International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 06 Issue: 07 | July - 2022 Impact Factor: 7.185 ISSN: 2582-3930

A SURVEY ON REAL-TIME EYE BLINK DETECTION USING FACIAL LANDMARKS

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Abstract:

In many contexts, such as facial movement analysis and signal processing, blink detection is a crucial approach. However, due of the blink rate, automatic blink detection is quite difficult. This study suggested a real-time technique for identifying eye blinks in a series of videos. Automatic facial landmark detectors show extraordinary resilience to a variety of environmental parameters, such as lighting conditions, face expressions, and head position, after being trained on a real-world dataset. The suggested method determines the locations of facial landmarks for each video frame and then uses those sites to extract the vertical distance between the eyelids. Our findings indicate that the identifiable landmarks are reliable enough to establish the consistency of eye opening and closure. The suggested approach calculates the positions of the facial landmarks, uses the modified eye aspect ratio (Modified EAR) to extract a single scalar quantity, and describes the closeness of the eyes in each frame. The Modified EAR threshold value and recognising eye blinks as a pattern of EAR values in a brief temporal window are the last methods for detecting blinks. The findings from a representative data set show that the proposed methodology is more effective than the most recent method.

Keywords: Facial Landmarks; Eye Closure Time; Eye Blinks; Eye Aspect Ratio (EAR); Blinks per Minute

Introduction

In systems that monitor human operator vigilance, such as those that check for driver drowsiness [1], in systems that alert computer users when they stare at the screen for an extended period of time without blinking to prevent dry eye and computer vision syndromes [2, 3], in human-computer interfaces that facilitate communication for people with disabilities [4], or for anti-spoofing protection in face recognition systems [5], eye blink detection is crucial. To automatically find eye blinks in a video series, many different techniques have been suggested. Their main flaw is that they typically implicitly place excessive demands on the setup, such as a relative pose for the face camera (head orientation), image resolution, lighting, motion dynamics, etc. Despite their real-time performance, heuristic approaches that use raw image intensity are particularly likely to be very sensitive. Today, however, there are reliable real-time facial landmark detectors [6, 7, 8] that can capture the majority of the distinguishing features on a human face image, including the corners of the eyes and the edges of the eyelids. In order to learn a mapping from an image into landmark locations or other landmark parametrization, the majority of modern landmark detectors frame the problem as a regression one. These contemporary landmark detectors are trained on datasets collected in the real world, making them resistant to changes in lighting, different facial expressions, and mild non-frontal head rotations. A state-of-the-art detector's average landmark localization error is often less than 5% of the interocular distance. Therefore, utilising a recent facial landmark detector, we propose a straightforward yet effective technique to detect eye blinks. The landmarks are used to create a single scalar variable that represents the degree of ocular opening. The eye blinks are finally recognised by two proposed approaches using a per-frame sequence of the ocular openness estimates. An SVM classifier trained on examples of blinking and nonblinking patterns is used in the first to detect blinks. Unsupervised is used in the second procedure. To estimate eye states, it learns a hidden markov model. Following that, based on the length of the blink, eye blinks are recognised using a simple state machine. Three common blink datasets with ground-truth annotations are used to assess the performance of the blink detectors. A small study to measure blink properties such as frequency over time and duration is carried out. These characteristics are important to determine a degree of drowsiness. We define a drowsiness index as a function of blink frequency and blink duration. Finally the blink detection is applied and an experiment measuring a subject drowsiness during a day while working on a laptop is presented.

What is eye blinking?

Eye blinking is partly subconscious fast closing and reopening of the eyelid. There are multiple muscles involved in eye blinking. Two main muscles are orbicularis oculi and levator palpebrae superioris that control the eye closing and opening. The main purpose of eye blinking is to moisten an eye cornea. It also cleans the eye cornea when eyelashes do not capture all the dust and a dirt gets into the eye. There are two types of unconscious blinking. The spontaneous blinking is done without any obvious external stimulus. It happens while breathing or digesting. The second type of involuntary blinking is called the reflex blinking. It is caused by contact with the cornea, fast visual change of light in front of the eye, sudden presence of near object or by a loud noise. Another type of blinking is the voluntary blinking which is invoked consciously under the control of the individual.

