Speaker Recognition Robust for Time Difference based on Subspace Method

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Abstract

This paper proposes a method to separate speaker information from phonetic information included in speech data. A speaker recognition method using the separated speaker information is also proposed and shown to be equivalent with a method based on speaker subspace. A new speaker recognition method robust for time session difference is also proposed. The validity of this proposed method was verified by carring out simple speaker recognition experiments.

1 Introduction

Speech recognition sometimes requires who is speaking, because intention of an utterance becomes different depending on speakers. This requirement leads to an idea that speaker recognition should be integrated into speech recognition. In other words, they are ought to be carried out simultaneously.

From this view point, this paper investigates speaker information and phonetic information included in speech signal and trys to separate them each other. As a result, using the separately extracted speaker information, we carry out speaker recognition.

A speech production model, we assume, is that speech data presented in an observation space as a sequence of short time spectra is produced by projecting speech data presented in an individual speaker space to the observation space. We also assume that the speech data presented in an individual speaker space are neutral and include only phonetic information. The individual speaker space is defined by orthonormal bases computed from the speech data. This concept coincides with a subspace method proposed by Oya.[1]

According to the subspace method, we prepare a projection matrix to each speaker by computing the orthonormal bases of the speech data. Using the projection matrices, we recognize who is speaking by finding a speaker subspace to which the projection length of the input speech data is maximized. We carried out three experiments including CLAFIC and principal component analysis and compared the results. A new speaker recognition

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method is proposed which uses relative feature vector originated from the speaker's mean vector, instead of absolute feature vector.

2 Separation Model

2.1 Singular Value Decomposition

Let us consider a situation where we are observing speech data X_A of speaker A and speech data X_B of speaker B in an observation space shown in Fig.1. The speech data are a sequence of spectral feature vectors x_{At} and x_{Bt} obtained at time t by short time spectral analysis. We denote the speech data X_A as a matrix whose row is a spectral feature vector x_{At}^T, $(1 \leq t \leq M)$. The column of the matrix corresponds to frequency i, $(1 \leq i \leq N)$.

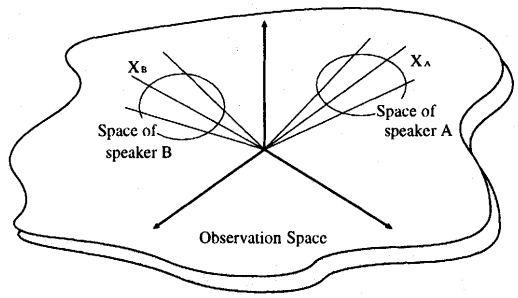

Figure 1: Observation space and speaker space

By singular value decomposition, the speech data matrix X_A is decomposed as

$$X_A = U_A \Sigma_A V_A^T \tag{1}$$

Here U_A and V_A are the matrices whose columns are eigenvectors of $X_A X_A^T$ and $X_A^T X_A$ respectively, and Σ_A is the singular value matrix of X_A.

If r numbers of the larger singular values are selected from the matrix Σ_A, the matrix U_A becomes M x r dimension and the row still corresponds to time. The matrix V_A^T becomes r x N dimension and the column corresponds to frequency. A new interpretation of equation (1) is that the speech data matrix $U_A \Sigma_A$ is produced by projecting the speech data matrix X_A in the observation space to the individual speaker space through the orthogonal transformation matrix V_A. The reverse projection is also interpreted as that the individual speaker space is projected to the observation space through the orthogonal transformation matrix V_A^T.

Since the speech data matrix $U_A \Sigma_A$ is represented in own speaker space, we can say that speaker information is less included in $U_A \Sigma_A$ than the speech data matrix X_A presented in the observation space. This interpretation means that $U_A \Sigma_A$ has mainly phonetic information and V_A has mainly speaker information.

