ILKOM Jurnal Ilmiah Vol. 16, No. 2, August 2024, pp. 108-114
Accredited 2nd by RISTEKBRIN No. 200/M/KPT/2020; E-ISSN 2548-7779 | P-ISSN 2087-1716

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Driver Facial Detection Across Diverse Road Conditions

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Article history: Received December 22, 2023; Revised March 20, 2024; Accepted June 28, 2024; Available online August 20, 2024

Abstract

This study emphasizes the importance of facial detection for improving road safety through driver behavior analysis. Its employs quantitative methodology to underscore the importance of facial detection in enhancing road safety through driver behavior analysis. The research utilizes the Python programming language and applies the Haar cascade method to investigate how environmental factors such as low light, shadows, and lighting changes influence the reliability of facial detection. Employing the AdaBoost algorithm, the study achieves face detection rates exceeding 95%. Practical testing with an ASUS A416JA laptop and Raspberry Pi under varied lighting conditions and distances demonstrates optimal performance in detecting faces between 30 cm and 70 cm, with reduced efficacy outside this range, particularly in low light conditions and at night. Challenges identified include decreased performance in low light conditions, emphasizing the need for improved algorithmic calibration and enhancement. Future research directions involve refining detection algorithms to effectively handle diverse environmental conditions and integrating advanced machine learning techniques, thereby enhancing the accuracy of driver behavior analysis in real-world scenarios and contributing to advancements in road safety.

Keywords: Driver Fatigue; Facial Detection Accuracy; Road Safety; Safety Enhancements.

Introduction

Traffic accidents caused by driver fatigue pose significant challenges to road safety in many countries, including the United States and Australia. According to the National Highway Traffic Safety Administration [1]–[6], approximately 684 fatigue-related accidents occurred on US highways in 2021 alone. In Victoria, Australia, driver fatigue is implicated in 20% of fatal traffic accidents; in Queensland, it contributes to 20-30% of traffic accidents. Indonesia National Transportation Safety Committee (KNKT) [7] reported similar findings. Between 2018 and 2022, KNKT identified human factors as the primary cause of 36 out of 57 accidents. Their investigations revealed that around 80% of accident causes were attributed to driver fatigue, leading to decreased alertness and microsleep episodes [8]. Driver attention [5], [9]–[11] can be distracted by various factors, including cell phone use [12]–[14], adjusting radio stations, eating, and daydreaming. Additionally, drowsiness from stress or fatigue can slow driver reaction times, increasing the likelihood of accidents. Various symptoms can indicate driver drowsiness or impairment, with driver facial expressions as a primary indicator [4]. This study aims to evaluate the performance and reliability of devices that detect driver facial expressions in various road conditions, particularly during morning, afternoon, evening, and nighttime. Facial expressions are a type of nonverbal communication that conveys information about an individual's emotional state. Due to their driving behaviors and habits [5], [9], [15]–[17], drivers exhibit different driving styles [16], experiences [16], and emotions [13], [18]–[20]. The detection and recognition of human emotions remain significant tasks in computer vision (CV) and artificial intelligence (AI) [21]. Driver facial detection is a critical technology for road safety and security. Facial detection is easy to implement, cost-effective, and can be performed using commonly available cameras [18], [22]–[26]. However, challenges may arise when detecting facial features such as hair, glasses, hats, and other accessories due to variations in lighting, facial expressions, and individual body postures [27]. While these systems find applications in security, control systems, and others, noise often occurs during face detection in digital images [28]. Real-time sleep detection models monitor driver behavior to detect moments when drivers feel drowsy [29]–[33]. Object detection systems have achieved a success rate of up to 80% [34]. However, these methods require expensive sensors for data processing [35]–[37]. To address these requirements, affordable, portable, secure, fast, and accurate systems have been proposed [4]. Successful face detection has been achieved within distances of 1-2 meters [28]. A tested system achieved an 82% accuracy in indoor environments and a 72.8% positive detection rate in outdoor environments [4]. OpenCV provides highly efficient object detection functions based on the Haar cascade Viola-Jones classifier for frontal face detection [5], face recognition using Eigenface and Haar in OpenCV [25] and eye detection on the Android platform for comparing closed-eye frequencies [38]. The Viola-Jones algorithm consists of four stages: integral image, Haar features, cascade, and AdaBoost [25],

