A Biometric-Based Adaptive Simulator for Driving Education

Paola Barra[1], Carmen Bisogni[2(✉)], and Chiara Pero[2]

[1] Parthenope University of Naples, 80133 Naples, Italy
paola.barra@uniparthenope.it
[2] University of Salerno, 84084 Fisciano, Italy
{cbisogni,cpero}@unisa.it

Abstract. Distracted driving emerges as a global threat, significantly contributing to the alarming toll of 1.3 million annual traffic fatalities. This paper presents an innovative solution employing a Unity-based driving simulator with biometric features to tackle distracted driving across educational and technological domains. The simulator uses the popular Mediapipe Solutions library and uncomplicated camera setups to capture pivotal biometric parameters: head rotation, gaze direction, and eyelid opening. The fusion of these parameters creates an immersive user experience, enabling self-assessment of distraction levels within simulated nighttime scenarios. The simulator incorporates alerts for incorrect gaze direction or signs of drowsiness, employing an acoustic signal. Furthermore, the simulator activates car headlights upon the driver's proximity to the dashboard, indicating compromised visibility. The proposed solution's efficacy is confirmed through experiments conducted under diverse conditions, including scenarios with sunglasses, eyeglasses, and low luminosity. With minimal hardware and software requirements, the simulator emerges as a valuable educational tool for drivers, holding potential for integration into assisted driving systems. The results highlight its significant contribution to road safety, effectively addressing the pervasive issue of distracted driving through a comprehensive and accessible framework.

Keywords: driver simulator · assisted driving · biometrics · adaptive simulator

1 Introduction

Annually, road traffic accidents claim around 1.3 million lives worldwide, as reported by the World Health Organization (WHO) [25]. Recent statistical insights shed light on distracted driving as a prominent contributor to accidents. Distracted driving, encompassing visual, manual, and cognitive distractions, emerges as a significant threat to road safety. Further complicating this challenge is driver drowsiness, positioned as the second leading cause of accidents, following alcohol consumption. Symptoms such as fatigue, yawning, and attention deficits heighten the associated risks.

P. Zaphiris and A. Ioannou (Eds.): HCII 2024, LNCS 14724, pp. 35–49, 2024.
https://doi.org/10.1007/978-3-031-61691-4_3

The term "*distraction*" is described as the "diversion of the mind, attention, etc. from a particular task" [26]. In the context of distracted driving, it refers to any activity that diverts attention away from the primary task of driving. Maintaining full attention is paramount for safe driving, and engaging in non-driving activities increases the risk of accidents [17]. Distraction is classified into three types: manual, visual, and cognitive [9]. Manual distraction involves the driver participating in activities such as using a cellphone, eating, or drinking. Visual distractions shift the driver's eyes and focus away from the road, while cognitive distraction occurs when the driver's mind is not concentrated on driving, such as talking to a passenger, daydreaming, or becoming lost in thoughts. Given that driver distraction and inattention are the primary causes of vehicle crashes, it is essential to identify instances of driver distraction and implement countermeasures to ensure safe driving.

The ongoing progress in Advanced Driver Assistance Systems (ADAS) has significantly contributed to enhancing road safety by providing crucial support throughout the driving process [24]. These cutting-edge technologies rely on a multitude of sensors to actively monitor the vehicle's surroundings, issuing timely warnings or taking preventive measures to mitigate potential hazards such as obstacles, lane departures, and speed infractions. The realm of ADAS includes various systems such as automatic emergency braking, forward collision warning, blind spot warning, and lane departure warning, all of which provide transient interventions in critical situations. In the contemporary automotive landscape, the continual evolution of ADAS is directed towards ensuring a secure and stress-free driving experience. Figure 1 shows various state-of-the-art ADAS features along with the corresponding sensors employed in their implementation.

