Recognition of Connected Japanese Vowel Utterances
Using Random Discriminant Structure Analysis

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Abstract Automatic speech recognition has to deal with the non-linguistic variations of speech signals. Many non-linguistic variations can be modeled as the transformations of features. The universal structure of speech proves to be invariant to the feature transformations, and thus provides a robust representation for speech recognition. One of the difficulties of using the structure representation is due to its high dimensionality. This not only increases computational cost but also easily suffers from the curse of dimensionality. In this paper, we introduce Random Discriminant Structure Analysis (RDSA) to deal with this problem. Based on the observation that structural features are highly correlated and include large redundancy, the RDSA combines random feature selection and discriminative analysis to calculate several low dimensional and discriminative representations from an input structure. Then an individual classifier is trained for each representation and the outputs from each classifier are integrated for the final classification decision. Experimental results on connected Japanese vowel utterances show that our approach achieves a recognition rate of 98.3% based on the training data of 8 speakers, which is higher than that (97.4%) of HMMs trained with the utterances of 4,130 speakers.

Key words random discriminant structure, structural representation of speech, speech recognition, Japanese vowel sequences

1. Introduction

Speech signals inevitably exhibit non-linguistic variations, such as speaker, communication channels, microphones and so on. One of the fundamental problems in speech recognition is to deal with these non-linguistic variations. Modern speech recognition studies largely make use of the statistical methods, for example GMM and HMM,
to solve this problem, which try to model the distributions of speech signals [4]. Extensive studies have shown that the statistical methods can achieve comparably high recognition rates when using proper models and sufficient training data. However, one of the disadvantages of these methods is that a large number of training samples must be prepared to estimate reliable distributions. The successful commercial speech recognition systems always make use of millions of data from thousands of speakers for training [7]. Contrary to this, the human perception of speech is robust to the curse of dimensionality [3], [8]). Moreover, we find that there exists large redundancy among them. Therefore, it is necessary to reduce the dimensionality for obtaining a more compact and discriminative representation.

2. Invariant Structure for Speech Representation

In this section, we will give a brief overview on invariant structure theory and on how to calculate structure representations from utterances [12], [13].

2.1 Theory of Invariant Structure

Consider feature space \( X \) and pattern \( P \) in \( X \). Suppose \( P \) can be decomposed into a sequence of \( m \) events \( \{p_i\}_{i=1}^{m} \). Each event is described as a distribution \( p_i(x) \) in feature space. Note \( x \) can have multiple dimensions. Assume there is a map \( f : X \rightarrow Y \) (linear or nonlinear) which transforms \( X \) into a new feature space \( Y \). In this way, pattern \( P \) in \( X \) is mapped to pattern \( Q \) in \( Y \), and event \( p_i \) is transformed to event \( q_i \). Thus if we can find invariant metrics in both space \( X \) and space \( Y \), these metrics can serve as robust features for classification.

The universal structure theory shows Bhattacharyya distance (BD) between two distributions is an invariant metric Fig. 1. BD is defined as,

\[
BD(p_i, p_j) = -\ln \int (p_i(x)p_j(x))^{1/2}dx. \tag{1}
\]

It is not difficult to calculate that under transformation \( f \), distribution \( q_i(y) \) can be expressed by,

\[
q_i(y) = p_i(f^{-1}(y))|J(y)|, \tag{2}
\]

where \( f^{-1} \) denotes the inverse function of \( f \), and \( J \) is the Jacobian matrix of function \( f^{-1} \). Then it can be proven that [14],

\[
BD(p_i, p_j) = BD(q_i, q_j). \tag{3}
\]

2.2 Structuralization of an Utterance

In the next, we show how to calculate a structural representation from an utterance. As shown in Fig. 2, at first,
we calculate a sequence of cepstrum from input speech waveforms. Then an HMM is trained based on a single cepstrum sequence and each state of HMM is regarded as an event $p_i$. Thirdly we calculate the Bhattacharyya distances between each pair of $p_i$ and $p_j$. These distances will form a $m \times m$ symmetric distance matrix $M_{BD}$ with zero diagonal, which can be seen as the structural representation. For convenience, we can expand the upper triangle of $M_{BD}$ into a vector $z$ of dimension $m(m-1)/2$. It is easy to see that this structural representation must be invariant to transformations in feature space.

