Neuroscience Letters 506 (2012) 235–239

Contents lists available at SciVerse ScienceDirect

Neuroscience Letters

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

Evaluation of driver fatigue on two channels of EEG data

Li Wei [a], He Qi-chang [a,b], Fan Xiu-min [a,b,*], Fei Zhi-min [c]

[a] School of Mechanical Engineering, Shanghai Jiaotong University, No. 800 Dongchuan Road, Minhang District, Shanghai 200030, China
[b] Shanghai Key Lab of Advanced Manufacturing Environment, Shanghai Jiaotong University, No. 800 Dongchuan Road, Minhang District, Shanghai 200030, China
[c] Department of Neurosurgery, Shu Guang Hospital, Affiliated to Shanghai University of Traditional Chinese Medicine, Shanghai 201203, China

ARTICLE INFO

Article history:
Received 8 June 2011
Received in revised form 23 October 2011
Accepted 8 November 2011

Keywords:
EEG
Driver fatigue
Ratio indices
GRA
KPCA

ABSTRACT

Electroencephalogram (EEG) data is an effective indicator to evaluate driver fatigue. The 16 channels of EEG data are collected and transformed into three bands (θ, α, and β) in the current paper. First, 12 types of energy parameters are computed based on the EEG data. Then, Grey Relational Analysis (GRA) is introduced to identify the optimal indicator of driver fatigue, after which, the number of significant electrodes is reduced using Kernel Principle Component Analysis (KPCA). Finally, the evaluation model for driver fatigue is established with the regression equation based on the EEG data from two significant electrodes (Fp1 and O1). The experimental results verify that the model is effective in evaluating driver fatigue.

1. Introduction

Drowsiness is a significant risk that substantially contributes to the increasing number of motor vehicle accidents each year [3]. Statistics show that traffic accidents caused by driver fatigue account for about 20% of the total number of accidents, and more than 40% of serious traffic accidents [13]. Thus, the immediate and efficient detection of driver fatigue is important.

Although several methods can be used to evaluate driver fatigue, electroencephalogram (EEG) signal is one of the most predicative and reliable indicator because it directly measures brain activity [11]. Lal and Craig showed that significant EEG changes of the four bands occur during fatigue [12]. Waard and Brookhuis found that the relative energy parameter $(\alpha+\theta)/\beta$ of the driver decreases as the driving task continues [15]. Hong et al. showed that α, β, β/α, and $(\alpha+\beta)/\theta$ of the EEG signal show significant difference in the driving periods based on the eight channels of EEG within 50 min of continuous recording [6]. Jap demonstrated that $(\alpha+\beta)/\theta$, α/β, $(\theta+\alpha)/(\alpha+\beta)$, and θ/β of the EEG signal can indicate driver fatigue [8]. Based on the four sites on the scalp (P3, P4, F3, and F4), Mark found that the overall value for α activity indicates an increasing pattern for repeat compared with driving, and the EEG changes are consistent with the idea of overall reduction in attention during the latter laps [14].

Although many EEG-based ratio indices have been proven to be indicators of driver fatigue, the optimal indicator has not yet been determined. Furthermore, the high cost of electroencephalograph EEG with more electrodes usually restricts its application in the evaluation of driver fatigue. Using the data from 20 subjects, the evaluation model for driver fatigue was developed with the fewest electrodes. The aims of the present study are as follows: (1) to determine the optimal indicator of driver fatigue from EEG-based ratio indices and (2) to reduce the number of significant electrodes to expand the application of EEG in the evaluation of driver fatigue based on its optimal indicator.

2. Materials and methods

2.1. Driving simulator

A self-developed driving simulator (Fig. 1) was introduced to evaluate the driver fatigue level. The hardware of the driving simulator consisted of the Logitech steering wheel called MOMO force feedback racing wheel and a Logitech camera. The software of the driving simulator was composed of the scene-rendering system, the audio rendering system, and the automobile dynamics model. The Logitech camera was installed on the dashboard to collect the facial expression of the driver at the wheel.

2.2. Subjects

Twenty healthy male drivers ranging from 22 to 32 (25.6 ± 2.56) years of age took part in the driving experiment. They all had legal driver's licenses and normal sleep-wake habits. They must have had more than 7 h of sleep prior to the experiment. In addition,

* Corresponding author. Tel.: +86 021 34206770; fax: +86 021 62932070.
E-mail address: xmfan@sjtu.edu.cn (X.M. Fan).

0304-3940/$ – see front matter © 2011 Elsevier Ireland Ltd. All rights reserved.
doi:10.1016/j.neulet.2011.11.014

Fig. 1. The driving simulator.

the drivers had no physical barriers to successfully complete all the driving tasks.

2.3. Experiment and data collection

2.3.1. Experimental procedure

The experiment was divided into three periods: dawn (02:00 am–05:00 am), noon (13:30 pm–16:30 pm), evening (19:00 pm–22:00 pm). The drivers were instructed to drive no more than 120 km/h in a straight line section and 60 km/h in a curved section. The drivers were required to complete all the tasks and ensure safe driving. Prior to the experiment, the drivers familiarized themselves with the operation of the driving simulator and the completion of the driving tasks.

2.3.2. Data collection

NicoletOne Ambulatory EEG is one of the smallest and lightest ambulatory recorders, which can record 16 channels of EEG data with robust signal quality for a wide range of recording needs, allowing drivers more flexibilities in driving without missing any data [18]. Sixteen channels of EEG data were recorded following the international 10–20 Montage system covering the major areas of the brain. The sampling frequency of NicoletOne is up to 200 Hz. However, the required frequency is from 0.3 Hz to 20 Hz. The EEG signal is usually divided into four bands: δ (0.3–3.5 Hz), θ (4–8 Hz), α (8–13 Hz), and β (13–20 Hz) [11]. As the band of δ usually appears in the state of deep sleep, it was not analyzed in the current paper.

