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Recognition of Facial Expressions in Image Sequence using Multi-Class SVM

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ABSTRACT: Facial expression conveys the emotional state of an individual to observers, which is in the form of non-verbal communication. Recognition of facial expression plays a vital role in the field of Human Machine Interfaces (HMIs). Most of the existing automated system regarding facial expression has an impact over recognition rate. The seven facial expressions used in this work are happy, surprise, sad, fear, anger, disgust, and neutral. This paper proposes the Multi-class SVM to obtain high accuracy for recognizing each facial expression. The face in an image sequence is detected using Viola-Jones algorithm. Geometric and Appearance based feature extraction is used here. The geometric features are extracted using Image normalization and Thresholding techniques and optimal feature points are selected by calculating the entropy. Local Directional Pattern (LDP) + Local Directional Pattern variance (LDPv) descriptor helps to extract the appearance based features which contains the edges, spots and corners of a facial image. Finally, the performance of the proposed classifier is evaluated. Cohn-Kanade database is used to train and test the facial expression recognition system.

KEYWORDS: Facial Expression Recognition; Viola Jones detection algorithm; Shannon Entropy; Local Directional Pattern descriptor; Local Directional Pattern variance descriptor; Multi-class Support Vector Machine

I. INTRODUCTION

Automatic analysis of human facial expression is an essential research area in the field of human machine interaction. It has many applications to data-driven animation, video conferencing, psychological theory, human emotion analysis etc. The impact of facial expression on the above-mentioned application area is constantly growing due to many factors includes subtlety, complexity, variability found in the different set of facial images. To overcome this, several research efforts have been done regarding facial expression recognition system. The human face exposes large variety of facial expressions. Psychologically, there are six basic facial expressions namely happy, surprise, sad, fear, anger and disgust. Human can easily interpret the facial expressions, but for a machine this task is rather difficult. The system that would perform the following process, such as face detection, feature extraction, and classification in real time with high accuracy brings big achievements for human-machine interaction.

Facial expression recognition is a process to analyze the shape and motion of facial features. Shape feature contains head height, mouth width, eyebrows vertical position, eyes width etc and motion feature contains lip stretch, nose wrinkle, inner brow raiser, outer brow raiser etc. Feature extraction is the key point for facial expression recognition. In this paper, two different feature extraction processes are used: Geometric and Appearance-based feature extraction. Shape features are deal with Geometric-based feature extraction and the edge features are deal with Appearance-based feature extraction. These features help to boost the accuracy of FER system.

In our system, Multi-class Support Vector Machine classifier is proposed. SVM is a well suited classifier for recognizing facial expressions, as it is robust to the number of features, and known to model data in a highly optimized way. The performance of proposed classifier is evaluated based on accuracy. The structure of this paper is organized as follows: Section II deals with the related work done for this system and Section III describes the proposed facial expression recognition system. The experimental results are presented in Section IV. Conclusion and future scope are discussed in Section V.

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II. RELATED WORK

Ekman and Friesen [1] proposed that there are a neutral and six basic facial expressions namely happiness, surprise, sad, fear and disgust. These seven facial expressions are used in this work. Facial Expression Recognition system is a computer application capable of identifying or verifying a person's expression from a digital image or video frame. A survey for facial expression recognition from image sequence can be found in [2, 3]. Lajevardi and Margaret [4] proposed a method for face detection in image sequences which is fully automatic. They have used Viola Jones detection method [5] based on Haar-like features and AdaBoost learning algorithm. The statistical characterization of the motion patterns in specified regions of the face is proposed by Yacoob and Davis [6]. They developed a region tracker for rectangles enclosing the facial features.

The two most common approaches to the facial feature extraction are the geometric-based methods and the appearance-based methods [7]. Appearance-based features are affected by the facial appearance variations between subjects and geometric-based features are affected by shape deformations corresponding to each facial expression. Differ from the local texture; geometric feature is an important visual cue for facial expression recognition.

