Automatic Detection of the Driver Distractions Based on the Analysis of Face Videos

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Keywords: Driver Fatigue State, Driver Drowsiness Detection, Driver Distraction, Driver Conversing and Eating, Daylight and Nightlight Conditions, Face Analysis.

Abstract: The objective of the paper is to propose a new driver fatigue detection method using Percentage of Mouth Openness (POM) and Percentage of Eye Closure (PERCLOS) as well as to show its robustness across various real-world conditions. The openness of the eyes and mouth was determined by calculating Aspect Ratios (AR) and checking if AR exceeded a given threshold. Six videos simulated different driving scenarios were recorded to test detection performance under diverse lighting, with and without corrective glasses, moreover with additional complexities such as blinking lights. Furthermore, the method ensures avoidance of misclassification during such driver's activities as conversing and eating. The method effectively detects fatigue in all test scenarios in which the fatigue state occurred.

1 INTRODUCTION

According to the European General Safety Regulation (European Parliament and Council, 2019), vehicle manufacturers are obliged to implement ADDW (Advanced Driver Distraction Warning) systems in all new vehicles from July 2024 (Regulation 32019R2144, 2019). Its goal is to drastically reduce the number of accidents related to distraction, mainly fatal accidents and serious injuries. ADDW systems are able to warn drivers when they are distracted and to stimulate drivers to pay more attention to the traffic situation and to warn about dangerous incidents on the road. These systems include warnings such as (Laxton et al., 2022) (Fu et al., 2024):

- driver drowsiness and attention warning – analysis of vehicle systems and driver warnings when necessary;
- lane departure warning system – warning when the vehicle is drifting out of its travel lane;
- advanced emergency braking system – automatic detection of a potential collision and activation the vehicle braking system to decelerate the vehicle with the purpose of avoiding or mitigating a collision;
- emergency lane-keeping system – assistance of the driver in keeping a safe position of the vehicle with respect to the lane or road boundary to avoid a collision;
- driver availability monitoring system – assessing whether the driver is in a position to take over the driving function from an automated vehicle in particular situations.

The ADDW systems focus on detecting visual distractedness in order to provide timely warnings to the driver. They should trigger an alert by displaying a light on the car instrument panel or produce an adequate warning sound. Driver monitoring can be achieved through a driver-facing camera embedded in the steering wheel or instrument cluster. The most popular solutions of driver monitoring are to track driver eye movements and gaze directions, as well as to observe the head and its strange rotations. There is a strong correlation between head and eye movements. By combining eye movement tracking and head tracking, it is possible to detect drowsiness, for example, when the driver is tired or intoxicated (e.g. after drinking alcohol), the head drops down or eyes are closed or barely opened. The cameras installed inside the vehicles play a key role in detecting and analyzing potential dangers to the driver. The methods generally perform well in normal daylight conditions, accurately detecting the onset of driver fatigue,

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but some obstructions occur with additional complexities such as blinking lights. In addition, yawning should be distinguished from openness and closure of the mouth while talking or eating.

The goal of the paper is to verify the efficiency of the algorithms of distractedness detection by analyzing the videos recorded by a camera under various real-world conditions: i.e. in day and night conditions, driver both with and without corrective glasses, and during activities such as conversing and eating. These evaluations aim to highlight the reliability of the algorithms in practical scenarios, providing insights into their potential deployment in modern driver-assistance systems.

The paper is structured as follows. The next section describes related work on methods for automatic detection of driver distractions. The third section presents the method for detecting mouth and eye openness. The next section discusses the problem of threshold estimation. The proposed approach is described in the fifth section. The next section presents the results of the tests performed on real videos recorded in various real-world conditions. The final conclusions are presented in the last section.

2 RELATED WORK

2.1 Methods Based on Artificial Neural Networks

(Dwivedi et al., 2014) developed a system using a Convolutional Neural Network (CNN) to capture latent facial features and implemented a SoftMax layer to classify driver drowsiness. They created a dataset with 30 subjects of varying skin tones and eye sizes, under diverse lighting conditions to simulate real-world scenarios. Subjects played an open-source avoidance game while their faces were recorded, achieving accuracy of 92.33% on the validation set. The algorithm was also tested on new subjects, yielding an average accuracy of 78%.

