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A NOVEL FATIGUE DETECTION SYSTEM COMBINING EYE IMAGES AND BRAINWAVES

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Abstract. *When car drivers have been on the road for a long time or are in poor physical condition, their driving might lead to incidents. In this paper, two methods were adopted to detect drowsiness. The first method was capturing images of a person's eyes in order to detect the distance between the upper and lower eyelids. First HSV (hue, saturation, value) skin-color detection was used to capture an image of the face, and the eye area was binarized. The distance between the eyelids was measured based on black and white contrast, and this was used to detect whether the driver was in a state of drowsiness. To circumvent errors in eye measurement caused by light sources, electroencephalograph signals were detected as a second method, and relaxation and concentration waveforms were used for diagnosis. To reduce costs, an ordinary webcam and an electroencephalography (EEG) head set were used to capture these two signals, which were transferred to a diagnosis system using Bluetooth. The Extension theory was applied in the identification algorithm for detection, and if the driver was diagnosed as tired or drunk, an alarm signal sounded and the control center was notified through a wireless connection to prevent traffic accidents. This method achieved an average accuracy of 92.5% in experimental tests.*

Keywords: Fatigue detection, Electroencephalograph, Safety detection

1. **Introduction.** According to the Taiwanese National Police Agency, Ministry of the Interior, 2014 road accidents occurred in 2012. Of these incidents, 18.4% resulted from drunk driving and 18.7% resulted from fatigue driving. Detection of drunkenness and fatigue before drivers begin driving is thus crucial for preventing road accidents, and is critical in transportation. Research on the human brain has become a popular topic due to rapid progress in this field. Subjects wear an EEG headset that resembles pair of headphones and detects waveforms in the subject's brain [1-3]. Relaxation and attention signals are more accurately detected when using this novel technology. The indicators of fatigue in a driver include [4] the degree to which the eyes are closed (hereafter referred to as eye size), closed-eye duration, blinking frequency, nodding frequency, facial-structure position, and state of daze. When a driver loses concentration [5-7], however, these methods easily cause errors when external light sources shift rapidly or when drivers make head movements. To overcome these defects, one method involves using eye image processing for driver fatigue detection [8,9]. This paper proposes a combined method of using eye

images and brainwaves for diagnosis of drowsiness. This combination compensates for the effect of changing light sources, and provides the merits of extension methods including rapid calculation, high accuracy, and easy hardware implementation. Experimental tests proved this method to show satisfactory results in preventing car accidents.

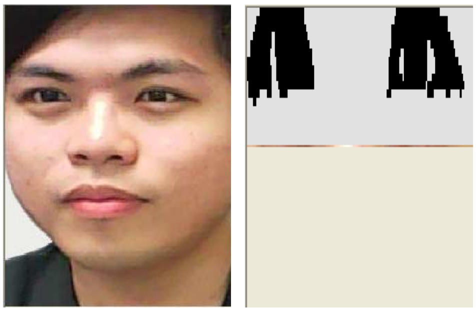
2. **Proposed Detection System Architecture.** Figure 1 shows the identification structure of the fatigue detection system. Charge-coupled device (CCD) webcam was used to capture facial images of subjects, and images of the eyeball area were retrieved and transferred to a database. CCD webcams are highly sensitive to light and can produce substantial errors when the surrounding lighting environment changes only slightly. Therefore, lighting conditions during image capturing are crucial.

FIGURE 1. Architecture of the drowsiness detection system

The human brain is composed of countless nerve cells, which constantly discharge when the brain is active, which is the fundamental principle involved in brainwave measurement. Brainwave control involves the conversion of analog signals to digital signals through special chips, and then expressing these signals in digits from 0 to 100. These scores can be used to determine if a person is concentrated or relaxed, and thus monitor whether that person is in a state of fatigue or alertness. Concentration and relaxation waveforms are transferred to a database through Bluetooth communication to serve as characteristics for differentiation. Subsequently, an Extension detection algorithm is applied to identifying the subject's current physical and mental status. If the driver's body displays signs of fatigue or intoxication, warning lights and sounds are produced to notify the driver, and these alarms are transferred through general packet radio service (GPRS) communication to a traffic control center so that they are aware of the driver's current state and can thus take immediate measures to prevent road accidents.

