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Singing speaker clustering based on subspace learning in the GMM mean supervector space

Mahnoosh Mehrabani, John H.L. Hansen *

Center for Robust Speech Systems (CRSS), Erik Jonsson School of Engineering & Computer Science, University of Texas at Dallas, USA

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Abstract

In this study, we propose algorithms based on subspace learning in the GMM mean supervector space to improve performance of speaker clustering with speech from both reading and singing. As a speaking style, singing introduces changes in the time-frequency structure of a speaker's voice. The purpose of this study is to introduce advancements for speech systems such as speech indexing and retrieval which improve robustness to intrinsic variations in speech production. Speaker clustering techniques such as k-means and hierarchical are explored for analysis of acoustic space differences of a corpus consisting of reading and singing of lyrics for each speaker. Furthermore, a distance based on fuzzy c-means membership degrees is proposed to more accurately measure clustering difficulty or speaker confusability. Two categories of subspace learning methods are studied: unsupervised based on LPP, and supervised based on PLDA. Our proposed clustering method based on PLDA is a two stage algorithm: where first, initial clusters are obtained using full dimension supervectors, and next, each cluster is refined in a PLDA subspace resulting in a more speaker dependent representation that is less sensitive to speaking style. It is shown that LPP improves average clustering accuracy by 5.1% absolute versus a hierarchical baseline for a mixture of reading and singing, and PLDA based clustering increases accuracy by 9.6% absolute versus a k-means baseline. The advancements offer novel techniques to improve model formulation for speech applications including speaker ID, audio search, and audio content analysis.

Keywords: Speaker clustering; Singing; Speaking styles; Subspace learning

1. Introduction

Speaker clustering is the task of identifying all segments from the same speaker in a set of speech segments, and can be considered to be a special form of unsupervised speaker recognition (Makhoul et al., 2000). The goal of this study is to introduce advancements into speech systems which improve robustness to intrinsic variations in speech production. As a first attempt to advance speaker clustering with alternative speaking styles for each speaker, this study has scientific value by distinguishing speaker dependent subspaces that are less sensitive to changes in speaking style, as well as contributing to audio indexing and retrieval applications.

Most studies regarding robustness for speaker recognition systems have focused on the impact of extrinsic variations such as noise and channel, while only a few have explored the effects of intrinsic variations in spoken data for speaker recognition systems (Hansen et al., 2000; Shriberg et al., 2008; Hansen and Varadarajan, 2009). As mentioned, speaker clustering is a type of unsupervised speaker recognition, which does not require training data. Speaker clustering systems can be viewed as a preprocessing stage, in order to provide training data for new speech systems such as speech and speaker recognition by grouping unlabeled speech data. Furthermore, with an increasing number of sources to obtain speech data such as the internet, television, radio, meetings, voice mails, etc., as well as virtually

* Corresponding author.
E-mail addresses: mahmehrabani@utdallas.edu (M. Mehrabani), john.hansen@utdallas.edu (J.H.L. Hansen).

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unlimited data storage capabilities, audio indexing and retrieval is attracting more attention with increased demands on effective speech and audio search applications. Speech segments obtained from any of these sources are more likely to be unlabeled, and carry unknown information including: who is speaking?, what is the topic?, what is the environment?

Speaker diarization (Tranter and Reynolds, 2006; Wooters and Huijbregts, 2008; Reynolds et al., 2009) which basically addresses the question of ”who spoke when?” is a combination of speaker segmentation and clustering. Although it is possible to perform these two tasks jointly, most speaker diarization systems perform speaker segmentation and clustering separately (Tranter and Reynolds, 2006). While the present study focuses on speaker clustering, the techniques developed here can be applied to speaker diarization. For speaker diarization systems, it is important to group all speech segments from the same speaker, even though the speaker may not speak in the same manner. In other words, in a public presentation or person to person conversation, the speaker may change her/his speaking style, such as getting excited (Wu et al., 2006), whispering (Fan and Hansen, 2008), increased stress (Hansen, 1996), etc. All these speaking styles are due to intrinsic changes in speech production, and will affect speaker clustering systems. Multi-style training was developed by Lippmann et al. (1987) to improve speech recognition when subjects vary production. Bou-Ghazale and Hansen (1998) explored ways to model training data under specific speaking styles (loud, angry, Lombard effect) to improve speech recognition for new speakers with only neutral training data.

Singing is a good example of speaking style which has not been considered in order to address robustness of speaker clustering systems. Due to the inherent deviation of singing speech production versus spoken text, time-frequency structure of a speaker's voice changes while singing. Fig. 1 and Fig. 2 depict examples of speech signals and spectrograms, respectively, in order to compare reading and singing, where the same speaker reads and sings the same text. As will be shown in the next section, from speaking to singing, there is a shift towards higher vocal efforts which is similar to loud and excited speech. In addition, as a speaking style, singing data is easier to collect in a Karaoke style, while for collecting other speaking styles, speakers will have to spontaneously produce excitement or anger, which takes on perhaps non natural traits (i.e., exaggerated).

For the above reasons, the results from studying and improving robustness of speaker clustering for singing, can be applied to a variety of speaking styles. Furthermore, speaker clustering for singing has applications in music information retrieval. Popular music is becoming one of the most dominant data types on the internet, and therefore singer based clustering of unlabeled music recordings has attracted more attention. Tsai et al. (2004) proposed a system to cluster recordings on the basis of a singer's voice. In this study, we consider a more challenging task by mixing reading and singing samples of the same speakers. In other words, we assume that we do not have information regarding speaking style (reading or singing) while performing speaker clustering. This can be applied to speaker diarization systems for audio where both speaking and singing samples are present from one or more speakers. Many instances of such audio streams are available on the internet, radio, or TV, from interviews or talk shows with popular singers. There is also an increasing interest in singing competitions which include auditions with speaking and singing speech samples of the participants.

Our speaker clustering system is based on modeling each speech segment in the GMM mean supervector space. Traditional speaker clustering techniques are based on statistical modeling of low level acoustic features such as Mel Frequency Cepstral Coefficients (MFCC) (Rabiner and Juang, 1993) for each speech segment. The statistical models typically used in speaker clustering are Gaussian Mixture Models (GMM) (Reynolds, 1995). The GMMs are usually obtained by Maximum A Posterior (MAP) adaptation (Reynolds et al., 2000) of a Universal Background Model (UBM), previously trained on a considerable amount of speech data, to each utterance or speech segment. Next, a similarity measure is used to compare the obtained statistical models for the purpose of clustering (Solomonoff et al., 1998; Ben et al., 2004). Recent studies in speaker recognition and verification have illustrated the benefit of a speaker representation known as the GMM mean supervector which is formed by stacking the means of the GMM model (Campbell et al., 2006). Speaker GMM mean supervectors have also proven to be successful in modeling speakers for speaker clustering (Faltlhauser and Ruske, 2001; Tsai et al., 2005; Chu et al., 2009a; Chu et al., 2009b).

