ISSN: 2321-2152

IJMECE

International Journal of modern electronics and communication engineering

E-Mail
editor.ijmece@gmail.com
editor@ijmece.com

www.ijmece.com

ISSN 2321-2152
www.ijmece.com
Vol 13, Issue 2, 2025

A Behavioural Parameter Analysis–Based System for Efficient Driver Drowsiness Monitoring and Its Comparison to a Vehicle Parameter–Based Approach

. [1]Dr.G Mahesh, [2] Dr.Reddeppa, [3]Dr.Anvesh

[1,2,3]Associate professor,

department of CSE,

Sree Institute of Technology,Tirupati

Abstract. Combining a hardware learning algorithm with a vehicular parameter based technique; this work aims to develop a computer-aided system that can detect when drivers are sleepy. As sets of classifiers, this work examines both the 320-person Behavioral Parameter Technique and the 320-person Vehicle Parameter Based Technique. The number of samples needed for the analysis with an 80% pre-test power may be determined using clincalc.com. We evaluate the hardware's performance to a method that uses car specs while measuring its accuracy and precision. Driver fatigue detection significantly outperforms the vehicular parameter, with an accuracy of 62.68% and a p-value of 0.021 ($p<0.05$). Researchers found that as compared to a technique based on vehicular parameters, the novel behavioral parameter strategy performed much worse in detecting driver fatigue.

Keywords: Driver Drowsiness Detection, transportation safety, face tracking, eye and mouth detection, Yawn detection, Novel behavioral parameter technique, Vehicular parameter.

INTRODUCTION

A person is considered to be engaging in sleepless driving when their mental capacities are impaired due to lack of sleep. Drivers who don't get enough sleep are more likely to be involved in car accidents. According to [1], a person's ability to perform well at work is diminished when they don't get enough sleep. Noted a complete lack of reaction time, a decline in memory and judgment, and an effect on their ability to work when this skill is impaired [2]. Released a possible the effects of sleep loss on driving are comparable to those of drinking, according to a number of studies. Drunk driving is on the rise, and one reason is because drivers aren't getting enough sleep [3].

There has been a lot of recent study on parameter approaches for automobile weariness detection. Google Scholar (58 articles) and IEEE Xplore (64 articles) are the databases in question. The popularity of smart automobiles is on the rise. The US Department of Transportation implemented a no-table driving policy for careful automobiles to decrease accidents on expressways [4, No. 2020]. Intelligent cars are constantly evaluating their surroundings, which might disrupt the future of driver-vehicle interactions [5]. The National Highway Traffic Safety Administration reports that in the United States alone, drivers who are either too sleepy or too exhausted to pay attention cause more than 100,000 accidents every year [5]. Given the lack of substantial evidence to support a police conclusion, it is possible that the state's disclosing entity is underreporting laziness. Therefore, many incidents may have been prevented if cars had sensors that could sense when drivers are tired. Here we lay out the process for Fatigue Detection and Prediction and the ideas that go into our strategy. As stated in [6], vehicle-integrated performance upgrades detect sluggishness by analyzing data collected from sensors attached to typical car parts like the accelerator and steering wheel. [7] Cites several earlier studies that used shifts in the driver's grasp on the wheel and other indicators of fatigue. A decrease in the availability of these minor treatments suggests a failing system [7]. Natural elements rely on micro corrections for regulation. According to [8], a number of developments monitor drivers' speed, whether they shift gears, if they veer off the road, and how far apart the cars are. These protocols must be driver-specific as there is no universally accepted way for drivers to depress the gas pedal. [8]. For example, formal approval tests have not been conducted or may not have been offered to mainstream researchers, thus it is unclear whether these frameworks are effective in terms of dependability, affectability, and legitimacy [9]. But they try to gauge depletion via vehicle-based execution and are now financially available.