2.2 Eigenvalue Decomposition

Here we investigate more the speaker information matrix V_A. V_A is the matrix whose columns are eigenvectors of a correlation matrix $X_A^T X_A$. It is expressed by eigenvalue decomposition as follows:

$$X_A^T X_A = V_A \Sigma V_A^T \tag{2}$$

The eigenvectors of the correlation matrix $X_A^T X_A$ are shown to be orthonormal bases, of the speech data X_A, computed based on a criterion that the total distance between an observed speech vector x_{At} and the orthonormal bases is minimized.

2.3 Subspace Method

Since the speaker information matrix V_A is composed of orthonormal bases $\{v_{A1}, \cdots, v_{Ar}\}$ of the speech data X_A, the matrix V_A constructs the speaker subspace. Here we consider a distance from an arbitrary speech feature vector x in the observation space to the speaker subspace V_A. It is presented as follows using a projection matrix P_A from the observation space to the speaker subspace.

$$Dist(V_A, x) = \| P_A x - x \| \tag{3}$$

where the projection matrix P_A is defined as:

$$P_A = \sum_{k=1}^{r} v_{Ak} v_{Ak}^T \tag{4}$$

because the projected vector $P_A x$ is presented as $\sum_{k=1}^{r} v_{Ak}(v_{Ak}^T x)$. Equation (4) is written as follows:

$$P_A = V_A V_A^T \tag{5}$$

Equation(5) means that the projection matrix from the observation space to the speaker subspace is obtained using the orthonormal bases of the speech data X_A. Once the projection matrix P_A is obtained, the distance from the speech feature vector x in the observation space to the speaker subspace (the projected vector $P_A x$) can be computed. The speaker is identified as one with the subspace nearest to the input speech feature vector x.

In practice, the length of the projected vector $\| P_A x \|$ is computed, instead of the distance, and the speaker is identified as one with the maximum length of the projected vector to his subspace. It can be expressed as follows:

$$x^T P_A x > x^T P_B x \quad \text{then the speaker is A} \tag{6}$$

The decision boundary of the subspace method is defined as non-linear.

$$\begin{aligned} Boundary_{AB} &= \{x | x^T P_A x = x^T P_B x\} \\ &= \{x | x^T (P_A - P_B) x = 0\} \end{aligned} \tag{7}$$

3 Speaker Recognition

Fig.2 shows a system of speaker training and speaker recognition based on the subspace method.

3.1 Speaker training

The training step of individual speaker information proceeds as follows:

(1) Speech signals sampled at 12KHz are converted into frequency domain by 256-point FFT analysis for each speaker.

(2) The frequency domain below 6,000Hz is converted into log scale and divided into 16 bands.

(3) A sequence of 16 order spectral feature vectors x_{At} is obtained by averaging and log-scaling the energy at each band.

(4) A correlation matrix $X_A^T X_A$ is computed.

(5) Orthonormal bases v_{Ak} of the speech data X_A is obtained by eigenvalue decomposition of the correlation matrix $X_A^T X_A$. The matrix V_A is composed of the bases v_{Ak}.

(6) The projection matrix P_A is computed by equation (5). Since V_A and P_A are the matrices with 16x16, speaker information of each speaker is presented by 256 parameters.

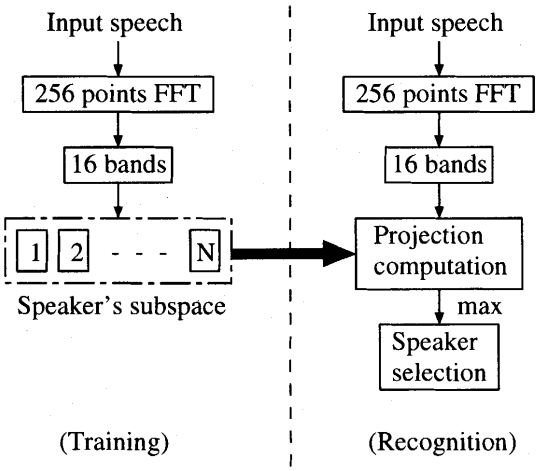

Figure 2: Speaker training and recognition

3.2 Speaker Recognition

Speaker recognition is performed by applying the projection matrices of each speaker to input speech. The step proceeds as follows.

