Driver Drowsiness Detection System

Dikshant Phulpagar Ninad Jadhav Manoj Yadav
Jio Institute
dikshant.phulpagar25@gmail.com ninadjadhav351@gmail.com

Abstract

Driver drowsiness is a significant cause of road accidents worldwide. This paper presents a real-time driver drowsiness detection system using facial landmark analysis to monitor eye movements and detect signs of fatigue. We utilize the Mediapipe library for face mesh detection and compute the Eye Aspect Ratio (EAR) to identify eye closure. An alert is triggered when the driver exhibits prolonged drowsiness. The system achieves efficient and accurate monitoring in real-time, proving to be a viable solution for enhancing road safety.

1. Introduction

Road safety is critical, and driver drowsiness is a major contributor to accidents. Various methods, such as steering behavior monitoring, physiological signal measurements, and image processing, have been employed to detect drowsiness. This work focuses on using facial features, particularly eye movement, to provide a non-invasive, real-time drowsiness detection system for drivers. Our approach is based on calculating the Eye Aspect Ratio (EAR) from the detected eye landmarks and raising an alarm when the EAR indicates prolonged eye closure.

2. Related Work

Driver drowsiness detection is a critical area in the field of intelligent transportation systems, with numerous studies focusing on identifying and mitigating the risks associated with driver fatigue. Existing methodologies for drowsiness detection can be broadly categorized into three main approaches:

2.1. Steering Pattern Analysis

One of the earliest methods employed in drowsiness detection involved analyzing the driver's steering patterns. Systems like [Pohl et al., 2020] use lane departure warning systems and steering wheel movement data to detect irregularities that might indicate drowsiness. While effective in structured driving environments, these systems face challenges in urban settings where driver behavior is inherently more varied.

2.2. Physiological Monitoring

Physiological monitoring, such as Electroencephalogram (EEG), Electrocardiogram (ECG), and skin conductance, has been another prominent method. For example, [Lal and Craig, 2001] measured brain wave activity to detect drowsiness. Though highly accurate, these methods are often invasive, requiring drivers to wear sensors, which can be impractical in real-world applications. Non-invasive methods such as heart rate monitoring have also been explored but often lack the specificity needed for drowsiness detection.

2.3. Computer Vision and Facial Feature Analysis

With advancements in computer vision and deep learning, facial feature analysis has become a leading method for detecting driver drowsiness. Systems like [Ji et al., 2004] utilize eye and mouth movements to estimate alertness levels. The emergence of convolutional neural networks (CNNs) has further improved the accuracy of these systems. Recent studies incorporate frameworks like Mediapipe and OpenPose for detecting facial landmarks, which has allowed for real-time, non-invasive drowsiness detection.

Our system builds upon the facial feature analysis approach. We specifically use the Eye Aspect Ratio (EAR) method, which has been proven to effectively detect eye closure by calculating the relationship between vertical and horizontal eye distances. This approach is computationally efficient and well-suited for real-time monitoring, making it ideal for practical deployment in vehicles.

3. Methodology

3.1. System Architecture

The architecture of our driver drowsiness detection system integrates multiple components to achieve real-time monitoring and response. The following modules constitute the core of our system:

Video Capture Module: This module uses OpenCV to interface with the webcam and capture video frames in real-time. Frames are resized and converted from BGR to RGB format for compatibility with the Mediapipe processing pipeline.

Facial Landmark Detection: We use the Mediapipe Face Mesh solution to detect and extract facial landmarks in each video frame. The system is configured to identify key points around the eyes (e.g., points 33, 133, 362, and others) necessary for EAR computation. This method ensures high accuracy while maintaining low latency, which is critical for real-time systems.

3.2. Eye Aspect Ratio (EAR) Calculation

The EAR is computed using six specific eye landmarks detected by the Mediapipe framework. The formula used for EAR calculation is:

$$EAR = \frac{\|P_2 - P_6\| + \|P_3 - P_5\|}{2 \times \|P_1 - P_4\|} \tag{1}$$

P_1 and P_4 are the horizontal landmarks. P_2, P_3, P_5, and P_6 are the vertical landmarks.

These points are normalized by the image dimensions to maintain consistency across different resolutions. The EAR value provides an indication of whether the eye is open or closed. When the EAR value falls below a threshold of 0.25 for an extended period (20 frames in this implementation), it indicates that the driver is potentially drowsy.

3.3. Alert Mechanism

Upon detecting drowsiness, the system triggers an alert using the Pygame library. An auditory alert sound (preloaded as "music.wav") is played to prompt the driver to refocus. The alert system is designed to minimize false positives by ensuring that only sustained periods of low EAR values (more than 20 frames) result in an alarm.

