

Driver Alertness Detection System: A Survey

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Abstract: Over 30% of the accidents happening all over the world are due to lack of driver alertness. Due to various accidents, there is an annual loss of over tens of billions each year. There is a need for driver assistance system to prevent the accidents, which occur due to the lack of alertness of the drivers. Researchers have been working on creating a reliable system for over a decade to alert the driver in time and avoid accidents. This can be achieved through the various detection techniques, most of which are being implemented in the next generation vehicles. The driver alertness detection can be divided into two groups; Visual Methods which focuses on gathering information through observing the driver's face via camera and tracking Percentage of eye Closure(PERCLOS) and Yawning, it can also be used to detect driver distraction. Non-Visual ways such as Physiological Signal (HRV, EEG, ECG, EOG) which uses body signal to analyze driver's alertness levels. In addition, Vehicle based features in which we take note of the vehicle movements such as lane keeping, braking, and acceleration. In this paper, we have conducted a comprehensive study of aforementioned groups and give out an estimation of their accuracies and limitations.

Keywords —Advanced Vehicle Safety, Commercial Systems, Driver Alertness, Driver Safety, PERCLOS, Physiological Signals, Vehicle Based anomaly

I. INTRODUCTION

Driver Alertness detection is an important factor on which automobile companies are working. According to National Sleep Foundation's survey in America over 60% of American have had an experience of being sleepy while driving and 37% have admitted to have fallen asleep while driving. According to the U.S National Highway Traffic Safety Administration, every year approximately 100,000 traffic accidents take place due to drowsiness of drivers. This has caused over 1,550 deaths, 71,000 injuries which ended up in an estimated of 12.5 billion monetary losses. These figures are not the actual values which represent the number of accidents occurring as various accidents go unreported and are never recorded [1]. The drowsiness of drivers results in 7% car crashes in United Kingdom and 3.9% in Norway [2], [3]. Majority of the driver drowsiness related car crashes, approximately 80% of them happen when driver loses control over the car, drives off road or smashes into something like the car ahead or the lane dividers [4]. The Government of various countries have implemented various laws to decrease the number of accidents such as mandatory rest on long duration journey. However, these laws and precautions are not enough to decrease the number of accidents. Therefore, researchers are trying to develop a system which will monitor the state of driver in real time and alert the driver of his state, be it drowsiness or distraction. Such systems are termed as

Advanced Driver Assistance System(ADAS), Driver Inattention Monitoring System, Driver Alert Control System [5], [6], [7], [8].

There are various ways to detect the alertness level of the driver. This can be divided into distraction of the driver and the drowsiness level. The alertness of the driver is related to the symptoms which can be measured through eye movement, facial expression, heart rate and brain activity [9], [10], [11], [12], [13], [14]. The researchers have divided the problem at various levels based on the area that is monitored, to detect these conditions. They have been divided into visual and non-visual detection techniques. Visual features involving eye movement measurement is used for detection of drowsiness based on PERCLOS, which was developed by W.W. Wirewille [15], [16]. Whereas the Distraction can be detected using the Head position and Pupil Activity of the driver and where driver is looking [17]. Facial Expression of the Driver varies when the driver is drowsy compared to the alert state of the driver. Detection of Yawns is also a good way to detect the drowsiness level of the driver [18], [19], Heart Rate is used indirectly to detect the autonomic nerve activity as heart rate reflects the autonomic nerve activity and is influenced when people are drowsy [20]. Heart rate measurement falls under the Physiological Signal section. These include brain activities, which can be monitored through the measurement of the EEG, ECG, EOG signals. These signals have produced very accurate detections as the bio-signals are



directly related to the drowsiness levels. Other than Bio-Signals the non-visual factor that can be consider are the driving pattern and the parameters such as steering wheel angle, Standard Deviation of Lateral Position(SDLP), abrupt Acceleration and deceleration, Galvanic Skin Response and Conductivity, Steering wheel grip pressure and body temperature. These parameters can also be used for the detection of drowsiness and alertness of the driver [21]. Some of these systems are developed under simulated conditions and the real life conditions vary compared to the simulated ones. There are some commercial systems which have been designed for the alertness monitoring and drowsiness detection.

