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Direct Visual Clustering Methods by Linear Subspace Learning for Speech Data

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Abstract: Visual access tendency methods (VATs) are used for accessing of number speakers from unlabeled speech data. These methods are Euclidean based VAT (VAT-E), cosine based VAT (VAT-C) and spectral version based VAT methods (SpecVAT- E and SpecVAT-C are used Euclidean and cosine metrics respectively). Speech clustering requires any one of VAT methods along with clustering method, because it derives the cluster tendency (i.e. number of speakers from VAT method) and respective speaker clustering results. It follows the hybrid approach for deriving of complete clustering results, so it is more expensive. Thus, this paper is proposed direct visual clustering method for obtaining of clustering results and it is more efficient than hybrid approach. It extends the idea of VAT for recognition of cluster memberships of various speech utterances spoken by speaker. Experimental results are presented of various subsets of speech datasets for demonstrating the efficiency of proposed method.

Keywords: Speech clustering, GMM, GMM meansupervectors, i-vectors,VAT.

1. Introduction

Hybrid methods are attractive speech clustering methods, because they are known about prior cluster tendency [11] by data visualization methods [1] for speech datasets in speech clustering. However, hybrid methods need to run two methods i.e, MVS-VAT, and k-means [2]. Thus, hybrid methods are expensive. It is required to develop smarter clustering methods for finding assessment of cluster tendency and clustering results of speech datasets. Extended data visualization methods are capable in finding the speakers information and respective clusters. The proposed work is directly derived the clustering results from the obtained speech cluster tendency. These results are with quality and robust. The proposed extended data visualization method is known as 'Direct Visual Clustering Method (DVCM). It is extended individually from the methods of VAT-E, VAT-C, SpecVAT-E, SpecVAT-C, and MVS-VAT, hence these methods are abbreviated as DVCM-VAT-E, DVCM-VAT-C, DVCM-SpecVAT-E, DVCM-SpecVAT-C, DVCM-MVS-VAT. All these proposed methods are experimentally conducted on benchmarked TSP Datasets [3] [8] for demonstrating the performance.

Data visualization methods such as all versions of VAT and SpecVAT are capable to assess the cluster tendency [11] only. The limitations of these methods that they can only show the number of speakers of speech data, but for clustering results it is needed to merge these methods with traditional clustering methods [9]. Due to expensive nature of these hybrid methods, this paper is concentrated on extended work of data visualization methods rather than using expensive approaches of hybrid techniques. The proposed works related to DVCM are more efficient than hybrid methods, such as VAT-based k-means clustering method and VAT-based MST clustering methods. This papercomputes the quality of DVCM methods by various performance measures schaptuch clustering accuracy, and normalized mutual information and reports the effectiveness of various proposed methods in the experimental study.

Summary of the contributions of the paper is as follows:

1. Data visualization method is developed using Euclidean and cosine distance metrics separately, namely, VAT-E, and VAT-C
2. Spectral VAT based methods are developed using using Euclidean and cosine distance metrics separately, namely, SpecVAT-E, and SpecVAT-C
3. Speech cluster tendency is derived for speech dataset
4. DVCM is developed for accessing of speech clustering results efficiently.
5. Speech clustering methods are evaluated using different performance parameters.

Remaining part of paper is organized as follows: Section 2 discusses the related work, Section 3 presents the proposed work, Section 4 discussed the experimental results and Section 5 presents the conclusion and future scope.

2. Related Work

Hybrid methods are attractive speech clustering methods, because they are known about prior cluster tendency by data visualization methods for speech datasets in speech clustering. Data visualization methods such as all versions of VAT and SpecVAT are capable to assess the cluster tendency only. The limitations of these methods that they can only show the number of speakers of speech data, but for clustering results it is needed to merge these methods with traditional clustering methods. Due to expensive nature of these hybrid methods, this paper is concentrated on extended work of data visualization methods rather than using expensive approaches of hybrid techniques. The proposed works related to DVCM are more efficient than hybrid methods, such as VAT-based k-means clustering method and VAT-based MST clustering methods.

