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EEG-based mental fatigue measurement using multi-class support vector machines with confidence estimate

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Abstract

Objective: Automatic measurement and monitoring of mental fatigue are invaluable for preventing mental-fatigue related accidents. We test an EEG-based mental-fatigue monitoring system using a probabilistic-based support vector-machines (SVM) method.
Methods: Ten subjects underwent 25-h sleep deprivation experiments with EEG monitoring. EEG data were segmented into 3-s long epochs and manually classified into 5 mental-fatigue levels, based on subjects' performance on an auditory vigilance task (AVT). Probabilistic-based multi-class SVM and standard multi-class SVM were compared as classifiers for distinguishing mental fatigue into the 5 mental-fatigue levels.
Results: Accuracy of the probabilistic-based multi-class SVM was 87.2%, compared to 85.4% using the standard multi-class SVM. Using confidence estimates aggregation, accuracy increased to 91.2%.
Conclusions: Probabilistic-based multi-class SVM not only gives superior classification accuracy but also provides a valuable estimate of confidence in the prediction of mental fatigue level in a given 3-s EEG epoch.
Significance: The work demonstrates the feasibility of an automatic EEG method for assessing and monitoring of mental fatigue. Future applications of this include traffic safety and other domains where measurement or monitoring of mental fatigue is crucial.

Keywords: Electroencephalogram (EEG); Mental fatigue; Classification; Support vector machines (SVM); Automatic detection

1. Introduction

Mental fatigue, defined by Grandjean (1980) as a "state of reduced mental alertness that impairs performance", has become one of the most significant causes of accidents throughout the modern society (Idogawa, 1991; Dinges, 1995; Lal and Craig, 2001). In recent years, there has been an increasing interest in mental fatigue tracking technology (Artaud et al., 1994; Gevins et al., 1995; Dinges and Mallis, 1998; Lal et al., 2003), with the widespread hope that such technology will become invaluable in the prevention of mental fatigue related accidents. One of the major obstacles for this "most wanted" technology (National Transportation Safety Board (NTSB), 2006) is the challenge of establishing an objective, reliable and non-intrusive mental-fatigue measurement and monitoring method. The objective of this study is to address this issue by establishing an automatic mental-fatigue measurement and monitoring system by using recently developed pattern recognition technology.

Despite its apparent importance, there is no gold method for mental fatigue measurement. The conventional mental fatigue measurement methods can be classified into two categories: subjective and objective measurements. Subjective mental fatigue measurement methods require

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subjects to rate their level of mental fatigue either indirectly (e.g. Piper et al., 1998; Zachrisson et al., 2002) or directly (e.g. Shapiro et al., 2002), whereas objective methods assess mental fatigue via quantifying subjects' performance on a specific task (e.g. Dinges and Powell, 1985; Thorne et al., 2005). There is a general agreement that these conventional measurement methods can have good reliability and good validity. However, they cannot be used in some domains, such as transportation industry, where an objective and non-intrusive mental fatigue measurement method is required.

In attempts to develop an objective and non-intrusive mental fatigue measurement method, some pilot studies have correlated mental fatigue with physiological measures such as electrocardiogram (ECG), electrooculogram (EOG) and EEG. A good review of these approaches can be found in the thesis by Mallis (1999) and a review by Lal and Craig (2001). More recently, several studies have reported the feasibility of measuring mental fatigue or drowsiness indexed by subject's task performance, based on EEG data in attention-sustained experiments using auditory or visual stimuli (Jung et al., 1997; Makeig et al., 2000; Sommer et al., 2002; Vuckovic et al., 2002; Lal et al., 2003; Duta et al., 2004; Peiris et al., 2004; Jones, 2006). Most of these pilot studies have focused on the detection of performance lapses in the specific tasks that they studied (i.e. the prediction of a mistake in a specific task) without measuring subjects' mental-fatigue levels directly. Moreover, most of these pilot studies used fairly simple linear or nonlinear regression or neural networks.

We set out to study whether a recently established technology similar to neural networks, probabilistic-based multi-class SVM, can be used to automate the measurement and monitoring of subjects' mental fatigue at different levels. Unlike standard multi-class SVM and other statistical learning methods which only give the bare classification, this technique provides not only superior classification accuracy but also useful estimates of confidence in the classification decision (Duan and Keerthi, 2005). This study tests whether the probabilistic-based multi-class SVM can be used to establish a robust EEG-based mental fatigue measurement and monitoring system that is potentially of use in automated fatigue detection systems.

2. Methods and materials

2.1. Hardware and software environment

Monopolar EEG data were acquired at a sampling frequency of 167 Hz using a Medtronic PL-Winsor 2.35 EEG system together with a 19-channel electrode cap, according to the international 10–20 system (Jasper, 1958). The EEG data were pre-filtered by the EEG system through its integrated low-pass filter (cut-off frequency at 35 Hz) and high-pass filter (cut-off frequency at 0.1 Hz) as well as a 50 Hz notch filter. The EEG data were piped to a laptop through a data acquisition card (DAQCard-6036E, National Instruments, USA) and then processed by a customized LabView software system running on a laptop for automatic measurement of subjects' mental fatigue at different levels. The predicted mental fatigue levels were shown as a curve varying with the time on the laptop monitor, together with plots of real-time EEG data. Although the developed system has real-time capacity, the present paper focuses on the offline analysis of its performance.

2.2. Data collection and preparation

Ten subjects were selected from right-handed volunteers of local tertiary institutions who fulfilled the inclusion criteria of not being on any medication, no history of sleep disorders and with regular sleep hygiene as evidenced by a one-week sleep diary prior to the experiment. The recruitment of human subjects for this study was approved by the National University of Singapore (NUS) ethical committee. Informed consents were obtained and nominal monetary incentives sufficient to cover transportation costs were given for their participation.

In order to train the system in a supervised regime, an auditory vigilance task (AVT) was used as a validation measurement of mental fatigue. The detailed account of AVT has been given previously (Shen et al., 2007). Four audio commands (left, right, up, down) with 500ms duration each were randomly ordered in one command set. Subjects were required to constantly concentrate and to press the pre-specified buttons, within 1.5 s after each complete command set, in the order of commands that they heard. Each AVT session had 50 command sets in about 3 min (1.5 s inter-set interval). For every AVT session, an AVT score was calculated in terms of percentage of correct responses.

Each subject underwent a 25-h sleep deprivation experiment in a temperature-controlled laboratory (23–25 °C) from 8:30 am to 9:30 am next day. Caffeine, tea, smoking were prohibited for about two days (from one-day before the experiment till the end of experiment). Subjects were required to perform AVT session once an hour throughout the experiment (with eyes open) and they were allowed to engage in non-strenuous activities in non-AVT-session period. EEG data were recorded simultaneously during every AVT session and they were labeled to 5-level mental fatigue according to the AVT performance score. Specifically, for each subject, his/her individual performance span (the highest AVT score to the lowest AVT score) was evenly divided into five segments corresponding to fatigue level 1–5, respectively. The label (i.e. mental fatigue at 5 levels) of the EEG data for an AVT session was determined by which segment the corresponding AVT performance score fell into.

The AVT test is similar to other objective measurements of mental fatigue in the literature, such as the Psychomotor Vigilance Test (PVT) (Dinges and Powell, 1985; Thorne