Affective, Natural Interaction Using EEG: Sensors, Application and Future Directions

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Abstract. ElectroEncephaloGraphy signals have been studied in relation to emotion even prior to the establishment of Affective Computing as a research area. Technological advancements in the sensor and network communication technology allowed EEG collection during interaction with low obtrusiveness levels as opposed to earlier work which classified physiological signals as the most obtrusive modality in affective analysis. The current article provides a critical survey of research work dealing with broadly affective analysis of EEG signals collected during natural or naturalistic interaction. It focuses on sensors that allow such natural interaction (namely NeuroSky and Emotiv), related technological features and affective aspects of applications in several application domains. These aspects include emotion representation approach, induction method and stimuli and annotation chosen for the application. Additionally, machine learning issues related to affective analysis (such as incorporation of multiple modalities and related issues, feature selection for dimensionality reduction and classification architectures) are revised. Finally, future directions of EEG incorporation in affective and natural interaction are discussed.

Keywords: EEG, Affective Computing, Natural Interaction, Affect aware applications.

1 Introduction

The use of ElectroEncephaloGraphy (EEG) to study electrical activity in the human brain was demonstrated for the first time approximately 80 years ago. This development has had far-reaching implications for the study of the human brain's activity changes in response to changes in emotion. Numerous studies have taken place in the last years aiming to understand the correlation between brain signals and emotional states. In EEG, the electrical activity of the brain is observed through scalp electrodes. The 10-20 system [19] is an internationally recognised method to describe and apply the location of the nineteen electrodes used originally. The "10" and "20" refer to the fact that the actual distances between adjacent electrodes are either 10% or 20% respectively of the total front-back or right-left length of the surface of the skull.

I. Maglogiannis, V. Plagianakos, and I. Vlahavas (Eds.): SETN 2012, LNAI 7297, pp. 331–338, 2012.

Brain signals are classified in five frequency bands, associated with different mental states. Delta waves (0-3.5 Hz) occur in deep sleep [9]. Theta waves (3.5-7.5 Hz) have been associated with drowsiness, daydreaming, creative inspiration and meditation, arousal [6], sensorimotor processing and mechanisms of learning and memory [10]. Alpha waves (7.5-12 Hz) are present during wakeful relaxation with closed eyes and are reduced with open eyes, drowsiness and sleep. Mu waves (8-13 Hz) are diminished with movement or an intent to move, or when others are observed performing actions. Beta waves (12-30 Hz) are associated with focus, concentration, high alertness, agitation and anxiety. Gamma waves (30-100 Hz) are associated with very high states of consciousness, focus and intellectual acuity, and have a strong presence during meditation.

Finally another important feature measured in EEG studies are Event-Related Potentials (ERP), which are brain responses as a direct result of a thought or perception, and more specifically the P300 signal which is one of the components of an ERP elicited by task-relevant stimuli.

2 Sensors Technology Overview

The first human EEG recording was obtained by Hans Berger in 1924. Since then numerous electroencephalographic studies have taken place using, until a few years ago, caps which were complicated to position on the subject due to their many wires. Recently, the wireless sensors' technology has evolved, making it possible for various systems to be developed. These sensors are inexpensive, easy to set up and are accompanied with out-of-the-box applications or easy to use SDK's, and provide freedom of movement for the user. Industry has shown strong interest in this field. Some examples are Imec, Neurofocus, OCZ, SmartBrain Technologies and QUASAR. Here we will focus on the two most popular, in terms of integration in EEG studies: Emotiv and Neurosky. Depending on the version of these sensors and their SDK there are some variations in the characteristics and properties provided. Here we are presenting the ones that are relative to our theme without separating them according to the edition.

The Neurosky sensor is able to measure frequencies in the range of 0.5-50 Hz and the Emotiv sensor measures frequencies in the range of 0.2-43 Hz. Through both sensors' simple interface the raw EEG, its Fast Fourier Transform and the alpha, beta, gamma, delta and theta waves can be displayed as well as the user's mental state: attention, meditation, anxiety and drowsiness for Neurosky, and long-term excitement, instantanious excitement, engagement, frustration, meditation, boredom for Emotiv. With Emotiv there is also the possibility to monitor the facial expressions (look left/right, blink, left/right wink, raise brow, clench teeth, smile) and the movements of the head calculated from the headset's gyroscope, whereas an animation of "explosions" simulates the action of blinking in Neurosky. The 10-20 system doesn't apply to Neurosky due to the fact that there is only one sensor on the forehead and one "ground" sensor on the earlobe whereas Emotiv is considered partially compliant to the 10-20 system.