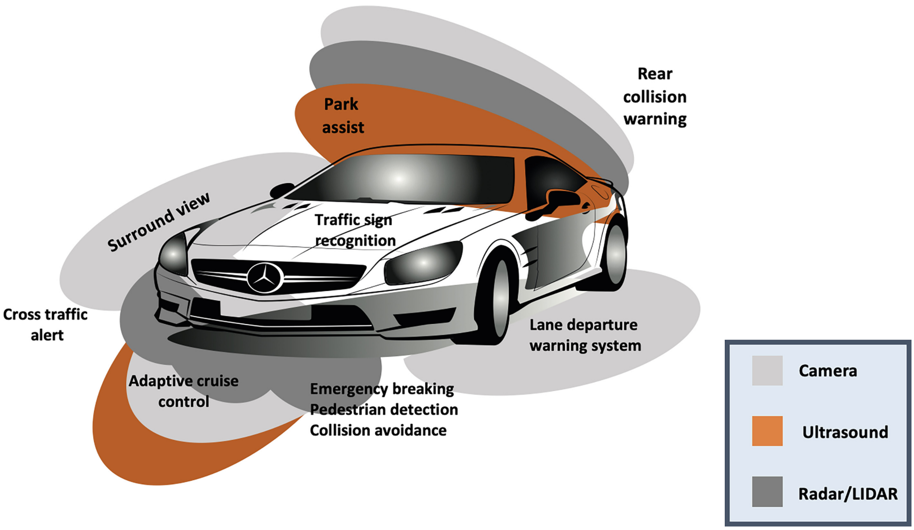

Fig. 1. State-of-the-art ADAS features and implementing sensors.

The seamless integration of multi-source data, specifically biometric information designed for driving scenarios and integrated with existing vehicle sensors, represents a significant leap forward in reinforcing ADAS security. Facial and eye movement indicators, including head rotation, eye blinks, and gaze direction, are conventionally utilized for deducing driver cognitive states [14]. Real-time head rotation recognition assumes a pivotal role in driver behavior analysis and monitoring attention levels [11,29,34]. Conversely, insights into gaze direction provide a detailed understanding of the driver's focal point, enabling precise interventions by ADAS. In controlled environments, gaze can be tracked with remarkable accuracy, particularly with the introduction of affordable devices in recent market offerings. On the other hand, eye-related metrics have demonstrated promising results in determining the driver's fatigue state [20,21,28]. Last but not least, monitoring the distance from the windscreen yields valuable data regarding driver posture and positioning, providing a complementary layer to existing sensor inputs.

Based on these premises, this study introduces an innovative driving simulator for distraction assessment and education, underscoring the practical integration of automated solutions into assisted driving scenarios. These include obstacle detection systems, assisted driving features, and drowsiness prevention mechanisms. By offering a comprehensive approach to tackling distracted driving and alleviating the risks linked to driver drowsiness, the simulator aims to reshape driving education for safer roads. The use of accessible biometric data capture techniques, especially through camera-based systems, introduces a pragmatic dimension to the proposed methodology. In essence, the main contributions can be summarized as follows:

- Development of a driving simulator for distraction assessment and education, allowing drivers to assess their distraction levels in simulated scenarios and offering a valuable tool for enhancing awareness of safe driving practices.
- Utilization of biometric features as distraction indicators, including head rotation, gaze, distance from the windscreen, and eyelid opening. These parameters serve as effective indicators of driver distraction levels during simulated driving experiences.
- Camera-based biometric data collection for practical implementation by using a simple camera for capturing biometric features. An RGB camera on a PC is employed for educational driving, while a near-infrared camera can be strategically positioned on the car dashboard for assisted driving scenarios.

The rest of this article is organized as follows: In Sect. 2, we provide an overview of recent literature, in particular on the themes of distraction detection and drowsiness detection while driving; in Sect. 3, we propose our framework with details about the biometrics techniques involved and the types of alerts; in Sect. 4, we present the framework developments and the findings of the test we conducted with such a framework, other than highlighting the open challenges and future directions; in Sect. 5, we resume our work and provide a complete but concise overview of the overall insights and future paths.

2 Literature Review

2.1 Distraction Detection

Exploring ADAS in the field of Computer Vision poses challenges given its pivotal role in enhancing automotive safety. According to [4], there are four categories deemed effective in measuring and identifying driver distraction: behavioral (such as eye and head movements), performance-based (including vehicle lateral and longitudinal control), psychological (utilizing driver electrocardiographic and electroencephalographic methods), and subjective (employing self-assessment questionnaires and expert evaluations) [8]. Among these, the first two categories, behavioral and performance-based, are the most commonly utilized for driver distraction analysis. Among these, the most frequently employed for driver distraction analysis are the first two [22].

