Driver's drowsiness warning system based on analyzing driving patterns and facial images

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ABSTRACT

Development of technologies to monitor the state of the driver is essential in order to provide appropriate services for various driving situations. For the last decade a variety of driver state monitoring techniques have been proposed from many studies. Driver state monitoring systems generally work based on driving patterns, driver's video or physiological signals. Driver's video or driving patterns are convenient to acquire, but to assess driver state accurately is difficult because these methods assess the driver state indirectly. On the other hand, the analysis based on driver's physiological signals can monitor the state of the driver directly, but the sensors are not adopted due to the sensor's low usability in vehicle environment.

The proposed driver state monitoring system aims to assess driver's drowsiness, fatigue, and distraction accurately while achieving high usability through analyzing the driving patterns and video of the driver together. The driver state monitoring system based on driving patterns is able to see the trend of driver state, but it is difficult to determine exactly when the driver is in a dangerous situation, like a microsleep. On the other hand, the video based driver state monitoring system makes it easy to determine the moment of falling asleep, but it needs an additional logic limiting the detection range to prevent increasing a wrong detection rate. The proposed logic finds drowsy driving sections by analyzing the driving patterns, and determines exact time when the alarm is triggered by analyzing the driver's video. This configuration makes the proposed logic decide driver state with a high accuracy and provide an alarm within an appropriate time. This study is preliminary to validate a possibility of the proposed algorithm. The proposed driving pattern based algorithm was validated by comparing with the self-assessment and driver's physiological signal. And the facial image based algorithm achieves a high accuracy of detecting face direction and eye blink.

INTRODUCTION

Sleepiness behind the wheel is the major contribution on fatal accidents. Especially in Korea, drowsiness is the number one cause of fatal accidents on the road. Sleep or drowsiness was a contributing factor in 27.4% of all accidents in 2010. Many different driver state monitoring (DSM) methods, such as driver facial image processing, driving pattern analysis, or biometric methods, have been proposed to detect dozing off at the wheel.

R Sayed et al. [1] developed a drowsy driving detection algorithm using datasets from a driving simulator. The algorithm relies on steering angle signal only, and used an artificial neural network as a classifier to detect drowsiness. They achieved a high accuracy on classifying the driver's state whether drowsy or awake. J Krajewski and his colleagues [2] also analyzed drowsy driver's steering wheel behavior. They proposed some feature sets to capture drowsy steering patterns, and compared five machine learning methods (linear kernel Support Vector Machine (SVM), radial kernel SVM, k-nearest neighbor, decision tree and logistic regression). They reported in a recognition rate of 86.1% based on a simulator database. M Rimini-Doering's study in 2005 [3] analyzed the relationships between drowsiness and lane departure events to figure out the effects of lane departure warning system (LDWS) on drowsy driving. According to the results of the study, 85% of the lane departure events caused by sleepiness could be prevented by LDWS. As well as these researches, there are many other existing researches on developing a drowsy driving detection system based on driving pattern, but most of them were conducted using databases acquired from a driving simulator. It makes difficult for the results of the researches to be used in practical environment.

Driver video analysis is another ordinary method for detecting drowsy driving. The eye blink is considered to be a suitable indicator for fatigue or drowsiness diagnostics. PERCLOS [4], the percentage of eyelid closure over a certain time period (usually a minute), is the most commonly used estimating method of drowsiness. P.C. Philipp and his colleagues [5] proposed several parameters of the eye blink which can be used as a drowsiness measure. They reported that blink duration, reopening time and the proportion of long closure duration blinks are closely related to drowsiness. P. Ilkwon et al. [6] developed a simple illumination compensation algorithm and a novel eyelid movement detection method for drowsiness detection systems using a single camera. The system achieved over 98% of the eye detection rate under various illumination conditions.

