sum_{j=1}^{J} y_j \beta_j = 0$ and $0 \leq \beta_j \leq C_\beta$, $\forall\, j$, where C_β is a penalty parameter [9]. This process can be performed with quadratic programming techniques [15]. Note that most elements of $\boldsymbol{\beta}$ are equal to zero, and training samples associated with nonzero β_j are called *support vectors*. A few support vectors play a key role in deciding the optimal margin between classes in SVM.

C. Mercer Kernels

The effectiveness of the above KFD or SVM approaches depends essentially on how the kernel function $k(\cdot)$ is designed. A kernel function must be symmetric, positive definite, and conform to Mercer's condition [16]. There are a number of kernel functions [16]. However, since we have converted speech utterances into characteristic vectors, the kernel function takes the form

$$k(U_1, U_2) = \Phi(U_1)^T \Phi(U_2) = \mathbf{x}_1^T \mathbf{x}_2 = k_1(\mathbf{x}_1, \mathbf{x}_2). \quad (24)$$

Equation (24) indicates that the sequence kernel function with two input utterances, U_1 and U_2, forms a dot product kernel with two input characteristic vectors, $\mathbf{x}_1$ and $\mathbf{x}_2$. Alternatively, if we use the closure property of Mercer kernels [16] to form a kernel function

$$k'(U_1, U_2) = \exp\left(-\frac{k(U_1, U_1) + k(U_2, U_2) - 2k(U_1, U_2)}{2\sigma^2}\right) \quad (25)$$

where σ is a tunable parameter, then $k'(U_1, U_2)$ is equivalent to the following radial basis function (RBF) kernel with two inputs $\mathbf{x}_1$ and $\mathbf{x}_2$

$$k_2(\mathbf{x}_1, \mathbf{x}_2) = \exp\left(\frac{-\|\mathbf{x}_1 - \mathbf{x}_2\|^2}{2\sigma^2}\right). \quad (26)$$

IV. Concepts Related to the Characteristic Vector

In this section, we compare the proposed classifiers with several approaches related to the characteristic vector. It is worth noting that the major advantage of our classifiers lies in a trainable mechanism, which tries to optimally exploit useful information from background models, rather than make an ad hoc modification or use a combination of existing approaches.

A. Direct Fusion of Multiple LRs

The most intuitive way to improve the conventional LR-based speaker verification method would be to fuse multiple LR measures directly. Similar to the fusion approaches in [17] and [18], we define a fusion-based LR as

$$\begin{aligned} L_{\text{Fusion}}(U) &= w_{\text{UBM}} L_{\text{UBM}}(U) + w_{\text{Max}} L_{\text{Max}}(U) \\ &\quad + w_{\text{Ari}} L_{\text{Ari}}(U) + w_{\text{Geo}} L_{\text{Geo}}(U) \\ &= \mathbf{w}^T \mathbf{x} \begin{cases} \geq \theta, & \text{accept} \\ < \theta, & \text{reject} \end{cases} \end{aligned} \quad (27)$$

where $\mathbf{w} = [w_{\text{UBM}} \quad w_{\text{Max}} \quad w_{\text{Ari}} \quad w_{\text{Geo}}]^T$, and

$$\mathbf{x} = [L_{\text{UBM}}(U) \quad L_{\text{Max}}(U) \quad L_{\text{Ari}}(U) \quad L_{\text{Geo}}(U)]^T. \quad (28)$$

As with WGC and WAC, the weight vector $\mathbf{w}$ can be trained using the methods described in Section III. A preliminary result reported in [19] shows that, compared to approaches that use a single LR, such a fusion scheme improves speaker verification performance noticeably. However, we found that direct fusion is often dominated by one particular LR, or it is limited by some inferior LRs.