http://dx.doi.org/10.33096/ilkom.v16i2.1996.108-114

[39]. The Haar cascade method is commonly used for face detection due to its efficient image processing and rapid identification of facial features. However, the reliability of face detection using the Haar cascade method for driver facial detection may be affected by environmental disturbances such as low light [35], shadows [40], or changes in lighting conditions [17], [39], [41]–[44]. This algorithm utilizes the AdaBoost method to train the face detector, employing a combination of different weak classifiers to form a strong classifier. The advantage of this technique lies in its ability to create layered detectors and perform intensive pre-processing in crucial regions. Detection rates using this method exceed 95%. This study aims to utilize the Viola-Jones algorithm (Haar Cascade) for driver facial detection, focusing on distinguishing between attentive and distracted driver behaviors in various road conditions and times. The objective is to produce practical outcomes for wide-ranging applications, especially on cost-effective devices with limited resources, thus validating the model's potential to enhance road safety under the complexities and uncertainties of real-world driving conditions.

Method

The Viola-Jones algorithm, developed by P. Viola and M. Jones in 2001 [45], is a powerful tool for detecting driver drowsiness by focusing on the eye region. By utilizing OpenCV's Haar classifier cascades, the algorithm efficiently detects both faces and eyes in images [5]. Mathematically,

$$F = \sum_{white} I(x,y) - \sum_{black} I(x,y) \tag{1}$$

where is $I(x,y)$ the pixel intensity at location (x,y)

$$II(x,y) = \sum_{i=0}^{x} \sum_{i=0}^{y} I(i,j) \tag{2}$$

$$J = \sum_{i=0}^{n} w_i \mid h(x_i) - y_i \mid \tag{3}$$

where w_i is the weights, $h(x_i)$ is the weak classifier prediction, and y_i is the actual label.

This feature-based approach enables direct monitoring of eye state, mouth state, and head pose, providing valuable insights into the driver's level of drowsiness [46]. Through a series of stages and the implementation of weak classifiers trained with the AdaBoost algorithm, the Viola-Jones algorithm accurately detects faces [47]–[49].