This study is focused on unsupervised and supervised subspace learning methods to improve speaker clustering performance for singing and a mixture of reading and singing. Fig. 3 represents the flow diagram of speaker clustering approaches in this study. Our investigation is based on a singing corpus we collected, in which each speaker reads and sings the lyrics of selected songs. In order to concentrate on vocal changes, and to eliminate effects of background music, only the singing voice of the speakers are recorded while singers are listening to the music. Section 2 describes the singing database. In Section 3 and 4, unsupervised dimensionality reduction techniques, namely Principal Component Analysis (PCA) and Locality Preserving Projections (LPP) are explored and compared to baselines for speaker clustering for reading, singing, and a mixture of reading and singing. It is shown that LPP significantly improves performance for a mixture of reading and singing. In addition, a novel similarity measure based on fuzzy c-means membership scores is proposed in Section 4 which estimates the degree of clustering difficulty or confusability between a pair of speakers. Section 5 explains our proposed clustering method based on supervised subspace learning,

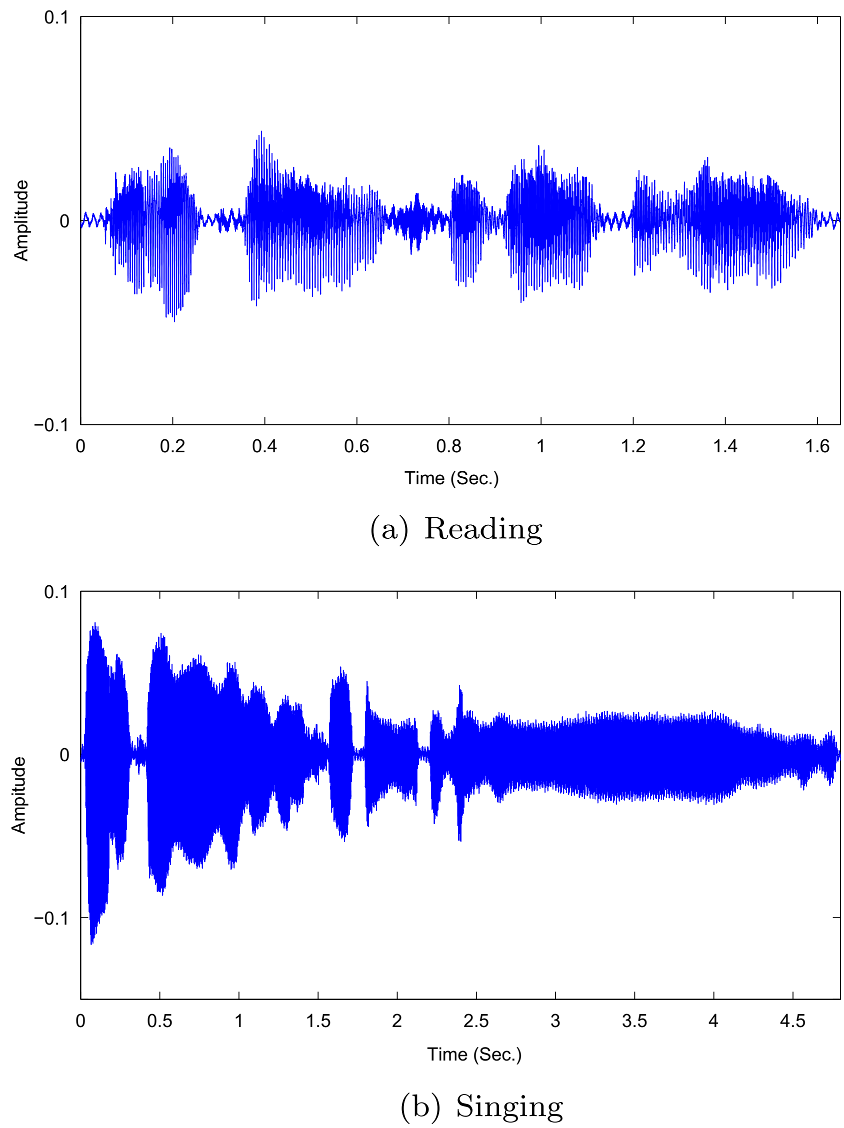


Fig. 1. Waveforms of reading and singing speech for “Any time she goes away”.

namely Probabilistic Linear Discriminant Analysis (PLDA). The proposed method consists of two stages. First, initial speaker clusters are built without considering the effects of speaking styles. Next, each cluster is refined in a subspace of the supervectors based on PLDA. Results of the proposed clustering technique is compared to baselines and shown to improve the average clustering accuracy by approximately $6-9\%$. A probe experiment is also presented to show the effect of adding background music to the singing on speaker clustering. Finally, conclusions are drawn in Section 6.

2. Database

Our experiments are based on a new database (UT-Sing) which includes singing and reading speech samples for each speaker. We collected UT-Sing for the purpose of comparing singing to reading speech, as well as analyzing the effects of singing on various speech systems. UT-Sing was collected in four languages: American English, Farsi, Hindi, and Mandarin. In the present study, the focus is on the English portion of the database based on the increased number of speakers for this language. We have recorded 33 subjects including 18 females and 15 males whose native language was English.

UT-Sing consists of two components: singing and reading. Each speaker selected 5 popular songs in their native language. Each song was approximately 3-5 minutes. We tried to have a variety of song styles, including pop, rock, and country. Though we had a list of suggested songs, we also let each subject select their songs even if it was not on the list, so they would be familiar with the songs they were singing, and could follow the melody.

Next, the speaker’s voice was recorded in a soundbooth with a close-talk microphone while singing as well as reading the lyrics of the same songs. The singing was collected using Karaoke system prompts. While subjects were listening to the music through headphones, the lyrics were dis-

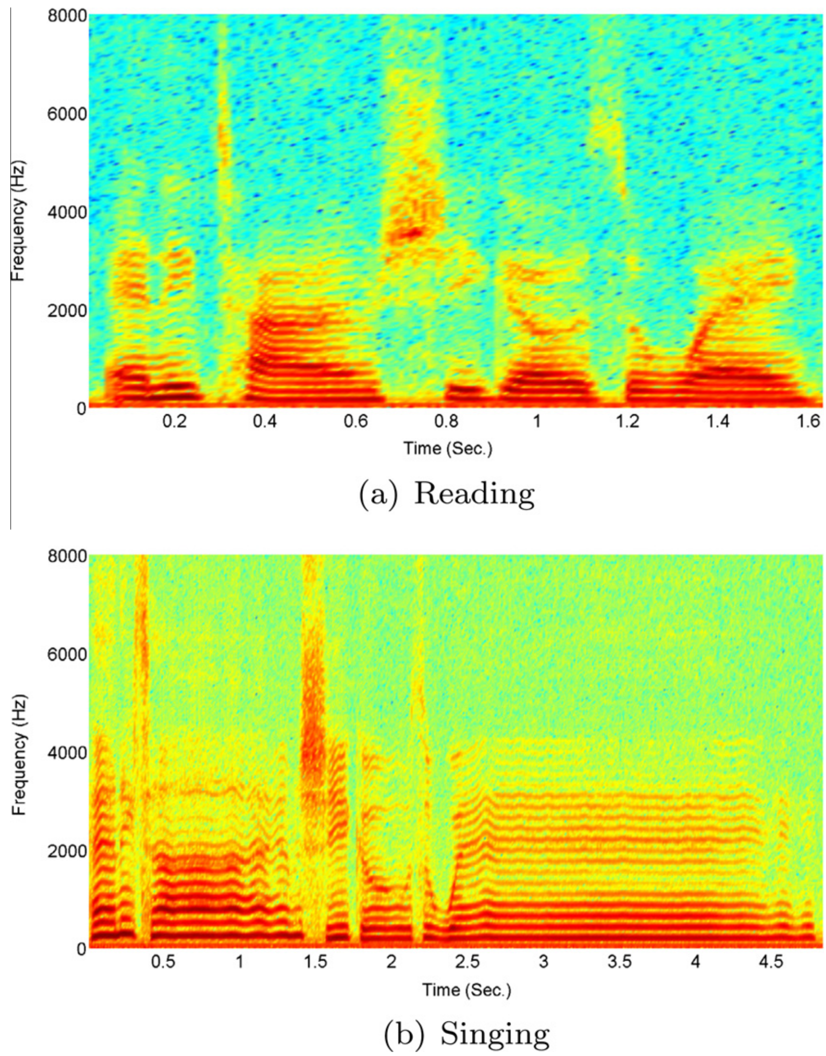


Fig. 2. Spectrograms of reading and singing speech for "Any time she goes away".

