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SVM – KNN based Emotion Recognition of Human in Video using HOG Feature and KLT Tracking Algorithm

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Abstract — This paper, introduce a robust HoG (Histogram of Oriented Gradients) feature and KLT tracker for emotion recognition in video. The main contribution of this work is to build HoG (Histogram of Oriented Gradients) features with different bins for emotion recognition from human in the video. First, the videos present in the GEMEP datasets are preprocessed. Then, plot the bounding box for human present in the preprocessed frames. Second, HoG (Histogram of Oriented Gradients) features are extracted from the human in every frame with different histogram bins. Each bin has different size of vector dimensions. The features are extracted for train and test data of GEMEP dataset. Finally, the extracted features are fed into the SVM and KNN classifier. Results show that the SVM classifier performs well than KNN classifier [1]. The motion corner points of human can be tracked using KLT tracking algorithm. The corner points are detected by Harris corner detector algorithm. The GEMEP corpus dataset are used for this experiment.

***Keywords*-Emotion Recognition; Motion Descriptors; HOG feature; KLT tracker algorithm;**

1. Introduction

Recent research on experimental psychology demonstrated that emotions are important in decision making and rational thinking. Over the years research in emotion recognition mainly concentrated on facial expression, voice analysis, full body movements and gestures. In a day to day communications human beings express different types of emotions. Emotion plays a major role in human life. The human communication includes not only the language spoken, but also non-verbal cues as hand, head and body gestures, tone of the voice. These non-verbal cues are also used to express feeling and give feedback like facial expression. The communication greatly improve by understanding and knowing how to respond to people's expression. The important role in psychological research area is to develop the concepts that may support the HCI (Human Computer Interaction) technologies and understanding human emotions [1], [3]. The human body movements expressing fundamental emotions like anger, neutral, happy, fear, disgust, sadness, surprise, etc. Certain body movements are related to specific emotions. For example: fear brings to contrast the body, joy brings to openness and upward acceleration of the fore arms, body turning away is signal of fear and sadness. Body turning towards indicates happiness, anger, surprise. Communications are classified into two types, one is verbal communication and another one is non-verbal communication. The sharing of information between individuals by using speech is called as Verbal communication. The transfer of wordless messages is called as Non-verbal communication [1]. A recent survey reviews the literature on affect recognition from body posture and movement, and discusses the main challenges in affect recognition from body posture and movement, including inter-individual differences, impact of culture and multi-modal recognition, and the challenges in collecting appropriate data sets and ground truth labelling. Computational models have been developed for both automatic recognition and generation of affect- expressive movements [2]. The applications of emotion recognition systems in several motivating areas: In surveillance field, to predict and prevent whether a person going to act any suspicious activity, estimate emotional state of students in intelligent tutoring systems, monitor player's motivation and interest in games, social robotics for social interaction, in medical field the applications used for autism and dementia patients by detecting and monitoring depression levels. Apart from these applications, emotion recognition systems find uses in a host of other domains like, Telecommunications, Video Games, Animations, Robotics, Psychiatry, affect sensitive HCI, Automobile Safety, Educational Software.etc [1] [2].

In this research paper, an emotion recognition method is proposed based on HOG feature with different bin levels. First, the video present in the datasets are preprocessed and plot bounding box for human present in the frame. Hence, using different bins, extract the HOG feature for that human in the frame for training set. Then, the feature points are stored as training sample and extract same feature points and stored it as testing sample. Finally, classify emotions using SVM and KNN classifier. The high motion corner points are tracked by KLT tracker. The experiments are conducted through GEMEP database.

