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Human Action Recognition in Video using Histogram of Oriented Gradient (HOG) Features and Probabilistic Neural Network (PNN)

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ABSTRACT: This paper presents a method to automatically recognize human activity from input video stream using Histogram of Oriented Gradient features (HOG) and Probabilistic Neural network (PNN) classifier. The action features are extracted from input video frames by means of HOG features and are concatenated to form an action pattern. The Probabilistic Neural network (PNN) is used as a classifier for classifying the actions of supplied video into six basic categories such as running, walking, jogging, waving, clapping and boxing. PCA is used for dimensionality reduction. Experiments are conducted on KTH database and gives better performance in terms of 100% recognition rate for training set and 89.8% accuracy for test set. The experiments have highlighted the efficiency of the proposed method in enhancing the classification rate. At the end we have experienced action recognition by Gabor feature and using SVM for classification. The performance of each feature set with respect to two classifiers is analyzed. The experimental result and its accuracy reveal that the proposed system is applicable to recognize human activity in real. The planned system is implemented in MATLAB version 8.1.604 R2013a.

KEYWORDS: Human Action Recognition, Histogram of Oriented Gradient Features, Feature extraction, Probabilistic Neural Network

I. INTRODUCTION

The goal of action recognition is to recognize common human activities in real life settings. Accurate activity recognition is challenging because human activity is complex and highly diverse. Human action recognition has been mainly focused on three leading applications: 1) surveillance systems, 2) entertainment environments, and 3) healthcare systems, which comprise systems to track or follow individuals automatically.

Generally, human action–recognition approaches involve two important blocks. The feature extraction is first of the important blocks, which extract a set of key parameters that best describe the particular set of human action so that the parameters can be used to distinguish among other actions. The classification of human action from the extracted feature is the second important block which performs a vital role in the action recognition system.

There are different types of methods to extract feature vector from action images such as histograms of 3D gradients (HOG3D) [23, 32], motion boundary histograms (MBH) [5, 21], shapes of point trajectories [20, 26, 21], local trinary patterns [22, 31] and bag-of-features (BOF), histograms of flow orientations (HOF) [24], others. Recent evaluation [21] reveals that MBH, HOF and HOG descriptors sampled along dense point trajectories do better than other methods on a number of challenging datasets [21]. Due to this our work uses HOG feature to represent action feature of the video frame.

Artificial neural network (ANN) [6] is a influential tool of information processing. There are a variety of neural-network architectures [11] together with multilayer perceptron (MLP) neural network, radial basis function (RBF) neural network, self-organizing map (SOM) neural network, and probabilistic neural network (PNN). Because of easiness of training and a sound statistical basis in Bayesian estimation theory, PNN has become an efficient tool for solving numerous classification problems (e.g., [7]-[10]). Due to its strong ability of modelling linear and nonlinear relationship, it has been widely used in pattern recognition .Our proposed work uses PNN for emotion classification

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from feature vector. Our conclusion points to that it is achievable to build an improved automatic human action recognition system based on a Gabor wavelet code and PNN together with PCA.

The rest of the paper is ordered as follows: Section 2 describes allied work on the design of HAR. In Section 3, we propose action classification using HOG feature and PNN. Validation of the proposed algorithm for action recognition is expressed in Section 4.In addition finally conclusion is drawn in Section 5.

II. RELATED WORK

Many techniques have been used for HAR since 1960.

Q. Cai, A. Mitiche et al. (1995) [2] introduced a framework for tracking human motion in an indoor environment from sequences of monocular greyscale images captured from multiple fixed cameras. Multivariate Gaussian models were applied to find the most likely matches of human actions between consecutive frames taken by cameras mounted in various locations.

R. Venkatesh Babu et al. (2003) [13] introduced the human action recognition through Motion Flow History (MFH). The encoded motion information presented in the compressed MPEG stream was used to construct the coarse Motion History Image (MHI) and the related MFH. The features extracted from the static MHI and MFH compactly characterized the spatio temporal and motion vector information of the action. The features extracted were used to train the KNN, Neural network, and SVM and Bayes classifiers for recognizing a set of seven human actions.

Piotr Doll´ar et al. (2005)[17] have shown the viability of doing behaviour recognition by characterizing behaviour in terms of spatiotemporal features. A new spatiotemporal interest point detector was presented, and a number of cuboid descriptors were analyzed. Their work showed how the use of cuboid prototypes gave rise to an efficient and robust behaviour descriptor.