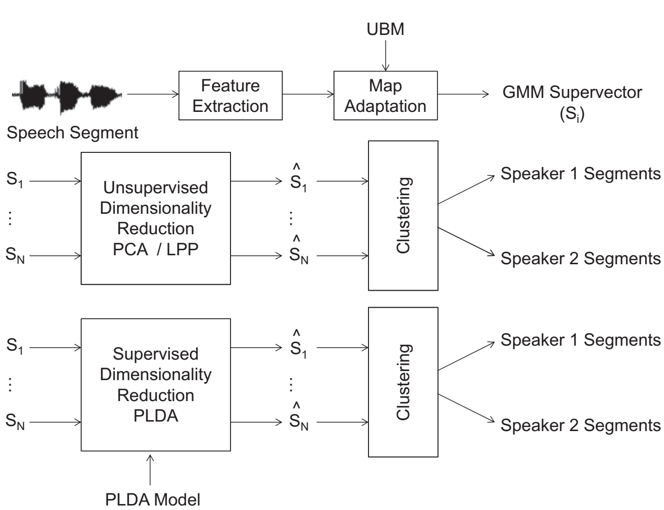


Fig. 3. Flow diagram of clustering approaches based on subspace learning in the GMM mean suprevector space.

played, and only the subject's singing voice was recorded. Recording the singing voice without the background music, lets us concentrate only on the vocal changes in singing compared to reading. Another unique advantage of this database is that singing and reading voices of the same speakers have been collected with the same text for each speaker. Therefore, the only factor that changes is the speaking style which is singing.

In order to illustrate the vocal effort variation from reading to singing, we used another corpus (UT-VocalEffort I) (Zhang and Hansen, 2007; Zhang and Hansen, 2011) , consisting of independent subjects. Vocal effort is a variation in a speaker's voice due to either speaker-listener distance, or due to relative background noise levels, or sensitivity of text content. UT-VocalEffort includes 12 native English speaking males, each reading 20 TIMIT sentences with five vocal efforts: whispered, soft, neutral, loud, and shouted. Each vocal effort was modeled using 19 dimensional MFCCs and 64 mixture GMMs. Utterances in UT-Sing corpus were first silence removed using an energy threshold, and then each reading or singing speech frame with the duration of 20 msec., and skip rate of 10 msec., was classified as one of the 5 vocal efforts using maximum likelihood classification. Since the vocal effort corpus was collected for male speakers, the vocal effort classification here is based on reading and singing data from English male speakers. Fig. 4 presents the results of vocal effort classification for reading and singing.

Comparing the two histograms shows the speech production differences between reading and singing. For singing speech frames there is a shift towards higher vocal efforts with 31.3% of frames classified as loud and shouted (i.e., some subjects were enthusiastic when singing their selected songs). This confirms a fundamental shift in the manner of speech production between reading and singing, which is more than a simple overall gain term.

3. Speaker clustering using unsupervised subspace learning in GMM mean supervector space

3.1. Baseline: no dimensionality reduction

Our baseline system is based on modeling each utterance or speech segment in the GMM mean supervector space, followed by clustering the obtained high dimensional supervectors in which each cluster represents a speaker. GMM mean supervectors have proven to be effective speaker representations in speaker verification (Campbell et al., 2006; Kuhn et al., 2000 as well as speaker clustering (Tang et al., 2009; Tang et al., 2012; Chu et al., 2009a; Chu et al., 2009b).

Our speaker clustering approach includes: preprocessing, feature extraction, model adaptation, and finally clustering of supervectors. In preprocessing, silence removal is performed for each utterance based on an energy threshold. Next, acoustic features, namely Mel Frequency Cepstral Coefficients (MFCC) are extracted from each utterance. A speaker-independent UBM is trained over all utterances and all speakers of a separate data set. In model adaptation stage, the pretrained UBM is MAP adapted to each speech segment to obtain a GMM on a per speech segment basis.

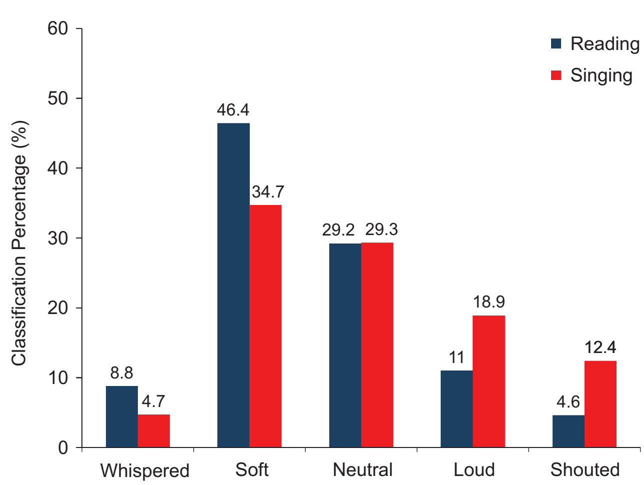


Fig. 4. Vocal effort classification for reading (left bars) and singing (right bars) speech frames.

Next, mean vectors for the obtained GMMs are stacked to build a supervector per each speech segment. Assuming that d-dimensional MFCCs are extracted from each speech segment and modeled by a GMM with M mixtures:

$$p(x|\lambda) = \sum_{i=1}^{M} w_i g(x|\mu_i, \Sigma_i) \tag{1}$$

where $\lambda = \{w_i, \mu_i, \sum_i\}, i = 1, \ldots, M$ is the Gassian Mixture Model, and $g(x|\mu_i, \Sigma_i)$ represents a d-variate Gaussian probability density function, with mean vector μ_i and covariance matrix $\sum_i$, and w_i's are the mixture weights that satisfy the constraint: $\sum_{i=1}^{M} w_i = 1$, the GMM mean supervector representing the speech segment is a vector with dimension: $M \times d$:

$$[\mu_1^T, \ldots, \mu_M^T]^T \tag{2}$$

Finally, the GMM mean supervectors are clustered using two traditional techniques: k-means and hierarchical. K-means clustering partitions the data into a predefined number of clusters, defining k centroids: one for each cluster, and each data point is associated to the nearest centroid. The following objective function is minimized in order to calculate the centroids:

$$\sum_{i=1}^{k} \sum_{j=1}^{n} \|x_j - c_i\|^2 \tag{3}$$

where $\|x_j - c_i\|^2$ is a chosen distance measure between a data point x_j and the cluster centroid c_i. In this study Euclidean distance is used for k-means clustering. Hierarchical clustering is a clustering method that builds a hierarchy of the data partitions. Hierarchical clustering algorithms are either top-down or bottom-up. Bottom-up hierarchical clustering or hierarchical agglomerative clustering starts with each data point being a cluster and subsequently links the closest clusters together based on a similarity measure until a stopping criterion is satisfied. Various objective functions can be applied as linkage criteria to merge the clusters. In this study, we used Ward's linkage method (Ward Jr, 1963). Ward's minimum variance criterion minimizes the total within-cluster variance. The initial cluster distances in Ward's minimum variance method are defined to be the squared Euclidean distance between points.