Detection and location of the face as well as extraction of facial features from images is an important stage for facial image interpretation tasks. Facial feature points normally include corners of eyes, eyebrow corners, lip corners, nostrils, and eyeballs. There are two types of methods for facial feature point detection: texture-based and shape-based methods. Local texture around a given feature point, is considered in texture-based methods [8, 9, 10]. While in shape based methods all facial feature points are treated as a shape [11, 12]. Neural network based feature detector proposed in [8]. This feature detector detect an eye from images by scanning an input window of i*j pixels across the image, where each gray value in the input window serves as an input for the neural network. A log Gabor wavelet for automatic facial feature point detection specifically identifies the facial feature points required for lip and head trackers [9]. The seven facial feature points were detected, namely the outer eye corners, one nostril, and the outer corners and top and bottom mid points of the lips. In [10], a two level hierarchical wavelet network for facial feature localization is presented. Hu et al. [11] proposed a method, called Active Wavelet Networks, in which a Gabor wavelet network representation is used to model the texture variation in the training set. The Gabor wavelet network approach represents a face image through a linear combination of 2D Gabor functions whose parameters position, scale, orientation, and weights are optimally determined to preserve the maximum image information for a chosen number of wavelets. Direct appearance model (DAM) [12] is applied for multi view face alignment. Haar feature based Adaboost classifier [13] combined with the statistical shape models to localize the relevant facial features. Boosting algorithm [14] determines the facial feature point candidates for each pixel in an input image and then uses a shape model as a filter to select the most possible position of feature points, like eyes, nostrils and lip comers. Vukadinovic et al. [15] propose a method using Gabor wavelets and AdaBoost classifier. They detect 20 facial feature points in images of expressionless face. The method consists of four steps: face detection, region of interest detection (ROI), feature extraction, and feature classification. For face detection they use fast and robust face detector based on a cascade scheme consisting of a set of Haar feature based Gentleboost classifier. The detected face region is then divided into 20 ROIs, each consisting of one facial feature using a combination of heuristic techniques based on the analysis of vertical and horizontal image histograms. Kimura and Yachida [16] use integral projection method to detect the facial features. Here the input image is normalized using the centre of the eyes and mouth. Rajesh et al. [17] proposed a technique to achieve high accuracy for feature point detection. This method detects the facial feature point in any image from image sequences with tilted faces under varying illumination conditions. It is comprised of five steps: Face detection, Region of interest detection, image normalization, thresholding, and corner detection.

Variance and entropy are the strong metrics for measuring the information content of data. The data obtained are informative around mean with known variance, such as Gaussian distribution [18]. Entropy provides reliable information about the variations occurred at particular moments in time and analyzes the evolutionary process over time. In general, entropy is a statistical measure of randomness that can be used to characterize the features. There are several applications of entropy in the field of industrial organization and innovation studies [19]. The concept of entropy originated from the studies of Ludwig Boltzmann in 1877 and then probabilistic interpretation in information theory by Claude Shannon in 1948. Later, Henri Theil developed several applications of information theory in economics and information theory (1967) and statistical decomposition analysis (1972) based on entropy [19]. In [20] entropy measurement extracts the feature points which are highly affected by expression deformation. More entropy

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denotes that the feature point is highly affected and it carries more information about the expression. Low entropy means a feature point is stable which does not affected by an expression deformation.

Appearance-based extraction methods deal with the changes occurred in facial appearance and these deformations are extracted using image filters such as Gabor-wavelet, Curvelet and local binary pattern [21, 22, 23]. Local Binary Pattern has many applications in the field of face detection, face recognition and facial expression recognition [23, 24]. Although LBP is efficient for better computation and robustness to the monotonic illumination changes, it is sensitive to the non-monotonic illumination variation and obtains poor performance in the presence of random noise. Taskeed and others proposed Local Directional Pattern (LDP) method to overcome the weakness of Local Binary Pattern (LBP) [25]. This technique applied successfully in the field of face recognition, gender recognition, object description and facial expression recognition [26, 27].

LDP feature extraction method represents curves, edge and texture characteristic of face [28]. Most existing appearance-based method only considers the whole facial feature to classify expressions. Due to changes of facial expression, the region of eyes and mouth has powerful influence. Therefore, highlight the local region which has more contribution on expression changes. Jabid et al. introduced additional contrast information to Local Directional Pattern descriptor and this weighted LDP method called Local Directional Pattern Variance (LDPv) [29]. It adjusts the different contributions of LDP descriptor using the variance of local structure and account that texture with significant contrast should impact more such as eyes and mouth that are more sensitive to high contrast regions. In [30] first extract the global LDP features which can guarantee basic expression difference and then LDPv descriptor extracts the local regions of eyes and mouth to extrude the distinction between expressions.