B. Relation to the Anchor Modeling Approach

The concept of our methods is similar to that of the anchor modeling approach [20], [21] used in speaker indexing and speaker identification applications. The objective of the anchor modeling approach is to construct a speaker space based on a set of pretrained representative models $\{A_1, A_2, \ldots, A_N\}$, called *anchor models*. Then, any speech utterance U can be projected into the space, and represented as a characteristic vector $\mathbf{x}$ [20]

$$\mathbf{x} = [p(U|A_1) \quad p(U|A_2) \quad \ldots \quad p(U|A_N)]T. \tag{29}$$

The speaker of an unknown utterance U can be identified by computing the distance between the characteristic vector $\mathbf{x}$ and the typical vectors of the target speakers. The characteristic vector defined in (29) is similar to the characteristic vector used in this study. However, to find the location of a target speaker in the speaker space, the anchor modeling approach only considers the projection of the speech utterance from the target speaker, which is different from the proposed discriminative framework. More specifically, the decision functions based on WGC and WAC characterize a target speaker by locating the boundary that optimally separates the characteristic vectors of a target speaker from those of nontarget speakers; hence, the proposed methods are expected to be more effective than the anchor modeling approach.

V. Background Model Selection

In general, the more speakers that are used as background models, the better the characterization of the alternative hypothesis will be. However, it has been found [2]–[5] that using a set of preselected representative models is usually more effective and efficient than using the entire collection of available speakers. For this reason, we propose selecting $B+1$ background models, including B cohort models used in $L_{\text{Max}}(U)$, $L_{\text{Ari}}(U)$, and $L_{\text{Geo}}(U)$, and one world model used in $L_{\text{UBM}}(U)$, to form the characteristic vector. As a result, the proposed decision functions based on WGC and WAC can be viewed as generalized and trainable versions of $L_{\text{UBM}}(U)$, $L_{\text{Max}}(U)$, $L_{\text{Ari}}(U)$, or $L_{\text{Geo}}(U)$.

We consider two widely used methods for selecting cohort models [4]. One selects the B closest speaker models $\{\lambda_{cst1}, \lambda_{cst2}, \ldots, \lambda_{cstB}\}$ for each target speaker; and the other selects the $B/2$ closest speaker models $\{\lambda_{cst1}, \lambda_{cst2}, \ldots, \lambda_{cstB/2}\}$, plus the $B/2$ farthest speaker models $\{\lambda_{fst1}, \lambda_{fst2}, \ldots, \lambda_{fstB/2}\}$, for each target speaker. Here, the degree of closeness is measured in terms of the pairwise distance defined in [4]

$$d(\lambda_i, \lambda_j) = \log \frac{p(U_i|\lambda_i)}{p(U_i|\lambda_j)} + \log \frac{p(U_j|\lambda_j)}{p(U_j|\lambda_i)} \tag{30}$$

where λ_i and λ_j are speaker models trained using the ith speaker's utterances U_i and the jth speaker's utterances U_j, respectively. As a result, each target speaker has a sequence of background models, $\{\Omega, \lambda_{cst1}, \lambda_{cst2}, \ldots, \lambda_{cstB}\}$ or $\{\Omega, \lambda_{cst1}, \ldots, \lambda_{cstB/2}, \lambda_{fst1}, \ldots, \lambda_{fstB/2}\}$, for (11) and (14).

VI. Experiments

We conducted the speaker-verification experiments on two databases: the XM2VTS database [22] and the ISCSLP2006 speaker recognition evaluation (ISCSLP2006-SRE) database [24].

For the performance evaluation, we used the detection error tradeoff (DET) curve [26], which shows the tradeoff between the false-alarm probability and the miss probability based on their corresponding Gaussian deviates. We also measured the NIST detection cost function (DCF) [27], which reflects the performance at a single operating point on the DET curve. The DCF is defined as

$$C_{\text{DET}} = C_{\text{Miss}} \times P_{\text{Miss}} \times P_{\text{Target}} + C_{Fa} \times P_{Fa} \times (1 - P_{\text{Target}}) \tag{31}$$

where P_{Miss} and P_{Fa} are the miss probability and the false-alarm probability, respectively; C_{Miss} and C_{Fa} are the respective relative costs of the detection errors; and P_{Target} is the *a priori* probability of the target speaker.

A. Evaluation on the XM2VTS Database

The first set of speaker verification experiments was conducted on speech data extracted from the XM2VTS multimodal database [22]. In accordance with "Configuration II" described in [23], the database was divided into three subsets: "Training," "Evaluation,"[2] and "Test." For our experiments, we used the "Training" subset to build each target speaker's model and the background models, and the "Evaluation" subset to estimate the decision threshold θ in (2), and the parameters $\mathbf{w}$ and b in (15). The accuracy of speaker verification was then evaluated on the "Test" subset. As shown in Table I, a total of 293 speakers[3] in the database were divided into 199 clients (target speakers), 25 "evaluation impostors," and 69 "test impostors." Each speaker participated in four recording sessions at approximately one-month intervals, and each recording session consisted of two shots. In each shot, the speaker was prompted to utter three sentences:

1) "0 1 2 3 4 5 6 7 8 9."
2) "5 0 6 9 2 8 1 3 7 4."
3) "Joe took father's green shoe bench out."

