A FISHERVOICE BASED FEATURE FUSION METHOD FOR SHORT UTTERANCE SPEAKER RECOGNITION

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Outline

- Introduction
- The FisherVoice based SUSR framework
- Experimental Results and Analysis
- Conclusions

Introduction

- Short Utterance Speaker Recognition (SUSR)
  - In some situations, only a short utterance containing only one or two words is available
  - Short utterances can provide a better user experience
  - The current technologies are unsatisfactory when the test speech is very short
- GMM-UBM / GMM-SVM
  - Dominant speaker recognition Technologies
  - The classic and effective methods when the test data is enough
  - The performance degrades sharply when the test speech is shortened

The Influence of the Length of Test Speech

- The length of the test data is a big factor that influences the performance of speaker recognition
  - R. Vogt, S. Sridharan and Michael Mason. IEEE Trans on ASLP 2010. On NIST SRE 2005 Database

Valid length	**EER(%)**	**MinDCF (10^{-2})**
Sufficient	6.34	2.93
20 Seconds	8.87	3.91
10 Seconds	12.15	4.89
5 Seconds	16.99	6.16
2 Seconds	23.89	7.94
< 2 Seconds	>35	>10

Existing Solutions

- Factor Analysis Subspace Estimation
  - Decrease the number of redundant model parameters to develop dominant speaker models [P. Kenny 2005]
- Speech Segments Selection
  - Select segments with higher discriminability on speaker characteristics [M. Nosratighods 2010]
- Score Fusion
  - Weighted bilateral scoring [A. Malegaonkar 2008]
- Most of the above mentioned approaches show improvements with test length among 5~10 seconds.

Feature Combination

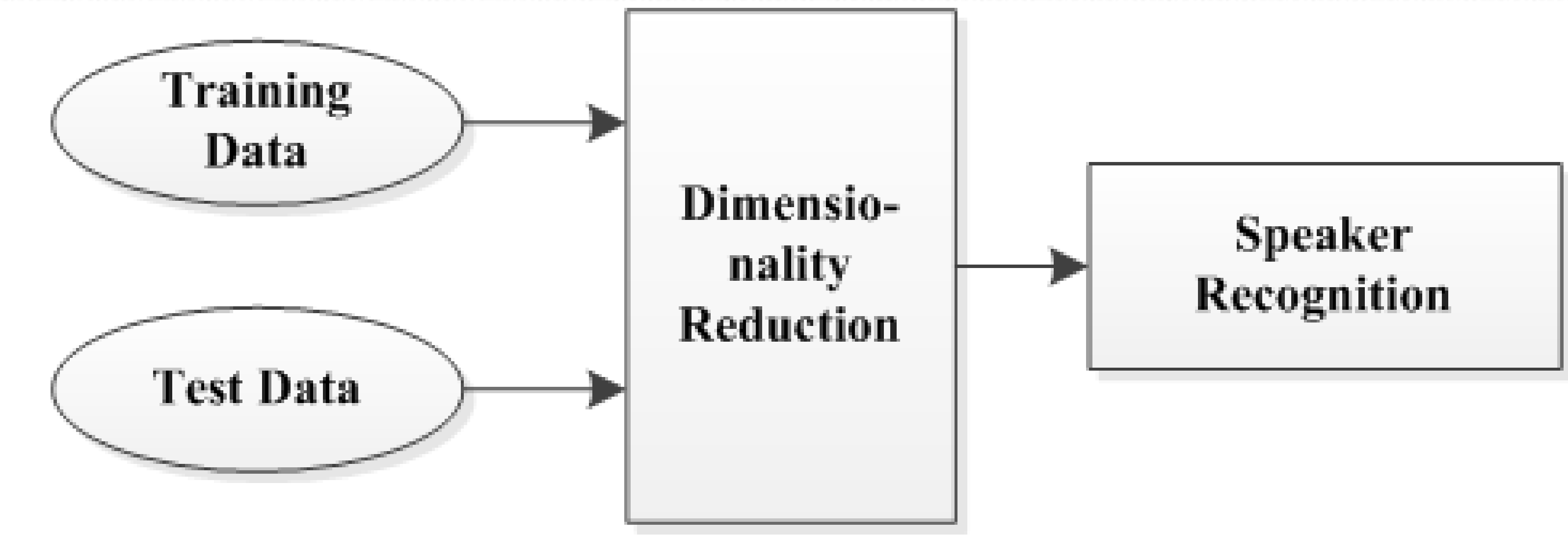
- The same speaker recognition system with different kinds of features will perform quite differently
  - Mel Frequency Cepstral Coefficients (MFCC)
- For short utterance, the information of one kind feature will not be enough
  - One single kind of feature can provide relatively enough speaker information to perform speaker recognition when the test utterance is long enough
- The combination of different features is useful to improve the recognition performance in many research fields
  - Feature Fusion. [J. Yang, 2003]

