Inter-correlative Histogram Feature and Dimension Reduction for Content Based Multimedia Retrieval

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Abstract: **Information retrieval based on motion descriptions in multimedia application has gained lot of importance and interest in the recent past. Content Based Multimedia Retrieval (CBMR) system retrieves the multimedia data based on the content of given multimedia query. That is, for a given motion query, relevant multimedia are to be retrieved. Here, an approach of human action detection and localization in a multimedia dataset and an improved histogram based approach for Multi-Instant action detection named as Multi-Instant Histogram (MI-HIST) is proposed. The proposed approach enhances the disadvantages like processing noise and system overhead with respect to the representation and retrieval performance. In the representation of descriptive features, a large feature count is observed, which results in the processing overhead. To reduce these descriptive features, this paper also presents a multi-linear kernel (MLK) technique for dimension reduction approach to feature reduction based on feature relations. The experiments have been conducted on the benchmark datasets. The experimental results show that the processing resource overhead and retrieval efficiency are improved with the present approach.**

Keywords: CBMR, Histogram features, PCA, LDA, Kernel, Accuracy, and Computation Time.

I.INTRODUCTION

Multimedia Retrieval is one of the most important and fastest growing research areas in the field of multimedia technology. Large collections of scientific, artistic and commercial data comprising image, text, audio and video abound in the present information based society. There is a need for an effective and precise method of assisting users to search, browse and interact with these collections. As per the present trend, people use not only pure images for daily purposes, but also video is a popular media for recording TV, diaries etc. As a consequence, effective and efficient methodsfor searching with large databases are needed. This motivates the need for using Content Based Multimedia Retrieval (CBMR) [1] System for images or videos which allowusers to search images or particular image frames according to their preferences. However, today's multimedia retrieval systems are more inclined towards image retrieval model and less focus is made on the retrieval of video content.

Video information is processed in real time applications such as surveillance, film making, home monitoring, CCTV, monitoring etc. with higher storage resources and new capturing units. In such applications, video information could result in more informative than their corresponding images, retrievals of information over such system that are limited. Current multimedia databases such as YouTube use a text based searching mechanism to search video content. A video annotation based retrieval [2, 3] and a video summarization based approach [4] to obtain keyword based action retrieval are proposed earlier. However, the retrieval performance is purely dependent on the tagging factor for applications. It is very difficult to extract video based on the content, such as action in a video samples. A motion based coding following energy and a history image[5] was also used as an action detection model. A local representation of the extracted spatio-temporal interest points (STIPs) [6, 7] from an action is developed earlier. The local representation is highly robust to statistical representation of action dataset [8, 9]. In the action detection model, Harris detector [10] and 3-D SIFT [11, 12] are used for action detection process. The SIFT operator performs a max/min searching over the difference of Gaussian (DoG) function. A combined format of histogram oriented gradient and histogram optical flow (HoG-HoF) [13] was also developed previously. The histogram of gradient is observed to be an effectively applied approach for action detection model. A 3D-HoG [14] is developed earlier with a set of descriptive approaches to obtain effective action model. Further, a histogram based coding [15] for video retrieval is developed for the optimization of action detection model. The system uses the localized temporal histogram features to detect an action model from a video dataset. However, as observed the Noise factor impacting the histogram representation is considered over two successive frames only. The global distribution of noise distribution over the video frames is not analyzed in representing the Histogram feature. This factor affects in the retrieval accuracy and increases the resource overhead in multimedia retrieval approach.Feature sets are very important in the approach of multimedia retrieval. Xin Geng et al. [16][17] have proposed the Representation pattern Subspace method for multimedia retrieval based on pattern recognition. Its idea is to model the representation pattern, which is defined as a sequence of personal representation pattern videos by learning a representative sub-space from EM-like (expectation maximization) iterative learning Principle Component Analysis (PCA).