Using a 32-ms Hamming-windowed frame with 10-ms shifts, each utterance was converted into a stream of 24-order feature vectors, each consisting of 12 Mel-scale frequency cepstral coefficients [28] and their first time derivatives.

We used 12 ($2 \times 2 \times 3$) utterances per target speaker from sessions 1 and 2 to train the target speaker model, represented by a GMM with 64 mixture components. For each target speaker, we used the utterances of the other 198 clients in sessions 1 and

[2]This is usually called the "Development" set in the speech recognition community. We use "Evaluation" in accordance with the configuration of the XM2VTS database.

[3]We omitted two speakers (ID numbers 313 and 342) because of partial data corruption.

TABLE I
CONFIGURATION OF THE XM2VTS SPEECH DATABASE

Session	Shot	199 clients	25 impostors	69 impostors
1	1	Training	Evaluation	Test
	2			
2	1			
	2			
3	1	Evaluation		
	2			
4	1	Test		
	2			

TABLE II
SUMMARY OF THE PARAMETRIC MODELS USED IN EACH SYSTEM

System	H_0	H_1	
	a 64-mixture target speaker GMM	a 256-mixture UBM	B 64-mixture cohort GMMs
L_{UBM}	√	√	
L_{Max}	√		√
L_{Ari}	√		√
L_{Geo}	√		√
L_{Bengio}	√	√	
L_{WGC}	√	√	√
L_{WAC}	√	√	√

2 to generate the world model (UBM), represented by a GMM with 256 mixture components. We then chose B speakers from those 198 clients as the cohort. In the experiments, B was set to 20, and each cohort model was also represented by a GMM with 64 mixture components. Table II summarizes all the parametric models used in each system. To estimate θ, $\mathbf{w}$, and b, we used six utterances per target speaker from session 3, along with 24 ($4 \times 2 \times 3$) utterances per evaluation-impostor over the four sessions, which yielded 1194 (6×199) target speaker samples and 119 400 ($24 \times 25 \times 199$) impostor samples. However, because a kernel-based technique can be intractable when a large number of training samples are involved, we reduced the number of impostor samples from 119 400 to 2250 using a uniform random selection method. In the performance evaluation, we tested six utterances per target speaker from session 4 and 24 utterances per test-impostor over the four sessions, which produced 1 194 (6×199) target speaker trials and 329 544 ($24 \times 69 \times 199$) impostor trials.

1) Weighted Geometric Combination Versus Geometric Mean: The first experiment evaluated the proposed weighted geometric combination of background models, i.e., $L_{\mathrm{WGC}}(U)$ defined in (10). The set of background models was comprised of 1) the world model and the 20 closest cohort models ("w_20c"), or 2) the world model and the ten closest cohort models, plus the ten farthest cohort models ("w_10c_10f"). The weight vector was optimized by kernel-based discrimination solutions (KFD or SVM). We derived the following eight WGC-based systems:

1) KFD with $k_1(\cdot)$ defined in (24) and "w_20c" ("WGC_dot_KFD_w_20c");
2) KFD with $k_1(\cdot)$ defined in (24) and "w_10c_10f" ("WGC_dot_KFD_w_10c_10f");
3) SVM with $k_1(\cdot)$ defined in (24) and "w_20c" ("WGC_dot_SVM_w_20c");
4) SVM with $k_1(\cdot)$ defined in (24) and "w_10c_10f" ("WGC_dot_SVM_w_10c_10f");
5) KFD with $k_2(\cdot)$ defined in (26) and "w_20c" ("WGC_RBF_KFD_w_20c");
6) KFD with $k_2(\cdot)$ defined in (26) and "w_10c_10f" ("WGC_RBF_KFD_w_10c_10f");
7) SVM with $k_2(\cdot)$ defined in (26) and "w_20c" ("WGC_RBF_SVM_w_20c");
8) SVM with $k_2(\cdot)$ defined in (26) and "w_10c_10f" ("WGC_RBF_SVM_w_10c_10f").

