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HYBRID APPROACH FOR FACIAL CUES BASED EMOTION PROFILE GENERATION

[1]BHARATI DIXIT, [2]ARUN GAIKWAD

[1]Sinhgad College of Engineering, Pune, India
dixit.bharati@gmail.com

[2]Zeal College of Engineering and Research, Pune, India
arungkwd47@gmail.com

ABSTRACT

Emotion analysis is very significant from the perspective of many applications like E-learning, cognitive assessment, driver alert system, pain monitoring system, healthcare services, interactive TV, animation etc. Outcome of the work is depicted in the form of emotion profile which is defined as graphical representation of the degree of presence or absence of all the universally accepted seven emotions on a single scale. This simple but unique representation helps in determining the presence of complex/naturalistic emotions. Complex emotions represents the emotional state of a person when he/she is able to feel and express more than one emotions simultaneously at the time of observation. Emotion analysis through facial expressions is experimented on JAFFE and MIST Database - a locally created context specific database of images. Images of the subjects under study are captured and experimented for all seven universally accepted emotions and depicted in the form of emotion profiles. Emotions are categorized as neutral, positive and negative for MIST database and in seven categories of emotions like happy, surprise, anger, sad, disgust, fear and neutral for JAFFE database. Average accuracy obtained as 91.31% for MIST database and 93.84% for JAFFE Database. FPR - false positive rate and FNR - false negative rate, values for JAFFE database are 6.38% and 6.62% respectively. FPR and FNR values for MIST database are 8.18% and 8.60% respectively. Emotion recognition time for JAFFE database 1.108 sec and for MIST database 1.392 Sec. These performance parameters especially the accuracy more than 90% which is at par with the research results published in renowned journals in this domain makes this work qualify to be used for various applications. Analysis of complex emotions is typically useful for the professionals working in the field of Human resource, clinical psychology, cognitive analysis etc. More accurate emotion recognition is still challenging and open research problem

Keywords: *Facial Expressions, Fusion Of Features, Emotion Analysis, Emotion Profiles, Context Specific Image Database*

1. INTRODUCTION

Emotions are integral part of human being. Emotion recognition has wide range of applications in domains like cognitive assessment, behavior analysis and prediction, healthcare etc. Emotion recognition approaches are categorized as verbal approach and non verbal approach. Non verbal approach can be implemented through facial expressions, cues, gestures, brain signals etc. Facial expressions based method is experimented for this study on publically available JAFFE database and locally created context specific MIST database.

Accurate and efficient emotion recognition by computer is a challenging task and the critical step involved is feature extraction. There are many model based methods like geometry based techniques, LBP, LDN, HoG etc which use local features. The other category of methods called appearance based methods which use global features like Eigen faces, Fisher faces, Gabor features, wavelets etc. Appearance based methods are better than model based methods because these methods have better performance reproducibility, efficient characterization of a low dimensional subspace within over all space of the raw image measurement and provides statistical framework for theoretical analysis of system performance. Benefits of combination of local and global features can be achieved through methods which are based on hybrid features.

The feature extraction method experimented for this study is hybrid in nature and has used HoG - histogram of oriented gradients to achieve illumination invariance, in combination with LBP - local binary pattern and Gabor filter bank to form features for emotion recognition. Dimensionality of feature vector is high as fusion of features obtained through HoG, LBP and Gabor filter bank is carried out. PCA - principle component analysis is used for dimensionality reduction of feature vector. k NN classifier is used further to classify the emotion in one of the seven categories for JAFFE database and in three polarities (i.e. neutral, positive and negative) of emotions for MIST database.

The theme of the paper is further developed under different sections. Overview of the related work done so far is discussed in section 2. Basics of emotion recognition and the details of databases used for experimentation is discussed in section 3. Section 4 explains methodology of implementation. Section 5 presents experimental results and performance analysis. Section 6 emphasizes on significance of work whereas section 7 comprises of conclusion.

2. RELATED WORK

This section summarizes the relevant work done by researchers and scientists across the world and published in renowned Journals.

Evangelos Sariyanidi et al [1] reviewed the progress across a range of affect recognition applications to highlight the fundamental questions of Registration, Representation, and Recognition. A comprehensive analysis of facial representations by uncovering advantages and limitations authors elaborate on the type of information is to be encoded and discuss to deal with the key challenges of illumination variations, registration errors, head-pose variations, occlusions, and identity bias.

Li Zhang et al [2] proposed a facial expression recognition system with a variant of evolutionary fire- fly algorithm for feature optimization. The proposed evolutionary firefly algorithm exploits the spiral search behavior of moths and attractiveness search actions of fireflies to mitigate premature convergence of the Levy-flight firefly algorithm (LFA) and the moth-flame optimization (MFO) algorithm. Diverse single and ensemble classifiers are implemented for the recognition of seven expressions. This system outperforms other state-of-the-art feature optimization methods and related facial expression recognition models by a significant margin.