Classification of facial expression depends on deformation of face corresponds to each expression. The facial expression classified into seven types: happy, surprise, sad, anger, fear, disgust, and neutral. A lot of classifier is used for facial expression recognition such as Naïve Bayesian classifier, Neural Networks, Bayesian classifier, K-Nearest Neighbour, Hidden Markov Model (HMM), Linear Discriminant Analysis, Multi-class SVM, K-Means Clustering and its performance varies according to the recognition rate accuracy obtained for each facial expressions. NB classifier is used for facial expression recognition in [4]. Wenming et al. introduces the Gabor wavelet transformation method which converts the 34 geometric points into a labelled graph vector. For facial expression recognition uses Kernel Canonical Correlation Analysis (KCCA) tested on Japanese female facial expression (JAFFE) [31].The recognition rate for six expression using KCCA achieved as 77.05%. Petar and Aggelos [32] extracts the facial animation parameter using active contour algorithm and Multistream Hidden Markov Model (MHMM) based automatic facial expression recognition have used. This technique achieves high recognition rate for fear and sadness facial expressions apart from another four expressions. Kotsia and Pitas [33] have proposed a method which is based on mapping and tracking of facial features from the video frame. They have used Candide wire frame model for feature tracking. Recognition is semiautomatic, in the sense means that the user has to manually place the candied grid nodes on facial landmarks depicted at the first frame of image sequence. Multi-class Support Vector Machine classifier classifies the six expression into its corresponding classes, neutral state is not considered here. It obtains high recognition rate accuracy. Hamid et al. proposed a fixed geometric model for geometric normalization of facial images. Multiclass Support Vector Machine with polynomial kernel representation for classifying the selected Extended Cohn-Kanade datasets. This eliminates geometric variability in emotion expressions and obtain high recognition rate for fear, surprise and happiness expressions with less computational cost [34]. Viola-Jones Algorithm detects the region of interest face and extracts the features using image normalization and thresholding technique. Active Appearance Model (AAA) [35] tracks the facial feature points and classifies the seven facial expressions using Multiclass SVM. This method is experimented on Cohn-Kanade and IMM database.

III. PROPOSED ALGORITHM

A. *Proposed Framework:*

Fig. 1 illustrates the proposed framework, which is composed of face detection, feature point detection, feature extraction and classification. Face detection is performed by Viola Jones algorithm and then crop the facial image according to the rectangle enclosed on the face. The geometric and appearance based features are used here. Facial feature points from the image sequence, such as eyebrow corners, eye corners, nostrils and lip corners are detected using image normalization and thresholding techniques. After, Shannon Entropy selects the deformable feature points which carry more information about the human emotions. Local Directional Pattern feature descriptor is an appearance-based feature extraction method. A LDP feature is obtained by computing the edge response values in all eight

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directions at each pixel position and generating a code from the relative strength magnitude. Each face is represented as a collection of LDP codes for the recognition process. In addition to this edge features, the contrast feature is extracted here. Local Directional Pattern variance (LDPv) characterizes the contrast variance of local texture information for more accurate facial expression recognition performance. The extracted geometric and appearance-based features are given as input to the classifier. Multi-class SVM classifier are trained for seven facial expressions using Cohn-Kanade database. It classifies the expression into one of the seven classes such as happy, anger, sadness, surprise, disgust, fear, and neutral.

