An Emotion Recognition Based on Physiological Signals

Arvind Kumar, Nidhi Garg, Gurpreet Kaur

Abstract*: Emotion recognition is alluring considerable interest among the researchers. Emotions are discovered by facial, speech, gesture, posture and physiological signals. Physiological signals are a plausible mechanism to recognize emotion using human-computer interaction. The objective of this paper is to put forth the recognition of emotions using physiological signals. Various emotion elicitation protocols, feature extraction techniques, classification methods that aim at recognizing emotions from physiological signals are discussed here. Wrist Pulse Signal is also discussed to fill the lacunae of the other physiological signal for emotion detection. Working on basic as well as non-basic human emotion and human-computer interface will make the system robust.

Keywords: Ayurveda, Emotion recognition system, Emotion elicitation protocols, Physiological signals, Wrist Pulse Signal

I. INTRODUCTION

Emotions are complex psychological processes that affect the facets of our lives. The human body and emotions are inseparable and affect each other [1]. Emotion recognition is a stimulating domain in the interaction of humans and machines [2, 3]. Machines should be able to discern human emotions and to interact with humans in a natural way. Emotions supersede, emerge and wane according to a set of laws [4]. Emotions are productive in designing tutoring and developing robots [5-7]. Emotions are worthwhile in making a decision, learning capability and diverse functions [6]. Consequently, there is a need to create an emotion recognition system that is able to achieve high classification accuracy and adaptable to any artifacts [8].

Emotions are discovered by facial, speech, gesture, posture, physiological signals, etc [9]. The emotional method, for instance, facial and speech [10,11] lack accuracy and rely on culture, age, and gender. By using these methods, emotions can be masked or suppressed. This lay the foundation for the physiological signals [12-16]. Human emotional experiences are dominated by two systems of human brain -

Central Nervous System (CNS) and the Peripheral Nervous System (PNS). PNS comprises – Autonomous Nervous System (ANS) and Somatic Nervous System (SNS) [8,17]. Physiological signals or Biosignals are governed by ANS The ANS system has outside voluntary control.

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Therefore, Masking is not possible in physiological signals. Physiological signals are manifold in nature and attracted less attention than facial and speech signals. Physiological signals or biosignals which also encompasses Electrocardiogram (ECG) [18], Electromyogram(EMG)[13], Electroencephalogram(EEG)[19], Photoplethysmography (PPG) [20] , Skin Conductance (SC) [3] are used to assess the emotional states of humans. ECG is related to the cardiovascular system which measures the activity of heart, EMG relates the electrical activity of muscles, a Wrist pulse signal is not only related to heart but also to nerves, muscles, skin, etc[13,14,21]. Any changes in body condition are reflected in the human wrist pulse signal.

The emotion recognition system depends on the subject independent [12] and subject dependent [22] system. The subject dependent approach is not acceptable universally so it has been generally challenged by the researchers. It cannot be considered a standard for any research. Recently, researchers in the field of emotion recognition are eyeing a Subject independent approach i.e. representation in which classification is done on multiple and distinct subjects. But subject independent approaches put up a poor show as compared to subject dependent. Researchers have to make a compromise between these two approaches according to the application

Defining Emotions is grueling tasks in distinct areas over a prolonged duration of time. There are manifold theories of defining emotions. Researchers in the field of emotion recognition pay attention to two types of emotion models – the discrete model and a dimensional model. These models have been used as a standard where emotions have their roots. The discrete model encompasses six basic emotions like happy, sad, fear, surprise, disgust, anger. Dimensional model represents emotions on two scales – valence and arousal. Valence scale symbolizes the polarity of emotion and ranges from positive to negative [23]. Arousal symbolizes the intensity of emotion and it varies from low to high [18]. Figure 2 shows the six basic emotions mapped on a two-dimensional valence- arousal plane.

There exists another category of signals i.e. Wrist Pulse Signal (WPS) [24-27] or Nadi Parikshan among the physiological signals. WPS has its roots in Ayurveda and is used by Indian physicians since the Twelfth century. It was acquired from wrist position non- invasively in a subjective manner using three fingers index, middle, ring finger (Vat, Pitt, Kaph or Cun, Guan, Chi). Consequently, it was transformed into a computerized approach with the development of sensor technology. But it is still not popular among the researchers.WPS are influenced by the flow of blood in the human body. It also gives an indication of the heartbeat and distinct organs of the human body. Pulse signals are not a deterministic signal i.e. it cannot be represented by mathematical relations. The emotion recognition system can also be explored using this signal. WPS is similar to ECG. Moreover, ECG is used for emotion recognition which gives information about the working of the heart. Similarly, WPS could be used for a similar task of emotion recognition [28-30].WPS also has edge over ECG as it unravels the additional information about organs. The distinct set of emotions can be invoked within the subject using emotion elicitation protocols and pulse signals are acquired from the radial artery.

