2021 IEEE International Conference on Consumer Electronics and Computer Engineering (ICCECE 2021)

Hybrid driver monitoring system based on Internet of Things and machine learning

Lian Zhu
Department of Computer
Zhuhai College of Jilin University
Zhuhai, China
bijounorth0906@gmail.com

Yijing Xiao
International College
Jiangxi University of Finance and Economics
Oulu, Finland
xyjdyx20010125@126.com

*Xiang Li
Department of Computer
Zhuhai College of Jilin University
Zhuhai, China
lixiang@jluzh.edu.cn

2021 IEEE International Conference on Consumer Electronics and Computer Engineering (ICCECE) | 978-1-7281-8319-0/20/$31.00 ©2021 IEEE | DOI: 10.1109/ICCECE51280.2021.9342092

***Abstract*—With the rapid development of intelligent mobile terminal equipment, more and more intelligent mobile terminal platforms are constantly emerging, and the types are gradually diversified. This process has also slowly promoted the spring up of the Internet of things (IOT). which can collect more information from more edge devices. Thanks to the increasing amount of data that can be collected, machine learning (ML) technology can make existing applications more intelligent and analyze more complex situations. This article reviews the existing popular methods developed in vehicles, consumer electronics products and smart transportation to assess driver state, detect the driver's environment, as well as vehicle performance, and propose a hybrid driver state monitoring system model. This model is designed to use IoT to collect all-round data from each edge devices to ensure the reliability and validity of the data, and then analyze it through ML technology, and finally give the driver appropriate instructions to help the driver in the safest driving conditions.**

Keywords-Internet of Things; Machine Learning; Consumer Electronics Hybrid Driver State Monitoring; Intelligent Transportation Systems

I. Introduction

The World Health Organization reports that 1.25 million deaths are caused by traffic accidents every year. According to the description in the literature NHTSA [1], only 6% of the existing observable traffic accidents have nothing to do with human error. Generally speaking, the human errors that cause traffic accidents are very complex, and it is often necessary to analyze multiple influencing factors to explain their reasons., such as insufficient attention or improper control. However, there is usually an important key reason in every road traffic accident related to human error, which is sometimes affected by events and related factors that occurred before the accident. It is important to track the various causes of human error caused by the driver in order to predict the possibility of high-risk accidents and try to eliminate the accident through the on-board safety and information system.

One way to reduce driver distraction is to use Advanced Driver Assistance Systems (ADAS) [2]. However, most of these systems are not enough to analyze the changing driver state and solve the problems that cause abnormal driving. To effectively predict the occurrence of human error that will lead to traffic accidents, it is necessary for us to continuously analyze the driver's state and track the changes in the driver's state in real time state, thereby potentially reducing the occurrence of traffic accidents related to human error. This function is commonly referred to as a Driver State Monitoring (DSM) system.

In the past few years, with the rapid development of smart mobile terminals, applications running on various smart mobile terminals have become smarter than ever in the process, and most of them can exchange information through the Internet. Thus, the real and reliable data we can collect is increasing at the same time, which makes ML technology more mature, so that intelligent devices can solve more complex problems. There is a new application that can analyze the collected data through ML technology and make reasonable decisions based on the results of the analysis, thus realizing Artificial Intelligence (AI). Further ensuring that the driver's state is in the best condition.

The purpose of this article is to establish a Hybrid DSM system by collecting information from smart wearable devices, smart phones, data collection devices in vehicles, and information collection devices in intelligent transportation, etc., to ensure the reliability of collected information. And uses ML technology to analyze the collected information, monitors the state of the driver while detecting the driving environment, predicts the possibility of traffic accidents, and reminds the driver of the situation that the driver may have to face and the driver's current driving state, avoid the traffic accidents caused by human error, and make sure drivers stay away from dangers.

II. Hybrid Drive Monitoring

In the early 1990s, De Waard & Brookhuis [4] discussed the concept in a publication as part of the "Dedicated Road Infrastructure for Vehicle Safety in Europe (DRIVE)" plan. In order to monitor the deviation between the driver's driving performance in a short period of time and the ideal driving state, they proposed to track the driver's driving state.

In recent years, some researchers have proposed the importance of supplementing existing ADAS and in-vehicle information systems (IVIS) by introducing different elements of DSM. Unfortunately, there is no mention in the literature about which driver state extraction method is necessary for practical DSM system. Because the state of the driver will change due to the influence of many factors during driving, it is inaccurate for people to feed back their subjective self-assessment report to the system before or after driving activities. Therefore, such an assessment method is not suitable for commercial DSM. Nowadays, researchers have explored many objective methods that have been proved to correspond

978-1-7281-8319-0/21/$31.00 ©2021 IEEE

to certain physiological phenomena to measure the driver's state.