L. Wang et al. (2007) [16] described a probabilistic framework for recognizing human activities in monocular video based on simple silhouette observations. Their methodology combined kernel principal component analysis (KPCA) based feature extraction and factorial conditional random field (FCRF) based motion modelling. Silhouette data was represented more compactly by nonlinear dimensionality reduction that explores the underlying structure of the articulated action space and preserved explicit temporal orders in projection trajectories of motions.

J. Niebles et al. (2007) [18] presented a novel model for human action categorization. A video sequence was expressed as a set of spatial and spatial temporal features by extracting static and dynamic interest points. They proposed a hierarchical model that can be described as a constellation of bags of-features and that was able to combine both spatial and spatial temporal features. From the input video sequence, the model is able to categorize human actions in a frame by-frame basis.

C.P.Huang et al. (2011) [19] presented a human action recognition method using histogram of oriented gradient (HOG) of motion history image (MHI). Their method generated MHI with differential images by frame difference of successive frames of a video. The HOG feature of the MHI was then computed. At last, support vector machine (SVM) was applied to train an action classifier using HOG features.

Alexandros Iosifidis et al. (2012)[27] proposed a novel view invariant action recognition method based on learning spatially related human body posture models using self organizing maps. Fuzzy distances from human body posture models were used to construct a time invariant action representation. Multilayer perceptrons were used for classification of human action. The algorithm was trained using data from a multi-camera setup. An arbitrary number of cameras can be used in order to recognize actions using a Bayesian framework.

Kai Guo, et al. (2013) [29] introduced empirical covariance matrices of features for fast and accurate recognition of actions in video. To provide a localized description of the action a dense set of spatio temporal feature vectors were computed from video, and subsequently aggregated in an empirical covariance matrix to compactly represent the action. Using feature covariance matrices two supervised learning methods for action recognition were developed. The first method followed nearest-neighbour classification using a suitable Riemannian metric for covariance matrices. The second method estimated the logarithm of a query covariance matrix by a sparse linear grouping of the logarithms of training covariance matrices. The action label was then determined from the sparse coefficients.

Shuiwang Ji et al. (2013) [30] extracted features from both the spatial and the temporal dimensions by performing 3D convolutions, and hence captures the motion information encoded in multiple adjacent frames. Their developed model generated information in multiple channels from the input frames, and the final feature representation

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combined information from all channels. To boost the performance of 3D CNN models further, they proposed to regularize the models with high-level features and combined the outputs of a variety of different models.

M. Selmi, et al (2016) [33] proposed a new approach that explicitly models the sequential aspect of activities. First, the video stream was split into overlapping short segments and were characterised by a local bag of words of IPs encoded by motion information. For each window a first-layer support vector machine provides a vector of conditional class probabilities that summarises all discriminant information that was relevant for sequence recognition. The sequence of these stochastic vectors was then fed to a hidden conditional random field for inference at the sequence level.

III. PROPOSED SYSTEM DESIGN

Figure 3.1 shows the proposed system design. The procedure of the entire system consists of four parts
A. Pre-processing
B. HOG Feature Extraction
C. Dimension Reduction using PCA
D. Recognition with ANN

The projected human activity recognition system is illustrated in Figure 1. In our approach, the data set containing activities such as such as running, walking, jogging, waving, clapping and boxing is divided into two sections: training set, and testing set. The proposed system is also divided into two phases: training and testing. In training stage, we extract the histogram of oriented gradient features (HOG) from each video frame. The HOG feature vectors from n consecutive video frames are processed to generate action pattern. The generated action patterns are used to train the Probabilistic Neural network (PNN) classifier for all activities. In testing stage, for each human activity we generate the action pattern and feed into the PNN classifier for action detection.

