



# Human Emotion Recognition from Video using Supervised Learning Algorithm

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**Abstract** -- Recently, increasing attention has been paid to the detection of spatio-temporal interest points (STIPs), which has become a key technique and research focus in the field of computer vision. The Local image features or interest points provide compact and abstract representations of patterns in frames. In this paper, an emotion recognition approach based on body movements is proposed. The videos are converted into frames and the frames are preprocessed using median filter. The Harris method is used for corner detection in human present in the frame. Then the STIP features are extracted for the human present in the frames. Similarly the trained and test data are extracted using this STIP feature. The extracted features are fed to the Support Vector Machine (SVM) classifier to classify the emotion of the human. The performance measure can be calculated using F-Score. The GEMEP corpus dataset are used for this experiment.

**Keywords:** Spatio-temporal interest points (STIPs), Harris, Support Vector Machine (SVM) classifier, Emotion Recognition.

## 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. 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. A video surveillance system observes action in open public areas like ATM, banks, railway station, airport, gas stations and commercial buildings for real-time or later analysis which is used to detect crime. Which is aims to recognize and classify the action of a person into certain categories like jumping, sitting, walking, bending and skipping. It is a complex process to recognize human activity due to many factors like speed, shadows, postures, illumination changes and occlusion. The recognition of whole body expressions is significantly durable, because the form of the human body has more degrees of freedom than the face on your own and its overall shape varies strongly during expressed motion. The large 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, and Psychiatry; affect sensitive HCI, Automobile Safety, and Educational Software.etc [1] [2].

### A. Outline of the Work

This paper deals with human emotion recognition from video sequences and then to identify their emotions from human body movements. The proposed method is evaluated using GEMEP emotion dataset with the person showing emotions such as angry, Joy, fear, sad and pride. Difference image is obtained by subtracting the consecutive frames. Cumulative motion image (CMI) is calculated by combining the five frame difference images and then SURF features are extracted from CMI. The extracted feature is fed to the Support Vector Machine (SVM). The rest of the paper is organized as follows. Section 2 explains the related works. Section 3 explains the workflow of the proposed approach and feature extraction method. Section 4 presents the Experimental results. Finally, Section 5 concludes the paper.



## 2. RELATED WORKS

The vision based emotion recognition turns into the huge objective to segregate the activities consequently. Recent surveys in the area of human action analysis in [1] and [2] focus on the feature descriptor, representation, and classification model in video sequences. Survey by Turaga et al. [3] centers around recognition of human activity. Wang et al. [4] propose a method which relies on optical flow and edge features, where these two discriminative features were combined to extract the motion and shape descriptors to distinguish one action from another. Reddy et al. [5] present a method to recognize action-based on sphere/rectangle tree structure that is built with spatio-temporal interest point features. J. Arunnehr et al. [6] proposed an Automatic human emotion Recognition in surveillance video based on gesture dynamic's features and the features are evaluated by SVM, Naïve Bayes and Dynamic Time Wrapping. Zhu et al. [7] address a multi-view action recognition algorithm based on local similarity random forests and sensor fusion, and normalized silhouettes are used as pose features and effective for multiple view human action recognition. In [8], vocabulary forest is constructed with local static and optical flow features and uses trees and forests for action recognition classification. M. Kalaiselvi Geetha et al. [9] developed a video retrieval applications for video classification and shot detection using Block intensity comparison code (BICC) and unsupervised shot detection. A novel AANN misclustering Rate (AMR) algorithm is used to detect the shot transitions. Haiyong et al. [10] present a novel classification method to recognize the actions from videos based on centroid-radii model descriptor and to train and classify video sequences by nonlinear SVM decision tree (NSVMDT). J. Arunnehr et al. [11] assigns motion intensity code for action recognition in surveillance video using Region of Interest (ROI) from the difference image. D. Wu, et al. [12] proposed a method which relies on optical flow and edge features, where these two discriminative features were combined to extract the motion and shape descriptors to distinguish one action from another. J. Arunnehr et al. [13] proposed an The 18 dimensional Block intensity vector are extracted and evaluated through SVM. Haiyong et al. [14] present a novel