Gaze direction and head pose estimation stand out as widely used attributes. For instance, in [5], the focus was on identifying a specific type of driver distraction–specifically, the rotation of the driver's head caused by a change in the yaw angle. The research involved training multiple classifiers on diverse video frames to evaluate and identify driver distraction. The authors demonstrated that the method utilizing motion vectors and interpolation outperformed other approaches in effectively detecting the rotation of the driver's head. Choi et al. [13] employed advanced deep learning techniques to classify a driver's gaze zones. Through the analysis of camera images, the sequential arrangement of these gaze zones offers valuable insights into the driver's behaviors, encompassing aspects like drowsiness, focus, or distraction. To achieve robust face detection, a combination of a Haar feature-based face detector and a correlation filter-based MOSS tracker is utilized. The study successfully identified nine gaze zone categories, indicating where the driver is looking while driving. Continuing in this line of investigation, Vora et al. [31] conducted a study to investigate systems capable of adapting to diverse drivers, cars, perspectives, and scales. Utilizing Convolutional Neural Networks (CNNs), they categorized a driver's gaze into seven zones, fine-tuning both AlexNet and VGG16 through three distinct input preprocessing techniques. The findings highlighted that concentrating on the upper half of the face yielded superior results compared to employing the entire face or face+context images for effective classification. A very recent study aims to identify instances of distraction by focusing on the true driver's focus of attention (TDFoA) [16]. The process involves two primary stages: predicting TDFoA and determining the Driver Distraction Degree (DDD) based on the driver's focus of attention (DFoA) and TDFoA. To accomplish this, they introduced a deep 3D residual network with an attention mechanism and encoder-decoder (D3DRN-AMED). This model is specifically designed to operate on successive frames using convolutional Long Short-Term Memory (LSTM), effectively minimizing the impact of momentary distractions by considering historical variations in driving scenarios. For an in-depth overview of driver distraction methods, a recent literature review is available in [18].

2.2 Drowsiness Detection

Artificial Intelligence-based systems designed for detecting driver drowsiness have explored various approaches by analyzing the geometric configuration of facial features [12]. Some methods focus exclusively on head pose along with the spatial relationships between specific facial elements [15]. Conversely, other approaches center on the eyes, considering factors such as eye orientation and gaze [3,20,23]. To overcome limitations associated with individual approaches, such as restricted applicability to specific scenarios or being confined to frontal-face driving scenarios, there is a need for a hybrid model that integrates both head pose and eye status [29]. In [35], a Deep Cascaded Convolutional Neural Network is utilized for face detection, followed by the application of the Dlib library to identify facial landmarks. Subsequently, the Eyes Aspect Ratio (EAR) is calculated, and a Support Vector Machine is employed to classify the drowsiness state. Another strategy, outlined in [30], integrates multimodal information, encompassing driver posture, blinks, vehicular data, and Heart Rate Variability (HRV), to discern both slight and severe drowsiness. In [33], a hierarchical temporal Deep Belief Network is deployed to detect drowsiness states in drivers, incorporating high-level facial and head features. Likewise, [36] employs a Neural Network architecture for drowsiness detection, analyzing motions through spatio-temporal representation learning. A particularity of this approach involves automatic scene understanding through an optimization algorithm, achieving a balance between drowsiness detection and scene comprehension. The analysis of multimodal data is further delved into in [6], where fusion also entails emotion detection. This approach combines information derived from yawning, eye movements, and lip gestures, contributing to a comprehensive approach for drowsiness detection. A comprehensive analysis of vehicle metrics, facial and body expressions, as well as physiological signals, aiming to enhance driving safety through adaptive interactions with the driver, is discussed in [2].

3 Proposed Framework

The proposed framework revolves around a sophisticated technology adept at discerning and mapping a driver's facial features, leveraging a strategically positioned webcam. The biometric data obtained includes:

– Facial rotation
– Gaze direction
– Distance assessment
– Eye closure

Primarily designed for integration within assisted driving frameworks, the technology vigilantly monitors the driver's attentiveness, detects signs of fatigue or drowsiness during the driving experience, and triggers high-beam illumination as the driver approaches the webcam. The workflow of the framework is depicted in Fig. 2.

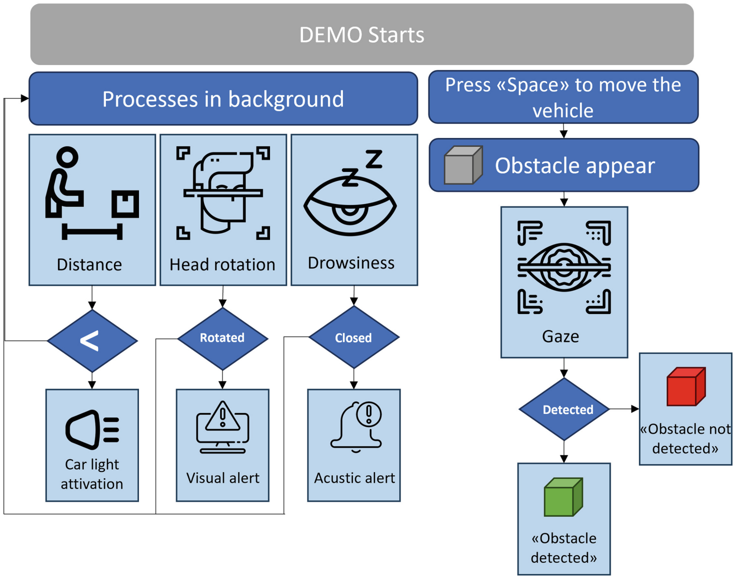

Fig. 2. Workflow of the proposed method. (Those graphs has been designed using images from Flaticon.com www.flaticon.com. Authors of the icons: Freepik, surang, mj.)