2.1 The VAT-C Method

The VAT [4] and SpecVAT [5] are present data visualization methods, which methods are used for assessment of clustering [6] tendency for some real datasets. These methods uses a Euclidean space. The image of VAT-E highlights the potential clusters; however, it cannot assess the potential clusters for some of datasets. Therefore, the proposed methods are designed in a cosine space, these are VAT-C and SpecVAT-C. In a VAT-C, the dissimilarity between the objects x and y is measured using cosine metric. Eqn. (2.1) shows the cosine metric.

$$D(x, y) = 1 - \left(\frac{x.y}{\|x\|\|y\|} \right) \tag{2.1}$$

2.2 The SpecVAT-C Method

The following SpecVAT-C performs the assessment of clustering tendency using spectral approach [7] using cosine space. The following algorithm illustrates the procedure of SpecVAT-C.

Algorithm

Step 1: Compute the local scale σ_i for every object o_i using $\sigma_i = d(o_i, o_k) = d_{ik}$, where o_k isthe kth nearest neighbor of o_i.

Step 2: The weighting matrix, $w \in R_{nxn}$, $w_{ij} = \exp(-d_{ij}d_{ji} / (\sigma_i \sigma_j))$ for i = j, and $w_{ij} = 0$.

Step 3: Let the M is diagonal matrix with $m_{ij} = \sum_{j=1}^{n} w_{ij}$

$L = M^{-1/2} W M^{-1/2}$ is a normalized version of the Laplacian matrix.

k=2;
kmax=10
Repeat

Step 4: Choose the k largest Eigen vectors v1, v2, · · · ,vk and the Eigen matrix is V.

V = [v1, · · · , vk] ∈ Rn×k by stacking the Eigen vectors in columns.

Step 5: Construct the new dissimilarity matrix Dnew between pair of objects using cosine distance (Use the Eqn. (3.1))

Step 6: Apply VAT to Dnew to obtain I(Dnew),k=k+1
Until k=kmax

2.3 The Multi-View Points similarity based cosine VAT (MVS-VAT)

The dissimilarity features of 'm' number of GMM-UBM mean supervectors is calculated using either an Euclidean space or cosine space. The cosine based dissimilarity [13] computation is more effective, thus, the proposed work is focusing on cosine space in this paper

. After the deep analysis of multi-viewpoints based cosine metric, it is noted that multi-viewpoints based cosine similarity (MVS) [6] is optimal measure than cosine metric. The similarity between two objects di and dj in MVS cosine space is calculated w.r.t. any other viewpoints. The equations (Eqn. (2.2) to Eqn.(2.6)) illustrates the MVS steps.

$$Sim(d_i, d_j) = \frac{1}{n-2} \sum_{d_h \in S, d_h \neq d_i, d_h \neq d_j} Sim(d_i - d_h, d_j - d_h) \quad (2.2)$$

$$\mathrm{Sim}(d_i, d_j) = \frac{1}{n-2} \sum_{d_h \in S, d_h \neq d_i, d_h \neq d_j} (d_i^t d_j - d_i^t d_h - d_j^t d_h + d_h^t d_h) \quad (2.3)$$

$$\mathrm{Sim}(d_i, d_j) = d_i^t d_j - \frac{1}{n-2} d_i^t \sum_{d_h} d_h - \frac{1}{n-2} d_j^t \sum_{d_h} d_h + 1 \quad (2.4)$$

$$\mathrm{Sim}(d_i, d_j) = d_i^t d_j - \frac{1}{n-2} d_i^t D_S - \frac{1}{n-2} d_j^t D_S + 1 \quad (2.5)$$

$$\mathrm{Sim}(d_i, d_j) = d_i^t d_j - d_i^t C_S - d_j^t C_S + 1 \quad (2.6)$$

Here, $D_S = \sum_{d_h \in S, d_h \neq d_i, d_h \neq dj} d_h$ is composite vector of objects except for di and dj. , CS is the centroid of DS , CS=DS/(n-2). The cosine based similarity features is measured between two objects, d_i and d_j with respect to viewpoints, the viewpoint $d_h \in S$ and d_h not be either d_i or d_j. So, the total number viewpoints is (n-2).

