A Machine Learning Approach to Classify Emotions using GSR

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Abstract—*Recognition of emotions from physiological signals has received wide attention from research community in recent years. While contemporary human computer interaction (HCI) systems lack of emotional intelligence, it is one of the most actively pursued goals in HCI. Electro-dermal response (EDR) is one way to measure peripheral sympathetic nerve activity that can encode emotions in terms of physiological signals. Galvanic skin response (GSR) is one of the facile techniques to measure electro-dermal responses and easy to use. This study reports an attempt to classify emotions by using GSR and Machine learning algorithm. Video stimuli of basic emotions based on Navarasa theory were shown to participants and GSR was recorded. By using artificial neural network four emotions were found to be classified with average accuracy of 70%.*

Keywords*: Electro-dermal response, GSR, HCI, ANN*

1. INTRODUCTION

Emotions are fundamental part of our every-day life which dominates our daily activity like communication, learning, decision making, cognition, perception etc. However, importance of emotions has been ignored by technology over the years. This lack of emotional interaction has made using technology dry and inhuman. To establish a good interaction between machine and human, there is a need to consider emotions and its role in human machine interaction. Role of emotion in human computer interaction has captivated wide attention of different research community across the globe. For last two decades, various attempts have been made to encode emotions in terms of physiological changes. Dr. Rosalind W Picard from MIT media lab coined the term “Affective computing” for this area of research where affects is synonyms of emotions [1].

Emotions bring different changes in human physiology like facial expressions, skin conductance, heart-rate, body temperature, pulse rate, brain signals etc. For example fear releases excessive amount of sweat and happiness makes our body warm [2]. Recent advancements in biomedical devices enable us to identify even a smallest change in these physiological parameters by using tools like (EEG), electrocardiogram (ECG), galvanic skin response (GSR), heart rate variability (HRV) [3] [4] [5].

Machine learning is one of the artificial intelligence (AI) tools that provide computers with the ability to learn without being explicitly programmed. Machine learning focuses on the development of computer programs that can teach themselves to evolve when exposed to new data. Nowadays Machine learning and Artificual intelligence have changed the way of complex computing technique completely. Machine learning is very useful tool to predict the outcome based on the probabilistic and fuzzy approach. All is the reason that motivated author to bring affective computing and machine learning together.

Affective computing could offer benefits in an almost limitless range of applications. For example, in e-learning situations, the computer could detect from available cues when the user was having difficulty and offer expanded explanations or additional information. Other applications include e-therapy: psychological health services, interactive applications for autistic kids, affective computer, affective user interfaces in mobile and PC’s.

1. Emotion and Electro-dermal response

Out of available physiological measurement tools, GSR is easy to use, comfortable to wear and low cost technique. Galvanic Skin Response (GSR) is one of several electro-dermal responses. Electro-dermal response (EDR) is more likely a medically preferred term for change of electric skin resistance due to psychological conditions. EDR is the change in the electrical properties of a person’s skin caused by environmental events as well as individual’s psychological state. The change is caused by the degree of which a person’s sweat glands are active. Since sweat gland activity is controlled by sympathetic nerve activity, it can be a significant characteristic in measurement of emotion physiologically. The main function of the skin is to protect the body from the environment. One aspect of this is to prevent the loss of water by the body. However, at the same time, the evaporation of water as a means of regulating body temperature must be facilitated. These requirements appear to be carried out by the stratum corneum as a barrier layer that prevents the loss of water to the outside except through the sweat glands, whose activity can be controlled. This in turn is mediated by the autonomic (sympathetic) nervous system. Measurement of the output of the sweat glands, which EDR is thought to do, provides a simple gauge of the level and extent of sympathetic activity. This is the simple and basic concept underlying EDR and its application to psychophysiology.

