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# A real-time wearable emotion detection headband based on EEG measurement

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ABSTRACT

A real-time emotion detection system based on electroencephalogram (EEG) measurement has been realised by means of an emotion detection headband coupled with printed signal acquisition electrodes and open source signal processing software (OpenViBE). Positive and negative emotions are the states classified and the Theta, Alpha, Beta and Gamma frequency bands are selected for the signal processing. It is found that, by using a combination of Power Spectral Density (PSD), Signal Power (SP) and Common Spatial Pattern (CSP) as the features, the highest subject-dependent accuracy (86.83%) and independent accuracy (64.73%) is achieved, when using Linear Discrimination Analysis (LDA) as the classification algorithm. The standard deviation of the results is 5.03. The electrode locations were then improved for the detection of emotion, by moving them from F1, F2, T3 and T4 to A1, F2, F7 and F8. The subject-dependent accuracy, using the improved locations, increased to 91.75% from 86.83% and 75% of participants achieved a classification accuracy higher than 90%, compared with only 16% of participants before improving the electrode arrangement.



## 1. Introduction

Emotion detection is an emerging topic and emotions influence much of daily life such as reasoning and attention [1], decision making [2], well-being [3] and the quality of life [4]. The immune system is also related to the emotions as a weaker immune response is generally induced by negative emotions [5]. People who experience positive emotions have a lower risk of suffering from disease than those with negative emotions [6]. In addition, people with positive emotions frequently live longer and healthier lives than those with negative emotions [7]. Emotion detection offers the potential to identify negative emotions and address the causal factors, potentially leading to more positive emotions.

In the past, emotion was detected from the facial expression or tone of voice; however, the accuracy cannot be guaranteed because of misleading tonal changes or spurious facial expressions [8]. Alternatively, physiological signals are used such as skin temperature, the Electrocardiogram and the Electroencephalogram (EEG), which records the electrical brain activity on the scalp [9]. EEG is the most direct method because it measures the voltage changes caused by ionic current flows within the neurons of the brain which result from emotions [10]. The left hemisphere is more active during positive emotions and the right hemisphere during negative emotions [11]. This is because the alpha wave of the right hemisphere decreases with negative emotions and that of the left hemisphere decreases with positive emotions [12]. Such brain asymmetry can be applied for emotion detection based on EEG signals.

The primary objectives of EEG-based emotion detection research are to implement real-time measurement with high accuracy [9]. Previous research has identified important six major factors which affect the outcome [9]:

- **Participant:** The method for building emotion classification can be divided into subject-independent and subject-dependent models. The former means that the classification model is built for the entire database, while the latter indicates the classification model is built for every new user [13]. The former is more difficult to achieve with high accuracy than the latter because of inter participant variability [14].
- **Model of Emotion:** The common dimensional model consists of two main dimensions which are valence and arousal [9]. The arousal emotion ranges from calm to excited and the valence emotion ranges from negative to positive [15]. This model is called the circumplex model [16] and is shown in Fig. 1. It is

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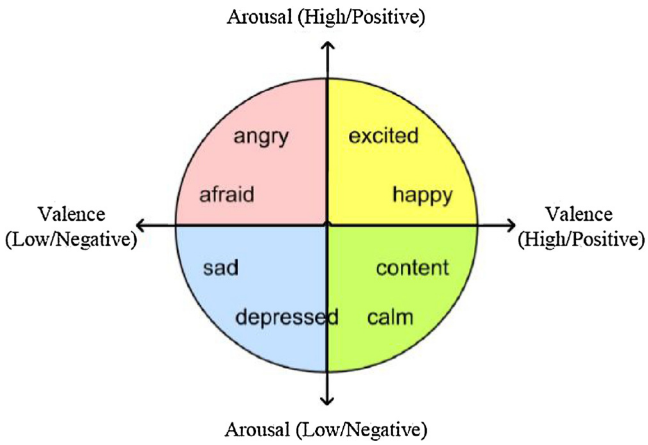


**Fig. 1.** Arousal-valence model [16].

the most widely used model, allowing emotions to be illustrated graphically and mapped on a coordinate system.

- **Stimuli:** External stimuli such as pictures, sounds and videos are commonly used to induce emotions in the participants.
- **Features:** Potential signal features are Power Spectral Density (PSD), Asymmetric Spatial Pattern (ASP), Spectral Power Asymmetry (ASM) and Asymmetric Spatial Pattern (ASP) [9].
- **Temporal Window:** The type of emotion targeted and the physiological signal determines the appropriate length of the temporal window for emotion detection which is typically from 0.5 to 4 s [17]. Our system is called real-time since it can provide a continuous display of emotions as they occur. However, we note there is a very short delay (<1 s) between, when the emotion occurs, and its display.
- **Classifier:** This factor determines the power consumption and the accuracy of the result. There are several machine learning algorithms which can be used as emotion classifiers such as Naive Bayes (NB) [18] and Support Vector Machine (SVM) [9]. In addition to the classifier, there is a Library for Support Vector Machines (LIBSVM) [18] which supports various SVM formulations for classification, regression, and distribution estimation.