Frequency domain analysis is the most popular method for extracting video features in video processing and pattern recognition. Guodong Guo et al. [20] have investigated the biologically inspired features (BIF) for pattern recognition from given videos. Unlike the previous works [18][19], Guoetal. simulated the human visual process based on bio-inspired models [21] by applying Gabor filters. A Gabor filter is a linear filter used in video processing for edge detection. Frequency and orientation representations of Gabor filters are similar to that of human visual system and have been found to be appropriate particularly for textural representation and discrimination. Though PCA based coding is observed to be applied over multiple applications, the feature representation is higher and the approach of selective operation minimizes the feature selection accuracy. In previous work multi instance histogram features from the MI-HIST [22] are processed for dimensionality reduction through MLK-DR presented[23]. In this paper, an approach for inter frame computation of histogram features and selection is proposed which extracts sufficient features for retrieval to overcome the representation of Histogram based coding considering noise factor. Further, this paper also proposes a dimensionality reduction technique which reduces the computational overhead of retrieval system. The content of this paper is organized into 6 sections. Section 1 presents the objectives and related work on information retrieval in content based multimedia retrieval system. Section 2 defines the system model and section 3 defines the approach of histogram for inter frame localization and representation. Section 4 outlines the dimensionality reduction technique. Section 5 outlines the obtained experimental results for the developed approach. The conclusionsof contributions are presented in section 6.

II. MULTIMEDIA RETRIEVAL SYSTEM

The general multimedia retrieval system consists of three stages: training, testing and classification. The training stage trains the various multimedia videos of benchmark datasets along with their features. Testing stage extracts the features of a query sample and gives it to classifier. The classifier classifies the given query sample by comparing it with the trained samples. The developed system for the proposed multimedia retrieval is given below:

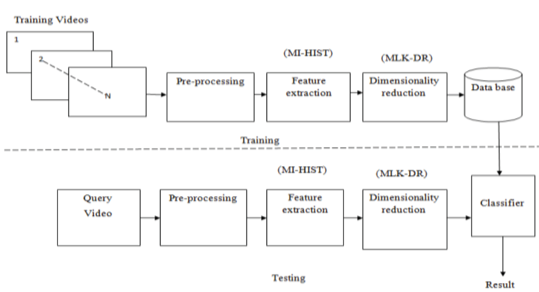


Figure 1. Model of proposed multimedia retrieval system

The developed approach is processed into two phases of execution of training and testing process. In training process, set of video samples of different actions like running, walking, jumping and sitting is taken andthese are processed for feature selection through the proposed Multi Instance-Histogram (MI-HIST) approach. Further, these features are then processed for Multi Linear Kernel Dimensionality Reduction (MLK-DR)technique. Finally, the reduced feature set is processed for classification using a SVM classifier.

III. MULTI INSTANCE-HISTOGRAM (MI-HIST)

An approach was proposed for information retrieval based on the actions of the objects through their histogram features [8]. This approach defines a temporal and spatial localization of an action model based on Histogram mapping. However, the noise effect leads to the reduction of retrieval performance. An inter frame correlation error for a set of time frames are considered to eliminate the impact of noise. Considering a set of Histogram for k class (H_k), for a given video dataset of i=1 to k,

$$H_i(k) = [H_i(kN), H_i(kN-1), \ldots\ldots, H_i(kN-M+1)\ ] \quad (1)$$

Where, $H_i$is the Histogram for a video frame, N is number of frame and $M$is the dataset samples. A frame error is computed to evaluate the noise effect in the temporal framesas defined by,

$$e_{i,H}(k) = H_{i,t}(k) - H_{i,t+1}(k) \qquad (2)$$

This error defines the difference in two frame components and the histogram errors with lower values $\min\left(e_{i,H}(k)\right)$are considered as feature element. However, this error deviatesmuch when observed over a period of frame observation and could be effective due to noise effect. Hence, the intersection histogram would be mode concentric with noise parameterin such coding. A Histogram bin selection computed over a time series is proposed to eliminate this problem and to improve the feature selection more accurately. In this approach, selection of the histogram bins is made rather than taking the whole histogram from single frame information. The histogram bins are initially normalized using a random weight factor to derive the bin selection.

$$H_i(k) = H_i(k)\, w(k) \qquad (3)$$

Where$w(k) = [w_0(k),\ w_1(k), \ldots\ldots, w_{M-1}(k)]^T$isthe allocated weight factor for each frame? Then the estimated error is then defined as:

$$e_{i,H}(k) = H_{i,t}(k) - H_i(k)w \qquad (4)$$

The error is recursively computed over the total frames (i=1,…, N) and the initial error is recorded as $e_{i,H,init}$.A weight factor is then updated as:

$$w(k+1) = w(k) + \mu \sum_{i=0}^{N-1} \frac{H_i^T(k)}{\|H_i(k)\|^2} e_{i,H,init}(k) \qquad (5)$$