Feature Fusion Method

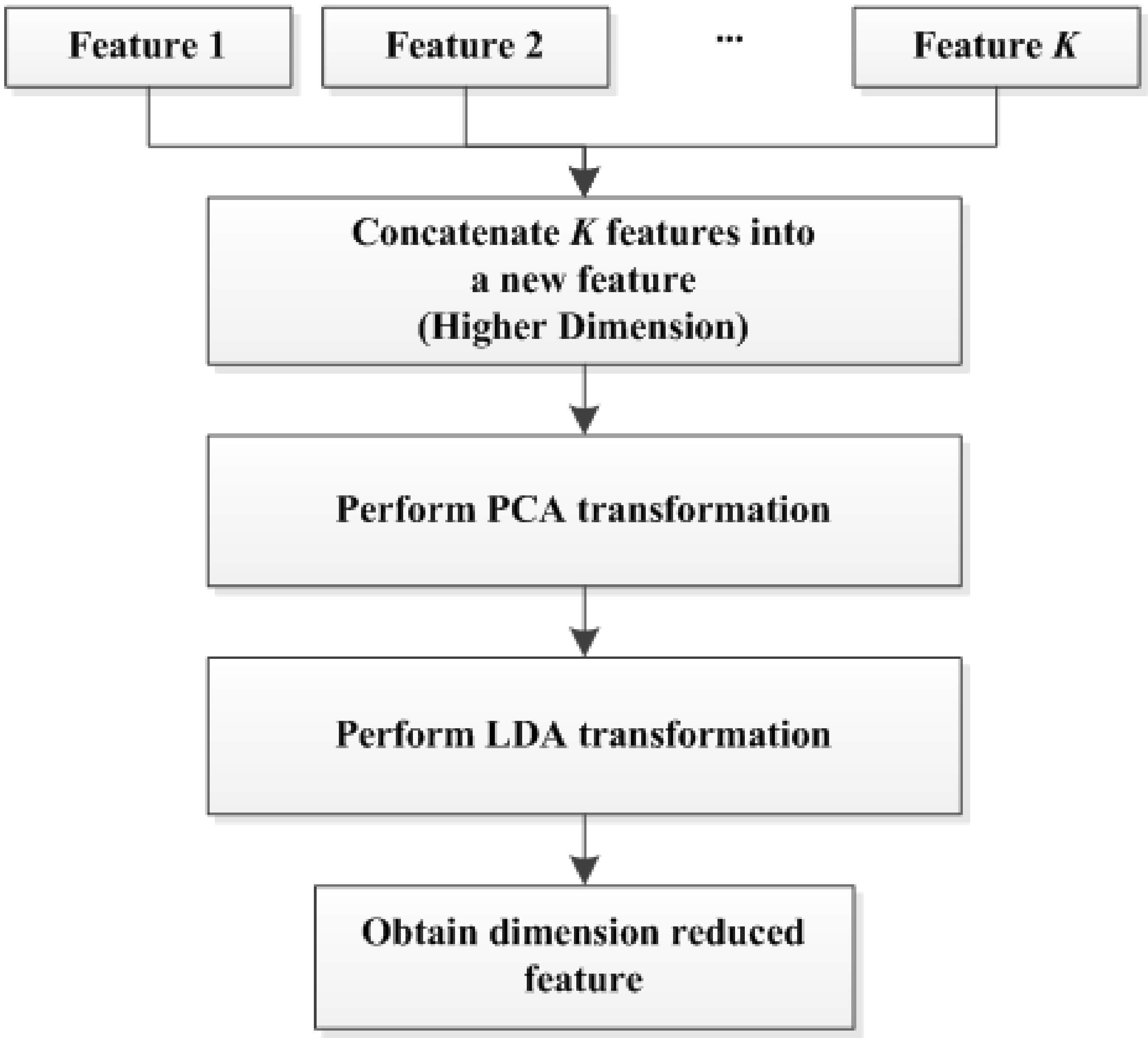
- Target: 2 aspects
  1. De-correlate the concatenated feature vectors into individual ones from multiple feature streams
  2. Eliminate the coefficients with redundant and unimportant information
- Linear Discriminant Analysis (LDA)
  - Maximize the between-class covariance and simultaneously minimizing the within-class covariance
  - Problem: The Singular Matrix
- The Fishervoice based method
  - Principal Component Analysis (PCA) plus LDA