Assumptions regarding the particular behavior, such as yawning, eye conclusion, and blink ratio, have mostly constituted approaches to fatigue recognition, according to computer vision techniques. We used artificial intelligence systems to track real people's actions while they were exhausted so we could compile this data set. The primary goal of this approach is to identify vulnerability indicators via nonverbal cues. As part of the research into driver sleepiness detection, an entirely automated method based on a fatigue action coding system was used to identify eye movement in videos on its own. Eye data collected by non-contact measurements is shown to include inaccurate information due to physiological and environmental factors that impact the system's effectiveness. An accelerometer placed close to the subject's head recorded data on their eye movements in addition to the findings from the planned FACS identification system. We also recorded data from the control panel. We have a long history of substantial contributions to research projects in many different fields of study. [8]

MATERIALS AND METHODS

The intended experiment is now underway at the image processing lab of the Saveetha Institute of Medical and Technical Sciences in Chennai, where researchers work in the Department of Electronics and Communication Engineering. The classifier group investigated this issue of driver fatigue identification using both the vehicular strategy and the distinctive behavioral parameter approach. Both groups consist of 640 individuals. The necessary samples for this experiment were determined using Gpower [9]. For this investigation, we have established a minimum G-power of 0.8.

Datasets for driver fatigue detection acquired from the UCI repository must be processed before the algorithm model can be used. It is common practice to divide the dataset in half and use each half for testing and training [3]. Some parts of data processing include filling in missing numbers, cleaning up your data, and replacing nulls with median or mean values. In the context of a development plan centered on automobiles [3]. The likelihood of driver weariness increases if the modification goes over a certain threshold [3]. Variation in route location, development of the steering wheel, pedal tension for speed growth, and a myriad of other metrics fall under this umbrella.

The maturation of the brain was monitored using an accelerometer that had three separate opportunity levels. This 3D accelerometer 5 can record accelerations between 5g and +5g (where g is the Earth's gravitational force) thanks to its three one-dimensional accelerometers on the right side. The participants tried their hands at both an open-source multi-stage game and a Windows system game using a steering wheel [3].Occasionally, a random wind effect would be introduced to the Windows version of the game, causing the automobile to move to the left or right and triggering the player's reaction correspondingly [4]. According to previous research, this kind of control is known to make people more exhausted. The car maintained a consistent speed throughout. Four people finished the driving duties in the three hours starting at midday. Subjects would violently crash their cars after often nodding off at this point. You can see what happens before and after the car careens off the road on camera. The whole three-hour session was captured on video using a DV camera [6].

To utilize the hardware with the vehicle-based approach face feature technology, you need Windows 10, a 64-bit operating system, and the Google Cloud Platform. With its 4 GB of RAM and 8th generation Intel Core i5 CPU, this setup is all set to go.

Statistical Analysis

We use the SPSS program [7] in tandem with the Google Colab cloud platform to analyze the statistical data. The novel behavioral parameter approach and the vehicular parameter methodology both make use of descriptive statistics, which include measurements of central tendency, dispersion, and error. Here, the dependent variables are the ones often thought of as independent. We use several t-tests to compare the hardware performance in the vehicle-based strategy. This study put the simulation hardware through its paces on the Google Cloud Platform using a vehicle-based approach. This method is executed using the Python programming language. An eighth-generation Intel Core i5 CPU with 4 GB of RAM powers this machine.

RESULTS

One activity unit is in a ready state while the other is not; both are shown in the histograms. To determine the extent of the difference between the distributions of ready and non-ready yields, we calculated the region under the ROC (A') for the yields of each facial activity locator. The signal recognition theory is the ancestor of both the A' action and the discriminative limit of the sign, which is the lack of a decision edge. The driver mount that may be detected by a camera is shown in Figure 1. This is equivalent to the theoretical maximum allowable data-driven accuracy of the system in a two-choice forced choice testing scenario. Time required performing the simulation using different approaches that account for behavioral and vehicle features is shown in Table 1.

FIGURE. 1. Camera used as driver mount detection represents the detection of the driver mount using a camera. That can be deciphered as identical to framework for collecting data

TABLE 1. Simulation time taken (seconds) with behavioral parameter and vehicular parameter technique.

