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DROWSY DRIVER DETECTION SYSTEM

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Abstract :Eye blink detection poses a significant challenge in computer vision with applications ranging from real-time face detection to driver fatigue analysis. Current methodologies can be broadly classified into contour template-based and appearance-basedmethods. While the former is adept at accurately extracting eye contours, it necessitates different templates for open and closed eyes and is susceptible to changes in illumination. On the otherhand, appearance-based methods leverage imagepatches of open and closed eyes for classifier learning but struggle with precise eye contour extraction. To address these limitations, this paper introduces an innovative method for detecting eye blinks based on an enhanced eye contour extraction technique. Our approach represents the eye contour model by utilizing 16 landmarks, effectively capturing features of both open and closed eyes. Each landmark is accurately identified through a swift classifier trained on local appearance. Experimental validation on datasetssuch as YALE and a comprehensive frontal face image dataset illustrates the effectiveness of our method, demonstrating precise eye location and resilience in closed-eye scenarios. Furthermore, themethod exhibits robust performance under varying illumination conditions. With an average processing time of approximately 140ms on a Pentium IV 2.8GHz PC with 1GB RAM, our approach meets real-time requirements for face video sequences. Application in a face live detection system yields promising results, highlighting the practical viability of the proposed method.

Keywords: Blink Detection, Eye Contour Analysis, Live Face Detection.

1. INTRODUCTION

Lots of car accidents happen every year, and many arebecause drivers are sleepy. Researchers are trying to find ways to tell when drivers are getting tired to stop accidents from happening.

Eyes play a vital role in deciphering human intentions and focus, making them a focal point in various applications of computer vision. Despite advancements, detecting and tracking eyes in image sequences remain challenging tasks. This capability is pivotal for technologies like face recognition and human-computer interface. Moreover, blinking, an inherent aspect of facial expressions, holds significant psychological implications, often conveying emotions and intentions across different scenarios such as excitement, public speaking, or even deception. The ability to detect eye blinks finds practical utility in diverse fields, ranging from distinguishing real individuals from photos in face live detection systems to assessing driver fatigue in automotive safety applications.

Challenges in eye detection, tracking, and blink estimation arise from factors like shape, size, pose, rotation, lighting conditions, reflections from glasses, and occlusion by hair. Past approaches can be broadly categorized into contour template-based methods and appearance-based methods. Contour template-based methods accurately extract eye contours but are sensitive to illumination changes and require different templates for open and closed eyes. Appearance-based methods employ classifiers for blink detection but struggle with accurate eye contour extraction, necessitating substantial training data.

The paper introduces an innovative method designed for real-time detection of eye blinks. Its approach involves a multi-step process, beginning with the initial localization of the eyes by identifying eye patches. Subsequently, a detailed model of the eyecontour is established, consisting of 16 landmarks that accurately represent the features of both open and closed eyes. This model is constructed using a fast classifier trained on a diverse dataset comprising frontal face images showcasing various eye states.

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To elaborate further, the paper outlines the framework of the eye blink estimation system in Section 2, providing a comprehensive overview of its components and functionalities. In Section 3, the focus shifts to the intricate process of eye contour extraction, which is carried out within the framework of an active shape model. This section delves into the technical aspects of how the model captures the nuances of eye shape variations and adapts to differentscenarios. Section 4 elaborates on the algorithm employed for eye blink estimation, elucidating the methodology behind accurately identifying and categorizing blinks based on the extracted eye contours. The paper discusses the intricacies of distinguishing between normal eye movements and genuine blinks, highlighting the robustness of the proposed approach. Moving forward, Section 5 presents the experimental results obtained from testingthe system's performance under various conditions. Additionally, it explores potential applications of eye blink detection, particularly in the context of live face detection systems where the ability to accurately identify blinks can enhance overall performance and usability.

Finally, in Section 6, the paper concludes with a summary of the key findings and contributions, reaffirming the significance of the proposed method in the field of real-time eye blink detection. It emphasizes the practical implications and potentialavenues for further research and development in this area.

