Various Approaches for Driver and Driving Behavior Monitoring: A Review

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Abstract

In recent years, driver drowsiness and distraction have been important factors in a large number of accidents because they reduce driver perception level and decision making capability, which negatively affect the ability to control the vehicle. One way to reduce these kinds of accidents would be through monitoring driver and driving behavior and alerting the driver when they are drowsy or in a distracted state. In addition, if it were possible to predict unsafe driving behavior in advance, this would also contribute to safe driving. In this paper, we will discuss various monitoring methods for driver and driving behavior as well as for predicting unsafe driving behaviors. In respect to measurement methods of driver drowsiness, we discussed visual and non-visual features of driver behavior, as well as driving performance behaviors related to vehicle-based features. Visual feature measurements such as eye related measurements, yawning detection, facial expression are discussed in detail. As for non-visual features, we explore various physiological signals and possible drowsiness detection methods that use these signals. As for vehicle-based features, we describe steering wheel movement and the standard deviation of lateral position. To detect driver distraction, we describe head pose and gaze direction methods. To predict unsafe driving behavior, we explain predicting methods based on facial expressions and car dynamics. Finally, we discuss several issues to be tackled for active driver safety systems. They are 1) hybrid measures for drowsiness detection, 2) driving context awareness for safe driving, 3) the necessity for public data sets of simulated and real driving conditions.

1. Introduction

Recently, the total number of serious car crashes is still increasing regardless of improvements in road and vehicle design for driver safety. The U.S. National Highway Traffic Safety Administration (NHTSA) data indicate that more than 40,000 Americans suffer serious injuries from 56,000 sleep related road crashes annually [1]. According to a study by the Sleep Research Center (UK), driver drowsiness at the wheel causes up to 20% of accidents on monotonous roads [2]. Several studies have produced various estimates of the level of sleep deprivation as it relates to road accidents. In addition, driver distraction or inattention is another critical problem for safe driving [3]. In summary, driver drowsiness and distraction are major causal factors behind road accidents.

To reduce the number of road accidents, it is necessary to monitor driver and driving behavior and alert the driver when he or she is drowsy or in distraction state. In addition, if it were possible to predict unsafe driving behaviors in advance, this would contribute to safe driving. According to one report [4], the amount of car crashes would be reduced by 10- 20% by monitoring and predicting driver and driving behaviors. A reliable and robust driver drowsiness and distraction detection system would send an alert to the driver and thus reduce the number of hazardous situations on the road. If it were possible to predict unsafe driving behavior in advance, this would also be helpful in preventing road accidents. Thus, it is desirable to design a framework consisting of two phases, that is, both monitoring and predicting driver and driving behavior. Figure 1 shows such a framework.

For a driver monitoring system, two issues such as driver fatigue measurement and distraction detection should be solved. Usually, driver fatigue or drowsiness may be related with symptoms including eye movement, facial expression, heart and breathing rate, and brain activity [5-10]. To detect driver drowsiness, visual features such as eye movement and facial expression are very important. Yawning measurement is also good indicator of a driver's drowsiness [11]. As non-visual features, heart rate variability (HRV), galvanic skin response (GSR) and conductivity, steering-wheel grip pressure, and body temperature are possible candidates for estimating the driver's fatigue level indirectly [12]. Electroencephalogram (EEG) and Electro-oculogram (EoG) give additional psychophysiological information about drowsiness or emotional reactions [13]. Driving behavior information such as steering wheel movement, lane keeping, acceleration pedal movement and braking, etc., should also be considered to detect driver drowsiness.

Recently, excessive uses of in-vehicle information systems such as navigation systems and mobile phones induce visual and cognitive distraction in the driver. Visual distraction refers to the state of "eye-off-road", and cognitive distraction is described as "mind-off-road" [14]. Driver distraction may lead to larger lane variation, slower response to obstacles, and more abrupt steering control, and its monitoring should be a feature of a safer driver-monitoring system. To detect driver distraction, it is necessary to extract head pose or gaze information efficiently.

