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Improving BCI-based emotion recognition by combining EEG feature selection and kernel classifiers☆

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ABSTRACT

Current emotion recognition computational techniques have been successful on associating the emotional changes with the EEG signals, and so they can be identified and classified from EEG signals if appropriate stimuli are applied. However, automatic recognition is usually restricted to a small number of emotions classes mainly due to signal's features and noise, EEG constraints and subject-dependent issues. In order to address these issues, in this paper a novel feature-based emotion recognition model is proposed for EEG-based Brain–Computer Interfaces. Unlike other approaches, our method explores a wider set of emotion types and incorporates additional features which are relevant for signal pre-processing and recognition classification tasks, based on a dimensional model of emotions: *Valence* and *Arousal*. It aims to improve the accuracy of the emotion classification task by combining mutual information based feature selection methods and kernel classifiers. Experiments using our approach for emotion classification which combines efficient feature selection methods and efficient kernel-based classifiers on standard EEG datasets show the promise of the approach when compared with state-of-the-art computational methods.

1. Introduction

Emotions play a critical role in rational decision-making, perception, human interaction, and human intelligence. Hence emotions are a fundamental component of being human as they motivate action and add meaning and richness to virtually all human experience. Traditionally, in *Human–Computer Interaction* (HCI), users must discard their emotional selves to work efficiently and rationality with computers (Sourina, Wang, Liu, & Nguyen, 2011; Wright, 2010).

Interfacing directly with the human brain is made possible through the use of sensors that can monitor some of the physical processes that occur within the brain that correspond with certain forms of thought. Researchers have used these technologies to build *Brain–Computer Interfaces* (BCIs), communication systems that do not depend on the brain's normal output pathways of peripheral nerves and muscles (Calvo & D'Mello, 2010). Instead, users explicitly manipulate their brain activity that can be used to control computers or communication devices.

State-of-the-art emotion recognition computational techniques have been successful on associating the emotional changes with the EEG signals, and so they can be identified and classified from EEG signals if appropriate stimuli are applied. However, automatic recognition is usually restricted to a small number of emotions classes mainly due to signal's features and noise, EEG constraints and subject-dependent issues.

Accordingly, in this research a novel feature-based emotion recognition model is proposed for EEG-based BCI interfaces. Unlike other approaches, our research explores a wider set of emotion types, claiming that combining a mutual information based feature selection method (i.e., *minimum-Redundancy-Maximum-Relevance*) and kernel classifiers may improve the accuracy of the emotion classification task.

This work is organized as follows: Section 2 describes the fundamentals and state-of-the-art emotion recognition techniques, Section 3 proposes a novel feature-based model for EEG emotion recognition, Section 4 discusses the main experiments conducted and the results for different model settings and finally, Section 5 highlights the main conclusions of the research and some further work.

2. Emotions recognition

Research of human emotional states via physiological signals involves recording and statistical analysis of signals from central and

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parietal cortex. A popular physiological signal that is highly adopted for human emotion assessment is the EEG, etc. Unlike other physiological signals, EEG is a non-invasive technique with good temporal and acceptable spatial resolution. Thus, EEG might play a major role on detecting an emotion directly from the brain at higher spatial and temporal resolution (Yisi, Sourina, & Minh, 2010).

A major problem with recognizing emotions is that people have different subjective emotional experiences as responses to the same stimuli (Wright, 2010; Yisi et al., 2010). Accordingly, emotions can be classified into two taxonomy models:

(1) **Discrete model:** it is based on evolutionary features (Calvo & D'Mello, 2010) that include basic emotions (*happiness, sadness, fear, disgust, anger, surprise*), and mixed emotions such as Motivational (*thirst, hanger, pain, mood*), Self-awareness (*shame, disgrace, guilt*), etc.
(2) **Dimensional model:** it is expressed in terms of two emotions provoking people: *Valence* (*disgust, pleasure*) and *Arousal* (*calm, excitement*) Yisi et al. (2010).

Emotion recognition enables systems to get non-verbal information from human subjects so as to put events in context based on underlying captured emotions. Humans are capable of recognizing emotions either from speech (voice tone and discourse) with an accuracy around 60% or from facial expressions and body movements with an accuracy of 78–90%. However, the recognition task is strongly dependent on the context and requires facial expressions to be deliberately performed or even in a very exaggerated manner, which is far away from the natural way a user interact with intelligent interfaces.

Other kinds of techniques use audio signals, obtaining classification accuracy close to 60–90% (Calvo & D'Mello, 2010), whereas some other methods use non-linguistic vocalizations (i.e., laughs, tears, screams, etc.) to recognize complex emotional states such as anxiety, sexual interest, boredom. Bi-modal methods also combine audio inputs and facial expressions based on the assumption that a human emotion can trigger multiple behavior and physiological responses whenever he/she experiences this emotion.