2.4. Method

2.4.1. EEG preprocessing

Muscle noise, heart signals, and eye movement usually produce artifacts in EEG raw data. The efficient elimination of artifacts is very important, both in visual and in quantitative EEG analysis because artifacts can mimic almost any kind of EEG pattern. Moreover, the artifacts included in the automated analysis can seriously affect efficiency [1]. The EEG raw signals larger than 50–70 μV are usually treated as artifacts [10,16]. However, many artifacts cannot be identified if their amplitude is lower than 50 μV, according to the present inference. The extended Independent Component Analysis (ICA) was introduced to isolate and remove a wide variety of EEG artifacts by linear decomposition caused by eye movement, blinking, and so on [9].

2.4.2. The computation of ratio indices

In the present paper, A1–A2 was chosen as the reference electrode. The six types of ratio indices were computed from the power spectrum of EEG data in the three bands (Eq. (1)).

$$\begin{cases} A_{\theta/\beta,k} = \dfrac{A_{\theta,k}}{A_{\beta,k}}, \quad A_{\alpha/\beta,k} = \dfrac{A_{\alpha,k}}{A_{\beta,k}}, \quad A_{\alpha/\theta,k} = \dfrac{A_{\alpha,k}}{A_{\theta,k}} \\ A_{\theta/(\alpha+\beta),k} = \dfrac{A_{\theta,k}}{A_{\alpha,k}+A_{\beta,k}}, \quad A_{(\theta+\alpha)/\beta,k} = \dfrac{A_{\theta,k}+A_{\alpha,k}}{A_{\beta,k}} \\ A_{(\theta+\alpha)/(\alpha+\beta),k} = \dfrac{A_{\theta,k}+A_{\alpha,k}}{A_{\beta,k}+A_{\alpha,k}} \end{cases} \quad k = 1, 2, \cdots, 16 \quad (1)$$

where A_θ, A_α, and A_β are the mean power spectra of θ, α, and β, respectively (i.e., $A_\theta = \Sigma f_i \times P_i / \Sigma P_i$; f_i is the whole number frequency in the θ band and P_i is the absolute power obtained using the Fast Fourier Transform in the θ band); $A_{\theta/\beta}$, $A_{\alpha/\beta}$, $A_{\alpha/\theta}$, $A_{\theta/(\alpha+\beta)}$, $A_{(\theta+\alpha)/\beta}$, and $A_{(\theta+\alpha)/(\alpha+\beta)}$ are the ratio indices, respectively; and k is the number of electrodes.

The six types of ratio indices were grouped with the time interval of 60 s. The mean value and mean square error (MSE) of the ratio indices were computed (i.e., the mean value and MSE of $A_{(\theta+\alpha)/\beta}$ can be computed as Eq. (2)).

$$\begin{cases} A_{(\theta+\alpha)/\beta,M} = \dfrac{1}{e}\displaystyle\sum_{i=1}^{e} A_{(\theta+\alpha)/\beta,i} \\ A_{(\theta+\alpha)/\beta,S} = \sqrt{\dfrac{1}{e-1}\displaystyle\sum_{i=1}^{e}(A_{(\theta+\alpha)/\beta,i} - A_{(\theta+\alpha)/\beta,M})^2} \end{cases} \quad (2)$$

where $A_{(\theta+\alpha)/\beta,M}$ and $A_{(\theta+\alpha)/\beta,S}$ are the mean value and MSE of $A_{(\theta+\alpha)/\beta}$, respectively, in each group; and e is the total number of EEG data in one group (time interval). The other types of energy parameters can be computed in the same way.

3. Results

3.1. The optimal indicator of driver fatigue

Twelve types of energy parameters were computed, and the optimal indicator was determined to immediately and efficiently evaluate driver fatigue. Multiple-attribute decision making was required, which involved multiple objectives and criteria. In the current paper, Grey Relational Analysis (GRA) was introduced to determine the relative optimal indicator from the alternative indicators of driver fatigue. GRA is a geometric proximity analysis among the different discrete sequences used to compute the weights in the criteria [7]. The grey relational grade indicates the relationship between the reference sequences and the compared sequences. The larger the grey relational grade of the compared sequences, the better the result [5].

The grey relational grade can be computed as follows:

$$\begin{cases} X_0(t) = \{x_0(p) | p = 1, 2, \ldots, n\} \\ X_s(t) = \{x_s(p) | p = 1, 2, \ldots, n\} \end{cases} \quad (3)$$

where X_0 (t) is the reference sequence, and the driver fatigue level is chosen as the reference sequence (alert state is assigned to 1 and drowsy state is 2); X_s (t) is the compared sequence (12 types of energy parameters of EEG signal); s is the number of the compared sequences; and p is the number of samples in a compared sequence.

The grey relational coefficients between reference sequences and compared sequences were computed as Eq. (4):

$$\zeta_s(t) = \frac{\min\limits_s \min\limits_t \left|x_0(t) - x_s(t)\right| + \rho \max\limits_s \max\limits_t \left|x_0(t) - x_s(t)\right|}{\left|x_0(t) - x_s(t)\right| + \max\limits_s \max\limits_t \Delta_s(t)} \quad (4)$$