Hongying Meng et al. [3] have proposed a novel two-stage automatic system to continuously predict affective dimension values from facial expression videos. In the first stage, traditional regression methods are used to classify each individual video frame, while in the second stage, a time-delay neural network (TDNN) is proposed to model the temporal relationships between consecutive predictions. Use of two-stage approach combined with the TDNN significantly improves the overall performance of continuous emotional state estimation in naturalistic facial expressions.

Emily Mower et al. [4] describes an emotion classification paradigm, based on emotion profiles (EPs). This paradigm is an approach to interpret the emotional content of naturalistic human expression by providing multiple probabilistic class labels, rather than a single hard label. Proposed approach has capability of dealing with naturalistic human emotional expressions which are often not well described by a single semantic label.

Tanjea Ane et al. [5] have proposed a new study of bit intensity with coefficient feature vector for facial expression recognition. All the binary patterns from gray color intensity values are grouped into possible number of attributes according to their similarity. Each attribute count the frequency number of similarity from binary patterns. Each image is divided into equal sized blocks and extracts 4-bit binary patterns in two distinct directions for a pixel by measuring the gray color intensity values with its neighboring pixels.

Happy S. L. et al. [6] uses salient facial patches for feature extraction. Authors have proposed unique framework to be operated on selected facial patches which is experimented on CK+ and JAFFE database. Due to use of selected patches the approach proves to be efficient in terms of improved recognition time parameter. The time required for expression recognition is less and accuracy achieved during training phase using fused data samples is around 95%.

Junkai et al. [7] have discussed facial expression recognition through videos. Authors have captured facial motions and also extended their study for audio modality for effective geometrical feature extraction through warp

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transformation of facial landmarks. A new feature descriptor called Histogram of Oriented Gradients from Three Orthogonal Planes (HOG-TOP) is proposed to extract dynamic textures from video sequences.

Marco Rathschlag, Daniel Memmert [8] have examined the relationship between self-generated emotions and physical performance. All participants took part in five emotion induction conditions (happiness, anger, anxiety, sadness, and an emotion-neutral state) and authors have investigated their influence on the performance of participants. All experiments showed that participants could produce significantly better physical performances when recalling anger or happiness emotions in contrast to the emotion-neutral state. Paper discusses results in relation to the cognitive-motivational-relational (CMR) theory framework.

The literature mentioned above discusses the emotion recognition methodologies in depth and highlights the criticalities of the problem taken for study.

The various approaches explored by different authors provide results with reference to emotion recognition accuracy in the range of roughly 68% to 96%. The reason for such large range of accuracy parameter is due to different feature extractors and different classifiers experimented by authors. The variety of databases like JAFFE, CK+, KDD etc. are experimented by authors to carry out their work. Some of the authors have extended their work on image sequences also.

The work carried out in this study has the objectives such as (i) Perform experiment on locally created context specific database. (ii) Inclusion of measure to cater to illumination variation in the algorithm (iii) Develop an algorithm by using hybrid approach to get the benefits of both local features and global features. (iv) To reduce space complexity and achieve reduced value of emotion recognition time. (v) To obtain the emotion recognition accuracy above 90% which is acceptable for many applications.

Outcome of the work is depicted in the form of emotion profile which is a unique approach of dealing with naturalistic/complex emotions. Author Emily Mower has used this concept of emotion profile partially but experimented the work on image sequences and got the accuracy around 68%. There is need to carry out the work further in this direction.

The work undertaken extends the emotion profiling approach to all seven universally accepted emotions and get the accuracy parameter well above 90%. The experimentation for this study is carried out using algorithm designed based on LBP as local feature extractor, Gabor filter bank as global feature extractor and HoG to address illumination variation. PCA is used for dimensionality reduction and kNN as classifier. The databases explored are JAFFE and MIST - locally created context specific database. Details of the work carried out is discussed in further sections of the paper.

3. EMOTION RECOGNITION AND DATABASE USED

This sections provides details related to basics of emotion recognition, databases used for experimentation carried out for this study.

3.1 Basics of Emotion Recognition

Automatic recognition of emotions by computers is becoming an increasingly important component in the design process for affect-sensitive human–machine interaction (HMI) systems.

Seven categories of emotions are universally accepted and these are neutral, sad, fear, disgust, anger, happy and surprise. As emotion recognition has wide application range so experimented worldwide and standard databases are made available to researchers to further carry out the work to improve the systems. Some of these databases are JAFFE, CK, KDEF etc.