By carefully monitoring driver and driving performance behavior, it is possible to predict minor and major accidents. In particular, the progress of pervasive computing technology with integrated sensors and networking has made it possible to build an ideal platform to predict accidents. Jabon et al. [15] identify a comprehensive set of driver's key facial features at various pre-accident intervals and use them to predict minor and major accidents. This approach is very important for active driver-safety systems designed to prevent accidents. The Signal Processing 5 Laboratory of the EPFL in Switzerland [16] analyzes facial expressions and muscle movements to detect distraction as well as emotions that could indicate that the driver is not up to the task at hand.

The aim of this paper is to discuss monitoring the driver's state as well as predicting unsafe driving behaviors. We explain several issues in developing a framework consisting of two phases: monitoring and predicting driver and driving behavior. The organization of this paper is as follows: Section 2 discusses driver drowsiness detection. We discuss driver behavior features such as visual and non-visual features, and driving performance behaviors related to vehicle-based features. Eye related measurement like PERCLOS, yawning detection and some current limitations in measuring visual features are discussed in detail. As for non-visual features, we explore physiological signals for detecting drowsiness. As for vehicle-based features, we describe steering wheel movement and the standard deviation of lateral position. Section 3 describes some issues related to driver distraction measurement, in particular, head pose and gaze direction methods. Section 4 presents prediction methods for unsafe driving behaviors. We explain predicting methods based on facial expression and car dynamics. Finally, Section 5 discusses some issues for active driver safety systems. They are 1) hybrid measures for drowsiness detection, 2) driving context awareness for safe driving, 3) the necessity for public data sets of simulated and real driving conditions.

2. Driver drowsiness measurement

For safe driving, it is necessary to construct a reliable driver monitoring system which could alert the driver when

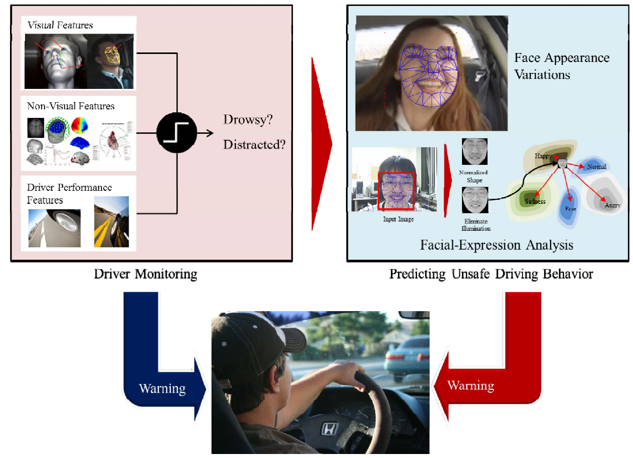

Figure 1: General framework of a monitoring and predicting unsafe behavior system

he or she is drowsy or a state of inattention. In this Section, we will discuss drowsiness measurement methods.

The word "drowsy" simply refers to an inclination to fall asleep. A drowsy driver who falls asleep at the wheel can be characterized by diminished alertness compared to a normal state. Sometimes a driver experiences sleep for a few seconds and may not even realize it. This is called micro-sleep. The duration of micro-sleep can last between a few seconds and as long as 30 seconds or even more. This is sufficient time to drift out from one's traffic lane and crash into a tree or another car. Therefore, the driver's drowsiness state, in which a transition occurs from awake to asleep, should be monitored.

To detect the drowsiness level of the driver, we have to extract driver behavior information as well as driving behavior information as shown in Table 1. Driver behavior information consists of both visual and non-visual features. Visual features include eye closure, eye blinking, yawning, head pose, facial expression etc. [10, 11, 17]. The frequency of eye blinking and degree of eyelid opening are a good index of the tiredness level [10]. Non-visual features consist of heart rate, pulse rate and brain activity. These physiological signals (electrocardiogram (ECG), electromyogram (EMG), electro-oculogram (EoG) and electroencephalogram (EEG)) are used to detect driver drowsiness [18-23]. Driving behavior information includes deviations from lane position, vehicle speed, steering movement, pressure on the acceleration pedal, etc. [24, 25].

