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Comparative Analysis Of Dimension Reduction Technique In CBMR Systems

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Abstract

Content Based Multimedia Retrieval is the upcoming area used to obtain descriptive features resulting in the form of huge feature count and processing overhead. The different dimension reduction methods are used to reduce the feature count and descriptive feature overhead, PCA Principle component Analysis, LDA Linear Discriminate Analysis, MLK Multi linear kernel Modeling are used were the histogram transformation features are used to eliminate the low significance features. The paper discusses about the comparison of the three dimension reduction technique, The benchmark data set is used for experimental result and to achieve the performance and accuracy they are taken for an analysis and compared among the three methods.

Keywords: Dimension reduction Analysis, Multi linear Kernel modeling, Accuracy, Processing Overhead, Benchmark data set

1. INTRODUCTION

Retrieval of information is the major research work in the Content based multimedia retrieval system which is carrying out very fast and is applied over wide range of applications, as the processed data is in the form of video the multiple frames are taken for processing towards the reduction of the descriptive feature [1] gives an flexible feature representation towards the efficient similarity measure [2] suggest the statistical approach, Content Based Multimedia Retrieval System which uses both video and audio retrieval systems [3], [4]represents the pattern subspace method which provides an ideas of modeling a sequence of video representation represented in the subspace to provide an interactive Principal component analysis based on the principal components, [5] [6] outlines the major study of the techniques were locally linear , embedding LLE are used by PCA and for Orthogonal locality preserving projection locally strong regression method LARR is used to know and get the increased accurate informational retrieval method,[7] uses the visual OLPP that is proposed for the automatic pattern re-colonization statics efficient similarity representation of the model to produce orthogonal features to represent the elements , [8] suggests the feature pattern re-colonization method active appearance model(AMM) which is used to extract the pattern ,[9] kernel patch method is Patch-based method is used to model two videos to create a relational mapping empirical coding by Kullback-Leib divergence refereed by Global Gaussian Mixture Model(GMM), 10][11] suggests the logical approach as the frequency decolonization , the investigation of biologically inspired approach for feature extraction in pattern reorganization method is done.

2. GENERAL OUTLINE OF DIMENSION REDUCTION IN CBMR

Multimedia retrieval system works on

1. First phase-Training
2. Second phase -Testing

In first phase all video are used for training and the trained data is kept in the database, in testing the query sample is trained and compared with the database sample in case of classification the trained query sample is compared with database sample using classification model such as SVM. The general multimedia retrieval system is shown in figure1 below

