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Facial Affect Recognition and Impact of Affect Arousal on Health Data

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Abstract: Automatic recognition of emotions is a challenging task and can be performed using single modal or multimodal inputs. It can enhance the effectiveness of human machine interaction systems and need of the time as it has applications in various domains. The study discusses the experiments carried out to capture and analyze the data which is related to human health. Images of the subjects under study are captured along with human health data and the degree of presence/absence of all seven universally accepted emotions is derived from images and depicted in the form of emotion profile. Facial affect recognition is performed on MIST database a locally created context specific database of images with health data like pulse rate, systolic and diastolic blood pressure. Emotions are categorized as neutral, positive and negative for MIST database. Accuracy obtained as 91.38%. Affect health data is analyzed for deviation in positive and negative emotion category with reference to neutral category. The inference derived from this affect health data analysis is that the observed deviation for negative emotions with respect to neutral emotion category falls into high deviation ranges for more No. of subjects as compare to deviation for positive emotions with respect to neutral emotion category.

Key words: Affect recognition, affect health data, emotion profile, blood pressure deviation, image database, respect

INTRODUCTION

Emotions are integral part of human being and have deep impact on social skills interpersonal skills and behavioral aspects (Rowe and Fitness, 2018; Takalkar and Xu, 2017; Oatley and Duncan, 1994). Emotions have close relation with human health and can impact directly or indirectly some of the physiological parameters like systolic and diastolic blood pressure, pulse rate, stress level, cardiovascular data/issues etc.

The study focuses on facial affect recognition and analysis of captured affect health data. The study further correlates emotions and affect health data as an application useful in healthcare domain. Active appearance approach which is based on hybrid features is used for facial affect recognition for this study.

Fusion of features is carried out in hybrid approach which is designed around combination of local features and global features. There are many databases available publically which can be used for facial affect recognition. These databases are JAFFE database, CK and CK+ database, KDEF database, TFEID, MMI database etc. These databases provide universally accepted seven emotions through varied number of subjects.

The emotion theories and emotion models suggests that some of the physiological parameters are related with affect. Parameters like systolic and diastolic blood pressure, pulse rate are studied in details. The impact of affect arousal on these health parameters is studied through experiments carried out specifically for the research undertaken and analyzed in details. The inference derived from this study is presented later in performance analysis subsection of the study.

The study is further developed under different headings such as overview of related work, details of database used for experimentation, health parameters captured through experiments, methodology of implementation, experimental results and performance analysis, application of the study, conclusion and future work.

Literature review: This study summarizes the relevant work done by researchers and scientists across the world and published in renowned Journals.

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Sariyanidi *et al*. (2015) have 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 researchers 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.

Ane and Patwary (2016) 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 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.

Sanchez-Gonzalez *et al*. (2015) examined whether Negative Affectivity (NA) and forgiveness were independently related to aortic hemodynamics and the Subendocardial Viability Index (SVI), a marker of coronary perfusion. Aortic hemodynamic parameters via. applanation tonometry were assessed at rest and during sympatho stimulation. Hierarchical multiple regression analyses of resting values showed that NA was related to higher Aortic Blood Pressure (ABP) and lower SVI. After controlling for demographics and for NA, Tendency to Forgive TTF scores were significantly associated with decreased ABP but increased SVI. Results indicate that NA significantly predicts ABP and decreased SVI. Conversely forgiveness seems to provide cardio protection by evoking decreased ABP while improving SVI.

Delgado *el al*. (2014) analyze differences in Blood Pressure (BP) and Baroreflex Sensitivity (BRS) in relation to trait worry. Cardiovascular parameters of the subject under study were obtained during rest, a self-induced worry period and defense reflex to intense auditory stimulation. Study concludes that low proneness to worry is associated with greater BP and BRS. Increases in BP during aversive stimulation activated a negative feedback mechanism to inhibit distress and emotional reactivity to negative stimulation. These results support the BP emotional dampening hypothesis and suggest that the baroreflex can be a relevant mechanism in mediating this effect.