3. Proposed Work

3.1 Direct Visual Clustering Method (DVCM)

The proposed data visualization methods could access the speech clustering tendency, however, for clustering results, it is required to merge these visual methods with traditional clustering algorithms and these hybrid approaches. The hybrid approaches are expensive for performing the complete clustering.

The DVCM method for various data visualization methods [4] i.e. VAT-E, VAT-C, SpecVAT-E, SpecVAT-C, and MVS-VAT for detecting the number of clusters as well as discovering the explicit clustering results. The following algorithm describes the procedure of proposed DVCM.

Algorithm

Input : D- Dissimilarity Matrix
N- Number of objects

Output : k- Number of Clusters

Step 1 : [RD] =VAT(D)
VAT_Im=Image(RD);
k=Number_of_Square_Shaped_Dark_Blocks(VAT_Im);

Step2 : For i = 1: k // k- number of partitions or clusters
Find the data objects at each partition 'i' using crisp partition matrix
End for

Step 3 : Map the data objects and find the ground truth labels using Khun-munkres function for finding the clustering accuracy

In step1, the DVCM method runs the VAT (is also called VAT-E) with the input of dissimilarity matrix 'D'. The output of VAT is the reordered dissimilarity matrix 'RD', and then the image of 'RD' stored in the variable 'VAT_Im'. The number of clusters (k) are extracted by counting the number of square shaped dark blocks in step1. In a step 2, the objects of each partition (or cluster) are detected by the crisp partition matrix of VAT_Im. This matrix consist the details of data objects i.e., it determines the cluster labels of data objects. The data objects of each square-shaped dark block (i.e, each cluster) are accessed by the crisp partition matrix. In this way, the DVCM discovers the clustering results from data visualization methods. The step3 describes the way for finding the clustering accuracy using Khun-munkres. Therefore, the DVCM is an efficient method for detecting the clustering tendency as well as discovering the speech clustering results.

3.2 Linear Subspace Learning Based Dvcm Approach

The speaker clustering is the method of assigning individual speech utterances to their respective clusters (or speakers). The speaker clustering is an either unsupervised [14] or semi-supervised [7] approach. In semi-supervised, the prior knowledge of speakers could assist the unsupervised clustering process. For the limitations of MVS approach in DVCM-MVS-VAT, it is emerging that to enhance the unsupervised DVCM-MVS-VAT approach using linear subspace learning (LSL). The GMMmean supervectors [12] are in high-dimensional space, and these vectors are represented in a low-dimensional manifold for enhancing the DVCM. The DVCM is used optimal distance metrics. The Fig. 3.1 shows the steps for proposed DVCM of linear subspace learning. After finding the GMM mean supervectors, the proposed work use the linear subspace learning for transforming the data points in a low-dimensional manifold. The dissimilarity features are computed using the optimal metrics of LSL. The VAT applies the linearly transformed dissimilarity features of LSL in the assessment of clustering tendency, and it is evidence that the modified LSL based VAT uses the linear subspace instead of original high-dimensional space. In the experimental study, the thesis uses the PCA, LPP, NPE, and LDA techniques [15] for accomplishing the clustering results of VCA in a linear subspace.