Nevertheless, most of these methods require humans to express their emotional (mind) states in a deliberated and exaggerated manner, so that emotions cannot spontaneously be expressed. On the other hand, extracting information from facial expressions requires monitoring a subject by using one of several cameras, whereas for audio-based approaches, emotions are very hard to recognize whenever a subject does not speak or produce any sounds (Giakoumis, Tzovaras, Moustakas, & Hassapis, 2011; Sourina et al., 2011).

A popular and effective non-invasive technique to measure changes on brain activity is called (EEG), which transforms brain activity into images of variations of electrical potential by using small low-cost devices (AlMejrad, 2010). There are several approaches for EEG-based emotion recognition which are usually based on four main tasks (Calvo & D'Mello, 2010):

(1) *Signal preprocessing:* an EEG device can directly get signals from the brain. However, there are some noise sources that are not neurologically produced known as artifacts (i.e., blinking, muscular effects, vascular effects, etc.), so digital signal processing techniques must be applied to represent signals using frequencies and harmonic functions (Petrantonakis & Hadjileontiadis, 2010; Yisi et al., 2010).
(2) *Feature extraction:* EEG signals are highly dimensional so computational processing becomes very complex. Hence different features must be extracted in order to simplify the further emotion classification task so to create input *Feature Vectors* (FV). Typical methods include *statistical* metrics of the signal's first difference (i.e., median, standard deviation, kurtosis symmetry, etc.), **spectral density** (i.e., EEG signals with specific frequency bands) Zhang, Yang, and Huang (2008), **Logarithmic Band Power (Log BP)** (i.e., power of a band within the signal based on its oscillatory processes) Brunner, an C. Vidaurre, and Neuper (2011), **Hjorth parameters** (i.e., EEG signals described by *activity, mobility* and *complexity*) Zhang et al. (2008), **wavelet transform** (i.e., decomposition of the EEG signal) Petrantonakis and Hadjileontiadis (2010), **fractal dimension** (i.e., complexity of the fundamental patterns hidden in a signal) Zhang et al. (2008).
(3) *Feature selection:* one little used technique of feature selection for emotions recognition combines a metaheuristic method known as **Genetic Algorithms** (GA) and a **Support Vector Machines** (SVM). This **GA-SVM** approach heuristically searches for the best sets of features initially represented as chromosomes of features which evolves as the GA goes on, so that these can then be provided as an input to an SVM classifier (Wang et al., 2011). A major drawback with this method is the time spent to converge toward good results and the redundancy of the selected features assessed in each iteration of the GA.
In order to deal with this issue, other EEG feature selection technique known as **minimum-Redundancy-Maximum-Relevance** (*mRMR*) selects the features that correlate the strongest with a classification variable, reducing information redundancy. This method selects features that are mutually different from each other while still having a high correlation make up the selection task of *mRMR* (Polat & Cataltepe, 2012), by reducing redundancy between bad and good features using *Mutual Information* (MI) methods, so that a subset of features that represents best the dataset can be obtained.
(4) *Emotions classification:* once the FVs are extracted from the previous task, emotions must be classified according to previously identified classes of emotions. Despite the large number of features used by these methods, no feature selection is usually carried out. There are plenty of state-of-the-art classifiers for automatic emotion identification. For example, Nearest Neighbor classifiers used features such as FFT and Wavelets to recognize 4 types of emotions (i.e., *joy, sad, angry, relaxed*) achieving accuracies ranging from 54% to 67%. On the other hand, statistical methods such as *Quadratic Discriminant Analysis* (QDA) used several statistical features for negative and positive arousal levels with an average accuracy of 63% (Koelstra et al., 2012; Petrantonakis & Hadjileontiadis, 2010; Wu et al., 2010; Yisi et al., 2010).

3. An adaptive BCI-based emotions recognition model

In this work, a novel approach that combines *minimum-Redundancy-Maximum-Relevance* (*mRMR*) based feature selection tasks and kernel classifiers for emotions recognition is proposed. The method takes EEG signals received from BCI devices and incorporates relevant features in order to detect several kinds of emotional states by using state-of-the-art classifiers. The main contribution of this research is that unlike other automatic emotion recognition methods our approach

(1) Incorporates a feature selection task into the classification task.
(2) Uses multi-label classifiers to simultaneously recognize a wider range of emotion types based on a dimensional model.

The overall model is composed of three tasks: signal preprocessing, feature extraction and selection, and emotions classification (see Fig. 1).

3.1. EEG signal preprocessing

In order to train the emotions classifier, a set of previously emotion-labeled EEG data extracted from subjects self-assessing