The organization of this paper is as follow. In Section II we discuss the Vehicle movement monitoring and the methods which can be used for detection of the driver's alertness. We are also looking in the disadvantages of Vehicle state monitoring systems. In Section III we discuss the Physiological methods for detecting the drowsiness or inability of the driver to driver the vehicle. We also shed some light on some of the disadvantages or limitations of the physiological signal. In Section IV we discuss the about how we can detect the driver's drowsiness based on the visual features of the face. The merits and demerits are included. In Section V we discuss the Commercially used Systems which are being implemented today. In Section VI we propose a fusion of the techniques to overcome the drawbacks of the currently existing methods.

Figure 1

The below figure shows the subdivisions of the Drowsiness-Detection System



II. DRIVER DROWSINESS DETECTION BASED ON VEHICLE MOVEMENT

This category involves techniques which are dependent on driver's driving behavior. This includes Steering Wheel Movement(SWM), Lane keeping, acceleration pedal movement and braking which can help to recognize the driver's drowsiness levels [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32]. The two important factor that are used in vehicle movement based drowsiness detection system are Steering Wheel Movement (SWM) and standard deviation of lane position [33], [24], [26]. The SWM is measured using steering angle sensor mounted on the steering column and few micro-corrections are needed for the small road bumps and crosswinds. With increase in level of drowsiness, drivers tend to reduce the number of microcorrections [33], [24]. SWM is being implemented but the implementation is very limited as it works well only in certain environmental conditions and are too dependent on geometric characteristics of the road [28], [29]. In [62] they proposed an algorithm which is based on the fact that human body conducts current. They used a conducting wire on a non-conducting steering wheel of vehicle and by using an Analog to Digital Converter(ADC) and connecting it through a transistor which act as a switch. The grip pressure on the steering wheel is measured in terms of current flowing through the designed circuit. When the current flowing through the circuit goes below a certain threshold alarm is generated as drowsy drivers tend to have loose grips. In [63] the author has taken three cues which includes (weaving, drifting, wide turns), (sudden acceleration, braking), (driving on wrong side of the road, driving without headlight). He has used statistical information for these cues and when multiple cues match the driving pattern, probability of the driver being drunk or fatigued becomes high. This is achieved through using four major parameters which can be detected via accelerometer of smartphones, these parameters being Longitudinal acceleration, speed control, lateral acceleration and lane position. However, it also creates a problem as smartphones need to be kept at static location and should not move much for good accuracy. Sometimes vehicle can become unstable due to slip or traction which is a dangerous condition and driver should be warned of it and some system are designed for this purpose as well. The Standard deviation of Lateral Position (SDLP) is used to detect the car's lateral positon. A camera records the lane data and a software analyzes it to compute the car's position relative to the roads middle lane [30], [31]. When the car's lane is found to be faulty it alerts the driver. SDLP systems have some limitations that are caused by external factors namely quality of good road markings, weather conditions and lighting conditions. These methods are not very reliable as the driving pattern of the drivers differ across the world. The driver's skill is another factor which can't be accounted for using these methods. And various other factors also affect such systems which range from vehicle characteristics, road conditions, vehicle speed. When the vehicles are equipped with sophisticated systems which can monitor the entire environment like those in the self-driving car models, the vehicle based feature will have much higher accuracy in preventing accidents all together. However, those sophisticated



techniques are not yet available for the general population and might take some time. Thus, these methods have not been able to give a robust solution to the problem till date. In future as vehicles become more smart we might see some significant changes with their contribution to the ADAS.

III. DROWSINESS DETECTION BASED ON PHYSIOLOGICAL SIGNALS

Physiological signals are generated by the body during the functioning of various physiological activities. These signals hold a lot of information about what is happening in our body which can be extracted. Hence these signal can be used to detect the drowsiness state of the driver and help in warning the driver before he is on the brink of sleep. Some examples of Physiological Signals are Electroencephalogram (EEG) and Electro-oculogram (EOG) which also gives additional information about the emotional state of the driver. This information is termed as psychophysiological index. When we are sleepy, the activities of delta wave and theta waves in our brain increases substantially and the activity of alpha waves are increased slightly [34]. EEG is accepted as an indicator of the transition between the different sleep stages by researchers [35]. The EEG signals are used to detect the drowsiness levels in simulated and real driving environments and have produced good results. Although the EEG signals are accurate but one major issue is the noise and artifacts which are unavoidable. We use Fast Fourier Transform(FFT) and Discrete Wavelet Transform(DWT) to extract the required feature. Then the extracted feature is passed through Machine Learning classification algorithms to get the drowsiness levels [34], [36], [37], [38], [39], [40]. The use of EEG makes the driver drowsiness detection system intrusive, which can be uncomfortable due to microelectrode or other signal recording devices being attached to n End the body of the driver. A study on single channel of EEG signal showed that Artificial Neural Network(ANN) performed better than Support Vector Machine(SVM) [41]. Although they tried to reduce the uncomfortability of the driver by using one channel reading, it is still not enough. During long journeys driver's sweat may result in improper signal reading which will lead to inaccurate prediction. And longer journeys are more prone to accidents due to drowsiness. Use of Steering Wheel grip to get the Heart Rate by placing a sensor on the steering wheel was also proposed. However, this will fail to get good read of the heart rate when a driver loosens his grip on the steering wheel as many drivers keep the grip loose throughout the driving. This method might turn out to be effective while using smartwatches which come with heart rate monitoring sensors. Another factor that must be considered while using this method is that the age variability of the driver and the physical and medical conditions, which will affect the signal being received. The medical conditions of the various driver