Three types of approaches are available for emotion recognition through facial expressions. These are based on local features, global features or combination of these two i.e. hybrid features based approach.

There are many model based methods like geometry based methods, LBP, LDN, HoG etc which uses local features. The other category is called appearance based methods which are designed around global features. Some of the prominently used appearance based methods are Eigen faces, Fisher faces, Gabor features, wavelets etc. Appearance based methods are better than model based methods because these methods have better performance reproducibility, efficient characterization of a low dimensional subspace within over all space of the raw image measurement and provides statistical framework for theoretical analysis of system performance. Benefits of combination of local and global features can be achieved through methods which are based on hybrid features.

There are three types of emotional corpus - simulated emotions, induced emotions and natural emotions. Simulated emotions are hard labeled whereas the possibility of presence of more than one emotion simultaneously can be there in induced and natural emotions. Emotion profile based approach can be used for induced and natural emotion corpus. EP - Emotion profile is graphical representation of degree of presence or absence of an emotion in a particular image. EPs provide an assessment of the emotion content of an utterance in terms of a set of simple categorical emotions anger, happiness, surprise, neutral, disgust, fear and sadness.

3.2 Details Of The Database Used For Experimentation

To perform the study, publically available JAFFE - Japanese Female Face Emotion database is used which consists of 10 subjects and total 213 images. As any of the publically available database does not provide any health data along with images so a context specific database is locally created wherein along with images health data such as systolic blood pressure, diastolic blood pressure and pulse rate is also captured. Experimentation with health data is not in the scope of the paper This locally prepared context specific database of Indian subjects is referred as MIST database in further sections of the paper.

3.2.1 Database preparation and validation - an overview

Total 45 students participated as subjects in the database preparation process. The age group of subjects is in the range 22 - 35 years with average age as 25 years. 30% participants are male and rest 70% participants are female. Two experiments are carried out for image database preparation and health data collection. 15 subjects participated in first experiment and total 315 images are captured along with measurement and recording of health data like blood pressure and pulse rate. 30 subjects participated in second experiment and 540 images are captured along with measurement of health data. Altogether total 855 images are captured. Validation of database is carried out by experts in psychology domain and inter rater agreement represented by kappa coefficient is achieved as 0.87 which indicates the database validity range as 64% to 81%. Experimentation is carried out on 79% images i.e. 679 images out of 855 images as experts could not identify the label for rest of the images.

3.2.2 Emotion corpus methods

There are three Emotional corpus methods and these are in the form of Natural Emotions, Simulated Emotions and Induced Emotions. Brief description of these emotional corpus is as follows.

Natural Emotions: Natural Emotions are recording of spontaneous emotional states naturally occurred. It is characterized by high ecological validity but suffers from limited no. of subjects and presents difficulty for annotation.

Simulated Emotions: Simulated Emotions are emotional states portrayed by professional or lay actors according to emotional labels or typical scenarios. Although this method permits easy to constitute an emotion corpus however it has been criticized that this kind of emotions are more exaggerated than natural or induced emotions.

Induced Emotions: Induced Emotions are specific emotional states experimentally induced in groups of subjects.

Induced emotion corpus is used while preparing MIST database. Emotions are categorized in only neutral, positive and Negative class for MIST database. Mapping of all seven universally accepted emotions to positive, negative and neutral class is as presented in Table 1

Table 1: Mapping Of Emotions With Polarity

Universally Accepted Emotions	Polarity of Emotions
Neutral	Neutral
Surprise	Positive Emotions
Happy	
Sad	Negative Emotions
Fear	
Disgust	
Anger	

3.2.3 Validation of MIST database

MIST database contains images of human faces revealing emotions through facial expressions. These images are provided to different raters to validate the emotional states represented by human face images. To calculate the agreement between various raters the kappa and Scotts Pi statistics are available. The Fliess Kappa statistics is used to check reliability in multi-rater scenario. The kappa is calculated as:

k = (P0 - Pe) / (1 - Pe) where P0 is relative observed agreement among raters and Pe is hypothetical probability of chance agreement. The

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value of k represent the inter rater agreement as shown in Table 2.

Table 2: Interpretation Of K Statistics [9]

Value of Kappa	Level of Agreement	% of Data that are Reliable
0.0 – 0.20	None	0–4%
0.21 – 0.39	Minimal	4–15%
0.40 – 0.59	Weak	15–35%
0.60 – 0.79	Moderate	35–63%
0.80 – 0.90	Strong	64–81%
Above 0.90	Almost Perfect	82–100%

4. THE PROPOSED METHOD

This section describes system block diagram, emotion recognition through facial expressions, algorithm designed for the study and obtained output in the form of emotion profile. Emotion profiles (EPs) is an approach to interpret the emotional content of naturalistic human expression by providing multiple probabilistic class labels rather than a single hard label. EPs provide an assessment of the degree of presence or absence of emotion content of an utterance.