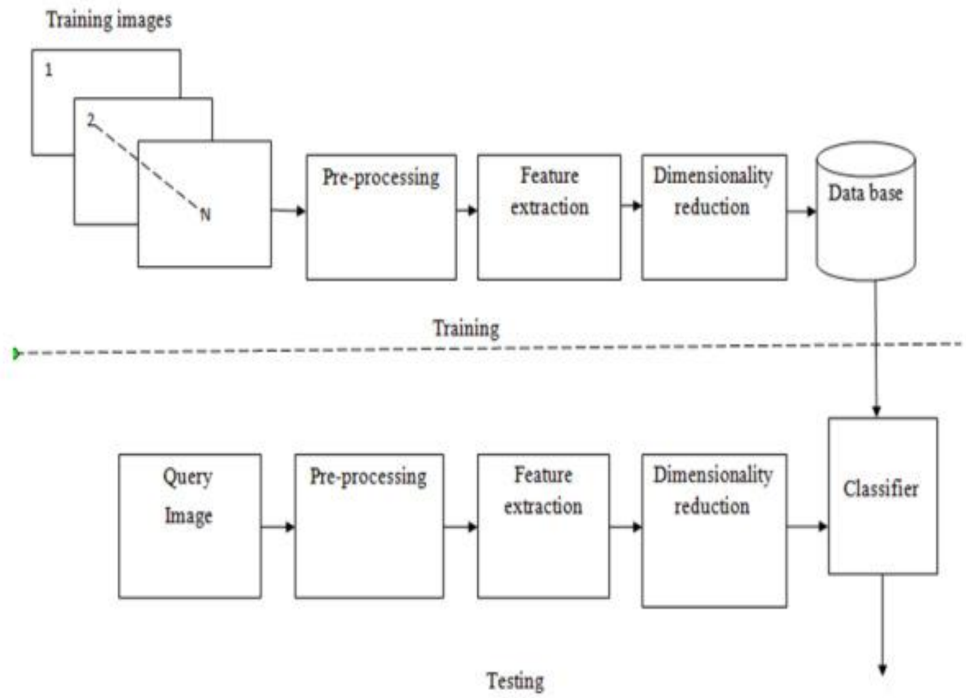

FIGURE 1: Overall Process of CBMR

2.1 Prepossessing

Prepossessing includes transformation, rotation scaling and correlation or light normalization, after prepossessing the prepossessed data is used for feature extraction to reduce the features.

2.2 Feature Extraction

Once the data is prepossessed, the prepossessed data is taken for feature extraction the values obtained after the prepossessing are used to remove irrelevant feature to reduce the feature count

2.3 Dimension Reduction

In dimension reduction the feature extracted are used for dimension reduction using dimension technique such as PCA, LDA, MLKDR

2.4 Classification

The output of dimension reduction is send to the classifier for classification where the reduced feature set is compared with feature of query sample for better performance using KNN, SVM, etc.

3. OUTLINE OF PCA, LDA, MLKDR

3.1 Principle component analysis (PCA)

This process works on new features is outlined as follows:
1. Get the values out.
2. Find mean average value refer it for each dimension.
3. Find the covariance matrix
4. Similarly find the different dimensions between all possible values
5. Find the Eigen value and Eigen vector sand sort in decreasing order
6. By multiplying the original data with new data set.

N*N dataset sample are taken from the PCA and defined as N2, M samples of the dataset is taken and mapped to higher dimensional space as $\Gamma_1,\Gamma_2,\Gamma_3,\ldots\Gamma_M$.
The Mean database is given by

$$\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n \qquad 3.1$$

Where t mean average deviation from the data set is represented as $\Phi_t = \Gamma_t - \Psi$ and the covariance matrix is given by $\Phi\Phi^T$ expected value s calculated by

$$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_{n-1}\Phi_n^T \qquad 3.2$$

From each frame data samples of different features are taken, and all the samples of data set are normalized perfectly to obtain the variance of each sample of data set as a covariance of the featureΦ, ΦT is transpose of the vector. Consider the covariance matrix $A=[\Phi_1,\Phi_2,\ldots\Phi_M]$, the 3.2 equation can be given as

$$C = \frac{1}{M}(AA^T) \qquad 3.3$$

1/M is used which effects the scaling Eigen vector results in the form of scaling factor

$$C = (AA^T) \qquad 3.4$$

Given the covariance matrix the optimal set is estimated for the Eigen values, data set variation between the data set sample with different set of Eigen vector and Eigen values. Eigenvector satisfying the condition is given by

$$C_{u_i} = \lambda_i u_i \qquad 3.5$$
$$u_i^T C_{u_i} = \lambda_i u_i^T u_j \qquad 3.6$$

The eigenvectors are orthogonal and normalized is given by

$$he\, u_j = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases} \qquad 3.7$$

After combining the equations 3.2 and 3.7 the 3.6 equation will be

$$\lambda_i = \frac{1}{M}\sum_{n=1}^{M} var(u_i\Gamma_n^T) \qquad 3.8$$

This is represented as a set of data taken from each sample normalized perfectly,
Given Covariance matrix $A=[\Phi_1,\Phi_2,\ldots\Phi_M]$ the equation 3.2 can be written as equation (3.8) were eigenvector represents a representative sample data set corresponding to variance showing eigenvalues

further the dimension reduction method PCA is applied to only the internal changes in that particular sample obtained by considering the reduced feature results feature dimension reduction.