James *et al*. (1986) have examined differences in blood pressure associated with reported happiness, anger and anxiety. The results show that emotional arousal significantly increases systolic and diastolic pressure ($p<0.00001$) an effect independent of posture and location of subject during measurement (at work, home or elsewhere). On average, pressures during reported angry or anxious states were higher than those during a happy state ($p<0.01$). Examination of arousal intensity showed that scores on the happiness scale were inversely related to systolic pressure ($p<0.01$) whereas the degree of anxiety was positively associated with diastolic pressure ($p<0.02$). Emotional effects were also related to the degree of individual daily pressure variation such that the greater the variability, the larger the blood pressure change associated with the emotions. The results suggest that happiness, anger and anxiety increase blood pressure to differing degrees and that emotional effect may be greater in individuals with more labile blood pressure.

Barnes *et al*. (2012) performed a study to determine the impact of school-based Williams Life Skills training on anger, anxiety and blood pressure in adolescents. The study finds that anger and anxiety scores decreased and anger control scores increased in the WLS group across the 6 months follow-up period compared to the CTL group (group x visit, $p<0.05$). The study concludes that daytime diastolic BP was lower across the follow-up in the WLS group ($p = 0.08$). The DBP was significantly lower across the follow-up period in the WLS group among those with higher SBP at baseline ($p = 0.04$).

With the literature surveyed, the health parameters like systolic and diastolic blood pressure and pulse rate are studied in depth. The literature also highlights the relation of negative affectivity with blood pressure and pulse rate and also motivates to study, experiment and analyze the impact of affect arousal on health data.

Details of the database used for experimentation: A context specific database is locally created wherein along with images health data such as systolic blood pressure, diastolic blood pressure and pulse rate are also captured. This database is referred as MIST database in further sections of the study.

Database preparation an overview: Total 45 subjects participated in the database preparation process. The age group of subjects is in the range 22-35 years with average age as 25 years. The 30% participants were male and rest 70% participants were female. Two experiments are carried out for image database preparation and health data collection. The 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. The 30 subjects participated in second experiment and total 540 images are captured along with measurement of health data. Altogether total 855 images are captured. Validation of database is carried out by experts and kappa statistics is used to verify the reliability of data using inter rater agreement. Kappa coefficient value achieved as 0.87

which indicates the database validity range as 64-81%. Experimentation is carried out on 679 images out of 855, i.e., 79% images as experts could not identify a unique label/label for single polarity of emotion for rest 21% of the images. The sample space is of valid database 679 which is sizable to perform the experiments.

Database preparation details: Emotional corpus methods are available in the form of natural emotions, simulated emotions and induced emotions. Experiments are carried out to induce emotions in subjects under study. Different stimuli used for arousing/inducing emotions. The details of experiments carried out, the No. of subjects participated in experiment etc. are as explained under following subsections titled as description of experiment 1 and description of experiment 2.

Description of experiment 1: As a part of database preparation the affect data like systolic blood pressure, diastolic blood pressure and pulse rate is recorded along with capturing images for induced emotion corpus method. Specific videos and different solo and group activities/fun, relaxing games are used as stimuli for induction and arousal of emotions. Data is collected for neutral state, positive emotional state and negative emotional state. The 15 subjects participated in this experiment.

Experiment is divided into three phases. In phase 1, images and blood pressure, pulse rate data is captured in neutral mode for all the participating subjects. Around 7/8 images are captured for each subject.

In phase 2, subjects are aroused for positive emotions via. playing some games, group activities and playing funny videos prior to capturing images and health data for all the participating subjects. Around 7/8 images are captured for each subject.

In phase 3, subjects are aroused for negative emotion polarity by some activities and making them to invoke their deep buried memories and experiences through creating an impact making environment via. narration and continued by playing sad videos. Around 7/8 images are captured for each subject. All the three phases provide 315 images for experimentation from experiment 1.

Description of experiment 2: The stimulation tool used for this experiment is significant and important academic evaluations. During the experiment images are captured and blood pressure and pulse rate are recorded for each subject before start of the evaluation process when subjects under study were in stress/tension, i.e., negative emotion polarity and after the evaluation process when subjects were relaxed, i.e., positive emotion polarity.