Both SVM and KFD used an RBF kernel function $k_2(\cdot)$ with $\sigma = 5$. We used the SSVM tool [29] to implement the SVM experiments, where the parameter C_β of SVM was set to 1. For the performance comparison, we used three systems as our baselines:

1) $L_{\mathrm{UBM}}(U)$ ("GMM-UBM");
2) $L_{\mathrm{Geo}}(U)$ with the 20 closest cohort models ("Geo_20c");
3) $L_{\mathrm{Geo}}(U)$ with the ten closest cohort models plus the ten farthest cohort models ("Geo_10c_10f").

Fig. 1 shows the speaker verification results of the above systems evaluated on the XM2VTS "Test" subset in terms of DET curves. Fig. 1(a) and (b) compare the DET curves derived by KFD-based systems and SVM-based systems, respectively.

From Fig. 1, we observe that all the WGC-based systems with kernel functions $k_1(\cdot)$ or $k_2(\cdot)$ outperform the baseline systems "GMM-UBM," "Geo_20c," and "Geo_10c_10f." We also observe that "Geo_10c_10f" in Fig. 1(a) yields the poorest performance. This is because the simple geometric mean may produce some singular scores if any cohort model λ_i is poorly matched to the input utterance U, i.e., $p(U|\lambda_i) \to 0$. In contrast, the results show that the WGC-based system sidesteps this problem with the aid of the weighted strategy. In addition, both Fig. 1(a) and (b) show that the WGC-based systems with $k_2(\cdot)$ outperform the WGC-based systems with $k_1(\cdot)$. Thus, in the subsequent experiments, we focused on investigating the performance achieved by the kernel-based discrimination solutions using the kernel function $k_2(\cdot)$.

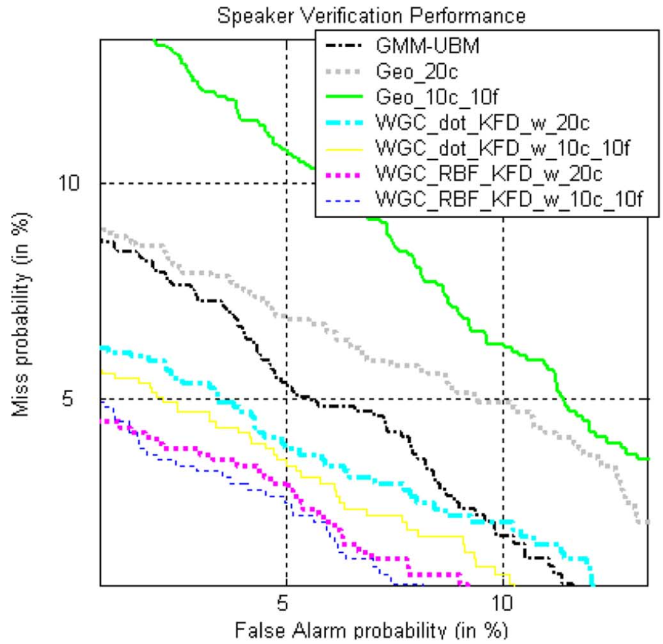
2) Weighted Arithmetic Combination Versus Arithmetic Mean: The second experiment evaluated the proposed weighted arithmetic combination of background models, i.e., $L_{\mathrm{WAC}}(U)$ defined in (13). We implemented the WAC-based systems using the kernel-based discrimination solution in four ways:

1) KFD with "w_20c" ("WAC_RBF_KFD_w_20c");
2) KFD with "w_10c_10f" ("WAC_RBF_KFD_w_10c_10f");
3) SVM with "w_20c" ("WAC_RBF_SVM_w_20c");
4) SVM with "w_10c_10f" ("WAC_RBF_SVM_w_10c_10f").