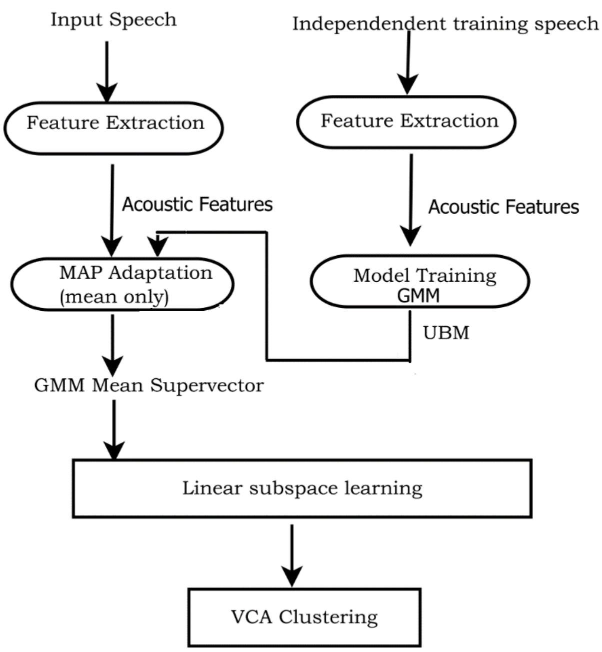

Fig. 3.1 LSL based DVCM Approach

The steps of the proposed LSL-based-DVCM are as follows:

1. Determine the GMM mean supervectors for speech utterances by UBM-GMM modeling.
2. Construct the affinity matrix (W) of GMM mean supervectors
3. Apply the linear subspace learning on W for finding the equivalent low-dimensional manifold of GMM mean supervectors 'S' (S with size n x m). The low-dimensional space of S is E (E with size n x d), and d ≤m.
4. Use the optimal distance metrics of a linear subspace for finding dissimilarity matrix of E.
5. Use the following steps of DVCM for determining the number of clusters and clustering results
   i. Apply VAT on E for assessment [10] of clustering tendency from VAT_Im, VAT_Im=VAT(E)
   ii. Determine the crisp-partition matrix from VAT_Im for determining the cluster labels of data points (or data objects).

4. Experimental Results

The GMM mean supervector is the best representation ofthe speech utterance in speech recognition. The GMM mean supervector representation allows us to denote an utterance as a single point in 2D space of principle components. The Fig. 4.1 illustrates this MST visualized transformation of various speech utterances (spoken by two different speakers) in 2D plot for more analysis purpose. For each speaker, there are total 40 speech utterances, and each utterance is denoted as a single point. However, most of the data points near or lay in a low-dimensional manifold, i.e., the data points uses the linear subspace of the original space.

(a) MST tree for 2-speaker data speaker data

(b) MST clusters for 2-

Fig. 4.1 : MST representation in 2D for 2-speaker data (number of utterances =80)

The speaker clustering on TSP speech datasets and this dataset is freely available in [8]. This dataset consists of the set of speech utterances for different sentences (in .wav files format), which are spoken by different speakers. Table 4.1 shows the details of experimental settings. This papertakes the training, and test data as varied in the experiment. The training set used in UBM design, which gives the universal model for determining the shape (or model) of the speaker's voice. It is called as a average speaker model.

Table 4.1: Experimental settings for speech clustering

Description of data	Independent training set	Test set
# speaker	30	5
# utterance	3000	200 (max)
# utterance / speaker	100 to 200	30 to 40
Utterance (.wav file) duration	10 to 20 sec	10 to 20s

4.1 The Performance Metrics

The thesis uses two performance measures for measuring the effectiveness of the proposed method. This paper presents the detailed report of experimental results based on three performance metrics- CA, NMI, and goodness by OTSU.

Eqn. (4.1) shows the formula for clustering accuracy (CA)

$$r = \frac{1}{N}\sum_{i=1}^{n}[c_i = l_i] \qquad (4.1)$$

The NMI is also another traditional measure that measures the clustering performance by Eqn. (4.2)

$$r = \frac{I(C,L)}{[H(C)+H(L)]/2} \qquad (4.2)$$

Where I(C, L) represents the mutual information and it shows in Eqn. (4.3)

$$I(C,L) = \sum_i \sum_j |c_i \cap l_j| \log \frac{|c_i \cap l_j|}{|c_i||l_j|} \qquad (4.3)$$

H (C) and H(L) refers entropy, which are defined in Eqn. (4.4)

$$H(C) = -\sum_i \frac{|c_i|}{N}\log\frac{|c_i|}{N},\ H(L) = -\sum_i \frac{|l_i|}{N}\log\frac{|l_i|}{N} \qquad (4.4)$$

In the formulas (Eqn. (4.3) to Eq. (4.4)), $|c_i|, |l_i|$, $|c_i \cap l_i|$ denotes the number of utterances from speakers $c_i, l_i, c_i \cap l_i$ respectively. The two metrics, i.e., CA and NMI are used for evaluating the proposed speech clustering methods.