This paper gives an insight into various emotion elicitation protocols, feature extraction techniques, classification methods that aim at recognizing emotions from physiological signals. The focus of this paper is to fill the lacunae in earlier researches like subject dependent, classification accuracy and propound a best possible solution. Distinct sections are given as follows: Section II Material and Methods narrates emotion elicitation protocols used, data acquisition, preprocessing, feature extraction, classification. Section III Comparison table highlights previous works done by researchers and their findings. Section IV Future work set forth the challenges and future trends, Section V Conclusion culminates with emotion recognition.

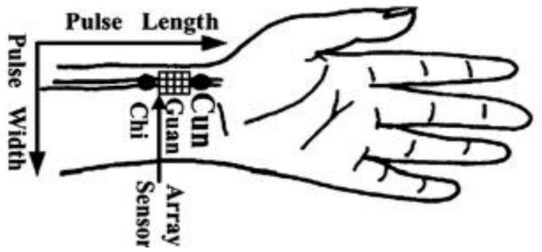

Fig. 1: Wrist pulse points[30]

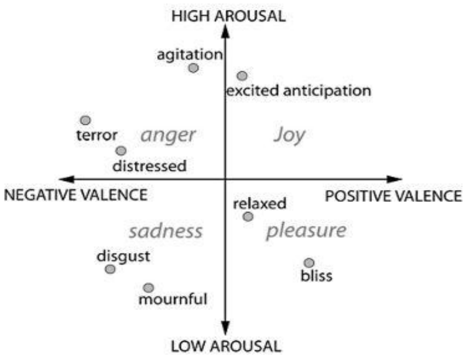

Fig. 2: Two- Dimension model of all emotions in AV plane[18]

II. MATERIAL AND METHODS

A. Emotion Elicitation Protocols

Physiological signals cannot be masked externally so there entails an emotion elicitation internally in the subject. The stimulus is pertinent for a notable response. There exists profuse emotion elicitation methods which encompass pictures of International Affective Picture System (IAPS) [31,32], music[3],audio and audio video[12,13] etc. The intensity of emotions differs from subject to subject. These physiological signals can only be comprehended by the specialists. The clips are espoused according to the specific rating from participants. These protocols must be capable of eliciting target emotion among the subjects. Audiovisual is found to be better to evoke the emotions [13]. Emotion elicitation protocols were used in the prior study for evoking basic emotions as shown in figure 3 .These protocols in prior studies manifest that emotion elicitation nearly requires half to one hour. This can be divided into two sessions. The selected video clips by rating are displayed for a specific time period Neutral emotions can be used in between the basic emotions. The two-dimensionally opposite emotions should not be used successively as specified in prior studies as it may not be helpful for the emotion elicitation within the subjects [11,12,28]. The clips should not be too long or too short. Before data acquisition, certain questions can be posed to the subject so as to emulate the data after the acquisition.

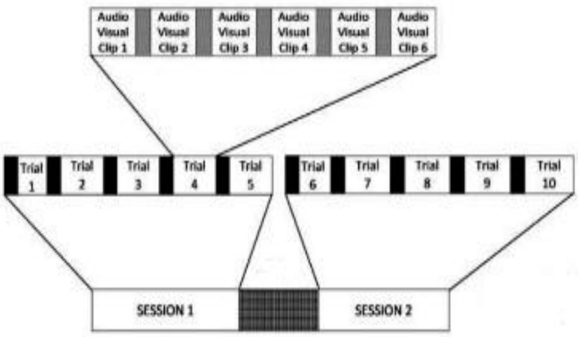

Fig. 3: Emotion Elicitation protocol [12]

B. Data Acquisition

Emotions are elicited using emotion elicitation protocol. These emotions are measured using a distinct number of data acquisition ways. The number of participants and their age, gender, etc is chosen according to the aim of work. The consent of the subjects is also pertinent and the goal of work is instructed to subjects [18]. The researchers should also take care that the subject should not be under undue pressure or stress. The experiment is performed in a quiet, isolated environment. Physiological signals are acquired at a required sampling frequency which depends on the type of physiological signals like ECG (0.5-100Hz), EMG (5-450Hz) and WPS (0-30Hz). The hardware encompasses Electrodes [8,9], ProComp Infiniti system [13,24], BIOPAC MP150 [15,22], Kendal media Trace 500[19] etc were used in prior works. The data collected is fed to software for processing in Matlab, Labview [19,33]. Various databases have been established for efficient research works such as MIT, DEAP [34], DREAMER, and MAHNOB-HCI [35]

