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Development of a real time emotion classifier based on evoked EEG

Moon Inder Singh *, *Mandeep Singh*

Department of Electrical and Instrumentation Engineering, Thapar University, Patiala 147004, India

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ABSTRACT

Our quality of life is more dependent on our emotions than on physical comforts alone. This is motivation enough to classify emotions using Electroencephalogram (EEG) signals. This paper describes the acquisition of evoked EEG signals for classification of emotions into four quadrants. The EEG signals have been collected from 24 subjects on three electrodes (Fz, Cz and Pz) along the central line. The absolute and differential attributes of single trial ERPs have been used to classify emotions. The single trial ERP attributes collected from each electrode have been used for developing an emotion classifier for each subject. The accuracy of classification of emotions into four classes lies between 62.5–83.3% for single trials. The subject independent analysis has been done using absolute and differential attributes of single trial signals of ERP. An overall accuracy of 55% has been obtained on Fz electrode for multi subject trials. The methodology used to classify emotions by fixing the attributes for classification of emotions brings us a step closer to developing a real time emotion recognition system with benefits including applications like Brain-Computer Interface for locked-in subjects, emotion classification for highly sensitive jobs like fighter pilots etc.

1. Introduction

Emotion is a complex mental state which controls the reaction of humans toward the happenings around them. An emotion is a complex interplay of love, anger, fear, contentment, sadness, arousal and hatred etc. and is associated with changes in biomedical potentials. The need to understand the human emotions and develop a Human–Computer Interface is ever increasing. The necessity of developing a Human–Computer Interface is not only to help the persons in locked in state and to enhance the mental and physical abilities [55,22] but as well to increase the productivity by keeping the workforce calm in demanding conditions. To classify emotions, the relationship between physiological signals and emotions must be known. Cacioppo and Tassinary [4] developed a psycho-physiological model to link the psychological elements with physiological signals. The use of physiological signals such as Electromyogram (EMG), Galvanic Skin Resistance (GSR), Blood Pressure (BP) and Heart Rate, Pulse and Electroencephalogram (EEG), fusion of EEG with other physiological signals and facial expressions to

* *Corresponding author at*: Department of Electrical and Instrumentation Engineering, Thapar University, Patiala 147004, India.
E-mail addresses: mooninder@gmail.com (M.I. Singh), mandy_tiet@yahoo.com (M. Singh).
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classify emotions have been effectively illustrated by various researchers [37,61,13,23,66,5,38,31,21].

The use of evoked EEG is gaining importance among the researchers studying emotions. Schupp et al. [59] observed encoding of emotional stimuli while the subjects performed an attention related task. The images from International Affective Picture System (IAPS) [36] and task related images were mixed together and each image was displayed for 333 ms. Though most of the users performed the task with minimal error, but the evoked signals were seen to be affected in N2 window due to pleasant and unpleasant stimuli. This shows the tendency of humans to get affected by emotions when performing tasks. The use of EEG signals to classify emotions in real time is gaining importance.

2. Related studies

Emotion is a short and intense feeling that occurs on account of some stimulus. Moors [46] listed the criteria for demarcation of emotions from the phenomena that are not emotions. Ekman [18] listed nine characteristics to distinguish between basic emotions and other affective states. The classification of emotions becomes necessary not only to help a small population in locked in state but as well to bring the transition of emotions since different emotions affect different aspects of cognition such as attention, performance, logical reason and decision making [26,1,49,20,30].

Russell [57] proposed an affective space model. The model has been refined and emotions can be represented on a 9 point scale along x axis (valence) and y axis (arousal). The third dimension dominance is as well gaining importance [2]. Under laboratory conditions, the emotions can be evoked by thinking about the past happenings from personal life [7] or selecting images and audio signals from datasets such as International Affective Picture System (IAPS) [36] and International Affective Digitized Sounds (IADS) [3].

