

Support Vector Machines versus Fast Scoring in the Low-Dimensional Total Variability Space for Speaker Verification

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Abstract

This paper presents a new speaker verification system architecture based on Joint Factor Analysis (JFA) as feature extractor. In this modeling, the JFA is used to define a new low-dimensional space named the total variability factor space, instead of both channel and speaker variability spaces for the classical JFA. The main contribution in this approach, is the use of the cosine kernel in the new total factor space to design two different systems: the first system is Support Vector Machines based, and the second one uses directly this kernel as a decision score. This last scoring method makes the process faster and less computation complex compared to others classical methods. We tested several intersession compensation methods in total factors, and we found that the combination of Linear Discriminate Analysis and Within Class Covariance Normalization achieved the best performance. We achieved a remarkable results using fast scoring method based only on cosine kernel especially for male trials, we yield an EER of 1.12% and MinDCF of 0.0094 on the English trials of the NIST 2008 SRE dataset.

Index Terms: Total variability space, cosine kernel, fast scoring, support vector machines.

1. Introduction

The Joint Factor Analysis (JFA) [1] approach has become the state of the art in the field of speaker verification during the last three years. This modeling proposes powerful tools for addressing the problem of speaker and channel variability in Gaussian Mixture Models (GMM) [2] framework. Recently [3], we proposed a new technique for combining the JFA and Support Vector Machines (SVM) for speaker verification. In this modeling the SVMs were applied for the total variability factor vectors which are obtained using the JFA model. The best results were obtained when the cosine kernel was applied in this new space [4]. We also proposed several techniques for compensating for channel effects in the total factor space.

In this paper we propose a new fast scoring method based on the cosine kernel applied on the total variability factors without using the SVM approach. We used the same channel compensation technique as proposed in [3]. The results obtained with this scoring are compared to those obtained with SVM-JFA and classical JFA scorings.

The outline of the paper is as follows. Section 2 describes the joint factor analysis model. In section 3, we present the SVM-JFA approach based on the cosine kernel. Section 4 in-

roduces the fast scoring technique. The comparison between different results is presented in section 5. Section 6 concludes the paper.

2. Joint Factor Analysis

Joint factor analysis is a model used to address the problem of speaker and session variability in GMMs. In this model, each speaker is represented by the means, covariance, and weights of a mixture of C multivariate diagonal-covariance Gaussian densities defined in some continuous feature space of dimension F . The GMM for a target speaker is obtained by adapting the UBM mean parameters (UBM). In JFA [1], the basic assumption is that a speaker- and channel-dependent supervector M can be decomposed into a sum of two supervectors: a speaker supervector s and a channel supervector c :

$$M = s + c \quad (1)$$

where s and c are normally distributed.

In [1], Kenny *et al.* described how the speaker-dependent supervector and channel-dependent supervector can be represented in low-dimensional spaces. The first term in the right-hand side of (1) is modeled by assuming that if s is the speaker supervector for a randomly chosen speaker, then

$$s = m + Dz + Vy \quad (2)$$

where m is the speaker- and channel-independent supervector (UBM), D is a diagonal matrix, V is a rectangular matrix of low rank, and y and z are independent random vectors having standard normal distributions. In other words, s is assumed to be normally distributed with mean m and covariance matrix $VV^* + D^2$. The components of y and z are respectively the speaker and common factors.

The channel-dependent supervector c , which represents channel effects in an utterance, is assumed to be distributed according to

$$c = Ux \quad (3)$$

where U is a rectangular matrix of low rank, and x has standard normal distribution. This is equivalent to saying that c is normally distributed with zero mean and covariance UU^* . The components of x are the channel factors.

3. Support Vector Machines

A Support Vector Machine (SVM) is a classifier used to find a separator between two classes. The main idea of this classifier is

to project the input vectors onto high-dimensional space called *feature space* in order to obtain linear separability. This projection is carried out using a mapping function. In practice, SVMs use kernel functions to perform the scalar product computation in the feature space. These functions allow us to compute the scalar product directly in the feature space without defining the mapping function.