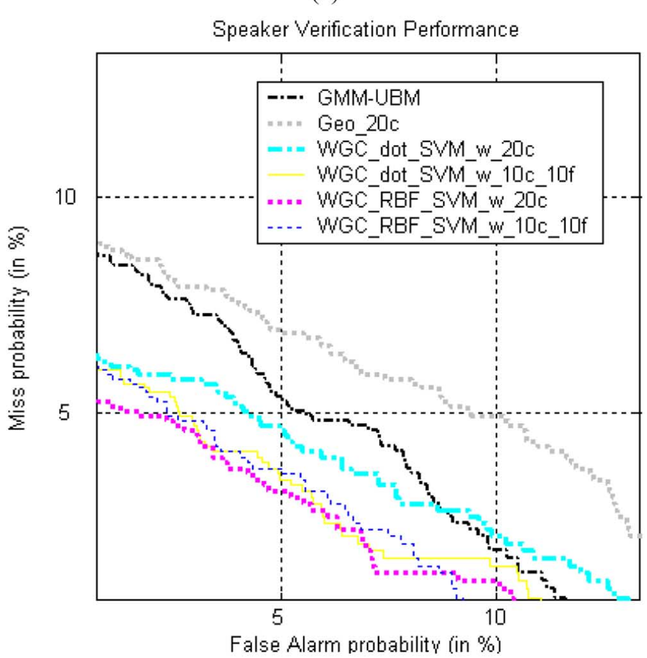
In the above cases, SVM and KFD used an RBF kernel function $k_2(\cdot)$ with $\sigma = 60$. For the performance comparison, we used three systems as our baselines:

1) $L_{\mathrm{UBM}}(U)$ ("GMM-UBM");
2) $L_{\mathrm{Ari}}(U)$ with the 20 closest cohort models ("Ari_20c");
3) $L_{\mathrm{Ari}}(U)$ with the ten closest cohort models plus the ten farthest cohort models ("Ari_10c_10f").

Fig. 2 shows the results of the above systems evaluated on the XM2VTS "Test" subset in terms of DET curves. Clearly, all the WAC-based systems based on either KFD or SVM outperform the baseline systems "GMM-UBM," "Ari_20c," and



(a)



(b)

Fig. 1. Geometric mean versus WGC: DET curves for the "Test" subset in the XM2VTS database.

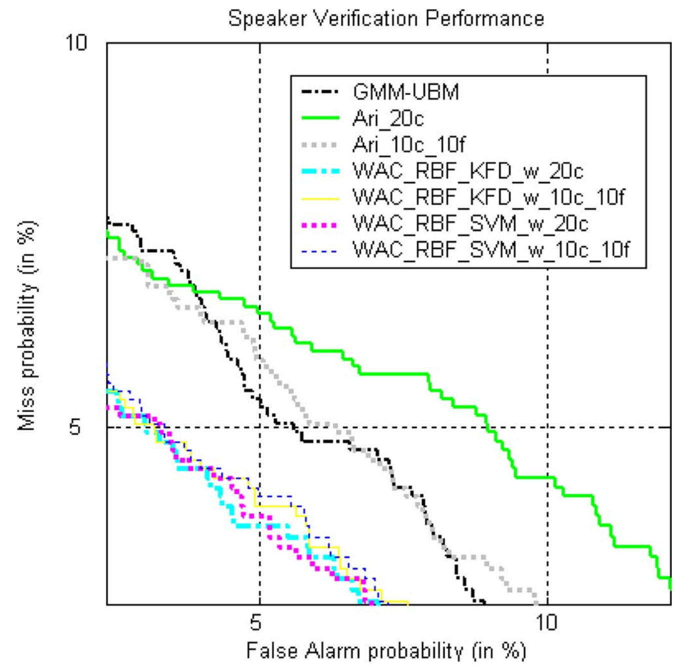


Fig. 2. Arithmetic Mean versus WAC: DET curves for the "Test" subset in the XM2VTS database.

TABLE III
DCFs FOR THE "EVALUATION" AND "TEST" SUBSETS IN THE XM2VTS DATABASE

System	min DCF for "Evaluation"	actual DCF for "Test"
GMM-UBM	0.0633	0.0519
Max_20c	0.0776	0.0635
Ari_20c	0.0676	0.0535
Ari_10c_10f	0.0589	0.0515
Geo_20c	0.0734	0.0583
GMM-UBM/SVM	0.0590	0.0508
Fusion_KFD	0.0496	0.0475
Fusion_SVM	0.0505	0.0469
WGC_RBF_KFD_w_20c	0.0247	0.0357
WGC_RBF_KFD_w_10c_10f	0.0232	0.0389
WGC_RBF_SVM_w_20c	0.0320	0.0414
WGC_RBF_SVM_w_10c_10f	0.0310	0.0417
WAC_RBF_KFD_w_20c	0.0462	0.0443
WAC_RBF_KFD_w_10c_10f	0.0469	0.0445
WAC_RBF_SVM_w_20c	0.0460	0.0454
WAC_RBF_SVM_w_10c_10f	0.0479	0.0450

"Ari_10c_10f." We also observe that the performances of SVM and KFD are similar.