It can be shown that many non-linguistic variances [12], [13], such as the length of vocal tract [16], can be modeled as the transformation of feature space. Suppose that $X$ and $Y$ represent the acoustic spaces of two speakers $A$ and $B$, and $P$ and $Q$ represent two utterances of $A$ and $B$, respectively. Then $f$ can be seen as a mapping function from $A$‘s utterance to $B$‘s. In fact, this problem has been widely addressed in the speaker adaption research of speech recognition and the speaker conversion research of speech synthesis. In Maximum Likelihood Linear Regression (MLLR) based speaker adaption [10], a linear transformation: $y = Hx + d$ is used, where $H$ and $d$ denote rotation and translation parameters respectively. For matching utterances $P$ and $Q$, the speaker adaption methods need to explicitly estimate transformation parameters (i.e. $H$ and $d$), which lead to the minimum difference (Fig.3). This minimum difference serves as a matching score of utterances. It has been shown that, using structural representation, we can approximate the minimum difference without explicitly estimating transformation parameters [13].

3. Random Discriminant Structure Analysis

One of the difficulties of using BDs for classification is its high dimensionality. Let $m$ denote the number of events. Then, the dimensionality of structural representation will be $m(m-1)/2$. The high dimensionality will increase the computational cost and make it difficult to train robust classifiers (known the Curse of Dimensionality [8]). Moreover, the BDs are highly correlated features (thinking $d_{p_i,p_j}$ can be largely affected by $d_{p_{i_k},p_{j_k}}$). If we consider the space of BD distances, only a small part (a low dimensional subspace) of this high dimensional space should contain discriminative information. Based on these observations, we think it is essential to reduce the input structure into a compact (low dimension) yet discriminative representation for obtaining a better recognition rate.

In this paper, we will develop a method called Random Discriminant Structure Analysis, which combines feature selection and feature transformation for estimating a low-dimensional discriminative representation of structures. This method includes three steps. Firstly, we randomly sample the edges from an input structure to obtain several random sub-structures. Then discriminative analysis is applied on each random sub-structure to train a classifier for that structure. Finally, the outputs of each classifier are combined to reach the final decision. The flow chart of RDSA is shown in Fig. 4. And the details will be explained as in 3.1.

3.1 Construction of Random Structure

In the first step, we construct $K$ random sub-structures $\{E_k\}_{k=1}^{K}$, each $E_k$ is obtained by randomly sampling $S$ edges $\{e_k\}_{e=1}^{S}$ from $E$. This can also be seen as randomly selecting a small number of dimensions from vector $z$. In the next,
we will apply discriminant analysis on each sub-structure \( E_k \) independently. The random sub-structure construction can reduce the dimensionality of original structures while the number of training data remains the same.

Here we use random feature selection instead of greedy selection methods. This is because, our structural features (BDs) are highly correlated features. The greedy selection methods can only reach the local optimal combination of some of the features, which makes it unsuitable for our task. Moreover, our method includes a classifier ensemble strategy. This requires the independence among individual classifiers, which can be largely satisfied through random selection. The efficiency of random feature selection in recognition had been exhibited in [6]. It was shown in [19] that a random subspace method (similar to random feature selection) is useful for discriminant analysis. We found that only a small number of edges can include sufficient information for an individual discriminative analysis. This can be verified by our experimental results given in Fig. 5 that shows the average recognition rates for using different number of edges (features). The detailed setting of the experiments are described in Section 4. The original pattern includes 3,900 edges. It is easy to see that when the number of edges is larger than 400 (about 10% edges), the increase of edge numbers in an individual classifier cannot improve the recognition rates very much.