4.2 Evaluation of Proposed Methods

More specifically, this paper has conducted the speech clustering as per the following experimental description

a. GMM mean supervector and PCA subspace
b. GMM mean supervector and LPP subspace
c. GMM mean supervector and NPE subspace
d. GMM mean supervector and LDA subspace

Table 4.2 shows the clustering accuracy for the DVCM methods. The clustering accuracy is improved in DVCM by learning linear subspace. It is noted that linear subspace based DVCM approaches i.e., DVCMP, DVCML, DVCMN, and DVCMLDA are more effective than DVCM-MVS-VAT with respect to runtime. Table 4.3 shows the NMI values of proposed DVCM methods and it also demonstrates that linear subspace based DVCM outperforms than DVCM-MVS-VAT. The key issue of speech cluster tendencyis effectively solved from the linear subspace based data visualization methods for achieving the quality of clustering results.

Table 4.2: Clustering Accuracy (CA) for VCA Methods

Dataset	Linear subspace learning based DVCM				MVS based DVCM(without Linear subspace)
	DVCMP	DVCM L	DVCMN	DVCMLDA	DVCM-MVS-VAT
Two-speaker dataset	1	1	1	1	1.0
Three-speaker dataset	0.90	0.90	0.90	0.90	0.90
Four-speaker dataset	0.85	0.785	0.85	0.85	0.82
Five-speaker dataset	0.811	0.705	0.823	0.82	0.80
Six-speaker dataset	0.755	0.9	0.85	0.8	0.69

Table 4.3: Normalized Mutual Information (NMI) for VCA Methods

Dataset	Linear subspace learning based DVCM				MVS based DVCM(without Linear subspace)
	DVCMP	DVCM L	DVCMN	DVCML DA	DVCM-MVS-VAT
Two-speaker dataset	1	1	1	1	1
Three-speaker dataset	0.812	0.812	0.812	0.812	0.81
Four-speaker dataset	0.78	0.667	0.766	0.766	0.70
Five-speaker	0.744	0.674	0.764	0.776	0.71

dataset					
Six-speaker dataset	0.745	0.766	0.82	0.766	0.65

Tables 4.4, 4.5, 4.6 shows the Davies-Bouldin Index(DB Index), Calinski Harabasz Index (CH Index), Silhouette Index (SH Index) for the proposed LSL based DVCM methods.

Table 4.4: Davies-Bouldin Index(DB Index) (Minimum Value is the Best)

Name of the Dataset	DVCM-PCA	DVCM-NPE	DVCM-LPE	DVCM-LDA
2-Speaker Dataset	20	5.9	**0.58**	**0.58**
3-Speaker Dataset	18	9.31	**6.31**	6.45
4-Speaker Dataset	33.24	15	13.64	**13.49**
5-Speaker Dataset	36	23	**19.27**	20
6-Speaker Dataset	39	26	**21.42**	23

From the Table 4.4, it is evident that DVCM-LPE and DVCM-LDA are outperformed with others, because these methods maintain the minimum DB Index value than other methods. Table 4.5 and 4.6 states the same conclusion of Table 4.4. Finally, it is investigated that DVCM-LDA is an efficient method for speech clustering. This method is recommended after observing the cluster validity index measure values of Table 4.4 to 4.6. In this experimental study, cluster validity parameter is tested using DB, CH, and SH index values.