3) Discussion: An analysis of the experiment results based on the DCF with $C_{\mathrm{Miss}} = 1$, $C_{Fa} = 1$, and $P_{\mathrm{Target}} = 0.5$ is given in Table III. In addition to the above systems, we evaluated four related systems:

1) $L_{\mathrm{Max}}(U)$ with the 20 closest cohort models ("Max_20c");
2) $L_{\mathrm{Bengio}}(U)$ using an RBF kernel function with $\sigma = 10$ ("GMM-UBM/SVM");
3) $L_{\mathrm{Fusion}}(U)$ with a fusion of five baseline LR measures, namely, "GMM-UBM," "Max_20c," "Ari_20c," "Ari_10c_10f," and "Geo_20c," by KFD ("Fusion_KFD");
4) $L_{\mathrm{Fusion}}(U)$ with a fusion of five baseline LR measures, namely, "GMM-UBM," "Max_20c," "Ari_20c," "Ari_10c_10f," and "Geo_20c," by SVM ("Fusion_SVM").

In the fusion systems, KFD and SVM used an RBF kernel function with $\sigma = 5$. We did not include "Geo_10c_10f" in the implementation of the fusion systems because of its poor performance. For each approach, the decision threshold was carefully

TABLE IV
COMPARISON OF ERRORS MADE BY "WGC_RBF_KFD_w_20c" AND "ARI_10c_10f," WHERE P AND N DENOTE THE NUMBER OF POSITIVE (TARGET SPEAKER) TRIALS AND THE NUMBER OF NEGATIVE (IMPOSTOR) TRIALS, RESPECTIVELY. THERE ARE 1,194P AND 329 544N IN TOTAL

Trial counts		Ari_10c_10f	
		Correct	Incorrect
WGC_RBF_KFD_w_20c	Correct	1,107P + 315,200N	32P + 6,019N
	Incorrect	5P + 3,056N	50P + 5,269N

tuned to minimize the DCF using the "Evaluation" subset, and then applied to the "Test" subset.

Several conclusions can be drawn from Table III. First, the two direct fusion systems, "Fusion_KFD" and "Fusion_SVM," as well as "GMM-UBM/SVM," outperform the baseline LR systems. Second, the proposed WGC- and WAC-based systems not only outperform all the baseline LR systems, "GMM-UBM," "Max_20c," "Ari_20c," "Ari_10c_10f," and "Geo_20c," they are also better than the fusion systems and the "GMM-UBM/SVM" system. The WGC- and WAC-based SVM systems are better than the "GMM-UBM/SVM" system because they consider multiple background models (including the world model), whereas the "GMM-UBM/SVM" system only considers the world model. Third, the WGC-based systems slightly outperform the WAC-based systems. Fourth, both KFD and SVM perform well in terms of finding nonlinear discrimination solutions. From the actual DCF for the "Test" subset, we observe that "WGC_RBF_KFD_w_20c" achieved a 30.68% relative improvement compared to "Ari_10c_10f" – the best baseline LR system. Table IV compares the correlation of correct and incorrect decisions between "WGC_RBF_KFD_w_20c" and "Ari_10c_10f" for the actual DCF [27]. Based on McNemar's test [30] with a significance $\text{level} = 0.001$, we can conclude that "WGC_RBF_KFD_w_20c" performs significantly better than "Ari_10c_10f," since the resulting $P - \text{value} < 0.001$.