Python serves as the programming language, offering a versatile selection of modules. The acquisition of biometric data involves the utilization of the MediaPipe and OpenCV libraries, complemented by essential data manipulation tools such as NumPy, itertools, math, and socket. More details can be found in the following subsections.

Facial Rotation Estimation. Face pose detection is achieved through the MediaPipe package, which employs methodologies for facial mapping utilizing 468 specific landmarks. These landmarks are strategically positioned on the nose, ears, eyes, and mouth, enabling the estimation of facial rotation. The face mesh is obtained by a convolutional neural network like MobileNetV2-like [27] with customized blocks for real-time performance. The rotation estimation is performed by the OpenCV function named "solvePnP" (Perspective-n-Point), designed to estimate face pose based on a set of points encompassing both 2D and 3D coordinates, along with the camera matrix and distortion coefficients. The primary concept involves estimating the position by utilizing the 3D coordinates of N points and their corresponding 2D projections.

Gaze Direction. Once the face mesh is obtained by the method above mentioned, the eye coordinates are used to create a mask for cropping the eye region. Subsequently, a gaussian and median blur are applied to remove the noise from the eye image. The eye is processed in three equal parts vertically. A pixel counter function is called to count the black pixel for each part of the eyes (right, center, left). Since the pupil is known as a black (or near black) pixel in the image, we can obtain the pupil position by counting. We will then have the right, left, or center positions of the gaze. For more detail, please refer to the code available at [1].

Fig. 3. Biometric-based measures to perform drowsiness detection, distance estimation, gaze position and head rotation.

Distraction and Drowsiness Detection. Distraction detection is accomplished by analyzing previously obtained information, specifically facial rotation. To determine eye closure, landmarks on the eyelids of both eyes–particularly those at the center–are utilized. The closure of an eye is identified when the distance between landmarks on the upper and lower rims is very small. Importantly, each eye is monitored independently, ensuring that the individual closure of one eye does not trigger a drowsiness alert.

Two potential warning types are implemented: distraction and drowsiness. Distraction is recognized when the driver fails to maintain a forward gaze for a specific duration. This may occur due to various reasons, such as engaging in conversation with passengers, turning attention towards them, looking at the radio or phone, or gazing out of the window. Drowsiness detection involves identifying the closure of both eyes for a specific duration. Both scenarios prompt an auditory signal, with its tempo increasing over time to alert the driver to remain attentive while driving. Time calculations for these detections are facilitated by the use of the "time" library, providing practical methods for time management.

Webcam-Based Distance Measurement. Utilizing the OpenCV library and Haar-cascade files for face detection, the system gauges the driver's distance from the webcam. Calibration involves capturing a reference image with a known distance and face width and subsequently computing the focal distance using the known parameters. The aim of this part is to automatically activate the car lights when needed. All of the above-mentioned techniques are integrated, as depicted in Fig. 3.

Client-Server Communication Protocol. The establishment of a data transmission system from Python to C# was essential to incorporating Python-acquired biometric data into the Unity demo. Python acts as the server, handling requests from C# for the necessary biometric data. The socket module plays a pivotal role in coordinating network communication, allowing Unity to solicit and receive biometric data. This module is integral to Python's Network Programming Toolkit, facilitating the creation, control, and management of network connections. The transmitted data from Python is meticulously formatted into a string, delineated by specific separators. This string includes face orientation, drowsiness alert, eye position, distance from the webcam, and distraction alert. The receiving process decodes the data from bytes, interprets them via tokenization, and manages each component individually. The system, characterized by low latency, provides real-time feedback throughout the execution of the demo.

4 Framework Development and Findings

The biometric data-driven simulator was developed within Unity, a versatile game engine created by Unity Technologies for game and interactive content development. The simulator showcases a driving scenario on a straight road at night and employs assets from the Unity Asset Store, such as the "Modular Lowpoly Streets" package for road construction and the "AllSky" package for creating the night skybox.

A car image was positioned in front of the camera, and a script was implemented to guide the camera's movement, simulating a moving vehicle. The car features a spotlight that simulates low beams, dynamically adjusting its range and intensity as the driver approaches the webcam, similar to high beams (Fig. 5). Upon starting the demo, the car begins its movement along the road, encountering strategically placed obstacles.