Where μ is the updation step size, with an error updation factor. The objective of this computation is to select the bins satisfying the $\min(e_{i,H}(k))$ condition. A joint adjacent weight difference is computed to optimize the recursion overhead and is defined as:

$$\widetilde{w}(k) = w^o - w(k) \qquad (6)$$

Where, w^o is the initial weight issued.The weight updation is then defined as,

$$\widetilde{w}(k+1) = \widetilde{w}(k) - \mu \sum_{i=0}^{N-1} \frac{H_i^T(k)}{\|uH_i(k)\|^2} e_{i,H}(k\ \ ) \quad (7)$$

The deviation in the bin variationof the histogram is then integrated over a period of 0 to N defined by,

$$\mathrm{E}\left(H_{i,N}\right) = \int_{\mathbf{0}}^{N} \mu \sum_{i=0}^{N-1} \left(2E\left[\frac{H_{i,n}(k)\tilde{w}(k)e_{i,NH}(k)}{\|H_{i,N}(k)\|^2}\right] - \mu E\left[\frac{e_{i,NH}^2(k)}{\|H_{i,N}(k)\|^2}\right]\right) \quad (8)$$

Wherein integrating the estimate, over 'n' observation period accumulates the estimation for 'n' inter frame errors. For each frame with minimum estimate error is then selected as the selected histogram bin and an intersection bin is then derived as:

$$s\left(H_q, H_t\right) = \sum_{i=1}^{k} \left(\frac{\min\left(H_q - H_t\right)}{H_n}\right) \quad (9)$$

Where $H_n$is the normalized histogram for the entire dataset.

The obtained multi instance histogram features are processedfor dimensionality reduction. The dimensionality reduction method reduces the dimensions of obtained feature setso that the computation overhead can be minimized.

IV. MULTI-LINEAR KERNEL DIMENSIONALITY REDUCTION (MLK-DR)

The main aim of any dimensionality reduction approach is to minimize the number of features to be processed. Less the number of features, less will be the computational overhead and less computation time. So the obtained multi instance histogram features from the MI-HIST[22] are processed for dimensionality reduction through MLK-DR presented [23]. MLK-DR stands for Multi Linear Kernel Dimensionality Reduction. It is a multi linear subspace learning method that extracts features directly from multi-dimensional objects. The MLK-DR is an extension to the conventional PCA [16], which operates linearly whereas MLK-DR operates multi-linearly. The PCA needs to reshape the multidimensional object into the vector, whereas MLK-DR operates directly on multidimensional object through two-mode processing. In this paper, the histogram features obtained through MI-HIST are given as inputto MLK-DR. The operation for the PCA is defined as: for a given data set of N-by-N dataset samples, I(x, y) as a vector of dimension N^2, so that the sample can be thought of as a point in N^2-dimensional space. A database of M samples can therefore map to a collection of points in this high dimensional "dataset space" as $\Gamma_1, \Gamma_2, \Gamma_3, \ldots, \Gamma_M$. The average dataset of the sample set is defined as:

$$\Psi = \frac{1}{M} \sum_{n=1}^{M} \Gamma_n \quad (10)$$

Each dataset is mean normalized and is represented as deviations from the average dataset by$\Phi_t = \Gamma_t - \Psi$. The covariance matrix is defined as the expected value of $\Phi\Phi^T$and can be calculated by the equation:

$$C = \frac{1}{M} \sum_{n=1}^{M} \Phi_{n-1} \Phi_n^T \quad (11)$$

Given the covariance matrix C, one can now proceed with determining the eigenvectors u and eigenvalues λ of C in order to obtain the optimal set of principal components and a set of Eigen datasets that characterizes the variations between dataset samples. Consider an eigenvector $u_i$of C satisfying the equation

$$C_{u_i} = \lambda_i u_i \quad (12)$$

$$u_i^T C_{u_i} = \lambda_i u_i^T u_j \quad (13)$$

The eigenvectors are orthogonal and normalized. Hence,

$$u_i^T u_j = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases} \quad (14)$$