3. **Methods for Capturing Identification Features.**

3.1. **Eye area capture.** Each pixel of an image has a grayscale value. Binarization involves comparing the gray scale value of every pixel in the original images against a preset threshold H; if the value was larger than H, the pixel was converted to white. Conversely, if the value was smaller than H, the pixel was converted to black. The facial area was thus transformed into a black and white image that highlights the eye region, as shown in Figure 2.



(a) Original image (b) Binarized image of the eye area

FIGURE 2. Binarization of facial image

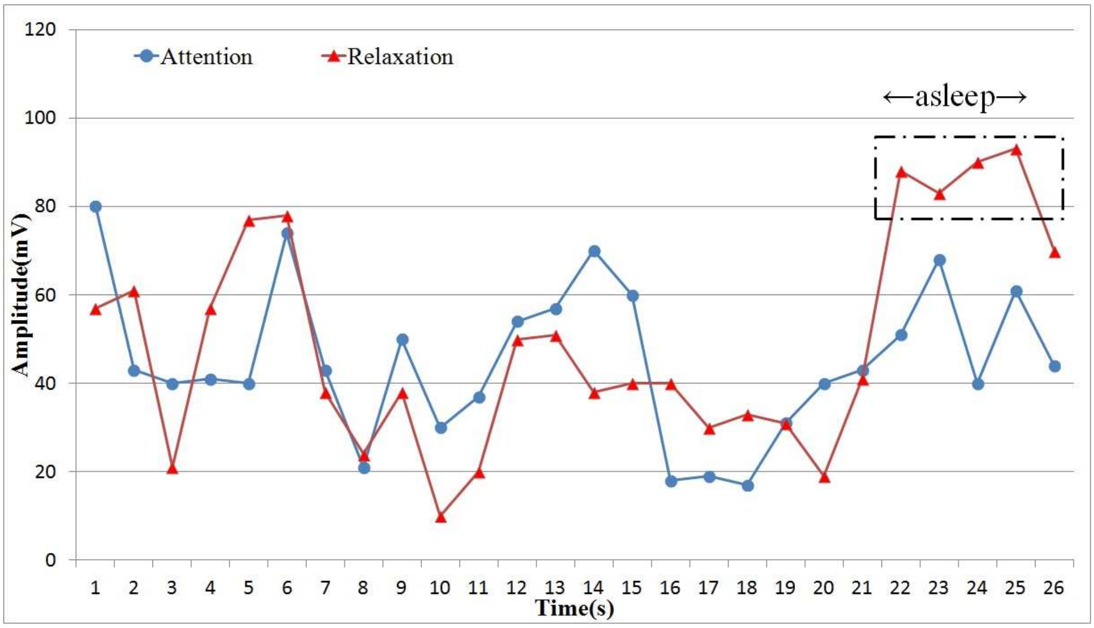


FIGURE 3. Waveform data of driver in asleep state

Each pixel's grayscale value was compared with the threshold H, and assigned a pixel value of 255 (black) or 0 (white) according to Equation (1).

$$G(i,j) = \begin{cases} 0 & \text{if } G(i,j) < H \\ 225 & \text{if } G(i,j) \geq H \end{cases} \tag{1}$$

The eye region was scanned and the coordinates of the black region were recorded to calculate the height of the open eye to obtain the eye size.

3.2. **Brainwave signal capturing.** Brain-parameter capturing was performed using the NeuroSky-developed USB headset integrated with a brainwave-frequency measurement system [10,11], and brainwave parameters were transferred to a computer through Bluetooth communication. Attention and relaxation waveforms were captured using a LabVIEW-developed interface, as shown in Figure 3. Relaxation waveform is higher than attention waveform obviously which means the status when driver was asleep.

To be able to utilize the attention and relaxation scores for determination, this study conducted measurements on several people. Five states were identified: normal, asleep, drowsy, under stress, and intoxicated.

