Detection of Driver’s Low Vigilance Using Vehicle Steering Information and Facial Inattention Features

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ABSTRACT
Driver’s low vigilance is a significant factor contributing to traffic accidents. Numerous methods were proposed to measure driver’s alertness level and warn driver when a potential risk exists. These techniques commonly detect driver’s vigilance from three different aspects, including physiological signal indicators, vehicle steering behavior, and facial inattention features. However, it is difficult to estimate driver’s distraction or drowsiness accurately from the observation of single aspect. This paper presents an integrated method which non-intrusively detects driver’s low alertness by considering both the performance of vehicle steering and the inattention facial features. We characterize driving performance by analyzing the manipulation behavior of steering wheel. A new image processing algorithm using Sobel operator is designed to estimate driver’s gaze direction efficiently. The analysis results of these two different aspects are generally complementary and thus can be integrated to obtain accurate detection of driver’s inattention. The proposed method continually estimates the parameters of vehicle steering model and thus it is adaptive to the variety of driving behavior across time and individuals. Conducted experiments showed the proposed technique achieved high true positive rate (>99%) with low false positive error (0.12 times per hour).

Keywords: Inattention, gaze direction detection, steering behavior analysis

1. INTRODUCTION
World Health Organization estimates that 1.2 million people are killed and 50 million people are injured in traffic accidents each year [1]. These accidents cause annual economic losses of 518 billion dollars in the whole world [2]. A significant factor contributing to road
accidents is driver’s low vigilance resulting from fatigue, asleep, lost in thought, or engaging in non-driving related activities. The National Highway Traffic Safety Administration reported that 78% of crashes and 65% of near-crashes are related to some form of the diminished alertness within three seconds before the event [3]. With the ever-growing traffic conditions, it is essential to avoid car accidents originate from the decline of driver’s vigilance.

Numerous methods were proposed to actively detect driving fatigue and/or distraction for reducing automobile accidents. These techniques can be classified into three main categories in accordance with the information adopted to measure the driver’s vigilance state. The first kind of methods identifies drowsy driving based on the analysis of physiological signals, including heart rate observed by electrocardiography (ECG) [4] and brain activity obtained from electroencephalography (EEG) [5-7]. The data acquisition sensors of ECG and EEG are generally nestled on subject’s body or scalp, thus these approaches are somewhat unrealistic as an on-road device for the detection of driver’s drowsiness.

The second kind of methods assesses driver’s mental state according to the evaluation of vehicle steering behavior [8]. For example, Pilutti et al. [9] and Volvo’s Driver Alert Control System used a camera to monitor the road environment ahead and regarded the context of lane departure as the indicator of driver’s alertness. Takei and Furukawa [10] and Krajewski et al. [11, 12] estimated driving fatigue based on the analysis of steering wheel operation. Moreover, Farid et al. [13], Zhong et al. [14] and Mercedes-Benz’s Attention Assist System adopted different vehicle-manipulation signals for better discrimination of driver’s alertness state. Because driving behavior may have significant variety across individuals, it is important for these techniques to be adapted to driver.

The third kind of methods detects the occurrence of inattention by analyzing driver’s facial features or body activities. For instance, Saradadevi and Bajaj tracked driver’s mouth and regarded the yawning state as drowsiness indicator [2]. Zhang et al. measured driving fatigue by evaluating the duration of eye closure [15]. Toward robust detection, some works adopted various facial features in the vigilance detection at the same time, including facial expression, eyelid movement or closure, and gaze direction [16-18]. These methods commonly extract necessary features from driver images. Therefore, both the camera quality and environmental factors influence the detection performance.

2. METHOD

The proposed vigilance detection method comprises two major components, as shown in Figure 1. For the estimation of driver's gaze direction, the face and nose are first roughly detected followed by the illumination analysis of face region and the determination of the leftmost and rightmost points of face. Meanwhile, driving behavior is evaluated according to the information of steering wheel manipulation. Warning of inattention driving will be issued on conditions that driver's gaze direction does not focus on the road and the steering
wheel has dramatic adjustment. A fair amount of steering wheel adjustment also resulted in alarm if driver's gaze direction cannot be estimated due to environmental factors. The information of steering wheel adjustment is continually applied to estimate the parameters of vehicle steering model in the case that driver concentrates on the driving task. Therefore, the proposed method is adaptive to the variety of driving behavior across time and individuals.

