An Attention Level Monitoring and Alarming System for the Driver Fatigue in the Pervasive Environment

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Abstract. In recently years, driver fatigue detecting system has gained increasing attentions in the area of public security. Researchers have succeeded in applying the EEG signals to accurately detect individuals fatigue state in sustained attention tasks. However, these studies were performed under laboratory-oriented configurations using tethered, ponderous EEG equipment, which are not feasible to develop the fatigue detecting system in the real environment. This study focused on developing a portable attention level monitoring and alarming (ALMA) system, featuring a mobile NeuroSky MindSet and an android pad based real-time EEG processing platform, for the driver fatigue in the pervasive environment. A brain feature rule which can represent the brain gradual process from focus state to the fatigue state has been formulated. We evaluated the ability of attention level of the system in the simulated driving cockpit and demonstrated that the system can classify the subjects attention level in accordance with the rule in the real time.

1 Introduction

A low attention level such as driver fatigue is a main cause of car accidents. Researchers have succeeded in applying the EEG signals to accurately detect The mental state of individuals in sustained attention tasks [9,10]. Lin et al. have studied the safe manipulation and control of various vehicles based on electroencephalographic (EEG) spectra and demonstrates that some adaptive feature can reflect drivers alertness accurately [1,2]. They further shown that feasibility of estimating the efficacy of arousing feedback presented to the drowsy subjects by monitoring the changes in EEG power spectra[13,14]. Nevertheless, the results were mostly based on laboratory-oriented equipment, which records multi-channel datum from multi-electrodes placed on the scalp. Those setups are always cumbersome, complicated to operate and required uncomfortable skin preparation. It is impractical for routine use by unconstrained and freely moving users in the real world.

In order to overcome those flaws, many studies such as Wang et al. begin to focus on launching a driving behavior model for the driver fatigue in the pervasive environment [3,8,12]. The model can get the input parameter from some

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pervasive computing devices and judge the attention level of drivers according to the model rules, deliver arousing feedback to users experiencing momentary cognitive lapses.

Our work is focused on the design of a real-time driver fatigue system based on Android platform and the NeuroSky Mobile MindSet for attention level recognition in a ubiquitous environment, shown in Fig.1, which can continuously monitor and assess the attention level of drivers and deliver arousing feedback if the driver experiencing momentary drowsiness. The structure of this paper is as follows: In section 1, we provide the background of our ALMA system for attention recognition. In section 2, we introduce our experiment details and driver fatigue feature extraction methodology based on NeuroSky MindSet. In section 3, we describe the implementation of the ALMA system. In section 4, we present the whole architecture of ALMA system and evaluate the ability of attention level of the system in a simulated cockpit. Finally, section 5 gives a summary of our work and future research directions.

(a)

(b)

Fig. 1. (a) A participant wearing the MindSet and holding the Sangsun pad based ALMA system. (b) The NeuroSky Mobile MindSet [16].

2 Feature Extraction Methodology for Driver Fatigue

2.1 NeuroSky MindSet

The pervasive computing device for this research was an off-the-shelf low cost EEG headset from NeuroSky, the MindSet headset shown in Fig.1 (b), which incorporate ThinkGear technology in a convenient, stylish headset from factor, complete with Bluetooth audio and microphone.ThinkGear includes the sensor that touches the forehead, the contact and reference points located on the ear pad, and the onboard chip that processes all of the data and provides those data to software and application in digital form. Both the EEG raw brainwaves [11] and the eSense [4] Meters (Attention and Meditation) are calculated on the ThinkGear chip.

Attention eSense [15] reports the current eSense Attention meter of the user, which indicates the intensity of a users level of mental focus or attention. Distractions, wandering thoughts, lack of focus, or anxiety may lower the Attention meter levels. Meditation eSense[16] reports the current eSense Meditation meter of the user and a persons mental level, which indicates the level of a users mental calmness or relaxation. The ranges of the two signals are from 0 to 100. The headset can output the two interpreted values based on raw brainwave at one-second intervals.