4. **The Proposed Extension Detection Method.** The Extension theory applies the Extension model to resolving contradictions between objective and subjective issues of

traditional mathematics and fuzzy mathematics. By introducing a correlation function, the range of fuzzy sets is extended from $< 0, 1 >$ to $< -\infty, \infty >$ [12,13]. The identification steps for the proposed Extension detection algorithm were as follows:

Step 1: Retrieve the established matter-element models as listed in Table 1.

TABLE 1. Matter-element model for each category

Category (N_t)	**Matter-element models**
Normal	$R_1 = \left\{ \begin{array}{lll} N_1 & c_1 & \langle 75, 88 \rangle \\ & c_2 & \langle 11, 40 \rangle \\ & c_3 & \langle 60, 100 \rangle \end{array} \right\}$
Drowsy	$R_2 = \left\{ \begin{array}{lll} N_2 & c_1 & \langle 49, 56 \rangle \\ & c_2 & \langle 63, 78 \rangle \\ & c_3 & \langle 15, 86 \rangle \end{array} \right\}$
Asleep	$R_3 = \left\{ \begin{array}{lll} N_3 & c_1 & \langle 28, 40 \rangle \\ & c_2 & \langle 81, 100 \rangle \\ & c_3 & \langle 35, 75 \rangle \end{array} \right\}$
Under stress	$R_4 = \left\{ \begin{array}{lll} N_4 & c_1 & \langle 75, 88 \rangle \\ & c_2 & \langle 33, 73 \rangle \\ & c_3 & \langle 27, 50 \rangle \end{array} \right\}$
Intoxicated	$R_5 = \left\{ \begin{array}{lll} N_5 & c_1 & \langle 28, 56 \rangle \\ & c_2 & \langle 66, 100 \rangle \\ & c_3 & \langle 25, 46 \rangle \end{array} \right\}$

The term c_1 refers to eye size, c_2 refers to the relaxation brainwave, and c_3 refers to the attention brainwave.

Step 2: Establish Neighborhood Domain: Neighborhood Domain is the total range of all features in a matter-element set, as follows:

$$R_p = \left\{ \begin{array}{lll} N_p & c_1 & \langle 20, 95 \rangle \\ & c_2 & \langle 8, 110 \rangle \\ & c_3 & \langle 10, 110 \rangle \end{array} \right\} \tag{2}$$

Step 3: Read the tested data as follows:

$$R_s = \left\{ \begin{array}{lll} N_s & c_1 & x_{s1} \\ & c_2 & x_{s2} \\ & c_3 & x_{s3} \end{array} \right\} \tag{3}$$

where N_S is a measured matter-element, $c_1 \sim c_3$ are characteristics of N_S, and $x_{s1} \sim x_{s3}$ are features.

Step 4: Calculate the correlation function and the correlation between matter-elements as follows:

$$k_{ij(x)} = \begin{cases} \frac{-0.5\rho(x,X_0)}{|X_0|}, & x \in X_0 \\ \frac{\rho(x,X_0)}{\rho(x,X_p)-\rho(x,X_0)}, & x \notin X_0 \end{cases} \tag{4}$$

$$\begin{aligned} \rho(x, X_o) &= \left| x - \frac{x_i^L + x_i^U}{2} \right| - \frac{x_i^U - x_i^L}{2} \\ \rho(x, X_p) &= \left| x - \frac{x_i^M + x_i^N}{2} \right| - \frac{x_i^N - x_i^M}{2} \end{aligned} \tag{5}$$

x_i^L: the low-bounds value of matter-element model
x_i^U: the up-bounds value of matter-element model
x_i^M: the low-bounds value of Neighborhood Domain
x_i^N: the up-bounds value of Neighborhood Domain

Regarding the importance of correlation functions to characteristics, relaxation brainwaves were more critical to fatigue detection in this study; therefore, the weights w of

c_1 to c_3 were 0.3, 0.4 and 0.3. Once the weights of the characteristics were determined, the correlation between categories was calculated according to Equation (6) (where w is weight).

$$\lambda_i = \sum_{j=1}^{3} k_{ij} w_j, \quad i = 1, 2, \ldots, 5 \tag{6}$$

Step 5: Normalization.