Table 4.5: Calinski Harabasz Index(CH Index) (Maximum Value is the Best)

Name of the Dataset	DVCM-PCA	DVCM-NPE	DVCM-LPE	DVCM-LDA
2-Speaker Dataset	20	28	**130**	124
3-Speaker Dataset	13	24	79	**239**
4-Speaker Dataset	10	24	79	**149**
5-Speaker	11	24.59	79	**109**

Dataset				
6-Speaker Dataset	24	45	25.4	**107**

Table 4.6: Silhouette Index (SH Index) (Maximum Value is the Best)

Name of the Dataset	DVCM-PCA	DVCM-NPE	DVCM-LPE	DVCM-LDA
2-Speaker Dataset	0.3	0.4	**1**	0.99
3-Speaker Dataset	0.19	0.31	**0.74**	**0.74**
4-Speaker Dataset	0.11	0.283	0.41	**0.58**
5-Speaker Dataset	0.11	0.254	0.293	**0.527**
6-Speaker Dataset	0.09	0.32	0.73	**0.47**

Fig. 4.3 to 4.6 shows the runtime comparison between LSL based DVCM method and DVCM-MVS-VAT. These results analysis of these figures demonstrate that the LSL based DVCM methods are faster than VCA-MVS-VAT. Fig. 4.6 shows the runtime comparison of LSL based DVCM methods versus different subsets of speaker datasets and it illustrates that LPP, NPE, and LDA based DVCM methods are faster than PCA based DVCM method. Therefore, the experimental research of this paper states that the LSL based DVCM methods are faster and efficient for speech clustering.