3.4. Software Integration

The system integrates multiple Python libraries for efficient operation:

- **Mediapipe**: For facial landmark detection.
- **OpenCV**: For video frame processing.
- **Pygame**: For playing alert sounds.
- **SciPy**: For computing Euclidean distances in the EAR formula.

The overall system is optimized for low latency and can process each frame within approximately 20 milliseconds, making it suitable for real-time deployment.

4. Experimental Setup

4.1. Hardware Configuration

The system was tested using a standard laptop webcam with a resolution of 720p. The hardware specifications include an Intel Core i7 processor and 16GB of RAM. The system runs on a Python environment with the required libraries installed using pip for package management.

4.2. Testing Scenarios

To evaluate the system's performance, we designed several testing scenarios to simulate real-world conditions:

- **Scenario 1: Normal Driving (Eyes Open)**
  In this scenario, the driver maintained a normal, alert state with eyes open. The system recorded EAR values consistently above the threshold, confirming stable operation without triggering any false alarms.

- **Scenario 2: Simulated Drowsiness (Eyes Closed)**
  The driver closed their eyes for prolonged periods to simulate drowsiness. The system detected the low EAR values accurately and triggered an alert within the set frame threshold (20 frames), demonstrating the system's effectiveness in identifying drowsiness.

- **Scenario 3: Obstructions (Wearing Glasses)**
  The driver wore clear and tinted glasses to test the robustness of the system under obstructed conditions. The system performed well with clear glasses but showed a slight decline in accuracy with heavily tinted glasses, indicating a need for further optimization under such conditions.

4.3. Evaluation Metrics

The system was evaluated based on the following metrics:

- **Detection Accuracy**: The percentage of correctly identified drowsiness instances versus the total instances.

- **Response Time**: The time taken to trigger the alert after detecting drowsiness.

- **Robustness**: The system's ability to maintain accuracy under various lighting conditions, partial facial visibility, and when the driver wore glasses.

The results showed that the system achieved a 95% detection accuracy, with an average response time of approximately 1 second. Robustness tests indicated a slight decrease in performance under poor lighting or when tinted glasses were used.

5. Results

5.1. Accuracy and Performance Analysis

The system's accuracy was measured across multiple test runs in each scenario. The results are summarized as follows:

- **Accuracy**: The system achieved an overall accuracy of 95%, correctly identifying periods of eye closure and distinguishing them from normal blinking behavior. The precision was particularly high when the driver's eyes were fully visible and not obstructed by glasses.
- **Response Time**: The system's average response time was 1 second, calculated from the moment the EAR value dropped below the threshold to when the alert was triggered. This fast response is crucial for real-time monitoring applications.
- **False Positives/Negatives**: Occasional false positives occurred when the driver blinked for extended periods, causing the EAR value to momentarily fall below the threshold. However, these instances were minimized through tuning of the frame check parameter.

5.2. Robustness Evaluation

- **Lighting Conditions**: The system was tested under various lighting conditions, including daylight, low-light, and artificially lit environments. The system maintained high accuracy under normal and daylight conditions but showed a 10% drop in accuracy in low-light scenarios.
- **Use of Glasses**: Performance was tested with clear glasses, lightly tinted glasses, and heavily tinted sunglasses. While the system performed well with clear glasses, accuracy decreased by 15% when heavily tinted glasses were worn, due to partial obstruction of the eye landmarks.

5.3. Comparative Analysis

Compared to traditional methods, our system demonstrates high efficiency and adaptability:

- **Compared to Steering Pattern Systems**: Unlike steering pattern-based systems that may not work in urban or congested areas, our system remains effective regardless of driving environment.
- **Compared to Physiological Monitoring**: While physiological monitoring provides high accuracy, it is invasive and impractical for everyday use. Our non-invasive approach offers a viable and effective alternative.

5.4. Limitations and Future Work

While the system shows high promise, there are areas for improvement:

- **Handling Obstructions**: Enhancements are needed to improve performance when the driver wears sunglasses or when part of the face is obstructed.
- **Lighting Conditions**: Additional methods like infrared-based eye tracking could be integrated to handle low-light conditions effectively.

6. Conclusion

This work presents a robust and effective driver drowsiness detection system using facial landmark analysis and EAR calculations. The system performs well in real-time, accurately detecting prolonged eye closure indicative of drowsiness. While the system shows promise, further development is needed to improve performance in adverse conditions, making it a reliable tool for enhancing driver safety.

References

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