(1) A sequence of 16 order spectral feature vectors x_t, $(1 \leq t \leq K)$ is obtained from speech signal in the same way as the training step.

(2) Projected length of the speech vector x_t to the subspace of speaker A is computed using the projection matrix P_A by equation (6). The averaged length y^A of the input speech projected to the subspace of speaker A is computed as follows:

$$y^A = \frac{1}{K} \sum_{t=1}^{K} x_t^T P_A x_t \tag{8}$$

(3) Speaker is identified by selecting the maximum averaged length of the input speech projected to the subspace.

4 Recognition Experiment

4.1 Database and Experimental Condition

Speech data are sentences spoken by 15 speakers (10 males and 5 females) at three time sessions during 10 months.[2] These sessions are denoted as 90-8, 91-3 and 91-6 in this paper.

The 15 speech sentences, including each 5 utterances with normal speed, fast speed and slow speed respectively were selected from each speaker for training. The averaged duration of the sentences is about 4 seconds. They were 256-point FFT analyzed and a time sequence of 16 order spectral feature vectors was produced. Table 1 shows the condition of speech analysis.

Table 1: Condition of speech analysis

Sampling frequency	12KHz
High-pass filter	$1 - 0.97z^{-1}$
Feature analysis	FFT spectrum(256)
Feature parameter	16 band energy
Frame length	20ms
Frame shift	5ms
Window type	Hamming window

4.2 Speaker Recognition Experiments

[Experiment 1] CCR

To investigate the dimension of the speaker subspace, we computed a cumulated contribution rate CCR which is defined by the following expression:

$$CCR(s) = \sum_{i=1}^{s} \alpha_i / \sum_{i=1}^{16} \alpha_i \tag{9}$$

Here, α_i indicates the ith eigenvalue obtained by eigenvalue decomposition of the correlation matrix $X_A^T X_A$. Table 2 shows the cumulated contribution rate as a function of a number of dimensions. From the table, it can be seen that the subspace dimension is enough up to 5.

Table 2: Cumulated contribution rate(%)

1dim	2dim	3dim	4dim	5dim	6dim
97.6	99.2	99.8	99.9	100.0	100.0

[Experiment 2] CLAFIC method

The projection matrices P_k $(1 \leq k \leq 15)$ were produced using the speech data at one time session 90-8 for each speaker, and registered as speaker templates.

Speaker recognition was carried out using 15 different sentences (text independent) spoken at normal, fast and slow speed for each 5 sentences. The time session used for the recognition was 90-8, 91-3 and 91-6. The speaker was identified by selecting the longest projection vector on the 15 speaker subspaces. This method corresponds with CLAFIC method in subspace based pattern recognition.

The result is shown in Fig.3. In the figure, the horizontal axes is the subspace dimension and the results at the three time sessions were shown by different lines. The highest recognition rate was 100 % at the same time session as training, and the lowest was 91 % at the different time session. From the figure, it can be seen that the subspace dimension is enough at 5 which corresponds well with the result by [Experiment 1].

[Experiment 3] Training by two different time session

To solve a problem that the recognition system is suffered from difference of the time session, speech data over two time sessions were used for training. Namely, the projection matrices P_k $(1 \leq k \leq 15)$ were produced using the speech data over two time sessions for each speaker.

Speaker recognition was carried out using 15 different sentences spoken at normal, fast and slow speed for 5 sentences respectively. The time session for the recognition was remaining one among 90-8, 91-3 and 91-6.