Table 1: Mapping of universally accepted emotions with polarity of emotions

Universally accepted emotions	Polarity of emotions
Neutral	Neutral
Surprise	Positive emotion polarity
Happy	
Sad	Negative emotion polarity
Fear	
Disgust	
Anger	

Table 2: Interpretation of k statistics

Value of kappa	Level of agreement	Percentage 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

Health data and images are captured in neutral emotion category as well. The count of subjects participated in experiment 2 is 30. For each of the neutral, positive and negative polarity, 7/8 images of each subjects are captured. The experiment 2 provides altogether 540 images for experimentation.

The images captured through experiment 1 and 2 constitutes MIST database comprising of total 855 images. Experimentation is carried out to recognize all seven universally accepted emotions but analyzed for 3 emotion polarities. Mapping of these 7 emotions with 3 emotion polarity is as represented in Table 1.

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 Fleiss 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 value of k represent the inter rater agreement (Viera and Garrett, 2005) as shown in Table 2.

For MIST database the k value is obtained as 0.87 which leads to an interpretation that raters are in strong agreement with each other and 64-81% of data is reliable. Experimentation is carried out on 679 images out of 855 images of database which counts as 79% of database. This is a sizable amount of data to perform experimentation.

Details of health data: Systolic blood pressure, diastolic blood pressure and pulse rate are the health related parameters chosen for study. Description of these physiological parameters is provided in following subsections.

Description of health data: Blood pressure is one of the health indicators and measured in mmHg-millimeters of mercury above the atmospheric pressure. Blood pressure is represented in the form of two numbers, the upper one is known as systolic blood pressure and the lower one is known as diastolic blood pressure. When blood is pumped by heart the force of blood pushing against walls of blood vessels is called as blood pressure. Systolic blood pressure is the maximum value during one heart beat and diastolic blood pressure is the minimum value between two heart beats. Pulse pressure is the difference between measured systolic pressure and diastolic pressure (Klabunde, 2007). The MAP mean arterial pressure is measured over a cardiac cycle and represented as average over the cycle which is also of significance. Mean arterial pressure is governed by Cardiac Output (CO), Central Venous Pressure (CVP) and Systemic Vascular Resistance (SVR). In practice CVP is ignored, so, mean arterial pressure is represented as $MAP = CO*SVR$. The mean arterial pressure can also be calculated through systolic and diastolic blood pressure (Klabunde, 2007). Mean arterial pressure is equal to summation of diastolic blood pressure and one third of the difference of the systolic and diastolic blood pressure. To measure the arterial pressure the measuring equipment used is sphygmomanometer which mainly uses the column of mercury. The height of column of mercury represents circulating pressure (Booth, 1977). Now a days measuring equipment is also used for blood pressure measurement which uses the oscillometric method (Forouzanfar *et al.*, 2015) for measurement. The device designed based on this method does not actually use mercury but reflects blood pressure readings in millimeters of mercury only. Recommended blood pressure range is as shown in Table 3.

Studies show that blood pressure is affected by various reasons like activities, relative health states, emotional states, situations and mainly influenced by total peripheral resistance, arterial stiffness and cardiac output. Blood pressure is regulated by baro-receptors which are activated by brain and impact nervous and endocrine systems. Observational studies states that those who are able to maintain the blood pressure at lower ends of the given ranges have better cardiovascular health, however, there is ongoing medical debate over the optimum level of blood pressure to target in case of prescribing medication specially for older people (Yusuf and Lonn, 2016).

Captured data through experiments: As a part of database preparation the affect data such as blood pressure and pulse rate is recorded along with capturing images for induced emotion corpus method. Table 4 indicates sample data collected through experiment 1 and 2.

This captured health data is in the form of pulse rate, systolic and diastolic blood pressure in all the three polarities of emotions which is analyzed in study titled as experimental results and performance analysis and further correlated with affect in study titled as application in healthcare.