R N Khushaba et al. [7] acquired electroencephalogram (EEG), electrooculogram (EOG) and electrocardiogram (ECG) from subjects during a simulation driving test. They analyzed the signals using fuzzy mutual information based wavelet packet transform to get drowsiness-related information. L. Chin-Teng et al. [8] developed a drowsiness estimation system using EEG. They evaluated the relationship between ICA (independent component analysis) component of EEG and driving errors. M. Szypulska et al. [9] developed an algorithm based on heart rate variability (HRV) for detecting the moment of sleep onset. They asserted that HRV could be an indicator for detecting sleep onset, and represented the changes of HRV at the moment of sleep onset.

This study proposed a DSM system based on driving patterns and facial images. These signals are able to be acquired unobtrusively, and therefore the proposed system makes no inconvenience coming from the acquisition of signals. The next section gives a detailed account of the proposed drowsy driving detection system. And the results and discussion section represents the evaluation of the system comparing with the self-assessment and the results from the physiological signal.

METHOD

In this section, the detail configurations of the proposed system are described. The proposed system evaluates the trend of driver's drowsiness using driving patterns, and determines the exact time of microsleep based on detecting long blinks.

Driving pattern based DSM

The proposed system detects three driving patterns related with drowsy driving. The first driving pattern is high lateral speed event. The event is detected when the current lateral speed exceeds the reference lateral speed. The lateral speed, the blue line in the figure 1, means an average lateral speed over a short period of time. And the reference lateral speed, the red line in the figure 1, is calculated as adding the average and a certain times the standard deviation of lateral speed over a long period of time. Excess of the lateral speed over the reference lateral speed is considered as the loss of lane keeping ability.

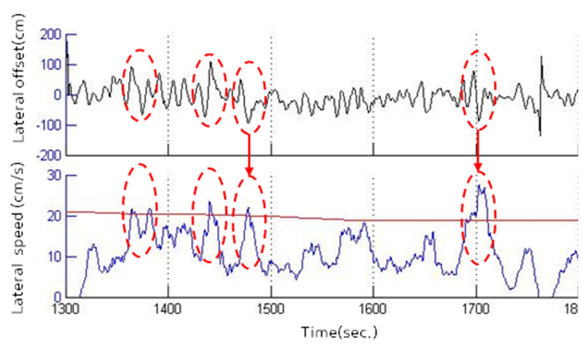

Figure 1. Examples of the high lateral speed drowsy driving patterns

The second driving pattern detects an abrupt counter-steering near the edge of the lane. As shown in Figure 2, steering value remains nearly constant during the driver is drowsy, and then over-reactive correction of steering value is occurred when the driver recognizes he is in danger. The detection logic of the second driving pattern examines three criteria. The three criteria are 1) the steering value changes less than a threshold during a few seconds, 2) the amplitude of the counter-steering value is greater than an ordinary counter-steering, and 3) the center of the car is far away from the center of the lane.

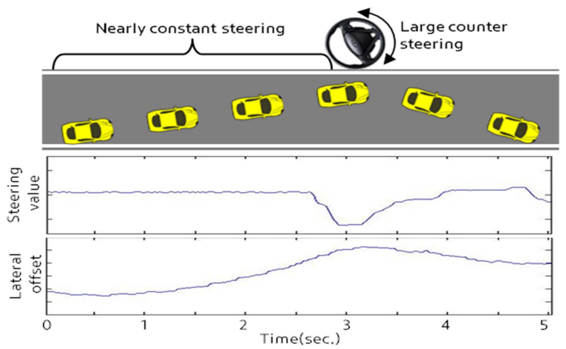

Figure 2. Examples of the over-reactive correction of steering based drowsy driving pattern

During getting sleepiness most of the driver is getting lost their hand from hold the steering wheel, and the last driving pattern measures tighten of hand to check whether the driver is under normal condition. When driver is drowsy, steering signal shows little change around zero because of weakening the gripping force. The detection logic of the third driving pattern checks that 1) the steering values changes less than a normal range around zero during a few seconds and 2) the lateral speed during that same period exceeds the reference lateral speed.