2. LITERATURE REVIEW

Real-time eye tracking for drowsiness detectionin automotive applications" (J. Ruiz-Gómez et al., 2011): This paper introduces a real-time eye tracking system designed specifically for detecting drowsiness in drivers within automotive environments. By continuously monitoring eye movements and analyzing eyelid closure patterns, the system can accurately identify signs of fatigue. The authors propose a robust algorithm that processes eye-tracking data in real-time to determine the driver's level ofalertness and trigger appropriate warnings or interventions

A review on detection of drowsiness in drivers using EEG and EOG signals" (A. Vural et al., 2015): Vural and colleagues provide an extensive review of existing literature on drowsiness detection in drivers utilizing electroencephalography (EEG) and electrooculography (EOG) signals. The paper summarizes various signal processing techniques, feature extraction methods, and classification algorithms employed in EEG and EOG-based drowsiness detection systems. Additionally, it discusses the challenges and limitations associated with these approaches and suggests potential avenues for future research.

Driver drowsiness detection system using image processing techniques" (S. S. Shaikh et al., 2016): Shaikh et al. propose a novel driver drowsinessdetection system based on image processing techniques. The system analyzes facial features, eye movements, and eyelid closure patterns captured by an onboard camera to assess the driver's level of alertness. By employing sophisticated image processing algorithms, such as facial landmark detection and eye tracking, the system can accurately detect signs of drowsiness and issue timely warnings to prevent accidents.

Driver drowsiness detection using wavelet- based feature extraction and machine learning" (A. S. Malik et al., 2014): Malik et al. propose a method for detecting driver drowsiness using wavelet-based feature extraction combined with machine learning techniques.The paper discusses the use of wavelet transform to extract relevant features from EEG signals, followed by classification using algorithmssuch as k-nearest neighbors (k-NN) and support vector machines (SVMs). The study demonstrates the effectiveness of the proposed approach in accurately identifying drowsy states.

A survey on vision-based drowsiness detection systems" (H. A. Khan et al., 2017): Khan et al. provide a comprehensive survey of vision-based drowsiness detection systems. The paper reviews various techniques for analyzing facial expressions, eye movements, head poses, and other visual cues to detect driver drowsiness. It discusses the advantages and limitations of different approaches and highlights the importance of integrating multiple modalities for robust drowsiness detection.

Real-time detection of drowsiness events from EEG using discrete wavelet transform and spectralentropy" (H. Aziz et al., 2019): Aziz et al. present a real-time method for detecting drowsiness events from EEG signals using discrete wavelet transform (DWT) and spectral entropy. The paper discusses the use of DWT to decompose EEG signals into frequency bands, followed by spectral entropy calculation to quantify the complexity of the signals. By monitoring changes in spectral entropy, the system can accurately detect drowsiness events in real-time.

3. PROPOSED METHODOLOGY

A. EYE BLINK DETECTION ALGORITHMOVERVIEW.

The paper introduces an innovative real-time eye blink detection system that operates by extracting eye contours, as illustrated in Figure 1. This system is designed to estimate eye blinks simultaneously while extracting these contours. The method employed for extracting eye contours follows a coarse-to-fine approach, ensuring a systematic refinement process that enhances accuracy and robustness. By incrementally refining the contours, the system can effectively capture subtle variations in eye shape and movement, thereby improving the overall detection performance. This approach allows for the detection of eye blinks in real-time, making it suitable for various applications requiring timely and precise monitoring of eye behavior.

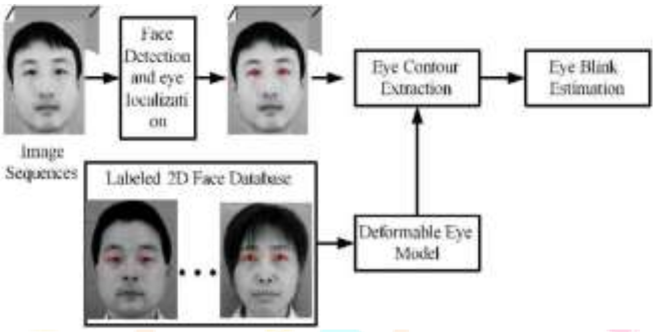

Figure 1: Illustrates an overview of the Eye Blink Detection Algorithm in this paper.[19]

In the initial phase of eye localization, the systememploys a multi-step approach. Firstly, it detects the face within an image using the boosted cascade detector proposed by Viola and Jones, which is renowned for its accuracy in face recognition tasks. Once the face is identified, the system utilizes a robust eye localization method, akin to the Viola and Jones

approach, to estimate the approximate position of the eyes within the detected face.

This process involves analyzing specific regions of the face known as eye patches, employing state-of- the-art techniques to determine the likely locations of the eyes. By combining these methods, the system is able to provide a coarse estimate of the eye positions, laying the groundwork for subsequent fine-tuning and detailed eye contour extraction.