Despite the fact that GMM mean supervectors effectively model speakers, in cluster analysis and pattern recognition tasks, they are burdened with "curse of dimensionality". Next, we employ unsupervised dimensionality reduction algorithms to perform the clustering in a subspace of the data set with lower dimensionality.

3.2. Locality Preserving Projections

Locality Preserving Projections (LPP) (He and Niyogi, 2003) is a linear unsupervised dimensionality reduction technique that optimally preserves the local neighborhood structure of the data. LPP is an alternative to Principal

Component Analysis (PCA), a classical linear unsupervised dimensionality reduction that projects the data along the directions with maximal variances. The observations in a high dimensional space, usually lie on a low dimensional manifold, and LPP and PCA seek the linearly embedded manifold in the data set. While PCA aims to preserve the global structure of the data set, LPP preserves the local structure. LPP has proven to perform better than PCA in face recognition applications (He et al., 2005). It has also been shown to be successful in speaker clustering (Chu et al., 2009b).

Given a set of n-dimensional data points: $x_1, \ldots, x_m$, a linear dimensionality reduction algorithm finds a transformation matrix A which maps these m data points to a set of vectors in an l-dimensional subspace: $y_1, \ldots, y_m$ such that $l \ll n$ and $y_i = A^T x_i, i = 1, \ldots, m$. LPP is in fact a linear approximation of nonlinear manifold learning technique: Laplacian Eigenmap (Belkin and Niyogi, 2002). The LPP subspace learning algorithm first constructs an adjacency graph G with m nodes, where each node represents a data point. Two nodes i and j are connected if the corresponding data points x_i and x_j are "close". The concept of "closeness" of two data points is defined either in the sense of k nearest neighbor (i.e., i and j are connected if x_i is among k nearest neighbors of x_j and vice versa), or in the sense of ε-neighborhood (i.e., i and j are connected if $\|x_i - x_j\|^2 < \varepsilon$). Next, a weight is associated with each edge or each two connected nodes. The common weight function is the Heat Kernel:

$$W_{ij} = e^{-\frac{\|x_i - x_j\|^2}{t}} \tag{4}$$

where W is the weight matrix. Finally, the following objective function is minimized:

$$\sum_{ij} (y_i - y_j)^2 W_{ij} \tag{5}$$

Simple algebraic formulation (He and Niyogi, 2003) reduces the objective function to:

$$XLX^T a = \lambda XDX^T a \tag{6}$$

where $X = [x_1 \ldots x_m]$ is an $n \times m$ matrix of data vectors, D is a diagonal matrix such that: $D_{ii} = \sum_j W_{ij}$, and $L = D - W$ is the Laplacian matrix. Eq. (6) is a generalized eigenvalue problem, and the solutions $a_1, \ldots, a_l$ which are the eigenvectors ordered based on their corresponding eigenvalues are columns of an $n \times l$ matrix A such that:

$$y_i = A^T x_i, A = [a_1, \ldots, a_l]. \tag{7}$$

We have applied both PCA and LPP to reduce the dimensionality in the supervector space. First, the dimensionality of supervectors which present test speech segments is reduced using PCA or LPP. Next, clustering is performed in the obtained subspace. The results are presented in the next section, and compared to the baseline with no dimensionality reduction. As it will be shown PCA renders approximately the same results as the baseline, while LPP improves the results. This suggests that local manifold structure is more important than global Euclidean structure.

4. Results and analysis

4.1. Experimental results

The results of speaker clustering for two types of speaking styles are presented here: reading and singing. In addition, we present results for a mixture of these speaking styles, seeking a subspace in the mean supervector space that is speaker dependent but is not sensitive to the changes in speaking style. Speaker clustering is performed on 10 sec. speech segments. The UT-Sing corpus includes 5 reading and 5 singing utterances for each speaker in which each reading utterance is approximately 1 min., and each singing utterance 2 min. after silence removal. Therefore, on the average there are 30 reading segments and 60 singing segments per speaker. We divided our data set into two sets: train and test. As will be explained later, the train set will be used to train our PLDA model. All clustering experiments are performed on the same test set, in order to have a reliable comparison between the results. The train set includes 15 speakers: 8 females and 7 males, and the test set includes 18 separate speakers: 10 females and 8 males. 19-dimensional MFCCs were extracted from each utterance using a 20 msec. window at 10 msec. intervals. We trained our UBM on all the TIMIT data with 64 mixtures, and MAP adapted the UBM to each reading or singing 10 sec. segment. MAP adaptation was performed only on the UBM means. Next, the mean vectors for each adapted UBM were concatenated to obtain a mean supervector of the dimension $64 \times 19 = 1216$ to represent each speech segment. In this study, we assume no prior knowledge about speaking style which makes the clustering very challenging. Therefore, to focus on the speaking style and make the interpretation of the results less complicated, the number of speaker clusters is considered to be known. In addition, in order to analyze and compare the confusion between any two speakers with a change in the speaking style, all the reported accuracies are for two-speaker clustering. However, the proposed speaker clustering algorithms can be expanded for more speakers, and even to the point of unknown number of speakers. For each two speaker set in the test space, all speech segments are mixed and then clustered. We present three clustering accuracies: first, when only the reading segments of the speakers are clustered; second, when the singing segments are clustered; and third, when all speech segments including reading and singing are mixed and then clustered. The clustering accuracy for each two speakers is the number of correctly clustered segments divided by the total number of segments. The clustering is performed for all unique pairs of speakers in the test set, which represents $\binom{18}{2} = 153$ pairs in our experiments and the reported clustering accuracy is the mean of all accuracies. (Chu et al., 2009a; Chu et al., 2009b) have also used average clustering accuracies to evaluate clustering techniques.

First row of Table 1 shows the speaker clustering results with the baseline system for reading, singing, and a mixture of reading and singing with two traditional clustering techniques: k-means and hierarchical. The baseline clustering system renders almost perfect results for reading, and more than 90% clustering accuracy for singing. However, speaker clustering for a mixture of reading and singing segments represents the most challenging task with an approximate 20% loss in clustering accuracy compared to a reading baseline.

Second and third rows in Table 1 present the clustering results with PCA and LPP, respectively, when the dimension is reduced to only 2 dimensions for clustering. As shown in the tables PCA subspace learning prior to speaker clustering renders approximately similar performance to the baseline system, while LPP subspace learning improves the clustering accuracies up to 2.1% for singing versus the k-means baseline, and 5.1% for a mixture of reading and singing versus the hierarchical baseline. As previously noted, LPP preserves the local manifold structure of the data, while PCA preserves the global structure. Therefore, LPP especially works better with nearest neighbor like classifiers, and has discriminating power even though it is unsupervised (He et al., 2005). Since clustering algorithms such as k-means and hierarchical are based on a distance measure between data points and clustering the closest vectors, LPP is a suitable subspace learning technique for speaker clustering. The results show that LPP increases clustering accuracy more when there are both reading and singing speech samples for each speaker. In our experiments, the best results were achieved when using 3 nearest neighbors to build the adjacency graph for LPP, with a cosine distance as the distance measure. Increasing the reduced dimension from 2, would change the accuracies less than 1%. Next, we will analyze speaker clustering results in more detail.