The result is shown in Fig.4. In the figure, the horizontal axes is the subspace dimension and the results at the three time sessions were shown by different lines. The line part1 shows the result recognized at time session 91-6, trained over 90-8 and 91-3. The line part2 and part3 are the result at time session 91-3 and 90-8 respectively, trained over remaining

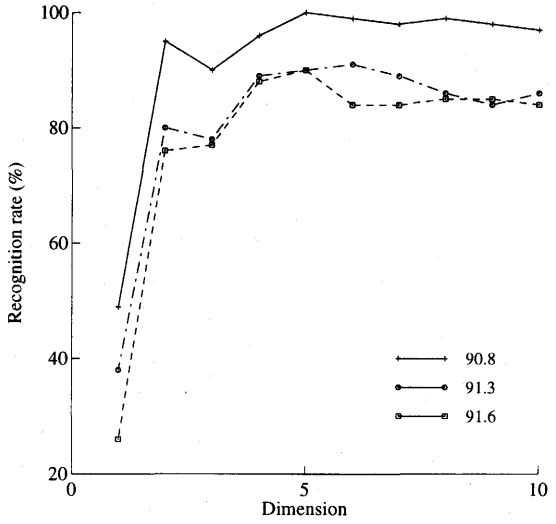

Figure 3: Result of speaker recognition by CLAFIC method
(Trained at 90-8)

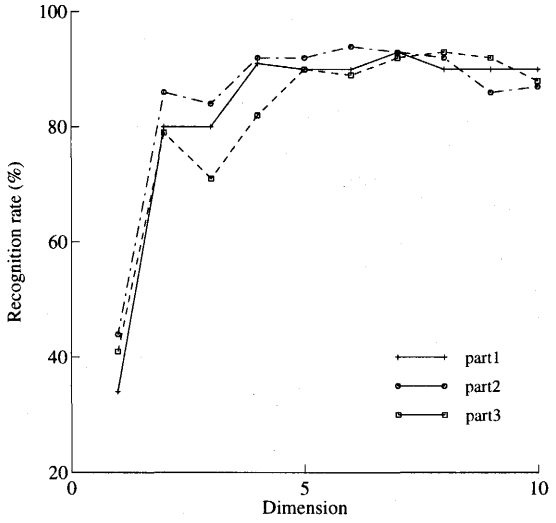

Figure 4: Result of speaker recognition
(Trained over two time sessions)

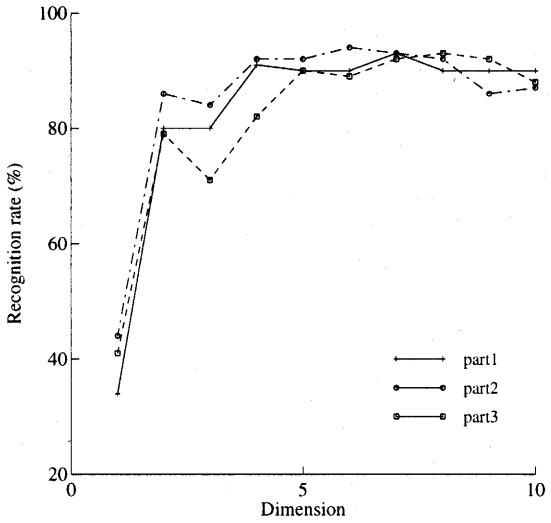

Figure 5: Result of speaker recognition by principal component analysis (Trained at 90-8)

two sessions. The highest recognition rate was 94.0 %. From the figure, it can be seen that training over two sessions improves the recognition a little.