3 Affective Aspects of EEG Application

3.1 Emotion Representation

Because of the user-friendly interface these sensors provide, the emotion representation is often quite straightforward. Emotiv provides as direct output frustration and excitement in [11], long-term excitement, instantaneous excitement and engagement in [4, 13] and excitement, engagement, boredom, meditation and frustration in [5] through its simple interface. In some cases information from the Emotiv sensor about the raw EEG and wave variations are combined with the information provided by other biological or non biological sensors, resulting in different types of emotion representation: anger, disgust, fear, happiness, sadness, joy, despisal, stress, concentration and excitement in [8], positive, negative and neutral state of mind in [3, 20]. In cases where the cognitive load of the subject is being studied during a task [7], changes in power of lower frequency (alpha, theta) brain waves detected by Emotiv are analysed in order to determine whether the cognitive load is low, medium or high. Finally, a different approach is adopted when attention or the wink movement is detected. In this case the raw EEG provided by the sensor is processed in order to detect the P300 signal [1, 21] or the signal caused by the winking [1]. The Neurosky sensor outputs, through its intuitive interface as well, attention and meditation in [2], attention level in [22], and relaxation and irritation in [14]. In a fatigue detection system in [12], when three conditions are met simultaneously the user is considered fatigued: a) attention decreases below a certain threshold, b) meditation increases above a threshold and c) either of the delta or theta wave signals maintain the highest value of all frequency bands.

3.2 Annotation

The most common process for annotating experimental corpora is self assessment. This includes questionaires or tasks prior to and/or after the experiment concerning the emotion or the cognitive feature examined [2, 7, 14, 17]. More specifically, certain well-known tasks are given to the subject in order to evaluate the results. As seen in [8, 20], International Affective Picture System (IAPS) is incorporated in order to provide a set of normative emotional stimuli for experimental investigation of emotion and attention. The goal is to develop a large set of standardized, emotionally-evocative, internationally accessible, color images which includes contents across a wide range of semantic categories [15]. In order to measure engagement in [4] the Independent Television Commission-Sense of Presence Inventory (ITC-SOPI) [16] questionnaire was used. This questionnaire offers a valid method of measuring cross-media presence which allows results from different laboratories to be compared. It studies four factors: Sense of Physical Space, Engagement, Ecological Validity, and Negative Effects. In the same study the Self-Assessment Manikin (SAM) is used as well. SAM is a non-verbal pictorial assessment technique that directly measures the pleasure, arousal, and dominance [18] associated with a person's affective reaction to a wide variety of stimuli [15]. Sometimes annotation is provided by the experiment itself. An example of that is [3] where positive, negative and neutral state of mind are measured. During this experiment the participants are asked to control a robot in a maze by thinking about the direction it must take (in reality they can't). The direction in which the robot should move is shown with an arrow. The robot follows a predefined path, sometimes the right one, sometimes the wrong one. When it follows the right path the participant is assumed to be satisfied (positive), when it follows the wrong path the participant is assumed to be unsatisfied (negative) and while the participant is looking at the arrow (before the robot moves) a neutral state is assumed. Another example is [21] where the P300 signal responding to a visual stimulus is measured. In this case the subject is asked to press a button when the stimulus appears. Another article [22] where attention is measured, builds on results from previous studies which suggest that attention is correlated with the errors made and the speed of the activity, as well as whether the participant gave-up or not.

3.3 Stimuli/Induction

The induction of the different mental states detected in EEG studies can be obtained by audio stimuli such as the sounds of a game in a CAVE environment [13] or wind, sea waves and a composition of slow violins, tinkling bells and oboes to induce a positive feeling and musical pop tracks which the subject strongly dislikes to induce a negative feeling like in the case of [14]. Visual stimuli can include displaying pleasant, neutral and unpleasant pictures from the International Affective Picture System [20], visuals in game-playing [13] or a robot's movement [3]. If the P300 signal is to be detected, examples of stimuli can be found in [21] where the subject is looking at a monitor where a ship appears intermittently or in [1] where the photo of each person in a mobile phone's addressbook flashes and when the photo of the person we want to call flashes the signal is detected. Furthermore, examples of interactive Brain Computer Interfaces (BCI) used to induce different emotions are encountered in [4, 8, 11]. Finally, learning activities and tasks such as the Stroop Test, Hanoi Towers, Berg's Card Sorting Task, and seeking information on the web can also be used as stimuli [2, 7, 17, 22].

4 Machine Learning Aspect

4.1 Multimodality

Biomedical studies, in their effort to be more accurate, combine multiple biological signals as well as information coming from the subject's face, voice, body movements and actions on the computer.

EEG information is combined with information taken from the subject's face using visual input or observations in [2, 5, 8, 11, 17]. For the latter, "MindReader" - a system developed at MIT Media Lab - infers emotions from facial expressions and head movements in real-time.

Often EEG is studied in combination with Galvanic Skin Response (GSR), which is a method of measuring the electrical conductance of the skin, which varies with its moisture level. This is of interest because the sweat glands are controlled by the sympathetic nervous system, so skin conductance is used as an indication of psychological or physiological arousal. Examples can be found in [5, 7, 13, 14].