2.1 Detection of Driver’s Gaze Direction

![Flowchart of the detection of driver’s low vigilance](image)

We apply cascade of boosted classifiers, the AdaBoost classifiers available at OpenCV (http://opencv.org), to find the rough locations of face and nose in image. Appropriate scales of face and nose regions are estimated by a scanning procedure before the detection of driver’s vigilance. Notice that the process of scale determination is only need to be executed
once because the alteration of facial feature size in image is generally small when vehicle is moving.

Driver’s gaze direction is measured by the yaw of face, the movement that changes the direction of face to the left or right. Because illumination is a significant factor affects the accuracy of an image based safety system, we analyze the intensity distribution of face area before the estimation of yaw angle. For the cases that environmental lighting does not cause overly bright on face, we estimate the yaw angle to be the ratio of distances from nose center to the leftmost facial point, $d_l$, and to the rightmost facial point, $d_r$. These two feature points can be efficiently determined using the Sobel operator because facial boundary generally shows much vertical edge information compared to other face region, as shown in Figure 2. Figure 3 shows the facial boundaries according to the detection results of the leftmost and rightmost facial points. For the cases that only the left (right) face is illuminated with high intensity or high illumination contrast, we measure the yaw angle by the ratio of distances between $d_l$ ($d_r$) and the width of face region, $d_w$, determined by AdaBoost classifier. Figure 4 illustrates the methods used to estimate the yaw angle of driver’s face.

![Figure 2. Detection of the leftmost and rightmost facial points.](image)

![Figure 3. Detection results of the leftmost and rightmost facial points. Red rectangles are the face regions determined by AdaBoost classifier and yellow lines are vertical segments pass the left and right fringe points of faces.](image)
Figure 4. The estimation method of facial yaw angle is varied according to the illumination conditions of face region. (a) The yaw angle is calculated by the ratio between $d_l$ and $d_r$ if driver’s face region shows high illumination or high intensity contrast, where $d_l$ is the distance between the nose center and the leftmost facial point, and $d_r$ is the distance between the nose center and the rightmost facial point. (b) In the case that high illumination or high intensity contrast is shown on the right face, the yaw angle is estimated by the ratio of $d_l$ and the width of face region detected by AdaBoost, $d_f$, and (c) vice versa.

2.2 Analysis of Vehicle Steering Behavior
The performance of vehicle steering is measured by the variation of steering wheel angle observed in car driving. Two indices are used to characterize driving behavior, which are the differential of steering wheel angle, $a_d$, and the difference between the max and min steering wheel angles observed in one second, $a_s$. We empirically divide the absolute values of both two indices into three ranks and then define three degrees of vehicle steering stability, as shown in Table 1. The proposed method issues alarms in case that driver’s steering behavior reaches Dangerous degree. Warnings are also issued in Vigil degree if driver's gaze direction cannot be estimated due to environmental factors.

Our method incessantly adjusts the value intervals for the ranks of $|a_s|$ and $|a_d|$ to tackle the significant variety of driving behavior across time and individuals. The analysis results of gaze direction provide guidance to continually collect the values of $|a_s|$ and $|a_d|$ when driver concentrates on driving task. These values generally form two Gaussian distributions which represent the driving characteristics of drivers, as shown in Figure 5. We align the baselines of $|a_s|$ and $|a_d|$ after the removal of the largest 10% data. Therefore, the value intervals of $|a_s|$ and $|a_d|$ ranks as well as the definition of steering stability degrees can adaptive to time and driver.
Table 1. Definition of vehicle steering stability. The ranks of the differential of steering wheel angle, $a_d$, and the difference between the max and min steering wheel angles observed in one second, $a_s$, define three degrees of steering stability.

| $|a_d|$ | $|a_s|$ | Steering stability |
|------|------|-------------------|
| Low  | Low  | Normal            |
| Median | Low  | Normal            |
| High | Low  | Normal            |
| Low  | Median | Normal          |
| Median | Median | Vigil            |
| High | Median | Vigil            |
| Low  | High  | Vigil             |
| Median | High  | Dangerous         |
| High | High  | Dangerous         |

Figure 5. The values of both steering behavior indices form Gaussian distributions.