The simulator incorporates an obstacle detection system, where the car identifies obstacles (depicted as red cubes; see Fig. 6) along the road, triggering alerts on the screen. When the driver directs their attention towards an obstacle, it transitions to green, signifying the system's acknowledgment of the driver's attentiveness. However, if the driver becomes distracted or closes their eyes for a specific duration, an escalating and intensifying auditory warning signal is initiated by the car. This setup aims to simulate real-world driving scenarios and test the driver's responsiveness to potential hazards (Fig. 4).

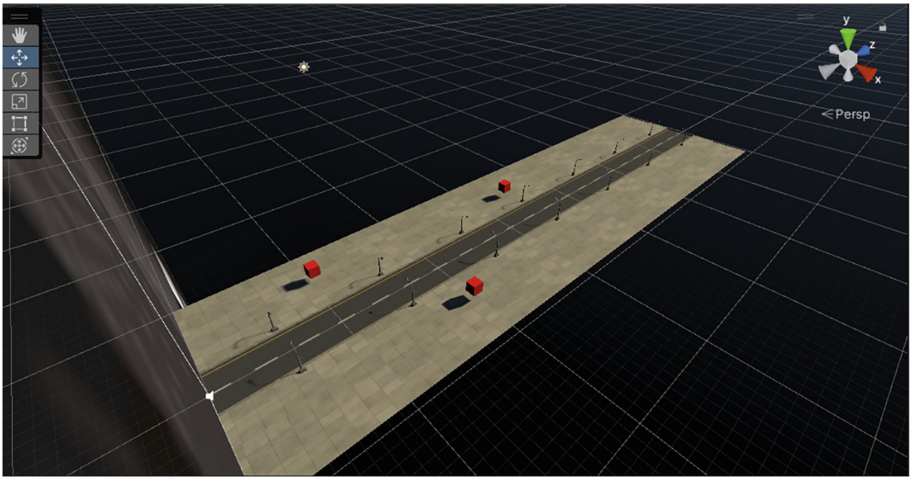

Fig. 4. Unity Simulation scene with lighting.

In order to prove the effectiveness of the method, we tested it under various scenarios:

- **Eyeglasses** The framework is robust in the case of eyeglasses. None of the involved methods presented a decrease in performance with the use of eyeglasses.
- **Sunglasses** The framework is robust in the case of sunglasses for the methods involving the pose of the user and the alert regarding distraction detection. Due to the absence of a visible pupil, the method is not able to work in this case to detect the gaze of the user and the closing eyes. For this reason, the drowsiness alert and obstacle detection will not work in this case.
- **Partially occluded face** Since the method involved uses landmark prediction, even in the case of partially occlusions, the framework is able to work without decreasing in performance. In particular, for the lower part of the face that is occluded, like the mouth, the nose, or both, the method works as usual. If the upper part is partially occluded (as an example, one eye is occluded), only the drowsiness detection will fall because it is calibrated to detect both eyes closed. However, this is a characteristic of the framework that can be easily modified as needed.
- **Low brightness** When the face is not sufficiently illuminated during the demo, both the accuracy of the gaze detection and the distance estimation decrease. This means that the obstacle detection and the car light activation functions are no longer reliable. In contrast, the landmarks are correctly detected, and the distraction and drowsiness alerts work as usual. This problem could be overcome by considering the use of a near-infrared camera. Those particular cameras are also able to capture the facial image at very low brightness, which would more realistically simulate a real car environment during night driving. In this case, the ability of Mediapipe to detect facial landmarks

Fig. 5. Unity Simulation: lighting variations (Top: Off, Bottom: On).

should be tested, since there is not, to the best of our knowledge, a literature on accuracy decreasing when using near-infrared cameras. However, other methods, like dlib [19], have been proven to be easily trainable on different input data, as in the case of the depth image of faces [10].

Based on our observations, we can define different paths for future directions of the work:

– **From 2D simulation to VR** Unity, which has been used to build the driving simulator, also provides a version, Unity3D, that allows you to create 3D environments. For this reason, a possible path would be to move the simulation from 2D to 3D in order to make the experience more immersive