4.1 System Block Diagram

The block diagram of system designed for study is as shown in Figure 1. The study is targeted for emotion detection through facial expressions.

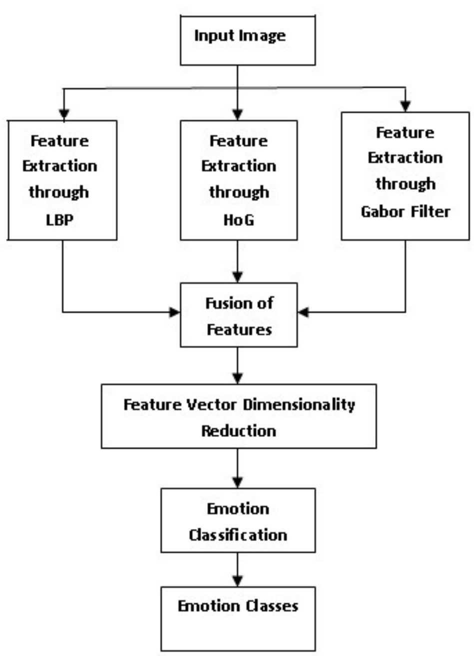

Figure 1: System Block Diagram

The method experimented for this study is based on fusion of features and hybrid in nature i.e. combination of local and global features. Input image is read and preprocessed before features are extracted. Normalized image is obtained after preprocessing which is further used for feature extraction. Illumination variation is addressed through HoG - Histogram of oriented gradients. It is necessary to take care of illumination variation as the experimentation is extended for locally prepared context specific MIST database along with JAFFE database. To extract local features LBP - local binary pattern method is used. Global features are extracted using Gabor filter bank. The fusion of features obtained through HoG, LBP and Gabor filter bank constitutes feature vector. PCA - principle component analysis is used for dimensionality reduction. Reduced feature vector is provided as input to KNN classifier to further classify the image in one of the seven classes. Classifier provides output as emotion profile which is a graph having X axis legend as emotions and Y axis legend as percentage of emotion using distance metric. The lowest amplitude bar depicted on the emotion profile is the recognized emotion.

Brief description about HoG, LBP, Gabor, PCA and KNN classifier is as follows.

HOG - Histogram of Oriented Gradients: The HOG[10] is a feature descriptor used in pattern recognition and computer vision applications specifically for object detection.

Appearance and shape of the object can be described by the distribution of intensity gradients. The image is divided into small regions called cells and some of these cells form connected regions. Histogram of gradient directions is compiled for pixels within each cell. Concatenation of these histograms forms the descriptor. Contrast normalization of these regions results in better invariance against changes in illumination and shadowing. To perform normalization intensity is measured across a larger region of the image called as block and then this value is used to normalize each cell within the block.

As HOG descriptor operates on local cells so it is invariant to geometric and photometric transformation and this is treated as advantage for invariance against illumination changes. The flow of operations to calculate HOG are as described as in Figure 2.

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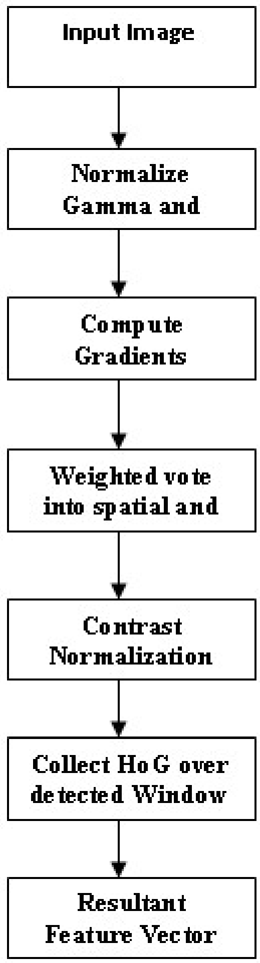

Figure 2: Steps To Obtain Hog Feature Vector [10]

The important step is computation of the gradient values. 1-D centered point discrete derivative mask can be used either in horizontal or vertical or in both directions. For color or intensity filtering kernel [-1, 0, 1] or its transpose can be used. More complex masks like 3x3 Sobel filtering can also be used.

The next step is creation of cell histograms. Based on the values found in the gradient computation every pixel casts a weighted vote for an orientation-based histogram channel. This computation is done for each cell.

Descriptor blocks are created by grouping the cells together into larger spatially connected blocks. The HOG descriptor is the concatenated vector of the components of the normalized cell histograms from all of the block regions. Block normalization is done for better accuracy.