B. Evaluation on the ISCSLP2006-SRE Database

We also evaluated the proposed methods on a text-independent single-channel speaker verification task conforming to the ISCSLP2006 Speaker Recognition Evaluation (ISCSLP2006-SRE) Plan [25]. Unlike the XM2VTS task, the ISCSLP2006-SRE database was divided into two subsets: a "Development Data Set" and an "Evaluation Data Set." The "Development Data Set" contained 300 speakers. Each speaker made two utterances, each of which was cut into one long segment, which was longer than 30 s, and several short segments. In the experiments, we collected each speaker's two long segments to build a UBM with 1024 mixture Gaussian components, and used the two long segments per speaker to train each speaker's 1024-mixture GMM through UBM-MAP adaptation [1]. For each speaker, B speakers' GMMs were chosen from the other 299 speakers as the cohort models. The remaining short segments of all the speakers were used to estimate θ, $\mathbf{w}$, and b. In the implementation, each short segment served as a positive sample for its associated speaker, but acted as a negative sample for each of the 20 randomly selected speakers from the remaining 299 speakers. This yielded 1551 positive samples and 31 020 (1551×20) negative samples for estimating θ or b. Moreover, we used 1551 positive samples and 1551 randomly selected negative samples to estimate $\mathbf{w}$ in the proposed systems.

The "Evaluation Data Set" contained 800 target speakers that did not overlap with the speakers in the "Development Data Set." Each target speaker made one long training utterance, ranging in duration from 21 to 85 s, with an average length of 37.06 s. This was used to generate the speaker's 1024-mixture GMM through UBM-MAP adaptation. For each target speaker, B speakers' GMMs were chosen from the 300 speakers in the "Development Data Set" as the cohort models. In addition, there were 5933 test utterances (trials) in the "Evaluation Data Set," each of which ranged in duration from 5 seconds to 54 s, with an average length of 15.66 s. Each test utterance was associated with the claimed speaker's ID, and the task involved judging whether it was true or false. The answer sheet was released after the evaluation finished.

The acoustic feature extraction process was same as that applied in the XM2VTS task.

1) Experiment Results: The GMM-UBM [1] and T-norm [6] systems are the current state-of-the-art approaches for the text-independent speaker verification task. Thus, in this part, we focus on the performance improvement of our methods over these two baseline systems. As with the GMM-UBM system, we used the fast scoring method [1] for likelihood ratio computation in the proposed methods. Both the target speaker model λ and the B cohort models were adapted from the UBM Ω. Because the mixture indices were retained after UBM-MAP adaptation, each element of the characteristic vector $\mathbf{x}$ was computed approximately by only considering the C mixture components corresponding to the top C scoring mixtures in the UBM [1]. In our experiments, C was set to 5, and B was set to 20.

The experiment results of the XM2VTS task showed that there was no significant performance difference between the two cohort selection methods used to construct the characteristic vector $\mathbf{x}$. Thus, in the following experiments, we only used one type of characteristic vector, i.e., the vector associated with the UBM and the 20 closest cohort models ("w_20c"), to compute WGC- and WAC-based decision functions. This yielded the following four systems:

1) $L_{\text{WGC}}(U)$ using SVM with $k_2(\cdot)$ and "w_20c" ("WGC_RBF_SVM_w_20c");
2) $L_{\text{WGC}}(U)$ using KFD with $k_2(\cdot)$ and "w_20c" ("WGC_RBF_KFD_w_20c");
3) $L_{\text{WAC}}(U)$ using SVM with $k_2(\cdot)$ and "w_20c" ("WAC_RBF_SVM_w_20c");
4) $L_{\text{WAC}}(U)$ using KFD with $k_2(\cdot)$ and "w_20c" ("WAC_RBF_KFD_w_20c").

We compared the proposed systems with the GMM-UBM system, the T-norm system with the 50 closest cohort models ("Tnorm_50c"), and Bengio *et al.*'s system ("GMM-UBM/SVM"). The kernel parameters for SVM and KFD were same as those used in the XM2VTS task. Following the ISCSLP2006-SRE Plan, the performance was measured by the DCF with $C_{\text{Miss}} = 10$, $C_{Fa} = 1$, and $P_{\text{Target}} = 0.05$. In each system, the decision threshold was tuned to minimize the DCF using the (1551+31 020) samples in the "Development Data