(Zhao et al., 2020) developed a Multi-Task Cascaded Convolutional Neural Network (MTCCN) system to detect facial features like the face, nose, mouth, and eyes. This system uses CNNs to determine whether eyes and mouth are open or closed, assessing driver fatigue through eye closure (PERCLOS – Percentage of Eye Closure) and mouth closure (POM – Percentage of Mouth Openness) metrics. Eye closure above 0.25 and mouth closure above 0.5 indicate potential fatigue. They used a dataset from Biteda, featuring 4,000 real-world driving images categorized by eye and mouth states. The system achieved accuracy of 93.62%, sensitivity of 93.64%, and specificity of 60.89%.

(Chirra et al., 2019) developed a drowsiness detection system based on eye analysis. Using the Viola-Jones algorithm, they identify the face and eye regions from video frames, which are then analyzed by a 4-layer CNN that classifies images as drowsy or non-drowsy. Their dataset of 2,850 images (1,450 drowsy, 1,400 non-drowsy) was split into training, validation, and testing sets. The method achieved accuracy of 96.42% on the test data.

(Rajkar et al., 2022) developed a deep learning system for driver drowsiness detection using OpenCV for video streaming. Haar cascade classifier was used to detect the region of the face and eyes. A CNN classified whether the eyes and mouth were open or closed over time. If eye closure or mouth openness exceeded a threshold, the system alerted the driver. The authors used the YawDD and Closed Eyes In The Wild datasets. They have used 80% of the data for training and 20% for testing, the system achieved accuracy of 97.9% for eye classification and 95.76% for yawning classification.

(Vijaypriya and Uma, 2023) developed a Multi-Scale CNN system for detecting drowsiness, using Dlib to detect facial points from video frames. Each frame was denoised with Cross Guided Bilateral filtering and wavelet transformation before feature extraction. Multi-scale CNNs was used to classify patterns for drowsiness detection. The YAWDD and NTHUDDD datasets were split 80% for training and 20% for testing. The system achieved accuracy of 98.38%, precision 97.67%, and recall of 97.85% on YAWDD, and accuracy of 98.26%, precision 99.45%, and recall of 98.11% on NTHUDDD, outperforming other methods.

(Yang et al., 2024) created a driver drowsiness detection method called VBFLLFA (Video-Based Driver Drowsiness Detection using Facial Landmarks and Local Facial Areas). This approach was designed to detect drowsiness by analyzing key facial features. By analyzing regions around the eyes and mouth, the model captured movement patterns indicative of drowsiness. They used the Common Spatial Pattern (CSP) algorithm to enhance the differentiation between sample classes and to lower the model's computational complexity when analyzing each sample. They have designed two-branch multi-head attention (TB-MHA) to extract features. The Multi-layer Perceptron was used to make the final classification of drowsiness. The authors have used three different datasets, the Video-Based Driver Drowsiness Detection (VBDDD) dataset specifically created for this study, the Yawning Detection Dataset (YawDD), and the National Taiwan University Driver Drowsiness Detection (NTHU-DDD). The proposed methodology achieved average accuracy of 88.37%, precision of 0.90, recall of 0.92, and F1-score of 0.91 .

(Cichocka and Ruminski, 2024) created a method for the detection of drowsiness based on analysis of Mouth Aspect Ratio (MAR) and Eye Aspect Ratios (EAR). Fristly Haar's cascade classifiers were used to detect face and region of eyes. Convolutonal Neural Network has been used to perform the final drowsiness classification. They have trained the model using MRL Eye Dataset which contains images of closed and opened eyes. Then the model was tested on the Drowsiness dataset (Perumandla, 2020) achieving precision, recall, accuracy, and F1-score of 94%.

2.2 Other Machine Learning Methods

(Mandal et al., 2016) developed a bus driver monitoring system with seven modules: head-shoulder detection, face detection, eye detection, eye openness estimation, fusion, drowsiness measure (PERCLOS), and fatigue level classification. The system uses existing in-vehicle cameras, making extra hardware unnecessary. It first detects the driver's head and shoulders, and then uses two models to detect the face. Eye detection was followed by estimation of eye openness and finally PERCLOS was calculated to measure drowsiness. The algorithm was trained on real-world bus driver videos, with simulations involving 23 participants, including those wearing glasses, under various lighting conditions.