In fact, the driver state is indeed multidimensional. However, due to differences in physiological indicators among individuals, their physiological evaluation may become blurred. For example, the heart rate patterns among individuals may be different because of differences in exercise patterns, i.e., whether they exercise regularly or not. So if we want to continuously track and analyze myriad changing physiological phenomena, we need a comprehensive sensory network. Due to the complex interrelationship between the driver's state structure and its indicators, and the physiological measurement is prone to errors and artifacts, complete reliability cannot be guaranteed. Therefore, in order to conduct effective and reasonable analyses, we must track physiological phenomena as much as possible, because any single physiological index cannot be guaranteed as completely related to the driver's state structure.

With the rapid development of the IoT in recent years, almost all intelligent devices can communicate with each other through the Internet, and can collect a large amount of data through various sensors. However, it is far from enough to collect data without making good use of it. These IoT devices should be able to analyze collected data and learn from it.

The ML algorithm can analyze the collected data offline or connect to the Internet, and make context-based decisions based on the analyzed results, so as to optimize resource allocation or avoid network congestion. Therefore, to improve the infrastructure and applications of IoT, we can apply ML technology to IoT. Intelligent transportation systems (ITS) have emerged in this process as IoT technologies are applied to the field of transportation and internet-connected transportation devices become smart.

In addition, it also proposes a road abnormality detection system through sensors connected to the car or the driver's smartphone, which can avoid accidents by real-time detecting the road conditions in the process of driving. Considering that the traffic conditions at some specific situations such as intersections are relatively complex, frequent information exchange between intelligent devices will be required, which has strict requirements on communication devices. However, with the continuous exploration of researchers, the M2M communication option of the Internet of Things provides a good solution to this problem, enabling vehicles to build a low-latency social network for efficient communication between vehicles [5].

Frost & Sullivan [3] offered insights through a comparative analysis of key global original equipment manufacturers' (OEMs') strategies to include health monitoring features in cars as standard, optional, or advanced—whether built in, brought in, or cloud-enabled. And in this article, we refer to a system that can process data from multiple sources as a hybrid DSM system.

Barua [6] and Dong et al. [7] respectively emphasized in their own papers that only considers one detection standard is not completely reliable, and also shows that a system which can detect various factors that affect the driver's driving, such as the driver's state indicators, driving performance, and driving environment, is needed to ensure the accuracy of information recognition. The DSM system is an ideal system that meets the conclusions of researchers and can provide more reliable and effective solutions.

III. Development State

A. *Smart wearable devices*

Rigas et al. [16] developed a method for simultaneous detection of driver's fatigue and stress levels. The system employs three types of information:(i) physiological features of the driver, (ii) the information extracted by the driver's facial monitoring system, and (iii) the conditions of the road. Each data stream combined by feature selection module runs through feature extraction mechanism. Next, use Support Vector Machines (SVM) for classification to achieve the purpose of finding driving obstacles in advance.

Healey & Picard [15] They came to the conclusion that the five minutes of electrocardiogram (ECG) and EDA have the highest overall correlation with the driver's stress level, and tried to test the driver's five-minute ECG and EDA through a sensor network composed of wearable smart devices, which not only does not interfere with the driver's perception of road conditions, but also promotes the development of intelligent transportation systems in the future.

B. *Intelligent Transportation System*

Operational prevention methods can help save lives. If the driver stays focused during the entire driving period, road traffic accidents can be prevented. The accident prevention system can notify drivers in advance whether the road ahead is dangerous and give them enough time to take actions. Using real-time traffic network to identify areas prone to traffic accidents and inform drivers can not only avoid traffic congestion, but also reduce the occurrence of accidents. It turns out that ML technology can efficiently detect traffic accidents, detect new accidents that may lead to new incidents and inform drivers to avoid dangers.