2.3 Performance Evaluation

The proposed method was implemented in a self-developed DSP platform (TMS320DM6437 processor) and was evaluated using a passenger car, as shown in Figure 6. An infrared sensitive NTSC camera and infrared LEDs were deployed facing inward to acquire driver images, thus our method can detect driver's low vigilance day and night. We mounted an outward camera behind the windshield for the observation of driver's steering behavior. A data recorder installed in the passenger car collected all the time points of alarms issued by DSP and the images obtained from inward and outward cameras (Figure 7). Twelve volunteers drove the passenger car and provided 43.1 hour-long data in total.
4,441-kilometer trips. Two testing engineers examined the collected data and determined the occurrences of distraction, drowsiness, or abnormal steering behavior according to driver’s facial features, the stability degree of vehicle steering shown in inward and outward camera images, and drivers’ reports. These events were regarded as the ground truths in our experiment. Then the time points of alarms issued by our method were compared to the ground truths for the measurement of detection accuracy.

We adopted true positive rate, TPR, and false positive rate, FPR, as the performance criteria in this experiment.

\[
TPR = \frac{TP}{TP+FN}, \\
FPR = \frac{FP}{FP+TN}.
\]

The true positive, TP, and false negative, FN, are the number of low vigilance events correctly and incorrectly classified, respectively. The false positive, FP, and true negative, TN, are the number of normal driving events incorrectly and correctly classified, respectively. TPR index measures the ability that system correctly identifies low vigilance events. On the other hand, FPR index quantifies the possibility that system issues false alarms for normal driving events.

![Passenger car equipped with the proposed system for performance evaluation.](image)

**Figure 6.** Passenger car equipped with the proposed system for performance evaluation.

![Experimental data recording for performance evaluation.](image)

**Figure 7.** Experimental data recording for performance evaluation.
3. EXPERIMENTAL RESULTS
This section presents our result of performance evaluation for the proposed method. Table 2 lists the sources of drivers’ low vigilance examined in the collected experimental data. Distraction events resulted from converse or looking around reached the highest percentage of 46. Another principal source of inattention in this experiment is drivers engaged in non-driving-related activities (31.7%). Driver’s drowsiness, abnormal steering behavior, and other sources constituted 12.4, 8.7, and 1.2 percent of the total low vigilance events.
Table 3 lists the experimental results of our method. The ground truths, the events need to be warned, are classified into two classes, including the occurrences of abnormal vehicle steering behavior and the events that distraction or fatigue features shown in driver’s face or activities. Our method achieves good TPR (100%) because all the 71 occurrences of drivers’ distraction, drowsiness, and abnormal steering in this experiment were detected. Experimental results also show that the proposed method issued five false alarms in the 43.1 hour-long trips. Therefore, the FPR value of our method is about 0.12 (false alarms per hour).

4. CONCLUSIONS
Our method integrates steering behavior analysis and facial image processing techniques to detect driver’s low vigilance in a complementary way. The analysis of gaze direction can estimate driver's inattention, even drowsiness, which directly reflects in the face or activities. Though vehicle steering performance is an indirect indicator of driver's alertness degree, the analysis in this aspect can tackle some distraction circumstances that beyond the ability of image analysis method, such as the detection of inattention resulted from lost in thought. The occurrences of concentrated driving determined by facial feature analysis support the establishment of adaptive mechanism required in steering performance measurement. On the other hand, the analysis of steering behavior complements to the detection of driver’s distraction and drowsiness if the gaze direction cannot be estimated due to environmental factors.
The proposed method achieved high TPR with low FPR in our experiment. There were five false alarms issued in the 43.1 hour-long data. The steering behavior when driving on a rugged road could quite similar to an abnormal event, and thus caused one of the false alarms. The remainder four false alarms were all resulted from the failure detection of driver’s face. Driver’s sitting posture as well as the stature caused improper spatial relationship between camera and face, such that the adopted AdaBoost classifier could not recognize the driver’s partial face region shown in image. Moreover, environmental illumination may be another factor that induced the failure of AdaBoost face classifier.
Driver’s gaze direction is regarded as distraction indicator in this work. Because the viewpoint of human being is generally moved along with face orientation, we assume driver
looks straight when driving and estimate gaze direction by face orientation. The yaw of face may be the most important indicator to detect distracted driving among three orientation parameters, pitch, roll, and yaw angles. To complete the detection of driver’s distraction, it is necessary to further estimate the facial pitch angle.

5. ACKNOWLEDGMENT
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6. REFERENCES