application for Action Recognition in automated surveillance. Classification method to recognize the actions from videos based on centroid-radii model descriptor and to train and classify video sequences by nonlinear SVM decision tree (NSVMDT). In [15], a method was proposed based on extended motion template from human silhouettes. The holistic structural features were extracted from motion templates to discriminate the human action, which represents local and global information. Zhang et al. [16] have used the spatial-temporal with optical flow features. The temporal consistence of motion is improved with an enhanced DTW method to recognize the human actions. Wang et al. H. Bay et al. [17] proposed a novel detector-descriptor scheme, coined SURF (Speeded-Up Robust Features). The detector is based on the Hessian Matrix, but utilizes a simple approximation, for example DoG (Difference of Gaussian) is a simple Laplacian-based detector. Ashwini Ann Varghese, et al [20] 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 [21] 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. R.Santhoshkumar, M.Kalaiselvi Geetha, et al [23] introduces 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. R.Santhoshkumar, M.Kalaiselvi Geetha, et al [24] an emotion recognition approach based on body movements is proposed. Human emotions are identified by gesture of body movements. Cumulative Motion Image based Speed up Robust Feature (CMI-SURF) is extracted as features.

## 3. FEATURE EXTRACTION

Feature is a descriptive characteristic extracted from an image or video sequences, which represent the meaningful data that are vital for further analysis. The following subsection present the description of the feature used in this work. The flow diagram of the proposed approach is shown in Fig.1

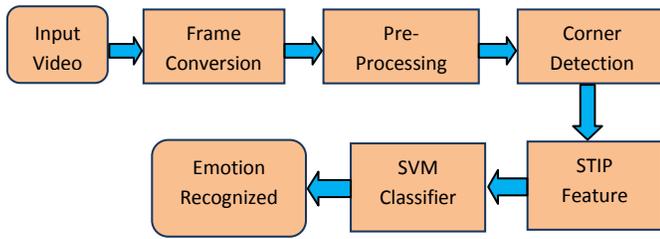


Fig. 1: Flow Diagram of the Proposed Approach

A. Spatio-Temporal Interest Point Detection

(i) Interest Points in the Spatial Domain

In the spatial domain, we can model an image  $f^{sp} : \mathbb{R}^2 \rightarrow \mathbb{R}$  by its linear scale-space representation (Witkin, 1983; Koenderink and van Doorn, 1992; Lindeberg, 1994; Florack, 1997)  $M^{sp} : \mathbb{R}^2 \times \mathbb{R}^+ \rightarrow \mathbb{R}$

$$M^{sp}(a, b; \sigma_m^2) = h^{sp}(a, b; \sigma_m^2) * f^{sp}(a, b) \quad (1)$$

defined by the convolution of  $f^{sp}$  with Gaussian kernels of variance  $\sigma_m^2$

$$h^{sp}(a, b; \sigma_m^2) = \frac{1}{2\pi\sigma_m^2} \exp(-(a^2 + b^2)/2\sigma_m^2) \quad (2)$$

The idea of the Harris interest point detector is to find spatial locations where  $f_{sp}$  has significant changes in both directions. For a given scale of observation  $\sigma_m^2$ , such points can be found using a second moment matrix integrated over a Gaussian window with variance  $\sigma_i^2$  (Forstner and Gulch, 1987; Bigun et al., 1991; Garding and Lindeberg, 1996):

$$\mu^{sp}(\cdot; \sigma_m^2, \sigma_i^2) = h^{sp}(\cdot; \sigma_i^2) * ((\nabla M(\cdot; \sigma_m^2)) (\nabla M(\cdot; \sigma_m^2))^T) \quad (3)$$

$$= h^{sp}(\cdot; \sigma_i^2) * \begin{pmatrix} (M_a^{sp})^2 & M_a^{sp} M_b^{sp} \\ M_a^{sp} M_b^{sp} & (M_b^{sp})^2 \end{pmatrix} \quad (4)$$