Recent studies have validated the headsets ability at detecting stimulus from raw EEG data [5] and production of correlating eSense values [6]. Paul et al. [7] used the two interpreted EEG data by headsets, the Attention and Meditation eSense values, in developing a brain interaction for a maze game. This indicates that the headset possesses the ability of developing a real time system. Consequently, we began to design a real time system and try to find out some fatigue feature based on a sort of experiments. We designed four experimental scenes and extract the feature which can reflect drivers attention level based on the Attention and Meditation.

2.2 Experimental Scene and Data Collection

Due to the mental state from focus to fatigue is a gradual process, we designed four experimental scenes named focus, clear-headed, light fatigue and deep fatigue. We collected the Attention and Meditation signals from MindSet in those four scenes so that we can find out some fatigue feature which can reflect the attention level accurately. The four scenes were depicted as follows.

a) Focus: a mental reading task or arithmetic task for which the subjects were asked to concentrate.

b) Clear-headed: the subjects were asked to wonder and walk around the campus so that they can get into a relaxing state with a clear mind.

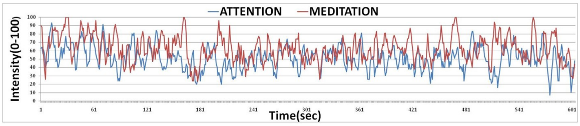
c) Light fatigue: a reading silently task after which the subject were asked to have their lunch, in this method they can get into the fatigue state easily.

d) Deep fatigue: a sleeping task during which the subjects were asked to sleep with MindSet. However, the subjects claimed that they cannot fall asleep and their state was closer to a light sleep state. Thus, we regard this scene as a deep fatigue state.

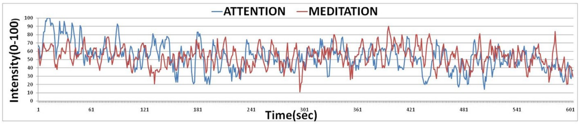
A total of 4 volunteers (ages from 20 to 25, 2 male and 2 female) participated in the experiments. All the participants are healthy and without the habit of staying up the whole night. Each subject takes three sessions and each session contains four mental tasks, which taking the subjects about 20 minutes to complete. The subjects were asked some questions before the experiment began, such as whether they have drunk wine or coffee; have had poor sleep in the previous night. If they indicated that they have experienced one of the above, the experiment is deferred for one or several days.

2.3 Feature Extraction

Considering the time span from putting on MindSet to get into the specific state, we extract and analysis the 10 minutes data of Attention and Meditation which is in the middle of mental tasks. Fig.2 shows the comparisons of Attention and Meditation signals of one of four students in four experimental scenes. As we can see, although there is no obvious regular pattern in the focus and clear-headed scene, it is noted that the two signals mirror each other and the correlation coefficient between the two signals in the deep fatigue scene is more than that in the light fatigue scene. However, this is a special example from one student and it cannot represent every entities. Consequently, we choose one session from each student and calculate the correlation coefficient between Attention and Meditation of the four sessions.



(a)



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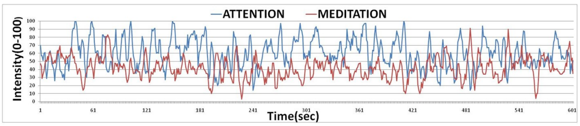