The correlation was normalized to facilitate detection. The correlation values of various categories were normalized and fixed between $(1, -1)$, as follows:

$$\lambda_i' = \frac{2\lambda_i - \lambda_{\min} - \lambda_{\max}}{\lambda_{\max} - \lambda_{\min}} \tag{7}$$

where, $\lambda_{\max}$: maximum$\{\lambda_i\}$, $\lambda_{\min}$: minimum$\{\lambda_i\}$.

Step 6: Conducting final determination of category.

When the resulting value after normalization was at a maximum of 1, the mental status of the subject could be identified. If the subject exhibited a normal mental status, Step 3 was performed on the next set of data. If the subject's mental status as abnormal, the system produced a warning to notify the subject.

5. **Experimental Results and Discussion.**

5.1. **Experimental data.** To verify the effectiveness of the proposed methods, the fatigue detection system was tested on 15 subjects. Because the mental status of the subjects was a prolonged rather than a momentary response, the sampling time was 1 s, and each recorded value was an average value of 5 samplings. Among all of the test data, 100 were training samples that were used to establish the matter-element model, and the remaining 200 records were used to test the accuracy of the test model, as shown in Table 2.

Table 2. Identification accuracy for various status

Status	Accuracy (%)
Normal	97.5% (39/40)
Under stress	87.5% (35/40)
Asleep	97.5% (39/40)
Drowsy	95% (38/40)
Intoxicated	85% (34/40)
Overall accuracy	92.5% (185/200)

5.2. **Human interface of the fatigue detection system.** This study used a charge-coupled device webcam for image capturing, and an electroencephalogram headset supporting Bluetooth communication. Captured data were transferred to the LabView interface to conduct Extension identification, as shown in Figure 4. When the subject dozed off or was intoxicated, the system produced both a warning message and warning sounds. The measured status can be transferred to a traffic control center to continuously monitor the subject's state.

6. **Conclusions.** A novel fatigue detection system measures relaxation and attention brainwaves as analysis data, instead of only visual indicators. This combined method enabled an increased amount of characteristics to be considered and resolved the shortcomings of the two separate detection methods. The diagnosis method proposed in this paper is a rapid measure that is appropriate for real-time monitoring while driving. The Extension theory-based detection algorithm which combines eye images and brainwaves

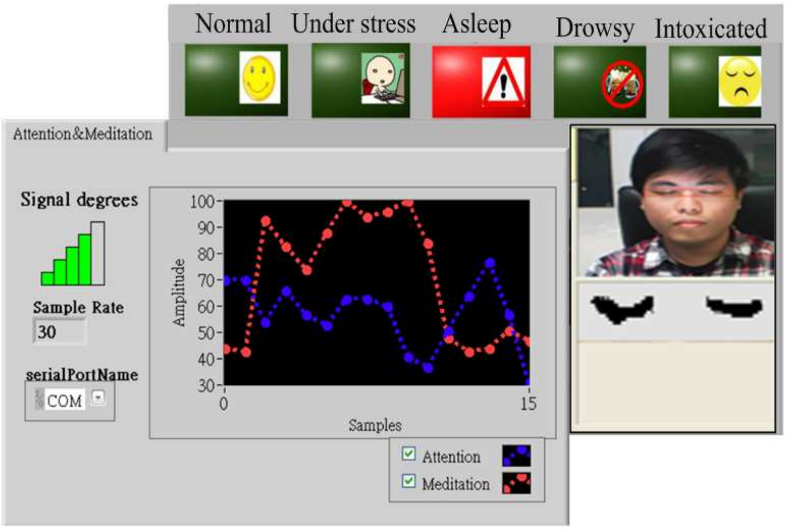


FIGURE 4. Asleep state of the driver

proposed in this paper possesses an average accuracy of 92.5%. To address the insufficient number of fatigue and drunk drivers tested in this study, future studies should examine a larger number of subjects in this category to enhance the accuracy of both the results regarding drunk drivers and the entire system.

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