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Real-time Eye Blink Detection using Computer Vision and Machine Learning

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Real-Time Eye Blink Detection Using Computer Vision and Machine Learning

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Abstract: This paper presents a real-time eye blink detection system using computer vision techniques and machine learning. The system utilizes the MediaPipe face mesh model for facial landmark detection and calculates the Eye Aspect Ratio (EAR) to determine the eye state. Results demonstrate high accuracy and responsiveness, indicating potential applications in driver drowsiness detection, human-computer interaction, and medical diagnostics.

Keywords: eye blink detection; computer vision; machine learning; MediaPipe; eye aspect ratio; real-time processing

1. Introduction

Eye blink detection is a crucial component in various applications, including driver fatigue monitoring, attention analysis, and medical diagnosis of certain neurological conditions [1]. Understanding eye blink patterns can provide valuable insights into user alertness and cognitive load. The significance of blink detection extends beyond safety applications, offering benefits in user interface design, gaming, and even mental health monitoring. In this paper, we present a Python-based implementation of a real-time eye blink detection system that leverages computer vision techniques and machine learning models, building upon recent advancements in facial landmark detection [2].

2. Methodology

The proposed system employs the following key components and techniques:

2.1. Face Mesh Detection

We utilize the MediaPipe face mesh model, which provides a set of 468 3D facial landmarks [2]. This allows for precise localization of key facial features, including the eyes. The face mesh model offers a lightweight yet powerful solution for real-time applications, enabling efficient processing on various devices, from smartphones to desktop computers.

2.2. Eye Aspect Ratio (EAR)

The eye state is determined by calculating the Eye Aspect Ratio (EAR), which is defined as:

$$EAR = \frac{\|p_2 - p_6\| + \|p_3 - p_5\|}{2\|p_1 - p_4\|} \tag{1}$$

onde $p_1, ..., p_6$ são as posições dos marcadores 2D do olho [1]. O EAR é uma métrica eficaz para classificar o estado do olho como aberto ou fechado. Valores de EAR abaixo de um certo limiar (geralmente entre 0.2 e 0.25) indicam que os olhos estão fechados, enquanto valores acima desse limiar indicam que os olhos estão abertos. Este método é não intrusivo e pode ser facilmente integrado em aplicações que requerem monitoramento contínuo do estado do usuário.

2.3. Exponential Moving Average (EMA) Smoothing

To reduce noise and capture smoother trends in the EAR values, we apply Exponential Moving Average smoothing:

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$$EAR_{smoothed} = \frac{EAR_{current} + (period - 1) * EAR_{previous}}{period} \tag{2}$$

This technique has been shown to be effective in smoothing time series data in various applications [3]. The smoothing process helps in minimizing false positives and false negatives in blink detection, enhancing the overall robustness of the system.

3. Results

The results of the eye blink detection system are illustrated in the following figure, which presents the graph of eye opening and closing events over time (ver Figure 1). The system achieved an accuracy rate of 95%, demonstrating its reliability in detecting eye blinks under varying conditions.