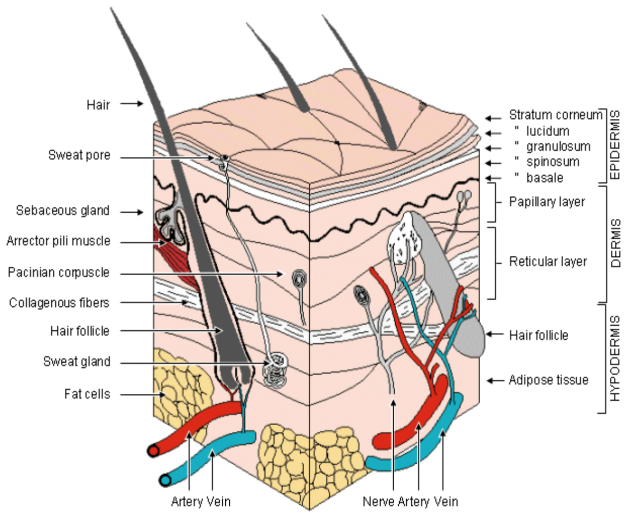

Fig. 1: Section of smooth skin taken fromthe sole of the foot (Redrawn from Ebling, Eady, and Leigh, 1992.)

EDR by using GSR can be one of the ideal ways to monitor the autonomic nervous activity. Skin electrodes, placed at the palmer surface because of the more involvement of the sweat glands in this area. Z. Khalili reports that GSR is one of the best peripheral tools to map autonomic nervous activity [6]. He used IAPS images as stimuli and classified six basic emotions with accuracy of 55% with peripheral signals. Mohammad Soleyman used video stimuli and recorder GSR with EEG [7]. He classified eight basic emotions with accuracy of 46-48 % with peripheral signals. But while using with EEG he achieved an accuracy rate upto 76%. P.A. Vijaya also used video stimuli recording GSR and classified four emotions, happy, surprise, disgust and fear with average accuracy of more than 80% [8]. Sander Koelstra reports in DEAP database that the skin resistance decreases due to an increase in perspiration, which usually occurs when one is experiencing emotion such as stress or surprise [4]. Lang mentions that mean value of the GSR is related to the level of arousal [9]. Wilson analyzed several physiological measures during different steps of flights and found out an increase in EDA response during take-off and landing which were expected to place the most cognitive demands on pilots [10]. Ikehara evaluated GSR in relation with two levels of cognitive load. In contrast with other studies, they found skin conductance to decrease as task difficulty increases and explained it as a result of the easy task being tedious and too easy [11]. Alterations in electro-dermal activity with respect to emotion gives raise the possibility of affect recognition in human computer interaction.

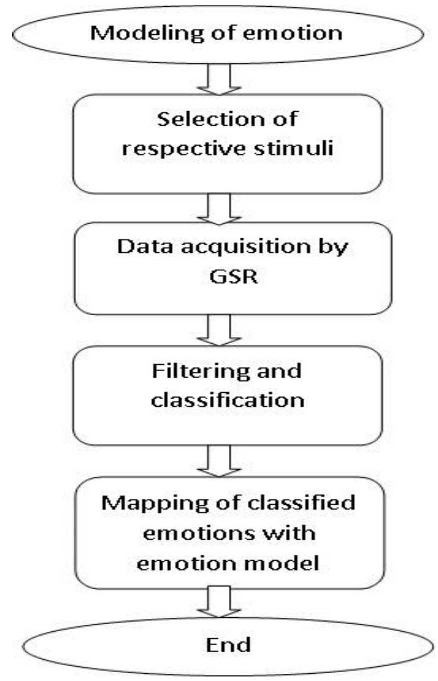

Fig. 2: Flow chart of classification model

1.2 Model of emotions for Computational purpose

Ever since the concept of understanding emotion through physiological means was recognized and term affective computing was coined by R. Piccard, It grabbed attention of many research community comprising Psychology, neuroscience, neuropsychology, physics, and engineering. To map emotions through physiological measures, it is very important to identify possible types of emotions. Two approaches can be found in literature to model emotions. One is mapping of individual emotions and another is representation of emotion on multidimensional space [12]. In first category, Plutchik proposed eight basic emotion states: anger, fear, sadness, disgust, surprise, anticipation, acceptance, and joy [13]. Ekman used model of six emotions while studying of relation associated with facial expressions: anger, disgust, fear, happiness, sadness and surprise. Later Ekman expanded the basic emotions by adding amusement, contempt, contentment, embarrassment, excitement, guilt, and pride in achievement, relief, satisfaction, sensory pleasure, and shame [14]. From the dimensional perspective, the most widely used classification is the bipolar model - valence and arousal dimensions advocated by Russell [15]. Valence represents the quality of an emotion, ranging from unpleasant to pleasant. Arousal denotes the quantitative activation level, from not aroused to aroused. Later a three dimensional Pleasure-Arousal-Dominance (PAD) model was proposed by Mehrabian and Russell [16] [17]. In this model, besides the arousal and valence dimensions, an additional dimension called dominance is added.