4.2. Speaker similarity measure for clustering tasks based on fuzzy c-means

Speaker clustering accuracy is a viable measure to show clustering performance. However, it does not exactly show the difficulty of a clustering task for a pair of speakers. In addition, perfect clustering scores for reading for a majority of speaker pairs, makes it difficult to compare reading and singing speaker clustering for two speakers. Therefore, we propose a similarity measure based on fuzzy c-means membership degrees, which estimates the clustering difficulty for a pair of speakers. Fuzzy c-means (Dunn, 1973; Bezdek, 1981) is a clustering technique which allows a data point to belong to more than one cluster. Its objective function is similar to k-means with the difference that it also includes a membership degree:

$$\sum_{i=1}^{k}\sum_{j=1}^{n}u_{ij}^{m}\left\|x_j - c_i\right\|^2 \tag{8}$$

where u_{ij} is the degree of membership, and $1 \leqslant m$. $\left\|x_j - c_i\right\|^2$ is a chosen distance measure between a data point x_j and the cluster centroid c_i, and k is the number of clusters. Fuzzy c-means clustering assigns k numbers in the interval [0 1] to each data point which is the membership degree of that data point to each cluster. The points closer to the edge of a cluster will have lesser membership degrees than the points closer to the center. Based on this feature of fuzzy clustering, we will define a similarity measure which shows the degree of confusion between speech segments from a pair of speakers, but first, we will compare the statistics of these membership degrees between reading and singing.

Previously we showed that the average speaker clustering accuracy decreases when speakers were singing, and decreases even more when speakers were reading and singing. In order to show the difficulty of the clustering task for singing, and mixture of reading and singing, compared to reading we performed a fuzzy c-means clustering on the same data. Our experiments show that fuzzy c-means two-speaker clustering in the GMM mean supervector space renders similar results to the k-means clustering. Data points with membership degrees more than 0.5 are considered to belong to the cluster. For the remainder of this section, all supervector dimensions are reduced to 2 using PCA to reduce the processing time. The fuzzy clustering accuracies were 99.9%, 91.5%, 81.1% for reading, singing, and mixture of reading and singing, respectively. Next, the membership degrees were compared for correctly clustered samples. Note that for each data point, there are two membership degrees for each of the two clusters which add

Table 1
Average clustering accuracies (%) for reading, singing, and a mixture of reading and singing with baseline system: no dimensionality reduction, PCA, and LPP subspace learning methods.

Subspace learning	Clustering method	Reading	Singing	Mixture
Baseline(Full dimension)	K-means	99.7	91.3	80.6
	Hierarchical	99.9	92.8	82.9
PCA	K-means	99.6	91.3	80.5
	Hierarchical	99.9	91.9	82.4
LPP	K-means	99.5	93.4	84.7
	Hierarchical	99.9	94.0	88.0

up to 1. Since the clustering decision is made based on the membership degree that is greater than 0.5, in our analysis only membership degrees in the interval [0.5 1] are considered.

Fig. 5 depicts the normalized histograms of the membership degrees for correctly clustered segments for reading, singing, and a mixture of reading and singing. Data points closer to the edge of the cluster which are more likely to be confused with data points in the other cluster, have membership degrees closer to 0.5. Data points closer to the center of the cluster which are classified with more confidence have membership degrees closer to 1. For reading, only 2.5% of data points which are accurately clustered have membership degrees less than 0.75. However, for singing, 10.6% of the data points which contribute to clustering accuracy, have membership degrees less than 0.75. This suggests that even though singing clustering accuracy decreases only by 99.9-91.5=8.4% compared to reading, 10.6% of the 91.5% accurately clustered segments are closer to the edge of the cluster than the center. For mixture of reading and singing, the percentage of membership degrees less than 0.75 increases to 14.3%. This analysis shows that in addition to a loss in clustering accuracies, the correctly clustered samples are more confusable and clustered with less confidence for singing and mixture of reading and singing, compared to reading.

Next, for analysis purposes, a similarity measure is proposed based on fuzzy c-means membership degrees which shows the degree of clustering difficulty for a pair of speakers. Given two speakers, with a set of utterances or speech samples for each speaker, first, all the speech segments from both speakers are modeled by GMM mean supervectors as explained in Section 3. For the obtained set of supervectors, two cluster centroids are calculated based on fuzzy c-means objective function, and a degree of membership to each cluster center is computed for each data point or supervector. The dimension of supervectors can be reduced previous to clustering using PCA. Next, data points are partitioned into two clusters such that a data point with cluster membership degree of more than 0.5 is considered to belong to that cluster. Since the ground truth for the clusters is known, correctly clustered and incorrectly clustered supervectors are distinguished. The proposed fuzzy cluster distance is defined as:

$$\left(\sum_{j=1}^{N_c} u_j - \sum_{k=1}^{N_i} u_k\right) / (N_c + N_i) \tag{9}$$

where N_c and N_i represent the number of correctly and incorrectly clustered samples, respectively. $u_j, j = 1, \ldots, N_c$ and $u_k, k = 1, \ldots, N_i$ are the fuzzy membership degrees of correctly and incorrectly clustered samples, respectively. Note that only the membership degrees which are more than 0.5 are used in this equation, where $N_c + N_i$ is the total number of data points. The proposed fuzzy cluster distance measure is in the interval [0 1]. The more the fuzzy cluster distance is, the less is the confusion between speech segments from the corresponding speaker pair. The distance is 1 when all the data points are correctly clustered with confidence or membership degree of 1. It should be noted that if the sum of the membership degrees for incorrectly clustered data points is more than the correctly clustered data points, simply switching the clusters will result in a higher overall clustering accuracy and higher fuzzy cluster distance. Therefore, the defined distance is greater than zero and the minimum distance is 0 instead of -1. Table 2 shows the statistics of the fuzzy cluster distances between pairs of speakers for reading, singing, and a mixture of reading and singing. Fuzzy cluster distance gives us a more accurate estimation of clustering difficulty than average clustering accuracy. Compared to reading, average fuzzy clustering accuracy reduces by 8.4% absolute for singing and 18.8% for mixture, while average fuzzy cluster distance reduces by 18% absolute for singing and 36% for mixture.

