WEIGHTED-FREQUENCY INDEX FOR EEG-BASED MENTAL FATIGUE ALARM SYSTEM

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ABSTRACT

Mental fatigue is another major cause of the serious car accidents. Ability to early predict the mental fatigue phenomenon is hence one of the challenging problems in brain-computer interface (BCI). In this paper, we propose the practical EEG-based mental fatigue alarm system including the weighted-frequency index of the linear combination among EEG theta, alpha and beta rhythms. The proposed system is tested with the simulated driving situations. By using only 1-channel EEG at the temporal area of the brain, more than 90% of prediction accuracies are reported compared to the opinion scores of the users.

1. INTRODUCTION

Mental fatigue is a phenomenon in which the brain cells become exhausted. Consequently, it makes the people lack of concentration or feel asleep in either short or long periods of time [1]. This phenomenon contributes to vehicle accidents at which the ranging has been approximated between 20-30% of all vehicle accidents. Ability to early predict the mental fatigue phenomenon is hence one of the challenging problems in brain-computer interface (BCI). According to the above problem, many researchers try to investigate the system for early detection of a mental fatigue phenomenon while driving. Many possible techniques employ physical behaviors to detect the metal fatigue, e.g. a rate of eye-blink, head nodding, body movement, eyes movement, countenance and facial expression [2-4]. Moreover, biomedical signals are also efficiently used for early detection of mental fatigue, i.e electrooculogram (EOG) [5], electrocardiogram (ECG) [6], pulse oximetry (SpO2), blood pressure (BP), respiration signals, and electroencephalogram (EEG) [7-11]. Among all of these biomedical signals, EEG is the only signals that can directly interpret the mental stage directly from the brain. Therefore, by using EEG, metal fatigue can be detected earlier than using other modalities. One of the most promising method in [10] investigates the contribution of four frequency components of EEG, i.e. Delta δ (0-4 Hz), Theta θ (4-8 Hz), Alpha α (8-13Hz) and Beta β (13-35 Hz). By using four frequency indexes, i.e. $(\theta+\alpha)/\beta$, α/β, $(\theta+\alpha)/(\alpha+\beta)$ and α/β; $(\theta+\alpha)/\beta$ index yields the highest metal fatigue detection accuracy. However, this index still lacks of the flexibility to adjust the merit of some frequency bands.

Therefore, in this paper, we propose the practical mental fatigue alarm system by investigating the effects of three different weighting factors applied to the index $(\theta+\alpha)/\beta$ in [10]. The proposed indexes are tested with the simulated driving situations. By using only 1-channel EEG at the temporal area of the brain, more than 90% of prediction accuracies are reported compared to the opinion scores of the users. Furthermore, the recommended design for the practical mental fatigue system is also illustrated.

2. THE PROPOSED MENTAL FATIGUE ALARM SYSTEM

The proposed mental fatigue alarm system can be divided into four main parts, i.e. EEG acquisition system, signal processing algorithm, decision making, and alarm system. The overall flow chart can be showed in Fig.1. The contribution of the proposed system will be mainly in the signal processing algorithm and the decision making parts.

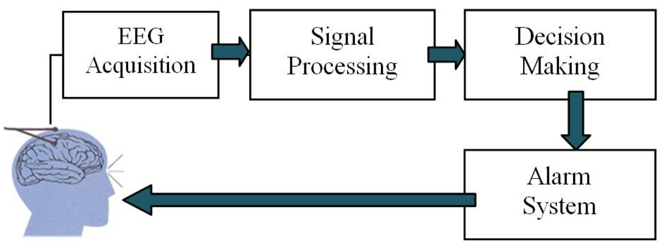

Fig.1: *Overview of the proposed mental fatigue alarm system.*

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2.1 EEG Acquisition

In this work, the electrode cap with Ag/AgCl electrodes is used in EEG acquisition process. Electrode positions will be opposite to the dominant hand as in Table I according to the 10-20 international electrodes placement system. Those selected locations are from the Temporal (T), Central, (C) and Parietal (P) regions. Single channel EEG amplifier of BIOPAC MP100 system is employed in the system with gain equal to 10,000. NI-DAQTM mx (NI USB 6008) multifunction I/O is used to convert analog signal into digital signal. To efficiently eliminate the power line artifact, A 50 Hz analog notch filter is employed together with an analog low-pass filter with cutoff frequency at 35 Hz. As the reference, other physiological signals such as SpO_2, blood pressure (BP) and heart rate are recorded everytime before and after the experiments via NIHON KOHDEN (Bedside) physiological signal monitoring device.