2. Related Works

Ashwini Ann Varghese, et al [1] proposes an emotion recognition system in real time and describes the advances different types of approaches used for recognizing human emotions. Stefano Piana, et al [2] introduced automatic emotion recognition in real-time from body movements. The real time video are captured and converted into 3D skeletal frames using advance d video capturing system. From the sequences of 3D skeletons, the kinematic, geometrical and postural features are extracted and given to the multi-class SVM classifier to categorise the human emotion. Michelle Karg, et al [3] summarizes the survey on generation of such body movements and the state of the art on automatic recognition of emotion. The important characteristics such as the representation of affective state, the body movements analyzed and the use of information systems are discussed. Donald Glowinski, et al [4] presents a framework for behaviour recognition from human upper body movements. The reduced amounts of visual information are used to analysis the affective behaviour of body movements. The aim of the work is to individuate a representation of emotional displays depends on nonverbal gesture features. W. Wang et al [5] propose an advanced real-time system for human body movements to recognize emotions continuously. The high-level kinematic features, geometrical features and the united 3D postural features are given to the input of random forests classifier. Nesrine Fourat, et al [6] describes a system for recognition of emotion depends on different actions, different expression of emotions and low-level body cues from human body movement. To recognition the emotion from these aspects, the features extracted from the various parts are fed to the Random Forest classifier. Nele Dael, et al[7] developed a body posture and body action coding system from body movement on an anatomical level is different articulations of body parts, a form level is direction and orientation of movement, and a functional level is communicative and self-regulatory functions. Ioanna-Ourania Stathopoulou, et al [8] conducts a survey on recognizing human emotion from hand/arms, gestures and body movements. M. Melissa Gross, et al [9] develops a robust technique for assessing human body expression based on movement characteristics with positive and negative emotions. Gokcen Cimen, et al [10] describes the study to analyze the spatial and temporal information structure of the motion capture data and extract features that are related to affective state descriptors. Haris Zacharatos, et al [11] performs the survey on recent advances in developing robust techniques and modalities for automatic human emotion recognition system from body movements. Here the importances of body movement segmentation are discussed and advanced application areas are described. Ginevra Castellano, et al [12] proposes an analysis of emotional behaviour system based on classification of time series and dynamics of expressive motion cues. Jyoti Joshi, et al [13] describes the automatic depression analysis system from human gestures and upper body expressions. The space-time interest points and bag of words is developed for the analysis of facial and upper body movements. Mohamed Bêcha Kaâniche, et al [14] introduced a robust gesture recognition system using learning local motion signatures (LMSs). The Histograms of Oriented Gradient (HOG) descriptor are tacked using these computed LMSs. Navneet Dalal, et al [15] study the robust visual object recognition and human detection using adopting linear SVM. They showed the performance of human detection using feature sets of Histograms of Oriented Gradient (HOG) descriptors. Pyry K.Matikainen, et al [16] proposes a quantized trajectory snippets method for tracked features. This method is a simple feature tracking method and computationally efficient for motion detection. J. Arunnehru, M. Kalaiselvi Geetha [17] proposed a new approach for automatic activity recognition from body movement using motion projection profile (MPP) feature on Region of Interest (ROI). Sudipta N. Sinha, et al [18] describes SIFT feature extraction algorithms and novel implementations of the KLT feature tracking for video analysis in real-time vision systems.

3. Feature Extraction

3.1 Pre Processing

In this paper, 5 basic emotions of GEMEP datasets are first convert videos into RGB frames. The RGB frames are converted into gray frames and mark human in each frame using bounding box. It is generated based on height, width, x and y points of the each frames. The figure 1 shows the overview of this work. Figure 2 illustrates (a) videos into RGB frames and RGB into gray frames (c) bounding box frames. The bounding box frames are given to the input for HoG feature extraction.