where ‘\*’ denotes the convolution operator, and  $M_a^{sp}$  and  $M_b^{sp}$  are Gaussian derivatives computed at local scale  $\sigma_m^2$  according to  $M_a^{sp} = \partial_a (h^{sp}(\cdot; \sigma_m^2) * f^{sp}(\cdot))$  and  $M_b^{sp} = \partial_b (h^{sp}(\cdot; \sigma_m^2) * f^{sp}(\cdot))$ . The second moment descriptor can be thought of as the covariance matrix of a two-dimensional distribution of image orientations in the local neighborhood of a point. Hence, the eigen values  $\lambda_1, \lambda_2$  of  $\mu^{sp}$  constitute descriptors of variations in  $f^{sp}$  along the two image directions. Specifically, two significantly large values of  $\lambda_1, \lambda_2$  indicate the presence of an

interest point. To detect such points, Harris and Stephens (1988) proposed to detect positive maxima of the corner function

$$I^{sp} = \det(\mu^{sp}) - K \text{trace}^2(\mu^{sp}) \quad (5)$$

$$= \lambda_1 \lambda_2 - K(\lambda_1 + \lambda_2)^2 \quad (6)$$

At the positions of the interest points, the ratio of the eigen values  $\alpha = \lambda_2/\lambda_1$  has to be high. From (4) it follows that for positive local maxima of  $H^{sp}$ , the ratio  $\alpha$  has to satisfy  $k \leq \alpha/(1 + \alpha)^2$ . Hence, if we set  $k = 0.25$ , the positive maxima of  $H$  will only correspond to ideally isotropic interest points with  $\alpha = 1$ , i.e.  $\lambda_1 = \lambda_2$ . Lower values of  $k$  allow us to detect interest points with more elongated shape, corresponding to higher values of  $\alpha$ . A commonly used value of  $k$  in the literature is  $k = 0.04$  corresponding to the detection of points with  $\alpha < 23$ . The result of detecting Harris interest points in image sequence of an anger person is shown in Fig. 2.

(ii) Interest Points in the Spatio-Temporal Domain

In this section, we develop an operator that responds to events in temporal image sequences at specific locations and with specific extents in space-time. The idea is to extend the notion of interest points in the spatial domain by requiring the image values in local spatio-temporal volumes to have large variations along both the spatial and the temporal directions. Points with such properties will correspond to spatial interest points with distinct locations in time corresponding to local spatio-temporal neighborhoods with non-constant motion. To model a spatio-temporal image sequence, we use a function  $f : \mathbb{R}^2 \times \mathbb{R} \rightarrow \mathbb{R}$  and construct its linear scale-space representation  $M : \mathbb{R}^2 \times \mathbb{R} \times \mathbb{R}^+ \rightarrow \mathbb{R}$  by

$$M(\cdot; \sigma_m^2, \tau_m^2) = h(\cdot; \sigma_m^2, \tau_m^2) * f(\cdot) \quad (7)$$

convolution of  $f$  with an anisotropic Gaussian kernel with independent spatial variance  $\sigma_m^2$  and temporal variance  $\tau$  where the spatio-temporal separable Gaussian kernel is defined as

$$h(a, b, t; \sigma_m^2, \tau_m^2) = \frac{1}{\sqrt{(2\pi)^3 \sigma_m^4 \tau_m^2}} \quad (8)$$

$$\exp(-(a^2 + b^2)/2\sigma_m^2 - t^2/2\tau_m^2) \quad (9)$$

Using a separate scale parameter for the temporal domain is essential, since the spatial and the temporal extents of events are in general independent. Moreover, events detected using our interest point operator depend on both the spatial and the



temporal scales of observation and, hence, require separate treatment of the corresponding scale parameters  $\sigma_m^2$  and  $\tau_m^2$ . Similar to the spatial domain, we consider a spatiotemporal second-moment matrix, which is a 3-by-3 matrix composed of first order spatial and temporal derivatives averaged using a Gaussian weighting function

$$h(\cdot; \sigma_i^2 \tau_i^2) \quad (10)$$

$$\mu = h(\cdot; \sigma_i^2, \tau_i^2) * \begin{pmatrix} M_a^2 & M_a M_b & M_a M_t \\ M_a M_b & M_b^2 & M_b M_t \\ M_a M_t & M_a M_t & M_t^2 \end{pmatrix} \quad (11)$$