Table 3: Range of blood pressure

Blood pressure category	Systolic blood pressure (mmHg)	And/or	Diastolic blood pressure (mmHg)	Suggestions/remarks
Hypotension	<90	and	<60	
Normal/desirable	<120 but more than 90	or	<80 but more than 60	Balance diet and enjoying regular physical activities
Pre-Hypertension	120-139	or	80-89	Adopting heart healthy lifestyle Balanced diet, low salt diet and regular exercise
Hypertension stage 1	140-159	or	90-99	Prescribe life style changes and doctors may consider adding blood pressure medication
Hypertension stage 2	160 or higher	or	100 or higher	Prescribe combination of medication and life style changes
Hypertensive crises	>180	or	>110	May require emergency medical attention

Table 4: Health data collected for positive and negative emotions

	N			PE			NE		
SC	S	D	PR	S	D	PR	S	D	PR
S1	132	84	74	145	87	78	150	91	80
S14	102	69	69	101	63	71	101	67	103
S29	137	85	102	134	68	91	143	86	105

N: Neutral; PE: Positive Emotion; NE: Negative Emotion; SC: Subject Code; S: Systolic blood pressure; D: Diastolic blood pressure; PR: Pulse Rate

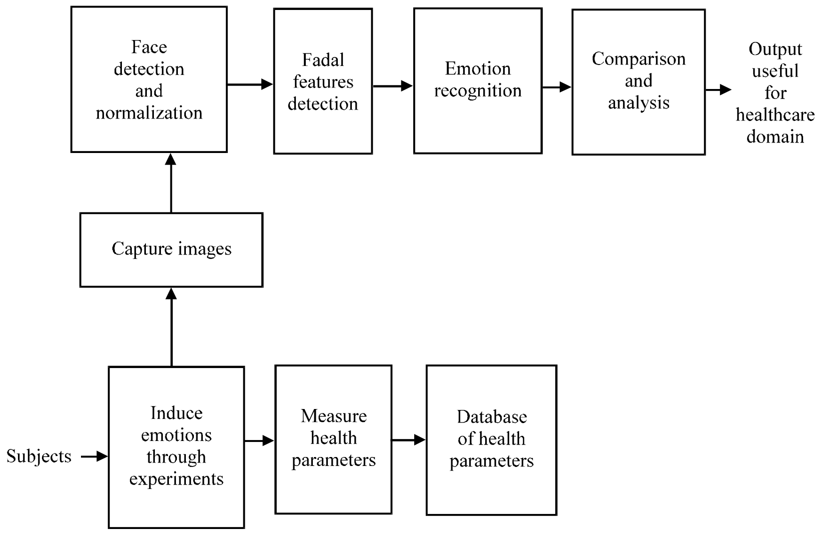

Fig. 1. System block diagram

MATERIALS AND METHODS

Methodology of implementation

Facial affect recognition: This study describes block diagram of proposed system, emotion recognition through facial expressions and obtain 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.

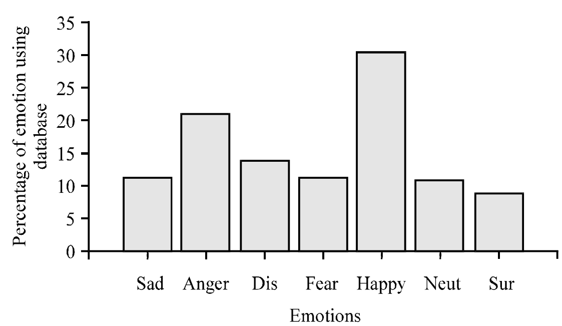

Fig. 2: Sample emotion profile

System block diagram: The block diagram of system designed for study is as shown in Fig. 1. The study is targeted for emotion detection through facial expressions and relation of negative and positive affect with health parameters. The researcher carried out described in three parts.

First part talks about preparation of image database along with health parameters like systolic blood pressure, diastolic blood pressure and pulse rate. This is already discussed in details in previous studies.

The second part describes emotion recognition through facial expressions as elaborated in this subsection. The third part is to correlate the recognize affect with health indicators. Analysis and comparison block integrates end result of first and second part and discussed in details in study titled as application in healthcare domain.