3.2 Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis LDA is the other dimension reduction method which decreases the number of variables in a data set while retaining as much information as possible. Linear Discriminant analysis is a classification model it works by calculating input summary of data statistically from the training data based on the Bayes theorem where the prediction are estimated by defining the probability which work on the it works on multi class. LDA classifier results in assuming the observation on each class.

LDA algorithm works in the following steps
Algorithm: Linear Discriminant analysis LDA
Input: multimedia data set having video test samples
Output: Multimedia sample action class
Step 1: get the multimedia video data from the database.
Step 2: resize the video data into uniform dimensions.
Step 3: convert the color videos into gray scale video.
Step 4: crop the gray-scale multimedia video data into area.
Step 5: extract the multimedia features by applying the Gabor filters and histogram methods.
Step 6: extracted features are further processed for dimension reduction
Step 7: Features are computed within class and between class scatter
Step 8: eigenvector and eigenvalues are computed for scatter matrices
Step 9: Sort the eigenvalues and eigenvector
Step 10: select the top k values from the sorted list.
Step 11: create a new matrix containing eigenvectors that map to the ***k*** eigenvalues
Step12: find the dot product of data and matrix from step4 to obtain the new features (LDA component)

3.3 Multi- Linear Kernel Modelling (MLK)

The MLK is a dimension reduction technique used to reduce dimensions which works on multi-mode direction which uses three dimension K*M*N where K number of frames, M number of sample, N number of classes.
MLK works on
1. First phase -Training
2. Second phase-Testing

First phase performs four operation such as prepossessing, feature extraction, dimension action and classification, the video data is taken for prepossessing in prepossessing the input data that is video data samples are taken from the database, samples are re sized , cropped and converted into gray scale in order to represent the features , after the prepossessing these feature representation are send to feature extraction process here all possible 8 orientation of Gabor filters are used to remove all possible variance and extract the feature , once the features are extracted these feature are send for dimensional reduction , dimensions are reduced in multi direction mode which reduces the feature vector .reduced features are stored in database for later used for classification .The classifier used here is SVM . SVM classification takes multidimensional e features from the database and transform to the multi-linear subspace that extracts features.

The Multi-linear dimensional reduction ML-DR the features are transformed into multi-linear subspace that extracts the multidimensional features from the database. When compared with the ML-DR, it directly operates in two mode process using multi linear ML-DR, with functional objectives. Video filtering is done using Gabor filters and feature extraction using histogram method in ML-DR results in feature projection matrix. Second phase performs same operation on the query samples as in the training samples
MLK algorithm works in the following steps
Algorithm: MLKDR

Input: video test samples from the multimedia data set
Output: multimedia samples with action class
Step 1: get the multimedia video data from the database.
Step 2: resize the video data into of uniform size dimensions

Step 3: convert the color video into gray scale video and crop into area.
Step 4: apply Gabor filters and histogram method for multimedia feature extraction
Step 5: the extracted features are processed for dimension reduction
Step 6: sparse the histogram from each frame and buffer it into the database
Step 7: send the reduced feature to the classifier for decision

4. EXPERIMENTAL RESULTS

The experiment is carried on **MATLAB** tool on benchmark data set for all the three reduction techniques PCA, LDA, MLKDR the simulation is carried out to per-from evaluation feature of all these technique are compared the work is carried on data-set as shown in figure 2 and query sample is shown in figure 3.

(a) walking

(b) Running

(c) Bending

(d) Jumping

FIGURE 2: Benchmark data set (a) Walking, (b) Running, (c) Bending, (d) Jumping

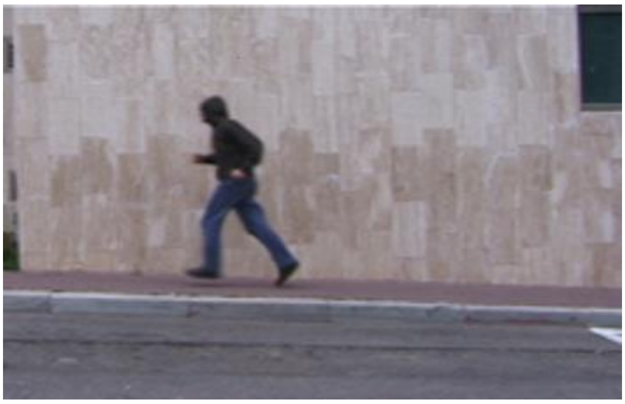

FIGURE 3: Query Sample

The overhead of all three methods are evaluated based on the results are shown in the **Table1** given below as