must be inputted for accurate prediction using this method. And it is practically not possible to keep the system updated with the latest medical condition of the driver. Some of these medical conditions might make driver unfit to drive but most medical conditions don't cause much issue. One more factor that hasn't been taken into consideration is the cost of the electrodes which will be used for detection of these signals. Keeping the previous issue asides these methods will be more effective for motor bikes as they require helmet which can have these electrodes installed. The heart rate monitoring can be done via smart watches which are becoming common these days. Getting EEG signals in other vehicles will still cause a lot of discomfort to the driver. Hence making this method ineffective under many circumstances.

IV. DRIVER DROWSINESS BASED ON VISUAL FEATURES OF THE DRIVERS FACE

The Visual Features which can be of help for the detection of the drowsy state are Eyes and Mouth. The eyes are the main focus of the researchers and they have used benchmark values of the eye blinking, eye closure rate. For mouth, the detection of yawns is an important factor in drowsiness detection. These methods are non-intrusive and does not cause any uncomfort to the driver. Researchers have been trying to develop a generalized system that can be used by most people. There are new and efficient algorithms being developed for face recognition which don't require high computational power and can be used on vehicle easily. These methods are also cost efficient and can be installed externally as well on low end vehicles.

There are various proposed algorithm which produced high accuracy but due to lack of a benchmark dataset the result cannot be treated valid for every situation and cases. The lack of a benchmark driver drowsy datasets in real-time is one of the big issues with this method. Most researcher have used different datasets and worked under simulated environments which can never produce the real time effects [49]. Another factor which affects this method is the obstruction of features, when people wear sunglasses eyes cannot be detected and various lighting conditions needs to be accounted for. The various proposed algorithm with good accuracy also require a high processing power to process the image and detect drowsiness which is hard to implement in vehicle. PERCLOS only works when the driver is not wearing glasses. Also it doesn't account for the fact that when driver is extremely sleepy they may fall asleep with their eyes open. However, among all the method of drowsiness detection, Visual methods cause least inconvenience to the driver and have acceptable accuracy but it also has its own challenges. The comparisons among the various algorithm is mentioned in the later section of this part along with their advantages and disadvantages.



Table 1 contains the comparison among algorithms. Some of the algorithm are explained in their respective sections.

Figure 2

The flowchart below shows a general model of Visual Based Driver Drowsiness Detection



The Table below shows the various algorithm and their accuracies along with advantage and disadvantage

Technique	Ref no.	Accuracy	Sampling rate	Methods	Advantage	Disadvantage
Eye Condition analysis	[53]	94	110fps	Voila Jones Algorithm, PERCLOS, STASM	Robust, Non-intrusive	High Computation Time
	[54]	98.4	30fps	Local Binary Pattern, Voila Jones Algorithm, AdaBoost	Ease of use, Reliable, Non-intrusive	Computational complexity
	[55]	80	18fps	Voila Jones Algorithm, AdaBoost, PERCLOS	Real-time, Reliable, Non-intrusive	Computational complexity
	[56]	97	24fps	Window Growing, PERCLOS	Reliable, Robust	Intrusive, Complexity
	[57]	95	30fps	AdaBoost, PCA and LDA, PERCLOS	Robust, User Identification, Non- intrusive	High Computation Time
Mouth and Yawning Analysis	[58]	81	N/A	Voila Jones Algorithm, AdaBoost, RBF Kernel	Reliable, Non-intrusive	Computational complexity
	[43]	91	N/A	Kalman Filter, HSV Space, Morphological Operations, YCbCr Method	Non-intrusive, Less complex	Expensive to install
	[59]	80	30fps	Hidden Markov Models, Discrete Wavelet Transform	Feasible, Less Complex, Non- intrusive	Need extra equipment
	[60]	60	30fps	Voila Jones Algorithm, AdaBoost	Reliable, Embedded system, Real-time	Computational complexity
	[61]	80	N/A	YCbCr color space, Canny Edge Detection	Non-intrusive	Not realistic