The FisherVoice based SUSR Framework

- Two Key Parts
  1. The Fishervoice based dimensionality reduction
     - combine different kinds of features
  2. The GMM-UBM based speaker recognition



The Fishervoice based Dimensionality Reduction



Linear Discriminant Analysis

- For the original data set **X**, the within-class scatter matrix and the between-class scatter matrix are:

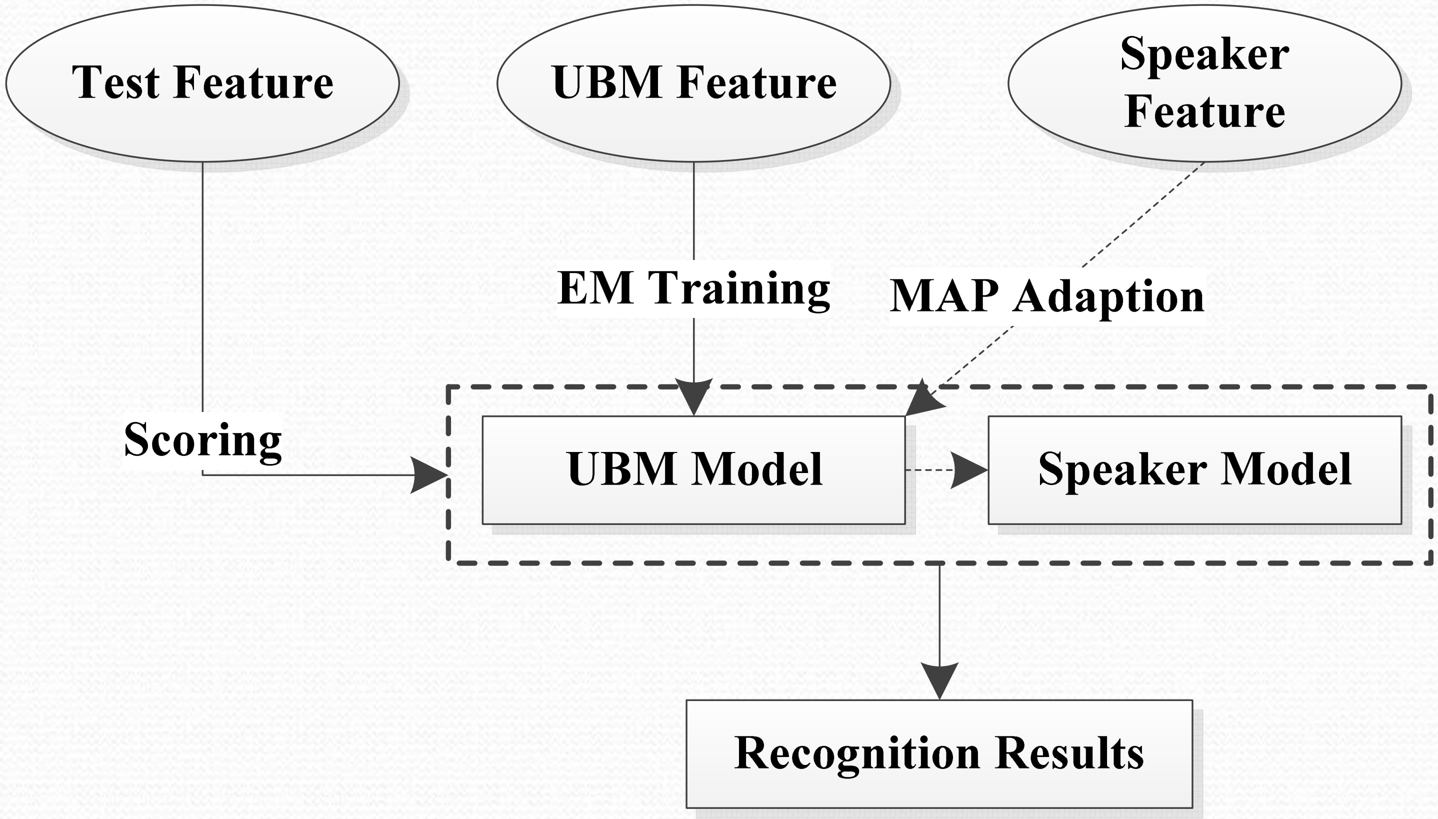
$$S_W = \sum_{c=1}^{C} \sum_{\mathbf{x} \in D_c} (\mathbf{x} - \mathbf{m}_c)(\mathbf{x} - \mathbf{m}_c)^T \qquad S_B = \sum_{c=1}^{C} n_c (\mathbf{m}_c - \mathbf{m})(\mathbf{m}_c - \mathbf{m})^T$$