Parameters of blinks

There are two main parameters of blinking: frequency and duration. Average frequency of blinking of an adult is 15-20 blinks/min but there are only 2-4 blinks/min physiologically needed. Children have lower blink rate. Newborns even blink only 2× per minute. Interestingly, women using oral contraceptives blink 32% more often than other women [9]. The rate of spontaneous blinking can be increased by a strong wind, dry air conditions or by emotional situations. On the other hand, when the eyes are focused on an object for longer time (e.g. reading), the blink rate decreases to about 3-4 blinks/min. Work [10] publishes a hypothesis that the blink frequency is increased by negative mood, stress, nervousness, fatigue, negative emotions, pain, boredom. On the other hand the frequency is decreased in positive states while relaxing, having pleasant feeling, after successful problem solving and also while reading and having greater attention. The duration of blinking depends on an individual, usually it is about 100-400 ms. The reflex blinking is faster then the spontaneous. Blink frequency and duration can be affected by relative humidity, temperature, brightness or by fatigue, disease or physical activity.

Related Work:

Tracking and Detection of Objects A significant area of study in computer vision is object recognition and tracking, but this topic is only applicable to event cameras. Particularly, there aren't many deep learning-based methods, which is probably because there aren't many big event-based datasets. Particularly in the case of face and eye detection. In order to detect blinks and consequently track the face and eyes, Lenz et al. (Lenz et al., 2018) propose an event-based face detection and tracking algorithm employing hand-crafted features. They use the distinct temporal signature of blinks in event space to their advantage and track faces appropriately. A single-image YOLO object detector and a correlation filter tracker in event space are proposed by Jiang et al. (Jiang et al., 2020). The output from the tracker and detector results are combined using Kalman filters (Jiang et al., 2020). Using a leaky surface event representation as input, Cannici et al. (Cannici et al., 2019a) propose YOLE (You Only Look at Events), a YOLO object identification network for event-based object detection.

Recursive adaptive temporal pooling is used by Li et al. (Jia Li et al., 2017) to extract motion invariant features, which is followed by object detection using an R-CNN for hand recognition. This approach deals with the issue of object detection in the presence of slower object motion. The pooling of feature maps from earlier time steps is based on a learnt weighting. As the event camera naturally responds to motion, other research use moving objects as zones of interest and classify them as a result (Cannici et al., 2019b; Ghosh et al., 2014).

These techniques, however, fail to address the issue of object recognition in varying motion speeds. Using exploits, Joubert D et al. (Joubert et al., 2019) suggest object detection at various frame rates. They combine events from several time frames to find moving and still objects. There aren't many studies that mention DVS's built-in ability to support numerous frame rates. Other techniques estimate an intensity image from events and then process these reconstructed images using current object identification or object classification algorithms (Rebecq et al., 2019; Scheerlinck et al., 2020). These strategies fill the gap between event cameras and regular cameras. Iacono and colleagues (Iacono et al., 2018) examine how commercial DL-based object detection algorithms perform on event representations in order to determine whether event representations have enough data to distinguish between different items. With the same lens, they employ a hybrid frame-based and event camera arrangement. The single shot detector (SSD) employed by the authors was pretrained using the COCO dataset (Lin et al., 2014). These techniques, however, are inappropriate for DMS since the majority of events take place outside the region of interest (ROI), such as an automobile background rather than face features. Moreover, these methods require the additional step of reconstruction which is computationally expensive and can diminish the inherent advantages of event cameras. 4 With conventional frame-based cameras, most object detection research relates to single image detection, processing frames independently. However, the natural input for most real-world applications are video sequences. Video detection methods have become more popular in recent years and can be generally categorised into feature-level and box-level approaches. Box-level tracking methods are often referred to as tracking-by-detection. Detections are performed on single images and temporal associations are based on detection outputs (Han et al., 2016; Lu et al., 2017; Ning et al., 2017). In contrast, feature-level methods integrate image features (Broad et al., 2018; Liu & Zhu, 2018; Zhu et al., 2017). The proposed GR-YOLO adopts this feature-level approach.