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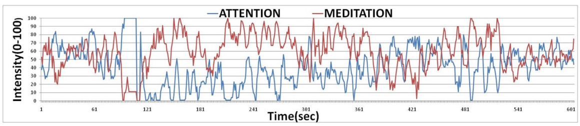
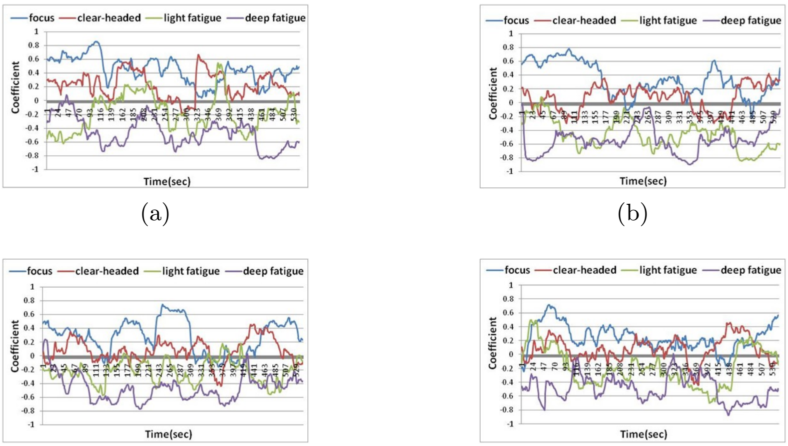


(d)

Fig. 2. (a) Comparisons of Attention and Meditation Signals in four different scenes in the focus scene. (b) Comparisons of Attention and Meditation signals of one of four students in clear-headed scene. (c) Comparisons of Attention and Meditation signals of one of four students in light fatigue scene. (d) Comparisons of Attention and Meditation signals of one of four students in deep fatigue scene.

We can use the Pearsons correlation coefficient formula to calculate the coefficient between the two signals.Because we want to develop a real time system and MindSet can output Attention and Meditation at one-second intervals, we calculate and analysis the correlation coefficient of Attention and Meditation every second after saving attention and meditation signal of one minute. Fig.3 shows the correlation coefficient curve graph, which was calculated every second, of four subjects. We can get the conclusion that the coefficient wave in different task fluxed within a fixed range. The approximate range of coefficient in four different scenes is shown in Table 1. Although sometimes the coefficient value of the state such as the clear-headed or deep fatigue is more than the value of other state such as focus or light fatigue, the value of light fatigue and deep fatigue is less than the value of focus in the most time. This phenomenon maybe caused by the subjects, who sometimes have difficulty in self-assessment of attention level or influenced by other people and the environment when they did the mental tasks. Therefore, we can use the correlation coefficient between Attention and Meditation as the driver fatigue brain feature and predict the gradual process from focus to fatigue. In other words, we take the coefficient range which is shown in the Table 1 as the rule to judge and predict driver fatigue.



(a) (b)

(c) (d)

Fig. 3. The correlation coefficient curve graph of four subjects

Table 1. The range of correlation coefficient in four different scenes

Experimental scene	Coefficient Range
Focus	More than 0.3
Clear-headed	-0.1 to 0.3
Light fatigue	-0.4 to -0.1
Deep fatigue	Less than -0.4

3 Implementation of the Attention Level Monitoring and Alarming System

The ALMA system includes three parts: (1) The NeuroSky Mobile MindSet as shown in Fig. 1 (b), which is an EEG signal collection device. (2) A KNN real-time detecting algorithm that processes the data from headset and judges the attention level of drivers. (3) An Android Sungsum pad that shows an intuitive graphic interface on the screen and delivers auditory alarming feedback to the drowsy driver.

3.1 System Software Design

NeuroSky provides a number of Application Programming Interfaces (APIs) to allow MindSet to connect with a wide range of devices such as Mac, Windows and Android. We design an ALMA system which is running on the Sungsum pad based on those APIs. The system mainly consists of two parts which is KNN real-time fatigue detecting algorithm and an intuitive interface which can show the correlation coefficient and classification result in two dynamic pictures. Fig.4 shows screenshot of the interface, which is comprised of three parts as we can see in the picture. The value of Attention, Meditation, coefficient result and the classification result are shown in the left part of the picture. The part of top right shows a curve graph of the classification result which comes from the real-time classification result. Level 0 to level 3 represent each focusing state to deep fatigue. The part of bottom right shows a curve graph of the correlation coefficient which is calculated and updated every second. Additionally, an alarming function was required and completed while an attention level such as light fatigue or deep fatigue was detected.