The electrical activity recorded on the scalp are decomposed into five frequency bands, which are: delta (1–3 Hz), theta (4–7 Hz), alpha (8–13 Hz), beta (14–30 Hz), and gamma (31–50 Hz) [19]. In order to acquire brain activity, the 10–20 system of electrode placement, shown in Fig. 2 [20], is used. This is an international standard of scalp electrode locations with each position identified by a name.

Liu et al. developed a real-time emotion detection system based on measuring EEG signals [21]. A Fractal Dimension algorithm was used and both arousal and valence were classified. Three channels were used with electrodes at the FC6, F4 and AF3 positions according to the 10–20 international standard [20]. An Emotiv headset [22] was implemented as the signal acquisition device and 12 participants were used to test the system. However, instead of using a standard classifier, Fractal Dimension (FD) values from a Higuchi Fractal Dimension (HFD) algorithm were compared with a predefined threshold. It is not clear as to how the threshold was defined and the accuracy of the emotion detection system was not specified [23].

Anh *et al*. demonstrated a real-time emotion detection system [23]. The channels used were the same as reported in [21]: FC6, F4 and AF3. Fractal Dimension values as well as AV (arousal and valence) values were used as the features while SVM was used as the classifier [23] to classify five emotions: happy, sad, relaxed, neutral and angry. The EEG signal was collected using a Emotiv headset and a SAM (Self-Assessment Manikin) was implemented together with the circumplex model for emotion evaluation. The average subject-dependent classification accuracy was 70.5% from 20 participants. The experimental results indicated that the model in [23] successfully achieved accurate subject dependent detection but could only achieve a subject independent detection accuracy of <10%.

Jatupaiboon et al. used the Support Vector Machine algorithm as the classifier for two channels to implement a real-time EEG-based happiness detection system using an Emotiv headset as the signal acquisition device [9]. The Power Spectral Density feature from the alpha, beta, delta, theta and gamma frequency bands was used. The temporal window was chosen as 1 s and the system classified the emotional state every 5 s. Pictures and music were used as the stimuli to induce emotions. 10 participants were used to test the real-time system. The average accuracies of subject-independent and subject-dependent models were 65.12% and 75.62% respectively.

Matiko et al. implemented another real-time emotion detection system in which the active electrodes were embedded within a headband and the data wirelessly transferred to a computer [24]. This design used flexible solar cells on the headband as a power supply and embedded the EEG signal processing electronics within the headband. The correlation coefficient between the signals from the printed active electrodes used and commercial passive electrodes was 70.88%. The highest average subject-independent classification accuracy achieved was 62.62% and the subject-dependent accuracy was 90% [24]. The two channel EEG signals were obtained from the asymmetrical locations of AF3 and AF4. The Signal Power and the Oscillation features of the alpha band from two channels were also used for emotion detection classified by a Fuzzy Logic algorithm.

This paper presents a real-time emotion detection system based on EEG signal measurement. Positive and negative emotions are the states classified. The signal is acquired using screen printed active dry electrodes which are assembled in a headband. The printing approach enables the fabric headband and electrodes to be customised in size to be suitable for a wide range of wearers. Active dry electrodes were selected because they reduce the noise and electrode impedance, compared with passive dry electrodes, thereby increasing signal quality. The signal is then processed by OpenViBE software to extract the features and classify emotions [25]. A novel algorithm, combining PSD, SP and CSP features, achieved the highest subject-dependent accuracy (86.83%) and subject-independent accuracy (64.73%) when using Linear Discrimination Analysis (LDA) as the classification algorithm. Subsequently improved electrode locations, at A1, F2, F7 and F8, increased the subject-dependent accuracy to 91.75% from 86.83%, which is the highest compared with other reported similar approaches. The use of the open-source OpenVibe software and standard interface hardware, allows replication by other researchers of the signal processing and classification algorithm developed in this paper and we will release the source code into the public domain after publishing this paper. In summary this paper presents a novel combination of extraction features (PSD, SP and CSP) together with an improved electrode arrangement which avoids hairs. This is implemented on a printed headband offering headband size adjustment and the system uses open source software to achieve the highest reported subject dependent/independent accuracies (91.75%/66.74%) in real-time.

In this paper, Section 2 presents a system overview followed by a description of the emotion detection headband, the EEG amplifier and microcontroller as well as the OpenViBE signal processing software. Section 3 provides the results together with a discussion starting with a performance analysis of the printed electrodes, the implementation of real-time emotion detection and the performance of a new electrode arrangement. Finally, Section 4 provides conclusions.