Facial affect recognition: Facial affect recognition is carried out for MIST database. Hybrid approach is used for emotion recognition. Face is detected from image of each subject. Image is normalized through preprocessing. Features are extracted using HoG (Histogram of Gradients) LBP (Local Binary Pattern) and Gabor filter bank. All these features are concatenated and dimensionality of feature vector is reduced through PCA (Principal Component Analysis). Classifier used is kNN (kNearest Neighbors) to classify the input images further in 7 different classes like neutral, anger, fear, disgust, sad, happy and surprise mapped to neutral, positive and negative polarity. Distance metric is used to represent the identified emotion and degree of presence/absence of all other emotions is represented in the form of a profile called as emotion profile. One of the sample output depicting detected dominant emotion is surprise as presented in Fig. 2. In computer vision and pattern recognition applications one of the popular feature descriptors used is HOG (Histogram of Gradients). HOG descriptor (Allaert *et al.*, 2018; Dalal and Triggs, 2005) is

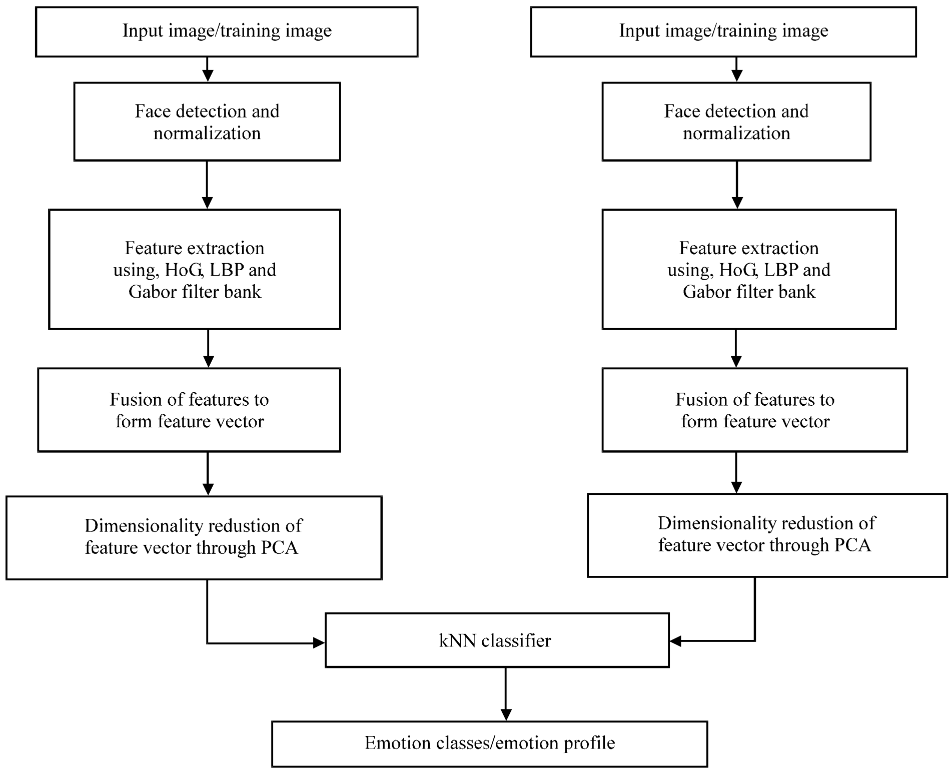

Fig. 3: Implementation flow and steps

concatenated vector of normalized cell histograms from all the block regions. HOG descriptor is invariant of geometric and photometric transformation as it operates on local cells. Block normalization offers better accuracy. Robustness against gray scale changes and computational simplicity is offered by LBP (Local Binary Pattern) (Zhang *et al*., 2010) and hence, it makes it qualify to be one of the popularly used feature descriptors for real world applications. LBP is an efficient operator in which pixels are labeled by thresholding the neighborhood of that pixel and result is obtained as binary number. The method experimented for this study is hybrid in nature, so, along with HOG and LBP feature descriptors, the use of global feature descriptor offers some additional benefits, hence, Gabor filter bank (Zhang and Tjondronegoro, 2011) of 8 scales and 5 orientations is used to extract global features. Final feature vector is fusion of HOG, LBP and Gabor filter bank, so, dimensionality of final feature vector is quite high. PCA (Principal Component Analysis) is used for