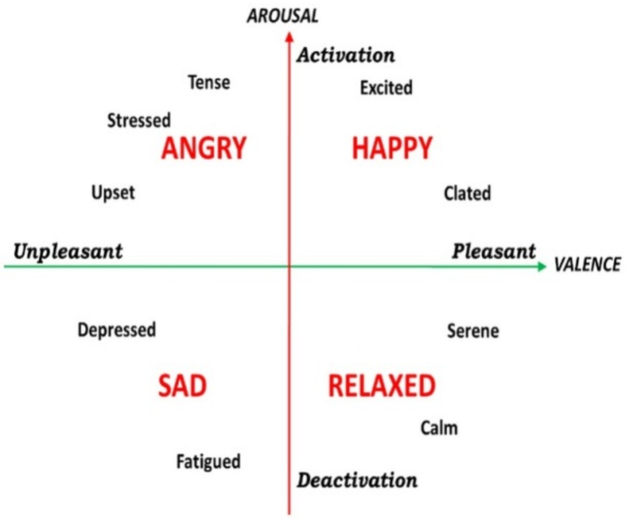

Fig. 3: Arousal valance bipolar model by Russel [15]

Ancient Indian dance and dramatics literature has described the process of elicitation of emotions and has identified nine emotions in called as Navaras [18]. This paper has taken its understanding of emotions form the 'rasa' theory and the 'Navaras model'. The nine emotions described in 'navarasa model' are Shringara (love), Hasya (laughter), karuna (compassion), Rudra (anger), Veera (courage), Bhayanaka (terror), Bheebhastya (disgust), Adbhuta (surprise), and Shanta (peace). Out of these nine emotions, Shringara (love), Raudra (anger), Veera (courage) and Bheebhatsya (disgust) are considered as four primary emotions [19]. This paper has selected the four emotions described as primary emotions in 'navarasa model".

2. EXPERIMENT DESIGN

2.1 Stimuli selection

In this study, the aim was to model emotion physiologically using GSR. As literature suggests in section 1.1, the video stimuli being the most impactful, in this study video clip of 4-5 minutes were used as experiment stimuli. The process for selection of the stimuli is as follows. Around 100 video clips were screened from available library as well as internet. Screening was done by author and two more scholars. Out of 100 clips, total of 10 clips were filtered out. As discussed in section 1.2, rasa is the developed relishable state of a permanent mood. Therefore it is necessary to take proper time gap to avoid the influence of the emotion depicted by previously seen videos. Time gap of 2-3 days was taken between different stages in selection process of the videos to avoid bias due to prior mood developed from past viewing of video clips leading to permanent mood. These 10 Video clips were selected based on the four primary emotions described in navarasa. Out of these 10 clips, final 4 videos were screened out based on verbal feedback rating of 15 people. Through feedback of participants in initial study, final four videos were selected for further experiment using GSR. It was ensured that video clips stimulate respective emotions.

Table 1: Video clip details causing stimulation of specific emotions

Video clip name	Stimulated Emotion	Participants feedback on 10 scale		
		Average	Max	Min
Pehla nasha	Love (happy)	8.5	10	5
Best inspirational	Courage	8.3	9.5	6
Nirbhaya BBC doc	Anger	8.1	9	6
Worms eating	Disgust	8.8	10	7

2.2 Participants selection

Total 10 participants (6 male and 4 female) of different age groups (24-51, with a mean of age 29.8) were selected. These participants were among the master's students, research scholars or project staff. Selection of the participants was based on the standard set of questionnaire which ensures that they fit for the experiment. It was ensured that the participants had proper sleep, no drugs consumption and no other health issues prior to the experiment. It was also ensured that they are not going through any mental stress or personally caused emotions.