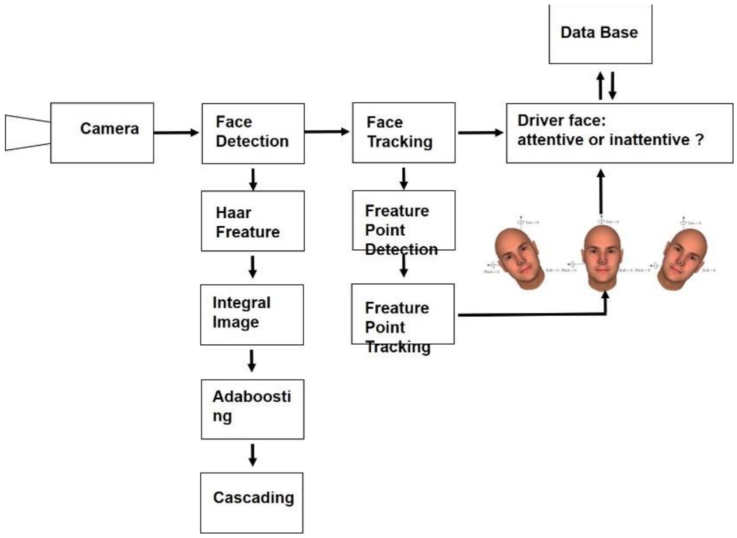

Figure 1. Stages of The Viola-Jones Algorithm

It facilitates the analysis of driver behaviors and attentiveness (**Figure 1**). The research methodology employed a quantitative approach to detect drivers' faces using an ASUS A416JA laptop and a Raspberry Pi. Data were collected through the laptop's webcam and the Raspberry Pi camera module, capturing images and videos under various lighting conditions and distances. OpenCV was utilized for image processing and face detection by Phyton. The analysis, which was conducted using Google Colab, examined the camera's response to motion over time, driver movement behavior, the suitable camera distance for successful face detection, and detection patterns at various light intensities. A relational matrix of detected motion, detected face features, and detected faces was analyzed to evaluate the system's detection effectiveness. The results aimed to provide insights into the optimal settings for accurate face detection in different driving scenarios.

The installed camera produces clear responses, indicating that the driver's behavior tends to be distracted and lacking focus. The driver's head movements reaching a 180-degree angle indicate significant inattentiveness to the road and the surrounding situation. The camera can capture the driver's face effectively and can classify whether the driver is attentive or not (**Figure 2**). The camera detected motion within the given time range, specifically from seconds 1 to 6 (**Table 1**).

Results and Discussion

Figure 2. Camera capture of the driver's attentive face and negligent driver behavior

Table 1. Camera Response to Detected Motion Over Time

Time (seconds)	Camera Response	Motion Detected
1	Detected	Not captured
2	Detected	Not captured
3	Detected	Not captured
4	Detected	Not captured
5	Detected	captured
6	Detected	captured

Although motion was detected by the camera from seconds 1 to 4, the camera's response was unsuccessful in capturing the motion. The camera detected motion but did not capture it for the first four seconds; it successfully captured the motion after four seconds (Figure 3).

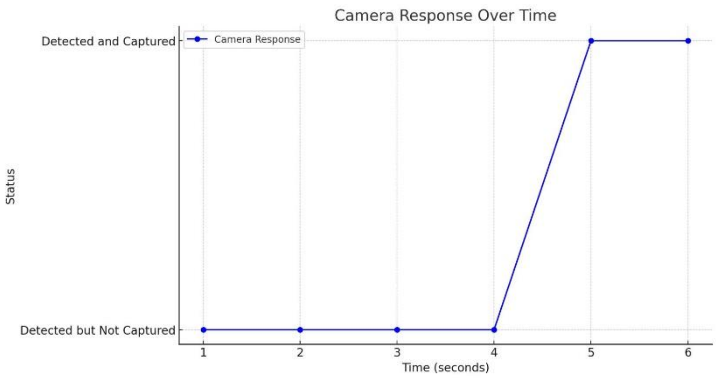

Figure 3. Camera Response Over Time

This could be attributed to various factors, such as data processing errors or the camera not recording them. However, at seconds 5 and 6, the camera's response successfully captured the detected motion (Figure 3). Table 2, A specific distance was the most effective in detecting the driver's face using the camera. The placement of the camera and proper distance settings can enhance the success of face detection and provide accurate data for driver behaviour analysis.

Table 2. Driver Movement Behavior and Camera Distance Suitable for Successful Face Detection

Distance (cm)	Face Detected
10	Not detected
20	Not detected
30	Detected
40	Detected
50	Detected
60	Detected
70	Detected
80	Not detected
90	Not detected
100	Not detected

Figure 4, an optimal range between 30 and 70 cm is where the camera consistently detects the driver's face. Beyond this optimal range, whether too close (below 30 cm) or too far (above 70 cm), the camera fails to detect the driver's face.