S.No	Behavioral Parameter (Seconds)	Vehicular Parameter (Seconds)
1	4.09	6.23
2	3.89	10.8
3	4.23	11.12
4	4.04	10.84
5	4.01	7.63
6	3.91	5.89
7	4.09	9.29
8	4.33	10.18
9	4.24	7.33
10	4.39	6.81

TABLE 2. Comparison between novel behavioral parameter and vehicular parameter technique. Accuracy (62.68) & (48.07) % values obtained

	Behavioral parameter (%)	**Vehicular parameter (%)**

Accuracy	62.68%	48.07%

Table 3 displays the tasks for which each topic achieved the highest possible grade. As expected, the flicker/eye conclusion measure performed best across the board for participants. Take notice that the external forehead rise was the most discriminative for Subject 2.

TABLE 3. Simulation time taken with hardware. The mean of Simulation time taken is obtained, as well as standard error, mean Timing value, and standard deviation for 10 samples. The mean=8.6 and std.error Mean=.64 of behavioral parameter technique are from a statistical analysis tool. States that behavioral parameters appear to be better.

	Algorithm	N	Mean	std.deviation	std.Error Mean
Methods	Vehicular parameter technique	10	4.1220	.17022	.05383
	Behavioural parameter	10	8.6120	2.05204	.64891

A statistically significant P value (less than 0.05) was used to generate the confidence interval, which is shown in Table 4. There was a significant independent sample test ($p=0.00<0.05$) with a mean of 4.49. The results of the comparison between the two techniques show that the time spent simulating using software is much superior to the time spent simulating with hardware. To predict drowsiness based on the resulting differentiated facial behavior, the facial activity yields were fed into a classifier.

TABLE 4. A statistically significant P value (less than 0.05) was used to determine the 95% confidence interval. There was a significant independent sample test ($p=0.00<0.05$) with a mean of 4.49. After comparing the two algorithms, it seems that the time spent simulating is much better than the time spent simulating with hardware.

Leven's Test For Equality of Variance				t-test for Equality of Variance					95% Confidence Interval of the difference	
		F	sig.	t	dif	Sig (2-tailed)	Mean difference	Std.Error or Difference	lower	upper
	Equal Variance assumed	59.672	.000	-6.896	18	.000	-4.49000	.65114	-5.85800	-3.12200
	Equal variance not assumed			-6.896	9.124	.000	-4.49000	.65114	-5.95994	-3.02006

Fig. 2 represents time taken for simulation drowsiness detection each person n=10 times taken to verify that the counted times of drowsiness of a person and each time's value remains constant.

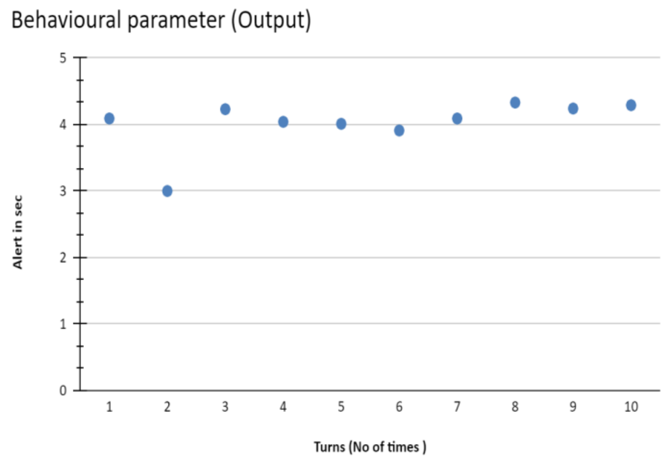

FIGURE. 2. Time taken for simulation drowsiness detection each person n=10 times take to verify that the counted times of drowsiness of a person and each times values remains constant

Fig. 3 shows that the time taken to detect drowsiness with hardware by increasing the number of times. The value goes significantly up and down the detection of drowsiness is less than t=6.23.