2.3 Experiment setup and procedure

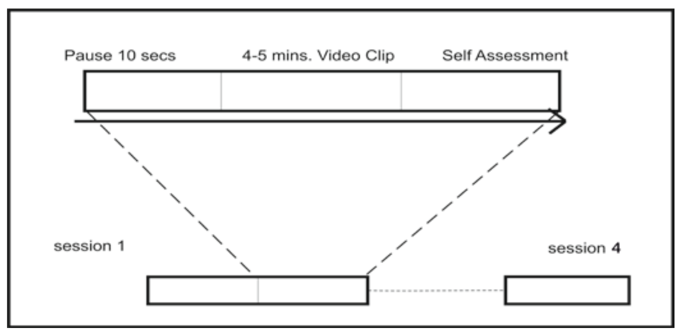

Fig. 4: The procedure of experiment session

An adequate environment was maintained that no external and unwanted stimuli like sound or light can disturb the participants. Each participant was presented with a trial case, followed by a 2 minutes baseline recording without the experimenter, which allowed them to familiarize with the system before the actual recordings. After this, the 4 trials were performed. Following steps are followed in experiment.

- Informing the participant of their progress
- 5 seconds baseline recording
- Displaying one of the 4 movie video segments
- Self-assessment feedback

All four videos of 4-5 minutes duration were played in a queue with a gap of 1 minute. After every video participant was asked to report self-assessment feedback for the emotion they have undergone through.

2.4 Apparatus

In all the experiments Neulog GSR with sapmling rate of 128 Hz and ADC resolution of 16 bits was used. EDA is best measured at palmer sites. Suggested locations for electrode placement are given in Figure 5. In general, the electrodes used were of the Ag/AgCl type which are recessed from the skin and require the use of a suitable electrode paste. Since this is a reversible type of electrode, polarization and bias potentials are minimized. Electrodes were placed in middle and index finger as per standard rule. Stimuli were played on 17 inches screen and with good quality of audio speakers. To calssify emotion, neural network toolbox of Matlab 2014 verson was used.

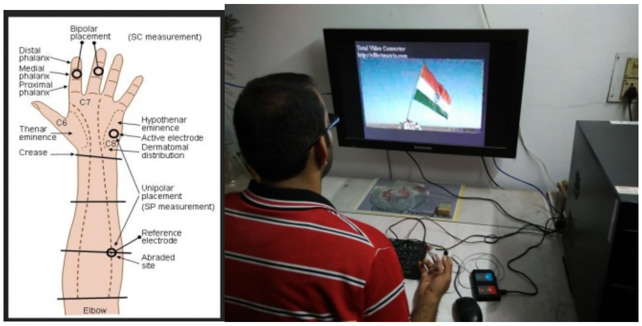

Fig. 5: Suggested electrode sites on the palm for the measurement of skin resistance and experimental set-up.

3. RESULTS AND ANALYSIS:

Results have been categorized in two parts, one is an observable comparison which shows the GSR characteristics over different emotions and other is artificial neural network approach to classify emotions.

3.1 Observable comparison:

While recording the data, a baseline was recorded in resting mode for two minutes. Baseline data was subtracted from the main database for every emotion. Final outcome for every emotion was compared in fig.6.

It is evident from the graph that love shows clearly distinct feature whereas anger and disgust show very minute difference which is in well agreement with verbally reported results by participants. Graph of Courage shows high conductivity which is significant mark of high arousal. It can be also conclude from the spectra that courage, anger and disgust show initially low arousal and later it reaches to peak and then settle down.

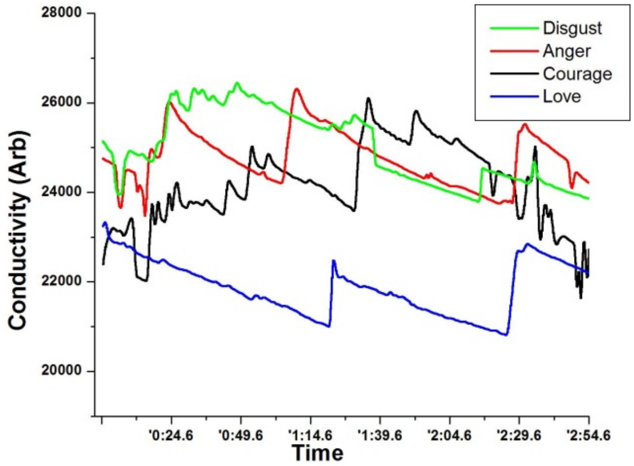

Fig. 6: GSR conductivity spectra for all four different emotions

Artificial neural network approach

To avoid the complexity and size of matrix, each dataset (4 emotions*10 participants) was broken in ten small datasets of similar string lengths. To extract features, mean deviation and standard deviation was calculated for every 400 datasets. Features of seven participants were used as training data and rest three as testing data. Four distinct classes were defined four different emotions. A network of two layers was created with 50 neurons.