Table 1: *Three conditions of the liver testing corresponding to Fig. 7*

Dominant hand	Electrode Positions		
	+	-	GND
Left	T3	P4	C3
Right	T4	P3	C4

2.2 Signal Processing: Weighted-Frequency Indexes

According to [10], the frequency index that yields the highest accuracy in fatigue alarm is the ratio of frequency contents among θ, α, and β rhythms, i.e. $(\theta+\alpha)/\beta$,

$$\theta = \sum_{f=4}^{7} PS(f) \tag{1}$$

$$\alpha = \sum_{f=8}^{13} PS(f) \tag{2}$$

$$\beta = \sum_{f=14}^{30} PS(f) \tag{3}$$

PS(f) denotes magnitude of the power spectral density at frequency f Hz. In order to increase the resolution and to enhance the performance of the mentioned index, the weighted-frequency index, I(t), is proposed by applying the selected weights to each frequency bands with respect to time interval as follows:

$$I(t) = \frac{w_1(t)\theta(t) + w_2(t)\alpha(t)}{w_3(t)\beta(t)} \tag{4}$$

where t is the selected time interval, e.g. 0 to 8 seconds. $w_1(t)$, $w_2(t)$, and $w_3(t)$ are the weights of theta $\theta(t)$, alpha $\alpha(t)$, and beta $\beta(t)$ activities, respectively, at time interval t. For practical use, in this paper, we will assume only one time interval, and assign$w_1(t)$, $w_2(t)$, and $w_3(t)$as the integer numbers. Hence Eq. (4) can be reduced to our three selected indexes as follows:

$$I_1(t) = \frac{0.5\theta + 0.5\alpha}{0.5\beta} \tag{5}$$

$$I_2(t) = \frac{0.4\theta + 0.6\alpha}{0.5\beta} \tag{6}$$

$$I_3(t) = \frac{0.6\theta + 0.4\alpha}{0.5\beta} \tag{7}$$

θ, α, and β are obtain from Eqs. (1)-(3)We can obviously see that Eq. (5) is actually the index proposed in [10].

2.3 Decision Making

The alarm will be on when the weighted-frequency index (I) is above the setting threshold T. T can be calculated as

$$T = 0.5 I_{eyeclosing} \tag{8}$$

where $I_{eyeclosing}$ is obtained from the weighted-frequency index (I) when the subjects close their eyes for 10 seconds prior to the session (during system calibration period). Since the eye closing EEG yields higher magnitude than awake EEG, 50% of its energy is selected as the threshold by multiplying 0.5 to $I_{eyeclosing}$.

3. EXPERIMENT AND RESULTS

In this paper we test the proposed system by creating the driving simulator. The accuracy of the system is evaluated according to the synchronization of the subjects' opinions and the alarms from the tested index

3.1 Simulator

In this experiment, we setup the driving scenario by letting the subjects play the play station II (PSII) car racing game called "Short Track Racing". The subjects drive the car using the PSII steering wheel and the gas pedal. Projector is used as the display unit (Fig.2).

3.2 Experiment

In this experiment, there are seven volunteer subjects. Each subject performs one hour simulated car driving. The accuracy of the system is evaluated according to the synchronization of the subjects' opinions and the alarms from the tested indexes by the home-made software shown in Fig. 3. In Fig. 3, each circle light represents each tested index, i.e. green light represents Eq. (5), yellow light represents Eq. (6), and blue light represents Eq. (7).

