Dataset-Invariant Covariance Normalization for Out-domain PLDA Speaker Verification

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Abstract

In this paper we introduce a novel domain-invariant covariance normalization (DICN) technique to relocate both in-domain and out-domain i-vectors into a third dataset-invariant space, providing an improvement for out-domain PLDA speaker verification with a very small number of unlabelled in-domain adaptation i-vectors. By capturing the dataset variance from a global mean using both development out-domain i-vectors and limited unlabelled in-domain i-vectors, we could obtain domain-invariant representations of PLDA training data. The DICN-compensated out-domain PLDA system is shown to perform as well as in-domain PLDA training with as few as 500 unlabelled in-domain i-vectors for NIST-2010 SRE and 2000 unlabelled in-domain i-vectors for NIST-2008 SRE, and considerable relative improvement over both out-domain and in-domain PLDA development if more are available.

Index Terms: speaker verification, PLDA, DICN, domain adaptation

1. Introduction

In the past few years extensive research has been conducted in the field of speaker verification. Numerous methods have been proposed, like joint factor analysis (JFA) [1] and i-vector [2] based subspace modelling techniques, that have resulted in excellent speaker verification performance. But most techniques have only been investigated in relatively clean environments, with huge amounts of ‘in-domain’ development data. However, if we use this clean data for development of real world applications, it would produce poor performance, because of many factors that are not always considered in clean development data. One of the key reason is the mismatch between development and evaluation dataset.

The performance variation due to cross-domain speaker verification development and evaluation was first addressed at the Summer Workshop at Johns Hopkins University (JHU) held in 2013 [3]. Results presented in that workshop clearly showed the performance gap between in-domain and out-domain development for speaker verification. This task was deemed the ‘Domain Adaptation Challenge’ (DAC) at that workshop.

In response to this poor cross-domain speaker verification performance, Garcia-Romero et al. [4] found that training UBMs and total-variability matrices on in-domain or out-domain data have very limited effect on overall performance, but the effect on PLDA parameters were more pronounced. They investigated four adaptation techniques for supervised domain adaptation of PLDA parameters: fully Bayesian adaptation, approximate MAP, weighted likelihood and SPLDA parameter interpolation. Each of these techniques performed very similarly. Villalba et al. [5] introduced a variational Bayesian technique for adapting PLDA models from labeled out-domain to unlabeled in-domain data. Recently, Garcia-Romero et al. also introduced an agglomerative hierarchical clustering (AHC) method to cluster unlabeled in-domain data for domain adaptation. To compensate the dataset shift in i-vector space Aronowitz [6] introduced an inter-dataset variability compensation (IDVC) technique based on nuisance attribute projection (NAP). Glembek et al. [7] proposed within-speaker covariance correction (WCC) and extended unsupervised adaptation of the LDA matrix to compensate the mismatch between training and testing datasets. Recently, Kanagasundaram et al. [8] introduced an improved IDVC technique, where dataset variability is captured using difference between out-domain i-vectors and average of in-domain i-vectors.

In this paper, a novel dataset invariant covariance normalization (DICN) approach is introduced to compensate the mismatch between in-domain and out-domain dataset in the i-vector space. Instead of capturing the mismatch directly between out-domain and in-domain data [8], we captured the mismatch as compared to the global mean i-vector. In this approach we used a set of unlabelled in-domain i-vectors and captured the mismatch using the difference between all i-vectors (in-domain and out-domain) and the global mean i-vector.

The rest of the paper is structured as follows: Section 2 details the i-vector feature extraction techniques. Section 3 details the DICN approach. Section 4 explains the linear discriminant analysis (LDA), and Section 5 presents GPLDA based speaker verification system. The experimental setup and corresponding results are given in Section 6 and Section 7. Finally, Section 8 concludes the paper.