[Experiment 4] Principal component analysis

In CLAFIC method, orthonormal bases are computed as eigenvectors of the correlation matrix $X_A^T X_A$. Bu in this principal component analysis method, the orthonormal bases are computed as eigenvectors $v_k^{(i)}$ of the covariance matrix $R^{(i)}$, which is the correlation matrix of feature vectors, after subtracting the mean vector $\mu^{(i)}$ from them. Here i indicates the seapker identification number. The projection matrix is computed by the equation (4). When input speech $\{x_t\}$ is given, the mean vector $\mu^{(i)}$ is subtracted, and $x_t - \mu^{(i)}$ is projected to the speaker subspace by $P^{(i)}(x_t - \mu^{(i)})$. Then the projected vector is obtained by adding the mean vector as $P^{(i)}(x_t - \mu^{(i)}) + \mu^{(i)}$. The averaged distance between the input speech $\{x_t\}$ and the speaker subspace is computed by the following expression.

$$\begin{aligned} Dist(V^{(i)}, \{x_t\}) &= \frac{1}{N} \sum_t \|x_t - \{P^{(i)}(x_t - \mu^{(i)}) + \mu^{(i)}\}\| \\ &= \frac{1}{N} \sum_t \|(I - P^{(i)})(x_t - \mu^{(i)})\| \end{aligned} \tag{10}$$

The speaker is identified as i when $Dist(V^{(i)}, \{x_t\})$ is minimum.

The speaker recognition experiment was carried out in the same way as the [Experiment 1]. The result is shown in Fig.5. The highest recognition rate was 95.1% for 91.6 testing data at 3 dimension. The recognition rate is higher by 4.1% than the [Experiment 1].

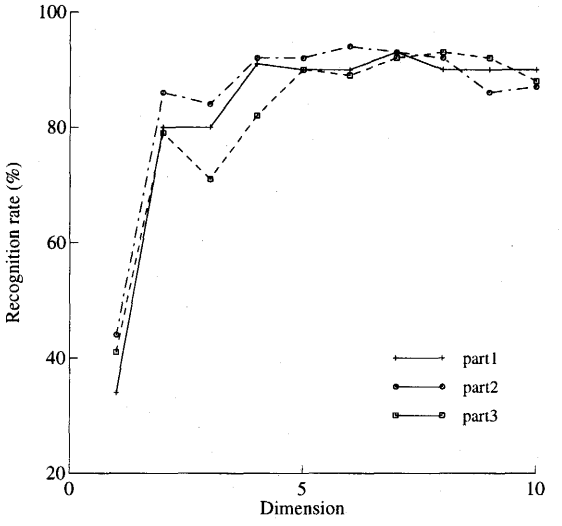

Figure 6: Result of speaker recognition by time difference normalization (Trained at 90-8)

[Experiment 5] Time difference normalization

This training method is completely same as principal component analysis method. In testing, the mean vector μ of the input speech $\{x_t\}$ is computed at first. The time difference for the speaker is regarded as $\mu - \mu^{(i)}$, and it is subtracted from the input speech $\{x_t\}$. The time difference normalized speech $x_t - (\mu - \mu^{(i)})$ is used in the principal component analysis method to identify the speaker. Then the following distance expression is obtained between speaker subspace and the input speech.

$$\begin{aligned} Dist(V^{(i)}, \{x_t\}) &= \frac{1}{N}\sum_t \|(I - P^{(i)})(x_t - (\mu - \mu^{(i)}) - \mu^{(i)})\| \\ &= \frac{1}{N}\sum_t \|(I - P^{(i)})(x_t - \mu)\| \end{aligned} \tag{11}$$

The speaker recognition experiment was carried out in the same way as the [Experiment 4]. The result is shown in Fig.6. The highest recognition rate was 96.0% for 91.3 testing data at 5 dimension. This is higher by 5% than [Experiment 1].

5 Conclusion

A model to separate speaker information from phonetic information was described on the basis of singular value decomposition. The speaker recognition using the separated speaker information was shown to be equivalent with the speaker subspace method. The experimen-

tal results show the effectiveness of the proposed method. Further work will be required to apply the system to many speakers about 100.

References

[1] E.Oja, : "Subspace Methods of Pattern Recognition", Research Studies Press, England, 1983.

[2] T.Matsui and S.Furui,: "Concatenated Phoneme Models for Text-variable Speaker recognition", ICASSP93, pp.II-391-II-394, 1993.