C. Preprocessing

Preprocessing is imperative in the examination of Physiological signals. The signal acquired by the hardware is affected by noise or outliers which degrade the signals [36,37]. The rationale behind these artifacts is the baseline wander (respiration), low-frequency noise (subject movement) wrongly placed electrode, high-frequency noise from devices, noise due to 50 Hz power line interference, white Gaussian noise. These outliers affect the signals and diminish accuracy. These artifacts should be removed to get accurate physiological signal analysis. Abating these degradations requires methods ,for instance, sliding window [38],wavelet denoising [12,18,24,39,40], cascade filter [21], curve fitting [21], discrete Mayer model[36],Finite Impulse Response(FIR) filter. Even filters can be taken into service like notch filter [41], Butterworth [22], Chebyshev, Bandpass [15,19,31].The sampling rate is even maintained much larger so that information will not be lost. Thus it becomes difficult for the researchers to analyze the behavior of physiological signals. Hence, the subject movement can also be controlled by the researcher so as to avoid the baseline wander.FIR Low pass filter can be designed in order to remove the high-frequency noise from power line interference.

Segmentation plays a pivotal role in the extraction of a single period from the absolute pulse signal. The signal obtained here is not of equivalent length due to a lot of variations. Consequently, Normalization is employed to equalize the physiological signals. The resulting signal is freed from the noise and ready for further processing.

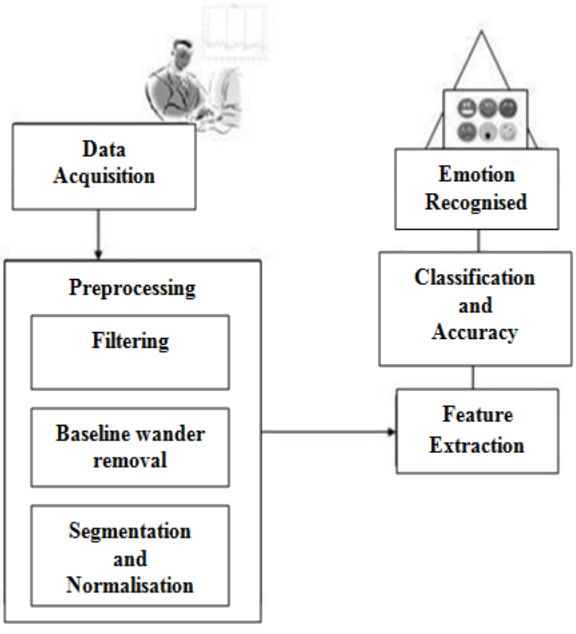

Fig. 4: Flowchart of the system

D. Feature Extraction

Once the signal is freed from unwanted outliers[5], succeeding development is feature extraction. Feature extraction is requisite for the further classification process so as to discern emotions. Researchers employ distinct domain to extract features from physiological signals, for instance, time domain, frequency, wavelet, neural network, etc. A total of 145 features were extracted from ECG and respiration by Cheng he et al [7]. Feature extraction methods encompass Empirical Mode Decomposition (EMD) [42-44] and Hilbert Huang Transform (HHT) [3,9,15], wavelet[45,46],Fourier transform [47,48]. Jerrita et al [12] employed an algorithm to integrate Empirical mode decomposition along with Hilbert transform and Fourier analysis extracted entropy and power of raw ECG signal. Haag et al [41] extract running mean, running standard deviation, Slope for ECG, BVP, Skin conductivity, EMG, Respiration, and Temperature using windowing techniques. These extracted features are processed to classification techniques.

E. Classification

Classification is an exemplar of supervised learning which is used to find the subcategories from the testing data. For instance, an animal is a super class and assigning given animals into the cat, dog, etc is classification. Classification implementation hinges on the data to be classified. Classifiers are problem dependent i.e. work well for particular problem vice versa. There are manifold classifiers available to classify emotional states using the feature extracted. These classifiers which encompasses Support vector machine (SVM) [3,14,15,31,32,46], K-Nearest Neighbour(KNN)[8,9,14,18, 49,50], Linear Discrminant Analysis(LDA)[8,11],Regression tree[3,9], Naiive Bayes[13], Fisher Linear Dicriminant [31], Artificial Neural Network(ANN)[2], RBF Neural Network[41,45] etc .The comparison among these classifiers is done on the basis of accuracy.ECG Signal gives 52 % accuracy [12,13] but accuracy surges if more physiological are counted[15].

III. PREVIOUS WORKS

Various research works have been done in the field of emotion recognition, employing physiological signals. The focus of the researcher shifted from a single subject to multiple subjects. Different Stimuli for elicitation unravel distinct ways of emotion elicitation. Table I shows the related work on emotion recognition using physiological signals.