LBP - Local Binary Pattern: Local Binary Pattern is a simple and efficient operator in which pixels are labeled by thresholding the neighborhood of that pixel and result is considered as binary number. LBP operators are popularly used in real world applications due to its robustness against gray scale changes and computational simplicity.

The original LBP operator labels the pixels of an image by thresholding the 3 x 3 neighborhood of each pixel with the value of the central pixel and concatenating the results binomially to form a number. The thresholding function for the basic LBP is represented as Equation (1)

$$f(I(Z_0),I(Z_i)) = \begin{cases} 0 & \text{if } I(Z_i) - I(Z_0) \leq \textit{threshold} \\ 1 & \text{if } I(Z_i) - I(Z_0) > \textit{threshold} \end{cases} \qquad (1)$$

Example of calculation of LBP is as shown in Figure 3.

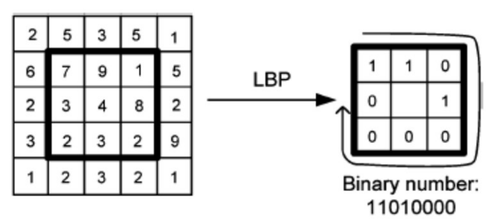

Figure 3: Local Binary Pattern Calculation [11-12]

Local features derived through LBP are used during fusion process while forming feature vector.

Gabor Filter Bank: As global features provides many benefits so the method uses global features obtained using Gabor Filter bank [13-14]. Gabor Filter bank of 8 scales and 5 orientations is used for experimentation. Gabor filters are explained as in equation (2)

$$F(x, y) = \exp(-(X^2 + \boldsymbol{\gamma}^2 Y^2) / 2\sigma^2)) * \cos(2\pi X/\lambda)$$

$$X = x\cos\theta + y\sin\theta, \qquad Y = -x\sin\theta + y\cos\theta \qquad (2)$$

Where θ is orientation, σ is effective width; λ is wavelength and $\boldsymbol{\gamma}$ is aspect ratio.

Features obtained through Gabor filter bank are concatenated with features obtained through HOG and LBP. As the features are hybrid

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in nature so carries the benefits of both local and global feature methods. The feature vector obtained through fusion of features is high in dimension so dimensionality of feature vector can be reduced using the technique PCA - principal component analysis.

PCA - Principal Component Analysis : This is a multivariate technique and used with various objectives such as extract the most important information from the data table, compress the size of the data set by keeping only this important information, simplify the description of the data set and analyze the structure of the observations and the variables [15-17].

These objectives are achieved when PCA computes new variables called principal components which are obtained as linear combinations of the original variables. The first principal component is required to have the largest possible variance. The second component should be orthogonal to the first one and must have maximum possible inertia. Similarly other principal components are calculated. The values of these new variables are called factor scores which are interpreted geometrically as projections of the observations on to principal components. Various models of PCA are available and depending upon the requirement of application chosen accordingly.

k-Nearest Neighbors Classifier: In k-NN classification [18] the output is a class membership. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of that single nearest neighbor.

The training examples are vectors in a multidimensional feature space each with a class label. The training phase of the algorithm consists only of storing the feature vectors and class labels of the training samples. In the classification phase k is a user-defined constant and an unlabeled vector (a query or test point) is classified by assigning the label which is most frequent among the k training samples nearest to that query point.

The best choice of k depends upon the data. Larger values of k reduce the effect of noise on the classification [19] but make boundaries between classes less distinct. The accuracy of the k-NN algorithm can be severely degraded by the presence of noisy or irrelevant features or if the feature scales are not consistent with their importance.

Dimensionality reduction inherently computes decision boundary and computation cost depends on complexity of boundary. The proposed methodology uses k-NN classifier with Euclidian distance for final class decision.

4.2 Proposed Algorithm

The designed algorithm is based on hybrid method where feature fusion approach is used. The important steps and pseudo code of algorithm is as mentioned in Table 3.

Table 3: Algorithm Steps And Pseudo Code

1	Start
2	Initialization: No. of Emotion Category = K, No. of Images per emotions = N Training Images = [(p-1)N] / p ,Test Images = N/p No. of iterations for validation = p
3	For iteration i = 1 to p
4	{
5	For Emotion Category j = 1 to k
6	{
7	For training images I_{train} = 1 to [(p-1)N] / p
8	{
9	Extract Features using HoG - Feat 1 Extract Features using LBP - Feat 2 Extract features using Gabor filter bank - Feat 3
10	Fusion of features Feat 1, Feat 2, Feat 3
11	Reduction in features using PCA
12	Get final feature vector and store in mat file
13	}
14	For Emotion category j = 1 to k
15	{
16	For Test Images I_{test} = 1 to N/p
17	{
18	Extract Features using HoG - Feat 1 Extract Features using LBP - Feat 2 Extract features using Gabor filter bank - Feat3
19	Fusion of features Feat 1, Feat 2, Feat 3
20	Reduction in features using PCA
21	Get Final feature vector