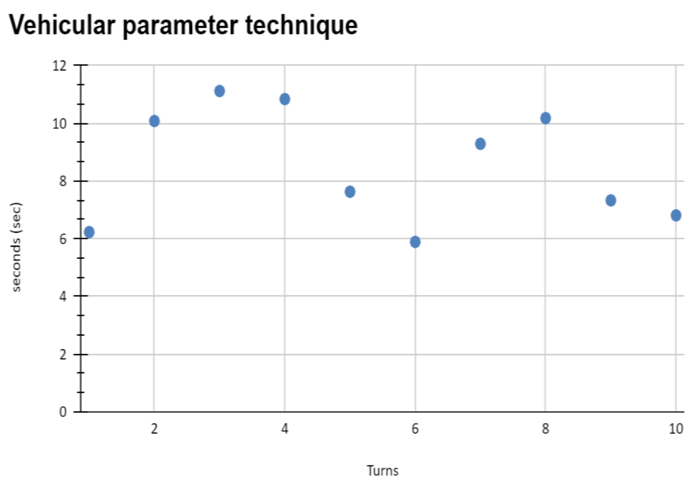

FIGURE. 3. Time taken to detect drowsiness with hardware by increasing the number of times. The value goes significantly up and down the detection of drowsiness is less than t=6.23.

Fig. 4 represents the graph describing the Simulation time taken for Hardware system for analysis of drowsiness detection results compared with analytical time taken for vehicular and behavioral techniques. Two learning based classifiers; Ad boost and multinomial edge relapse are analyzed. Inside subject forecast of languor and across (subject free) expectation of laziness were both tried?

ISSN 2321-2152
www.ijmece.com
Vol 13, Issue 2, 2025

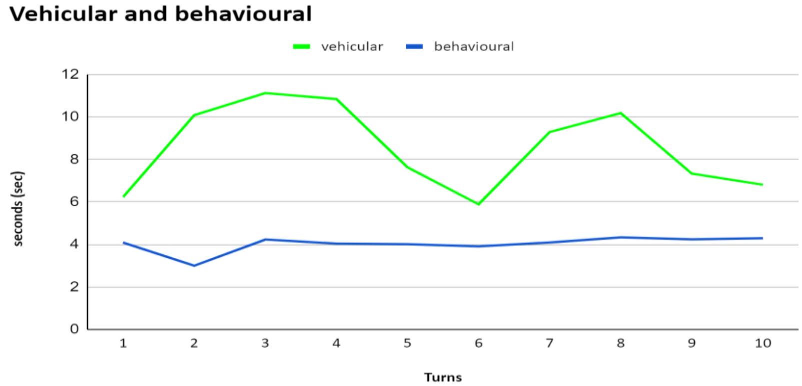

FIGURE. 4. Simulation time taken for Hardware system for analysis of drowsiness detection results compared with analytical time taken for vehicular and behavioral techniques.

At 200 iterations, the unique behavioral parameter attains a high accuracy of 62.68%, as shown in Fig. 5. Beyond this point, the accuracy rises with increasing iterations. The parameter stays the same regardless of the values of iteration.

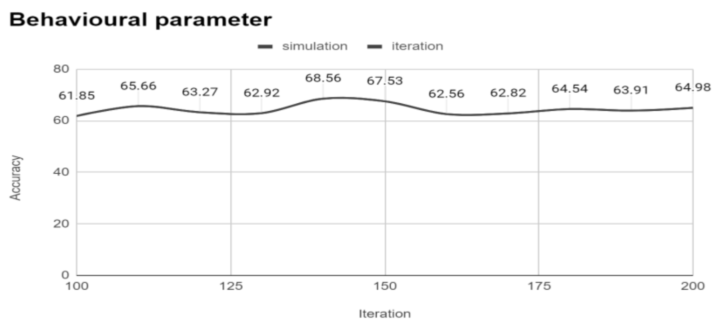

FIGURE. 5. Various iterations of behavioral parameters. The accuracy values on the X-axis are 61.85, 63.27, 67.53, 62.82, 64.98, and the iteration values on the Y-axis are 100th, 125th, 150th, 175th, 200th. Completely trending decreasing accuracy values are acquired for each repetition.