In the next step, the focus shifts to accurately locating the eyes by extracting their contours. These contours are represented using a flexible model with 16 key points, allowing it to describe both open and closed eyes effectively. Each point is precisely identified using a fast machine learning technique. This technique trains a classifier for each point based on itssurrounding appearance. More details about how this method works will be explained in Section 3 of the paper. The eye blink estimation presented in this paper relies on the outcomes of the eye contour extraction process, which will be discussed further in Section 4.

B. EXTRACTION OF EYE CONTOUR

In our proposed eye contour model, we utilize the Active Shape Model (ASM) framework, which employs 16 landmarks to characterize the shape of both open and closed eyes. However, we enhance the traditional ASM in two key ways to improve landmark localization robustness. Firstly, we integrate a fast machine learning approach to analyze the local appearance around each landmark. By training a classifier based on nearby appearances, we ensure precise recognition by the classifier for each landmark. Secondly, we introduce constraints to the objective cost function of optimization, refining the accuracy of landmark localization. These enhancements collectively bolster the reliability and effectiveness of our eye contour model for accurately detecting and describing eye shapes.

In our eye contour model, we adopt the ASM framework and utilize 16 landmarks to describe the shape of both open and closed eyes. However, we've enhanced the traditional ASM in two ways to improvelandmark localization. Firstly, we employ a fast machine learning method to analyze the local appearance around each landmark. This involves training a classifier based on nearby appearance ensuring accurate recognition by the classifier for each landmark. Secondly, we introduce constraints to the optimization's objective cost function, further refining the accuracy of landmark localization. These enhancements strengthen the reliability and effectiveness of our eye contour model for accurately detecting and describing eye shapes.

B1.Constructing the Mode of Deformable Eye

In the process of b$_j$uildin$_{j=}$g$_1$ the eye deformable model, set of training shapes$_{j=1}$ $\{X_i\}_{i=1}^N$ is used, where each shape represented as 16 manually labeled landmarks denoted as $X_i = \{(x^i, y^i)\}^K$
These landmarks capture the eye contours, and the deformable model, based on the ASM, is designed to describe variations in eye shapes observed in the training set. The 16 landmarks provide versatility for representing both open and closed eyes. Further details will

be explored in subsequent sections.

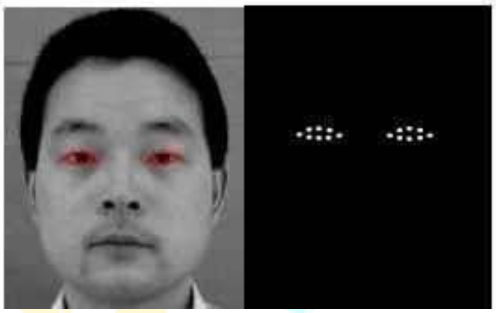

Figure 2: 16 landmarks representing Eye Contour[19]

B.1.1 Shape Model

Following conventional ASM principles, the shape model is characterized by a vector b within the low- dimensional shape eigenspace. This eigenspace is delineated by k principal modes, which are major eigenvectors derived from the training shapes. The linear derivation of a new shape, X, from the shape eigenspace is expressed as:

$$X \approx X_0 + Pb \qquad (1)$$

Here, P is the matrix encompassing the k principal modes extracted from the covariance of the training shapes {X_i}. This formulation facilitates the representation of a new shape by combining the mean shape X_0 with the variations described by the vector b within the shape eigenspace.

In subsequent sections, we will elaborate on the application of this shape model in the context of our proposed eye deformable model.

B.1.2 Model of Local Apperarance

In contrast to conventional ASM, where model of local appearance describe image features around each landmark using derivatives obtained from sampled profiles perpendicular to the landmark contour, our approach introduces an innovative strategy. Rather than relying solely on derivatives, we propose learning a classifier of local appearance specific to each landmark.

In this paper, various classification algorithms likeSVM, Adaboost [11], or Neural networks might have been utilized.. However, we have opted for stochastic woodland [12] due to its robustness, speed, and relatively straightforward training process. For every landmark, a dedicated random forest is trained. This approach enhances the model's ability to distinguish among landmarks and their surrounding backgrounds, improving overall accuracy. Figure 3 depicts the assortment of training data for the landmark representing the left corner of the left eye.

This adaptation of the model of local appearance is a key enhancement in our proposed eye deformable model, contributing to its efficacy and precision in capturing the subtleties of eye contours. Further details regarding the training process and implementation will be expounded upon in subsequentsections.