TABLE1: Feature count and Overhead Comparison of PCA, LDA, MLKDR

Test samples	DR-method	F_{Org}	F_{Dec}	Overhead
Walking	PCA	37794	15600	70.29%
	LDA	37794	14565	62.71%
	MLKDR	37794	12748	50.20%
Running	PCA	14460	6140	73.80%
	LDA	14660	5380	59.25%
	MLKDR	14600	4780	49.38%
Jumping	PCA	20400	8500	71.43%
	LDA	20400	7520	56.75%
	MLKDR	20400	6350	47.38%
Bending	PCA	18560	7150	62.56%
	LDA	18560	6320	52.35%
	MLKDR	18560	5870	45.28%

$$Overhead = \frac{F_{DEC}}{F_{ORG}}$$

The Table 1 gives the decimated features and processing overhead of Bending, Running, Jumping, Walking using MLKDR, PCA, LDA. Processing overhead is the ratio of reduced feature over the difference of original feature and decreased feature. Consider F_{DEC} is the decreased set of features and F_{ORG} is the original set of features, the overhead is measured as

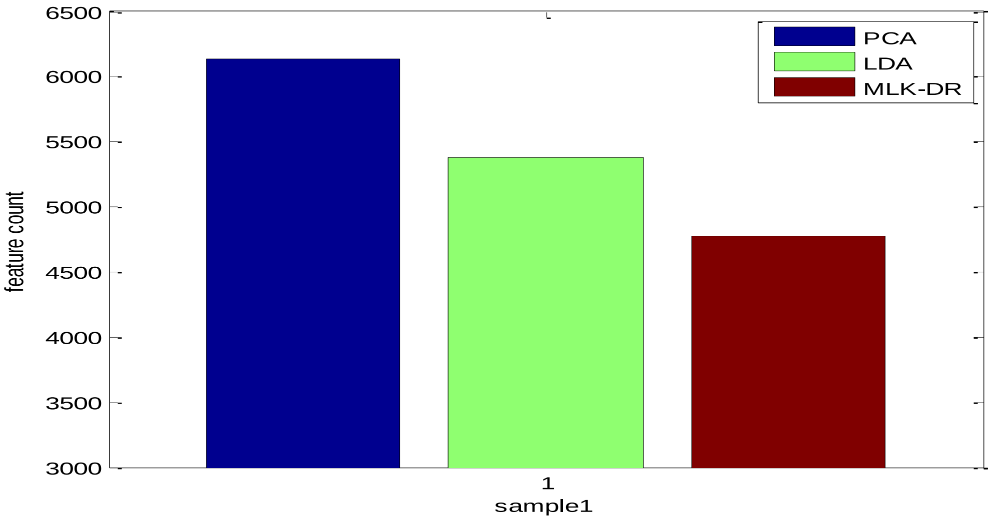

FIGURE 4: Bar plot of running sample showing the result of Feature count of PCA, LDA, MLK-DR.