$$\mathbf{m}_c = \frac{1}{n_c} \sum_{\mathbf{x} \in D_c} \mathbf{x} \qquad \mathbf{m} = \frac{1}{\sum_{c=1}^{C} n_c} \sum_{c=1}^{C} n_c \mathbf{m}_c$$

- LDA maximizes the criterion as:

$$J(W) = \frac{\tilde{S}_B}{\tilde{S}_W} = \frac{W^T S_B W}{W^T S_W W}$$

The GMM-UBM based speaker recognition



Database

- Database: SUD12
  - 60 Chinese speakers: 30 males and 30 females
  - 163 Chinese sentences:
    - 100 long sentences for train / 63 short sentences for test
  - The Distribution of the length of the test utterances

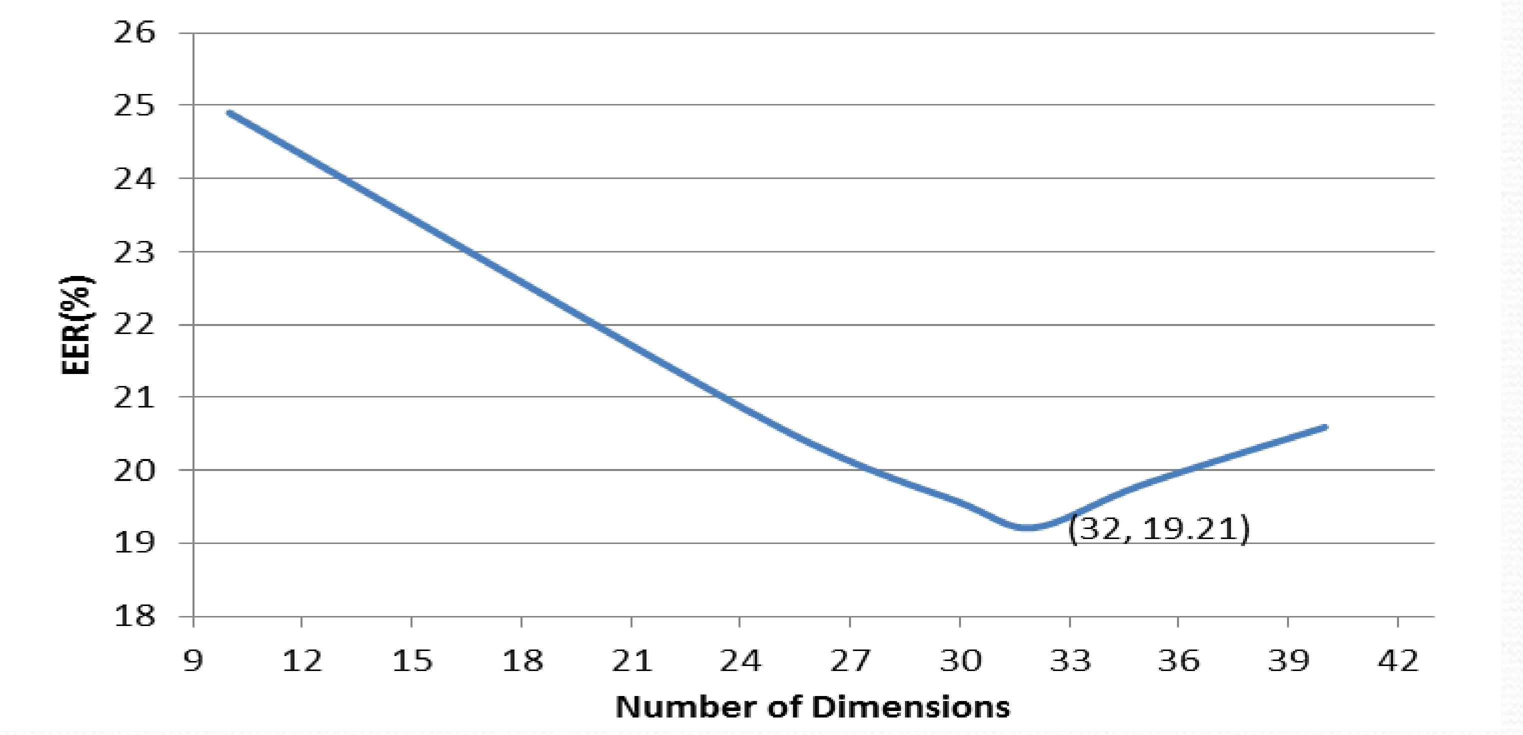
Length in second	# of Sentences	Percent (%)
less than 0.5	38	60.32
0.5 to 1.0	15	23.81
1.0 to 2.0	10	15.87

  - Recorded in clean environments using a microphone at 8 kHz sampling rate with 8-bit precision

Experimental Conditions

- Three kinds of features were and they are:
  - **MFCC** - 20-dimensional Mel Frequency Cepstral Coefficients (MFCC)
    - 30 Mel filter banks.
  - **PLAR** - 20-dimensional Perceptual Log Area Ratio (PLAR) Be robust to the noise and other environments [19], is derived from the Perceptual Linear Prediction feature (PLP) [20].
  - **LPCC** - 12-dimensional Linear Predictive Cepstrum Coefficients (LPCC)
- 52-dimensional feature vector

Results and Analysis



EER of the Fishervoice based method as a function of number of dimensions

Results and Analysis

Feature	EER (%)
MFCC	26.52
PLAR	22.98
LPCC	23.44
Concatenated Feature	28.78
LDA based	20.03
Fishervoice based	19.21

Conclusions

- The feature fusion method can improve the performance when the test utterance is short.
- The proposed Fishervoice based method can achieve a better result compared with the traditional features and the LDA fusion method in short test utterance situations.
- The feature domain method can be combined with methods from other domains to achieve a better performance for SUSR

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Thank you!