### 3.2 Discriminant Analysis

We use Fisher Discriminant Analysis (FDA) for discriminant analysis due to its simplicity and effectiveness. FDA is a classical method to find the discriminant linear transformation \( W \) of features \( z \) [3]:

\[
t = W^T z,
\]

where \( t \) denotes the discriminant features and usually has lower dimension than \( z \). Mathematically, this is achieved by maximizing the following ratio (generalized Rayleigh quotient),

\[
\hat{W} = \arg \max_W \frac{W^T S_b W}{W^T S_w W},
\]

where \( S_b \) is the between-class scatter matrix, and \( S_w \) is the within-class scatter matrix of features. Assume we have \( M \) training samples \( \{z_i\}_{i=1}^M \) belonging to \( N \) classes \( \{C_j\}_{j=1}^N \). Let \( n_j \) denote the number of training samples in \( C_j \). Then \( S_b \) and \( S_w \) can be calculated by the following equations:

\[
S_w = \sum_{j=1}^{N} \sum_{z_i \in C_j} (z_i - m_j)(z_i - m_j)^T,
\]

\[
S_b = \sum_{j=1}^{N} n_j (m_j - m)(m_j - m)^T,
\]

where \( m_j \) is the mean of class \( C_j \) and \( m \) is the mean of all the training samples. \( W \) can be computed as the eigenvectors of \( S_w^{-1} S_b \). Once \( W \) is known, we can determine the discriminative features as \( W^T z \) for sample \( z \). For each random set \( E_k \), we apply FDA on it to obtain \( W_k \). Then the nearest mean classifier \( F_k \) can be built by using the discriminant features:

\[
\arg \min_j |W_k^T z^k - W_k^T m_j^k|,
\]

where \( z^k \) denotes the distance vector of edges in \( E_k \) and \( m_j^k \) denotes the mean distance vector of edges in \( E_k \) for \( j \)-th class.

FDA can be used to determine the discriminative structure. However, it is well-known that FDA may suffer from overfitting when the dimensionality of the features is high and the number of training samples is limited [3]. This fact can influence the performance of FDA. Another serious problem of FDA is that the within-class scatter matrix \( S_w \) can be singular and have no inverse. In our approach, these problems can be largely circumvented through the use of random edge selection which reduces the dimensionality of input features. The final performance is further improved through classifier combination.

### 3.3 Classifier Ensemble

In the final phase, we integrate the outputs from each classifier to reach the final classification decision. It has been shown that classifier ensemble is an efficient method to reduce the variance and bias of an individual classifier [2]. There are two typical strategies for classifier ensemble: summation and voting. Assume the outputs of each individual classifier is a vector containing the confidence score for each category. For the summation method, the output vectors are added together and the final class is decided as the one with the highest summarized confidence. This can be expressed by

\[
\arg \min_j \sum_k |W_k^T z^k - W_k^T m_j^k|.
\]

In voting, the final decision is identified as the category supported by the largest number of individual classifiers. We experimentally compared the two ensemble methods and found that summation has better performance. In the experiments, we will use summation for classifier for ensemble without special notification.
4. Experiments

To examine the performance of random discriminant structure analysis, we use the connected vowel utterances [1] for experiments. It is known that acoustic features of vowel sounds exhibit larger between-speaker variations than consonant sounds. The data used includes all combinations of five Japanese vowels ‘a’, ‘e’, ‘i’, ‘o’ and ‘u’, such as ‘aeiou’, ‘aeiou’, ... . So there are totally 120 words. The samples of 16 speakers (8 males and 8 females) are recorded. Every speaker provides 5 utterances for each word. So the total number of utterances is 9,600. Among them, we use 4,800 utterances from 4 male and 4 female speakers for training and the other 4,800 utterances for testing.

We calculate twelve Mel-cepstrum features and one power feature for every frame of an utterance. HMM training is used to convert cepstrum vector sequence into events (distributions). Since we have only one training sample, an MAP-based learning algorithm [5] is adopted. The trained HMM includes 25 states, and each state has a 13-dimension Gaussian distribution with a diagonal covariance matrix. Following [1], we divide a cepstrum feature steam into 13 multiple sub-streams, and calculate the structures for each sub-stream. So an utterance is represented as a set of $25C_2 \times 13 = 3,900$ edges. More details can be found in our works [1], [13]. We use a regularized version of Fisher discriminant analysis (RDA) [11] to train an individual classifier of each random structure. It can be shown that the regularization can reduce the unfavorable effects of noisy samples and overfitting problem.