A. Face Detection

Face detection is the preliminary step of the driver drowsiness detection as face contains all the clues we need to predict the drowsiness. A fixed camera is mounted in the vehicle near steering wheel. It captures the images or video of the driver. If the image or video frames that are being capture are not very clear the algorithms will fail to detect the face. Under such circumstances the system will not remain effective. To solve this problem, we can apply various image processing techniques to make the face more visible for the system. During night time we can make use of IR camera for clear image. Face is detected through Viola Jones algorithm [42] is used mostly due to its high performance for frontal and few lateral face positions. This algorithm was developed in early 2000s when the computational power wasn't high and this is still an effective algorithm for face detection which is being used in multiple devices. The training time for this algorithm is high but the detection time is significantly reduced. The Viola Jones algorithm uses Haar-like features, that is, a scalar product between the image and some Haar-like template. It scans the input matrix to detect something close to the template, which are related to eyes, nose and mouth. This algorithm is not very effective under bad lighting conditions so filtering of image must be done beforehand. Even though this algorithm is faster and puts less computational load on the system compared to the various deep learning techniques. To complement the speed of this algorithm AdaBoost has been used in a lot of researches. AdaBoost, short for Adaptive Boosting, was the first practical boosting algorithm proposed by Freund and Schapire in 1996. It focuses on classification problems and aims to convert a set of weak classifiers into a strong one which helps in Viola & Jones algorithm a lot. The AdaBoost algorithm makes sure that the algorithms with less than 50% accuracy also contributes to the output. However, an algorithm with exactly 50% accuracy will create problem as it cannot have any effect according to the equation of the AdaBoost. There is a huge variation in face which may make the algorithm less robust. So [43] proposed a color based Algorithm which detects the face based on the color of the face with respect to its surroundings after applying some filter it extracts the face. They used the Hue Separation Value(HSV) for separating face from other areas in the image as hue values exhibit the most noticeable separation between skin and non-skin areas. After that they used YCbCr color space as Cb-Cr color-space is a strong determination of skin color and it has default ranges. The algorithm then highlights the skin location and same technique is applied to detect eye. The symmetry of the eye is checked to verify the face detection. Once face is detected, it is stored as a template for Kalman filter motion tracking. This algorithm keeps track of the face by matching the pixel values of the matrices and matching it with the



matrix pixel value of template that is stored earlier. The face is constantly being tracked using the template and when correlation of template and image falls below a certain threshold the system loses track of the face. Many have used Machine learning algorithm for feature extraction. [44], [45] proposed VGG-FaceNet and Long-Term Recurrent Convolutional Networks(LRCN) respectively. However, these algorithm requires high computational power so these might not turn out to be a viable solution in low end vehicles.

B. Eye tracking

The YCbCr color-space for Eye is very different from the rest of the facial area. The color difference is used to detect eye in color-space based methods. When using the Viola Jones algorithm, the two rectangular boxes are formed when the template is matched. We can also use circular Hough transform on the rectangular boxes to detect pupils and check whether the eye is closed or open, this is an alternative approach for eye tracking with low computational load on the system. After detection of nose, mouth and other facial features a cross checking is done using symmetry for the face. Eye state analysis is most commonly used technique for drowsiness detection. Percentage of Eye Closure (PERCLOS) is measured after detection of the eye region, it is treated as Region of Interest(ROI) and when the eye is closed over 80%, it can be said that driver is drowsy. Let Na be the number of eye frames which belongs to the open or attentive category out of Nm number of eye frames captured in a minute. Hence (Nm - Na) is the number of eye frames belonging to the inattentive category. Then PERCLOS value per minute is

Percentage of Eye Closure = $\frac{Nm - Na}{Nm} \times 100\%$

The aforementioned equation is used to calculate the PERCLOS. Eye Monitoring can also give us blink frequency of the driver which can help us evaluate the driver's drowsiness state. According to [46], [47] when driver is not sleepy, the proportion of close eye frame is less than 30%. The normal blink frequency of a person is 10-15 times per minute but when they are drowsy the blink frequency is higher than 25 times per minute or lower than 5 times per minute the driver is considered to be fatigued [48]. However, there are no appropriate algorithm when the driver is wearing sun glasses. During such situations we might have to depend entirely on Yawns, Physiological signs and vehicle based anomaly