Combining Eq. (11) and (14), Eq. (13) thus become

$$\lambda_i = \frac{1}{M} \sum_{n=1}^{M} var\left(u_i \Gamma_n^T\right) \quad (15)$$

Eq. (15) shows that the eigenvalue corresponding to the i_{th} eigenvector represents the variance of the representative dataset sample. By selecting the eigenvectors with the largest corresponding eigenvalues as the basis vector, the set of dominant vectors that express the greatest variance are being selected. The PCA algorithm applied for dimensionality reduction reduces the dimensions of obtained feature set only by considering internal variations in that particular sample only. However, the inter class variations, i.e., the features of other frames in a sequence are not considered. The PCA operates in one dimensional mode, whereas MLK-DR operates along multi-dimensional mode. For a given feature space of a single class, PCA evaluates the principal components individually, whereas MLK-DR evaluates by considering the feature space of remaining classes also. The pseudo-code for MLK-DR is described as follows:

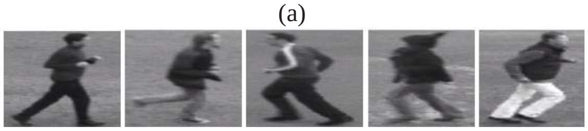
***Pseudo Code**:*
Input: *Features of large size*
Output: *Feature set with less size*
Step 1: take the whole feature set having MxN dimensional space
Step 2: compute the mean along each 'n' dimensions
Step 3: obtain a new matrix by subtracting the mean from all values of dataset.
Step 4: evaluate a covariance matrix
Step 5: compute Histogram vectors and the corresponding Histogram values
Step 6: sort the Histogram vectors by decreasing the Histogram values and choose k Histogram vectors with largest Histogram values from n x k dimensional matrix W_1.
Step 7: perform the same operation of step7 for each class of feature set and find out some more Histogram values those having effect on the retrieval accuracy.
Step 8: finally form a new projection matrix by considering inter class Histogram values and also intra class Histogram values.
Step 9: form a dimensionally reduced subspace by multiplying the projection matrix with original values.

Then, the feature vectors are compared with the database using SVM classifier and classify the multimedia video as to which class it matches.

V. SIMULATION RESULTS

The proposed system is developed over Matlab tool and tested over Weizmann benchmark dataset and KTH dataset [7]. The KTH video database contains six types of human actions (walking, jogging, running, boxing, hand Waving and hand clapping) performed several times by 25 subjects in four (4) different scenarios: outdoors s1, outdoors with scale variation s2, outdoors with different clothes s3 and indoors s4 as illustrated below. Currently the database contains 2391 sequences. All sequences are taken over the homogeneous backgrounds with a static camera with a frame rate of 25fps. The sequences are down sampled to the spatial resolution of 160x120 pixels and have a length of four seconds in average.A comparative analysis of PCA based feature dimension reduction is compared with the proposed MLK-DR to evaluate the performance of the proposed approach. The simulation is performed over KTHdataset for which MI-HIST features are computed. The test dataset is shown in Figure 2.

(a)



(b)

(c)

(d)

Figure 2: Dataset with (a) Handclapping (H), (b) Jogging (J), (c) Running (R) and (d) Walking (W) sample

The samples are captured with 180 x144 resolution by using a static camera with a homogenous outdoor background.The processing test sample that has a running action is illustrated in Figure 3.

Figure 3: Test sample with running action

The obtained features of the MI-HIST and MLK-DR are represented in Table 1.

Table 1. Feature table of various approaches

Class	Feature Extraction			Dimensionality Reduction		
	HoG[14]	HIST[15]	MI-HIST [22]	PCA[16]	LDA[19]	MLK-DR [23]
C1(H)	43246	21452	14712	6210	5342	4640
C2(J)	72478	52984	37862	14980	14320	12546
C3(R)	61146	44102	21476	8480	7742	6320
C4(W)	44528	35284	18438	7245	6242	5540

Table 1 illustrates the obtained feature count for both feature extraction methods and dimensionality reduction methods. The feature extraction methods extract only features. After feature extraction, the entire features obtained are trained as well as tested through the classifier, whereas in dimensionality reduction methods, the dimensions of obtained feature set are reduced first and then only they are processed for training as well as testing. Hence, the feature count of dimensionality reduction methods is less. In Table 1, the obtained features for PCA, LDA and for MLK-DR are compared with HOG, HIST and MI-HIST. The obtained feature count of various approaches at feature extraction stage and at dimensionality reduction stage is shown in Figure 4.