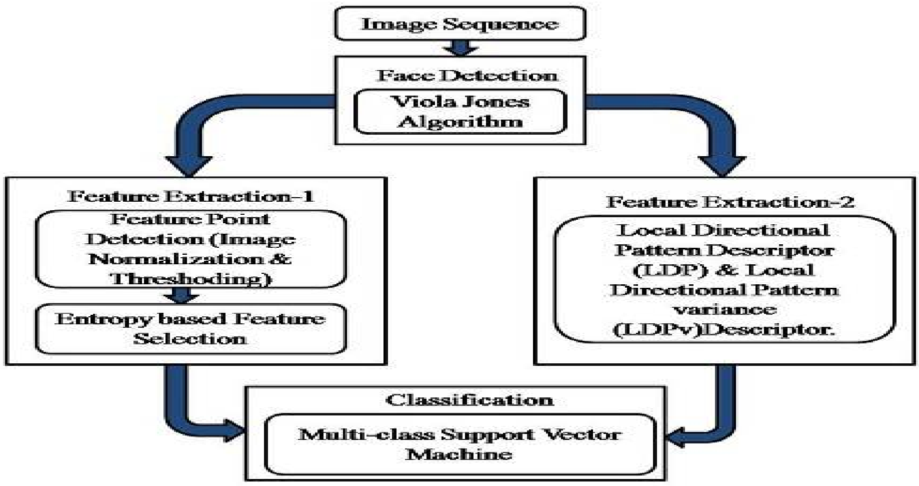

Fig. 1. Architecture of Facial Expression Recognition System

B. *Face Detection:*

The facial expression recognition system is to be fully automatic in real time applications. The high variability present in different types of face make as difficult to detect the face. In this work, Viola Jones detection technique is used. In general, Viola Jones algorithm is a object detection technique helps to detect the object in real time with good detection rate, atleast two frames per second is processed. Viola Jones algorithm based on Haar features detects the face area includes eye, nose and mouth regions. These regions are selected by enclosing a rectangle box on the face. Crop the outer portion of the rectangular box; thereby remove the ear and hair portions. When compared to eye, nose and mouth region, the ear and hair portion doesn't give any information about the emotion.

C. *Geometric based Feature Extraction:*

The shape features play an important role in facial expression recognition system. These features define the shape of each facial region changed during expression deformation. Geometric based feature extraction consists of two steps: feature point detection and selection of optimized feature points. The feature points, such as eye corners, eyebrow corners, eyeballs, lip corners and nostrils are detected using [17].

For feature point detection, divide the face into different regions. First divide the cropped facial image into three equal halves horizontally as upper part, middle part, and lower part. The upper part contains eye region, middle part contains nostril region, and lower part contains mouth region. Then the upper part is divided vertically into two parts such that each part contains one eye. Each eye region is again divided horizontally into two parts, thereby separate the eye and eyebrow. The position of the eyeball is detected using horizontal and vertical histogram analysis. Vertical histogram shows the intensity difference between the row pixels wise. The peak of this histogram gives the y coordinate of the eyeball. Horizontal histogram shows the intensity difference between the column pixels wise. The peak of this histogram gives the x coordinate of the eyeball. In each separated facial region, perform image normalization and thresholding techniques. Image normalization is a linear process. For example, if the intensity range is 50 to 180 and the desired range is 0 to 255, subtract the minimum value of image from each of pixel intensity, making the range 0 to 130. Then the pixel intensity is multiplied by 255/130, making the desired range 0 to 255. Compute the average of normalized image using eq. (1).

$$\text{avg} = \frac{1}{N_1 N_2}\sum_{x=1}^{N1}\sum_{y=1}^{N2} R(x,y) \qquad \text{eq. (1)}$$

where, N1×N2 is the size of the image and R(x,y) is a pixel value at coordinate (x,y). Select the threshold value as avg/3, which converts the gray scale image into binary image using eq. (2).

$$\text{if } R(x,y) > \frac{avg}{3},\ R(x,y) = 1, \text{ else } R(x,y) = 0 \qquad \text{eq. (2)}$$

Then detect facial feature points from each region.

Entropy based feature selection chooses the accurate feature points which are highly affected by expression deformations. More entropy means the feature point is more affected and therefore carries information about the expression. Low entropy means a stable feature point which does not change throughout an expression deformation.

Shannon entropy is used here to select the deformable features of seven facial expressions. The computation of entropy is shown in eq. (3).

Shannon entropy is defined as:

$$H(x) = -\sum_i P(x_i) log_b P(x_i) \qquad \text{eq. (3)}$$

Here, b = 2(entropy uses two bins of logical arrays). P(x_i) is the probability of occurrence for each symbol encountered in the image. Normalize the image by the total number of pixels to get the probability distribution function.

D. *Appearance-based Feature Extraction:*

Local Directional Pattern (LDP) extracts the appearance changes of face during expression deformation. LDP descriptor contains detail information of face such as edges, spots, corners and other local textures. This feature is obtained by computing the edge response values in all eight directions at each pixel in an image and encoding the edge response value into an 8 bit binary number using the relative strength of the edge responses. LDP features are less sensitive to noise and illumination changes, which describes the local primitives in a more stable manner and also retains more information.

Eight directional edge response values of a particular pixel is computed using Kirsch mask in eight different orientations Mi centred on its own position. It is a 3×3 matrix shown in the Fig. 2.