C. Mouth tracking

Using Viola-Jones algorithm we detect the mouth by matching the lips template which is just below the nose rectangular box. Detection of mouth is also key factor for the drowsiness detection system. For detection of yawning we need to first detect the lips. [43] proposed that the color difference between lips and face is obvious. The lip region has the red component as strongest and blue as weakest component. Using this fact, we can easily detect the lips. Once the detection part is done, next comes the tracking part and the YCbCr color-space will have very different from color inside the mouth as compared to outside. Even if we don't consider the color-spatial difference. Yawning can be detected by detecting the large hole or opening on the face near the lip area. Moreover, the color inside the mouth is completely different from other facial areas as mentioned before. We can also detect the upper lip and lower lip and use their separation beyond a certain threshold as sign of yawning. This can be achieved by measuring and tracking the vertical and horizontal component detected on the lips. When we yawn the distance between the edge points of the horizontal component decreases while the distance between the edge points of the vertical component increase. In general, when people are drowsy the yawn usually last 5 seconds. While during non-drowsy state it won't last as long. Using these clues, we can predict drowsiness level based on yawning.

The deep learning approaches are very demanding when it comes to computational power and fulfilling these requirements on vehicle is often very difficult especially on low end vehicles or old vehicles. So we have not discussed much of the deep learning approach in this literature.

V. COMMERCIAL DRIVER DROWSINESS DETECTION SYSTEM

There are various algorithms and systems already being used to detect the drowsiness of the drivers and make the driving safe. These systems have been developed by the automobile industry and other independent companies.

Lexus and Toyota developed driver monitoring system [6], this system contains a Charge-couple device(CCD), camera attached on the steering column to monitor driver behavior using eye tracking and head motion technique.

Volvo presented a driver drowsiness detection system [7] by combining two safety features namely Driver Alert Control System(DACS) and Lane Departure Warning(LDW). However, it depends on good road marking and good lighting conditions.

Mercedes-Benz started to develop Attention Assist System for its upcoming series [8]. This system differs from other systems because it first forms a driver profile by monitoring steering wheel movement and steering speed. Once Driver profile is generated it can easily determine the anomaly in driver driving behavior.

Ford presented its Driver Alert System [50]. The system consists of a forward looking camera and monitors the lane position to detect alertness of the driver.

Some of the system which are in the market also helps in driver drowsiness detection. Attention technologies [51], SmartEye[52]. In the paper [48] author proposes a new algorithm DriCare which gives a very high accuracy for driver drowsiness.

There are many more method being used, most of which are limited to certain conditions which cannot be full filled in all environments. A need for a generalized system is still there.

VI. CONCLUSION

With the advancement in the field of technology better methods are coming up every day. All the algorithms being used have room for improvement. The vehicle based algorithm has issues related to driver skill, demographic and vehicle characteristics. This issue can be fixed by having similar approach mentioned in [8] to record and monitor and create a profile. Approaches that use Physiological Signals have good accuracy but can be of inconvenience to the driver. However, the use of smart watches has become very common practice today which comes with a Heart Rate Monitor which can be used to track drowsiness. A fusion of the techniques will give better results. The drawbacks of PERCLOS can be covered by using Smart Watches Heart rate monitor. Regardless of what existing method we use there are limitations or drawbacks. All the commercial and non-commercial methods that have been proposed have their limitations. So these systems should not be considered anything more than warning system or alert generation systems. In future we can switch the controls over to the self-driving vehicles when driver is detected to be drowsy. For the current improvement of the driver drowsiness methods we need to hybrid methods. Driver Drowsiness issue can ultimately be solved by using a fusion of various different algorithms and methods to alert the driver and assist the driver for a safer driving.