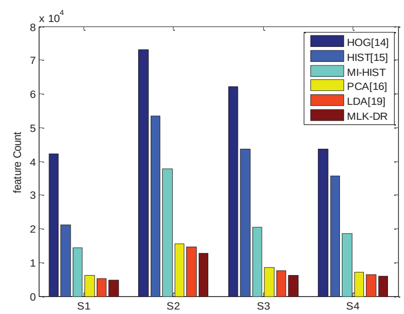


Figure 4. Feature count for four actions

The complete system is simulated in two phases: training phase and classification phase. The training phase establishes a database with a set of features using feature extraction techniques. The classification phase performs the classification for a given query input. The time taken for training is termed as training time and the time taken for classification is termed as classification time. These two timings vary from approach to approach. The complete analysis of the time consumption for various approaches is represented in Figure 5.

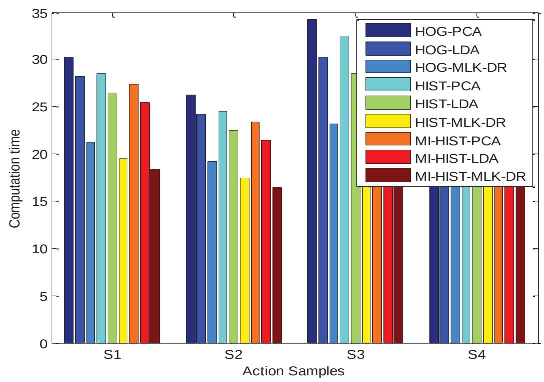


Figure 5. Computation time

Figure 5 illustrates the details of computation time in seconds. The training phase has a large number of samples to process. Hence, the computation time for training is more when compared to that of classification. The details of the computation time are represented for the combination of feature extraction methods with dimensionality reduction methods in Figure 5. It can be observed from Figure 5 that, for each class, the combination of MI-HIST with MLK-DR has less computation time when it is compared with remaining combinations. The following parameters are used to evaluate the performance of the developed approach:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (16)$$

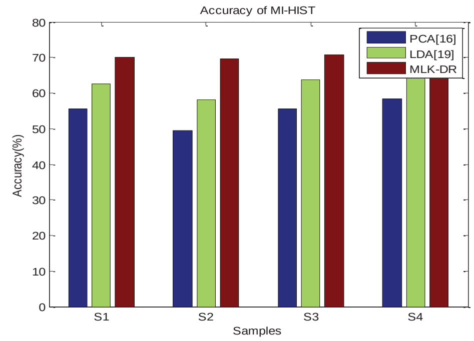
Where,
TP =True Positive (correctly identified)
FP= False Positive (incorrectly identified)
TN=True Negative (correctly rejected)
FN=False negative (incorrectly rejected)

For the above given simulation model, there are totally four classes and each class has five subjectsthat are processedfor training. In the testing phase, a query sample with running action is selected and is given for SVM classifier. The SVM classifier compares the sample features of given query with database features.

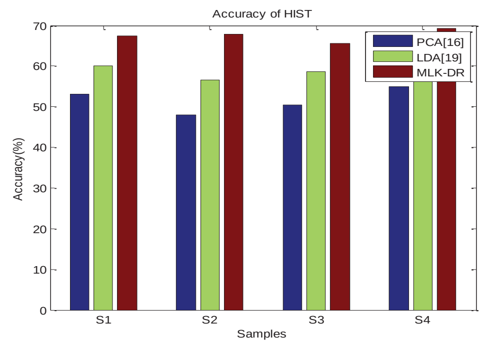
To show the enhancement of proposed approach and also to compare the proposed approach with previous approaches, precision along with accuracy is evaluated as:

$$Precision = \frac{TP}{TP+FP} \qquad (17)$$

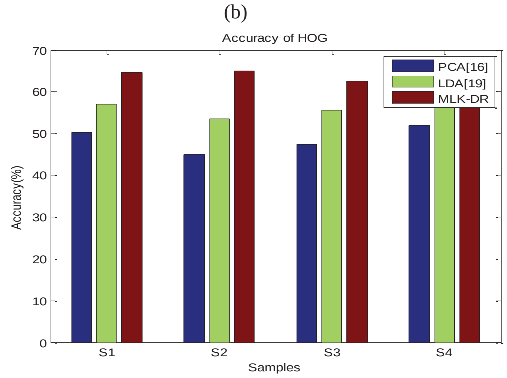
The obtained accuracy and precision details are illustrated in Figure 6 and Figure 7 respectively.