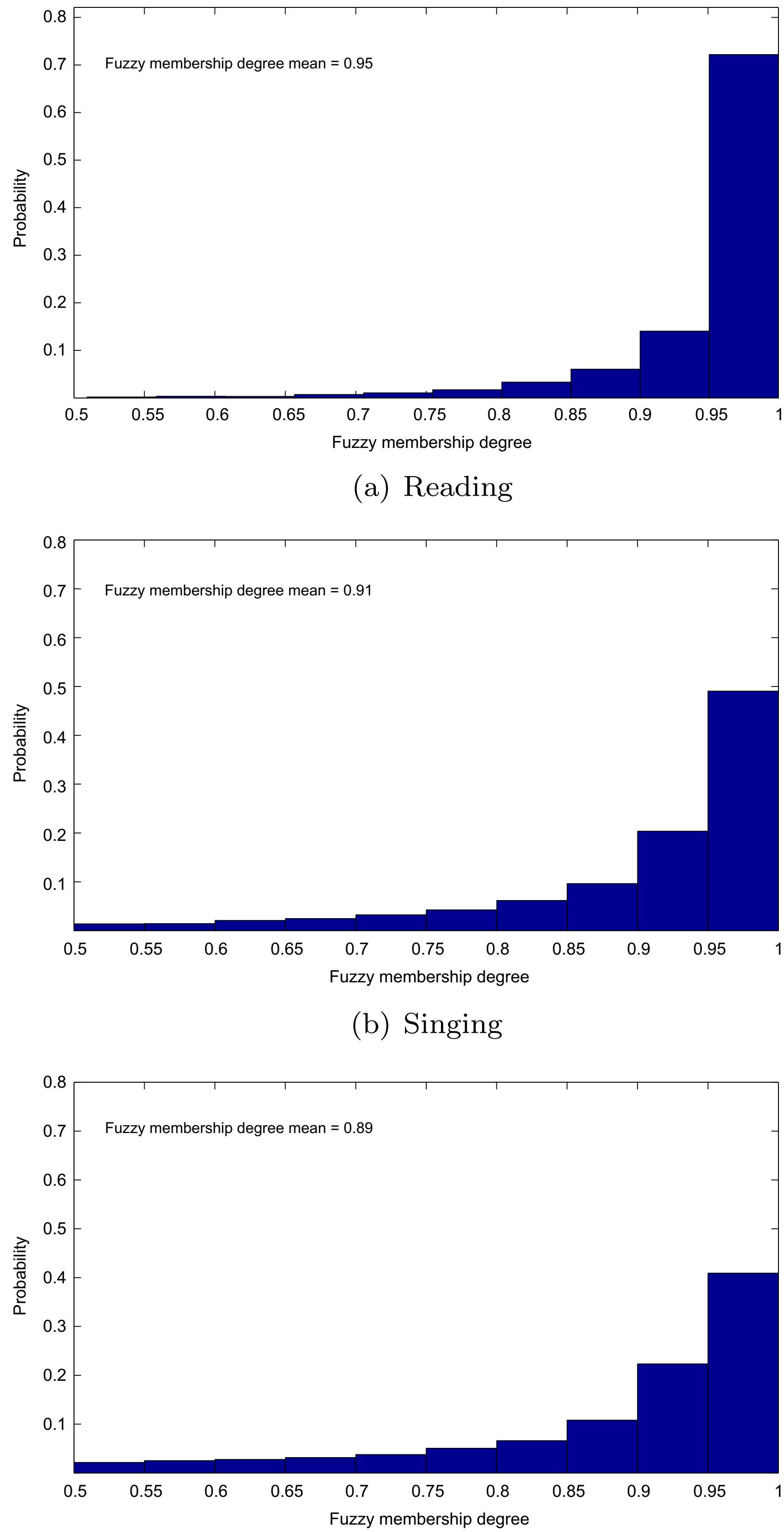
Next, fuzzy cluster distances are compared between reading and singing for all speaker pairs. As mentioned, with 18 test speakers we have 153 unique speaker pairs. For each two speakers, fuzzy cluster distance is calculated using their reading speech segments. Fuzzy cluster distance is also calculated for the same speakers with their singing speech segments. This results in two 153-dimensional vectors of distances. The obtained correlation coefficient between the two vectors is 0.4. This correlation coefficient indicates how much the confusion between two speaker's reading voices contributes to their confusion of singing voices.

5. Speaker clustering for a mixture of reading and singing based on supervised subspace learning

As was shown in Section 4 the most challenging speaker clustering task occurs when reading and singing speech samples of a speaker are mixed. In this case, the purpose is to cluster speech segments based on unique characteristics of a speaker's voice regardless of their speaking style. In this section, a speaker clustering algorithm is proposed using the scores from a Probabilistic Linear Discriminant Analysis (PLDA) model which improves the speaker clustering performance for a mixture of reading and singing. PLDA is a supervised subspace learning method in that it assumes there exist some reading and singing data available for training. However, the training speaker set is independent from test set. In other words, PLDA model is trained on reading and singing samples of training speakers, and the model is used to cluster test speakers which were not present in training.

5.1. Probabilistic Linear Discriminant Analysis

Linear Discriminant Analysis (LDA) is a common method in pattern recognition using a linear combination of the features which best separate two or more classes. Fisher linear discriminant criterion, maximizes the between-class data separation while minimizing the within-class



(a) Reading

(b) Singing

(c) Mixture

Fig. 5. Normalized histograms of fuzzy membership degrees for correctly clustered segments.

Table 2
Mean and standard deviation of fuzzy cluster distances between pairs of speakers for reading, singing, and a mixture of reading and singing.

	Reading	Singing	Mixture
Mean	0.95	0.77	0.59
Standard deviation	0.03	0.24	0.28

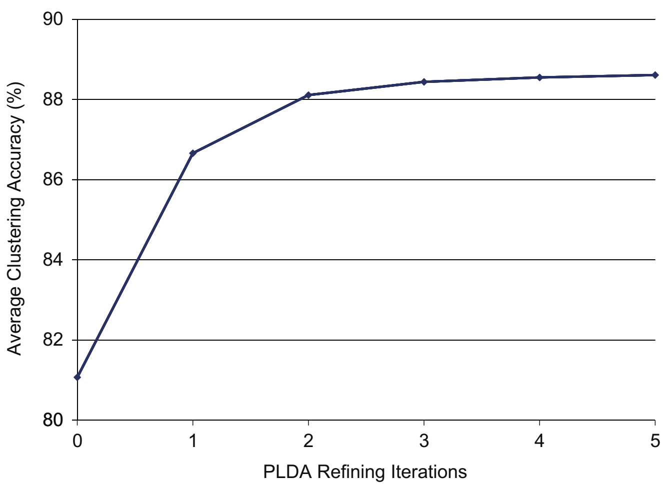


Fig. 6. Average clustering accuracy for a mixture of reading and singing with c-means baseline when the number of iterations for PLDA refining algorithm varies from 0 to 5.

scatter (Bishop, 1995). Probabilistic LDA is a generative model in which probability models are derived as a result of training, in addition to the usual LDA features (Ioffe, 2006). This suggests that PLDA is more suitable for the tasks where recognition is performed on previously unseen classes.

PLDA has proven to be successful in face recognition with uncontrolled conditions including variabilities in pose, lighting, and facial expressions (Prince and Elder, 2007). Speaker clustering with variations in speaking style defines a similar problem, replacing image vectors with GMM mean supervectors for our task.

Assuming that the training data set consists of I speakers with J speech samples for each speaker, the $j'th$ GMM mean supervector from the $i'th$ speaker is denoted by x_{ij}, with $i = 1, .., I$ and $j = 1, \ldots, J$. The data generation is modeled as:

$$x_{ij} = \mu + Fh_i + Gw_{ij} + \varepsilon_{ij} \tag{10}$$

where the signal component: $\mu + Fh_i$ depends only on the speaker, while the noise component : $Gw_{ij} + \varepsilon_{ij}$ depends on both the speaker and speaking style. The term μ is the overall mean of the training data, and F and G are matrices which contain bases for between-speaker and within-speaker subspaces, respectively. h_i and w_{ij} are latent variables and finally ε_{ij} is the residual noise term which is defined to be Gaussian with a diagonal covariance matrix Σ (Prince and Elder, 2007). The output of PLDA training is the model $\theta = \{\mu, F, G, \Sigma\}$ which is trained using Expectation Maximization (EM) algorithm.