3.1. Total Variability

Classical joint factor analysis modeling based on speaker and channel factors consists in defining two distinct spaces: the speaker space defined by the eigenvoice matrix V and the channel space defined by the eigenchannel matrix U . The approach that we propose is based on defining only one space, instead of two separate spaces. This new space, which we refer to as the total variability space, simultaneously contains the speaker and channel variabilities. It is defined by the total variability matrix that contains the eigenvectors corresponding to the largest eigenvalues of the total variability covariance matrix. In the new model, we make no distinction between speaker effects and channel effects in GMM supervector space [1]. Given an utterance, the new speaker- and channel- dependent GMM supervector M defined the equation 1 is rewritten as follows:

$$M = m + Tw \quad (4)$$

where m is the speaker- and channel-independent supervector (which can be taken to be the UBM supervector), T is a rectangular matrix of low rank and w is a random vector having standard normal distribution $\mathcal{N}(0, I)$. The components of the vector w are the total variability factors. In other words, M is assumed to be normally distributed with mean vector m and covariance matrix TT^* . The process of training the total variability matrix T is equivalent to learning the eigenvoice V matrix [1], except for one important difference: in eigenvoice training, all the recordings of a given speaker are considered to belong to the same person; however, in the case of the total variability matrix, a given speaker's entire set of utterances are regarded as having been produced by different speakers. The new model that we propose can be seen as a principal component analysis that allows us to project speech recording frames onto the total variability space. In this new speaker verification modeling the factor analysis plays the role of feature extraction. These new features are the total factor vectors.

3.2. Cosine Kernel

In [4, 3], we found that the appropriate kernel between two total variability factors vectors w_1 and w_2 is the cosine kernel given by the following equation:

$$k(w_1, w_2) = \frac{\langle w_1, w_2 \rangle}{\|w_1\| \|w_2\|} \quad (5)$$

Note that the cosine kernel consists in normalizing the linear kernel by the norm of both total factor vectors. The power of the cosine kernel in total factor space can be explained by the fact that the channel effects carry out a dilatation of the total factor vectors which can not be compensated for with classical linear techniques.

3.3. Intersession Compensation

In this new modeling based on total variability space, we propose carrying out channel compensation in the total factor space

rather than in the GMM supervector space, as is the case in classical JFA modeling. The advantage of applying channel compensation in the total factor space is the low dimension of these vectors, compared to GMM supervectors. We tested three channel compensation techniques in the total variability space for removing the nuisance effects. The first approach is Within Class Covariance Normalization (WCCN), which is already applied in the speaker factor space [4]. This technique used the inverse of the within class covariance matrix to normalize the cosine kernel. The second approach is Linear Discriminant Analysis (LDA). The motivation for using this technique is that, in the case where all utterances from a given speaker are assumed to represent one class, LDA attempts to define new spatial axes that minimize the intra-class variance caused by channel effects, and to maximize the variance between speakers. The third and last approach is the Nuisance Attribute Projection (NAP), presented in [5]. This technique proposed a channel space definition based on the eigenvectors of the within class covariance matrix. The total factor vectors are projected onto the orthogonal complementary channel space, which is the speaker space.

3.3.1. Within Class Covariance Normalization

Within class covariance normalization is presented in detail in [6] and is successfully applied in speaker factor space [4]. It consists in computing the within class covariance matrix in the total factor space using a set of background impostors. The computation of this matrix is given by:

$$W = \frac{1}{S} \sum_{s=1}^S \frac{1}{n_s} \sum_{i=1}^{n_s} (w_i^s - \bar{w}_s) (w_i^s - \bar{w}_s)^t \quad (6)$$

where $\bar{w}_s = \frac{1}{n_s} \sum_{i=1}^{n_s} w_i^s$ is the mean of the speaker factor vectors of each speaker, S is the number of speakers and n_s is the number of utterances for each speaker s . We use the inverse of this matrix in order to normalize the direction of the total factor components, without removing any nuisance direction. The new cosine kernel is given by the following equation:

$$k(w_1, w_2) = \frac{w_1^t W^{-1} w_2}{\sqrt{w_1^t W^{-1} w_1} \sqrt{w_2^t W^{-1} w_2}} \quad (7)$$

where w_1 and w_2 are two total variability factor vectors.

3.3.2. Linear Discriminant Analysis

Linear discriminant analysis is a technique for dimensionality reduction that is widely used in the field of pattern recognition. The idea behind this approach is to seek new orthogonal axes to better discriminate between different classes. The axes found must satisfy the requirement of maximizing between-class variance and minimizing within class variance. These axes can be defined using projection matrix A comprised of the best eigenvectors (those with largest eigenvalues) of the general eigenvalues equation:

$$S_b v = \lambda S_w v \quad (8)$$

where λ is the diagonal matrix of eigenvalues. The matrices S_b and S_w correspond respectively to the between class and within class covariance matrices. These are calculated as follows:

$$S_b = \sum_{i=1}^S (w_i - \bar{w}) (w_i - \bar{w})^t \quad (9)$$

$$S_w = \sum_{s=1}^S \frac{1}{n_s} \sum_{i=1}^{n_s} (w_i^s - \bar{w}_s) (w_i^s - \bar{w}_s)^t \quad (10)$$