In order to enable vehicles to share information with each other to avoid accidents, Liu et al. [17] developed a method for collaborative vehicle perception based on CHMM technology. Ozbayoglu et al. [18] proposed real-time autonomous accident detection by using FF-NN, regression tree and k-NN algorithm to analyze data obtained from road sensors. V2V communication and road traffic accident detection use RF method rather than ANN or SVM. [19]. Kwon et al. [20] applied FCN as a new method to detect the blind spots of intelligent vehicles. Celesti et al. [21] proposed a cloud platform based on the IoT that can realize traffic visualization and notify drivers of the risks that could lead to accidents through this platform. Software as a Service (SaaS), Infrastructure as a Service (IaaS), Platform as a Service (PaaS) and a novel approach called IoT as a Service (IoTaaS) will be provided by the implemented setup. The GPS data is collected through the data collection device installed in the volunteer vehicle and uploaded to the cloud server via the Internet. The cloud server uses the OpenGTS platform to process GPS data and uses OpenStreetMaps to enable traffic visualization. The data is stored in SQL and distributed MongoDB for further analysis. Using Docker containers can support back-end scalability. An essential factor of success is the reaction speed of the system. If an unexpected situation occurs, the proposed system can send proper warnings to drivers a kilometer away within about 120 milliseconds. Road anomaly detection plays an important role in intelligent transportation, because the condition of the road can directly affect the traffic in many ways. Poor road conditions increase the probability of damage to the vehicle, leading to traffic accidents and traffic congestion. Therefore, the main purpose of the road anomaly detection system is to detect whether the road surface is flat and inform the driver of bad conditions.

Chowdhury et al. [22] proposed a vehicle to vehicle (V2V) communication framework using IoT, which enables moving vehicles to communicate when the standards for establishing connections are met. To provide a safer driving environment for drivers, the system ensures that important road information is shared in real time when the vehicle comes within range. In this way, traffic accidents can be avoided by informing the driver of sudden changes in the driving conditions of the surrounding vehicles.

C. *Smart phone-based induction*

Lee & Chung [14] developed a smart phone-based DSM system that uses a fuzzy Bayesian network (FBN) to focus on predicting and analyzing the driver's vigilance index such as percentage of eyelid closure (PR), blood pressure (BP), speed (SP) and so on. If his or her safety level is suspiciously compromised a fake incoming call will alert the driver. Engelbrecht et al. [13] proposed a smartphone-based approach which is categorized as driver behavior vehicle telematics, collaborative driving and road condition monitoring system. The embedded sensors of smart phones such as accelerometers, gyroscopes, magnetometers and GPS collect information about driving behavior and driving environment to monitor the driver's state.

D. *Automakers adopt DSM*

BMW has developed a DSM system that can obtain data from three information sources: driver, driving environment and driving vehicle [10]. The company pointed out the limitation of existing ADAS and IVIS that lack the physiological information of the driver while they are driving [11]. The company particularly emphasizes the importance of machine learning technologies such as Neural Networks and Support Vector Machine, which complement the Lane Departure Warning System (LDWS), with features that enable them to adjust the level of awareness of LDWS according to the changing driver's state, making it a truly non-invasive driving experience. Ford Motor Company and the Massachusetts Institute of Technology (MIT) New England University Transportation Center (NEUTC) have been continuously exploring automotive technology solutions designed to reduce driver stress and improve overall driver safety and well-being [8]. The newer version of the system combines driver data such as breathing, heart rate, temperature and even sweaty palms with data from cars including speed and direction changes and braking situation to keep drivers out of danger [9]. To ensure the integrity of the collected information. Jaguar Land Rover is also trying to use advanced technology to track drive's state [12]. If the system detects that the driver is fatigued, it will communicate with the driver via pulses and vibrations through the pedal and help the driver's attention return to the best state.

IV. The Model

In this section, we will propose a hybrid DSM system model, which combines a variety of currently available technologies and illustrates the possible development trend of DSM in the future. This model solves the needs of hybrid DSM for more complex analysis of the driver's state by analyzing the dynamic relationship between the driver's physiological condition, driving vehicle performance, driving environment and other factors. If the factors that affect the driving state of the driver are divided into two categories of long-term accumulation effect and short-term sudden impact for comprehensive analysis, DSM can finally obtain a more reliable analysis result [23]. The long-term cumulative effects usually include accumulated physical and mental fatigue and stress from all aspects of life, while short-term sudden effects are usually caused by unexpected accidents during driving. Both situations may be quite important for the driver's state analysis, and we must consider both of them.