reduction in dimensionality. PCA computes principal components (Abdi and Williams, 2010; Deng *et al*., 2005; Sun and Wen, 2017) which are obtained as linear combination of original variables. k nearest neighbors is used as classifier which provides output in the form of class membership. The best choice of k depends on data. The accuracy of k-NN classifier (Coomans and Massart, 1982; Nugrahaeni and Mutijarsa, 2016) is impacted to a large extent by presence of noisy or irrelevant features or if feature scales are not consistent with their significance. The implementation steps involved are as presented in Fig. 3. Identified emotion from emotion profile can be correlated with the appropriate values present in health database and can be analyzed further.

RESULTS AND DISCUSSION

Experimental results and performance analysis: Experimentation is carried out on MIST database. Classifier is trained using 66% of images and tested using 33% of images. After testing the image emotions revealed by image are given as output in the form of emotion profile. Sample snapshots show 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. Some of the sample screen shots for the emotion class happy are shown from Fig. 4a-d.

Performance analysis is carried out for image database and affect health data captured through experiments. The details are discussed in following subsections.

Table 5: Confusion matrix for MIST database

Predicted class (column wise) Actual class (row wise)	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 (%)	

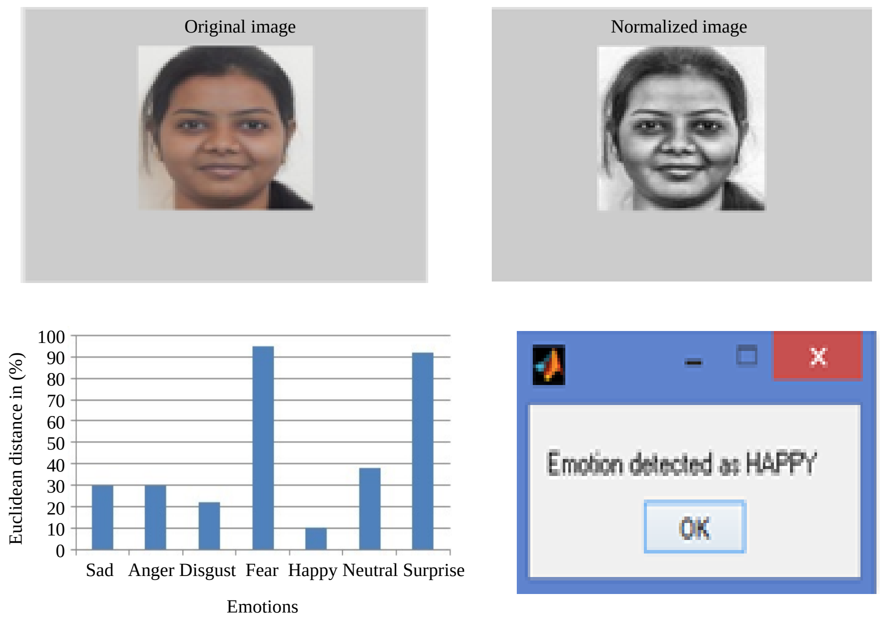

Fig. 4: a) Original image; b) Normalized image; c) Emotion profile and d) Output

Performance analysis of image database: Experimentation is carried out for 679 images of MIST database. The images are classified in three polarities such as neutral, positive and negative. The results are tabulated in the form of confusion matrix and shown in Table 5. Average accuracy = [90.18%+89.09%+94.88%]/3 = 91.38%.

Class wise accuracy, false positive rate and false negative rate is as depicted in Table 6 and graphically represented in Fig. 5.

Facial affect recognition time obtained for MIST database 1.392 sec. Experimentation is also carried out on JAFFE database which is publically available standard database popularly used by researchers.