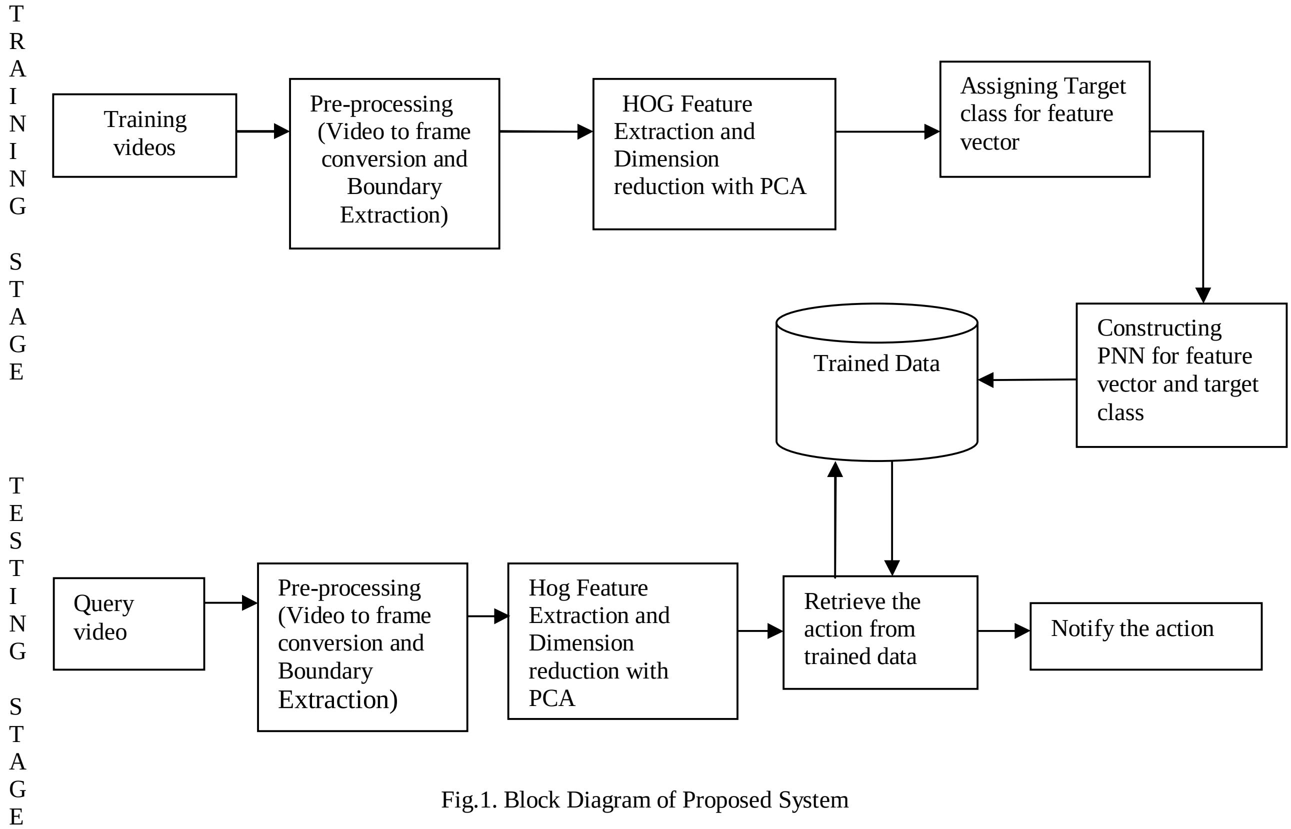

Fig.1. Block Diagram of Proposed System

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A. *Pre-processing*

The input video is converted into frames as in Fig.2. Each frame is eroded with morphological structuring element. The eroded frame is subtracted from the actual input frame to get the boundary extracted frame (Fig. 3).

Fig.2. Input image

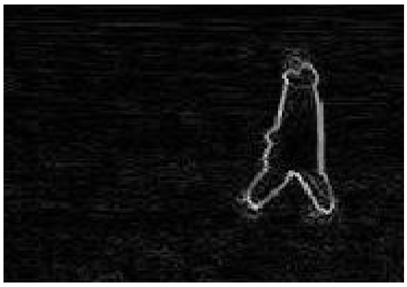

Fig.3. Boundary Extracted Image

B. *HOG Feature Extraction*

In our research, we use the histogram of oriented gradient (HOG) features from each video frame to represent human action. The method is developed by N. Dalal and B. Triggs in [1] for human detection purposes. HOGs are well-recognized for human detection and mostly independent regarding illumination and contrast changes. The method is based on computing well-normalized local histograms of image gradient orientations in a dense grid. The fundamental belief is that local object shape and appearance can often be represented quite well by the distribution of local intensity gradients, even without accurate knowledge of the corresponding gradient or edge positions. This is implemented, by separating the image window into small spatial regions, and for each cell accumulating a local 1-D histogram of gradient directions or edge orientations over the pixels of the cell. The collective histogram entries form the representation. For better invariance to illumination, shadowing, it is also supportive to contrast-normalize the local responses before applying them. This can be done by accumulating a measure of local histogram energy over to some extent larger spatial regions (*blocks*) and using the results to normalize all the cells within the block. We refer to the normalized descriptor blocks as Histogram of Oriented Gradient (HOG) descriptors.