where $\overline{w_s} = \frac{1}{n_s} \sum_{i=1}^{n_s} w_i^s$ is the mean of all total factor vectors for speaker s , S is the number of speakers and n_s is the number of utterances for speaker s . In the case of speaker factor vectors, the mean vector of all the speakers' population \overline{w} is equal to the null vector since, in JFA, the speaker factors have a standard normal distribution $w \sim \mathcal{N}(0, I)$ with zero mean and identity covariance matrix. The total factor vectors are subjected to the projection matrix A obtained by LDA. The new cosine kernel between two total factor vectors w_1 and w_2 can be rewritten as:

$$k(w_1, w_2) = \frac{(A^t w_1)^t (A^t w_2)}{\sqrt{(A^t w_1)^t (A^t w_1)} \sqrt{(A^t w_2)^t (A^t w_2)}} \quad (11)$$

The motivation for using LDA is that it allows us to define a new projection matrix aimed at minimizing the intra-class variance and maximizing the variance between speakers, which is the key requirement in speaker verification.

3.3.3. Nuisance attribute projection

The nuisance attribute projection algorithm is presented in [5]. It is based on finding an appropriate projection matrix intended to remove the channel components. The projection matrix carries out an orthogonal projection in the channel's complementary space, which depends only on the speaker. The projection matrix is formulated as:

$$P = I - vv^t \quad (12)$$

where v is rectangular matrix of low rank whose columns are the k best eigenvectors of the same within class covariance matrix (or channel covariance) given in equation 6. These eigenvectors define the channel space. The cosine kernel based on the NAP matrix is given as follows:

$$k(w_1, w_2) = \frac{(Pw_1)^t (Pw_2)}{\sqrt{(Pw_1)^t (Pw_1)} \sqrt{(Pw_2)^t (Pw_2)}} \quad (13)$$

where w_1 and w_2 are two total variability factor vectors.

4. Fast scoring

In this section, based on the results obtained with SVM in the total variability space using the cosine kernel, we propose to directly use the value of the cosine kernel between the target speaker total factors w_{target} and the test total factors w_{test} as decision score:

$$\text{score}(w_{\text{target}}, w_{\text{test}}) = \frac{\langle w_{\text{target}}, w_{\text{test}} \rangle}{\|w_{\text{target}}\| \|w_{\text{test}}\|} \geq \theta \quad (14)$$

The value of this kernel is then compared to the threshold θ in order to take the final decision. The use of the cosine kernel as a decision score for speaker verification makes the process faster and less complex than other JFA scoring [7].

5. Experiments

5.1. Experimental setup

Our experiments operate on cepstral features, extracted using a 25 ms Hamming window. 19 Mel Frequency Cepstral Coefficients together with log-energy were calculated every 10 ms.

This 20-dimensional feature vector was subjected to feature warping [8] using a 3 s sliding window. Delta and double-delta coefficients were then calculated using a 5-frame window to produce 60-dimensional feature vectors. We used gender-dependent Universal Background Models (UBM) containing 2048 Gaussians. These UBMs were trained using LDC releases of Switchboard II, Phases 2 and 3; Switchboard Cellular, Parts 1 and 2; and NIST 2004-2005 speaker recognition evaluation data.

For classical JFA, we used two gender-dependent factor analysis models comprised by 300 speaker factors, 100 channel factors, and common factors. We used decoupled estimation of the eigenvoice matrix V and diagonal matrix D [1]. The eigenvoice matrix V was trained on all the UBM training data, except for the NIST 2004 SRE data. The D matrix was trained on 2004 SRE data. The decision scores obtained with factor analysis were normalized using zt-norm normalization. We used 300 t-norm models and around 1000 z-norm utterances for each gender. All these impostors were taken from the same dataset used for UBM training.

In our SVM-JFA system, we used exactly the same UBM as the classical JFA described above. The total variability matrix T was trained on LDC releases of Switchboard II, Phases 2 and 3; Switchboard Cellular, Parts 1 and 2; NIST 2004 and 2005 SRE; and Fisher English database Part 1 and 2. We used 400 total factor vectors. The within class covariance matrix was trained on NIST 2004 and 2005 SRE data. LDA and NAP projection matrices were trained on the same data as the total variability matrix training except for the Fisher English database. We used around 250 t-norm impostor models taken from NIST 2005 SRE data and around 1200 impostor models taken from Switchboard II, Phases 2 and 3; Switchboard Cellular, Parts 1 and 2; and NIST 2004 SRE data in order to train the SVM.