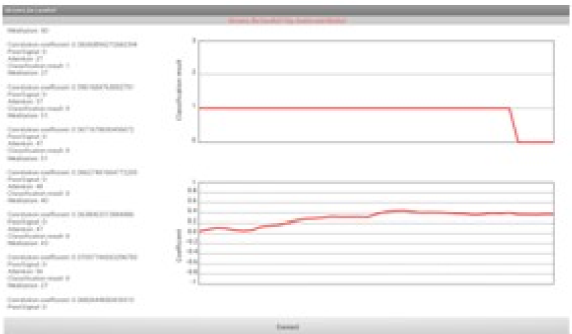


Fig. 4. Screenshot of the ALMA system software interface

3.2 The KNN Real-Time Fatigue Detecting Algorithm

A KNN real-time fatigue detecting algorithm is used in the ALMA system, as shown in Fig. 5, which can continuously monitor a subject's cognitive state. Two

60 points sliding windows were created to save Attention and Meditation values, and to calculate calculated the coefficient every second and save the result into another 60 points sliding window. Furthermore, the KNN algorithm is used to classify the current coefficient data and take the classification result as a rule to decide whether deliver auditory arousing feedback. We take the coefficient data in the 60 point sliding window as the testing sample, the training sample we used came from the data of 4 students in the four experimental scenes. Considering the mistake could be caused by the subjects who sometimes have difficulty in self-assessment of attention level or influenced by the environment, we pick up the data which is in line with the rules shown in Table 1 as the training sample. Metadata in the training samples are classified by subjects self-assessment which was comprised of focus, clear-headed, light fatigue and deep fatigue. At last we implemented the algorithm in the Sungsum pad.

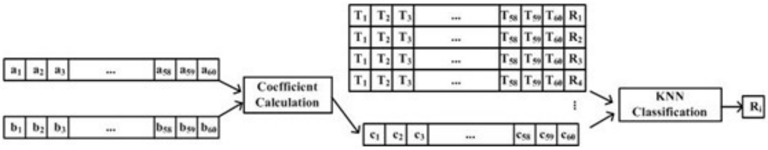
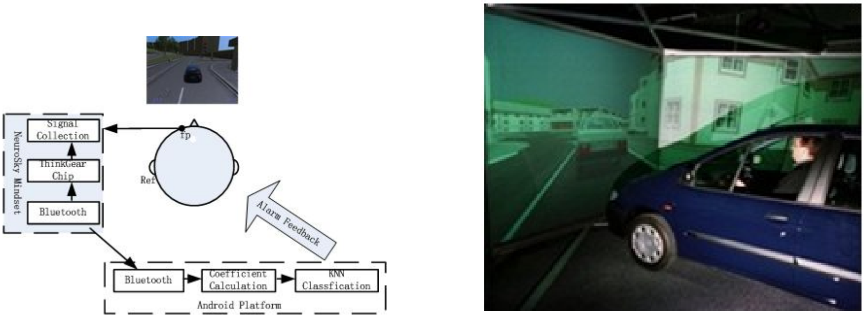


Fig. 5. The KNN real-time fatigue detecting algorithm running on the Android platform