The computation proceeds as follows.

Following the notation of [3] the transform from pixels to output in HOG features can be written as,

$$\Phi_f(\mathbf{x}) = \mathbf{D}\mathbf{b} * [(\mathbf{g}_f * \mathbf{x}) \odot (\mathbf{g}_f * \mathbf{x})] \qquad (1)$$

where a vectorized input image X € R^D is convolved with an oriented edge filter g_f [6], rectified through the Hadamard operator, then finally blurred with b and down sampled by the sparse selection matrix D to get histogram. Performing this operation over a bank of oriented edge filters and concatenating the responses leads to the final descriptor,

$$\Phi(\mathbf{x}) = [\Phi_1(\mathbf{x}) \;\; \Phi_2(\mathbf{x}) \;\; \ldots \;\; \Phi_F(\mathbf{x})] \qquad (2)$$

This reformulation omits the contrast normalization measure. Each sub-descriptor can be expressed in the form,

$$\Phi_f(\mathbf{x}) = \mathbf{DBM}(\mathbf{G}_f \otimes \mathbf{G}_f)(\mathbf{x} \otimes \mathbf{x}) \qquad (3)$$

Where M is a selection matrix and B, G are matrix forms of their convolution prototypes. The overall response to a bank of filters can be written as,

$$\Phi(\mathbf{x}) = \mathbf{L}(\mathbf{x} \otimes \mathbf{x}) \qquad (4)$$

where the projection matrix L is obtained by concatenating the bank

$$\mathbf{L} = \begin{bmatrix} \mathbf{BM}(\mathbf{G}_1 \otimes \mathbf{G}_1) \\ \vdots \\ \mathbf{BM}(\mathbf{G}_F \otimes \mathbf{G}_F) \end{bmatrix} \qquad (5)$$

Under this reformulation, HOG features can be observed as an affine weighting of quadratic interactions among pixels in the image. In our work, the convolution output produce HOG feature vector which has 9576 features for each 256×256 frame.

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C. Dimension Reduction and Action Pattern generation

As a consequence of HOG feature extraction, a high dimensional feature vector is obtained. The obtained feature vector has 9576 feature for each frame. Therefore, it is mandatory to reduce the dimensionality of the feature vector. Principal component analysis PCA [4] is a technique used to lesser the dimensionality of a feature space that takes a set of data points and constructs a lesser dimensional linear subspace that best describes the variation of these data points from their mean. In effect of this some principal components can be removed because they give details only a small amount of the data, whereas the largest amount of information is contained in the other principal components. Dimensionality reduction of PCA is as follows in equation (6):

$$Y = P \times X \qquad (6)$$

Where Y defines lower dimensional feature vector, $P = [P_1 P_2 \ldots .. P_n]$ consists of the n eigenvectors representing the leading eigen values of the matrix of X. The lower dimensional vector Y captures the most expressive features of the original data X. Our work reduced 9756 features into 350 for each frame. The feature vector of 50 frames of the given video are concatenated and applied to the next level PCA for feature reduction to form an action pattern with 750 features for each video.

D. Recognition with ANN

Probabilistic neural network is a sort of radial basis network suitable for classification problems. Probabilistic neural network (PNN) was developed by Specht [12]. It features a feed-forward architecture and supervised training algorithm similar to back propagation. However, a back-propagation neural network has to be trained for a long time to learn the relationship between input and output variables. furthermore, a sufficient dataset must be available to partition the data into a training set, a test set and a validation set to avoid over fitting[6].An alternative method is probabilistic neural network. Instead of adjusting the input layer weights using the generalized delta rule, each training input pattern is used for the connection weights to a new hidden unit. PNN offers several advantages over back-propagation network. Training is much quicker, usually a single pass. Moreover, PNN allows true incremental learning where new training data can be included at any time without the necessity of retraining of the entire network. The PNN also possesses some useful characteristics as the back-propagation algorithm such as generalization capability

