ARTICLE IN PRESS

International Journal of Psychophysiology xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

International Journal of Psychophysiology

journal homepage: www.elsevier.com/locate/ijpsycho

Registered Report

Assessment of driver drowsiness using electroencephalogram signals based on multiple functional brain networks

Jichi Chen, Hong Wang*, Chengcheng Hua

Department of Mechanical Engineering and Automation, Northeastern University, 110819 Shenyang, Liaoning, China

ARTICLE INFO

Keywords:
Electroencephalography
Driver drowsiness
Classification
Minimum spanning tree
Functional brain networks

ABSTRACT

This paper proposes a comprehensive approach to explore whether functional brain network (FBN) changes from the alert state to the drowsy state and to find out ideal neurophysiology indicators able to detect driver drowsiness in terms of FBN. A driving simulation experiment consisting of two driving tasks is designed and conducted using fifteen participant drivers. Collected EEG signals are then decomposed into multiple frequency bands by wavelet packet transform (WPT). Based on this, two novel FBN approaches, synchronization likelihood (SL) and minimum spanning tree (MST) are combined and applied to feature recognition and classification system. Unlike other methods, our approaches focus on the interaction and correlation between different brain regions. Statistical analysis of network features indicates that the difference between alert state and drowsy state are significant and further confirmed that brain network configuration should be related to drowsiness. For classification, these brain network features are selected and then fed into four classifiers considered namely Support Vector Machines (SVM), K Nearest Neighbors classifier (KNN), Logistic Regression (LR) and Decision Trees (DT). It is found that combining MST method and SL method is actually increasing the classification accuracy with all classifiers considered in this work especially the KNN classifier from 95.4% to 98.6%. Moreover, KNN classifier also gives the highest precision of 98.3%, sensitivity of 98.8% and specificity of 98.9%. Thus this kind of methodology might be a useful tool for further understanding the neurophysiology mechanisms of driver drowsiness, and as a reference work for future studies or future ‘systems’.

1. Introduction

Driver drowsiness is considered to be a state that varies between wakefulness and sleep, which impairs cognitive skills and affects the ability to perform a driving task (Chen et al., 2015; Craig et al., 2006; Jap et al., 2010). Thus it is extremely useful to understand the neurophysiology mechanisms of driver drowsiness and even to develop an efficient methodology that intelligently assesses the driving in a state of drowsiness in the future ‘systems’ and as a reference work for future studies (Mu et al., 2017; Qingjun et al., 2018).

In broad terms, the existing assessment methods of driver drowsiness are mainly divided into three categories. More specifically, one type is driver behavior and the driving performance based measure (Chang et al., 2008; Sandberg et al., 2011). Another type is image-based measure (Azim et al., 2014; Smith et al., 2003). The other type is biomedical signal based measure (Chiang, 2015; Garces Correa et al., 2014; Li et al., 2012; Vicente et al., 2016; Zhao et al., 2011). Usually, biomedical signals such as electroencephalogram (EEG), electrooculogram (EOG), and electromyogram (EMG) are of utmost importance to collect information from the body's response during the drowsiness. Among these biomedical signals, EEG is the most-widely used technique and most predictive indicator to measure the electrical activity of the brain (Artameeyanant et al., 2017; Chuang et al., 2015; Jap et al., 2009; Razavipour et al., 2014; Ubeyli, 2009). Additionally, all the physical and mental activities associated with driving are reflected in EEG signals, and hence EEG signals can contribute to the driving status recognition (Kar et al., 2010; Zhang et al., 2014).

Actually, most methods of studying driver drowsiness based on EEG signals can be divided into two categories: (1) power spectrum based analysis (Eoh et al., 2005; Jap et al., 2009); (2) brain networks based analysis (Zhao et al., 2017). More specifically, power spectrum analysis is a commonly-used and traditional approach to analysis an individual's drowsy level (Jap et al., 2009) however the performances of power spectrum analysis are susceptible to EEG amplitude because the research methods are related to amplitude. In recent years, brain networks have been considered as complex network systems, as suggested by many studies (Zhao et al., 2017). Moreover, complex interactions by electrical activity of neuronal elements will impact functional

* Corresponding author.
E-mail address: hongwang@mail.neu.edu.cn (H. Wang).

https://doi.org/10.1016/j.ijpsycho.2018.07.476
Received 11 June 2018; Received in revised form 9 July 2018; Accepted 31 July 2018

Please cite this article as: Chen, J., International Journal of Psychophysiology (2018), https://doi.org/10.1016/j.ijpsycho.2018.07.476