2. I-vector based speaker verification

Single subspace-based i-vector speaker verification was first proposed by Dehak et al. [2]. This approach was inspired by his previous work, finding speaker discriminant information was lost in the discarded channel space of the earlier joint factor analysis (JFA) technique [9]. Unlike the JFA approach, in i-vector feature extraction the GMM super-vectors are represented in a single subspace called total-variability subspace. Both speaker and channel dependent GMM super-vector in i-vector can be represented by,

\[
M = m + Tw, \tag{1}
\]

where \(m\) is the speaker and session independent UBM supervector, \(T\) is a low rank matrix. \(w\) is total variability factor
which is normally distributed. We used only out-domain (SWB) data for total-variability subspace (R_w = 500) training. A detail procedure of total-variability subspace, T, training and i-vector extraction is described in [2, 10].

3. DICN approach

One of the prime reasons of poor out-domain PLDA speaker verification performance is the mismatch between in-domain and out-domain data in the i-vector subspace. Aronowitz proposed the IDVC [6, 11] approach to compensate dataset shift in i-vector space based on nuisance attribute projection (NAP). In this approach, the out-domain data is first partitioned into 12 separate subsets and the centers of these subsets are used to find a subspace (the inter-dataset variability subspace) spanned by the 12 centers using principal component analysis (PCA). Later, Kangasundaram et al. [8] proposed another IDVC approach where dataset variability is directly captured using average of unlabelled in-domain data.

In this section we introduce our novel DICN approach to capture the dataset variability more efficiently in the i-vector space. In this approach a global mean i-vector is determined using all in-domain and out-domain i-vectors and domain variability is captured using the outer product of the difference between all in-domain and out-domain i-vectors and domain variability is captured more efficiently in the i-vector space based on nuisance attribute projection (NAP). In this approach, this is used to scale the subspace, where

\[
S_{DICN} = \frac{1}{N} \sum_{n=1}^{N} (\mathbf{w}_n - \bar{\mathbf{w}})(\mathbf{w}_n - \bar{\mathbf{w}})^T
\]

where \( N \) is the total number of i-vectors (in-domain and out-domain) and \( \bar{\mathbf{w}} \) is the global mean, which can be calculated as follows,

\[
\bar{\mathbf{w}} = \frac{1}{N} \sum_{i=1}^{N} \mathbf{w}_i
\]

The matrix \( \mathbf{A} \) is used to scale the subspace, where \( \mathbf{A} = S_{DICN}^{-1} \). Later, DICN compensated out-domain i-vectors are extracted as follows,

\[
\mathbf{w}_{DICN} = \mathbf{A}^T \mathbf{w}_{out}
\]

4. Linear discriminant analysis (LDA)

LDA is a channel compensation method [2, 12], which attempts to define new spatial axes that minimize the intra-class variance caused by channel effects and maximize the variance between speakers through the eigenvalue decomposition of,

\[
S = \frac{1}{r} \sum \mathbf{r} S_{\mathbf{w}} \mathbf{r}^T
\]

where \( \tau \) is the eigenvalues, \( \mathbf{v} \) is the eigenvector, \( S_{\mathbf{w}} \) is within class matrix and \( S_{\mathbf{w}} \) is between class matrix.

We compute the within class and between class matrix as follows,

\[
S_b = \sum_{s=1}^{S} \frac{1}{n_s} (\mathbf{w}_s - \bar{\mathbf{w}})(\mathbf{w}_s - \bar{\mathbf{w}})^T
\]

\[
S_w = \sum_{s=1}^{S} \sum_{i=1}^{n_s} (\mathbf{w}_i^s - \bar{\mathbf{w}}_s)(\mathbf{w}_i^s - \bar{\mathbf{w}}_s)^T
\]

where \( S \) is the total number of out-domain speakers, \( n_s \) is the number of sessions of speaker \( s \), \( \bar{\mathbf{w}}_s \) is the mean i-vector for each speaker and \( \bar{\mathbf{w}} \) is the mean of all speakers which are defined by,

\[
\bar{\mathbf{w}}_s = \frac{1}{n_s} \sum_{i=1}^{n_s} \mathbf{w}_i^s
\]

\[
\bar{\mathbf{w}} = \frac{1}{N} \sum_{s=1}^{S} \sum_{i=1}^{n_s} \mathbf{w}_i^s
\]

where \( N \) is the total number of sessions.