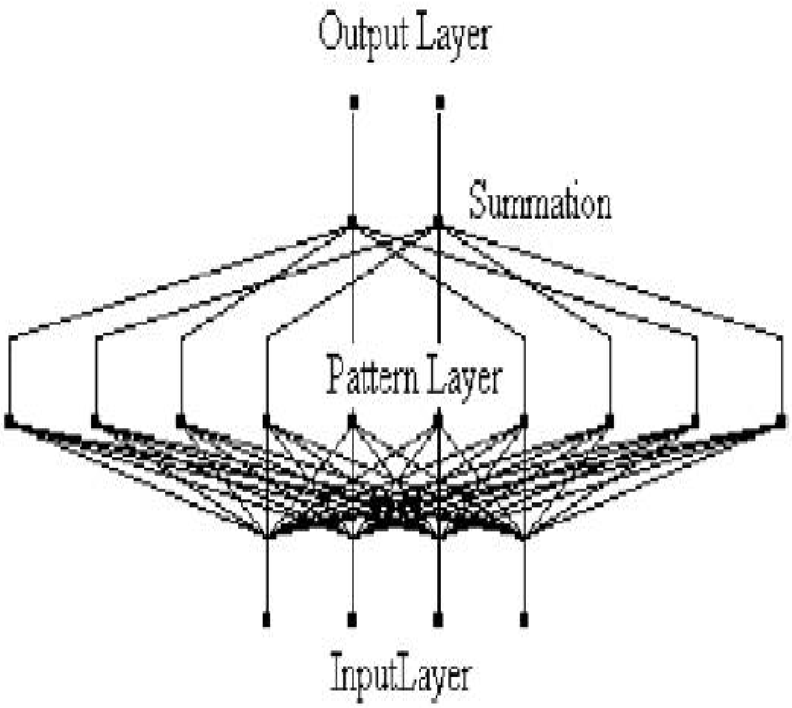

Fig.4. Diagram of a three-layer probabilistic neural network

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A pattern of a probabilistic neural network is shown in Fig.4. It has three layers [12]. The network contains an input layer, which has several elements as there are distinguishable parameters needed to describe the objects to be classified. It has a pattern layer, which makes the training set such that an individual processing element corresponds to each input vector. And at last the network contains an output layer, called the summation layer, which has as many processing elements according to the number if classes to be recognized. Each element in this layer combines by means of processing elements within the pattern layer which relate to the same class and prepares that class for output. The transfer function is radial basis function for the first layer and is competitive function for the second layer. Only the first layer contains biases. Training of the probabilistic neural network is much easier than with back-propagation neural network. It can be simply done by setting the weights of the network using the training set. Our work constructed PNN with 750 input units and 6 hidden units and 6 output units. The results showed that the predictive capacity of the probabilistic neural network is stronger than the others in this study.

IV. Experimentation and Results

Data required for experimentation is collected from KTH database for neural network training and testing. The KTH is a well-recognized publicly available dataset for single human action recognition. The dataset has 25 people for 6 actions (running, walking, jogging, waving, clapping and boxing) in 4 different scenarios (indoors, outdoors and outdoors with different scales and clothes). Different people perform the same action at different directions and speeds. It has 598 videos, of which we used 398 for training, and the remaining for testing. As designed by [15], the test set contains the actions of 9 people, and the training set corresponds to the 16 remaining persons. Figure 5 shows sample action images from KTH activity data set.