Table I: Related works on emotion recognition using physiological signals

Ref No.	Biosignals used	No. of subjects	Emotions	Stimuli	Technique and Features	Classification	Accuracy %
[3]	Electrocardiogram, Electromyogram, Skin Conductivity, Respiration changes	MIT database	Joy,Pleasure,Anger, Sadness	Music	Hilbert Huang Transform (mean frequency)	Support vector Machine	76(Fission)
							62 (Fusion)
[12]	Electrocardiogram	30	Basic emotions except Anger	Audio visual	Hilbert Huang Transform Discrete Fourier Transform (Amplitude frequency power Entropy)	K Nearest Neighbour	48.53(DFT)
						Linear discriminant analysis	52.11 DFT
[13]	Electromyogram	15	Happy,Sad ,Afraid Disgust Neutral	Audio Visual	Higher order statistics	K Nearest Neighbour	64.89
						K Nearest Neighbour, Principal component analysis	69.5
[15]	Electrocardiogram, Electrodermal activity, Skin temperature	217	Boredom , Pain,Surprise	Audio	Heart rate ,Heart rate variability,Ratio of low to high frequency power	Discriminant function analysis	84.7
						Linear discriminant analysis	74.9
						Support vector machine	62
						Classification and regression tree	67.8
						Naiive Bayes	71.9
						Self organizing map	61.5
						Self organizing map	61.5
[31]	Blood Volume pulse, Electromyogram, Electro dermal activity Skin Temperature Respiration	10(International Affective Picture System)	Fear, Disgust Contentment, Neutral Sadness Amuse	Images	Statistical features (Mean, Standard deviation,etc)	Support vector Machine	45(subject independent)
						Fisher linear discriminant analysis	100(subject dependent)

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[18]	Electrocardiogram	60	Basic Emotions except Anger	Audio Visual	Rescale Range Statistics, Finite Variance Scaling, Higher order Statistics(Hurst,Skewness, Kurtiosis)	Finite Variance scaling and Higher order statistics	92.87 (random)
							76.45 (subject independent)
[32]	Electromyogram	Inter National Affective Picture system	Fear, Disgust, Sadness	Images	Wavelet Transform	Support Vector Machine	81.82 (subject Dependent)
[41]	Electromyogram, Electrocardiogram, Electrodermal activity, Skin temperature Blood Volume pulse	IAPS	Basic emotions	Images	Running mean, Standard deviation, Slope	Neural Network (Running mean, Standard deviation, Slope)	96.6 arousal 89.9 valence
[7]	Electrocardiogram	Augus--berg database	Joy , anger, Sadness, pleasure	Music	Db5 Multi scale wavelet Decomposition (maximum and standard deviation)	Neural Network	91.67 (RBF) 87.5(BP)
[51]	Electrocardiogram Electroencephalogram Respiration	6	Negative Neutral	Videos	Hilbert Huang Transform	Support Vector Machine	92.5(subject dependent)

Though the prior studies take into account various methods and techniques there are certain lacunae that need to be addressed. The association of physiological signals with emotions becomes grueling task. Emotions rely on age, culture, time etc so physiological signals vary from person to person. Another problem is subject dependent and subject independent emotion recognition system. There is a dilemma in the mind of the researcher about these above systems. More emotions can also be classified apart from only basic emotions.

IV. FUTURE WORK

In a current scenario, an emotion recognition system from the physiological signal is facing many challenges like subject independent approach gives less accuracy due to fewer data available. The number of emotions can also be added. Wrist pulse signals can also be explored using different ways. The number of subjects affects emotion recognition accuracy so more subjects to be included. The emotions which we encounter in our daily life cannot be elicitated up to the mark. Emotions recognition can contribute to the field of robotics. The genesis of proposed WPS was subjective but with the advancement in sensor technology it's shaped into objective field. WPS is an alluring field in the physiological signals using emotion recognition. The proposed WPS has more potential in the emotion recognition system as compared to other physiological signals.

V. CONCLUSIONS

This paper put forth the distinct phases of the emotions recognition system from physiological signals which provide analysis to the research. Recently, this field is in the nascent stage of its development due to the ample challenges it is facing today. The revolutionary approach is pertinent to have efficient feature extraction, classification techniques so as to get the subject independent system with maximum possible classification accuracy. Considerable data analysis is pertinent for emotion recognition. The researchers might contend to make the tradeoff between subject independent and subject dependent. Recently, developments in the wearable products will provide a platform for the emotion recognition system. The contemporary researches and its application will pave the way for more developments in the interaction of human and machine.

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