(Saradadevi and Bajaj, 2008) developed a fatigue detection system based on analysis of mouth and yawning. Using a Viola-Jones classifier, they track the driver's mouth and then apply SVM to classify yawning. From over 1,000 collected images, they trained on yawning and normal images, achieving accuracy of 86% for normal images and 81% for yawning.

(Bakheet and Al-Hamadi, 2021) developed a drowsiness detection system that uses adaptive histogram equalization to enhance image contrast, a Haar AdaBoost classifier for face detection, and an active shape model (ASM) to locate the eyes. HOG features are extracted from the eyes, and a Naïve Bayes classifier predicts eye status. Tested on the NTHU Driver Drowsiness Detection dataset, which includes various lighting conditions and subjects with bare faces, glasses, and sunglasses, the system achieved accuracy of 85.62%, F1-score of 87.84% for drowsiness, and F1-score of 81.09% for non-drowsiness.

(Tang and Guo, 2024) proposed a method of detecting driver fatigue by using infrared cameras and classification using Yolov8n + transfer learning. Due to the lack of a publicly available dataset of the face made by infrared cameras, the new dataset was specifically developed for this study. In each frame, the model classifies whether the mouth and eyes were closed or opened. The authors implemented the method of fatigue detection based on Percentage of Mouth Openness (POM) and Percentage of Eye Closure (PERCLOS). They were checking the 60 seconds of the video and checking if the POM and PERCLOS exceeded their thresholds. The method achieved accuracy of 98% of fatigue detection.

3 MAR, LEAR, REAR FACTORS

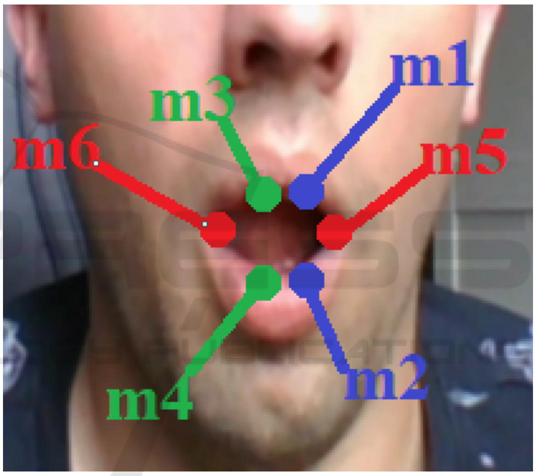

Figure 1: Mouth landmarks.

Based on the preliminary research, it was decided in our further experiments to use Mouth Aspect Ratio (MAR) and Left/Right Eye Aspect Ratios (LEAR/REAR) to classify the mouth and eyes openness. MAR is calculated by summing the distance between two points of the inner lips and the distance between two points of the outer lips. Then the sum is divided by the distance between mouth corners multiplied by 2 (Figures 1 and 2).

$$\mathrm{MAR} = \frac{\|m_1 - m_2\| + \|m_3 - m_4\|}{2 \cdot \|m_5 - m_6\|} \tag{1}$$

where:

- MAR - mouth aspect ratio,
- $m_1 \ldots m_6$ - mouth landmarks position.

The LEAR (analogously REAR) factors are calculated in similar way as MAR.

$$LEAR = \frac{\|e_1 - e_2\| + \|e_3 - e_4\|}{2 \cdot \|e_5 - e_6\|} \quad (2)$$

where:

- LEAR - Left eye aspect ratio,
- $e_1 ... e_6$ - Eye landmarks position.

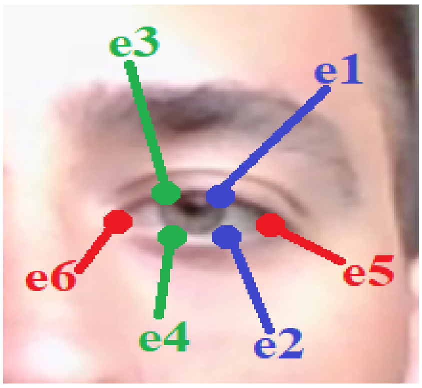

Figure 2: Left eye landmarks.