In the low dimensional space resulting from the linear transformation \( \mathbf{G} \), the within class and between class matrices become \( S_w = \mathbf{G}^T S_b \mathbf{G} \). An optimal transformation \( \mathbf{G} \) would maximize trace \( (S_b) \) and minimize \( (S_w) \),

\[
\max_{\mathbf{G}} \{ S_w^{-1} S_b \}
\]

Finally, the DICN compensated LDA projected i-vector can be calculated as follows,

\[
\mathbf{w}_{DICN-LDA} = \mathbf{G}^T \mathbf{w}_{DICN}
\]

5. Length-normalized GPLDA system

Recently, Garcia-Romero et al. [13] have introduced the length-normalized GPLDA approach, which is comparable to, but computationally more efficient than heavy-tailed (HTPLDA). This approach is used to transform the non-Gaussian i-vector feature behaviour into Gaussian i-vector feature behaviour. This technique consists of two steps: (1) linear whitening and (2) length-normalization. A linear-whitened i-vector \( \mathbf{w}_{DICN-LDA-wht} \) can be estimated as follows,

\[
\mathbf{w}_{DICN-LDA-wht} = \mathbf{d}^{-\frac{1}{2}} \mathbf{U}^T \mathbf{w}_{DICN-LDA}
\]

where \( \mathbf{U} \) is an orthonormal matrix containing the eigenvectors and \( \mathbf{d} \) is a diagonal matrix containing the corresponding eigenvalues. A length-normalized i-vector \( \mathbf{w}_{norm} \) can be found as follows,

\[
\mathbf{w}_{norm} = \frac{\mathbf{w}_{DICN-LDA-wht}}{||\mathbf{w}_{DICN-LDA-wht}||}
\]

A speaker and channel dependent length-normalized i-vector can be defined as,

\[
\mathbf{w}_{norm} = \mathbf{w}_{DICN-LDA-r} = \mathbf{w}_{norm} + U_1 \mathbf{x}_1 + U_2 \mathbf{x}_2 + \epsilon_r
\]

where for given speaker recordings \( r = 1, 2, \ldots R \), \( \mathbf{w}_{norm} + \epsilon_r \) is the channel specific part and \( U_1 \mathbf{x}_1 + U_2 \mathbf{x}_2 + \epsilon_r \) is the channel specific part; The covariance matrix of the speaker part is \( U_1^T U_1 \) and the covariance matrix of the channel part is \( U_2^T U_2 + A^{-1} \). Training of the eigenmatrices \( U_1 \) and \( U_2 \) are also same as learning the eigenvoice matrix \( V \) in JFA.

GPLDA scoring is calculated using the batch likelihood ratio [14]. Given target i-vectors \( \mathbf{w}_{DICN-LDA-target} \) and test i-vectors \( \mathbf{w}_{DICN-LDA-test} \), batch likelihood ratio can be calculated as follows,

\[
\ln \frac{P(\mathbf{w}_{DICN-LDA-target}, \mathbf{w}_{DICN-LDA-test} | H_1)}{P(\mathbf{w}_{DICN-LDA-target} | H_0)P(\mathbf{w}_{DICN-LDA-test} | H_0)}
\]

where \( H_1 \): The speakers are same, \( H_0 \): The speaker are different.
Figure 1: The performance comparison of DICN compensated out-domain PLDA system against in-domain baseline, out-domain baseline and IDV compensated [8] out-domain PLDA system on the common set of the 2008 NIST SRE short2-short3 condition. (a) EER. (b) DCF.

Figure 2: The performance comparison of DICN compensated out-domain PLDA system against in-domain baseline, out-domain baseline and IDV compensated [8] out-domain PLDA system on the common set of the 2010 NIST SRE core-core condition. (a) EER. (b) DCF_{old}.