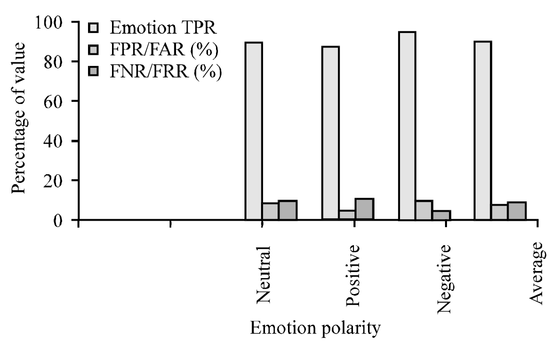

Fig. 5: Graphical representation of accuracy, FPR and FNR for MIST database

Performance analysis of affect data: Sample health data containing values of blood pressure and pulse rate of both the experiments is tabulated in Table 4. This data is analyzed and the deviation for positive and negative emotions with respect to neutral emotion is calculated. The deviation is distributed into various ranges and calculation is performed for No. of subjects falling into which deviation range. Deviation range vs. number of subjects is plotted in graphical form represented from Fig. 6-9. The inference derived from graphs shown in Fig. 6-10 is as follows: more No. of subjects have shown deviation for systolic blood pressure in positive emotion but the range of deviation is small, so, fluctuation in blood pressure may remain in prescribed range by American Medical Association.

Table 6: Class wise TPR, FPR and FNR for MIST database

Motion	TPR (%)	FPR/FAR (%)	FNR/FRR (%)
Neutral	90.18	8.96	9.81
Positive emotion class	89.09	5.52	10.90
Negative emotion class	94.88	10.07	5.11
Average values (%)	91.38	8.18	8.60

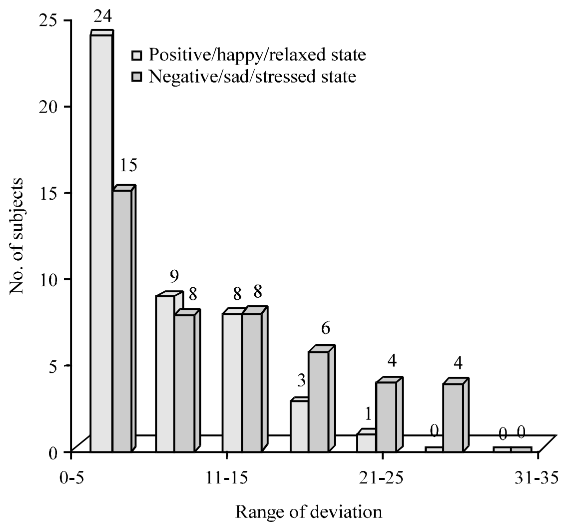

Fig. 6: Range wise deviation of systolic blood pressure

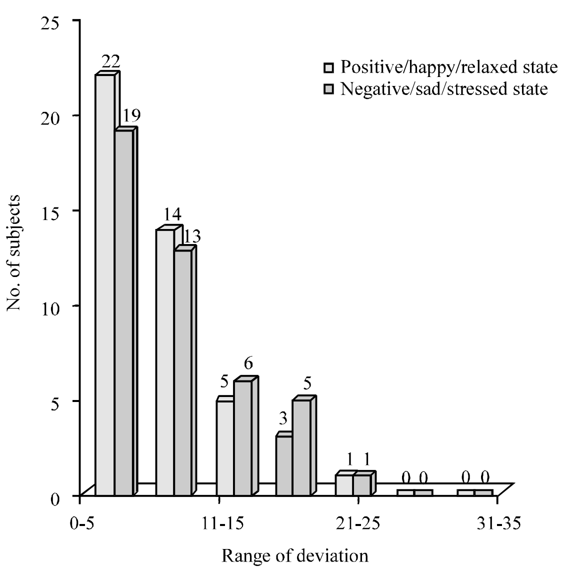

Fig. 7: Range wise deviation of diastolic blood pressure

Large deviation is observed for more No. of subjects for systolic blood pressure in negative emotion. His large value, (i.e., around 20) of fluctuation in blood pressure may shift blood pressure in next higher range prescribed by American Medical Association.