2.1. Visual features

Usually, facial movements such as eye blinking, frequent yawning and nodding or swinging head are key elements among visual features used for detecting drowsiness. Much research work is focused on eye behaviors in particular to determine a driver's alertness [26, 27]. A reliable and valid determination of a driver's alertness level is known as PERCLOS (Percent Eye Closure) [28-30]. PERCLOS is

Table 1: Summary of various features for detecting and predicting driver drowsiness.

Category	Features	Measurement	Function	Characteristics
Driver Behavior	Visual Feature	PERCLOS, Yawn Detection Facial Expression	Monitoring Monitoring, Prediction	Non-intrusive
	Non-visual Feature	EEG(electroencephalogram) ECG(electrocardiogram) EoG(electro-oculogram) PPG(Photoplethysmography)	Monitoring	Intrusive
Driving Behavior	Vehicle-based Feature	Steering Wheel Movement Standard Deviation of Lateral Position	Monitoring	Variations from vehicle type and individual

the percentage of total time that the driver's eyelid is closed 80% (or more) over the pupil and also reflects slow eyelid closure. When PERCLOS exceeds a predetermined threshold, the proposed system generates a drowsiness warning. However, one disadvantage of PERCLOS is that sometimes a driver who is trying to stay awake is able to fall asleep with his eyes open.

To calculate PERCLOS, we have to extract the eye region including the pupil area. However, there are some limitations in extracting those visual features. One of them is the problem of proper lighting. Drowsiness should be detected under real conditions, i.e., throughout daytime and night, and regardless of whether the driver is wearing glasses or sunglasses. Usually, a simple CCD or web camera is used during the day, and an IR camera is used at night [31-34]. Moreover, for eye detection with a driver who is wearing sunglasses, it is necessary to find a proper wavelength of Near IR (NIR) illumination. One possible candidate wavelength is 850nm. In a real automotive environment, reflected sunlight is also generated on the outer surface of the eyeglasses. To diminish the reflection effect, Jo et al. [34] used a NIR illuminator with a narrow bandpass filter which restricts the incoming wavelength of light to 850nm. This is because the high-power LED illuminator is more powerful than the sunlight in the car. Figure 2 shows that the reflected sunlight is removed by an NIR illuminator with narrow bandpass filter [34].

Another method is faceLAB used in the commercial product such as the Seeing Machine [35]. A passive pair of video cameras is used and the video images are processed in real-time to determine the 3D position of each feature. The system is able to determine a precise 3D head pose and computes eye gaze direction. Its advantages include coping well with low light conditions and head movements while the driver is wearing sunglasses.

Yawning is another sign of driver drowsiness. This is detected from measuring both the rate and the amount of changes in the driver's mouth contour [7, 11]. Head pose estimation and head motion detection of movements such as nodding are also important in monitoring driver alertness [36, 37]. In addition, facial wrinkles of the driver appearing on the brows, mouth and nasolabial fold are good physical signs that drowsiness is being resisted, and that therefore it is present [38].

2.2. Non-visual features

Non-visual features or physiological signals such as heart rate and brain activity are useful in predicting drowsiness, with fewer false positives compared to visual features because the determination of a drowsy state from visual features can be possible only after the driver is well on the way to sleep. In other words, the prediction of drowsiness based on these physiological signals makes it possible to warn a drowsy driver in a timely manner. Electrocardiogram (ECG), electroencephalogram (EEG), electromyogram (EMG), electro-oculogram (EoG), and Photoplethysmography (PPG) may all be used as physiological signals.

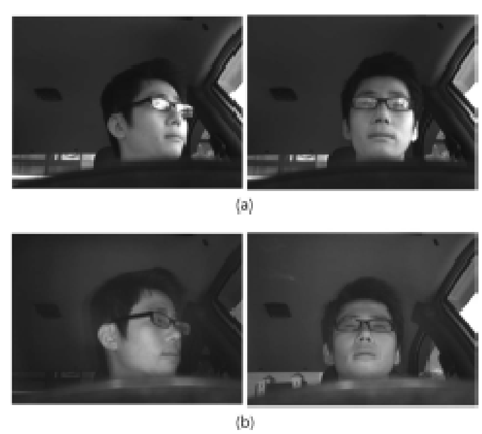

Figure 2: Reflected sunlight is dealt with by an NIR illuminator with a narrow bandpass filter in [34]. (a)NIR illuminator only, (b) NIR illuminator with bandpass filter.