Maximum no of validation checks was defined as 1000.

Mean square error was obtained very low of 0.032 at epoch 1000.

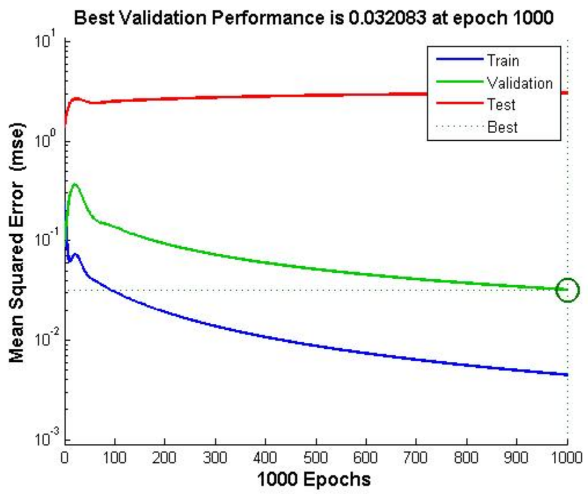

Fig. 7: training and validation spectra

Performance curve was plotted in fig.8 which clearly shows all four distinct classes with R-value of 0.76. Well linear training curve was obtained in log plot.

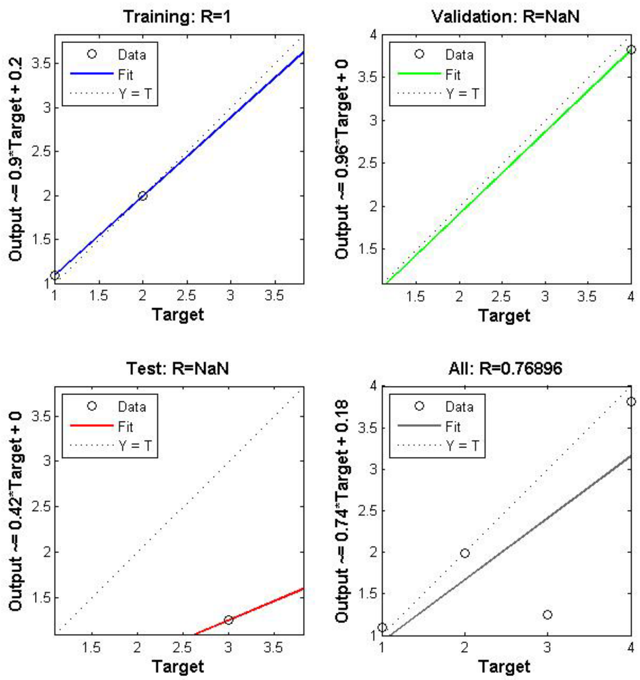

Fig. 8: Performance plot and regression curve

Emotions were predicated by using testing samples and classification accuracy was calculated for all different emotions. Maximum accuracy of 76% for emotion love was achieved whereas anger shows minimum accuracy.

Table 2: classification accuracy for all four classes

Emotion	Love	Courage	Anger	Disgust
Accuracy	76%	69%	61	63%

4. CONCLUSION

This paper has explored the possibility that emotions can be decoded in terms of physiological signals. GSR can be an effective and supportive tool to measure peripheral nervous activity. Verbal reported feedback and physiological results were found in well agreement which shows our system follows almost ground reality. Average classification accuracy of more than 70% was achieved when neural network tool was used to model the affect maps. By the study we can analyze and conclude that positive emotion like love and courage is easy to predict but negative emotion like anger and disgust was hard to distinct. In future larger sample size and multimodal approach with EEG, ECG, HRV, and BP etc can lead to better accuracy and precision.

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