Fig.2: *Simulator of for the Fatigue Alarm Experiment.*

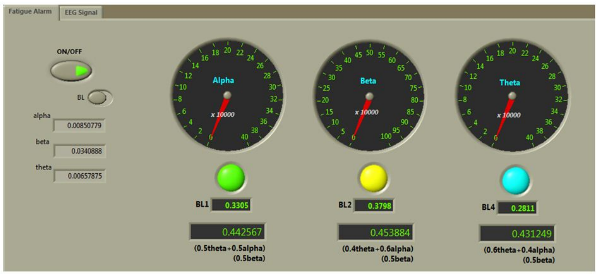


Fig.3: *Home-Made Software Interface of the Mental Fatigue Alarm System.*

3.3 Results

Tables II and III illustrate the opinions and the number of detected decisions from the software of subject 1 and subject 2, respectively. The fatigue opinions are collected by letting the subjects push the provided button (which is synchronized with our recording software) when they feel fatigue. We start recording the data after 30 minutes from the beginning to avoid the false alarms of the fatigue recording from the opinion scores. From Tables II and III, The blood pressure (BP) and heart rate (HR) of subject 1 are decreased, but they are increased in subject 2. For Pulse Oximeter Oxygen Saturation (SpO_2), all of subjects have the same amount of percentage. These results show that we cannot clearly distinguish the phenomenon of mental fatigue of both subjects from BP, HR, and SpO_2. However, according to EEG, we obtain the accuracies ranging from 63.25% to 93.16%. The proposed index in Eq. (7), $(0.6\theta + 0.4\alpha)/0.5\beta$, yields the highest accuracies of 85.47% and 93.16% for subject 1 and subject2, respectively. The conventional index in [10] $(0.5\theta + 0.5\alpha)/0.5\beta$ yields slightly lower accuracies in both subjects, while the proposed index in Eq. (6) yields the lowest accuracies in both subjects. To further emphasize on the proposed index, Tables IV-VIII reveal the same conclusion according to five more subjects. To emphasize on the total number of alarms for each index in each time interval, Figs. 4(a) and 4(b) compare the number of alarm detected from all of the three indexes among three periods of time (31-40 minutes, 41-50 minutes, and 51-60 minutes) in Subject 1 and Subject 2, respectively. As mentioned, the last 30 minute time interval is the period that is likely to contain fatigue behavior. Therefore, we further divide this period into 10 minute sub-period. To further analyze in different time intervals, Figs. 4(c)-4(g) compare the number of alarm detected from all of the three indexes among three periods of time (11-20 minutes, 21-30 minutes, and 31-40 minutes) in Subjects 3-7, respectively. In all cases, the proposed index in Eq. (7), $(0.6\theta + 0.4\alpha)/0.5\beta$, yields the highest number of alarms (but it still yields slightly lower number than the total number of fatigue opinions in the purple color bars) for every time interval. This implies that all of the tested indexes did not tend to lead to too many false alarms.

3.4 Practical Design of EEG-based Mental Fatigue Alarm System for Car Driver

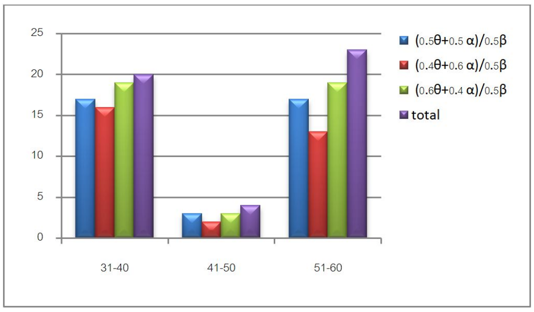
According to the results in Section IIIC, we can obtain the suitable index used for the practical design of mental fatigue alarm system. The idea of the design is summarized in Fig.5. The proposed design can be divided into two parts:

1. Since the system must alarm once the drivers close their eyes for a few seconds and we know that closing the eyes will lead to the increasing in magnitude of power spectrum in alpha band, therefore the proposed system must include the alpha detector algorithm. The selected threshold is obtained from the initial calibration, i.e the subjects need to close their eye for 10 seconds prior to use the system. After that 75% of the sum of the spectrum in alpha band (8-13 Hz) will be used as the threshold of the alpha detector algorithm.

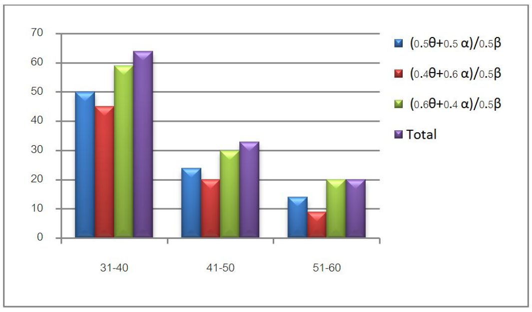
2. The software will also use the same data obtained from the initial calibration to obtain the threshold in Eq. (8) of the weighted-frequency index. The index can be freely selected (Eqs. (5-7)) according to the users. In accordance with the results in Section IIIC, we recommend either index from Eq. (5): conventional index in [10] or Eq. (7): the proposed index.