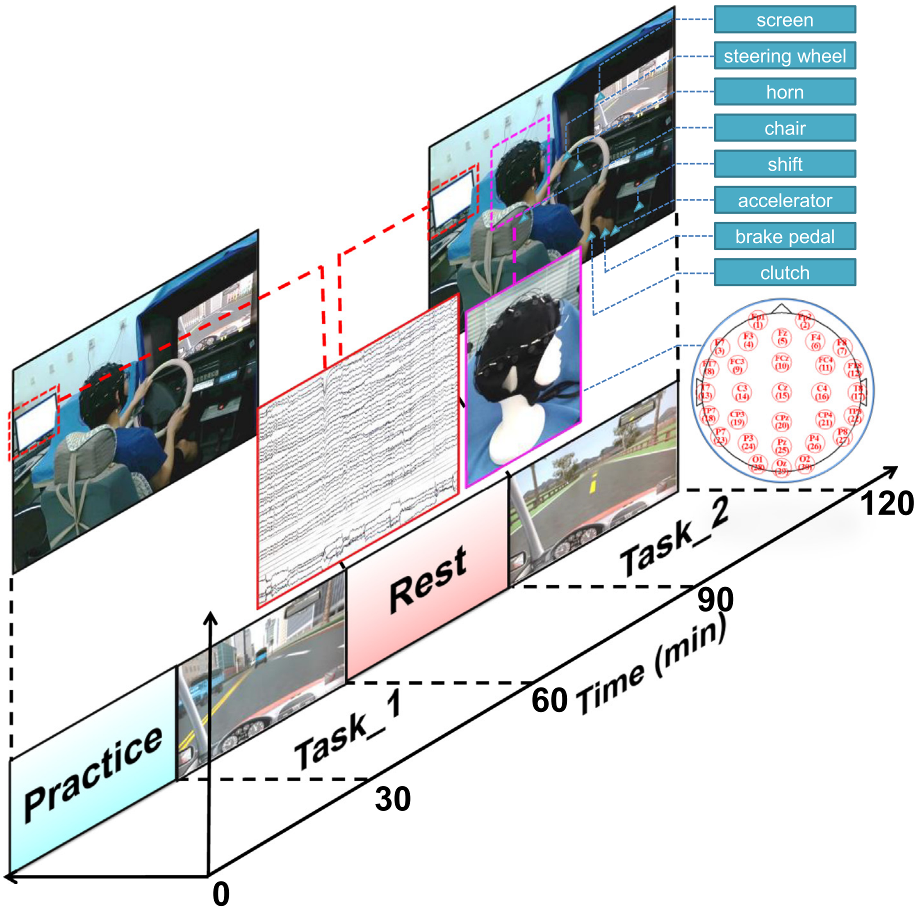

Fig. 1. Experimental protocol and driving tasks. For details, see text please.

connections between different regions of brain, which can help us further understand the relationship between brain topology and driver drowsiness.

The synchronization likelihood (SL), introduced by (Stam and van Dijk, 2002), was adopted to investigate the general synchronization and functional connectivity of the underlying neuronal network during sleep (Leistedt et al., 2009). They found that the mean SL is lower in the delta, theta and sigma frequency bands in the depressed group. (Coullaut-Valera et al., 2014) researched on the cortical brain connectivity in a population of polydrug users by applying the SL algorithm in a recent study. Results showed that higher synchronization of brain electrical activity at rest in the theta band between frontal and posterior cortical regions compared to controls is found. Although being widely used and having achieved good results already, conventional brain network analyses exist the problems in comparing network parameters across different conditions (Stam et al., 2014). More recently, some EEG based functional brain network studies using minimum spanning tree (MST) method showed that this approach may provide a sensitive tool overcome the problem of bias (Stam et al., 2014; Tewarie et al., 2015; van Wijk et al., 2010) for the tracking of developmental network changes and the detection of abnormal brain network topology (Boersma et al., 2013; Dubbelink et al., 2014). MST method is superior to traditional network method as it abandons the need to choose an arbitrary threshold to reconstruct the graph and also has a lot simpler structure since it concentrates on the most significant link in sub-graph.

In this work, besides the SL method, a novel method of MST is also adopted to construct brain networks to attempt to explore whether the configuration of the functional brain network is related to driver drowsiness. The goal of the current study is to propose a comprehensive approach based on electroencephalogram (EEG) signals to explore whether FBN changes from the alert state to the drowsy state and to find out ideal neurophysiology indicators able to detect driver drowsiness in terms of FBN. Based on this, two functional brain network (FBN) approaches, SL and MST are first combined and applied to feature recognition and classification. For classification, these brain network features are fed into four classifiers considered namely Support Vector Machines (SVM), K Nearest Neighbors classifier (KNN), Logistic Regression (LR) and Decision Trees (DT).

We set out to address that: (1) whether the brain network topology is affected by driver drowsiness; (2) which features or the combinations of features derived from network analysis contribute to classifications; (3) In order to provide reference for future studies or future 'systems', whether combining efficient feature extraction methods and classification algorithm selection can enhance the detection of driver drowsiness.

The rest of this paper is described as below. Section 2 describes the details of the experimental setup and procedure, brief information about the FBN that we have used as features and the various classifiers which we have adopted in this work. Section 3 presents the experimental results obtained in this work. Section 4 presents the discussion and evaluates the performance of different classifiers based on these features and feature combinations.

2. Materials and methods

2.1. Subjects

Subjects are recruited from the students at the School of Mechanical Engineering and Automation, Northeastern University (NEU). All the procedures in the experiment are performed in accordance with the