REFERENCES

- P. Schroeder, M. Meyers, and L. Kostyniuk, "National survey on n Engineed distracted driving attitudes and behaviors—2012," Washington, DC, USA, Tech. Rep. DOT HS 811 729, 2013
- [2] G. Maycock, "Sleepiness and driving: The experience of UK car drivers," J. Sleep Res., vol. 5, no. 4, pp. 229–231, 1996.
- [3] F. Sagberg, "Road accidents caused by drivers falling asleep," Accident Anal., Prevention, vol. 31, no. 6, pp. 639–649, 1999.
- [4] A. I. Pack, A. M. Pack, E. Rodgman, A. Cucchiara, D. F. Dinges, and C. W. Schwab, "Characteristics of crashes attributed to the driver having fallen asleep," Accident Anal., Prevention, vol. 27, no. 6, pp. 769–775, 1995.
- [5] The Royal Society for the Prevention of Accidents, Driver Fatigue and Road Accidents: A Literature Review and Position Paper, Birmingham, U.K., 2001.
- [6] www.testdriven.co.uk/lexus-ls-600h
- [7] www.media.volvocars.com
- [8] www.emercedesbenz.com
- [9] E. Rogado, J. Garcia, R. Barea, L. Bergasa and E. Lopez, "Driver Fatigue Detection System," Proc. IEEE Int. Conf. Robotics and Biomimetics, 2009.
- [10] T. Nakagawa, T. Kawachi, S. Arimitsu, M. Kanno, K. Sasaki, and H. Hosaka, "Drowsiness detection using spectrum analysis of eye

movement and effective stimuli to keep driver awake," DENSO Technical Review, vol. 12, pp. 113–118, 2006.

- [11] B. Hariri, S. Abtahi, S. Shirmohammadi, and L. Martel, "A Yawning Measurement method to Detect Driver Drowsiness," Technical Papers, 2012
- [12] C. Lin, L. Ko, I. Chung et al., "Adaptive EEG-based alertness estimation system by using ICA-based fuzzy neural networks," IEEE Transactions on Circuits and Systems, vol. 53, no. 11, pp. 2469– 2476, 2006.
- [13] H. Cai and Y. Lin, "An experiment to non-intrusively collect physiological parameters towards driver state detection," in Proceedings of the SAE World Congress, Detroit, MI, USA, 2007
- [14] Q. Ji, Z. Zhu, P. Lan, "Real-Time Nonintrusive Monitoring and Prediction of Driver Fatigue," IEEE Transactions on Vehicular Technology, vol. 53, 2004.
- [15] D. Dinges, and R. Grace, *PERCLOS:* "A valid psychophysiological measure of alertness as assessed by psychomotor vigilance," US Department of Transportation, Federal highway Administration. Publication Number FHWA-MCRT-98-006
- [16] E. Bekiaris, S. Nikolaou, A. Mousadakou, "System for effective Assessment of driver vigilance and Warning According to traffic Risk Estimation," Project Report in Proceedings of the Design Guidelines for Driver drowsiness detection & avoidance, AWAKE Consortium, 2004.
- [17] R. Oyini Mbouna, S. G. Kong and M. Chun, "Visual Analysis of Eye State and Head Pose for Driver Alertness Monitoring," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 3, pp.1462-1469, Sept.2013.
- [18] S. Abtahi, B. Hariri and S. Shirmohammadi, "Driver drowsiness monitoring based on yawning detection," 2011 IEEE International Instrumentation and Measurement Technology Conference, Binjiang, 2011, pp. 1-4.
- [19] M. Omidyeganeh, A. Javadtalab and S. Shirmohammadi, "Intelligent driver drowsiness detection through fusion of yawning and eye closure," 2011 IEEE International Conference on Virtual Environments, Human-Computer Interfaces and Measurement Systems Proceedings, Ottawa, ON, 2011, pp. 1-6.
- [20] A. Tsuchida, M. S. Bhuiyan and K. Oguri, "Estimation of drowsiness level based on eyelid closure and heart rate variability," 2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Minneapolis, MN, 2009, pp. 2543-2546.
- [21] J. F. Nasoz, O. Ozyer, C. Lisetti, and N. Finkelstein, "Multimodal affective driver interfaces for future cars," in Proc. ACM Int. Multimedia Conf. Exhibition, pp. 319–322, 2002.
- [22] P. M. Forsman, B. J. Vila, R. A. Short, C. G. Mottd, and H. P. A. Van Dongen, "Efficient driver drowsiness detection at moderate levels of drowsiness," Accident Anal. Prevent., vol. 50, pp. 341–350, Jan. 2013
- [23] W. W. Wierwille and R. R. Knipling, "Vehicle-based drowsy driver detection: Current status and future prospects," in Proc. IVHS Amer. 4th Annu. Meet., Atlanta, GA, USA, Apr. 17–20, 1994, pp. 1–24
- [24] Y. Takei and Y. Furukawa, "Estimate of driver's fatigue through steering motion," in Proc. Int. Conf. Syst., Man Cybern., 2005, pp. 1765–1770
- [25] C. Wylie, T. Shultz, J. Miller, M. Mitler, and R. Mackie, "Commercial motor vehicle driver fatigue and alertness study: Technical summary," Federal Highway Admin., Washington, DC, USA, FHWA-MC-97-001, 1996.
- [26] C. C. Liu, S. G. Hosking, and M. G. Lenné, "Predicting driver drowsiness using vehicle measures: Recent insights and future challenges," J. Safety Res., vol. 40, no. 4, pp. 239–245, Aug. 2009.