-3	-3	5
-3	0	5
-3	-3	5

East M_0

-3	5	5
-3	0	5
-3	-3	-3

Nort East M_1

5	5	5
-3	0	-3
-3	-3	-3

North M_2

5	5	-3
5	0	-3
-3	-3	-3

North West M_3

5	-3	-3
5	0	-3
5	-3	-3

West M_4

-3	-3	-3
5	0	-3
5	5	-3

South West M_5

-3	-3	-3
-3	0	-3
5	5	5

South M_6

-3	-3	-3
-3	0	5
-3	5	5

South East M_7

Fig. 2. Eight directional Kirsch edge response masks

Fig. 3(a) and (b) shows eight directional edge response positions and LDP binary bit positions. Comparing to other existing mask this mask consider eight directional neighbours of corresponding pixel. The eight directional edge response values ranges {m_i}, i = 0, 1 …7. The response values are not equally important in all directions.

m_3	m_2	m_1
m_4	x	m_0
m_5	m_6	m_7

(a)

b_3	b_2	b_1
b_4	x	b_0
b_5	b_6	b_7

(b)

Fig. 3(a). Eight directional edge response positions;
(b). LDP binary bit positions

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The presence of a corner or an edge shows high response values in some particular directions. Therefore, the k most prominent directions are considered to generate the LDP. The top-k directional bit responses, bi, are set to 1 and the remaining 8-k bits of the 8 bit LDP pattern are set to 0. Finally, the LDP code is derived by formula eq. (4), where m_k is the k-th most significant directional response value. The code formation is shown in Fig. 4.

$$LDP_K = \sum_{i=0}^{7} bi(m_i - m_k) \,.\, 2^i \,, b_i(a) = \begin{cases} 1, a \geq 0 \\ 0, \quad a < 0 \end{cases} \qquad \text{eq. (4)}$$

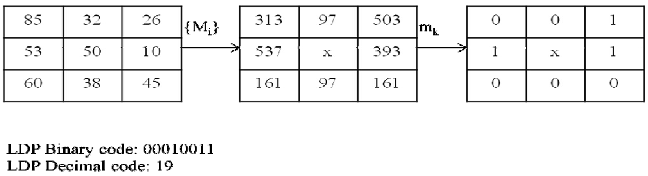

Fig. 4. LDP code formation with k=3

LDP histogram for an input image with size M×N is represented in eq. (5).

$$H(i) = \sum_{r=1}^{M} \sum_{c=1}^{N} f(LDP_k(r,c), i),\ f(a,i) = \begin{cases} 1, & a = i \\ 0, & a \neq i \end{cases} \qquad \text{eq. (5)}$$

Compute all the LDP code for each pixel (r,c), where i is the LDP code value. For a particular value k, there are C_8^k different bins for the histogram. Resulting histogram vector has the size of 1× C_8^k is produced for the image. Local Directional Pattern variance (LDPv) method is considered to obtain corner information to LDP operator. Therefore the variance σ is introduced as an adaptive weight to adjust the contribution of the LDP code in the histogram generation.

$$LDPv(\tau) = \sum_{r=1}^{M} \sum_{c=1}^{N} w(LDP_K(r,c), \tau) \qquad \text{eq. (6)}$$

$$w(LDP_k(r,c), \tau) = \begin{cases} \sigma\big(LDP_k(r,c)\big), & LDP_k(r,c) = \tau \\ 0, & otherwise \end{cases} \qquad \text{eq. (7)}$$

$$\sigma\big(LDP_K(r,c)\big) = \frac{1}{8} \sum_{i=0}^{7} (m_i - \overline{m})^2 \qquad \text{eq. (8)}$$

Where, $\overline{m}$ is the average of all directional responses $\{m_i\}$ which is calculated for a position (r,c).

E. *Multi-class Support Vector Machine:*

The classification is performed on the basis of geometric and local texture information. Extracted feature vectors are used as an input to the classifier. Support Vector Machine is a supervised machine learning model which maximizes the hyper plane margin between different classes. They map input space into a high-dimension linearly separable feature space. This mapping does not affect the training time because of the implicit dot product and the application of the kernel function. In principle the SVM technique finds the hyper plane from the number of candidate hyper-planes, which has the maximum margin. The margin is enhanced by support vectors, which are lying on the boundary of a class. Basically SVM is a binary classifier, which classifies data in two classes. If the number of classes is more than two, then the Multi-class SVM is used. Mainly this classifier characterized into two schemes: 1-against-1 and 1-against-all.

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1) 1-against-1 multi-class SVM classifier: In this approach $C(C-1)/2$ classifiers are constructed. where C is the number of classes. Classifier i, j is trained using all patterns from class i as positive instances, and all patterns from class j as negative instances and disregarding the rest. To combine obtained classifiers a simple voting scheme is used. When classifying a new instance each one of the base classifier casts a vote for one of the two classes used in its training. The class that gets maximum vote will be declared as class of new instance.