The fast scoring is based on the same total variability matrix and total factor vectors as the previous SVM-JFA system. In this modeling, the scores are normalized using the zt-norm technique based on the same t-norm model impostors as in the SVM-JFA system. Data from the preceding training SVM impostors are used as z-norm utterances.

5.2. Results

All our experiments were carried out on the telephone data for the core condition of the NIST 2008 SRE dataset. In the next sections, we compared the results obtained with SVM-JFA and fast scoring approaches with those obtained with classical JFA scoring based on integration over channel factors [1].

5.3. SVM-JFA

We first start by comparing the results obtained with SVM-JFA and classical JFA scoring. Table 1 and 2 give comparison result between SVM-JFA and JFA scoring for both genders. In [3], we proved that both LDA and NAP techniques need to be combined with WCCN in order to obtain the best results. The new WCCN matrix is computed after projecting the total factors with LDA and NAP. We have also found that the best LDA dimension reduction is $\text{dim} = 200$ and the best NAP corank is 150.

We conclude from both tables that the combination of LDA and WCCN definitively gave the best performance compared to other channel compensation techniques. Generally, the SVM-JFA achieves better results than the full configuration for joint factor analysis (with speaker and common factors), especially in male trials. We obtain 1.23% absolute improvement in EER on

Table 1: Comparison of results from JFA scoring and several SVM-JFA channel compensation techniques. The results are given as EER and DCF on the female part of the core condition of the NIST 2008 SRE

	English trials		All trials	
	EER	DCF	EER	DCF
JFA scoring	3.17%	0.0150	6.15%	0.0319
WCCN	4.42%	0.0169	7.09%	0.0357
LDA (200) + WCCN	3.68%	0.0150	6.02%	0.0319
NAP (150) + WCCN	3.95%	0.0157	6.36%	0.0321

Table 2: Comparison of results from JFA scoring and several SVM-JFA channel compensation techniques. The results are given as EER and DCF on the male part of the core condition of the NIST 2008 SRE

	English trials		All trials	
	EER	DCF	EER	DCF
JFA scoring	2.64%	0.0111	5.15%	0.0273
WCCN	1.48%	0.0113	4.69%	0.0283
LDA (200) + WCCN	1.28%	0.0095	4.57%	0.0241
NAP (150) + WCCN	1.51%	0.0108	4.58%	0.0241

the English trials of the NIST 2008 SRE dataset. These results show that there is a quite linear separation among speakers in the total variability space, which motivated us to not use SVM and to apply the cosine kernel directly as decision score.

5.4. Fast scoring

Table 3 and 4 present the results obtained with fast scoring and JFA scoring for both genders. We used the same channel compensation techniques as in the SVM-JFA experiments. The results given in both tables show that fast scoring based on total factor vectors definitively gave the best results in all conditions of the NIST evaluation compared to JFA scoring. If we compare these results with those obtained with SVM-JFA system in tables 1 and 2, we find that fast scoring achieves the best results, especially for female trials. Using fast scoring, we obtained an EER of 2.90% and MinDCF of 0.0124 for English trials versus an EER of 3.68% and MinDCF of 0.0150 for the SVM-JFA

Table 3: Comparison of results from JFA scoring and fast scoring with several channel compensation techniques. The results are given as EER and DCF on the female part of the core condition of the NIST 2008 SRE

	English trials		All trials	
	EER	DCF	EER	DCF
JFA scoring	3.17%	0.0150	6.15%	0.0319
WCCN	3.46%	0.0159	6.64%	0.0349
LDA (200) + WCCN	2.90%	0.0124	5.76%	0.0322
NAP (150) + WCCN	2.63%	0.0133	5.90%	0.0336

Table 4: Comparison of results from JFA scoring and fast scoring with several channel compensation techniques. The results are given as EER and DCF on the male part of the core condition of the NIST 2008 SRE

	English trials		All trials	
	EER	DCF	EER	DCF
JFA scoring	2.64%	0.0111	5.15%	0.0273
WCCN	1.32%	0.0140	4.46%	0.0269
LDA (200) + WCCN	1.12%	0.0094	4.48%	0.0247
NAP (150) + WCCN	1.32%	0.0111	4.46%	0.0247

system. The main contribution of both new modelings (with and without SVM) is the use of the cosine kernel on new features, which are the total variability factors extracted using a simple factor analysis.

6. Conclusion

In this paper, we compare two scoring techniques, SVM and fast scoring. Both techniques are based on a cosine kernel applied in the total factor space, where vectors are extracted using a simple factor analysis. The best results are obtained using fast scoring when LDA and WCCN combination are applied in order to compensate for the channel effects. The use of the cosine kernel as a decision score make the decision process faster and less complex.

7. References

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