- [27] A. Sahyadehas, K. Sundaraj, and M. Murugappan, "Detecting driver drowsiness based on sensors: A review," Sensors, vol. 12, no. 12, pp. 16 937–16 953, Dec. 2012.
- [28] R. Feng, G. Zhang, and B. Cheng, "An on-board system for detecting driver drowsiness based on multi-sensor data fusion using Dempster–Shafer theory," in Proc. in Networking ICNSC, 2009, pp. 897–902
- [29] E. Vural, "Video based detection of driver fatigue," Ph.D. dissertation, Dept. Comput., Eng., Sabanci Univ., Istanbul, Turkey, 2009.
- [30] M. Ingre, T. Akerstedt, B. Peters, A. Anund, and G. Kecklund, "Subjective sleepiness, simulated driving performance and blink duration: Examining individual differences," J. Sleep Res., vol. 15, no. 1, pp. 47–53, Mar. 2006
- [31] Volvo Driver Alert Control and Lane Departure Warning System, 2007. [Online]. Available: http://www.zercustoms.com/news/VolvoDriver-Alert-Control-and-Lane-Departure-Warning.html
- [32] Y. Liang and J. D. Lee, "Combining cognitive and visual distraction: Less than the sum of its parts," Accid. Anal. Prev., vol. 42, no. 3, pp. 881–890, May 2010
- [33] J. Krajewski, D. Sommer, U. Trutschel, D. Edwards, and M. Golz, "Steering wheel behavior based estimation of fatigue," in Proc. 5th Int. Driving Symp. Human Factors Driver Assessment, Train. Veh. Des., 2008, pp. 118–124
- [34] G. R. Kumar, S. V. P. Raju, and D. Kumar, "Classification of EEG signals for drowsiness detection in brain and computer interface," Comput. Sci. Telecommun., vol. 4, no. 36, pp. 1512–1232, 2012
- [35] U. Svensson, "Electrooculogram analysis and development of a system for defining stages of drowsiness," M.S. thesis, Dept. Biomed. Eng., Linköping Univ., Linköping, Sweden, 2004.
- [36] C. T. Lin et al., "A real-time wireless brain-computer interface system for drowsiness detection," IEEE Trans. Biomed. Circuits Syst., vol. 4, no. 4, pp. 214–222, Aug. 2010
- [37] M. Li, Z. Cheng, and J.-F. Fang, "An EEG-based method for detecting drowsy driving state," in Proc. 7th Int. Conf. FSKD, 2010, pp. 2164–2167.
- [38] M. V. M. Yeo, X. P. Li, K. Shen, and E. P. W. Smith, "Can SVM be used for automatic EEG detection of drowsiness during car driving?" Safety Sci., vol. 47, no. 1, pp. 115–124, Jan. 2009
- [39] K. Q. Shen, X. P. Li, C. J. Ong, S. Y. Shao, and E. P. V. Wilder-Smith, "EEG-based mental fatigue measurement using multiclass support vector machines with confidence estimate," Clin. Neurophys., vol. 119, no. 7, pp. 1524–1533, Jul. 2008
- [40] J. Hyun, S. Gih, K. Ko, and S. Kwang, "A smart health monitoring chair for nonintrusive measurement of biological signals," IEEE Trans. Inf. Technol. Biomed., vol. 16, no. 1, pp. 150–158, Jan. 2012.
- [41] I. Belakhdar, W. Kaaniche, R. Djmel and B. Ouni, "A comparison between ANN and SVM classifier for drowsiness detection based on single EEG channel," 2016 2nd International Conference on Advanced Technologies for Signal and Image Processing (ATSIP),

Monastir, 2016, pp. 443-446.