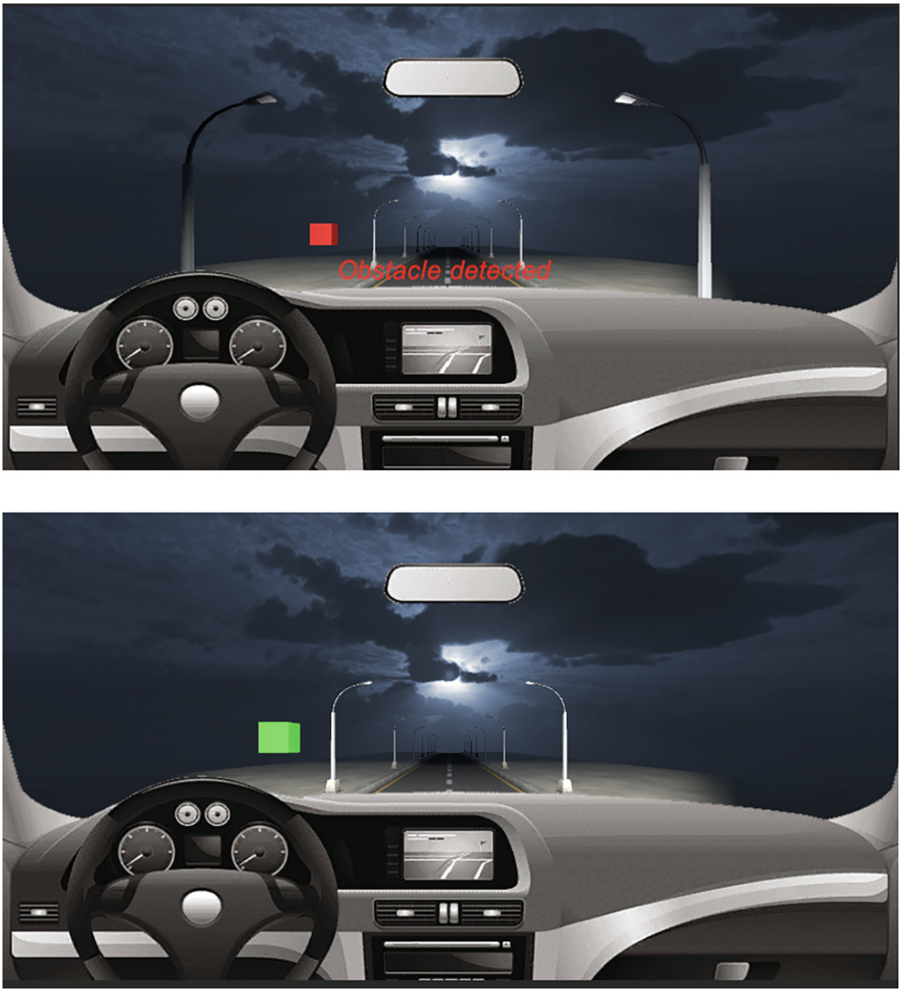

Fig. 6. Unity Simulation: recognized obstacle (Top: Driver's Detection, Bottom: Driver's Perspective).

for the learner. In this case, however, the facial landmark and the eye position should be captured by different devices. The integrated gaze devices in the visors for the second case [32], and the webcam as usual in the first case, since Mediapipe is able to work also in case half the face is occluded.

- **From 2D simulation to AR** Other than VR, one possibility could be to test the demo in a context of mixed reality, where the car seat, the illumination conditions, the steering wheel, and the accelerator are real, and the moving road and the appearance of the obstacle are simulated. This would help not only in the immersive learning of the driver but also in the calibration of sensors.

– **From 2D simulation to car** One possible test to conduct would be to mount a camera on the dashboard of a real car, integrate the above-mentioned sensors, and test the alarms installed in the demo to obtain feedback from experienced drivers on possible improvements to the learning phase and calibration.

5 Conclusions

The continuous evolution of technology is making the integration of simulation techniques into user educational processes increasingly seamless. This study specifically focuses on safe driving practices, introducing a simulation framework designed to replicate a driving scenario while considering its intricate elements. These encompass critical aspects like obstacle detection, identification of drowsiness, distraction management, and addressing challenges posed by low luminosity. The techniques presented in this work, combined with an autonomous driving algorithm as [7], could prevent accidents. The proposed framework is versatile and compatible with personal computers equipped with RGB cameras, including integrated options. It capitalizes on established biometric analysis algorithms to evaluate the aforementioned driving situations. The framework not only identifies potential issues but also provides users with diverse alerts and feedback mechanisms to enhance their driving skills. Moreover, the adaptability of the framework extends to immersive experiences in virtual reality and augmented reality settings. This potential integration aims to elevate the user experience, contingent upon the availability of appropriate hardware devices. The incorporation of structured feedback, manifesting as alerts, facilitates the translation of insights gained within the simulation environment into tangible perspectives for assisted driving scenarios.