Table 2: *The fatigue alarm results of subject 1*

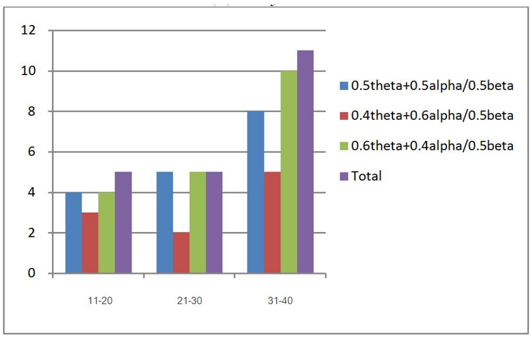
Index	Total Opinion	Score alarm	% Accuracy
$\frac{0.5\theta+0.5\alpha}{0.5\beta}$	48	37	77.08
$\frac{0.4\theta+0.6\alpha}{0.5\beta}$	48	31	64.58
$\frac{0.6\theta+0.4\alpha}{0.5\beta}$	48	41	85.42
Physiological Signals	**BP (mmHg)**	**HR (bmp)**	SpO_2(%)
Pre-Test	143/80	78	97
Post-Test	140/75	74	97



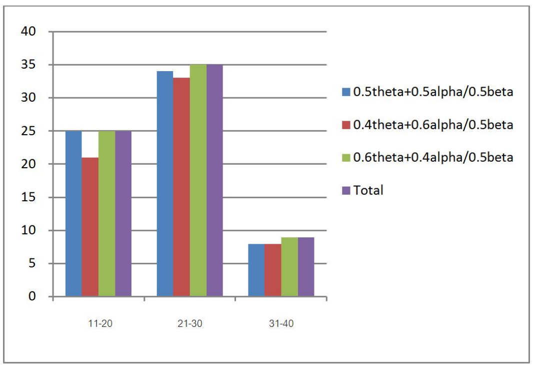
(a)Subject1



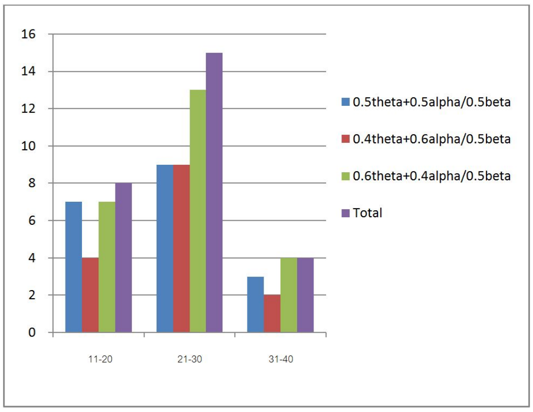
(b)Subject2



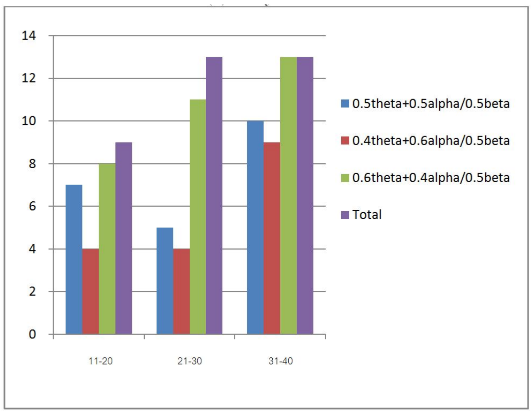
(c)Subject3



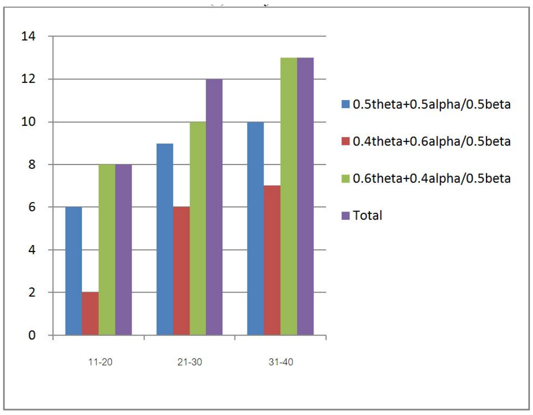
(d)Subject4



(e)Subject5



(f)Subject6



(g)Subject7

Fig.4: *Number of detected mental fatigue alarms (a)-(g) for Subjects1-7, respectively. x-axis represents time during the experiment and y-axis represents the number of detected alarms compared to the subjects' opinions (Total).*