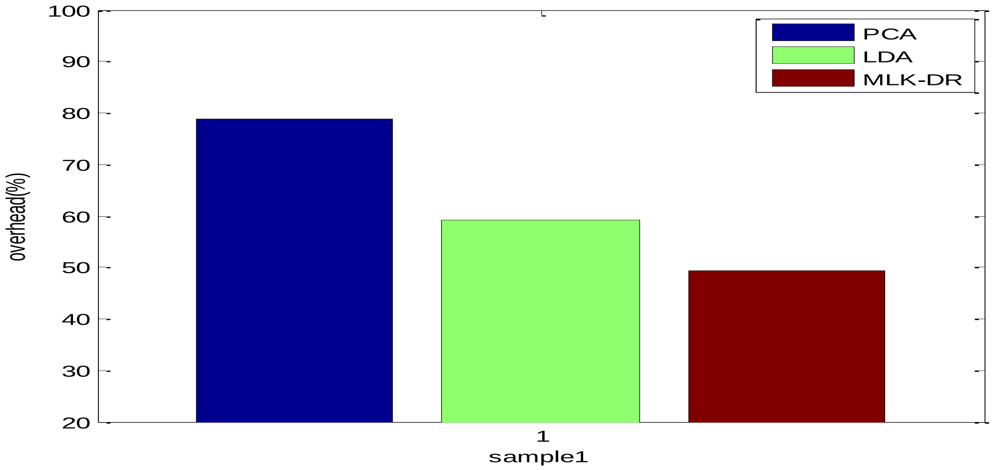

FIGURE 5: Bar plot of running sample showing the result of overhead of PCA, LDA, and MLK-DR.

When compared all the three methods the feature count and overhead of running sample of MLKDR is decreased to 24.42% and 12.51% compared to PCA and LDA techniques is shown in Figure 4 and Figure 5, similarly 19.48% and 12.51% in case of Walking, 24.05% and 9.37% in case of Jumping, 17.28% and 7.07% in case of Bending. To achieve the better performance the parametric evaluation is done the metric Accuracy, Specificity, Sensitivity, Precision, Recall, F-measure, Commutation time are performed using mathematical expression. The confusing matrix is used, the confusion matrix is a combination of True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN). The confusion matrix is given as

TP	FP
FN	TN

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Specificity = \frac{TN}{TN + FP}$$

$$F - Measure = \frac{2 * Recall * Precision}{Recall + Precision}$$

TABLE2: Comparison of Parametric Evaluation PCA, LDA, and MLK-DR of Walking, Running, Jumping and Bending.

Test samples	DR methods	Accuracy (%)	Sentivity	Specificity	Recall	Precision	F-Measure	Computation Time
Walking	PCA	49.484	0.432	0.712	0.432	.0.508	0.542	0.273
	LDA	58.1341	0.458	0.854	0.458	0.666	0.621	0.143
	MLKDR	69.5	0.524	0.946	0.524	0.82	0.652	0.137
Running	PCA	55.67	0.22	0.608	0.22	0.68	0.478	0.545
	LDA	62.5	0..315	0.752	0.315	0.74	0.523	0.348
	MLKDR	70	0.444	0.909	0.444	0.8	0.571	0.138
Jumping	PCA	55.67	0.42	0.762	0.421	0.65	0.569	0.31
	LDA	63.824	0.452	0.886	0.452	0.72	0.6	0.813
	MLKDR	70.84	0.484	0.908	0.582	0.81	0.68	0.132
Bending	PCA	58.36	0.446	0.738	0.446	0.65	0.583	0.374
	LDA	65.42	0.558	0.824	0.558	0.745	0.6	0.183
	MLKDR	72.82	0.582	0.908	0.582	0.81	0.68	0.132

When compared MLKDR with PCA the accuracy is increased by 29.01% in case, of walking, 14.33% in case of Running, 15.12% in case of Jumping, 14.46% in case of Bending and when compared MLKDR with LDA the accuracy is increased by 11.45% in case,. of walking, 7.50% in case of Running, 15.12% in case of Jumping, 7.07% in case of Bending.

5. CONCLUSION

As the high dimensional data effect in accuracy and processing overhead there is need of dimensional reduction technique which results in transforming data into smaller dimension. Evaluation is performed on three algorithms. The paper presents the analysis and comparison of PCA, LDA, MLKDR giving the optimal of feature intimation in multiple direction resulting in terms of processing overhead, Accuracy, the evaluation is done based on considering all metrics for parameters of all the three method the MLKDR work much better than LDA, PCA. In future the technique can benefit in using the topology learning thus extending the capability of dimensionality reduction techniques for real-world data.

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