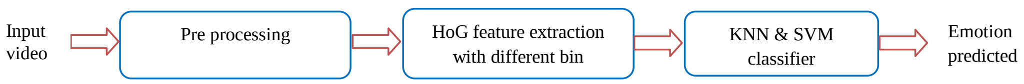


Fig.1: overview of this work

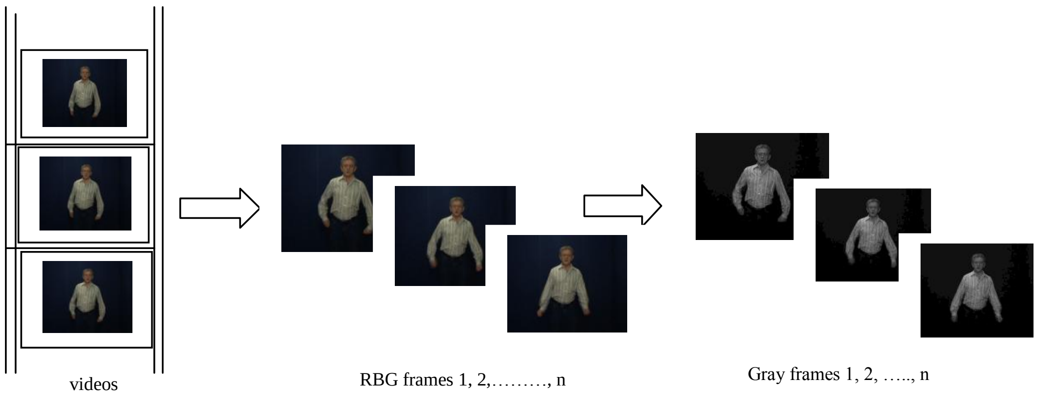


Fig. 2: (a) Videos into RBG frames and RGB frames into gray frames

Fig. 2: (b) sample bounding box of human detection in one frame

3.2 Computing HoG Feature

The HoG feature is defined as Local object appearance and shape can often be characterized rather well by the distribution of local intensity gradients of the corresponding gradient [27]. The last line said that the description of the HOG method that has been used in its higher form in Scale Invariant Features Transformation (SIFT) and it has been broadly demoralized in human detection [27]. The subsequent building of a 1D histogram whose concatenation supplies the feature vector from the HOG descriptor using gradient directions among the pixels in the cell. The image to be analyzed as intensity function L. The image is further divided into cells of size 3 × 3 pixels with different histogram bins (6, 9, 12, 15, 25, 30). The equation 1 and equation 2 defined the gradient magnitude g and the gradient orientation θ used to compute for all the pixels in the block from the image gradients.

$$g(a,b) = \sqrt{g_x(a,b)^2 + g_y(a,b)^2} \qquad (1)$$

$$\Theta(\mathrm{a,b}) = arctan\,\frac{g_y\,(a,b)}{g_x\,(a,b)} \qquad (2)$$

Compute a feature vector v_{ij} for each cell c_{ij} in the block. The equation 3 defines the weighted gradient magnitude by quantizing the unsigned orientation into K orientation bins.

$$v_{ij} = [v_{ij}\,(\beta)]^T{}_{\beta \in [1 \ldots K]} \qquad (3)$$

The equation 4 defines the $v_{ij}\,(\beta)$

$$v_{ij}\,(\beta) = \sum_{(a,b)\in c_{ij}} g(a,b)\delta[bin(a,b) - \beta] \qquad (4)$$

The index of the orientation bin with the pixel (a, b) returns the function bin (a, b) and the function δ [] is the Kronecker delta. The coefficient ρ normalize the feature vector in all cells from 2D descriptor of block.

$$\rho = \sum_{i=1}^{3} \sum_{j=1}^{3} \sum_{\beta=1}^{K} v_{ij}(\beta) \qquad (5)$$

3.3 Corner Points Detection

Harris corner detector is one of the best corner detector algorithms. It is used to detect corner points for human in the frame. For every frame the corner points can be changed due to movement in the human body like hands and heads. Depends upon the human body movement all frame have different corner points. By maximizing the corner strength, the most important two corners are selected and ensuring a minimum distance between them. Then, the two most important corner points are tracked throughout the sequence of frames. From this method, the maximum motion of human body parts can be tracked using KLT algorithm.

3.4 KLT Tracking Algorithm

The KLT tracking algorithm is described respectively in this section. The selected most important corner points from Harris corner detector are to be tracked using KLT tracker. A new computed corner points connected to a newly detected corner, when an old corner points are vanished. Wherever the image motion is high (most important corner points) the interest points between consecutive video frames are generated by KLT tracking algorithm [24, 25]. The Newton's method is used to minimize the sum of squared distances (SSD) within a tracking window. Let $F(*,*,t)$ be the video frame at time t. If the dislodgment of an image point (g, h) between time t and $t+ \Delta t$, denoted by $(\Delta g, \Delta h)$ is small, then

$$F(g, h, t + \Delta t) = F(g + \Delta g, h + \Delta h, t) \qquad (6)$$

Approximating $F(g + d,t)$ by its Taylor expansion, To estimate the unknown d obtains the next linear system, where $H = \left[\frac{\partial I}{\partial x} \frac{\partial I}{\partial y}\right]$ is the image gradient vector at position x.