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22	Use KNN classifier to estimate degree of emotion present
23	Store this value in an array
24	}
25	Draw EP - emotion profile using array elements
26	Recognize emotion for the image under test
27	}
28	Calculate Accuracy and other performance parameters for each emotion category
29	}
30	Calculate average accuracy and other performance parameters using results of all the iterations
31	} End

This algorithm is implemented and tested for JAFFE and MIST Database.

5. EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

This section represents the experimental results obtained in the form of snap shots and discusses performance analysis of the emotion recognition on the parameters accuracy, false positive rate, false negative rate and recognition time.

5.1 Experimental Results

Designed algorithm is tested on images of JAFFE database[20]. The proportion of images used for training is 66% and for testing is 33%. After testing each image the obtained snap shots shows the original image, normalized image and emotion profile for the image under test. Recognized emotion class through the emotion profile is the one having lowest amplitude on the emotion profile. One of the sample emotion profile is as represented in Figure 4 depicting identified emotion class as surprise.

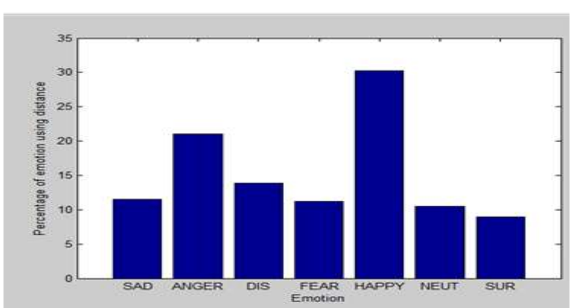

Figure 4: Sample Emotion Profile

The detected dominant emotion class is also represented through text box as an outcome of experimentation however the emotion profile also provides details of rest of the emotion classes useful for analysts as an assistive tool for their profession.

Some of the sample screen shots for the emotion class neutral from JAFFE database are shown from Figure 5(a) to Figure 5(d).

Figure: 5(a)

Figure: 5(b)

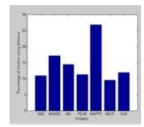

Figure: 5(c)

Figure: 5(d)

Figure 5(a): represents original image from emotion class Neutral. Figure 5(b): represents normalized Image. Figure 5(c): represents emotion profile for class neutral Figure 5(d): shows text box for detected emotion.

Another set of screen shots for the emotion class sad from JAFFE database are shown from Figure 6(a) to Figure 6(d)

Figure: 6(a)

Figure: 6(b)

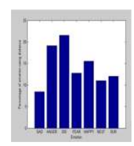

Figure: 6(c)

Figure: 6(d)

Figure 6(a): represents original image from emotion class Sad. Figure 6(b): represents normalized Image. Figure 6(c): represents emotion profile for class Sad Figure 6(d): shows text box for detected emotion.

Testing on MIST database is carried out as well. The proportion of images used for training is 66% and for testing is 33%. After testing each image the obtained snap shots shows the original image, normalized image and emotion profile for the image under test. Recognized emotion class through the emotion profile is the one having lowest amplitude on the emotion profile. The detected emotion class is also represented through text box.

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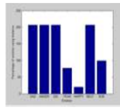
Some of the sample screen shots for the emotion class Happy for MIST database are shown from Figure 7(a) to Figure 7(d).



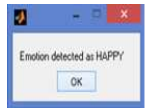


Figure: 7(a) *Figure: 7(b)* *Figure: 7(c)* *Figure: 7(d)*

Figure 7(a): represents original image from emotion class Happy i.e. positive Emotion class Figure 7(b): represents normalized Image Figure 7(c): represents emotion profile for class Happy and Figure 7(d): shows text box for detected emotion.

Both JAFFE and MIST databases are tested and performance analysis is presented in next subsection.

5.2 Performance Analysis

Performance analysis is done for image database JAFFE and MIST. The details are discussed in this section.

Experimentation is performed on 213 images of JAFFE database and result is represented in the form of confusion matrix. The database contains 31 images of emotion class Sad, 30 images of emotion class Anger, 29 images of emotion class Disgust, 32 images of emotion class Fear, 31 images of emotion class Happy, 30 images of emotion class Neutral and 30 images of emotion class Surprise.

Calculation of class wise accuracy and other parameters are as shown in Table 4.