Multiple tests have been performed to analyze the Mouth Aspect Ratio and Eye Aspect Ratio while performing different actions. The tests consisted of capturing the frames from the desktop camera and simulating different scenarios such as talking, eating, yawning, blinking, and normal state. Performing these tests allowed us to estimate MAR and EAR thresholds. It was discovered that a person had closed their eyes when the EAR was smaller or equal to 0.19, therefore this value was selected as the EAR threshold. A more challenging threshold estimation was for the mouth aspect ratio, as the mouth aspect ratio must be considered when the person is talking, eating, and yawning. All of these actions involve mouth openness, making the MAR value higher. It has been found that when the person is talking or eating the MAR does not exceed 0.4, therefore this value was set as the MAR threshold.

4 PERCLOS AND POM FACTORS

Fatigue detection checks whether the eye and mouth are closed or open. Since constant blinking and frequent yawning may suggest a fatigued state, the system checks the 120 seconds and analyzes the frequencies of eye closure and mouth openness. Each frame comes with some time interval. This time interval is then used to check if the PERCLOS or the POM thresholds are exceeded or not. The Percentage of Eye Closure (PERCLOS) checks the eyes state on each frame and assigns the check result to it. After that the system checks if the PERCLOS threshold has been exceeded by summing all time intervals of the frames where both eyes were closed. If the sum exceeds the PERCLOS threshold, the system will alert about the fatigue state.

A similar logic was assigned to calculate the Percentage of Mouth Openness (POM). The system checks all frames in a given time period (120 seconds) and sums all time intervals of the frames where the mouth was opened (which may suggest yawning). If the sum exceeds the POM threshold the system will alert about the fatigue state.

5 PROPOSED APPROACH

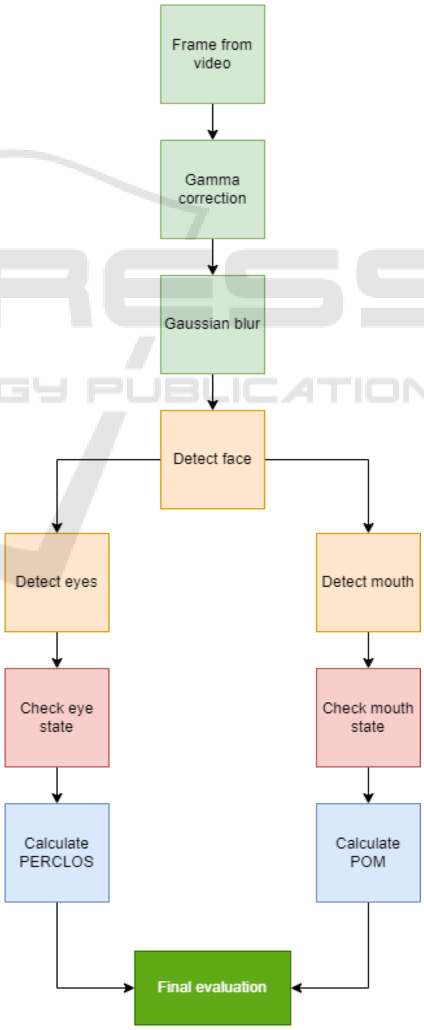

Figure 3: Diagram of the drowsiness detection algorithm.

The diagram (Figure 3) shows how the drowsiness detection algorithm works. Two additional image processing steps are performed after capturing the frame from the camera. Firstly, the brightness of the image is adjusted by using gamma correction:

$$V_{\text{out}} = V_{\text{in}}^{\gamma} \tag{3}$$

The γ is set to $\frac{1}{2.5}$ (Setiawan et al., 2022). The Gaussian blur is then used to smooth the image and reduce the noise. Gaussian blur is based on the Gaussian function that determines the weights of the blur effect (Desai et al., 2020):

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{4}$$

where:

- x, y - coordinates of a pixel relative to the center of the blur area,
- σ - standard deviation, which controls the spread of the blur.

Those two additional image processing steps help the frontal face detector to detect faces in low-light images. Then, the Dlib package is used on each frame to detect the face and key landmarks such as mouth points and eye points. The authors have used the shape-predictor-68-face-landmarks model which was trained on iBUG 300-W face landmark dataset. The dataset consists of several thousand labeled images covering a wide range of ethnicities, ages, and genders (Kazemi and Sullivan, 2014).

Next the mouth aspect ratio (MAR), left eye aspect ratio (LEAR) and right eye aspect ratio (REAR) are calculated. The openness or closure was determined by the threshold, if AR exceeded the given threshold the mouth/eye was classified as open, otherwise, it was classified as closed. Then we calculate two factors PERCLOS and POM. Having these values we can evaluate if the person is fatigued or not.