(a)



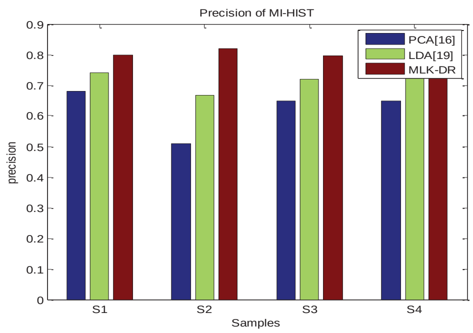
(b)



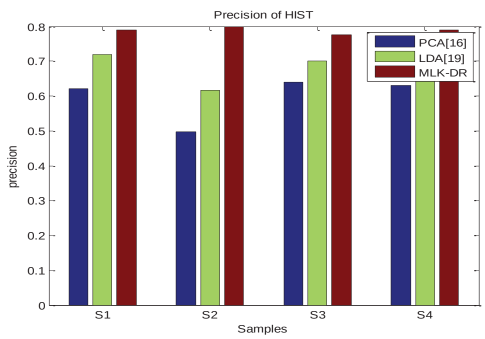
(c)

Figure.6 Accuracy of four action samples with dimensionality reduction methods, PCA, LDA and MLK-DR (a) MI-HIST, (b) HIST [15], (c) HOG [14]

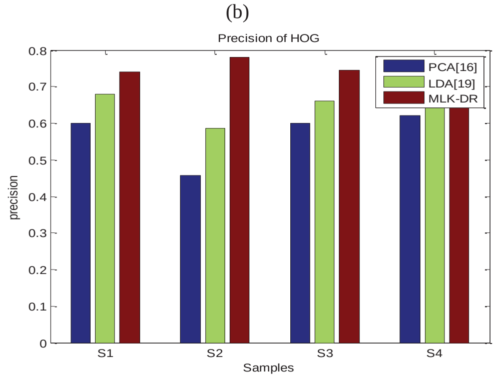
Figure 6 illustrates the accuracy details of the proposed work. The proposed work combines the feature extraction with dimensionality reduction approaches. Compared with alone, the combination will have more accuracy. The proposed work combined the HOG, HIST and MI-HIST with PCA, LDA and MLK-DR. the individual details of MI-HIST, HIST and HOG are shown in Figure 6 (a), (b) and (c) respectively. From Figure 6, it can be observed that for the combination of MI-HIST with MLK-DR having more accuracy.



(a)



(b)



(c)

Figure.7 Precision of four action samples with dimensionality reduction methods, PCA, LDA and MLK-DR (a)MI-HIST, (b)HIST [15], (c)HOG[14]

Figure 7 illustrates the precision details of the proposed work. The proposed work combines the feature extraction with dimensionality reduction approaches. It can be observed from Figure 7 that the combination of MI-HIST with MLK-DR gives more precision than these individual techniques.

VI. CONCLUSION

A new coding approach for histogram based action model detection is proposed. A process of inter frame histogram coding for feature selection and its representation is developed. The respective dominant features are obtained with the application of Histogram on video. Histogram features are extracted after obtaining all possible variations from the frame information. In conventional approach, the Histogram features are directly extracted from multimedia video thus finding the dominating features become complex. The proposed work applies dimensionality reduction method in a multi-nature and it reduces the dimensions of feature set by considering the intra class feature and also inter class features, whereas the conventional approach reduces the dimensions by considering intra class featuresonly.The retrieval performance is improved with the optimal selection of histogram features by the application of feature extraction and dimensionality reduction method. The results of the extensive simulation have shown the effectiveness of proposed work with improved performance.

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