Where, we here relate the integration scales  $\sigma_i^2$  and  $\tau_i^2$  to the local scales  $\sigma_m^2$  and  $\tau_m^2$  according to  $\sigma_i^2 = s\sigma_m^2$  and  $\tau_i^2 = s\tau_m^2$ . The first-order derivatives are defined as

$$M_a(\sigma_m^2, \tau_m^2) = \partial_a(h * f) \quad (12)$$

$$M_b(\sigma_m^2, \tau_m^2) = \partial_b(h * f) \quad (13)$$

$$M_t(\sigma_m^2, \tau_m^2) = t(h * f) \quad (14)$$

To detect interest points, we search for regions in  $f$  having significant eigenvalues  $\lambda_1, \lambda_2, \lambda_3$  of  $\mu$ . Among different approaches to find such regions, we propose here to extend the Harris corner function (4) defined for the spatial domain into the spatio-temporal domain by combining the determinant and the trace of  $\mu$  as follows:

$$H = \det(\mu) = K \text{trace}^3(\mu) \quad (15)$$

$$\lambda_1 \lambda_2 \lambda_3 = k(\lambda_1 + \lambda_2 + \lambda_3) \quad (16)$$

To show how positive local maxima of  $H$  correspond to points with high values of  $\lambda_1, \lambda_2, \lambda_3$  ( $\lambda_1 \leq \lambda_2 \leq \lambda_3$ ), we define the ratios  $\alpha = \lambda_2/\lambda_1$  and  $\beta = \lambda_3/\lambda_1$  and re-write  $H$  as

$$H = \lambda_1^3(\alpha\beta - k(1 + \alpha + \beta)^3) \quad (17)$$

From the requirement  $H \geq 0$ , we get  $k \leq \alpha\beta/(1+\alpha+\beta)^3$  and it follows that  $k$  assumes its maximum possible value  $k = 1/27$  when  $\alpha = \beta = 1$ . For sufficiently large values of  $k$ , positive local maxima of  $H$  correspond to points with high variation of the image values along both the spatial and the temporal directions. In particular, if we set the maximum value of  $\alpha, \beta$  to 23 as in the spatial domain, the value of  $k$  to be used in  $H$  (8) will then be  $k$

$\approx 0.005$ . Thus, spatio-temporal interest points of  $f$  can be found by detecting local positive spatio-temporal maxima in  $H$ . Using this method the STIP feature are extracted, which is shown in the fig. 2.

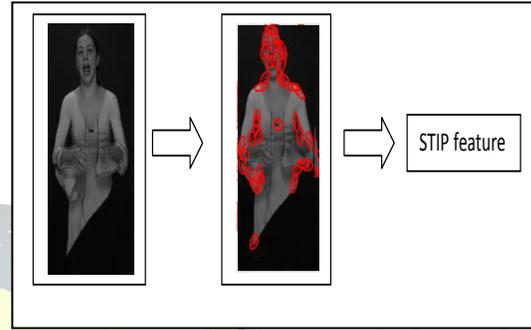


Fig. 2: STIP feature extraction from gray frame

#### 4. 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 Support Vector Machines (SVM) classifiers are used for recognizing the emotion from GEMEP dataset.

##### A. 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  $720 \times 576$  and each video has 25 frames per second (fps).

##### B. 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.

$$F - Score = 2 \frac{Precision \times Recall}{Precision + Recall} \quad (20)$$

$$Specificity = \frac{tn}{tn+fp} \quad (21)$$

$$Precision = \frac{tp}{tp+fp} \quad (22)$$

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.