6 TESTING

To thoroughly examine the system's performance under various conditions, several tests have been designed. A series of six videos have been created, each lasting seven minutes, recorded under different lighting conditions, with and without corrective glasses. These videos are created to simulate real-world driving scenarios and to test the system's ability to detect the driver's fatigue state. The first video is recorded in normal daylight conditions, providing a baseline scenario where the lighting is consistent and natural. This video is intended to test the functionality of the system under optimal driving conditions. The second video is recorded under similar daylight conditions but with the driver wearing corrective glasses. This setup aims to evaluate whether the glasses have any impact on the system's performance and its ability to detect fatigue. The third video shifts to a more challenging environment by being recorded under nightlight conditions. This scenario tests the system's performance in low-light situations, which are common during nighttime driving and can significantly affect the detection algorithms. The fourth video is recorded under nightlight conditions with additional complexity: a blinking bright screen is used to imitate the effect of passing car lights. This setup is designed to test the system's robustness in handling sudden and intermittent light changes, which can be distracting and may affect the drowsiness detection. The fifth video is recorded in normal daylight conditions, but the driver is eating. This scenario tests whether the proposed methodology is capable of distinguishing yawning from chewing food. The sixth video is also recorded in normal daylight conditions, but the driver is talking. This setup is designed to check the ability to differentiate between conversation and yawning. Each of these videos is divided into three distinct parts to simulate different states of the driver. In the first part, the driver simulated a non-fatigue state, maintaining a normal state and vigilance. This serves as the control segment, where the system should ideally detect no signs of fatigue. In the second part, lasting for two minutes, the driver began to blink more frequently and yawn, simulating a state of fatigue. This is the critical segment where the system's ability to detect fatigue and issue alerts is tested. Finally, in the third part, the driver returned to a normal state.

The purpose of this structured simulation is to assess whether the system can accurately detect the onset of fatigue, alert the driver in a timely manner, and then stop the alerts once the fatigue state is no longer present. By doing so, the system's efficiency in maintaining driver alertness and safety can be thoroughly evaluated. These tests are crucial to ensure that the system can adapt to various real-world conditions and reliably support the driver in maintaining a high level of alertness, thus enhancing overall road safety. In each of the charts, the red line represents the simulated state, and the blue line represents the state detected by the system.

6.1 Daylight Conditions Without Corrective Glasses

The first video provides a baseline scenario for the testing phase, serving a controlled environment to evaluate the system's performance. This video

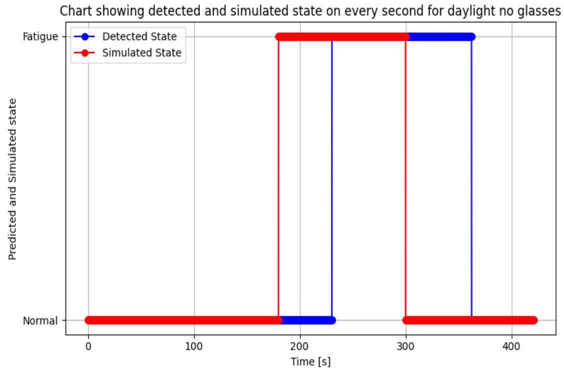

Figure 4: Chart showing detected and simulated state for video with daylight conditions without corrective glasses.

was recorded in natural daylight without corrective glasses. This scenario ensures minimal interference from external variables that could affect the system's accuracy. Figure 4 shows the simulation of the fatigue state which started at 180 seconds of the video and stopped at 300 seconds. The system detected the fatigue state at 236 seconds and stopped detecting it at 352 seconds of the video.