The iteration increase for various vehicular parameter methodology performances is shown in Fig. 6. The average accuracy of the vehicular parameter is 48.07% after 200 iterations.

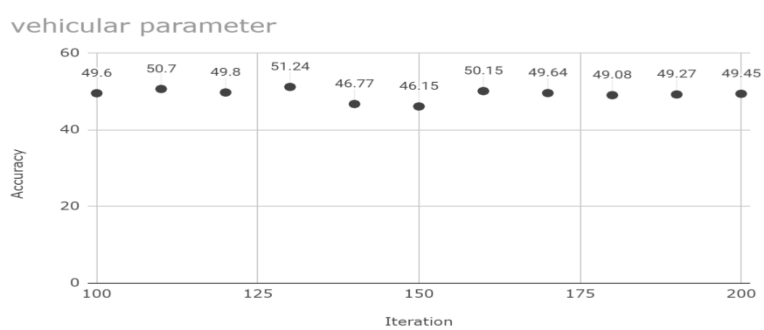

FIGURE. 6. Evolution of a vehicular parameter. The accuracy of each X-axis was 49.6, 49.8, 49.8, 46.15, 49.64 and 49.45, and the Y-axis was 100, 125, 150, 175, and 200 iterations were used. Accuracy parameters are obtained to be completely shifted downwards.

The statistical analysis of simulation with hardware and without hardware comparison was shown in box plot representation in Fig. 7 and it proves to be significantly better with the simulation of Novel behavioral parameter technique.

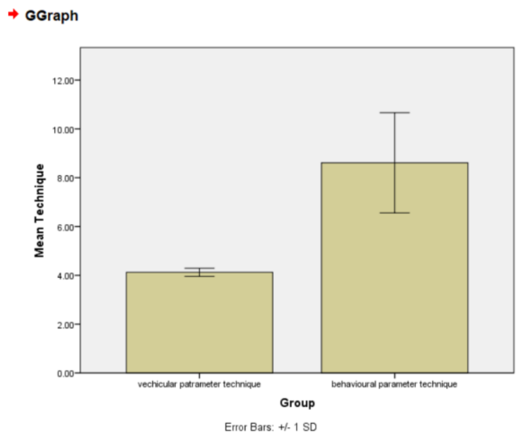

FIGURE. 7. Comparison of Simulation time and Simulation time with hardware.

The mean accuracy and standard deviation of behavioral parameters appears to be better than vehicular parameter technique. It is observed that the behavioral parameter time appears to perform significantly ($p=0.00<0.05$) better than vehicular parameter technique. X-axis: Simulation time vs. Simulation time with hardware & Y-axis mean accuracy of detection ±1SD.

DISCUSSION

In this study, a timing of 62.68% ($p<0.05$) is used for classification using simulation time. Using data from Kaggle and the UCI repository, we evaluate how well Simulation time and Simulation time with hardware predict weariness. There is a wide range of normal to tired ratios and EEG signal characteristics among these datasets. Our research shows that two methods—Simulation time and Simulation time with hardware—can handle an unbalanced dataset and come up with improved timing findings (62.68% and 62.68%, respectively).

[8] The suggested approach is able to accomplish both early imprecision and rapid adaptability thanks to online simulation time in research analysis. Measurement stability proves that the suggested approach avoids the first error. Using two simulation periods to increase detection timeliness by 67.43%, Jiang's suggested technique is compatible with these study findings. Jiang has also run several simulations to fine-tune the timing according to the values of each characteristic. A 67.95% improvement in timing is achieved in [10] using simulation time and hardware. It was determined that McDonald could manage the dataset imbalance and provide superior Simulation Time. When the suggested approach is used in conjunction with the article described earlier, the timeliness will rise substantially, going from 67.95% to 96.76%. [10] Finds a timing of 69.36% using simulation time. Zhang found that although utilizing simulation time with hardware to create classification metrics originally yielded identical results, improving accuracy and precision could be achieved by changing the seed of Random forests.