- [42] P. Viola and M. J. Jones, "Robust real-time face detection," Int. J. Comput. Vision, vol. 57, no. 2, pp. 137–154, 2004.
- [43] S. Abtahi, B. Hariri and S. Shirmohammadi, "Driver drowsiness monitoring based on yawning detection," 2011 IEEE International Instrumentation and Measurement Technology Conference, Binjiang, 2011, pp. 1-4.
- [44] O. M. Parkhi, A. Vedaldi, and A. Zisserman, "Deep face recognition," in Proc. BMVC, vol. 1, 2015, p. 6.

- [45] J. Donahue et al., "Long-term recurrent convolutional networks for visual recognition and description," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2015, pp. 2625–2634.
- [46] S. Kaplan, M. A. Guvensan, A. G. Yavuz, and Y. Karalurt, "Driver behavior analysis for safe driving: A survey," IEEE Transactions on Intelligent Transportation Systems, vol. 16, no. 6, pp. 3017–3032, Dec. 2015.
- [47] R. K. Satzoda and M. M. Trivedi, "Drive analysis using vehicle dynamics and vision-based lane semantics," IEEE Transactions on Intelligent Transportation Systems, vol. 16, no. 1, pp. 9–18, Feb. 2015
- [48] W. Deng and R. Wu, "Real-Time Driver-Drowsiness Detection System Using Facial Features," in *IEEE Access*, vol. 7, pp. 118727-118738, 2019.
- [49] H. Kang, "Various Approaches for Driver and Driving Behavior Monitoring: A Review," 2013 IEEE International Conference on Computer Vision Workshops, Sydney, NSW, 2013, pp. 616-623.
- [50] Ford Driver Alert. [Online]. Available: http://corporate.ford.com/ microsites/sustainability-report-2012-13/vehicle-technologies.html
- [51] Attention Technologies, "S.a.m.g-3-steering attention monitor," www.zzzalert.com, 1999
- [52] Smart Eye, "Smarteye," https://smarteye.se/, 2018
- [53] T. Danisman, I. M. Bilasco, C. Djeraba, and N. Ihaddadene, "Drowsy driver detection system using eye blink patterns," Université Lille 1 & Telecom Lille 1, Marconi, France, 2010.
- [54] M. Sabet, R. A. Zoroofi, K. Sadeghniiat-Haghighit, and M. Sabbaghian, "A new system for driver drowsiness and distraction detection," in Proc. 20th ICEE, Tehran, Iran, May 15–17, 2012, pp. 1247–1251.
- [55] C. Sun, J. Li, Y. Song, and L. Jin, "Real-time driver fatigue detection based on eye state recognition," Appl. Mech. Mater., vol. 457/458, pp. 944–952, 2014.
- [56] B. Cyganek and S. Gruszczynski, "Hybrid computer vision system ' for drivers' eye recognition and fatigue monitoring," Neurocomputing, vol. 126, pp. 78–94, Feb. 2014.
- [57] J. Jo, S. J. Lee, K. R. Park, I.-J. Kim, and J. Kim, "Detecting driver drowsiness using feature-level fusion and user-specific classification," Expert Syst. Appl., vol. 41, no. 4, pp. 1139–1152, Mar. 2014.
- [58] M. Saradadevi and P. Bajaj, "Driver fatigue detection using mouth and yawning analysis," Int. J. Comput. Sci. Netw. Security, vol. 8, no. 6, pp. 183–188, Jun. 2008.
- [59] B. Hariri, S. Abtahi, S. Shirmohammadi, and L. Martel, "A yawning measurement method to detect driver drowsiness," Distrib. Collab. Virtual Environ. Res. Lab., Univ. Ottawa, Ottawa, ON, Canada, 2011.
- [60] S. Abtahi, S. Shirmohammadi, B. Hariri, D. Laroche, and L. Martel, "A yawning measurement method using embedded smart cameras," Distrib. Collab. Virtual Environ. Res. Lab., Univ. Ottawa, Ottawa, ON, Canada, 2012.
- [61] G. M. Bhandari, A. Durge, A. Bidwai, and U. Aware, "Yawning analysis for driver drowsiness detection," Int. J. Res. Eng. Technol., vol. 03, no. 2, pp. 502–505, Feb. 2014.
- [62] H. Singh, J. S. Bhatia and J. Kaur, "Eye tracking based driver fatigue monitoring and warning system," *India International Conference on Power Electronics 2010 (IICPE2010)*, New Delhi, 2011, pp. 1-6.
- [63] J. Dai, J. Teng, X. Bai, Z. Shen and D. Xuan, "Mobile phone based drunk driving detection," 2010 4th International Conference on Pervasive Computing Technologies for Healthcare, Munich, 2010, pp. 1-8.