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Optimal set of EEG features for emotional state classification and trajectory visualization in Parkinson's disease

R. Yuvaraj [a,*], M. Murugappan [a], Norlinah Mohamed Ibrahim [b], Kenneth Sundaraj [a], Mohd Iqbal Omar [a], Khairiyah Mohamad [b], R. Palaniappan [c]

[a] School of Mechatronic Engineering, University Malaysia Perlis (UniMAP), Campus Ulu Pauh, Arau, 02600, Perlis, Malaysia
[b] Neurology Unit, Department of Medicine, UKM Medical Center, Jalan Yaacob Latiff, 56000, Bandar Tun Razak, Kuala Lumpur, Malaysia
[c] School of Computing, University of Kent, Medway, UK

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ABSTRACT

In addition to classic motor signs and symptoms, individuals with Parkinson's disease (PD) are characterized by emotional deficits. Ongoing brain activity can be recorded by electroencephalograph (EEG) to discover the links between emotional states and brain activity. This study utilized machine-learning algorithms to categorize emotional states in PD patients compared with healthy controls (HC) using EEG. Twenty non-demented PD patients and 20 healthy age-, gender-, and education level-matched controls viewed happiness, sadness, fear, anger, surprise, and disgust emotional stimuli while fourteen-channel EEG was being recorded. Multimodal stimulus (combination of audio and visual) was used to evoke the emotions. To classify the EEG-based emotional states and visualize the changes of emotional states over time, this paper compares four kinds of EEG features for emotional state classification and proposes an approach to track the trajectory of emotion changes with manifold learning. From the experimental results using our EEG data set, we found that (a) bispectrum feature is superior to other three kinds of features, namely power spectrum, wavelet packet and nonlinear dynamical analysis; (b) higher frequency bands (alpha, beta and gamma) play a more important role in emotion activities than lower frequency bands (delta and theta) in both groups and; (c) the trajectory of emotion changes can be visualized by reducing subject-independent features with manifold learning. This provides a promising way of implementing visualization of patient's emotional state in real time and leads to a practical system for noninvasive assessment of the emotional impairments associated with neurological disorders.

1 . Introduction

Parkinson's disease (PD) is a neurodegenerative disorder associated with the loss of dopamine-producing neurons in the basal ganglia. The cardinal symptoms of the disease are tremor, muscular rigidity, bradykinesia (i.e., slowness of movement), and postural instability. These motor impairments are often accompanied by a wide range of non-motor symptoms (e.g., depression, executive dysfunctions, sleep disturbances, autonomic impairments), both symptom categories having a great impact on the quality of PD patient's life (Martinez-Martin et al., 2011).

Over the last decade, there has been an increasing attention to the role played by emotional processes in PD (Gray and Tickle-Degnen, 2010; Péron et al., 2012). Evidence indicates the individuals with PD have deficits in recognizing emotions from prosody (Dara et al., 2008; Pell and Leonard, 2003; Yip et al., 2003) and facial expressions (Ariatti et al., 2008; Clark et al., 2008; Dujardin et al., 2004), although not all findings have been consistent. Several studies have failed to find impaired performance in the recognition of facial expressions related to emotion in their PD samples (Adolphs et al., 1998; Pell and Leonard, 2005), whereas others have failed to find deficits in recognition from prosody (Clark et al., 2008; Kan et al., 2002). In a recent meta-analysis of the literature comparing emotional recognition abilities of individuals with PD and healthy controls (HC), Gray and Tickle-Degnen concluded that there is a robust link between PD and deficits in emotion recognition using both voice and faces, with impairments particularly marked with respect to negative emotions (Gray and Tickle-Degnen, 2010). A commonly drawn inference is that the emotion recognition deficit experienced by individuals with PD is likely to be cross-modal (Peron et al., 2010), yet only a small number of studies have examined emotion recognition performance in both facial and prosodic modalities with same participants. A number of these reports found deficits in both modalities (Ariatti et al., 2008; Yip et al., 2003), whereas others found

* Corresponding author at: School of Mechatronic Engineering, University Malaysia Perlis (UniMAP), Campus Ulu Pauh, Arau, Perlis 02600, Malaysia. Tel.: +60 14 6011990; fax: +60 4 988 5167.
E-mail address: yuva2257@gmail.com (R. Yuvaraj).

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problems in only one modality (facial, Pell and Leonard, 2003); prosody, Pell and Leonard, 2005), and at least one failed to find deficits in recognition in either modality (Caekebeke et al., 1991).

Furthermore, there is sparse event related potential (ERP) evidence that early processing of emotional prosody (mismatch negativity, Schröder et al., 2006) and faces (early posterior negativity, Wieser et al., 2012) may be affected in PD. Altogether, experimental evidence does support the view of deficits in emotion processing in PD patients. However, much of the research in this area focused on the patient's behavioral responses (i.e. participants were asked to match, identify or rate the emotional stimuli) and few studies have measured physiological response to emotions (e.g., ERPs). The existing literature mentioned above used traditional statistical analysis tools for the investigation of emotion processing in PD. There is little quantitative objective measurement that correlates with the emotional impairment in neurological disorder patients compared to healthy control participants. This underlines the need for an objective quantitative measure of emotional processing that can identify and compute subtle changes in emotional states and hence help in a group based comparative analysis between PD patients and HC, thereby enabling the assessment of emotional impairment treatment efficacy and progression of the disease.