The factual evaluation of Accuracy, Recall, F-Score, Specificity and Precision are given as follows

$$Accuracy = \frac{tp+tn}{tn+fp+tp+fn} \quad (18)$$

$$Recall = \frac{tp}{tp+fn} \quad (19)$$



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

### C. 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  $(s_1, t_1), (s_2, t_2), \dots, (s_n, t_n)$  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.  $w \cdot s + b = 0$  is the hyper plane of binary classification, where  $w \in R^N$ , The two classes are separated by  $b \in R$  [23].

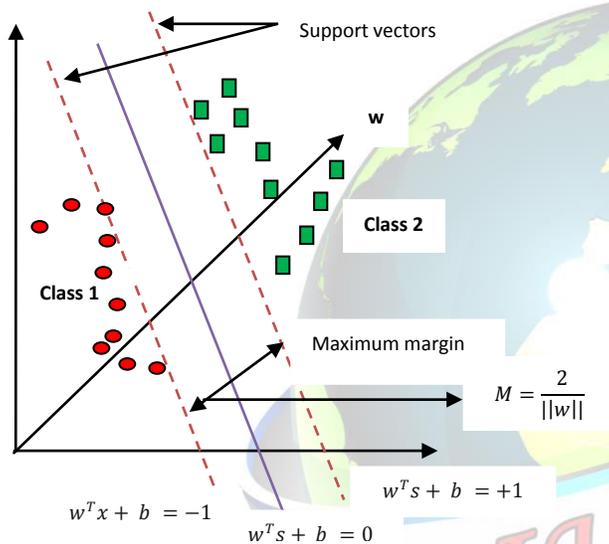


Fig. 4: Illustration of hyperplane in linear SVM

$M = 2/\|w\|$  is the large margin as show in Fig. 4. The Lagrange multipliers  $\alpha_i$  ( $i=1 \dots m$ ) are used to solve the minimization problem, where  $v$  and  $y$  are optimal values obtained from Eq. 12.

$$h(s) = \text{sgn}\left(\sum_{j=1}^n x_j b_j L(s_j, s) + y\right) \quad (23)$$

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

$$\min_{v, y, \varepsilon} \frac{1}{2} v^R v + D \sum_{j=1}^k \varepsilon_j \quad (24)$$

$$b_j (v^R \phi(s_j) + y) \geq 1 - \varepsilon_j, \varepsilon_j \geq 0 \quad (25)$$

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

**Linear:**

$$L(s_j s_k) = s^R j^s k \quad (26)$$

**Polynomial:**

$$L(s_j, s_k) = (\alpha s^R j^s k + \alpha)^c, \alpha > 0 \quad (27)$$

**Radial Basis Function (RBF):**

$$L(s_j, s_k) = \exp(-\alpha \|s_j - s_k\|^2), \alpha > 0 \quad (28)$$

**Sigmoid:**

$$L(s_j, s_k) = \tanh(\alpha s^R j - s_k + t) \quad (29)$$

Where,  $\alpha$ ,  $t$ , 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  $j^{\text{th}}$  class of the training sets has positive labels and all others with negative labels. The  $j^{\text{th}}$  SVM solves  $j^{\text{th}}$  decision function given in Eq. 23. Finally, the feature vectors from the STIP feature are given into multiclass-SVM for classification of human emotion.

#### D. Evaluation of GEMEP Dataset

The normal recognition exactness is 91.47 % 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 STIP feature has a better exactness, recall, F-score and Specificity for SVM with RBF kernel on GEMEP dataset.



Table 1: Recognition exactness (%) in SVM classifier

	ANGRY	JOY	FEAR	SAD	PRIDE
ANGRY	80.3	21.7	0	0	0
JOY	20.5	81.5	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

## 5. CONCLUSION AND OUTLOOK

The techniques for recognizing emotion from video using spatio temporal interest points are presented in this paper. The five different basic emotions are angry, joy, fear, sad and pride from GEMEP dataset are used for this experiment. The multiclass-SVM classifier with polynomial and RBF kernels 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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