Due to the small dataset used in the research, there is room for improvement in terms of both time and accuracy. You may increase the dataset size and run the simulation many times with the hardware to get more accurate and consistent results. One big problem with the study is that the simulation timings don't work when the target classes overlap. Training becomes increasingly challenging as the dataset size increases. Raising the seed value is one way to update the simulations in the future. Another option is to provide extra data to the training sets. Enhance the detection accuracy via the use of the behavioral parameter approach by gradually expanding the dataset size over the duration of the simulation.

CONCLUSION

A model for the autonomous identification of driver sleepiness was presented in this work. One early behavior-based system could detect whether a person was really drowsy only by looking at their face and the things they were doing. Evidence from this study shows that behavioral strategy is superior to other methods for detecting driver sleepiness. The Vehicular Parameter Approach has a much lower accuracy rate of 48.07% compared to the Novel Behavioral Parameter's 62.68%. The sleepiness detection technology used in the study was fine-tuned after extensive testing in real-world driving conditions to ensure its reliability and applicability to future studies.

REFERENCES

1. M. Keyvanara, N. Salehi, and A. Monadjemi, “Robust real-time driver drowsiness detection based on image processing and feature extraction methods,” International Journal of Vehicle Safety, vol. 10, no. 1. p. 24, 2018. doi: 10.1504/ijvs.2018.093055.
2. M. Zhu, J. Chen, H. Li, F. Liang, L. Han, and Z. Zhang, “Vehicle driver drowsiness detection method using wearable EEG based on convolution neural network,” Neural Comput. Appl., pp. 1–16, May 2021.
3. A. R. Sparrow, C. M. LaJambe, and H. P. A. Van Dongen, “Drowsiness measures for commercial motor vehicle operations,” Accid. Anal. Prev., vol. 126, pp. 146–159, May 2019.
4. J. A. Misener and D. J. Gorsich, “Vehicle intelligence and the 21/sup st/ Century Truck Initiative: A new application for a new century,” Proceedings of the IEEE Intelligent Vehicles Symposium 2000 (Cat. No.00TH8511). doi: 10.1109/ivs.2000.898434.
5. A. Breg, Y. L. Murphey, and T. Yu, “Neural Network Predicting Remote Vehicle Movement with Vehicle-to-Vehicle Data,” 2018 IEEE Symposium Series on Computational Intelligence (SSCI). 2018. doi: 10.1109/ssci.2018.8628886.
6. M. Peden, “Saving lives through vehicle safety,” The Lancet Global Health, vol. 8, no. 6. pp. e746–e747, 2020. doi: 10.1016/s2214-109x(20)30189-3.
7. A. Moawad, N. Kim, N. Shidore, and A. Rousseau, “Assessment of Vehicle Sizing, Energy Consumption and Cost Through Large Scale Simulation of Advanced Vehicle Technologies.” 2016. doi: 10.2172/1245199.
8. J. M. Anderson, K. Nidhi, K. D. Stanley, P. Sorensen, C. Samaras, and O. A. Oluwatola, Autonomous Vehicle Technology: A Guide for Policymakers. Rand Corporation, 2014.
9. G. Anitha, P. Nirmala, S. Ramesh, M. Tamilselvi and G. Ramkumar, "A Novel Data Communication with Security Enhancement using Threat Management Scheme over Wireless Mobile Networks," 2022 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI), 2022, pp. 1-6, doi: 10.1109/ACCAI53970.2022.9752584.
10. Kumar, R.V., Vanitha, M., Prabu, R.T. *et al.* Multiband miniaturisefrequency reconfigurable patch antenna using PIN diodes. *Wireless Netw* **28**, 2485–2497 (2022). https://doi.org/10.1007/s11276-022-02946-6