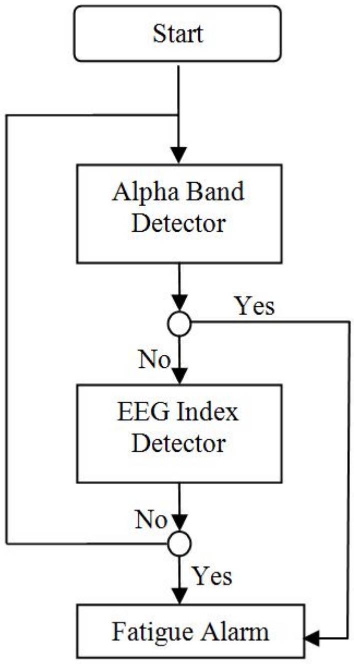


Fig.5: *Work flow of the practical design of the EEG-based mental fatigue alarm system.*

Table 3: *The fatigue alarm results of subject 2*

Index	Total Opinion	Score alarm	% Accuracy
$\frac{0.5\theta+0.5\alpha}{0.5\beta}$	117	84	75.21
$\frac{0.4\theta+0.6\alpha}{0.5\beta}$	117	74	63.25
$\frac{0.6\theta+0.4\alpha}{0.5\beta}$	117	109	93.16
Physiological Signals	**BP (mmHg)**	**HR (bmp)**	$SpO_2(\%)$
Pre-Test	114/75	75	97
Post-Test	117/78	77	97

Table 4: *The fatigue alarm results of subject 3*

Index	Total Opinion	Score alarm	% Accuracy
$\frac{0.5\theta+0.5\alpha}{0.5\beta}$	29	25	86.21
$\frac{0.4\theta+0.6\alpha}{0.5\beta}$	29	16	55.17
$\frac{0.6\theta+0.4\alpha}{0.5\beta}$	29	27	93.10

Table 5: *The fatigue alarm results of subject 4*

Index	Total Opinion	Score alarm	% Accuracy
$\frac{0.5\theta+0.5\alpha}{0.5\beta}$	86	82	95.35
$\frac{0.4\theta+0.6\alpha}{0.5\beta}$	86	73	84.88
$\frac{0.6\theta+0.4\alpha}{0.5\beta}$	86	86	100.00

Table 6: *The fatigue alarm results of subject 5*

Index	Total Opinion	Score alarm	% Accuracy
$\frac{0.5\theta+0.5\alpha}{0.5\beta}$	37	26	70.27
$\frac{0.4\theta+0.6\alpha}{0.5\beta}$	37	21	56.76
$\frac{0.6\theta+0.4\alpha}{0.5\beta}$	37	31	83.79

Table 7: *The fatigue alarm results of subject 6*

Index	Total Opinion	Score alarm	% Accuracy
$\frac{0.5\theta+0.5\alpha}{0.5\beta}$	52	31	59.62
$\frac{0.4\theta+0.6\alpha}{0.5\beta}$	52	24	46.15
$\frac{0.6\theta+0.4\alpha}{0.5\beta}$	52	44	84.61

Table 8: *The fatigue alarm results of subject 7*

Index	Total Opinion	Score alarm	% Accuracy
$\frac{0.5\theta+0.5\alpha}{0.5\beta}$	41	29	70.73
$\frac{0.4\theta+0.6\alpha}{0.5\beta}$	41	18	43.9
$\frac{0.6\theta+0.4\alpha}{0.5\beta}$	41	38	92.68

4. CONCLUSION

In this paper, we have proposed the generalized index for the mental fatigue alarm system called weighted-frequency index. The possible indexes are tested with the simulated driving scenario. The results reveal that the proposed weighted-frequency index yields slightly higher accuracies on detecting the metal fatigue compared to the conventional index. Furthermore, we have also presented the practical design of the metal fatigue alarm system which employs the hybrid decision making while using only one-time calibration. As the future works, time-dependent weight indexes need more investigation together with their physiological models.

5. ACKNOWEDGMENT

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