Heart rate measurement is another way to index state of mind and the fusion of it with EEG has been studied in [8, 13, 14].

The eyes' movement is another cue that provides information about the user's attention or focus point. In [5] "Tobii Eye Tracking System" was incorporated in the system, providing data about the user's attention and focus time while performing a task on the computer. This information is combined with the information provided by the EEG sensor. In the case of [7], the eyes' movements and the EEG were used to predict mental states of a person engaged in interactive seeking of information.

Other inputs used to determine mental states can be mouse clicks, keyboard strokes, screen cam recordings [7], body posture, finger pressure (usually on the mouse) [5] and acoustic features [8].

4.2 Feature Processing

Due to the huge variability of features collected in biometric studies, in order to reduce the dimensionality of the problem, eliminate the noise or extract particular characteristics from the signal, the need to preprocess them is common. [20, 21] use Independent Component Analysis (ICA). [14, 20] use Principal Component Analysis (PCA). Noise reduction is also a very important issue in biosignal processing. The use of Notch filters (50 and 60 Hz) and bandpass filters (for example 1-20 Hz in order to isolate the P300) are commonly used.

4.3 Classification

An abundance of classification approaches is being used in EEG research. K-nearest neighbor algorithm and Support Vector Machines (SVM) are incorporated in [11] in order to create predictive models of frustration and excitement, and in [17] to classify numerous features of raw EEG in order to create a model of human academic emotion (boredom, confusion, engagement and frustration). [17] also makes use of a multilayer perceptron (MLP). All of the above classifiers have been used in [14] along with Logistic Regression, Decision Trees, Naïve Bayes and ensemble classifiers.

[11] uses Linear Regression as well and [20] uses the K-means algorithm. [3] makes use of Linear Discriminant Analysis (LDA) to determine the satisfaction level as categorical representation (satisfied, neutral, unsatisfied) and in [21] the Adaptive Neuro Fuzzy Inference System (ANFIS) is used to detect P300-rhythm.

At this point it is worth mentioning that different types of open-source data mining software with embedded algorithms have been a very useful tool for EEG studies. Important examples are "RapidMiner" in [11, 17], and "Weka" in [14].

5 Application Domains

For research purposes various systems have been created in order to study emotion recognition in BCI's [2, 5, 14] as well as attention detection [21]. The main fields in which the wireless EEG sensors find application are games (subsection 5.1), learning (subsection 5.2) and health (subsection 5.3). They are also used in mobile phones [1, 20], Human-Robot Interaction (HRI) [3] and interactive information seeking [7].

5.1 Games

One of the most common fields of use of wireless EEG sensors is game play. The EEG signal is used as feedback to the game so that the game scenario adjusts to the player's needs. For example, detection of boredom will cause changes in the game to make it more challenging whereas detection of anxiety will cause the game to slow down or decrease the levels of difficulty. The portability of these devices is even more useful in cases where they are combined with games played in virtual reality environments. In these cases the player's immersion is augmented further. A good example can be seen in [13] where the environment used is "CAVE" (projectors are directed to three, four, five or six of the walls of a room-sized cube).

5.2 E-Learning

E-Learning is an application domain aiming to create virtual learning environments that will simulate and enhance conventional learning environments [4, 17]. In [11] a tutoring system predicts the student's appraisal of the feedback given and in [22] the system adapts and modifies the learning activity according to the student's level of attention. [8] is proposing a virtual environment for job interview training that senses the applicant's emotions.

5.3 Health and Universal Access

Wireless sensors are now being introduced to the P300 Speller, contributing to its portability. The P300 Speller is a 6x6 matrix of alphanumeric characters where one of its rows or columns flashes randomly. When the character the subject wants flashes, the P300 signal is measured. In this domain we can also find a fatigue detection system proposed by [12].

6 Conclusions and Future Directions

The current article provides a critical survey of research work dealing with broadly affective analysis of EEG signals collected during natural or naturalistic interaction by wireless sensors. EEG analysis in relation to emotion, while having a long history, has always been considered an extremely obtrusive emotional cue capture technique, establishing it as unsuitable for natural interaction. Recent releases of sensors enabling wireless collection of EEG signals enable affect-aware applications using natural interaction. It is expected that application domains such as gaming and e-learning will dominate the field. A related milestone could be the release of a gaming platform with EEG sensors included or at least available as an add-on. As Microsoft's Kinect sensor and OpenNI framework boosted research and applications on Natural Interaction, a similar explosion could follow if a major industry released a gaming platform (similar to the Xbox 360) which would collect EEG data. On the other hand, enabling low-cost and widely available collection of EEG activity during learning activities through e-learning applications would boost research on correlation of brain and cognitive functions as well as adaptive, educational interfaces.

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