6.2 Daylight Conditions with Corrective Glasses

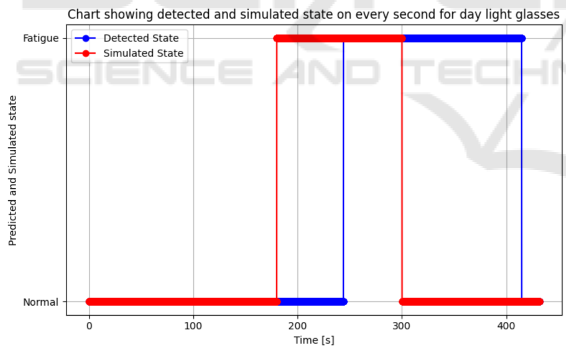

Figure 5: Chart showing detected and simulated state for video with daylight conditions with corrective glasses

The second video introduces a new variable to the baseline scenario by adding corrective glasses. This is designed to evaluate the system's ability to detect fatigue when visual obstructions or distortions caused by the glasses are present. Figure 5 shows a graphical representation of the result, similarly, as before the fatigue state has been simulated after third minute and lasts for the next two minutes. The system detected a fatigue state at 244 seconds and stopped detecting it at 415 seconds of the video. Even though the system detected the fatigue and returned to normal, the duration was extended. Comparing these results with the baseline scenario suggests that corrective glasses may increase the system's detection latency and false-positive duration.

6.3 Daylight Conversing

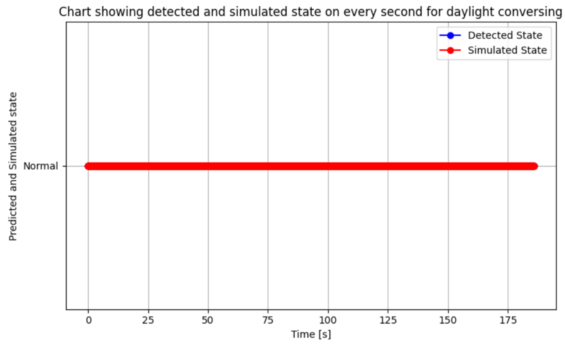

Figure 6: Chart showing detected and simulated state for video with daylight conditions while conversing.

The third video was also taken in normal daylight conditions but the subject was talking with another person. Figure 6 shows a graphical result of this scenario. The video is three minutes long, the fatigue state was not simulated, and the system has not detected it either. However, despite the physical movement of the mouth during the conversation, the system did not determine that such activity met its threshold to recognize a fatigue state. This indicates the ability to differentiate between ordinary facial activities and fatigue-related indicators.

6.4 Daylight Eating

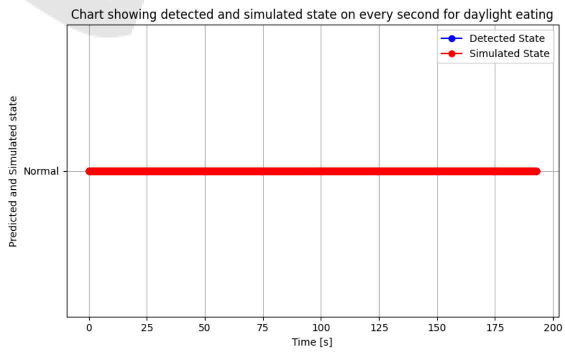

Figure 7: Chart showing detected and simulated state for video with daylight conditions while eating.

The fourth video was taken in daylight conditions and the subject was eating for three minutes without simulating the fatigue state. This scenario checks if the system detects such activity as fatigue. Figure 7 shows a graphical representation of the detection result. Those findings demonstrate that the system operates effectively in this real-world scenario, as it accurately retained from detecting any fatigue state during this activity. Even though eating involves noticeable mouth movements, the system did not classify such activity as a fatigue state. This highlights the system's ability to distinguish between context-specific facial movements and the physiological signs associated with fatigue such as yawning. The system proved once more its robustness and reliability in a real-world scenario.

6.5 Nightlight Conditions

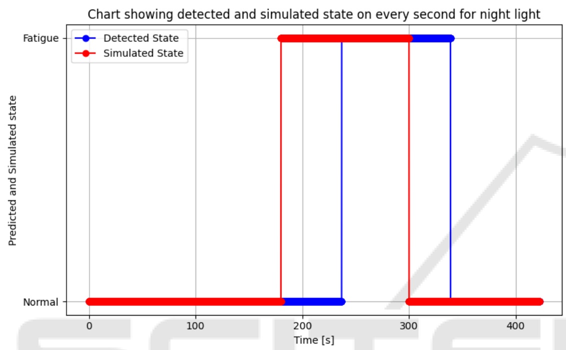

Figure 8: Chart showing detected and simulated state for video with nightlight condition.