$$\left(\sum_{w} H^T H\right)(d) = \sum_{W} H^T \Delta I(Y, \Delta t) \qquad (9)$$

The difference of the KLT equation is proposed by Tomasi, which uses both images symmetrically. This equation, derived in [26] is identical to Equation 9 except that here

$$H = \left[\frac{\partial(I(*,t) + I(*,t+\Delta t))}{\partial x} \frac{\partial(I(*,t) + I(*,t+\Delta t))}{\partial y}\right] \qquad (10)$$

The tracking points are selected by important corner points from Harris corner detector

$$c = \min\left(eig\left(\sum_{W} \left[\frac{\partial I}{\partial x} \frac{\partial I}{\partial y}\right]^T \left[\frac{\partial I}{\partial x} \frac{\partial I}{\partial y}\right]\right)\right) \qquad (11)$$

4. Properties of Classifier

4.1 Support Vector Machine

The Support Vector Machine (SVM) is an important and efficient technique for classification in visual pattern recognition [19], [20]. The SVM is most extensively used in kernel learning algorithm. The elegant theory used to separate two classes by large-margin hyper planes. It cannot be extended easily to separate N mutually exclusive classes. The most popular "one-vs-others" approach is used for the multi class problem where, one class is separated from N classes. The classification task are typically involves with training and testing data. The training data are separated by (s_1, t_1), (s_2, t_2), ...(s_n, t_n) into two classes, where $b_j \in \{+1,-1\}$ are the class labels and $s_j \in t_N$ contains n-dimensional feature vector. The goal of Support Vector Machine is to develop a model which predicts target value from testing set. $w.s + b = 0$ is the hyper plane of binary classification, where $w \in R^N$, The two classes are separated by $b \in R$ [23].

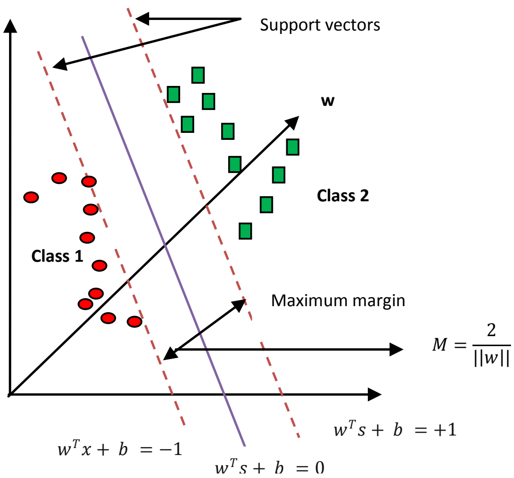


Fig. 3: Illustration of hyperplane in linear SVM

$M = 2/||w||$ is the large margin as show in Fig. 3.The Lagrange multipliers α_i (i=1, ...m) are used to solve the minimization problem, where v and y are optimal values obtained from Eq. 12.

$$h(s) = sgn\left(\sum_{j=1}^{n} x_j b_j L(s_j, s) + y\right) \quad (12)$$

Maximize the margin and minimize the training error using non-negative slack variables ε_j . The Eq. 13 and Eq. 14 obtain the soft margin Classifier.

$$\min_{v,y,\varepsilon} \frac{1}{2} v^R v + D \sum_{j=1}^{k} \varepsilon_j \quad (13)$$

$$b_j \left(v^R \emptyset(s_j)\right) + y \geq 1 - \varepsilon_j, \varepsilon_j \geq 0 \quad (14)$$

When the training sample is not linearly separable, the input space mapped into high dimensional space using kernel function $L(s_j s_k) = \emptyset(s_j) . \emptyset(s_k)$ [20].