6. Experimental setup

In our experimental setup, the out-domain dataset is defined as the Switchboard I, II phase I, II, III corpora which consists of 1115 male speakers with 13380 total sessions and 1231 female speakers with 14772 total sessions. The in-domain data is defined as NIST 2004, 2005 and 2006 SRE corpora. We adopted 13 dimensional feature-warped MFCCs with appended delta coefficients. Two gender dependent universal background models (UBM) with 512 Gaussian mixtures were trained on the out-domain (SWB) data. Baum-Welch statistics were calculated using those UBMs before training gender dependent total-variability sub-space with dimension of $R_w = 500$. Total-variability sub-spaces were also trained on the out-domain data. Prior to PLDA training, the out-domain i-vectors were projected using DICN and a 150-dimensional LDA space. We used length-normalized out-domain i-vectors for GPLDA parameter training. We empirically selected 120 best eigenvoices (dimension of $U_1$) according to speaker verification performance. A full precision matrix was used for $\Lambda$, rather than the diagonal. $S$-normalisation was used in the experiments as defined...
Table 1: Comparison of PLDA speaker verification on the common set of the NIST-2008 short2-short3 and NIST-2010 core-core evaluation conditions. GPLDA and score normalization are trained using both in-domain and out-domain data.

<table>
<thead>
<tr>
<th>GPLDA training</th>
<th>Score normalization</th>
<th>NIST-2008</th>
<th>NIST-2010</th>
</tr>
</thead>
<tbody>
<tr>
<td>In-domain</td>
<td>In-domain</td>
<td>3.38%</td>
<td>0.0162</td>
</tr>
<tr>
<td>Out-domain</td>
<td>Out-domain</td>
<td>3.62%</td>
<td>0.0177</td>
</tr>
<tr>
<td></td>
<td>In-domain</td>
<td>3.85%</td>
<td>0.0183</td>
</tr>
<tr>
<td></td>
<td>Out-domain</td>
<td>4.70%</td>
<td>0.0230</td>
</tr>
</tbody>
</table>

7. Results and discussion

This section presents the speaker verification performance with GPLDA parameters trained on in-domain (NIST) and out-domain (SWB) data. Evaluation was performed on NIST 2008 short2-short3 condition and NIST 2010 core-core condition. Table 1 represents the in-domain and out-domain PLDA speaker verification performances. The results clearly show the performance gap between in-domain and out-domain GPLDA speaker verification performance. Accordingly, the best performance was achieved by training both the GPLDA parameters and score normalization statistics using only the in-domain data.

The out-domain PLDA speaker verification results with DICN trained on all in-domain data are shown in Table 2. Results clearly indicate that DICN with all in-domain data yields a 14% relative improvement in EER and a 15% relative improvement in DCF over the out-domain baseline for NIST-2008 evaluation and a 20% relative improvement in both EER and DCF over the out-domain baseline for NIST-2010 evaluation.

We also trained the DICN matrix with limited, unlabelled, in-domain data to replicate a data scarce condition. We selected unlabelled data in a random manner with three different seeds to show the performance variation of the system with different data subsets. Figure 1 represents the performance of NIST-2008 evaluation on short2-short3 condition and Figure 2 represents the performance of NIST-2010 evaluation on core-core condition with DICN compensated PLDA system against in-domain baseline, out-domain baseline and IDVC compensated [8] out-domain PLDA systems. The average performance over the three trials is indicated by the solid line between the actual trials. For NIST-2008 evaluation there is a 14% relative performance improvement in EER and a 13% relative performance improvement in DCF with respect to the out-domain baseline. Also, for NIST-2010 evaluation there is an 11% relative performance improvement in EER and also a 12% relative performance improvement in DCF with respect to the out-domain baseline performance. Results also indicate that we require only 500 in-domain i-vectors for NIST-2010 evaluation and 2000 in-domain i-vectors for NIST-2008 evaluation to perform better than in-domain baseline PLDA. The performance variation between the three trials is mostly due to small data mismatch between NIST-2004, 2005 and 2006 datasets.

8. Conclusions

One of the main reason for poor out-domain PLDA speaker verification performance is the dataset mismatch between in-domain and out-domain data. In this paper we introduced a dataset-invariant covariance normalisation (DICN) approach to compensate this dataset variability. We carried out the evaluation on both NIST-2008 and NIST-2010 SRE corpora, and demonstrated the performance of the out-domain PLDA system with DICN, without DICN and IDVC approach. For DICN training we presented the data scarce condition to replicate the real world scenario. Results clearly indicate that with DICN compensation PLDA speaker verification performs well enough to beat the out-domain as well as in-domain baseline performance.

9. Acknowledgements

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10. References