This video was recorded in nightlight conditions and the subject did not wear corrective glasses during recording to ensure that the system was tested without interference from reflective surfaces. Figure 8 shows the detected and simulated state from the recording. Similarly, as before when fatigue was simulated, the subject started the simulation after third minute and finished the simulation after two minutes. The system detected a fatigue state at 236 seconds and stopped detecting at 339 seconds of the video. This scenario demonstrates the system's capability to detect fatigue states even in challenging lighting conditions. These findings underscore the robustness of the system in maintaining reliable performance in low-light environments. This highlights its potential utility in nighttime scenarios without the usage of infrared cameras.

6.6 Nightlight Conditions with Blinking Screen

This video was recorded in nightlight conditions and the subject did not wear corrective glasses. This scenario introduces a blinking screen to simulate the effect of passing car lights. The aim was to replicate

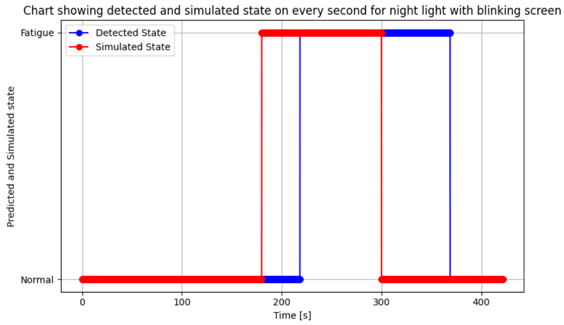

Figure 9: Chart showing detected and simulated state for video with nightlight condition with blinking light.

a common-world scenario such as driving at night, where intermittent light sources may influence visual clarity and fatigue detection. Figure 9 shows a graphical result of the detection. The fatigue simulation started in the third minute and lasted for the next two minutes. The system detected a fatigue state at 218 seconds of the video and stopped detecting it at 369 seconds. The accurate detection of fatigue under these conditions demonstrates the robustness and reliability of the system. Importantly, the blinking screen did not cause any false positives in the accuracy of the system, indicating its resilience to environmental lighting fluctuations. This result showcases the system's potential in scenarios where users are exposed to different lighting conditions.

6.7 General Results

Table 1: Detection results for different test scenarios.

Test case	Start of fatigue simulation [s]	Start of fatigue detection [s]	End of fatigue simulation [s]	End of fatigue detection [s]	Simulation duration [s]	Fatigue duration [s]
Daylight conditions without corrective glasses	180	236	300	352	120	116
Daylight conditions with corrective glasses	180	244	300	415	120	171
Daylight conversing	-	-	-	-	-	-
Daylight eating	-	-	-	-	-	-
Nightlight conditions	180	236	300	339	120	103
Nightlight conditions with blinking screen	180	218	300	369	120	151

Table 1 shows results for different test scenarios with simulation duration and fatigue duration. In tests 6.1, 6.2, 6.5, and 6.6 the blue line (fatigue detection) is shifted to the right. This is expected behavior since the system checks the 120 seconds and then examines whether the threshold has been exceeded. The same applies to the time after the simulation of the fatigue state when the system still detects drowsiness even when it was not simulated. This phenomenon results from the inertia of the detection process.

7 CONCLUSIONS

The results indicate that the system performs effectively in both daylight and nightlight scenarios, accurately identifying fatigue states when they were simulated. These results suggest that the method is robust and reliable, even in the presence of corrective eyewear. Importantly, the system also demonstrated its ability to ignore non-fatigue activities, such as conversing and eating, under daylight conditions, further confirming its accuracy and relevance in real-world driving scenarios. Nightlight conditions presented a more challenging environment, yet the system still detected fatigue with similar accuracy, even with the presence of fluctuating light sources, such as a blinking screen simulating passing car lights. These findings show that the method holds promise for practical applications in driver monitoring systems, especially in varying environmental conditions.

In conclusion, this fatigue detection method has the potential to significantly improve road safety by providing a reliable real-time solution to identify fatigued drivers. Further research and testing can be conducted to refine the response times and adaptability of the system to other driving scenarios, but the results indicate a strong foundation for future development. In addition, the authors plan to conduct broad research to compare the presented method with other existing SOTA methods, ensuring a comprehensive evaluation of its performance and potential advantages. Furthermore, the authors intend to test the performance of the system under dynamic lighting changes to assess its robustness and reliability in varying environmental conditions.

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