Our future endeavours involve refining biometric techniques tailored to three applications: 2D simulations, 3D simulations, and assisted driving contexts. Additionally, we plan to conduct comprehensive testing using images from various input sources under diverse and challenging conditions. This includes scenarios where visors partially or fully cover the driver's face, using near-infrared images, and experimenting with different camera positions, such as mounting the camera on the dashboard. In summary, the proposed simulation framework addresses immediate concerns related to driving distractions and demonstrates adaptability for emerging technologies like virtual reality and augmented reality. The structured feedback mechanism ensures that the insights gained from the simulation environment contribute meaningfully to assisted driving, promising a safer and more informed driving experience for users in diverse conditions.

Acknowledgment. We would like to thank Marco Pastore, a 'Graphics and Interaction' student, for his assistance with the game graphics as part of his internship and bachelor thesis.

References

1. Gaze detector using mediapipe. https://github.com/Asadullah-Dal17/Eyes-Position-Estimator-Mediapipe. Accessed 25 Jan 2024
2. Aghaei, A.S., et al.: Smart driver monitoring: when signal processing meets human factors: in the driver's seat. IEEE Signal Process. Mag. **33**(6), 35–48 (2016)
3. Akshay, S., Abhishek, M., Sudhanshu, D., Anuvaishnav, C.: Drowsy driver detection using eye-tracking through machine learning. In: 2021 Second International Conference on Electronics and Sustainable Communication Systems (ICESC), pp. 1916–1923. IEEE (2021)
4. Aksjonov, A., Nedoma, P., Vodovozov, V., Petlenkov, E., Herrmann, M.: Detection and evaluation of driver distraction using machine learning and fuzzy logic. IEEE Trans. Intell. Transp. Syst. **20**(6), 2048–2059 (2018)
5. Ali, S.F., Hassan, M.T.: Feature based techniques for a driver's distraction detection using supervised learning algorithms based on fixed monocular video camera. KSII Trans. Internet Inf. Syst. (TIIS) **12**(8), 3820–3841 (2018)
6. Altameem, A., Kumar, A., Poonia, R.C., Kumar, S., Saudagar, A.K.J.: Early identification and detection of driver drowsiness by hybrid machine learning. IEEE Access **9**, 162805–162819 (2021)
7. Anzalone, L., Barra, P., Barra, S., Castiglione, A., Nappi, M.: An end-to-end curriculum learning approach for autonomous driving scenarios. IEEE Trans. Intell. Transp. Syst. **23**(10), 19817–19826 (2022). https://doi.org/10.1109/TITS.2022.3160673
8. Arun, S., Sundaraj, K., Murugappan, M.: Driver inattention detection methods: a review. In: 2012 IEEE Conference on Sustainable Utilization and Development in Engineering and Technology (STUDENT), pp. 1–6. IEEE (2012)
9. Baheti, B., Talbar, S., Gajre, S.: Towards computationally efficient and realtime distracted driver detection with mobileVGG network. IEEE Trans. Intell. Veh. **5**(4), 565–574 (2020)
10. Bilotti, U., Bisogni, C., Nappi, M., Pero, C.: Depth camera face recognition by normalized fractal encodings. In: Foresti, G.L., Fusiello, A., Hancock, E. (eds.) Image Analysis and Processing - ICIAP 2023. LNCS, vol. 14233, pp. 196–208. Springer, Cham (2023). https://doi.org/10.1007/978-3-031-43148-7_17
11. Bisogni, C., Cascone, L., Nappi, M., Pero, C.: IoT-enabled biometric security: enhancing smart car safety with depth-based head pose estimation. ACM Trans. Multimedia Comput. Commun. Appl. **2**, 1–24 (2024)
12. Bisogni, C., Hao, F., Loia, V., Narducci, F.: Drowsiness detection in the era of industry 4.0: are we ready? IEEE Trans. Ind. Inform. **18**(12), 9083–9091 (2022). https://doi.org/10.1109/TII.2022.3173004
13. Choi, I.H., Hong, S.K., Kim, Y.G.: Real-time categorization of driver's gaze zone using the deep learning techniques. In: 2016 International Conference on Big Data and Smart Computing (BigComp), pp. 143–148. IEEE (2016)
14. Dubs, A., et al.: Drive a vehicle by head movements: an advanced driver assistance system using facial landmarks and pose. In: Stephanidis, C., Antona, M., Ntoa, S. (eds.) HCII 2022. CCIS, vol. 1580, pp. 502–505. Springer, Cham (2022). https://doi.org/10.1007/978-3-031-06417-3_67
15. Friedrichs, F., Yang, B.: Camera-based drowsiness reference for driver state classification under real driving conditions. In: 2010 IEEE Intelligent Vehicles Symposium, pp. 101–106. IEEE (2010)