Table 4: Confusion Matrix For JAFFE Database

PC → / ↓AC	SA	AN	DI	FE	HA	NE	SU
SA	**29**	0	0	1	0	1	0
AN	0	**27**	2	1	0	0	0
DI	0	0	**27**	0	1	1	0
FE	1	0	0	**31**	0	0	0
HA	1	0	1	0	**29**	1	0
NE	0	0	0	0	2	**28**	0
SU	0	0	0	0	1	0	**29**
Total Images	31	27	30	33	32	31	29
Accuracy (in %)	93.5	90.0	93.1	96.8	93.5	93.3	96.6

SA-Sad, AN-Anger, DI-Disgust, FE-Fear, HA-Happy, NE-Neutral and SU-Surprise
[PC - Predict Class, AC - Actual Class]

Average Accuracy = (93.54% + 90.00% + 93.10% + 96.87% +93.54% + 93.33% + 96.66%) / 7 = **93.86%.**

Class wise TPR - True positive rate, FPR - False positive rate and FNR - False negative rate is calculated and tabulated in Table 5 and graphically represented in Figure 8.

Table 5: Class Wise TPR, FPR and FNR for JAFFE Database

Emotion	TPR (In %)	FPR/FAR (In %)	FNR/FRR (In %)
SAD	93.54	6.45	6.45
ANGER	90.00	0.00	10.00
DISGUST	93.10	10.00	6.89
FEAR	96.87	6.06	3.34
HAPPY	93.54	12.5	9.67
NEUTRAL	93.33	9.67	6.67
SURPRISE	96.66	0.00	3.34
Average	**93.86**	**6.38**	**6.62**

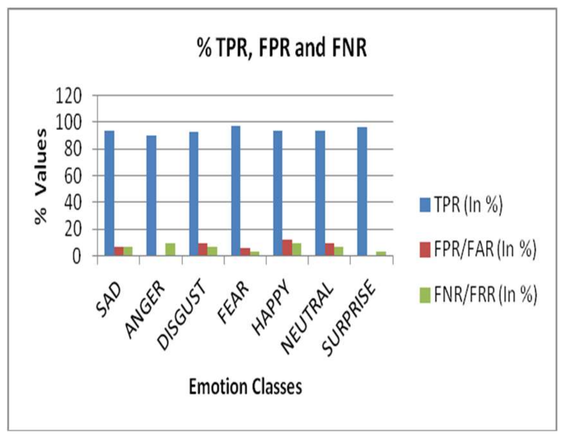


Figure 8: Graphical Representation of Accuracy, FPR and FNR for JAFFE Database

Experimentation is carried out for 679 images of MIST database. The images are classified in three polarities like neutral, positive and negative. The results are tabulated in the form of confusion matrix and shown in Table 6.

Table 6: Confusion Matrix For MIST Database

Predicted Class / Actual Class	Neutral	Positive Emotion Class	Negative Emotion Class	Total
Neutral	**193**	8	13	214
Positive Emotion Class	9	**188**	14	211
Negative Emotion Class	10	3	**241**	254
Total Images	212	199	268	**679**
Class wise Accuracy	**90.18**	**89.09**	**94.88**	

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Average Accuracy = [90.18 % + 89.09% + 94.88%] / 3 = **91.38%**

Class wise accuracy, false positive rate and false negative rate for MIST database are as depicted in Table 7 and graphically represented in Figure 9.

Table 7: Class Wise TPR, FPR and FNR

Emotion	TPR (%)	FPR/FAR (%)	FNR/FRR (%)
Neutral	90.18	8.96	9.81
Positive Emotion Class	89.09	5.52	10.90
Negative Emotion Class	94.48	10.07	5.11
Average values (in %)	**91.31**	**8.18**	**8.60**

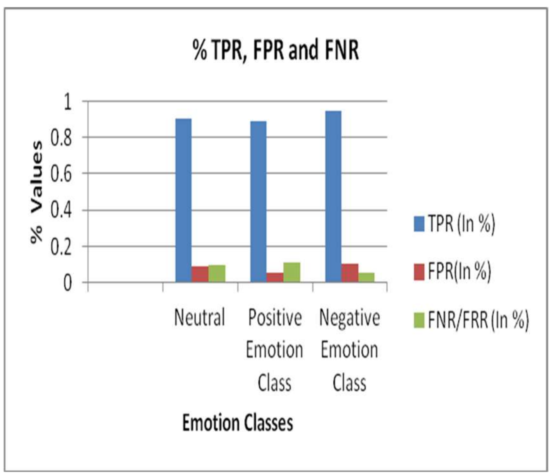

Figure 9: Graphical Representation of Accuracy, FPR and FNR for MIST Database

After mapping the emotions happy and surprise to positive emotion class; anger, fear, disgust and sad to negative emotion class and neutral as neutral class the TPR, FPR and FNR for JAFFE and MIST database are tabulated in Table 8 and graphically represented in Figure 10.