Similar observations are true for diastolic blood pressure with respect to positive and negative emotions

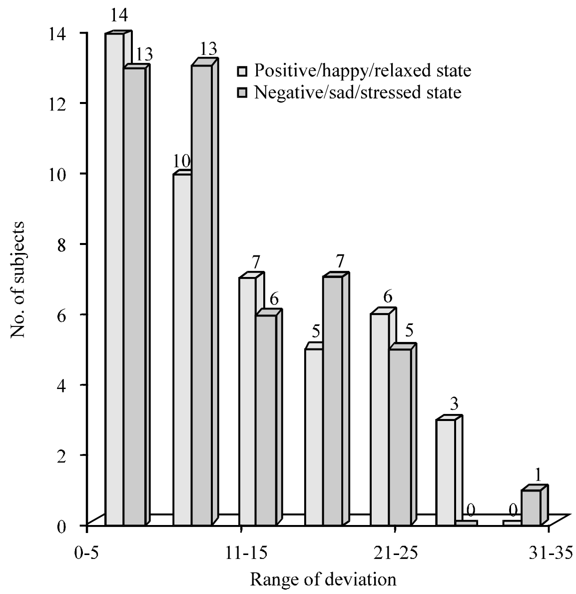

Fig. 8: Range wise deviation of pulse rate

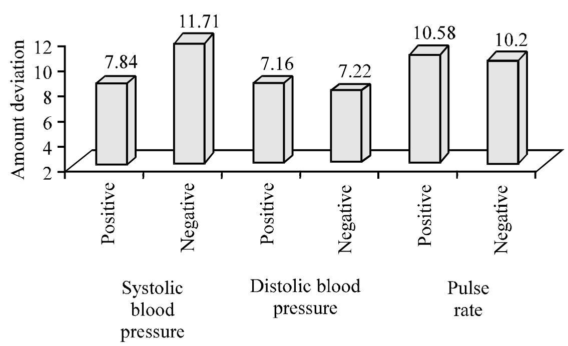

Fig. 9: Average deviation of affect data

but the No. of subjects undergone through large fluctuations are less in No. so, impact of deviation in blood pressure does not seem to be significant.

No consistent observation is found w.r.t pulse rate variation for negative as well as positive emotion. The No. of subjects undergoing the change varies and count is high for some deviation ranges for positive emotion and high for some other deviation ranges for negative emotions.

Average deviation for affect health data is more for negative emotion category. So, the frequent mood swings are not good from health perspective. Frequent and large fluctuations in blood pressure must be taken seriously as the values of health parameters may fall into next category as specified in Table 3. Awareness about this aspect can be spread in community at large for well-being of society.

Application in healthcare: Affect detection and analysis is much needed from the perspective of many applications prominently as e-Learning, cognitive assessment, behavioral analysis etc. Impact of emotions on health can be studied and it may have applications in healthcare domain.

One of the applications of this study is usefulness from the perspective of clinical psychologist and psychometric counselors. As a part of therapy/treatment, there might be multiple sessions of counselor and patient. For each session and during session the images of the patient can be captured and variation in emotion polarity can be observed by counselor. There are past records of the patient about deviation of blood pressure, pulse rate, mean artery pressure etc. which are indirect indicators of stress. With the help of history of image data and records of the health parameters the probabilistic values can be predicted. This application can serve as assistive tool for clinical psychologists, psychometric counselors etc.

CONCLUSION

Emotion analysis is performed for locally created MIST database using emotion profile based method. The accuracy parameter obtained is 91.38% on MIST database with affect recognition time as 1.392 sec. The health data of systolic blood pressure, diastolic blood pressure and pulse rate captured through experimentation is analyzed and gives the inference that large deviation is observed for more No. of subjects for systolic blood pressure in negative emotion. This large value, (i.e., around 20-25) of fluctuation in blood pressure may shift blood pressure in next higher range prescribed by American Health Association. Deviation in blood pressure is indirect indicator of stress level. Probable application of integration of emotion recognition and health data analysis can be used as assistive tool in clinical psychology domain. This study can have application for behavior analysis, stress prediction etc.

The study can be extended for video analysis as future research. Innovative experimentation can be carried out for arousal of emotions.

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