16. Huang, T., Fu, R.: Driver distraction detection based on the true driver's focus of attention. IEEE Trans. Intell. Transp. Syst. **23**(10), 19374–19386 (2022)
17. Kaplan, S., Guvensan, M.A., Yavuz, A.G., Karalurt, Y.: Driver behavior analysis for safe driving: a survey. IEEE Trans. Intell. Transp. Syst. **16**(6), 3017–3032 (2015)
18. Kashevnik, A., Shchedrin, R., Kaiser, C., Stocker, A.: Driver distraction detection methods: a literature review and framework. IEEE Access **9**, 60063–60076 (2021)
19. Kazemi, V., Sullivan, J.: One millisecond face alignment with an ensemble of regression trees. In: 2014 IEEE Conference on Computer Vision and Pattern Recognition, pp. 1867–1874 (2014). https://api.semanticscholar.org/CorpusID:2031947
20. Khan, M.Q., Lee, S.: Gaze and eye tracking: techniques and applications in ADAS. Sensors **19**(24), 5540 (2019)
21. Ledezma, A., Zamora, V., Sipele, Ó., Sesmero, M.P., Sanchis, A.: Implementing a gaze tracking algorithm for improving advanced driver assistance systems. Electronics **10**(12), 1480 (2021)
22. Li, W., Huang, J., Xie, G., Karray, F., Li, R.: A survey on vision-based driver distraction analysis. J. Syst. Architect. **121**, 102319 (2021)
23. Maior, C.B.S., das Chagas Moura, M.J., Santana, J.M.M., Lins, I.D.: Real-time classification for autonomous drowsiness detection using eye aspect ratio. Expert Syst. Appl. **158**, 113505 (2020)
24. Nidamanuri, J., Nibhanupudi, C., Assfalg, R., Venkataraman, H.: A progressive review: emerging technologies for ADAS driven solutions. IEEE Trans. Intell. Veh. **7**(2), 326–341 (2021)
25. World Health Organization, et al.: Global status report on road safety 2023: summary. In: Global Status Report on Road Safety 2023: Summary (2023)
26. Regan, M.A., Hallett, C., Gordon, C.P.: Driver distraction and driver inattention: definition, relationship and taxonomy. Accid. Anal. Prev. **43**(5), 1771–1781 (2011)
27. Sandler, M., Howard, A.G., Zhu, M., Zhmoginov, A., Chen, L.C.: MobileNetV2: inverted residuals and linear bottlenecks. In: 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 4510–4520 (2018). https://api.semanticscholar.org/CorpusID:4555207
28. Schwehr, J., Willert, V.: Driver's gaze prediction in dynamic automotive scenes. In: 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC), pp. 1–8. IEEE (2017)
29. Sharara, L., et al.: A real-time automotive safety system based on advanced AI facial detection algorithms. IEEE Trans. Intell. Veh., 1–12 (2023)
30. Sunagawa, M., Shikii, S.i., Nakai, W., Mochizuki, M., Kusukame, K., Kitajima, H.: Comprehensive drowsiness level detection model combining multimodal information. IEEE Sens. J. **20**(7), 3709–3717 (2019)
31. Vora, S., Rangesh, A., Trivedi, M.M.: On generalizing driver gaze zone estimation using convolutional neural networks. In: 2017 IEEE Intelligent Vehicles Symposium (IV), pp. 849–854. IEEE (2017)
32. Wei, S., Bloemers, D., Rovira, A.: A preliminary study of the eye tracker in the meta quest pro. In: Proceedings of the 2023 ACM International Conference on Interactive Media Experiences, IMX 2023, pp. 216–221. Association for Computing Machinery, New York (2023). https://doi.org/10.1145/3573381.3596467
33. Weng, C.H., Lai, Y.H., Lai, S.H.: Driver drowsiness detection via a hierarchical temporal deep belief network. In: ACCV Workshops (2016)
34. Yang, Y., Liu, C., Chang, F., Lu, Y., Liu, H.: Driver gaze zone estimation via head pose fusion assisted supervision and eye region weighted encoding. IEEE Trans. Consum. Electron. **67**(4), 275–284 (2021)

35. You, F., Li, X., Gong, Y., Wang, H., Li, H.: A real-time driving drowsiness detection algorithm with individual differences consideration. IEEE Access **7**, 179396–179408 (2019)
36. Yu, J., Park, S., Lee, S., Jeon, M.: Driver drowsiness detection using condition-adaptive representation learning framework. IEEE Trans. Intell. Transp. Syst. **20**(11), 4206–4218 (2018)