Table 8: Class Wise TPR, FPR And FNR For JAFFE And MIST Database

Emotion	TPR (%)		FPR/FAR (%)		FNR/FRR (%)	
	JAFFE	MIST	JAFFE	MIST	JAFFE	MIST
NE	93.33	90.18	9.67	8.96	6.67	9.81
PE	95.10	89.09	6.25	5.52	6.51	10.90
NE	93.37	94.48	5.62	10.07	6.67	5.11
NE-Neutral Emotion Class, PE - Positive Emotion Class, NE - Negative Emotion						

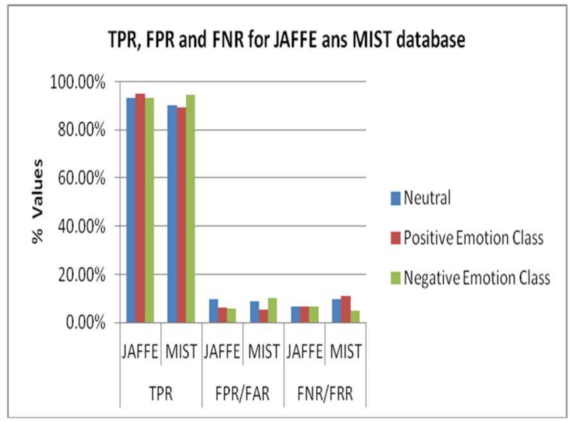

Figure 10: Graphical Representation of Accuracy, FPR and FNR for JAFFE and MIST Database

Emotion recognition time obtained for JAFFE database 1.108 sec and for MIST database 1.392 Sec.

In a nutshell, the results obtained for the proposed approach are compared with some of the relevant research carried out in the same domain and tabulated as in Table 9.

Table 9: Comparison of results

Author (Year) [Ref. No./Citation]	Feature Extraction Technique	Accuracy (In %)	Classification technique	Database Used	No of Emotions
Chao Qi et al. (2018) [21]	LBP - Local Binary Pattern	84	SVM - Support Vector Machine	CK+	6
Bing-Fei Wu et al.(2018) [22]	Deep CNN	87.78 90.57	Adaptive Feature mapping	CK+ Amsterdam DB	7
S. L. Happy et al. (2015) [23]	Facial patch based local features	94.09 96.66	SVM	CK+ JAFFE	6
Wenfei Gu et al. (2012) [24]	Radial encoding of local Gabor Features	89.67 91.51	Hierarchical Classifier	JAFFE CK	7
Proposed Approach	HoG, LBP, Gabor Filter bank	93.84 91.38	k-NN Classifier	JAFFE MIST	7

Usefulness and applicability of the work is highlighted in following section.

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6. SIGNIFICANCE OF THE WORK

Apart from predominantly classifying an image under one of the seven classes of emotion, the emotion profile allows the depiction of all the emotions for professionals to observe the degree of presence of other emotions and do the analysis accordingly. The unique representation of outcome in the form of emotion profile is significant from the perspective of recognition of complex/naturalistic emotions. The typical result for emotion recognition accuracy is above 90% which makes the approach very useful and applicable for many important applications.

The experimentation is carried out for frontal faces whereas it can be extended for pose variation and occlusion. The work can be further extended for image sequences.

7. CONCLUSION

Emotion analysis is performed on publically available JAFFE database and locally created MIST database using hybrid method and outcome is generated in the form of emotion profiles. The accuracy parameters obtained are 93.84% for JAFFE database and 91.38% on MIST database with emotion recognition time for JAFFE database 1.108 sec and for MIST database 1.392 Sec. The work undertaken has emerged into promising results which are at par with the research results published in this domain in renowned journals. The work carried out is focused on emotion detection and analysis which is much needed from the perspective of many applications prominently as e-learning, cognitive assessment, driver alert system, behavioral analysis etc. Impact of emotions on health can be studied and it may have applications in the domain of clinical psychology, behavioral analysis useful for psychometric counselors.

The outcome of this work in the form of emotion profiles which depicts naturalistic/complex emotions in unique manner. This unique approach of profiling the emotions can serve as an assistive tool for clinical psychologists, counselors, HR professionals etc. The emotions are well read even if combination of emotions are revealed by any subject under study. So this work is very apt for naturalistic emotions.

Many researchers are working on combinations of emotions and this study of complex emotions is of great help to HR professionals during recruitment process, to psychologists while interrogation of criminals, to clinical psychologists while doing behavior analysis etc.

The work can be extended to address some of the challenges like variation in pose, occlusion. The experimentation can also be extended on image sequences as future work.

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