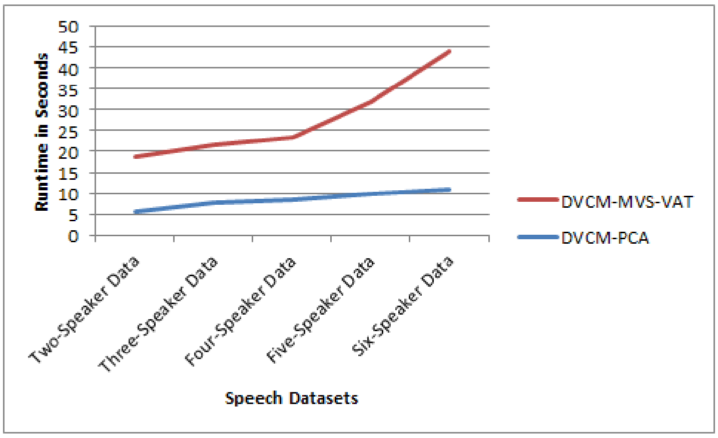

Fig. 4.2 Runtime Comparison between DVCM-MVS-VAT and DVCM-PCA

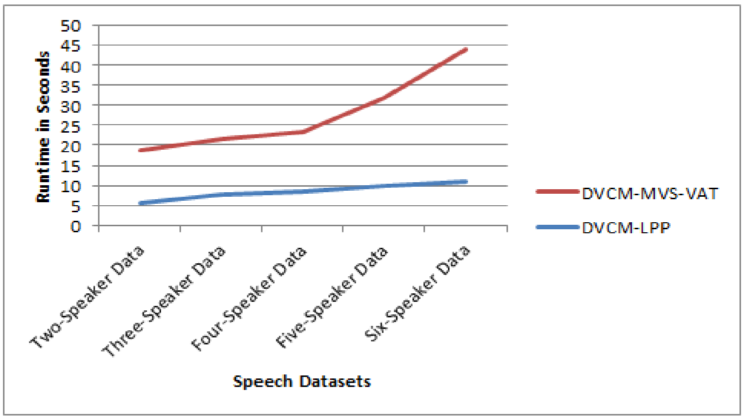

Fig. 4.3 Runtime Comparison between DVCM-MVS-VAT and DVCM-LPP

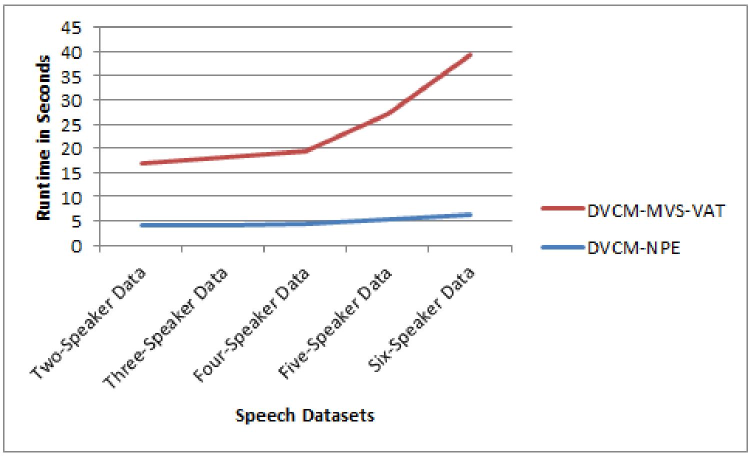

Fig. 4.4 Runtime Comparison between DVCM-MVS-VAT and DVCM-NPE

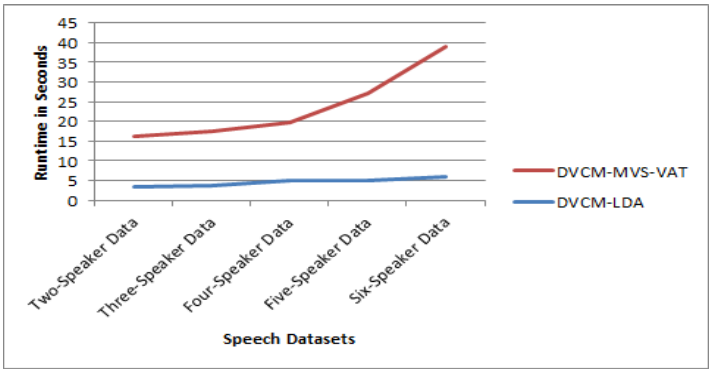

Fig. 4.5 Runtime Comparison between DVCM-MVS-VAT and DVCM-LDA

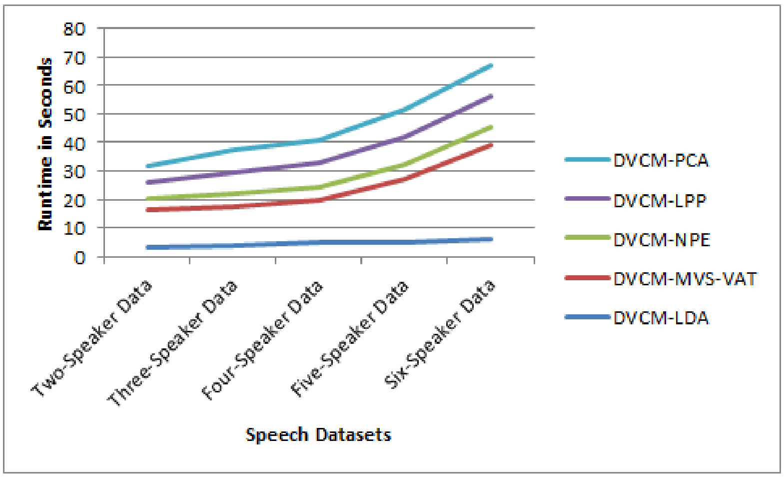

Fig. 4.6 Runtime of LSL-based DVCM Methods

5. Conclusion and Future Scope

Speech cluster tendency and clustering results are effectively derived using proposed DVCM methods. DVCM is the extension of data visualization method that access the unknown speakers information visually and finds the speech utterances for every speaker saperatly. It finds the model parameters of speech utterances for recognition of speaker identity of speech utterances in speech clustering. It uses a well known statistical GMM model for finding the accurate values of model parameters of speech utterances. Proposed DVCM achives the accurate speech clusterings results with LSL approaches. Future scope of the work is to extends the ideas of DVCM for video data clustering.

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