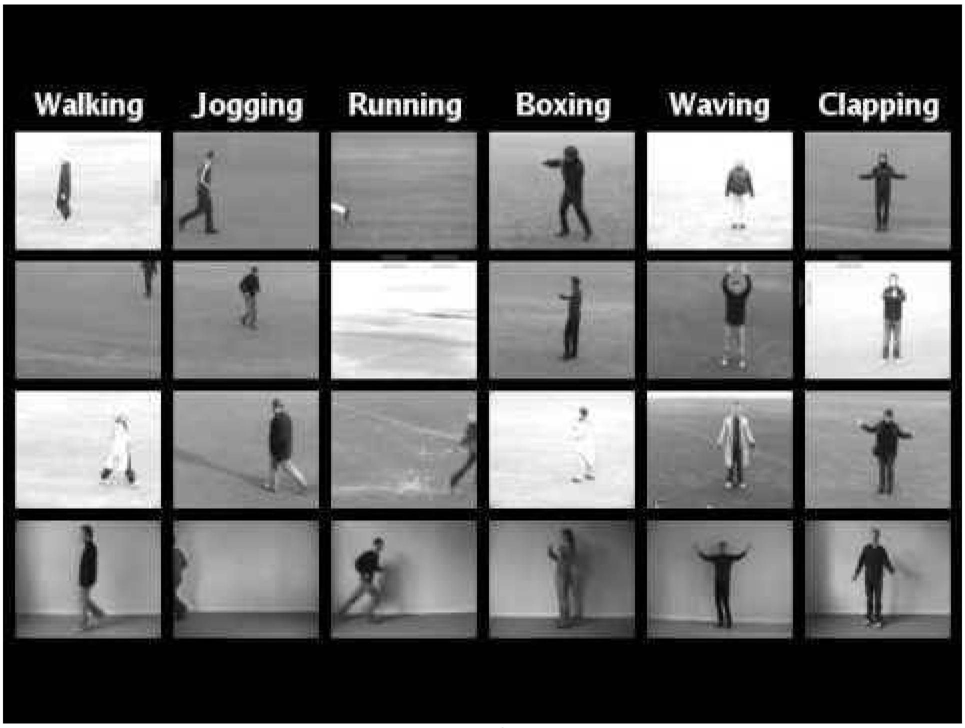

Fig.5. Sample action images from KTH activity dataset

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Table I
Confusion matrix for 6 class action recognition

	Walking	Jogging	Running	Boxing	Waving	Clapping
Walking	.95	.03	.02	.00	.00	.00
Jogging	.05	.92	.03	.00	.00	.00
Running	.06	.09	.85	.00	.00	.00
Boxing	.00	.00	.00	.91	.05	.04
Waving	.00	.00	.00	.08	.85	.07
Clapping	.00	.00	.00	.05	.04	.91

Table I shows the confusion matrix for walking, running, running, boxing, waving and clapping obtained by our method on the KTH dataset. The average recognition rate is 89.8 % which is comparable to the state-of-the-art approaches.. It is observed that the main error factor comes from confusion between jogging and running, and waving and clapping which is a typical problem in reported methods.

In Table II the result of the study is compared to ours where as Gabor feature is used instead of HOG feature and SVM is used instead of the PNN. The evaluation metric recognition rate is evaluated for various methods. It shows that the approach presented here is better in discriminating actions as compared with Gabor feature and SVM classifier. The HOG + PNN algorithm only provides good recognition rate among all these methods .Then HOG + SVM, Gabor + PNN and at last Gabor + PNN. We also observed that as the size of Gabor feature vector is larger than HOG feature vector, hence it takes more time for training. Compared with the previously reported work on 6-class action recognition tasks our work reported recognition rate of 89.8%.

Table II
Comparison of proposed algorithm

	Walking	Jogging	Running	Boxing	Waving	Clapping	Over all Recognition rate
Gabor+PNN	78	82	79	82	82	83	81
HOG+PNN	95	92	85	91	85	91	89.8
Gabor+SVM	79	86	75	81	79	76	79.3
HOG+SVM	94	91	83	87	83	91	88.1

In accordance with the table II, we can generate a graph for the recognition rate furnished in fig.6 given below.

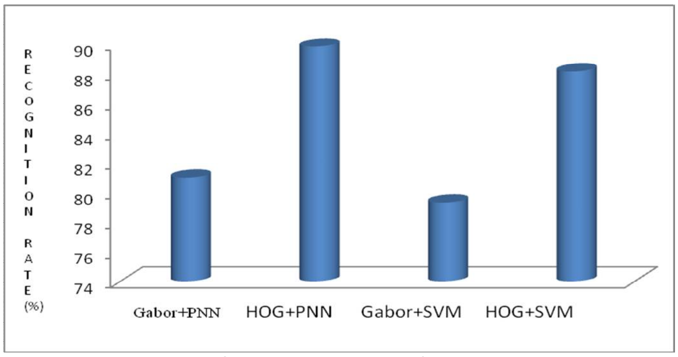

Fig.6. Recognition Rate for various methods for human action recognition

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V. CONCLUSION AND FUTURE WORK

This paper presented a new method using PNN for action recognition and HOG features and PCA as the feature extraction tool. The result is hopeful enough to discover real-life applications of action recognition in fields like surveillance entertainment and healthcare systems.

Additionally, though KTH remains the most widely used dataset for human action recognition; recent works are increasingly interested by other more challenging datasets, which contains complex actions and realistic scenarios. Therefore, we plan to prove the generality of our approach by testing it on recent challenging datasets, e.g. UT-Interaction dataset or LIRIS human activities dataset2, UCF sports action dataset, YouTube action dataset, Hollywood-2 dataset .

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