From the ECG signal, heart rate (HR) can be extracted; the heart rate can be used to detect drowsiness because it varies significantly between alertness and drowsiness states [19, 39]. Heart rate variability (HRV) which measures the beat-to-beat changes in the heart rate is also used to detect drowsiness. As the driver goes from an alert to a drowsy state, the ratio of low frequency to high frequency beats in the ECG signal progressively decreases [20, 40].

One critical issue in handling physiological signals is to eliminate noise and artifacts inevitable in real environment driving conditions. Following effective filtering, various feature extraction techniques such as Fast Fourier Transform (FFT) and Discrete Wavelet Transform (DWT) are used. Then, the extracted features are classified using Support Vector Machine (SVM), Artificial Neural Networks (ANN), Linear Discriminant Analysis (LDA), etc. [40-43].

Even though the reliability and accuracy in detecting driver’s drowsiness based on physiological signals is high when compared to visible features, an important limitation of physiological signal measurement is its intrusive nature. One possible way to solve this limitation is to use wireless technologies such as Zigbee and Blutooth for measuring physiological signals in a non-intrusive way by placing the electrodes on the steering wheel or in the driver’s seat [44, 45]. Figure 3 shows ECG measurement on the driver seatback [45]. Finally, the signals are handled by smart phones and driver drowsiness is determined [46]. However, this kind of non-intrusive system is less accurate compared to intrusive systems due to improper electrode contact.

To obtain reliable driver’s drowsiness detection results, some attempts had been done to fuse various measurements [20, 47]. A mixture of PERCLOS, ECC and EEG were used to detect driver drowsiness and resulted in a higher success rate than individual measures [20]. Cheng et al. [47] used fusion of PERCLOS, blink rate, maximum close duration and percentage of non-steering measures to detect drowsiness.

2.3. Driving behavior features

Driving behavior features or driving performance measures include steering wheel movement, lane keeping, acceleration pedal movement and braking, etc. [48-50]. These features correlate to vehicle type and variability among drivers in their driving habits, skills and experience. The two most commonly used driving behavior measures for detecting the level of driver drowsiness are the steering wheel movement and the standard deviation in lateral position.

Steering Wheel Movement (SWM) is measured using steering angle sensor mounted on the steering column. When the driver is drowsy, the number of micro-corrections to the steering wheel, which are necessary in normal driving, is reduced [51]. The driver’s

Figure 3: ECG measurements on driver's seatback in [45].

drowsiness state is determined from small SWM’s of between 0.5° and 5°. SWM’s are being adopted by car companies such as Nissan and Renault, but work in very limited situations due to their reliability only in particular environments [23].

Standard Deviation of Lateral Position (SDLP) is another sleepiness sensitive continuous performance measure. Ingre et al. [52] found that SDLP is correlated with the Karolinska Sleepiness Scale (KSS), a nine-point scale that has verbal anchors for each step. However, SDLP is dependent on external factors such as road markings, lighting and climatic conditions. Sometimes, these driving performance measures are not specific to the driver’s drowsiness. In particular, these kinds of driving behavior measures are dependent on the vehicle type, driver experience, and conditions of the road.

3. Driver distraction detection

Distraction is another important factor causing impairment of driver attention, involving a driver not paying sufficient attention to the road in spite of the presence of obstacles or other people. In particular, there is a trend toward increasing use of in-vehicle information systems, which also leads to driver distraction.

A good first step in detecting driver distraction or inattention is to monitor the driver head pose and gaze direction. A forward warning system [53] uses driver behavioral information to determine driver distraction and to determine whether the driver is looking straight ahead. Murphy-Chutorian et al. [54] use head pose information extracted from a localized gradient histogram and support vector regressors (SVRs) to recognize driver awareness. Kaminski et al. [55] propose a system to estimate continuous head orientation and gaze direction. Distractions can be categorized as visual, that is, “eye-off-road”, and cognitive, that is, “mind-off-road” [17]. Liang [3] proposes a method to detect the interactions of visual and cognitive distractions.

To detect driver distraction, it is necessary to extract head pose or gaze information [56, 57]. Head pose estimation provides a driver’s field of view and current focus of attention. It is intrinsically linked to visual gaze direction. When the eyes are not visible, head pose is used to estimate the gaze direction. The combination of both head pose and eye direction provides a person's gaze information [58].

Murphy-Chutorian et al. [56] categorize eight conceptual approaches to head pose estimation. These are appearance template methods, detector array methods, nonlinear regression methods, manifold embedding methods, flexible models, geometric methods, tracking methods, and hybrid methods. Feature-based methods are the most commonly used gaze direction estimation methods [57]. With these methods, local features such as contours, eye corners, and reflections from the eye images are used. However, in vehicular environments, general gaze direction is sometimes good enough to reduce false warnings in forward collision warning (FCW) systems [59]. General gaze direction can be approximated by using only head orientation, which is computed by shape features with/without eye position, texture features or hybrid features consisting of shape and texture features [60].

4. Predicting unsafe driving behavior

Monitoring driver state, driving behavior performance and vehicle state is very important for improving active driver safety systems. The driver state is monitored by measuring drowsiness, fatigue or stress levels [61-64]. Driving behavior performance and vehicle state are also monitored by analyzing the information regarding driving speed, steering wheel angle, braking, and acceleration [48-50, 65, 66]. After detecting drowsiness or distraction, an alert is sent to the driver.

Another important issue for an active driver safety system is to develop a mechanism to predict minor and major accidents in advance. Jabon et al. [15] used facial features to aid in driver accident prediction. They combined both vehicle dynamics and driver face analysis for accident prediction. First, a comprehensive set of 22 raw facial features are analyzed. Then, the most valuable statistics for predicting accidents are extracted from a range of time and frequency domain values, so that both major and minor accidents are can be predicted. Even though the experimental results of Jabon et al. [15] are not based on real road situations, it has been found that facial features show most predictive accuracy four seconds prior to accidents and are more helpful in predicting minor accidents than major ones. This is because predictive accuracy for major accidents comes primarily from vehicle features rather than facial features.

EPFL and PSA Peugeot Citroen [16] are developing a technology to detect the driver distraction as well as emotions that could indicate that the driver is not up to the task at hand. In other words, facial expressions and muscle movements are important in analyzing whether the driver is too distracted, too tired or even too angry to safely control their vehicle.

Although facial features have proven to aid in predicting minor accidents, their predictive efficacy should be improved. To predict accidents more accurately, it is necessary to capture other physiological signals either from the driver or from some other part of the driver-environment system. Based on these data, a new model can be generated for predicting impending driver accidents. In particular, various populations of participants, traffic cultures and driving contexts should be handled in constructing a more extensive and general accident prediction model.

5. Discussion

For active driver safety systems, we have discussed various topics such as driver drowsiness detection, driver distraction detection, and prediction of unsafe driving behavior. To develop a better driver safety system, several issues should be addressed. The most important ones are a) hybrid measures for drowsiness detection, b) driving context-awareness for safe driving, c) the necessity for public data sets for simulation and real driving conditions.

5.1. Hybrid measures for drowsiness detection

Among driving behavior and driver behavior features in detecting driver drowsiness, driving behavior may sometimes not detect a driver's drowsiness reliably. Driver behavior features are better than driving behavior features, but visual features have sometimes limitations due to illumination conditions and driver posture [34]. Non-visual features such as physiological features are reliable and accurate, but their nature is intrusive. This should be solved before they can be used in real vehicular environments. Even though a less intrusive measurement of ECG has been developed [45], EEG and EoG still require electrodes placed on the scalp or eye area in an intrusive manner. However, non-intrusive measurement of physiological signals may be developed in the near future.

For reliable drowsiness detection, a hybrid measure fusing from visual, physiological and driving behavior features is desirable. The fusion method usually shows good performance in drowsiness detection even when certain sensors lose validity. Figure 4 shows an example of hybrid measurement for driver state detection. One issue is to develop a reliable data fusion method at the feature-level or decision-level [20].

5.2. Driving context-awareness for safe driving

For safe driving, driving context awareness is necessary because various information related to driving conditions and environment should be explored effectively. We can divide driving context into global and local. The global driving context refers to driving environment parameters such as vehicle type, road type, driving time, driving circumstances, road conditions, etc. The local driving context refers to the driver status. In other words, local context is related to the driver's visual and cognitive perceptiveness and its deterioration because of distraction, drowsiness and / or emotions.

In particular, a driving context-based computational model combining driving environment and driver status seems to be a promising avenue of development. Using such a model, the detection rate for distraction and drowsiness will increase, which will be helpful in predicting unsafe driving behavior.

5.3. Necessity for public data sets for simulation and real driving conditions

To monitor driver and driving behavior, various hardware and software algorithms are being developed, but they are tested mostly in the simulated environments instead of real driving ones. This is due to the danger of testing drowsiness in real driving environments. Philp et al. [67] found that reaction times and sleepiness as derived from self-evaluations increase in a simulated environment compared to a real driving environment due to the monotony of the experience. Engstorm et al. [68] stated that physiological workload and steering activity were both higher under real driving conditions compared to simulated environments. In real driving conditions, various factors including variations in lighting and noise can also affect the driver's attention. Thus, it is necessary to make simulated environments looks more like realistic.

Even though various kinds of methods for drowsiness and distraction detection are proposed and tested, it is very difficult to compare them directly. This is because there are no benchmark data sets available. To develop reliable drowsiness detection systems, public data sets covering simulated and real driving environments should be released in the near future.

6. Conclusion

In this paper, we have reviewed the various methods available to determine the drowsiness and distraction state of the driver. Driver behavior such as visual features, non-visual features and driving performance behavior are explored to detect driver drowsiness. PERCLOS, eye-closure duration (ECD), frequency of eye closure (FEC) are visual feature-based systems used to detect driver drowsiness. Among these, PERCLOS shows good performance in detecting drowsiness but has some limitations, such as illumination conditions. To overcome this problem, an 850 nm IR illuminator is used. Physiological signals such as ECG, EEG, EoG and PPG signals are used as non-visual features to detect driver drowsiness. Even though physiological signals show better performance than visual features, they have some limitations, particularly their intrusive nature. To overcome

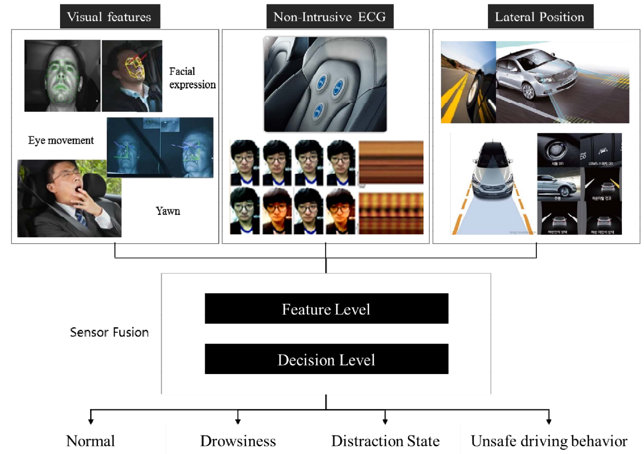

Figure 4: Hybrid measurement for detecting driver state.

this problem, less intrusive sensors should be developed. Currently, ECG signals can be captured using a less intrusive manner. Driving performance behavior such as steering wheel movement and standard deviation of lateral position are also used to detect drowsiness.

Driver distraction is detected using head pose and gaze direction. Driver distraction may lead to larger lane variation, slower response to obstacles, and more abrupt steering control. Thus, distraction should be monitored for developing a safer driver-monitoring system.

For active driver safety systems, it is desirable to predict unsafe driving behavior. We have explained prediction methods based on facial expression and car dynamics. Based on facial expression, the driver's emotion is detected, which is helpful in predicting driving behavior.

Finally, we have discussed several issues to tackle in future development of active driver safety systems. They are a) hybrid measures for drowsiness detection, b) driving context-awareness for safe driving, c) the availability of public data sets for simulation and real driving conditions.

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