4 The Architecture of ALMA System and Attention Level Recognition Evaluation

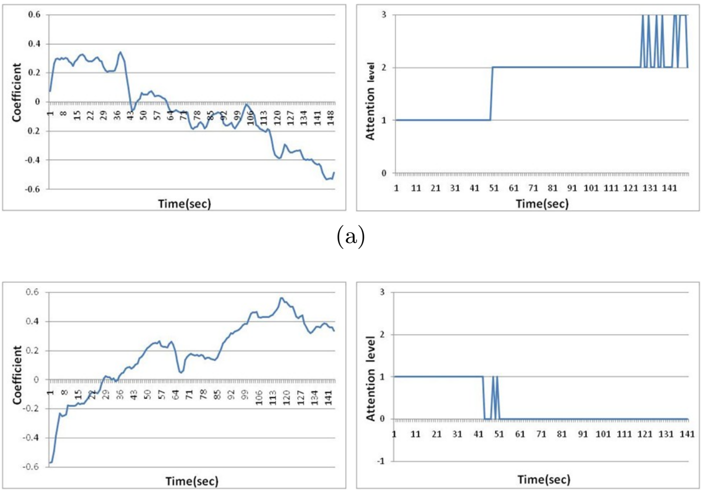
4.1 The Architecture of ALMA System

We did experiments in a simulated cockpit to simulate a real driving environment so that we can monitor and predict the gradual process from focus to fatigue. Fig.6 shows the system architecture diagram of the portable ALMA system and the simulated cockpit. The ALMA system mainly includes two parts: (1) the NeuroSky MindSet which measures and amplifiers the EEG signals from the prefrontal point (fp) without requiring skin preparation. A ThinkGear chip inside the MindSet uses ThinkGear technology which adapts some slow-adaptive algorithms to adjust to natural fluctuations and trends of each user, accounting for and compensating for the fact that EEG in the human brain is subject to normal ranges of variance and fluctuation. The MindSet transfers the two interpreted eSense values and other data such as raw data and poor signal to the ALMA system, running on an Android Sungsum pad, by bluetooth. (2) The ALMA system firstly receives the Attention and Meditation data from bluetooth, secondly calculates the coefficient between the two signals every second, and thirdly runs the KNN real-time fatigue detecting algorithm to judge the attention level of drivers, which will deliver auditory arousing feedback as soon as detecting the fatigue state.



(a) (b)

Fig. 6. The system architecture diagram of the ALMA system. (b) The simulated cockpit [17]



(a)

(b)

Fig. 7. (a) The correlation coefficient curve graph of the subject who experienced the mental state from focus to fatigue and the classification result of Attention level by ALMA. (b) The correlation coefficient curve graph of the subject who experienced the mental state from fatigue to focus and the classification result of Attention level by ALMA.

4.2 Attention Level Recognition Evaluation

The ability of attention level of the system has been evaluated in the simulated driving cockpit. A total of 12 volunteers (ages from 20 to 45, 10 males and 2 females) joined in the experiment. All the participants have already got their driving license with the driving experience more than one year. Every subject spent about 1 hour in the experiment. During the experiment period, the subject assessed their own attention state and recorded the time when they feel fatigue.

At last, 6 volunteers experienced the gradual process from focus to fatigue. In order to explain the ability of attention level of the system clearly, we choose and analyzed two volunteers' data of Attention and Meditation, one of them experienced the mental state from focus to fatigue and the other is reverse. Moreover, we calculated the coefficient and classified the attention level. Fig.7 shows the coefficient curve graph and the classification result of the two subjects. As we can see in the picture, the system can detect the attention level in the real time. When the subject got into the light fatigue state, the system almost classified the state correctly in the meanwhile and vice versa. In addition, the classification result is accordance with the rules shown in Table 1. Thus, the ALMA system can judge the drivers attention level based on the correlation coefficient between Attention and Meditation in the real time.

5 Conclusion

This study aims to develop an attention level monitoring and alarming driving fatigue system in the pervasive environment. Firstly, we explored a brain feature based on Attention and Meditation signal produced by NeuroSky MindSet and formulated a model rule which can represent the brain gradual process from the focus state to the fatigue state. Secondly, we developed and implemented an ALMA system on a Sungsum pad which is a real-time signal-processing platform. Thirdly, we evaluated the ability of attention level of the system in the simulated driving cockpit and got the conclusion that the system can classify the attention level of subjects in accordance with the rules in the real time. In particular, the portability and worn ability of such a system improve the usability and practicality of the ALMA system over traditional laboratory-oriented EEG-based brain-computer interface designs. The NeuroSky Company sells their ThinkGear chip online. Thus, we can buy and design our own brain-computer device which is more comfortable than NeuroSky MindSet.

However, the system also has some flaws. As we can see in Fig.7, there are some fluctuations when the classification results transferred from light fatigue to deep fatigue or from clear-headed to focus. Probably it is because of false classification origin from the training samples of the KNN algorithm. Thence, we need to improve our classification algorithm or attempt to use other algorithms in the future.

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