4.1 Experiment 1

In the first experiment, we examine the performance of various numbers of edges used in sub-structures and various numbers of discriminative classifiers. We set the numbers of edges as 100, 200, 300, ..., and 2,000, and the numbers of discriminative classifiers from 1 to 30. For each combination of edge number and classifier number, we repeat the training procedure 20 times to get 20 sets of RDSA classifiers and calculate their average recognition rates.

The results are summarized in Fig. 6. It can be seen that when the number of discriminative classifiers is larger than 10 and the edge numbers is larger than 300, the increase of classifier number can only improve the recognition rates very little. Also when edge number is larger than 700 and classifier number is larger than 10, there is no improvement of the recognition rates observed if we increase the edge numbers of individual classifier. In fact, as we can find in Fig. 6, the highest average recognition rate is achieved when edge number equals to 700 and classifier equals to 22. This is because: although, for an individual classifier, the addition of edges can increase recognition rates, this may reduce the independence among different classifiers and impair the performance for classifier ensemble. These results indicate that we need not to use a large edge number and a large classifier number for achieving a good recognition rate. This is important in practice, since for small edge number (1/4-th of all the edges) and classifier number (about 20), we don’t have to do large computation in both training and testing procedures.

4.2 Experiment 2

We also make comparisons with other classical classification methods: nearest neighbors (NN), nearest mean (NM), Gaussian distribution model (GM) and Mahalanobis distances (MD). For nearest neighbors and nearest mean, Euclidean distance is used. For Gaussian distribution and Mahalanobis distances, we use diagonal covariance matrices. The results of using 8 speakers’ data for training are summarized in Table 1. We can see the proposed method achieves the highest recognition rate. We also examine the effect of using smaller numbers of speakers for training data. We randomly selected $k$ (1 $\leq$ $k$ $\leq$ 7) speakers from the 8 training speakers and use their data for learning the classifiers. For each $k$, we repeat this procedure 8 times and calculate their average performance. Note that testing data are the same and no testing data is used in training. For all the experiments, the proposed method always has the best performance and is less influenced by the reduction of training speakers. With the training utterances from only 5 speakers, the proposed RDSA can achieve a higher recognition rate than that of HMM (97.4%) trained by the utterances of 4,130 speakers [9]. (HMM trained by the 260-speakers has a
The proposed method is more robust to the reduction of the numbers of training speakers. For future work, we are considering to develop a mechanism which can integrate edge selection and classifier ensemble in a more effective way, and to evaluate the proposed methods on larger utterance databases that includes both vowels and consonants.

6. Acknowledgment

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Table 1: Comparisons of recognition rates. The 2nd row shows the numbers of training speakers. The first five methods use the structural representation as input.

<table>
<thead>
<tr>
<th>method</th>
<th>NN</th>
<th>NM</th>
<th>MD</th>
<th>GM</th>
<th>RDSA</th>
<th>HMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>#speaker</td>
<td>8</td>
<td>4,130</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>rate</td>
<td>93.1%</td>
<td>95.2%</td>
<td>94.1%</td>
<td>96.2%</td>
<td>98.3%</td>
<td>97.4%</td>
</tr>
</tbody>
</table>

The recognition rate of 82.1%. Two facts should be noted here. 1) The structural representations are reliable features, since the simple classifiers such as nearest neighbors and nearest mean can achieve relatively high recognition rates with limited training data. 2) The reduction of training speakers can lead to significant decrease of recognition rates. This means that we still depend on sufficient training data (although it is much less than that of HMM in our experiments) for achieving a good performance.

5. Conclusions

This paper proposed a novel method, Random Discriminant Structure Analysis (RDSA) for universal structure based speech recognition. RDSA has the advantages of random structure construction, discriminant analysis and classifier ensemble. Compared with the original structural representation, the representation calculated by RDSA has lower dimensions and is more discriminative. It also preserves the desirable invariant property of input structure. In RDSA, the random structure construction can circumvent the overfitting and singularity problem of FDA. For classification, RDSA makes use of discriminant analysis and classifier ensemble to improve the recognition rates. In the experiments, the proposed method achieved a recognition rate of 98.3% on the connected vowel utterances based on the training speech of 8 speakers, which is higher than all compared methods, and the HMM trained by the utterances of 4,130 speakers.

The following references are cited in the text: