A Review on Driver Drowsiness Detection Techniques

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Abstract— Number of accidents during driving is increasing day by day and drowsy driving has been implicated as a causal factor in many accidents. Goal of driver drowsiness detection systems is to reduce these accidents. It has been seen that most of the accidents occur due to driver's fatigue and a small due to inattention factor, therefore this paper reviews driver's fatigue monitoring techniques in detail with a little overview of others also.

Keywords-Driver drowsiness; Driver monitoring; Review

I. INTRODUCTION

DRIVERS' drowsiness has been noticed as a major factor in many of the accidents because of the noticeable decrease in drivers' perception of risk and recognition of danger, and diminished vehicle-handling abilities due to fatigue [1]–[5]. Drowsiness involves physical as well as physiological changes. Physical changes involve sleeplessness while physiological changes involves rate of actions and reactions taken by subject.

Driver's fatigue not only impacts the alertness and response time of the driver but also increases the chances of being involved in accidents. Data from the National Highway Traffic Safety Administration (NHTSA) shows that drowsy driving is a contributing factor to 22 to 24% of car crashes, and that driving while drowsy results in a four- to six-times higher near-crash/crash risk relative to alert and non-sleepy drivers [6]. When the driver goes drowsy, his/her ability levels, driving behavior, proficiencies and decisions are adversely affected and, in these situations, accident rate increases as the subject fails to take correct actions prior to a collision. Even though driver safety has been taken during road and vehicle design, the number of serious crashes is still increasing, indicating a need for automatic detection systems.

Driver's drowsiness can be detected through various measures like eye movement detection, yawning monitoring, driver- vehicle interaction etc. Techniques have been reviewed in the next section keeping in mind that it should be valuable and useable for the researchers who want to drive a new driver drowsiness system.

II. DRIVER DROWSINESS DETECTION TECHNIQUES

Three driver drowsiness detection techniques are described in detail in this section. These are:

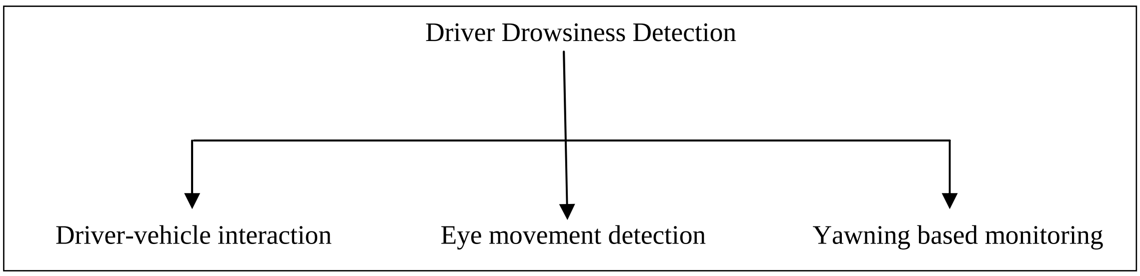

Figure 1. Type of drowsiness detection techniques.

A. *Driver-vehicle interaction [35]*

Indications of driver drowsiness can be noticed on the basis of driver–vehicle interaction. There are moments when a driver still looks awake (eyes wide open) but does not process any information and therefore his performance degrades [7]. This justifies that falling asleep may not be the only cause of fatigue-related accidents; performance deterioration due to drowsiness may not be induced only by indications such as eye closure, yawning but may be affected by controller degradation such as brain functions associated with sleep deprivation. To address this issue, approach has been addressed which measures the performance of drivers from the driver–vehicle interaction. Driver-vehicle interaction is measured in three phases. These are:

1) Sleep deprivation measurement.

2) Task observation.

3) Performance measures.

1) Sleep deprivation measurement

Sleep deprivation level of the human subjects is used to measure the level of homeostatic need for sleep. Two sleep-deprivation levels are considered, one is "partial sleep-deprivation" and another "no sleep-deprivation." The level of sleep deprivation is proportional to the amount of sleep that each subject had before the day of driving. The non sleep deprived subjects slept for at least 7–8 h per 24 h for more than a week before the day of driving. The partially sleep-deprived subjects had less than 7 h in bed two days before driving and less than 4 h in bed on the eve of that day.

2) Tasks observation

A series of simulated driving and non-driving tasks were given to the subjects and their respective actions were observed. Deterioration in lane-tracking performance can lead to overall driving malfunction; therefore lane-tracking is generally considered a main indicator for detecting driver's drowsiness [9]–[13]. However, the validity of this indicator is still controversial because performance in lane tracking varies under various road or weather conditions. Thus, for non sleep-deprived and partially sleep-deprived subjects, lateral lane-tracking performance under several conditions is examined to evaluate their ability to handle a vehicle and take corresponding action inside the roadway. Five different tracking tasks and four simulated response tasks were given to each subject in a random order while driving.

The five tracking tasks involved the followings:

a) a curved road;

b) a straight road with changes in steering dynamics;

c) a straight road with a lead vehicle;

d) a straight road without any disturbance; and

e) a straight road with disturbances (e.g., wind gusts), respectively.

Although external or environmental disturbances can be easily applied such as wind gust, bumpy roads, and fog in simulated driving, we cannot control the presence of the environmental disturbance in real driving. It was observed how the drivers adapt themselves to disturbances and then applied this to real-driving situations.

Four stimulus-response tasks were given to each subject in a random order during the simulated driving and their instantly response was observed. Stimulus was an auditory ringing signal, a visual red triangular symbol, or an overhead lane-change sign on the driving lane.

The four simulated-response tasks involved the followings:

a) Single Lane Change Task (SLCT): Once an overhead lane-change sign appeared, the drivers were supposed to immediately change lanes. The SLCT sign refers to the moment when the lane indicated by the arrow is adjacent to the current driving lane.

b) Double Lane Change Task (DLCT): The lane-change sign had the same format as described in SLCT. However, the DLCT sign refers to the moment when the lane indicated by the arrow is separated from another lane, and the drivers need to shift two lanes at once.

c) Auditory Psychomotor Vigilance Task (APVT): The drivers were supposed to press a green button on the steering wheel immediately after hearing a ringing tone. The ringing tone lasted for about 1 s.

d) Visual Psychomotor Vigilance Task (VPVT): The drivers were supposed to press a green button on the steering wheel immediately after recognizing a red stimulus on the screen. The stimulus was shown for 5 s if there was no response from the subjects.

3) Performance measures

a) RMT: The root-mean-square (RMS) error with threshold (RMT) is a parameterized variation of the conventional RMS error, which is usually used to measure the general tracking performance observed through various experiments. RMT have been devised instead of the RMS to capture common driving characteristics. The drivers tend to ignore a certain level of errors, as they generally try to stay within the driving lane instead of trying to follow a single line on the road and this driving characteristic is usually called "good enough" or "satisfying" characteristics of drivers [8]. Therefore, looking at the driver's general thinking and nature, a threshold γ has been used so that RMT is vanished as long as driving trajectories stay within the threshold γ.

The RMT is defined as

$$RMT = \sqrt{\frac{\sum_{t=t_o}^{t_f} \max\{|x_t| - \gamma, 0\}^2}{N}} \tag{1}$$

where $x(t)$ is the lateral lane position of a driver with respect to the centerline of the driving lane at time t, γ is a threshold value varying from 0% to 50% of the road width, N is the number of data within the sampling window, t_o is the initial time in the sampling window, and tf is the terminal time in the sampling window. It is apparent that RMT is reduced to a typical RMS error when $\gamma = 0$.

b) RT: The reaction time (RT) is a measure of how fast a driver reacts to stimuli presented abruptly, i.e.,

$$RT = t_{action} - t_{stimulus} \quad (2)$$

where *t*stimulus is the time during which a stimulus is presented to the driver, and *t*action is the time the man–vehicle system takes to react upon the given stimulus. (For SLCT and DLCT, *t*stimulus is the time when the lane-change sign appears on the screen, and *t*action is the time when the driver starts to steer toward the lane indicated.)

c) ETL: The effective time delay (ETL) of continuous tasks and RT of discrete tasks [14] can be considered equivalent. The ETL is estimated by applying McRuer's crossover model to continuous tasks. *The McRuer's driver model* represents the driver performance in auditory and visual display tracking tasks. This model is referred to as a crossover model of a human operator from experiments with compensatory tracking task. The block diagram of this model has been shown in Figure 1. The pure time delay in the model is approximated by a first order approximation of the form

$$\frac{1}{\tau_s + 1} \quad (3)$$

With this approximation, the model of the human operator becomes

$$\frac{K}{s(\tau_s + 1)} \quad (4)$$

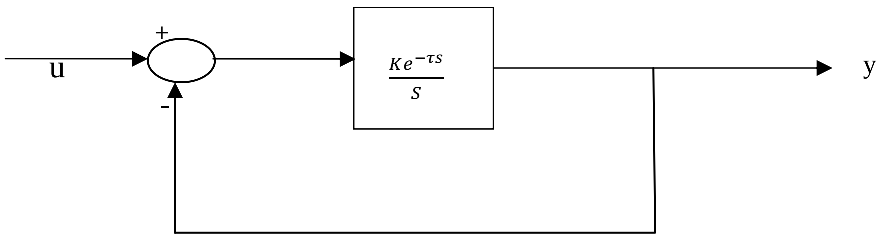

Figure 2. McRuer's Model for Compensatory Tracking Task [15].

Therefore, the human behavior is defined by the value of K and τ which are known as *gain and effective delay*. To identify these values, actual testing was performed for three different subjects. A simple step input of the audio signal was provided to the each subject to produce a transient response of the operator. The results showed larger τ and smaller K values. The discrepancies are due to the saturation of audio signal and tracking skills of the operator. The tracking task can be improved by training and can have better performance close to the values presented by McRuer as humans adapt themselves to the system in such a way as to make the total open-loop transfer function behave as a first-order system with *gain* and *effective time delay*. Thus, the total open-loop transfer function can be expressed as

$$Y_H Y_P = \frac{Ke}{s}^{-ts} \quad (5)$$

where *YH* models the human operation, *YP* is a plant.

d) CRR: The accuracy of the drivers' response is measured by the correct response rate (CRR), i.e.,

$$CRR = \frac{\sum_{i=1}^{n} 1(R_i)}{n} \quad (6)$$

where n is the total number of responses under consideration, and 1(*Ri*) is equal to 1 when *Ri* (denoting the *i*th response) is correct, i.e., the drivers do what they are supposed or instructed to do. On the other hand, 1(*Ri*) is equal to 0 when the *i*th response is incorrect. The CRR measures the accuracy of the drivers' response, whereas the RT measures the speed.

B. Eye movement detection [36]

Various measuring systems like electrooculography (EOG), infra-red cameras or other image-based detectors can be used for detecting eye movements. Relevant eye movements such as eye blinks are detected first. Secondly, based on the detected eye movements, various features like blink duration, amplitude etc. are defined and extracted [16] and, then classification methods are applied to the extracted features [17]- [20], [19]. Detection method plays a vital role in detection scenarios, more efficient the detection method, the more informative the extracted features and the higher is the correlation to drowsiness.

In an experiment, the subjects were asked to drive as long as they could and their drowsiness level was estimated based on the Karolinska Sleepiness Scale (KSS) [21] every 15 minutes (see Table I).

TABLE I. KAROLINSKA SLEEPINESS SCALE (KSS)

KSS	Description
1	Extremely alert
2	Very alert
3	Alert
4	Rather alert
5	Neither alert nor sleepy
6	Some signs of sleepiness
7	Sleepy, but no effort to keep alert
8	Sleepy, some effort to keep alert
9	Very sleepy, great effort to keep alert

EOG signals were measured at 250Hz with six electrodes: four electrodes for horizontal (*H*) and vertical (*V*) movements and two as reference and ground. *H* and *V* are defined as follows

$$V = \text{electrodeup} - \text{electrodedown} \quad (7)$$

$$H = \text{electroderight} - \text{electrodeleft}\ . \quad (8)$$

Generally, human eye movements can be categorized in four ways; *smooth pursuit*, *saccade*, *fixation* and *eye blink*. Smooth pursuits are the slow eye movements while tracking a moving object [22]. Saccades describes fast eye movements of both eyes occurring due to the change of the looking direction in order to reposition the fovea from one image to another one [23].

Since these eye movements occur only in one direction (either horizontal or vertical), noticeable changes are there only in one of the EOG components. In contrast, diagonal eye movements like looking in the rear-view mirror while driving lead to saccades present in both directions vertical as well as horizontal. The time interval between two successive saccades during which the eyes fixate on the new location is known as fixation. Regular and rapid opening and closing of the human eyes is eye blink. It has been categorized into three ways: *opening, closed and closing* [24]. In the case of drowsiness, all stages of the blink events will be affected and take longer in comparison to awake state.

Various methods employed to detect driver's drowsiness by eye's movement are:

1) Blink detection by median filter

When awaken, time at which a person does not suffer from sleep deprivation, blinks often follow similar characteristics, i.e. their amplitude and duration do not change remarkably. This implies that blink detection can easily be done by applying few constraints, e.g. by comparing the $V(n)$ signal with a fixed threshold. However, a fixed threshold does not lead to correct blink detection since dc amplifiers are used in the EOG measurement, and drift which is not related to any type of eye movements is considered inevitable in the EOG signal. Therefore, a median filter has been applied to V (n) [25] for eliminating the drift in the EOG signal and improving the blink detection. In this case,

$$\ddot{V}(n) = V(n) - V_{\text{med}}(n) \quad (9)$$

where $V_{\text{med}}(n)$ refers to the median filter processed $V(n)$ with empirically chosen window size of $w_{\text{med}} = 2(f/4) + 1$ and $f = 50$Hz in this study. Now, blinks can be easily detected due to the eliminated drift in $\ddot{V}(n)$ and by applying an amplitude threshold like $th_{\text{amp}} = 100\mu V$.

It matters a lot to decide th_{amp} and w_{med} values, as setting a small value for th_{amp} does not help, and saccades or noise might be incorrectly detected as blinks. Also, the median filter method is highly dependent on the chosen *w*med, since more it matches the blink duration; the less blink information is lost in $\ddot{V}(n)$.

As blink duration not only varies from person to person, but also for an individual according to the level of drowsiness, therefore, applying a fixed-window size median filter is not a good solution for blink detection because all fast eye movements (blinks and saccades) are of interest and a median filter removes both slowly varying dc drift as well as some blinks and saccades.

2) *Fast eye movement detection based on blink's pattern*

In the above blink detection method and [17], [18] is based on the derivative of the EOG signal and doesn't take into account saccade detection into account. This method takes saccade detection into consideration as well so that blinks and saccades are detected simultaneously. The derivative of the $V(n)$ signal, $V'(n)$, calculated by the Savitzky-Golay filter [26], concludes that a blink can be detected by the following steps:

a) Detecting potential blinks: Potential blink events can be detected by setting an amplitude threshold to consider all peaks of $V'(n)$

$$|V'(n)| > \mathrm{th}_{\mathrm{vel}} \tag{10}$$

Afterwards, around all accepted peaks, three successive sign changes are looked for. These points define start, middle and end points of a blink as a, b and c, respectively. Positive to negative transitions of $V'(n)$ are defined by a and c, while negative to positive transitions by b. Transitions a to b and b to c describe closing and opening of eyes during a blink event. At the end of this step, all potential blinks have been detected.

b) Blink amplitude definition: After detecting all potential blinks, the blink amplitude is extracted. For normal blinks, the difference between closing and opening amplitudes, namely $B - A$ and $B - C$, is negligible. For saccadic blinks, however, this difference is equivalent to the amplitude of the saccade time-locked to the blink and is non-zero. Therefore, in order not to consider the amplitude of the saccade in the blink amplitude, the blink amplitude for the i-th blink is defined as

$$amp_i = \min(B_i - A_i, B_i - C_i) \tag{5}$$

c) Classifying potential blinks with respect to their amplitude: Now the question is whether all detected patterns are indeed eye blinks. In order to assess this, the histogram of the amplitude was analyzed; the histograms were normalized with respect to the maximum number of occurrences for each subject separately. For almost all subjects only two clusters of amplitude were distinguishable. One, the cluster with the smaller amplitude describes the vertical saccades and micro-sleep events.

On the other hand, saccades and blinks with long eye closures have similar patterns. Therefore, analogous to saccades, opening and closing stages of such blinks are detected by the algorithm and considered in the group with smaller amplitudes. After identifying different clusters, a clustering method such as k-means clustering is required in order to find the exact order between them. At first sight, applying a 2-class clustering seems to be sufficient. However, besides saccades and micro-sleep events, the data includes blinks from both awake and drowsy phases. In fact, three clusters are available:

- saccades/micro-sleeps,
- blinks during a drowsy phase (or with longer eye closure and smaller amplitude due to drowsiness) and
- blinks during an awake phase (or with short eye closure). Therefore, applying a 3-class clustering algorithm is recommended.

d) Distinguishing between vertical saccades and blinks with longer eye closure: The goal of this step is to distinguish between saccades and other eye movements which are all classified in a common group in the previous step. Only the minimum amplitude of $B - A$ and $B - C$ were of interest there while now the actual amplitude of these events are studied. The amplitude of the eye movements of this group, $amp_{em,i}$, is defined as

$$amp_{em,i} = |Ci - Ai| \tag{6}$$

In fact, the relative variation of the amplitude is considered, overcoming the overshoots in saccadic eye movements. The group with smaller amplitudes refers to vertical saccades while the other group describes blinks with long eye closure. Due to smaller vertical than horizontal space of human eyes, the amplitude of vertical saccades is limited so that saccades with large amplitudes comparable to micro-sleep events do not occur during common driving tasks. On the other hand, it is clear that if micro-sleep events based on the saccadic pattern do not occur often, the clusters will not be as distinguishable.

e) Plausibility check of detected fast eye movements: Since EOG signals are very sensitive to any muscle artifact around the electrodes, it might be possible that some artifacts are confused with eye movements. A possible method for overcoming this problem is to ascertain which eye movements are related to each other. This sounds logical during driving, as it is assumed that the driver looks straight ahead most of the time. Therefore, a *main looking direction* can be defined. In other words, for all saccades representing looking away from the main looking direction, another saccade in the opposite direction should be present. However, for saccades occurring as saccadic blinks, a threshold, th_s, is required to avoid confusing them with non-saccadic (normal) blinks. Based on a similar argument, micro-sleep events can be checked as well, as all eye closures should be followed by an eye opening during driving. Finally, all detected eye movements which are not assigned to other movements are considered as false detection and removed from the dataset.

f) Horizontal saccade detection: Similar to the vertical saccades, horizontal saccades are detected by comparing |*H’* (*n*)| with a threshold as explained in Step 1. As blinks are not available in *H*(*n*), detected patterns are either saccades or artifacts. Therefore, just the saccades which passed the plausibility check are considered as horizontal saccades in the end.

Based on the measured signals, an adaptive detection approach is introduced to simultaneously detect not only eye blinks, but also other driving-relevant eye movements such as saccades and micro-sleep events. Moreover, in spite of the fact that drowsiness influences eye movement patterns, the proposed algorithm distinguishes between the often confused driving-related saccades and decreased amplitude blinks of a drowsy driver.

C. Yawning based monitoring [37]

Driver’s drowsiness can be measured based on yawn of the subject and there are various ways of doing it. Gravity-Center template, Viola face detection method etc. has been used for detecting face, and then grey projection and Gabor wavelet to detect mouth corners or mouth window is extracted and spatial Fuzzy c mean clustering to know the lips position[27][28]. LDA has been applied to classify feature vectors to detect yawning. Geometric and haar-like features also have been used for detecting mouth and thus ratio of mouth height and width which ultimately detect the yawn of the subject [29][30]. One of the easy ways employed to detect yawn of the subject is as follow:

Step1: Detect face of the subject

Face of the driver is detected using degree of variability in size, shape, color and texture using RGB, HSV schemes and lightening conditions.

Step2: Tracking the face

Detected face is used as a template in tracking upcoming frames and matched based on its location and various other correlation factors.

Step3: Eye detection

After locating face, eyes are detected to make sure that mouth is tacked correctly using the equation having chrominance component [31]:

$$Eye_{Location} = \frac{1}{3}\{(C_b)^2 + (C_r)^2 + (\frac{C_b}{C_r})\} \tag{7}$$

Step4: Mouth detection

This is an important step as it detects position of lips and mouth and therefore ultimately helps in yawn monitoring of the subject. Mouth is also detected based upon color components, here red is the strongest component and blue is the weakest. Equations used to generate the mouth map are:

$$Mouth_{map} = (C_r)^2 \times \left((C_r)^2 - \frac{\eta\times C_r}{C_b}\right)^2 \tag{8}$$

$$\eta = 0.95\frac{\frac{1}{n}\sum_{(x,y)} C_r(x,y)^2}{\frac{1}{n}\sum_{(x,y)}(C_r(x,y)/C_b(x,y))} \tag{9}$$

Mouth map will then go through some post processing steps such as black and white conversion, erosion, dilation in the same way as eye detection scheme and geometrical features of the face and relative location of the mouth with respect to eyes are exploited to crosscheck validity of mouth.

Step5: Yawn detection

Yawning is first detected by measuring the hole in the mouth as a yawning component, and then location of mouth is verified to see the validity of detected component. The verification criteria is number of pixels located in yawning mouth with respect to number of mouth pixels as well as relative location of the open mouth with respect to the lips.

III. EXISTING RULES, POLICIES AND MEASURES

There are few existing measures given and suggested by government keeping in mind road safety and how to reduce accidental risks. These are [36]:

A. Transportation Policies

The National Center on Sleep Disorders Research and NHTSA expert panels on driver fatigue [33] recommend three priorities for an educational campaign:

- educate young males (ages 16–24) about drowsy and rough driving and how to reduce accidental risks;
- promote shoulder rumble strips as an effective countermeasure for drowsy driving and, in the same context, raise public awareness about drowsy driving risks and harms and how to reduce them; and
- educate shift workers about the risks of drowsy-driving and how to reduce them.

B. Law Enforcement

The first federal bill focusing on drowsy driving was introduced in the House of Representatives in October 2002 by Republican Robert Andrews [34]. The bill, i.e., HR 5543, is called *Maggie's Law: National Drowsy Driving Act of 2002*. The law narrowly defines *fatigue* as being without sleep for a period in excess of 24 consecutive hours. Under Maggie's law, anyone causing a fatality after being awake for 24 h or more can be prosecuted for vehicular homicide. Currently, a number of states, including New York, Massachusetts, Tennessee, Oregon, Kentucky, and Illinois, are considering similar drowsy-driving legislation [34].

C. Fatigue Detection Techniques

Along with transportation policies, reliable and applicable drowsy-driving detection techniques may help detect fatigue. Researchers have developed a number of different drowsiness-detection methods, which can be classified in terms of their specific procedure and measure used to detect fatigue [8], [9]. References [32] and [8] have summarized the detection techniques based on:

- physiological signals, including pulse rate and EEG;
- physical changes, including changes of head position, eye-closure rate, and eyelid movement;
- driver–vehicle data, including steering angle, throttle/brake input, and speed; and
- secondary tasks that periodically request responses from drivers.

IV. CONCLUSIONS

Driver drowsiness detection systems have been very advantageous in reducing day by day road accidents and thus encouraged to use. This paper gives a review of few driver drowsiness detection techniques and existing measures supported by government. Paper has revealed characteristics of drowsy driving and its adverse effects can be seen clearly. Three drowsiness detection methods; driver-vehicle interaction, eye movement detection and yawning based monitoring systems are explained in detail with simple and understandable procedure used.

REFERENCES

[1] J. A. Horne and L. A. Reyner, “Sleep related vehicle accidents,” Brit.Med. J., vol. 310, pp. 565–567, 1995.

[2] G. Maycock, “Sleepiness and driving: The experience of UK car drivers,” J. Sleep Res., vol. 5, pp. 229–237, 1996.

[3] G. Maycock, “Sleepiness and driving: The experience of heavy goods vehicle drivers in the UK,” J. Sleep Res., vol. 6, pp. 238–244, 1997.

[4] J. Connor, R. Norton, S. Ameratunga, E. Robinson, I. Civil, R. Dunn, J. Bailey, and R. Jackson, “Driver sleepiness and risk of serious injury to car occupants: Population based case control study,” Brit. Med. J., vol. 324, pp. 1125–1128, 2002.

[5] K. A. Brookhuis, D. D.Waard, and S. H. Fairclough, “Criteria for driver mpairment,” Ergonomics, vol. 46, pp. 433–445, 2003.

[6] S.G. Klauer , T. A. Dingus, Neale, V. L., Sudweeks, J.D., and Ramsey, DJ, ”The Impact of Driver Inattention on Near-Crash/Crash Risk: An Analysis Using the 100-Car Naturalistic Driving Study Data,” Virginia Tech Transportation Institute, Technical Report # DOT HS 810 594.

[7] G. Renner and S. Mehring, “Lane departure and drowsiness—Two major accident causes-one safety system,” in 4th World Congr. Intell. Transp. Syst., Berlin, Germany, Oct. 21–24, 1997.

[8] M. Kaneda, H. Iizuka, H. Ueno, M. Hiramatsu, M. Taguchi, and M. Tsukino, “Development of a drowsiness warning system,” presented at the 14th Int. Tech. Conf. Enhanced Safety Vehicles, Munich, Germany, 1994, Paper 94-S3-O-08.

[9] Q. Wang, J. Yang, M. Ren, and Y. Zheng, “Driver fatigue detection: A survey,” in Proc. 6th World Congr. Intell. Control Autom., Dalian, China, Jun. 21–23, 2006, pp. 8587–8591.

[10] A. Kircher, “Vehicle control and drowsiness,” Swedish Nat. Road Trans. Res. Inst., Linköping, Sweden, Tech. Rep. VTI Meddelande 922A, 2002.

[11] J. Arnedt, G. Wilde, P. Munt, and A. Maclean, “Simulated driving performance following prolonged wakefulness and alcohol consumption: Separated and combined contributions to impairment,” J. Sleep Res., vol. 9, no. 3, pp. 233–241, Sep. 2000.

[12] R. R. Mackie and C. D. Wylie, “Countermeasures to loss of alertness in motor vehicle drivers: A taxonomy and evaluation,” in Proc. Human Factors Soc. 35th Annu. Meeting, San Francisco, CA, Sep. 2–6, 1991, pp. 1149–1153.

[13] T. Pilutti and A. G. Ulsoy, “Identification of driver state for lane-keeping tasks,” IEEE Trans. Syst., Man, Cybern. A, Syst., Humans, vol. 29, no. 5, pp. 486–502, Sep. 1999.

[14] C. Wickens, S. Gordon, and Y. Liu, An Introduction to Human Factors Engineering. Reading, MA: Addison-Wesley, 1998.

[15] McRuer, D., Graham, D., Human Pilot Dynamics in Compensatory systems, AFFDL-TR-65-15, July 1965.

[16] Y. Dong, Z. Hu, K. Uchimura, and N. Murayama, “Driver inattention monitoring system for intelligent vehicles: A review,” Intelligent Transportation Systems, IEEE Transactions on, vol. 12, no. 2, pp. 596 –614, June 2011.

[17] S. Hu and G. Zheng, “Driver drowsiness detection with eyelid related parameters by support vector machine,” Expert Systems with Applications, vol. 36, no. 4, pp. 7651 – 7658, 2009.

[18] Z. Wei and B. Lu, “Online vigilance analysis based on electrooculography,” in Neural Networks (IJCNN), The 2012 International Joint Conference on, June 2012, pp. 1 –7.

[19] F. Friedrichs and B. Yang, “Camera-based drowsiness reference for driver state classification under real driving conditions,” in Intelligent Vehicles Symposium, 2010 IEEE, 2010, pp. 101–106.

[20] R. Schleicher, N. Galley, S. Briest, and L. Galley, “Blinks and saccades as indicators of fatigue in sleepiness warnings: looking tired?” Ergonomics, vol. 51, no. 7, pp. 982–1010, 2008.

[21] T. Akerstedt and M. Gillberg, “Subjective and objective sleepiness in the active individual.” The International journal of neuroscience, vol. 52, no. 1-2, pp. 29–37, 1990.

[22] R. Leigh and D. Zee, The Neurology of Eye Movements, ser. Contemporary Neurology Series. Oxford University Press, 1999, ch. 3.

[23] J. Enderle, Models of Horizontal Eye Movements: Early models of saccades and smooth pursuit. Part 1, ser. Synthesis Lectures on Biomedical Engineering Series. Morgan & Claypool Publishers, 2010.

[24] R. Hammoud, Passive Eye Monitoring: Algorithms, Applicationsand Experiments, ser. Signals and Communication Technology. Springer London, Limited, 2008, ch. 14, p. 315.

[25] M. Martinez, E. Soria, R.Magdalena, A. Serrano, J.Martin, and J. Vila, “Comparative study of several fir median hybrid filters for blink noise removal in electrooculograms,” WSEAS Trans. Sig. Proc., vol. 4, no. 3, pp. 53–59, Mar. 2008.

[26] A. Savitzky and M. J. E. Golay, “Smoothing and differentiation of data by simplified least squares procedure.” Anal. Chem. (1964), pp. 1627–1639, 1964.

[27] X. Fan, B. Yin, Y. Fun, “Yawning Detection For Monitoring Driver Fatigue,” In: Proc. Sixth International Conf. on Machine Learning and Cybernetics, Hong Kong, 2007, pp. 664-668.

[28] T. Azim, M. A. Jaffar, A.M. Mirza, “Automatic Fatigue Detection of Drivers through Pupil Detection and Yawning Analysis,” In: Proc. Fourth International Conf. on Innovative Computing, Information and Control, 2009.

[29] L. Li, Chen, Z. Li, “Yawning Detection for Monitoring Driver Fatigue Based on Two Cameras,” In: Proc. 12^{th} International IEEE Conf. on Intelligent Transportation Systems, St. Louis, MO, USA, 2009, pp. 12-17.

[30] T. Wang, P. Shi, “Yawning Detection For Determining Driver Drowsiness,” IEEE International Workshop VLSI Design & Video Tech, Suzhou, China, 2005, pp. 373-376.

[31] Hsu Rein-Lien, M. Abdel-Mottaleb, and A. K. Jain, “Face detection in color images,” IEEE Trans. Pattern Analysis and Machine Intelligence, Vol. 24, issue 5,2002.

[32] J. Yang, “Analysis and detection of driver fatigue caused by sleep deprivation,” Ph.D. dissertation, Dept. Aeronaut. Astronaut., MIT, Cambridge, MA, 2007.

[33] K. P. Strohl, “Drowsy driving and automobile crashes,” US Dept. Health Human Service, NHTSA, Washington DC, Tech. Rep. DOT HS 808707, Apr. 1998.

[34] National Sleep Foundation, 2007. [Online]. Available: http://www.sleepfoundation.org

[35] Ji Hyun Yang, Zhi-Hong Mao, Louis Tijerina, Tom Pilutti, Joseph F. Coughlin, and Eric Feron, “Detection of Driver Fatigue Caused by Sleep Deprivation,” IEEE Trans. ON SYSTEMS, MAN, AND CYBERNETICS—PART A: SYSTEMS AND HUMANS, VOL. 39, NO. 4, pp. 694-705, JULY 2009.

[36] Parisa Ebrahim, Wolfgang Stolzmann and Bin Yang, “Eye Movement Detection for Assessing Driver Drowsiness by Electrooculography,” in IEEE International Conference on Systems, Man, and Cybernetics, 2013, pp. 4143 –4148.

[37] S. Abtahi, B. Hariri, and S. Shirmohammadi, “Driver drowsiness monitoring based on yawning detection,” in Instrumentation and Measurement Technology Conference (I2MTC), 2011 IEEE, 2011, pp. 1–4.