Linear: $L(s_j s_k) = s^R j^s k$ (15)

Polynomial: $L(s_j, s_k) = (\alpha s^R j^s k + \alpha)^c, \alpha > 0$ (16)

Radial Basis Function (RBF): $L(s_j, s_k) = \exp(-\alpha ||s_j - s_k||^2), \alpha > 0$ (17)

Sigmoid: $L(s_j, s_k) = \tanh(\alpha s^R j - s_k + t)$ (18)

Where, α, t, and c are parameters of kernel.

The multiclass Support Vector Machine (SVM) is constructed by N-binary classifiers and one class was separated from rest of the class. Here "one-vs-others" approach is used in this SVM. The five classes of emotions are used in this work. The j^{th} class of the training sets have positive labels and all others with negative labels. The j^{th} SVM solves j^{th} decision function given in Eq. 12. Finally, the feature vectors from the HoG are given into multiclass-SVM for classification of human emotion.

4.2 *K* nearest neighbor

K nearest neighbor algorithm have been used since 1970 in many fields like statistical estimation and pattern recognition etc. *K* nearest neighbor is a simple and popular technique for pattern recognition field. It is a type of supervised learning method. It is said to be a lazy learning where the function is only approximated locally. *K* nearest neighbor is a non-parameter algorithm where samples are classified depends on the category of their nearest neighbor. According to the *k* learning samples, the classification algorithm finds the test sample's categories which are the nearest neighbor to the test sample. However, the classification algorithm needs to compute all distance between training sample and testing sample. The process of *K* nearest neighbor algorithm to categorize sample S. Assume *q* training samples A1,A2,…,Aq. After feature reduction N is the addition of the training samples and get n-dimension feature vector. The all training samples (S1, S2,…, Sn) have the same feature vector of sample S and evaluate the similarities among them. For example taking the p^{th} sample b_p (b_p1, b_p2,…,b_{pn}) and the similarity SIM(S, b_p) is:

$$SIM(S, b_p) = \frac{\sum_{q=1}^{n} S_q . b_{pq}}{\sqrt{\left(\sum_{q=1}^{n} S_q\right)^2} . \sqrt{\left(\sum_{q=1}^{n} b_{pq}\right)^2}}$$

The Larger N similarities, SIM(S, bp), (p=1, 2,…, N), of *k* samples are chosen and consider them as a *K* nearest neighbor collection of S. Then, the probability of S can be calculated using this formula.

$$R(S, A_q) = \sum_{b} (S, b_p) . y(b_p, A_q)$$

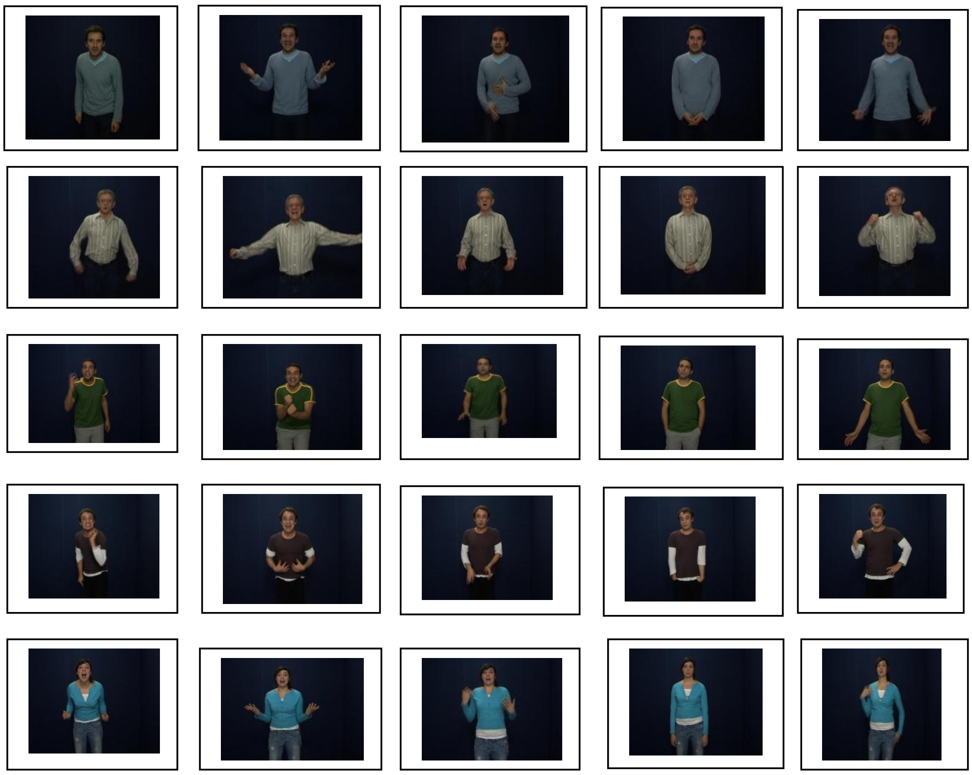
Where $y(b_p, A_q)$ is a category attribute function.