Chanel et al. [6] used the fusion of EEG signals with other physiological signals to classify emotions along arousal axis. Horlings [25] used the combination of self collected and eNTERFACE 2006 [58] collected EEG signals to obtain five class emotion classification along arousal and valence axis. The EEGLab toolbox was used for processing raw EEG signals [15]. It was found that the classification accuracy increased when classifying emotions subject-wise. The features determined from EEG signals by decomposing them into different frequency bands have been used by number of researchers to classify emotions [40,41,52,48,42,47,71].

Jenke et al. [29] tested features collected as per the 33 previous studies on EEG based emotion recognition and found that the features such as higher order crossings (HOC) [53], fractal dimension [65] and Hjorth parameters and features obtained from frequency bands β and γ [42] gave better emotion classification accuracies. Considering that the ERP extraction requires averaging of multiple number of EEG signals, the ERP feature was not considered in this subject dependent study. The studies based on using ERP for emotion classification are few. The studies on single trial ERP analysis and real time emotion recognition system are even rarer.

Nicolaou et al. [50,51] successfully analyzed single trial ERPs for BCI by applying Independent Component Analysis technique. Frantzidis et al. [19] developed a subject independent emotion classifier model by acquiring average ERP features [45] from Fz, Cz and Pz electrodes. The emotions were classified into four classes by first classifying emotions into low arousal and high arousal classes and then used two separate classifiers to classify low arousal and high arousal data along the valence axis. Since high accuracy results have been reported in this study, the methodology of their data acquisition and analysis has been used in our study as well for comparison of results.

Koelstra et al. [33] classified arousal with a maximum accuracy of 67% and valence with a maximum accuracy of 76% by using single trial EEG. Debener et al. [14] developed a low cost wireless EEG for field recordings and used single trial P300 to classify indoor and outdoor recordings.

Zhu et al. [73] used rapid serial visual presentation paradigm to elicit emotions and analyzed variation in ERP amplitudes (P2 and late positive potential) corresponding to three emotional states along the valence axis (neutral, positive and negative). The P2 amplitude varied in response to emotional stimuli as compared to non emotional stimuli. The rapid serial visual presentation system has been successfully used to analyze single trial ERP and latency features for emotional related research [70,69]. Zhang et al. [70] found evidence that average amplitude differences can be attributed to the variations in single trial amplitudes (P1, N170, VPP, N3 and P3) between experimental conditions. Leyh et al. [39] determined the variation in ERP specifically P3 amplitudes on subjects with different attachment levels. The subjects performed an oddball experiment with IAPS images belonging to negative, positive and neutral contexts running in the background. The attenuation in P3 amplitudes was noticed on subjects with insecure-dismissing attachment. Also, the authors calculated lower hit rates for subjects with insecure-dismissing attachment under low valence emotional stimuli as compared to other category of subjects. Van Dongen et al. [67] related the attenuation in LPP (late positive potential) amplitudes in EEG in response to the low valence and high valence IAPS pictures when presented in art form as compared to the presentation of images as pictures. Importantly, it was found that emotional assessment of visual stimuli happened quickly causing changes in EEG. The LPPs were found to be symmetrically distributed over the scalp with maximum amplitude found at midline electrodes.

The ERP features have been used by some other researchers for analysis [11,10,16,17,45,63,8,56,50,51,44,68,24,27]. The studies on real time emotion classification are limited. Cowie et al. [9] developed an instrument 'FeelTrace' to detect the type of emotional stimuli. The observers recorded the perceived emotion on a circular evaluation space.

Jatupaiboon et al. [28] made an attempt to design a real time EEG based happiness detection system. The authors decimated 5 s EEG signals into five 1 s EEG signals. The Wavelet Transform was then applied to decompose EEG signals into five frequency bands. The power spectrum density feature was determined from frequency bands and then normalization of the features was done to classify happy and unhappy emotions of the subjects. The accuracy of classification lied between 65.12% and 75.62%. It is worth mentioning that the

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