The data source is also the key to ensuring the safety of the driver. This model combines several data sources, such as the built-in sensors in actual vehicles, consumer electronics carried by drivers, and intelligent transportation system connected to the cloud, to improve the effectiveness and reliability of recorded data. In addition, this model integrates and analyzes the data from these three data sources through ML technology, and finally gets an analysis result of the driver's state, which then confirms whether the driver's state is suitable for driving at this time based on the analysis result. If the model detects that the driver's state is abnormal at this time, it will communicate with the driver via pulses and vibrations through the pedal, or promote some adaptive auditory, visual or tactile feedback from IVIS, to restore the driver's attention to the best state. At the same time, the model can track drivers' specific physiological indicators according to special driving scenarios such as driving at night or in congested roads, thereby attempting to estimate drivers' safety level under such circumstances. Furthermore, with the rapid development of IoT technology, the amount of data that can be collected is also rising with the number of devices that can connect to the Internet keeps increasing. In IoT applications, it is very common to deal with "big data". However, problems related to big data usually require special technologies and specific infrastructures to process a large amount of structured and unstructured data, which are difficult to solve by conventional databases [24]. To effectively deal with issues related to big data, we can make use of machine learning algorithms such as Clustering or Deep Learning.

V. Discussion And Conclusion

This paper presents an overview of hybrid driver state monitoring system technology based on the IoT and machine learning. This research highlights the fact that the hybrid system advocates the use of a comprehensive sensor network to enhance the validity and reliability of data. At the same time, many machine learning algorithms are proposed and analyzed in this review. And a model that not only enables devices to communicate with each other and collect data, but also enables them to learn and make context-based decisions based on the collected information is also discussed. However, the current methods may alert the driver at an inappropriate time, which may cause the driver to be distracted, or provide feedback when the driver is taking corrective actions, which will overload the driver at the moment and affect the safety of the driver. If the future ADAS and IVIS can change the safety level based on changes in the driver's state and assess the time it takes the driver to react, then the critical alerts can be delivered at the most appropriate time. Finally, in order to provide a true, non-intrusive driving experience, it is expected that hybrid DSM system in the future can notify the driver when there is a real risk of danger according to the driver's warning preferences or through the driver's personalization of the warning alert.

ACKNOWLEDGMENT

This work supported by Guangdong Province Universities Innovation Development Project.

REFERENCES

[1] NHTSA, "Critical Reasons for Crashes Investigated in the National Motor Vehicle Crash Causation Survey," Washington, US, 2015.

[2] C. David M., C. Caroline, L. Benjamin D. and Y. Douglas, "Driver Distraction and Advanced Vehicle Assistive Systems (ADAS): Investigating Effects on Driver Behavior, " Advances in Human Aspects of Transportation, vol. 484, pp. 1015-1022, 7 July 2016.

[3] Frost & Sullivan, "Executive Outlook of Health, Wellness, and Wellbeing Technologies in the Global Automotive Industry Volumedriving OEMs Leading the First Wave of Proliferation," 2015.

[4] D. De Waard and K. a. Brookhuis, "Assessing driver status: A demonstration experiment on the road," Accid. Anal. Prev., vol. 23, no. 4, pp. 297–307, August 1991.

[5] Jain, B., Brar, G., Malhotra, J., Rani, S., Ahmed, S.H. "A cross layer protocol for traffic management in Social Internet of Vehicles," Future Gen. Comput. Syst. November 2017, pp. 707–714.

[6] Y. Dong, Z. Hu, K. Uchimura, and N. Murayama, "Driver inattention monitoring system for intelligent vehicles: A review," IEEE Trans. Intell. Transp. Syst., vol. 12, pp. 596–614, December 2010.

[7] S. Barua, "Intelligent Driver Mental State Monitoring System Using Physiological Sensor Signals," Mälardalen University, 2015.

[8] Ford Motor Company, "Want Stress-Free Driving? Use In-Vehicle Technology," 2012. [Online]. Available: goo.gl/8MYF17. [Accessed: 3-Nov-2020].

[9] Ford Motor Company, "Ford Biometric System Can Track Your Breathing, Heartbeat And Sweaty Palms," 2012. [Online]. Available: goo.gl/uIv99N. [Accessed: 3-Nov-2020].

[10] S. Hoch, M. Schweigert, F. Althoff, and G. Rigoll, "The BMW SURF Project: A Contribution to the Research on Cognitive Vehicles," in 2007 IEEE Intelligent Vehicles Symposium, August 2007, pp. 692–697.

[11] S. Hoch, F. Althoff, and G. Rigoll, "The ConnectedDrive Context Server – flexible Software," in Advanced Microsystems for Automotive Applications 2007, 2007, pp. 201–214.

[12] Jaguar Land Rover, "Jaguar Land Rover Road Safety Research Includes Brain Wave Monitoring To Improve Driver Concentration And Reduce Accidents," 2015. [Online]. Available: goo.gl/X8I0d4. [Accessed: 3-Nov-2020].