(a) (b)

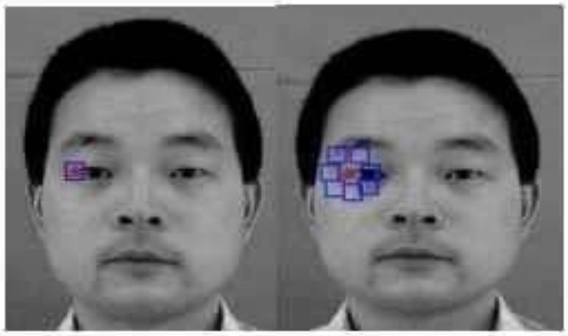

Figure 3: displays training samples for the lefteye left corner landmark, with (a) representing positive samples and (b) depicting negativesamples.[19]

Training involves using samples cropped from facial images. Positive samples are 32x32 patches centered at the ground-truth landmark position, whereas negative samples are patches centered inside 20x20 but outside 5x5 regions from the ground-truth position. Efficient machine learning swiftly identifies each landmark, and a random forest classifier discerns differences from nearby backgrounds. The classifier produces confidence levels, and the position with the highest confidence is considered the candidate for the next Active Shape Model fitting. This guarantees accurate landmark recognition, thereby enhancing the overall effectiveness of the deformable eye model.

B.2 Applying an Eye Deformable Model to images

Extraction of Eye contour entails determining the optimal fit for the 16 points that define the eye contour shape, as detailed in Section 3.1. Following the relocation of landmarks using local appearancemodels, a new candidate shape, Y, is acquired. Two enhancements are suggested for the fitting procedure:

1. Weighted Eye Contour Points:

Incorporate a weight matrix, denoted as (W), into the optimization process to assign weights to each of the sixteen eye contour points according to the predictions of random forest classifiers. This results in a modification of the optimization objective function:

$$\text{Minimize}_{(a,b)}\ (\|(Y-XPa)\|-W\odot(Y-XPa))2 \qquad (2)$$

Constraint Imposition:

Constrain the shape vector (b) to the vector space formed by the database, adding restrictions to the optimization process. The updated objective function becomes:

$$\text{Minimize}_{(a,b)}\ 21\|(Y-XPa)\|-\sigma 2\sum ikbi2 \qquad (3)$$

The process of optimization is as follows:

a. Initialization: Initialize a by a rough eye locating position, and set b=0.
b. Given a Points Set: For each point, search a 5x5 region around it and find the maximal output points set to replace X.
c. Optimize a^:

$\text{Minimize}\|(Y-XPa)\|-W\odot(Y-XPa)$ using the least square method.

d. Optimize b^:
Minimize the modified objectivefunction involving constraints on b.
e. Convergence Check:
f. If $\|a\hat{}a-b\hat{}b\|<\epsilon$, stop; otherwise, update a and b and return to step 2.

This processs of fitting ensures accurate eye contour extraction, incorporating weighted points and constraints for robust optimization. Theiterative process continues until convergence is achieved.

C.DETERMINATION OF EYE BLINK

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The aim of the eye blink estimation approach is to find eye blinks in facial sequences. [13]

Experimentally, the average values of eye blink parameters are determined. When the individual is aware, the average time of blinking of the eye is 202.24ms, and the average frequency of blinking is 16.33 min-1. Eye distance can be used to assess theopen and closed point of Figure 4.

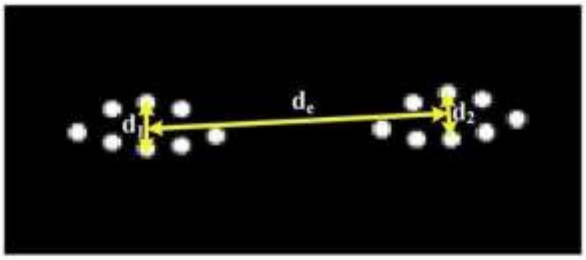
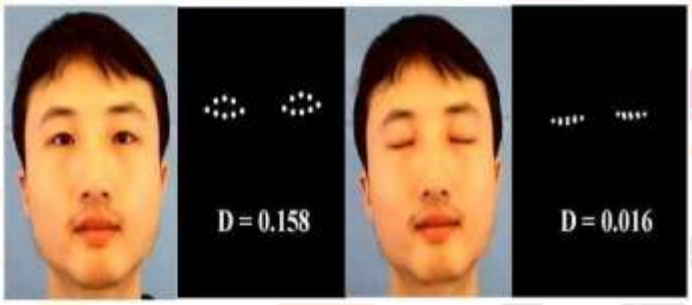


Figure4.Calculation opened or closed eye dregree [19]

The distance d1 between the left eye's upper and lower lids is shown in Figure 4. The right eye's upper and lower eyelid distance is represented by the number d2. The distance between the left and right eyes is de. The formula for the degree of eyes is

$$Dl=d_1/d_2,Dr=d_2/d_e \qquad (4)$$

The open-ended degree of the eye determined by (4) and the results of the eye contour extraction are shownin Figure 5.