In the testing phase, the likelihood that N supervectors: $x_1, \ldots, x_N$ belong to the same speaker, is the likelihood that these supervectors share the same speaker variable or h regardless of the noise variables $w_1, \ldots, w_N$. The following equation combines N generative models for these supervectors (Prince and Elder, 2007):

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix} = \begin{bmatrix} \mu \\ \mu \\ \vdots \\ \mu \end{bmatrix} + \begin{bmatrix} F & G & 0 & \cdots & 0 \\ F & 0 & G & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ F & 0 & 0 & \cdots & G \end{bmatrix} \begin{bmatrix} h \\ w_1 \\ w_2 \\ \vdots \\ w_N \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_N \end{bmatrix} \tag{11}$$

which can be rewritten as:

$$x' = \mu' + Ay + \varepsilon'. \tag{12}$$

The likelihood of N supervectors being from the same speaker can now be determined as:

$$\Pr(x') = N(x' | \mu', AA^T + \Sigma'). \tag{13}$$

$$\Sigma' = \begin{bmatrix} \Sigma & 0 & \cdots & 0 \\ 0 & \Sigma & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \Sigma \end{bmatrix} \tag{14}$$

5.2. Proposed speaker clustering algorithm based on PLDA

Our proposed clustering algorithm includes two stages: 1. baseline clustering with full dimensional supervectors; 2. refining the clusters obtained in the first stage in a PLDA dimensionality reduced subspace (Mehrabani and Hansen, 2012). A PLDA model is trained on the training data set which includes 15 speakers with reading and singing samples for each speaker. The trained model can then be used to refine the speaker clusters on the test set with speakers which were not present in training.

After the initial clustering, each supervector is compared to other supervectors in its cluster, as well as supervectors in the other clusters based on a likelihood ratio. For each two supervectors x and y, this likelihood ratio is calculated using the trained PLDA model:

$$\begin{aligned} LLR(x,y) &= Log(Likelihood(same)/Likelihood(diff)) \\ &= Log(Likelihood(same)) - Log(Likelihood(diff)) \end{aligned} \tag{15}$$

where $Likelihood(same)$ is the likelihood that x and y belong to the same speaker, and $Likelihood(diff)$ is the likelihood that x and y belong to different speakers. Based on Eq. (10), x and y can be written as:

$$\begin{aligned} x &= \mu + Fh_1 + Gw_1 + \varepsilon \\ y &= \mu + Fh_2 + Gw_2 + \varepsilon \end{aligned} \tag{16}$$

where there are two hypotheses: H_1 is the hypothesis that x and y belong to the same speaker, and H_2 is the hypothesis that x and y belong to different speakers. If two supervectors x and y belong to the same speaker: $h_1 = h_2 = h$. The likelihood for each hypothesis can be calculated as conditional probabilities based on PLDA model (Prince and Elder, 2007):

$$\Pr(x, y|H_1) = \int \left[\int \Pr(x|h, w_1)\Pr(w_1)dw_1 . \int \Pr(y|h, w_2)\Pr(w_2)dw_2\right]\Pr(h)dh \qquad (17)$$

$$\Pr(x, y|H_2) = \int\int \Pr(x|h_1, w_1)\Pr(h_1)\Pr(w_1)dh_1dw_1 . \int\int \Pr(y|h_2, w_2)\Pr(h_2)\Pr(w_2)dh_2dw_2 \qquad (18)$$

If $LLR(x, y_1) > LLR(x, y_2), x$ and y_1 are more likely to be from the same speaker than x and y_2. Therefore, LLR can directly be applied in clustering as a distance measure. However, our experiments show that using LLR for refining the obtained clustered from the baseline, renders better clustering results. The refining algorithm is as follows:

- Step 1: For each supervector x_i^c in cluster c, calculate the LLR with all the supervectors in cluster $c : LLR(x_i^c, x_j^c), i = 1, .., N_c, j = 1, .., N_c$.
- Step 2: For each supervector x_i^c in cluster c, calculate the LLR with all the supervectors in other clusters $c' = 1, \ldots, C, c' \neq c : LLR(x_i^c, x_j^{c'}), i = 1, .., N_c, j = 1, .., N_{c'}$.
- Step 3: If $c_m = \arg\max median(LLR(x_i^c, x_1^{c'}), \ldots, LLR(x_i^c, x_{N_{c'}}^{c'})) \neq c$, move $x_i^{c'=1,\ldots,C}$ to cluster c_m.

Table 3 shows results of the proposed clustering method for reading, singing, and a mixture of reading and singing. Our experiments show that repeating the refining stage improves the clustering accuracy. The first row represents baseline results with no dimensionality reduction, and the second row represents clustering accuracies with 3 iterations of the proposed refining algorithm in the PLDA subspace when the first stage clustering method is k-means, and hierarchical. Since the PLDA subspace learning is based on reading and singing data for 15 training speakers, the reduced dimension for PLDA is chosen to be 14. Compared to the baseline clustering accuracies, the clustering accuracy for a mixture of reading and singing increases by 9.6% with k-means as the baseline, and 7.6% with hierarchical clustering as baseline. The clustering accuracies increase for singing, and are similar to baseline for reading. The best clustering performance for the mixture after 3 refining iterations is 90.5%.

In Section 4.2 we noted that the fuzzy c-means clustering baseline has similar clustering accuracies to k-means. It was also explained that c-means clustering is based on fuzzy membership degrees and for two-speaker clustering, data points with membership degrees more than 0.5 are considered to belong to a cluster. Here, we use c-means clustering as baseline and its membership degrees in PLDA refining to reduce the processing time. An analysis of the fuzzy membership degrees for all the reading and singing supervectors from all 153 speaker pairs in the test set shows that 68.5% of the incorrectly clustered supervectors have membership degrees less than 0.9, while 63.2% of the correctly clustered samples have membership degrees more than 0.9. This suggests that performing the refining algorithm on data points with membership degrees in the interval [0.5 0.9] should render similar results. Note that our membership degree decision threshold for clustering is set to 0.5. The average clustering accuracy for a mixture of reading and singing with c-means baseline and no PLDA refining is 81.1%. This accuracy increases to 86.6% with one iteration of PLDA refining algorithm. Performing the refining algorithm only on data points with membership degrees less than 0.9 results in the same accuracy, while processing time reduces to half the processing time for all the data points. Fig. 6 shows the average clustering accuracy for a mixture of reading and singing, when the number of PLDA refining iterations increase from 0 (baseline with no refining) to 5. The baseline clustering in this experiment is fuzzy c-means. As shown in the figure, with the first refining iteration, the clustering accuracy increases the most. The second and third iterations also show an increase in accuracy, but after that it does not change significantly.

5.3. Frontend supervised subspace learning based on LDA

In this section, various frontend configurations are evaluated and compared to 19-dimensional MFCCs. Next, we show that LDA based supervised subspace learning in feature space improves the clustering performance. Finally, the frontend LDA transformed features are combined with the proposed backend PLDA based cluster refining algorithm to achieve higher clustering accuracies, especially for the mixture of reading and singing.

Table 4 represents speaker clustering accuracies for reading, singing, and a mixture of reading and singing with

Table 3
Average clustering accuracies (%) for reading, singing, and a mixture of reading and singing with proposed algorithm based on PLDA.

Subspace learning	Clustering method	Reading	Singing	Mixture
Baseline(Full dimension)	K-means	99.7	91.3	80.6
	Hierarchical	99.9	92.8	82.9
3 PLDA Refining	K-means	99.6	93.9	90.2
	Hierarchical	99.6	93.9	90.5

Table 4
Average clustering accuracies (%) for reading, singing, and a mixture of reading and singing with various frontend configurations and baseline clustering.