5. Experimental Results

The successive five emotions are mind for emotion recognition: angry, joy, fear, sad and pride from GEMEP dataset. The demonstrations are conducted on Windows 7 Operating System using MATLAB 2015a on a computer with Intel Core i7 Processor 3.40 GHz with 8 GB RAM. The *K* nearest neighbor (KNN) and Support Vector Machines (SVM) classifiers are used for recognizing the emotion from GEMEP dataset.

5.1 GEMEP dataset

The GEneva Multimodal Emotion Portrayals (GEMEP) is a set of audio and video recordings. The 18 affective states of emotional expression can be acted by 10 actors. They acted in various types of expression and verbal contents. From that five basic emotions (Angry, Joy, Fear, Sad and Pride) have been chosen for this work. There are 10 actors (5 male and 5 female) were acted in each emotion videos. The resolutions of the recorded videos are 720 × 576 and each video has 25 frames per second (fps).



Angry Joy Fear Sad Pride

Fig. 3 Sample frames of five basic emotions (Angry, Joy, Fear, Sad, Pride)

5.2. Performance Evaluation

According to the histogram bins, different sets of features were extracted with different dimensional levels. There are six different dimensional levels of feature were used. Those extracted features are given to the KNN and SVM classifiers one by one. Accuracy, Recall, F-Score, Specificity and Precision are the measuring assessment for this execution. Accuracy is a measure of precision. Recall provides how extraordinary an emotion is recognized accurately. The symphonious mean of Precision and Recall is called as F-score. Specificity shows an evaluation of how great a strategy is recognizing negative emotion accurately. At last, Precision shows the general accuracy of the movement recognition. The factual evaluation of Accuracy, Recall, F-Score, Specificity and Precision are given as follows

$$Accuracy = \frac{tp + tn}{tn + fp + tp + fn} \quad (19)$$

$$Recall = \frac{tp}{tp + fn} \quad (20)$$

$$F - Score = 2\frac{Precision \; X \; Recall}{Precision + Recall} \quad (21)$$

$$Specificity = \frac{tn}{tn+fp} \tag{22}$$

$$Precision = \frac{tp}{tp+fp} \tag{23}$$

where, *tp* and *tn* are the quantity of true positive and true negative prediction of the class and *fp* and *fn* are the quantity of false positive and false negative expectations.

5.3 Evaluation of GEMEP Dataset

The normal recognition exactness is 90.42 % on the GEMEP dataset and the confusion matrix appeared in Fig.4. The corner to corner of the confusion matrix illustrates the percentage of instance that was classified accurately. The each emotion class occurrence is spoken to by the lines and the emotion class anticipated by the classifier is spoken to by the sections. The emotions like sad, fear and pride are grouped well with precision more noteworthy than 90%. From this, angry and joy emotions are confused as curve, where these two emotions instinctively appear to be difficult to separate and it needs promote consideration. The execution assessment comes about are computed for the evaluated HoG feature has a better exactness, recall, F-score and Specificity for KNN and SVM with RBF kernel on GEMEP dataset.