2) 1-against-all multi-class SVM classifier: In this scheme there is one binary SVM for each class to separate members of that class from members of other classes. We have number of classifiers equal to number of classes. Classifier i, j is trained using all patterns from class i as positive instances, and all patterns from rest of the classes is assumed to be in class j as negative instances. The class for which decision function gives maximum value will be declared as class of new instance**.**

In this paper we have used one against all schemes, because the database contains the facial image sequences. This database is clustered into seven different classes, each one representing one of the seven basic facial expressions.

IV. SIMULATION RESULTS

This section deals with the performance of the proposed approach. The performance of the proposed Multi-class Support Vector Machine classifier is computed here.

A. *Cohn Kanade Database:*

The proposed algorithm has been tested on Cohn-Kanade database [36]. This database includes 388 image sequences from 100 subjects. Each sequence contains 12-16 frames. The subject's age ranges from 18 to 30 years. Sixty-five percent of subjects were female and thirty-five percent were male. Fifteen percent of subject comes from the Africa-American background and three percentage from the Latin-American and Asian based subjects. The image sequences represented 100 different subjects expressing different stages of expression development, starting from a low arousal stage, reaching a peak of arousal and then declining. Facial expressions of each subject represent seven basic expression include anger, disgust, fear, happy, surprise, sad. The seven facial expressions from this database are shown in Fig. 5.

Fig. 5. Cohn Kanade facial expressions

B. *Recognition Performance:*

The performance of the facial expression recognition system is evaluated based on accuracy. In this experiment 40 images per expression are selected randomly from Cohn-Kanade database for training and testing. The size of each image in this database is (640×490). Viola Jones algorithm successfully detects the face in an image sequence with good detection rate. Two types of extraction process are done to obtain better features: appearance and geometric based extraction. Extracted feature vector for seven facial expressions are trained using Multi-class Support Vector Machine. Finally, compute the recognition rate for each facial expression.

Table 1 shows the Confusion matrices and accuracy using Multi-class SVM. The confusion matrix is an n×n matrix containing the information about the actual class label (in its columns) and the label obtained through classification (in its rows). The diagonal entries of the confusion matrix are rates of facial expression that are correctly classified while

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the off-diagonal entries correspond to misclassification rates. Recognition rate level is reduced due to the corresponding expression makes confusion with other expression.

Happy expression makes confusion with surprise, sad, and disgust, while sad makes confusion with disgust and fear. It obtains the recognition rate of 90%. Surprise makes confusion with happy and fear, and obtains the recognition rate of 92%. Sad make confusion with disgust and fear, and obtains the recognition rate of 84%. Anger make confusion with happy, sad and disgust, and obtains the recognition rate of 86%. Disgust make confusion with happy, sad and fear, and obtains the recognition rate of 78%. Fear make confusion with sad and anger, and obtains the recognition rate of 81%. Neutral make confusion with happy and sad, and obtains the recognition rate of 96%. By comparing other expressions, neutral expression obtains high recognition rate and disgust has low recognition rate. The recognition rate is not stable for seven facial expressions.

The geometrical and appearance features are combined to train the classifier. Therefore, the overall accuracy obtained for seven expressions using Multi-class SVM is 86.7 %.

Table 1: Confusion Matrices and Accuracy using Multi-Class SVM

Expression (%)	Happy (%)	Surprise (%)	Sad (%)	Anger (%)	Disgust (%)	Fear (%)	Neutral (%)
Happy	90	3	1	0	6	0	0
Surprise	5	92	0	0	0	3	0
Sad	0	0	84	0	4	12	0
Anger	2	0	8	86	4	0	0
Disgust	2	0	12	0	78	8	0
Fear	0	0	9	10	0	81	0
Neutral	3	0	1	0	0	0	96

V. Conclusion and Future Work

The proposed system recognizes the seven facial expressions with high accuracy. Multi-class Support Vector Machine achieves 86.5% of recognition rate. Therefore, the performance of facial expression recognition system is improved using proposed system which is experimented on Cohn-Kanade Database. Our approach fulfils requirement for a real time system as it employs automated procedure. This system is applicable for frontal faces and face with seven expressions. The recognition of facial expressions in image sequence with tilted faces is a challenging problem in present days. The head movement is required by many applications such as computer graphics animation, communication etc. Further, efficient techniques can be used to recognize the tilted faces with high accuracy and also to include more samples for testing.

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