[13] J. Engelbrecht, M. J. Booysen, F. J. Bruwer, and G.-J. van Rooyen, "Survey of smartphone-based sensing in vehicles for intelligent transportation system applications," IET Intell. Transp. Syst., vol. 9, pp. 924–935, July 2015.

[14] B.-G. Lee and W.-Y. Chung, "A smartphone-based driver safety monitoring system using data fusion," Sensors (Basel)., vol. 12, no. 12, pp. 17536–17552, December 2012.

[15] J. a. Healey and R. W. Picard, "Detecting Stress During Real-World Driving Tasks Using Physiological Sensors," IEEE Trans. Intell. Transp. Syst., vol. 6, no. 2, pp. 156–166, June 2005.

[16] G. Rigas, Y. Goletsis, P. Bougia, and D. I. Fotiadis, "Towards Driver's State Recognition on Real Driving Conditions," Int. J. Veh. Technol., vol. 2011, pp. 1–14, 2011.

[17] Liu, W., Kim, S.W., Marczuk, K., Ang, M.H, "Vehicle motion intention reasoning using cooperative perception on urban road," Proc. 2014 IEEE 17th International Conference on Intelligent Transportation Systems (ITSC), Qingdao, China, 8–11 October 2014, pp. 424–430, doi: 10.1109/ITSC.2014.6957727.

[18] Ozbayoglu, M., Kucukayan, G., Dogdu, E., "A real-time autonomous highway accident detection model based on big data processing and computational intelligence," Proc. 2016 IEEE International Conference on Big Data (Big Data), Washington, DC, USA, 5–8 December 2016, pp. 1807–1813, doi: 10.1109/BigData.2016.7840798.

[19] Dogru, N., Subasi, A. "Traffic accident detection using random forest classifier," Proc. 2018 15th Learning and Technology Conference (L&T), Jeddah, Saudi Arabia, 25–26 February 2018, pp. 40–45, doi: 10.1109/LT.2018.8368509.

[20] Kwon, D., Park, S., Baek, S., Malaiya, R.K., Yoon, G., Ryu, J.T, "A study on development of the blind spot detection system for the IoT-based smart connected car," Proc. 2018 IEEE International Conference on Consumer Electronics (ICCE), Las Vegas, NV, USA, 12–14 January 2018, pp. 1–4, doi: 10.1109/ICCE.2018.8326077.

[21] Celesti, A., Galletta, A., Carnevale, L., Fazio, M., ´Lay-Ekuakille, A., Villari, M., "An IoT Cloud System for Traffic Monitoring and Vehicular Accidents Prevention Based on Mobile Sensor Data Processing," IEEE Sens. J. November 2017, pp. 4795–4802.

[22] Chowdhury, D.N. Agarwal, N. Laha, A.B. Mukherjee, A, "A Vehicle-to-Vehicle Communication System Using Iot Approach," Proc. 2018 IEEE Second International Conference on Electronics, Communication and Aerospace Technology (ICECA), Coimbatore, India, 29–31 March 2018, pp. 915–919, doi: 10.1109/ICECA.2018.8474909.

[23] B. C. Ahlström, K. Kircher, C. Fors, T. Dukic, C. Patten, and A. Anund, "Measuring driver impairments: sleepiness, distraction, and workload," IEEE Pulse, vol. 3, no. 2, pp. 22–30, April 2012.

[24] Madden, S, "From databases to big data," IEEE Internet Comput. 2012, pp. 4–6.

[25] F. Zantalis, G. Koulouras, S. Karabetsos, and D. Kandris, "A Review of Machine Learning and IoT in Smart Transportation," Future Internet, vol. 11, no. 4, p. 94, April 2019, doi: 10.3390/fi11040094.

[26] S. Elzeiny and M. Qaraqe, "Machine Learning Approaches to Automatic Stress Detection: A Review," Proc. in 2018 IEEE/ACS 15th International Conference on Computer Systems and Applications (AICCSA), Aqaba, October 2018, pp. 1–6, doi: 10.1109/AICCSA.2018.8612825.

[27] R. K. Nath, H. Thapliyal, A. Caban-Holt, and S. P. Mohanty, "Machine Learning Based Solutions for Real-Time Stress Monitoring," IEEE Consum. Electron. Mag., vol. 9, no. 5, pp. 34–41, Sep. 2020, doi: 10.1109/MCE.2020.2993427.