Features	Clustering method	Reading	Singing	Mixture
Baseline (19d MFCC)	K-means	99.7	91.3	80.6
	Hierarchical	99.9	92.8	82.9
Delta MFCC (38d)	K-means	99.7	90.9	77.9
	Hierarchical	99.6	91.8	78.8
PLP (19d)	K-means	99.9	90.6	79.7
	Hierarchical	100.0	92.4	80.7
Delta PLP (38d)	K-means	99.7	90.9	82.5
	Hierarchical	99.9	92.4	83.7
LDA PLP (32d)	K-means	100.0	86.7	76.0
	Hierarchical	100.0	88.1	77.0

Table 5
Average clustering accuracies (%) for reading, singing, and a mixture of reading and singing with frontend LDA supervised subspace learning, and combination with backend PLDA cluster refining.

Subspace learning	Clustering method	Reading	Singing	Mixture
Baseline (Full dimension)	K-means	99.7	91.3	80.6
	Hierarchical	99.9	92.8	82.9
Frontend LDA	K-means	100.0	96.7	89.5
	Hierarchical	100.0	97.5	91.9
Frontend LDA&Backend PLDA	K-means	99.8	96.8	94.5
	Hierarchical	99.8	96.9	94.5

Table 6
Clustering accuracies (%) for a mixture of reading and singing with background music.

SNR (dB)	∞	15	10	5	0
PLDA Clustering (accuracy in %)	68.9	67.6	56.8	56.8	55.4
Baseline Clustering (accuracy in %)	51.3	51.3	50	50	50

5 frontend configurations using the baseline clustering system. First row shows the results with 19-dimensional MFCCs, and second row shows the results when 19-dimensional MFCC features are concatenated with delta coefficients. The third row represents clustering accuracies with Perceptual Linear Predictive (PLP) features (Hermansky, 1990), and fourth row shows the results of concatenating PLP features with delta PLPs, with a 5 frame window. The last row of Table 4 represents the clustering results with the features proposed in (Tang et al., 2012) which replace delta coefficients with LDA transformed features to account for temporal dynamics of the speech signal. Since we were using TIMIT to train our UBM, we also used TIMIT for LDA training. 19-dimensional PLP features extracted from every five consecutive frames (two frames before, and two after the current frame) were concatenated to create long 95-dimensional vectors (five frame window was chosen to be comparable to the window size used to calculate delta PLPs). An LDA model was trained with TIMIT data based on known speaker labels. The feature dimension was reduced to 32 using the LDA mapping which was applied to UBM data as well as test data. As shown in Table 4, PLP and LDA transformed PLP features, increased the clustering accuracies for reading, but had worse performance for singing and mixture compared to the baseline. None of the other features showed improvement for singing, and only delta PLPs improved speaker clustering performance for a mixture of reading and singing.

Next, LDA transformed features (Tang et al., 2012) were evaluated including some singing data to train the LDA model. Two LDA models were trained: one with TIMIT for the feature transformation of UBM data, and one with 15 train speakers from UT-Sing corpus with reading and singing data for each speaker. Since there were only 15 speakers to train the second LDA model, dimension of all features were reduced to 14. Feature transformation from the second LDA was used for dimensionality reduction of test data which included both reading and singing. Note that there was no overlap between train and test. Second row of Table 5 shows clustering accuracies using the explained LDA PLP features. As shown, clustering accuracies increase, especially for the mixture.

Finally, the LDA PLP features were combined with PLDA clustering algorithm, and the results are summarized in the third row of Table 5. The clustering accuracy for a mixture of reading and singing increased to 94.5%. Compared to the second row, proposed PLDA cluster refining improves the speaker clustering for mixture by 5% with k-means, and 2.6% with hierarchical clustering.

This shows that PLDA cluster refining algorithm in the GMM supervector space adds complimentary information to the supervised LDA transformation in the feature space, both using reading and singing samples to train models. Next, we will show the effects of adding background music to the singing for speaker clustering.

5.4. Speaker clustering for singing with background music

So far, we have proposed a speaker clustering algorithm based on PLDA which considerably improves the performance when clustering both reading and singing speech samples of the speakers. This has real applications in information retrieval, and speaker diarization for audio streams available on the internet, radio, or TV that include speaking and singing of one or more of the speakers. A good example of such audio is interview with famous singers or when they appear on a talk show. In addition, there is an increasing number of singing competitions on TV, and auditions which include both speaking and singing voice of the participants. In some of these examples, the singing voice might be accompanied by background music.

In the literature, several studies have focused on singing voice separation from music accompaniment in single channel and monaural recordings (Li and Wang, 2007; Ozerov et al., 2007). For stereo recordings this task is less challenging and there are many tools available to make acapellas. Though singing voice separation is out of the scope of this paper, here we perform a probe experiments to show the performance of our speaker clustering system with background music. It should be noted that singing voice separation techniques do not completely remove the background music, therefore, we conduct an experiment in which the performance of the system is evaluated by increasing the background music. In addition, our goal is to perform unsupervised speaker clustering on speech segments which may or may not be singing and may or may not have background music. Therefore, it is important to have an acceptable performance when music is also present.

In this probe experiment, two female speakers are selected who sing the same song. Next, the correct matched music is added to the singing with varying Signal to Noise Ratio (SNR), considering the music as noise. The resulting audio streams are then segmented. In order to make the task more challenging and closer to real applications which include shorter segments, the clustering is performed on 5 sec. segments instead of 10 sec. For each SNR, the read lyrics from the same speakers are also segmented and mixed with the singing segments. Table 6 shows the speaker clustering accuracies with the proposed clustering algorithm with 5 refining iterations, compared to the hierarchical baseline when SNR varies from 0 to ∞ (when there is no background music). Note that in a two-speaker clustering task, 50% represents the lowest accuracy, since for accuracies lower than that, the clusters can simply be switched. As shown, this is a very challenging task with low clustering accuracy even with no music. The proposed system increases the performance by 17.6% when there is no background music. Adding the music does not reduce performance considerably up to SNR = 10. For 0, 5, and 10 dB SNR, the performance is similar with a 13.5% decrease in accuracy for SNR = 0, compared to no music. However the clustering accuracy for 0 dB SNR is still 5.4% better than the baseline.

6. Discussion and conclusions

Speaker clustering systems were explored for singing and a mixture of reading and singing. It was shown that introducing various speaking styles decreases speaker clustering accuracies by up to 20%. Unsupervised subspace learning for singing speaker clustering was studied. It was shown that dimensionality reduction techniques such as PCA which are based on global structure of the data set do not improve the clustering accuracy, while LPP which preserves local structure of the data improves results for singing and a mixture of reading and singing. Supervised subspace learning for singing speaker clustering was also studied. An algorithm was proposed for refining speaker clusters based on the log likelihood ratio which decides if two speech samples belong to the same speaker or not. This ratio is calculated based on probabilistic discriminant analysis which attenuates the effect of speaking style on speaker clustering.

While this study was focused on the model domain and speaker dependent subspaces, robustness in the feature domain including features that are less dependent on speaking style, or feature compensation techniques can also be studied which is our plan for future work. In addition, the results from this study can be evaluated for a wider variety of speaking styles. These advancements offer an important step towards improving the acoustic modeling of speech and speakers for speech applications including speaker ID, spoken document retrieval, and audio search applications.

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