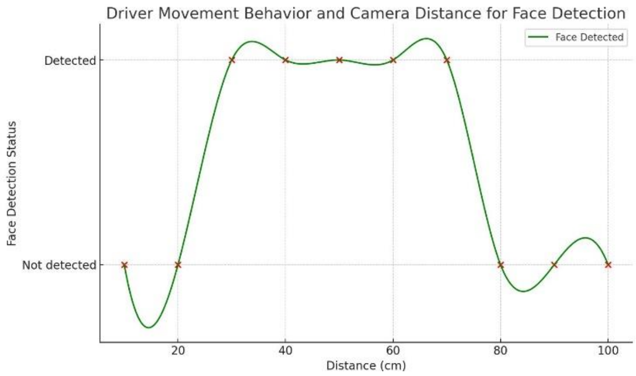

Figure 4. Driver Movement Behavior And Camera Distance For Face Detection

The camera successfully detected the driver's face during the morning and daytime when the light intensity was high. However, in the evening, although the driver's face was still detected, the number of detections tended to be lower. During the nighttime, the camera could not detect the driver's face due to low light intensity. Thus, light intensity was an important factor that affected the camera's ability to detect the driver's face (Table 3).

Table 3. Detection Patterns at Various Light Intensities

Time Days	Face Detected	Min (Lux)	Average (Lux)	Max (Lux)
Morning	Yes	3276	3655	4034
Afternoon	Yes	8775	9765	10755
Afternoon	Yes	450	490	530
Evening	No	274	282	290

Although movements were detected at certain seconds, the camera's response failed to capture those movements. It was also observed that the camera did not always successfully detect the driver's face at a specific distance. The importance of optimal camera settings and conditions for generating accurate responses and detections was evident. Improvements in data processing or camera settings may be necessary to enhance the response to detected movements.

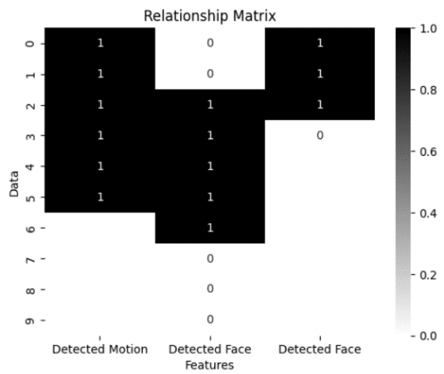

Figure 4. Relation Matrix Detected Motion, Detected Face Features, and Detected Face

The significance of the appropriate distance for the camera to consistently detect the driver's face was highlighted. In both cases, understanding the factors that influence the camera's response, such as settings, data processing, light intensity, and distance, is crucial to ensure good performance and accurate results from the camera (Figure 4). The relationship matrix revealed the correlation between detected motion, detected face features, and detected faces. The data showed that motion detection was consistent in data sets 0 through 6, while face features were detected only in specific instances (data sets 3 and 5). The face itself was detected in data sets 3 and 6. However, no detections (motion, face features, or faces) occurred in data sets 7 through 9. These findings indicated that while motion detection was reliable, it did not always lead to the detection of face features or the face itself. This underscored the need for optimized detection algorithms and conditions to ensure that detected motion consistently resulted in accurate face detection.

Conclusion

In conclusion, this research revealed that the effectiveness of using the Haar cascade method for detecting driver facial features is influenced significantly by environmental factors such as low light, shadows, and variations in lighting conditions. By employing the AdaBoost algorithm, the system achieved a robust detection rate exceeding 95%. The study also utilized the Viola-Jones algorithm (Haar Cascade) to distinguish between different levels of driver attentiveness across various road and time conditions. Images and videos were successfully captured using an ASUS A416JA laptop and Raspberry Pi under different lighting and distances. Motion detection consistently operated from seconds 0 to 6, while optimal facial detection primarily occurred during seconds 5 and 6, specifically within distances ranging from 30 cm to 70 cm. However, performance declined noticeably outside of this range, especially in low light situations such as nighttime. The study underscored the necessity for refining algorithms to ensure consistent facial feature detection. Future research should concentrate on enhancing detection algorithms to effectively manage diverse environmental conditions, refining data processing and camera calibration to enhance accuracy, particularly in low-light settings. Validating these systems on cost-effective devices would demonstrate their potential to enhance road safety. Moreover, integrating advanced machine learning techniques could further elevate the precision and dependability of driver behavior analysis.

Acknowledgment

Politeknik Keselamatan Transportasi Jalan and Universitas Kristen Satya Wacana supported this work.

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