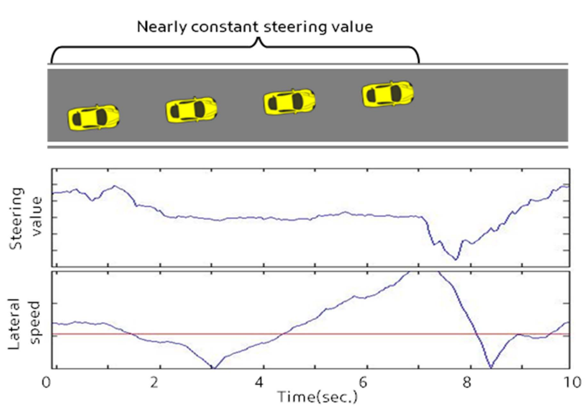

Figure 3. Examples of the excessive lack of steering based drowsy driving pattern

Facial image based DSM

Camera based DSM system detects the driver's face direction and the eye closure by using IR camera and image processing ECU. As shown in Figure 4, the IR camera is comprised of a image sensor, a MCU for controlling a image sensor, and a IR pass filter for preventing the interference of sunlight. The specification of the IR camera is as follows. The IR camera was installed on the steering column cover and its view angle is 45° in the horizontal direction. The image sensor is VGA level, and its dynamic range is more than 100 dB. Two IR-LEDs and IR pass filter were equipped for reducing the disturbance such as reflection from glasses and strong sunlight. The ECU including image processing DSP controls the synchronization between the image sensor and LEDs, and communicates with the image sensor and the vehicle CAN. And it also processes the DSM algorithm.

Figure 5 shows the configuration of the proposed camera based DSM algorithm for detecting face direction and eye blink. First, facial area detection is performed. The facial area detection adopts Modified Census Transform (MCT) [10] as a feature extraction method, which can get robust features against changes of illumination, and cascaded AdaBoost [11] as a classifier. Training database includes 300,000 non-face images and 300,000 face images.

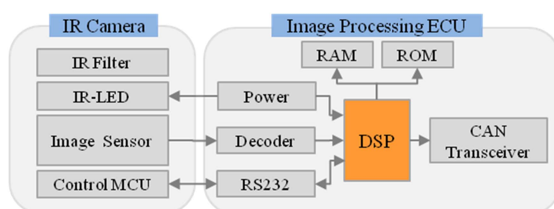

Figure 4. The block diagram of the IR camera

After the facial area detection, left and right face contour were detected through the projection of the binary image of facial area onto the horizontal axis. Next, face direction is defined according to the position of eyes, nose and mouth. The algorithm for detecting eyes, nose and mouth is also composed of MCT and AdaBoost. The face direction would be determined according to the face contour and facial parts position. For dealing with changes of illumination and glasses wearers, eye blink detection was performed by detecting upper and lower eyelids detection and applying

AdaBoost. Lastly, driver's inattention and drowsiness level are estimated by the analysis of face angle and eye blink pattern.

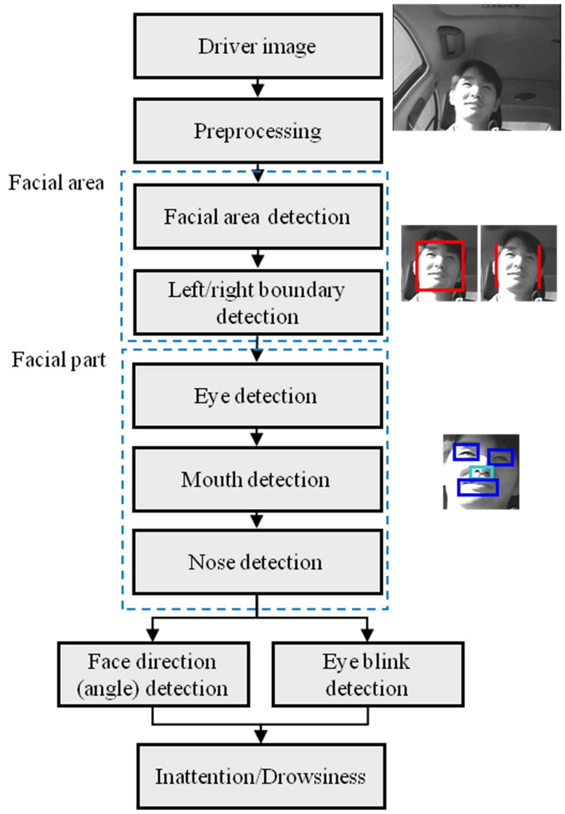

Figure5. The configuration of the image based DSM algorithm for detecting face direction and eye blinking