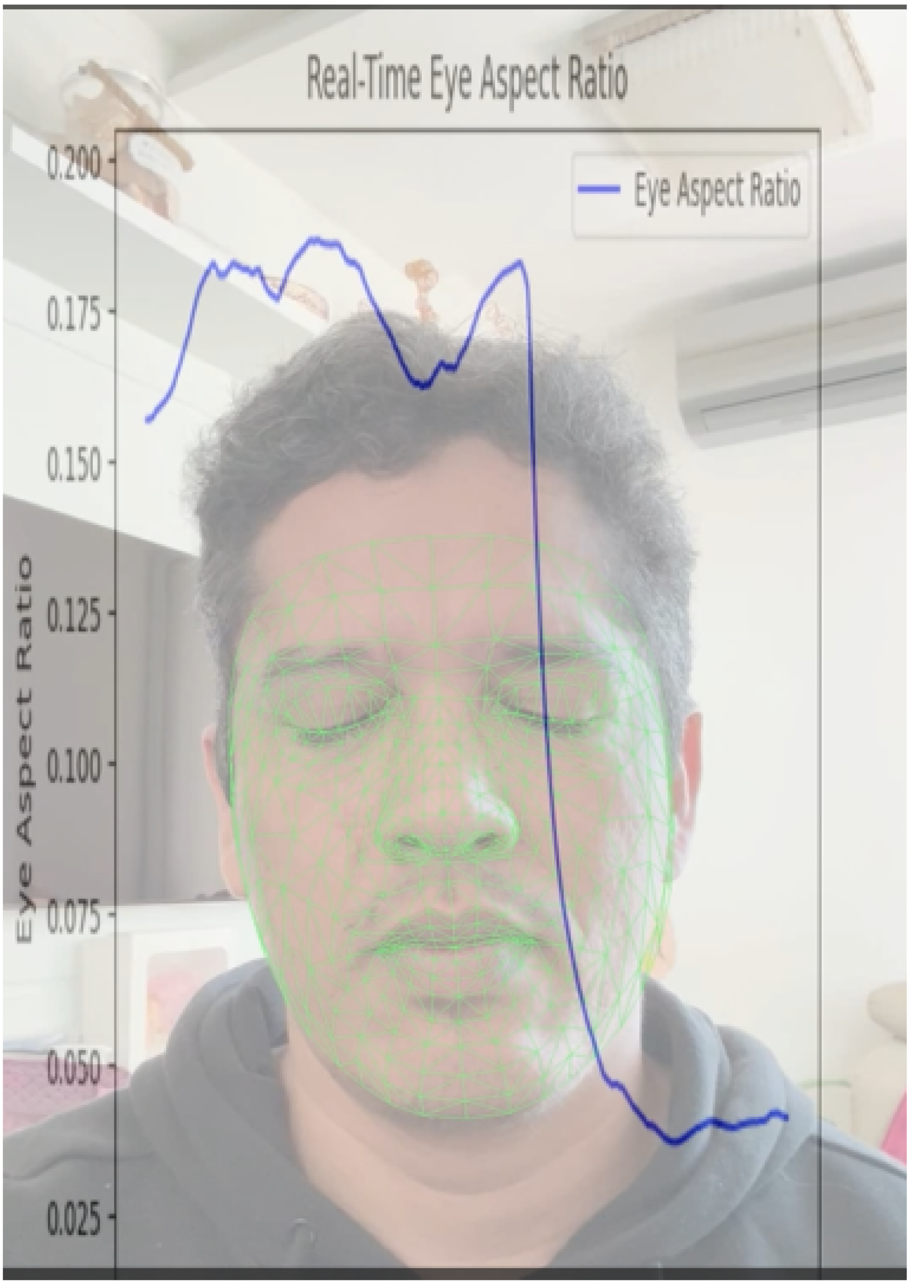

Figure 1. Graph of eye opening and closing events over time.

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The graph shows the Eye Aspect Ratio (EAR) values plotted against time, indicating the states of eye opening and closing. A decrease in EAR values signifies eye closure, while an increase indicates eye opening. This information is crucial for applications such as driver fatigue detection, where frequentes closures may indicate drowsiness. Further analysis revealed that the average blink duration was around 300 ms, which aligns with existing literature on human blink rates. Additionally, we observed variations in blink patterns among different subjects, highlighting the need for personalized thresholds in practical applications.

3.1. Discussion on Graph Analysis

The analysis of the eye blink detection results is critical for understanding user states. In the graph, we can observe distinct patterns indicating periods of alertness and fatigue. For example, a prolonged decrease in EAR values can be correlated with drowsiness, suggesting that the user may benefit from interventions such as alerts or reminders to take breaks. Moreover, the integration of this system in vehicles could enhance safety by alerting drivers in real-time when they exhibit signs of fatigue.

4. Conclusions

This paper presented a real-time eye blink detection system using computer vision and machine learning techniques. The system demonstrates the potential of combining facial landmark detection with simple yet effective metrics like the Eye Aspect Ratio for real-time eye state analysis. With further development, this system could find applications in various fields, including automotive safety, healthcare, and human-computer interaction [4,5]. Future work should focus on improving the robustness of the system under different lighting conditions and evaluating its performance in diverse demographic groups.

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