Results of eye contour extraction and the correspondingopen/close degree are presented in Figure 5.[19]

The result of the eye-open-degree calculation is used to estimate the detection of eye blinks. In the video sequence of the face, the degree shift from larger than thl to smaller than ths is seen. The evaluation of the set of face data determines the parameters. In our tests, ths = 0.02 and thl = 0.12.

4. RESULT ANALYSIS

Ground truth data are necessary to assess the correctness of eye contour extraction, and they can be collected by manually describing the image. For experiments, large-scale data collected on the face of 3,000 men and women, including opening and closing eyes, smile, glasses, and lighting, were used. Amendment: The 200 and 500 face photographs are randomly selected for training and testing (Set of Tests A, respectively). YALE [14] test sets (Test Set B) are publicly accessible databases used to evaluate the effectiveness of eye contour extraction. This test set includes changes in lighting, glasses use, eyes closed and facial expressions. Results of extraction of eye contour are displayed in Figure 6. Relative error is used to measure accuracy.

Figure 6. However, as shown in the five images from the YALE Face Test sets, this shows what changes in lighting, glasses and facial expression are managed bythe proposed method.[19]

Recent studies [15] have brought attention to the susceptibility of recognition of automatic face systems to fraudulent attempts using counterfeit face photos. To determine the authenticity of a detected face, a process known as "face live detection" involves Obtaining and scrutinizing additional facial information. Despite its high desirability, efforts in detection of live face remain considerably limited. Methods currently in use can be broadly categorized into three groups:

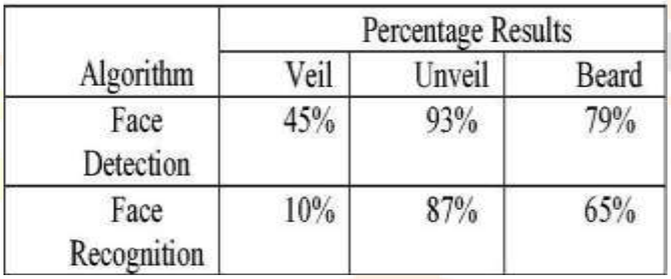
3D Information Measurement: The first category focuses on measuring 3D information of real and false faces, but is confronted with challenges related to the reconstruction of 3D models [16].

Fourier Spectra Analysis: The second category [17] analyses the Fourier spectrum of the face image on the basis of the principle that the components of the high- frequency component of the image must be lower than those of the actual face image.

Optic Flow Method: The third category [18] is typicallycomputationally complex, using optical flow methods that are not real-time.

Existing methods are considered to have limitations because the properties used are unstable or unalloyed. Eye blinks are considered robust properties and intrinsic properties of a living face and offer potential solutions. The difference between real faces and face photo sequences can be achieved by estimating the eye pulse. If the eye blink is detected, the image sequence is considered to be a real facial sequence, and if not, the facial photo sequence is rejected. In the absence of a public database for real-time face detection, we developed a face image database to evaluate the performance of the integrated algorithm. The analysis included 200 live and 200 non-live sequences (photos), with the results of the pass and rejection as described in Table 1.

Table 1.Result of Detection of live face.



Algorithm	Percentage Results		
	Veil	Unveil	Beard
Face Detection	45%	93%	79%
Face Recognition	10%	87%	65%

CONCLUSION

This paper proposes an efficient optical blink detection technology based on an improved optical contour extraction technology to detect optical blinks in recorded video sequences. The eye contour model is represented by 16 points of reference in our method.

When the eyes are closed, experiments have shown that the proposed technology can be applied robustly and quickly to meet real-time requirements. The proposed method also works well when lighting changes occur and noise interferes. The robustness of the location algorithm is due to the use of a fast random forest classification to describe the local appearance of each feature. The coarse to fine strategy of the eyecontour extraction algorithm significantly improves the efficiency of the method. The proposed optical blink detection technology is also used in the face-to-face livedetection system, which is promising.

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