RESULTS & DISCUSSION

The driving pattern based DSM and the facial image based DSM are separately evaluated for safety reasons. The results of the driving pattern based DSM was compared with the drowsy level of self-assessment and the results of physiological analysis. As shown in Figure 6, a test car equipped with CAN data logging tool and biosignal acquisition tool was used for the evaluation of driving pattern based DSM. The recorded CAN signals included velocity, steering value, and lateral offset from LDW, etc. And ECG was recorded through a Biopac ECG 100C system. HRV is analyzed based on the recorded ECG signal to assess the state of the driver. Two drivers are involved in this evaluation experiment. They drove 100 km on highway course after lunch, and it took about an hour. During the experiment the driver was supposed to assess self-drowsy levels, and they could input the self-assessment signal through a button on the wheel. And using radio and talking are prohibited.

The evaluation results of the driving pattern based DSM is shown in Figure 7. The high lateral speed events, over-reactive correction of steering related events, and excessive lack of steering related events are respectively represented as red lines, blue diamonds, and red diamonds. The amplitude of red line means time duration when the current lateral speed exceeds the reference lateral speed. The self-assessment drowsy level has 4 levels; awake (level 0), slightly drowsy (level 1), extremely drowsy (level 2), and micro-sleep (level 3). The blue line in figure 7 represents LF/HF signal of HRV.

Figure6. The configuration of the test car for evaluating the driving pattern based DSM; 1) LDW, 2) facial image based DSM (IR-camera), 3) CAN data logging tool (Labview), and 4) Biosignal acquisition tool (Biopac)

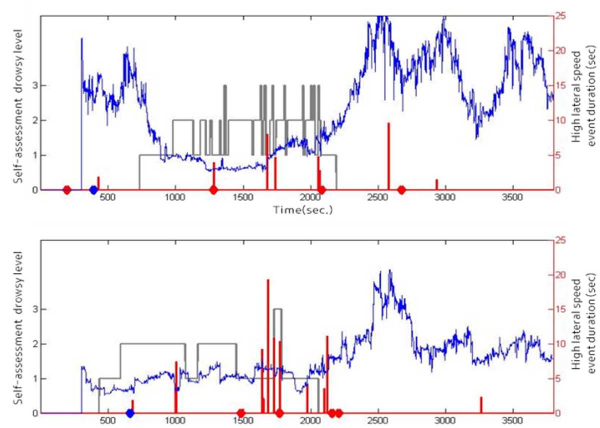

Figure7. The evaluation results of the driving pattern based DSM.

The LF/HF generally has low value when the subject is drowsy [9]. As can be seen in Figure 7, the LF/HF shows an inverse relationship with the self-assessment drowsy level. And the detected drowsy driving pattern events more frequently appear when the driver feels drowsy.

The evaluation of the facial image based DSM was performed using testing dataset acquired from 100 subjects in a standing car. Among them, 25 subjects were wearing glasses and the others were not. The subjects were supposed to blink at predefined interval and look nine different sites in the car, such as cluster, side mirror, AVN etc. As shown in Table 1, the performance of facial image based DSM achieved over 95% in a detection rate.

Table1.
The performance of the facial image based DSM

Detection rate of face direction (%)		Detection rate of eye blink (%)	
Wearing glasses	Without glasses	Wearing glasses	Without glasses
96.8%	96.3%	97.2%	90.3%

CONCLUSIONS

In this study, we proposed a drowsy driving warning system based on analyzing driving patterns and facial images. Although the proposed algorithm shows possibilities for detecting driver state and delivering an alarm at microsleep, i.e. long blink, farther experiments are necessary to develop a robust DSM system. The future work will be concentrated on the improving and validating the performance of the algorithm with large dataset to deal with a variety of environment.

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