Blink Detection and Pattern Analysis

Blink detection and blink analysis is well researched with the use of conventional cameras (Muller, 2019). The relationship between blinking patterns and driver drowsiness is also well established (Baccour et al., 2019). In particular, oculomotor parameters including blink duration, re-opening delay, blink interval and closure speed are proven to be significant factors in drowsiness estimation (Schleicher et al., 2008). That said, a frame rate of over 100 fps is needed for precise parameter measurements. This is beyond the capabilities of current DMS systems that typically operate at 30-60 fps.

To detect blinks, most studies locate landmarks around the eyes and subsequently detect blinks based on the distance between upper and lower eyelids (Soukupova & Cech, 2016). However, these methods require accurate facial landmark estimation and a high framerate camera. To date, limited attention has been given to the potential of neuromorphic event cameras for blink detection and blink analysis. Recently, Lenz et al (Lenz et al., 2018) detect blinks over the full image based on the characteristic distribution of events exhibited during a blink.

Detections are based on sparse cross-correlation between the observed distribution of events and their blink model. However, the authors process the entire image and thus cannot accurately detect blinks if there is significant motion elsewhere in the field of view. Chen et al (Chen, Hong, et al., 2020) propose a method to detect blinks from event cameras for drowsiness estimation. Detections are performed through a twostage filtering process to remove events unrelated to eye and mouth regions and detect blinks based on the spikes in event recordings. No eye tracking is used, and a clustering algorithm is employed to determine whether the spike in events is due to eyes or mouth. Anastasios et al (Angelopoulos et al., 2020) propose a hybrid frame and event-based eye tracking system. Based on a two-dimensional parametric eye model, the authors identify blinks based on the premise that blinks will deform the fitted eye ellipse.

Dataset

There are no available datasets for face and eye detection for event cameras. To overcome this, we generated a large synthetic event-based dataset using Helen (Le et al., 2012) and mapping facial landmark annotations to event space. We call this dataset Neuromorphic Helen (N-Helen). Our approach takes any existing RGB datasets comprising of single images with facial landmark annotations. First, a set of random transformations and augmentations are applied to each image, simulating a video sequence with homographic camera motion with 6-DOF. At the same time, using the same transformation matrix for each image, we transform the annotated facial landmarks. From this, face and eye bounding boxes can easily be obtained. This results in a video sequence with annotations for each frame. This is a novel approach enabling us to train CNNs to operate in eventspace without intermediary intensity representations.

Methodology

Blink Recognition Event cameras' natural polarity output is especially well suited for the detection of quick movements like blinks. Positive and negative polarity denote pixel intensity changes above a predetermined threshold. The eye regions experience a large number of events as a result of blinking. Particularly, an unusual increase in both good and negative occurrences is frequently caused by the eyelid's downward movement over the pupil.

Table 1 **Dataset Information.**

Variable	Description
frame ID	In a separate file, a frame counter may be used to get a timestamp.
blink ID	A unique blink ID is defined as a series of identical blink ID frames. An eye blink interval is defined as a sequence of identical blink ID frames.
non frontal face (NF)	While the individual is gazing to the side and blinking, the supplied variable changes from X to N.
left eye (LE),	Left eye.
right eye (RE),	Right eye.
face (F)	Face.
eye fully closed (FC)	If the subject's eyes are closed between 90% and 100%, the provided flag will change from X to C.
eye not visible (NV)	While the subject's eye is obscured by the hand, poor lighting, or even excessive head movement, this variable shifts from X to N.
face bounding box (F_X, F_Y, F_W, F_H)	x and y coordinates, width, height.
left and right eye corners positions	RX (right corner x coordinate), LY (left corner y coordinate)

Conclusion:

In this paper, a novel fully convolutional recurrent neural network is used to recognise and track faces and eyes for event cameras. Additionally, a simple technique for detecting blinks is provided. On test datasets that were manually collected, both approaches' effectiveness was evaluated qualitatively and quantitatively. There are no benchmark datasets available right now to contrast with. in particular, the better temporal resolution and the capacity for task-specific dynamic frame rate adaptation. Additionally, their innate reaction to object motion allows for a more direct method of blink detection. These traits enable a sophisticated DMS with capabilities beyond those of existing fixed frame rate solutions. The characteristics suggested in this work are not the only features that event camera-based driver monitoring is capable of; other potential applications include low-latency eye gaze tracking, saccadic eye motion recognition, and collision analysis.

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