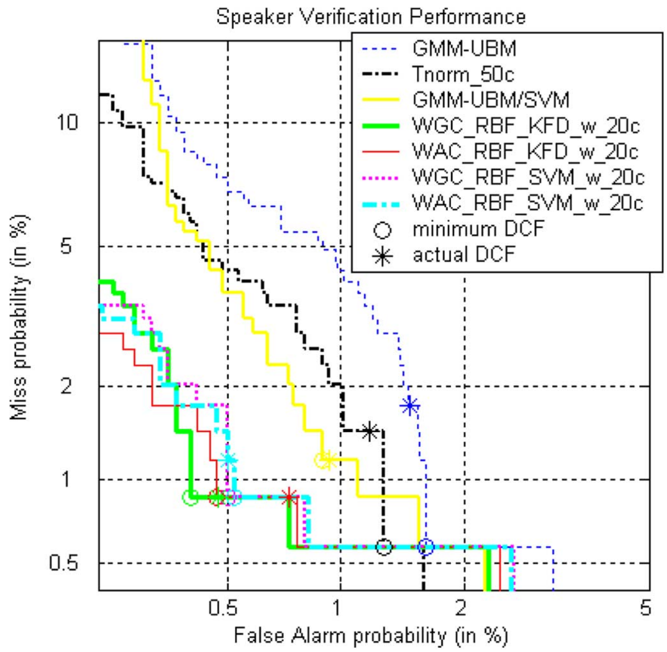


Fig. 3. Baseline systems versus WAC and WGC: DET curves for the ISCSLP2006-SRE "Evaluation Data Set." The stars and circles indicate the actual and minimum DCFs, respectively.

TABLE V
MINIMUM DCFS AND ACTUAL DCFS FOR THE ISCSLP2006-SRE "EVALUATION DATA SET"

	Minimum DCFs	Actual DCFs
GMM-UBM	0.0184	0.0228
Tnorm_50c	0.0151	0.0184
GMM-UBM/SVM	0.0143	0.0146
WGC_RBF_KFD_w_20c	0.0081	0.0087
WAC_RBF_KFD_w_20c	0.0087	0.0112
WGC_RBF_SVM_w_20c	0.0091	0.0105
WAC_RBF_SVM_w_20c	0.0093	0.0105

Set," and then applied to the "Evaluation Data Set." Table V summarizes the minimum DCFs and the actual DCFs derived from 5933 trials in the "Evaluation Data Set," and Fig. 3 shows the experiment results for all systems in terms of DET curves. It is clear that all the proposed systems outperform "GMM-UBM," "Tnorm_50c," and "GMM-UBM/SVM." The actual DCFs in Table V show that "WGC_RBF_KFD_w_20c" achieved a 52.72% relative improvement over "Tnorm_50c." Table VI compares the correlation of correct and incorrect decisions between "WGC_RBF_KFD_w_20c" and "Tnorm_50c" for the actual DCF. Based on McNemar's test with a significance level $=$ 0.001, we can conclude that "WGC_RBF_KFD_w_20c" performs significantly better than "Tnorm_50c," since the resulting $P -$ value < 0.001.

VII. CONCLUSION

We have presented two novel WGC- and WAC-based decision functions for solving the speaker-verification problem. The functions improve the characterization of the alternative hypothesis by combining the likelihoods of all the background models based on two perspectives: a weighted geometric combination and a weighted arithmetic combination. These combinations are more effective and robust than the simple geometric mean and arithmetic mean used in conventional approaches. The new decision functions are treated as nonlinear discriminant classifiers that can be solved by using kernel-based techniques, such as the Kernel Fisher Discriminant and Support Vector Machine, to optimally separate samples of the null hypothesis from those of the alternative hypothesis. The results of experiments on two speaker verification tasks show notable improvements in performance over classical approaches. Finally, it is worth noting that the proposed methods can be applied to other types of data and hypothesis testing problems.

TABLE VI
COMPARISON OF ERRORS MADE BY "WGC_RBF_KFD_W_20C" AND "TNORM_50C", WHERE P AND N DENOTE THE NUMBER OF POSITIVE (TARGET SPEAKER) TRIALS AND THE NUMBER OF NEGATIVE (IMPOSTOR) TRIALS, RESPECTIVELY. THERE ARE 347P AND 5,586N IN TOTAL

Trial counts		Tnorm_50c	
		Correct	Incorrect
WGC_RBF_KFD_w_20c	Correct	342P + 5,508N	2P + 52N
	Incorrect	0P + 12N	3P + 14N

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