Numerous studies on engineering approaches to automatic emotion recognition have been performed with healthy participants in the past few decades. They can be categorized into three main approaches. The first kind of approach focuses on the analysis of facial expressions, speech, or gesture (Anderson and McOwan, 2006; Gunes and Piccardi, 2007; Kessous et al., 2010). These audio-visual based techniques allow noncontact detection of emotions, so they do not give any discomfort to the subject. However, these techniques might be more prone to deception, and the parameters vary in different situations. The second kind of approach focuses on peripheral physiological signals. Various studies show that peripheral physiological signals varying for different emotional states can be observed through changes of the autonomic nervous system (ANS) in the periphery, such as electrocardiogram (ECG), skin conductance (SC), electromyogram (EMG), respiration rate (RR), and pulse (Valenza et al., 2012). In comparison with audio-visual based methods, the responses of peripheral physiological signals tend to provide more detailed information as indicator for estimating emotional states. The third kind of approach focuses on brain signals captured from the central nervous system (CNS) such as electroencephalogram (EEG), Magnetoencephalogram (MEG), Positron Emission Tomography (PET), and functional Magnetic Resonance Imaging (fMRI). Among these, EEG appears to be less invasive and the one with best time resolution as compared to the other methods (MEG, PET, and fMRI). In addition, EEG signals have been proved to provide informative characteristics in responses to the emotional states (Petrantonakis and Hadjileontiadis, 2011).

Recently, emotion classification using EEG data has attracted much attention with the rapid development of dry electrodes, digital signal processing methods, machine-learning techniques, and various real-world applications of brain computer interface (BCI) for healthy controls. However, there still exist some limitations on traditional EEG-based emotion recognition framework. One of the major limitations is that almost all existing methods do not consider the characteristics of EEG and emotion. In general, EEG is unsteady rapidly changing voltage signal and the features extracted from EEG usually change dramatically, whereas emotions only change gradually. This leads to wider differences among EEG features, even with the same emotional state in adjacent time periods. Moreover, existing studies with HC are only able to predict the labels of emotion samples, but could not reveal the trend of changes in the emotion. To overcome these limitations, in this paper, we introduce an approach to track the trajectory of emotion changes in PD patients compared to HC. In order to validate the effectiveness of the proposed method we compare four kinds of EEG-emotion-specific features, and evaluate the classification performance of six emotional states (happiness, sadness, fear, anger, surprise and disgust) of PD patients in comparison with age-, education level- and gender-matched HC.

The rest of the paper is organized as follows: Section 2 provides an overview of related work on various methods for EEG-based emotion classification in HC. Section 3 presents the participants' characteristics and experiment setting for emotion induction. A description of feature extraction, feature dimensionality reduction, classification, and trajectory of emotion changes is given in Section 4. Finally in Section 5, we present the experimental results that we obtained. Conclusions and future work are presented at the end.

2 . Related work

Since EEG not only indicates emotional states, but also reflects other cognitive activities of the brain. The selection of independent variables to discriminate emotions from the EEG across various electrode locations is not very self-evident, thus recently researchers explored complex methods to find the correlation between the emotional changes and EEG signals. Zhang and Lee reported an average accuracy of 73.00% $\pm$ 0.33% by using EEG features to categorize subject's status into two emotional states (Zhang and Lee, 2009). Chanel et al. obtained an average accuracy of 63% by using EEG time–frequency information as features for three emotional classes (Chanel et al., 2009). Lin et al. (2010) used EEG signals to recognize emotions in response to emotional music. Their study achieved a recognition rate of 82.29% $\pm$ 3.06% for four emotional states (Lin et al., 2010). Murugappan et al. (2010) attained a maximum average accuracy of 83.26% for distinguishing five emotional states using different set of EEG channels (Murugappan et al., 2010). Petrantonakis and Hadjileontiadis (2010) proposed a user-independent emotion-estimation system for recognizing six emotional states; with the average accuracy of 83.33% achieved (Petrantonakis and Hadjileontiadis, 2010). Moreover, evidence of brain activity relating to affective responses is reported in the majority of EEG frequency bands, i.e., *theta* (4–8 Hz), *alpha* (8–13 Hz), *beta* (13–30 Hz), and *gamma* (30–49 Hz) (Aftanas et al., 2004; Davidson, 2004). Frontal midline (Fm) *theta* power modulation is suggested to reflect affective processing during emotional stimuli (Sammler et al., 2007). The *alpha*-power asymmetry on the prefrontal cortex has been proposed as an index for the discrimination between positively and negatively valenced emotions (Davidson, 2004; Schmidt and Trainor, 2001). *Beta* activity has been associated with emotional arousal modulation (Aftanas et al., 2006) and also, asymmetric activity in this band is linked to the emotional dimensions of approach or withdrawal (Schutter et al., 2001). Finally, *gamma* band has been mainly suggested as related to arousal effects (Balconi and Lucchiari, 2008).

3 . Materials

3.1 . Recruitment of eligible participants

Twenty non-demented PD patients (10 men and 10 women) and 20 healthy controls (9 men and 11 women) matched for age (range from 40 to 65 years), education level, and gender participated in the study. The PD patients were recruited through the Neurology Unit outpatient service at the Department of Medicine of the Hospital University Kebangsaan Malaysia (HUKM) medical center in Kuala Lumpur, Malaysia. All of them had been diagnosed with Idiopathic PD by a neurologist. Patients who had coexisting neurological disturbances (e.g., epilepsy, stroke) or who had undergone deep brain stimulation were not included in the study. The HC participants were recruited through the hospital community and/or from relatives of PD patients.

Exclusion criteria for controls included any current psychiatric or neurological disorder. Exclusion criteria for both groups were dementia or depression as indicated by a score of 24 or lower on the mini mental state examination (MMSE) (Folstein et al., 1975; Wieser et al., 2012) or 18 or higher on the Beck Depression Inventory (BDI) (Beck et al., 1961;