Table 1: Recognition exactness (%) for angry, joy, fear, sad and pride in KNN classifier

	ANGRY	JOY	FEAR	SAD	PRIDE
ANGRY	77.6	22.4	0	0	0
JOY	24.9	75.1	0	0	0
FEAR	1		97.9	0	1.1
SAD	0	0	0	98.6	1.4
PRIDE	1	1	0.9	1	96.1

Table 2: Recognition exactness (%) for angry, joy, fear, sad and pride in SVM classifier.

	ANGRY	JOY	FEAR	SAD	PRIDE
ANGRY	78.3	21.7	0	0	0
JOY	20.5	79.5	0	0	0
FEAR	1	0	97.8	0	1.2
SAD	0	0	0	99.6	0.4
PRIDE	0.1	1	1	1	96.9

6. Results and discussions

As discuss in the sec. 3, the different bin levels results showed here. For 3 x 3 cell with 6 bin gives 54 dimensional feature vector, similarly 9 bin gives 81 dimension, 12 bin gives 108 dimension, 15 bin gives 135 dimension, 20 bin gives 180 dimension, 25 bin gives 225 dimension, 30 bin gives 270 dimension. From that 25 bin provides better results than all other bins. Table 1 and 2 shows the recognition exactness for 5 basic emotions on KNN and SVM classifier. From the table 20% to 23% of angry emotion is miss-classified as joy, because the two emotions are high arousal emotion and which is difficult to predict accuractly. This was taken as future challenge to predict it in a correct manner. The rest of the emotions have more than 95%. Table 3 Shows the F-Score performance for KNN and SVM classifier with different bin levels. From the different bin levels SVM gives better performance on 25^{th} bin. The figure 5 shows the accuracy level for different bin on KNN and SVM classifiers.

Table 3: Different bin level of F-Score performance for KNN and SVM classifier

	6_BIN	9_BIN	12_BIN	15_BIN	20_BIN	25_BIN	30_BIN
F_Score(KNN)	74.4	77.3	82.1	83.3	85.2	88.3	84.5
F_Score(SVM)	74.8	79.6	85.5	87.3	89.4	90.4	88.6

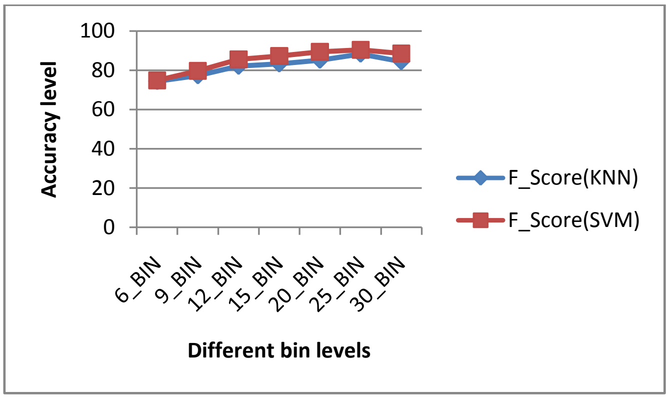


Fig. 5 Line chart of F-Score for KNN and SVM

6.2 Snap shot of KLT tracker algorithm

The following snap shot shows the motion part of human body tracked by KLT tracker. The maximum motion points are selected and it was tracked though out the end of the frames.

Fig. 6: Tracking motion from body parts for Angry emotion

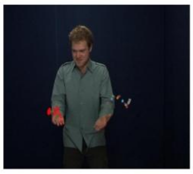


Fig. 7: Tracking motion from body parts for Joy emotion

Fig. 8: Tracking motion from body parts for Fear emotion

Fig. 9: Tracking motion from body parts for Sad emotion

Fig. 10: Tracking motion from body parts for Pride emotion

7. Conclusion and Outlook

The techniques for recognizing emotion from surveillance video using HoG (Histogram oriented Gradients) feature are presented this paper. The five different basic emotions are angry, joy, fear, sad and pride from GEMEP dataset are used for this experiment. The local motion descriptors extracted from Temporal HoG descriptors for different frames are used for used for classification based on the motion information. The multiclass-SVM classifier with polynomial and RBF kernals are used to evaluate the performance of the feature in the video sequences. From the observation of this experiment, the system could not differentiate with higher accuracy for Angry and Joy results and it is taken as our future work.

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