Eye Blink Detection

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Abstract

Eye blink detection has many uses, the most common are human computer interaction for disabled people, dry eye monitoring systems, and fatigue detection. We analyze the state-of-the-art methods with emphasis on usability. We focus on real-time methods working in the real-world environment and using a common webcam. We introduce two new datasets which are the biggest datasets available. The proposed annotation contains face and eye corners positions, so the eye blink detection performance is not influenced either by face or eye detection methods. An evaluation procedure defines *True positives* with intersection over union metric. Two state-of-the-art methods are introduced. The first method analysis motion vectors using an average motion vector with standard deviation. These are the input to the carefully designed state machine. With the second method, we evaluate different features from the related work as the input to a Recurrent Neural Network (RNN). This method achieves the best results on the biggest and the most challenging dataset *Researcher's night*.

Categories and Subject Descriptors

I.4.0 [**Image Processing and Computer Vision**]: General—*feature extraction*; I.5.0 [**Pattern Recognition**]: General—*classification*

Keywords

eye blink detection, incomplete blink, blink completeness, motion vectors, Recurrent neural network, shifting network's output

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1. Introduction

Under eye blink detection, we refer to an ability to identify individual video frames which are part of the concrete blinks. Eye blink is defined as a rapid closing and reopening of eyelids. Mostly due to dry eye syndrome, only partially closed eye blink often occurs. This is called an incomplete blink [25]. Extended blinks [28] are the opposite when the eye closure (fully closed eye) lasts from 70 ms to around 1 second. Some people blink multiple times in a sequence; for example, double blinks or even quadruple blinks can occur.

Eye blinks can be also detected by electrooculography (EOG) [23] or electroencephalography (EEG) [4, 18]. We focus on visual detection using webcam placed about half a meter in front of the subject. Endogenous eye blink typically lasts from 100 to 400 milliseconds [34], thus a standard camera with 25–30 fps is sufficient. Later on, we focus on blink categorization, based on the eyelids touch, to complete and incomplete blinks.

1.1 Motivation and Applications

Analyzing blinks and acquiring blink statistics have much to offer. Recently, there has been an increased attention to eye blink detection mostly because of face liveness detection [24, 35] (photo can not blink). Eye blinks are often used as a way of interaction between disabled people [13] and computers. Eye blink frequency and duration are reliable signs of sleepiness [7] that can be used to detect driver's fatigue [6] and eventually to prevent microsleep.

Dry eye, also known as *keratoconjunctivitis sicca*, can occur due to insufficient tear production or excessive tear evaporation, both resulting in tear hyperosmolarity that leads to symptoms of discomfort and ocular damage [11]. The tear film is a microscopic protecting coat of the eye against dust and microorganisms. It lubricates the ocular surface and protects it from evaporation. The tear film consists of three layers, organized from the ocular surface: mucin, water, and lipid layer. The first two layers provide moisture to the eye and the third layer prevents their evaporation. The lipid layer consists of meibum produced by Meibomian glands and it is spread on the eye surface during the complete blink only. Meibomian glands are placed at the rim of eyelids inside the tarsal plate. During eye blink, eyelids need to touch, so the meibum can be spread over the ocular surface to protect it from evaporation [3]. Portello et al. [25] observe the negative influence of the incomplete blinks on dry eye.

One of the main causes of dry eye syndrome is also low blink rate. A healthy human blinks 10 to 15 times per minute. 70% of computer users have decreased blink rate up to 60% [1].

2. Related Work

The majority of methods are initialized with a Viola–Jones type algorithm to detect the face and eyes e.g. [12, 6]. Based on circumstances, the detector is often not able to detect non frontal faces/eyes which can be compensated with region tracking [20, 2].

Eye blink detection can be based on motion tracking within the eye region [8]. Some methods try to estimate the state of an eye (open, closed [20] or the eye closure [12]) for individual frames which is consequently used in a sequence for blink detection. Other methods compute a difference between frames (pixels values [19], descriptors [21], etc.).

Divjak & Bischof [8] use eyelid movements to detect blinks. Features are detected using FAST [29] and tracked with Lucas–Kanade tracker [36]. Features are classified using their location; face, left and right eye. Eye and face regions are tracked based on the features. The authors calculate a normal flow of the regions in the direction of intensity gradients. Eyelid motion also includes head movements, thus compensation based on the already extracted head movement takes place. Dominant orientations of the local motion vectors for the individual classes are extracted from a histogram of orientations, due to which partial invariance to eye orientation is achieved. To filter the eyelid motion, only the flow in the direction perpendicular to the line segment between the eyes is considered. The angle between this line and the horizon is calculated and flow vectors are transformed correspondingly. Corrected and normalized flow is used to calculate an average flow magnitude of the eye regions. The dominant flow direction is recognized based on the individual orientation of local motion vectors (optical flow) in a histogram with 36 bins, each bin representing 10 degrees. Normal flow orientation and magnitude are used as the input parameter for a state machine.

Radlak & Smolka [27] introduce the Weighted Gradient Descriptor (WGD) which is based on computing of partial derivatives per each pixel in the eye region over time. Feature vectors are averaged in two orientations ("up" and "down") based on location. The vertical distance between their points of origin is used as the feature. Closing and opening of the eye is represented by negative as well as positive peak within the feature vector. After noise filtering, zero-crossing point between the local maximum and minimum represents the detected eye blink. In this modification Gauss weighting is used to suppress eyebrow movements often falsely detected as eye blinks. The maximum and minimum of the entire feature vector (for given video) are found and used to estimate proper thresholds, which reduces the usability for cameras. A new dataset of 5 people recorded by Basler 100 fps camera is introduced, which is part of Silesian Deception Database [26]. We will refer to it as *Silesian5* dataset. The reported detection rate on *Silesian5* is around 90% and 98.8% on *ZJU* dataset. In evaluation, only the right eye of the subject is used. The authors report the best obtained results for given datasets while tuning parameters.

Template matching using histogram of Local Binary Pattern (LBP) can be used to detect eye blinks [21]. First, the initialization takes place. An open eye template is calculated from several initial images where eye is open and not moving. For each image in a sequence, LBP histogram is computed from the eye region and compared with the template using the Kullback–Leibler divergence measure. The output is a curve where noise is filtered out using Savitzky–Golay filter and the top hat operator. Afterward, peaks are detected using Grubb test and considered as eye blinks. Detection rate of 99% is reported on *ZJU* and *Silesian5* dataset (different parameters are used for each dataset). Because of the Grubb test, this method is not suitable for a real-time stream from camera.

Different evaluation procedures take place over the mentioned methods. Often, they are not even specified. For example *false positive rate* and *mean accuracy*. We assume (because it is not specified) that the number of images with open eyes is used as *Negatives* (N). This is not proper because blink usually consists of 7 frames in average at 30 fps. Many of the mentioned papers do not even define what is considered as true positive blink detection. Whether they use per frame annotation or just threshold a distance of the detected blink from the ground truth.

Based on the overview of the related work, we observe superior performance of motion based methods. Divjak & Bischof [8] achieve interesting results. The authors try to compensate head movement by subtracting the average face motion vector from the individual eye motion vectors. The problem is that this motion vector is affected by facial mimics and hand touches over the face. Instead of compensating the head move we analyze the behavior of motion vectors.

3. New Datasets and the Evaluation Procedure

All available datasets are small in size, both in blink count as in the number of recorded individuals. *Talking face*[1] is just one person with 55 blinks. *ZJU* [24] contains 20 people with 255 blinks and *Silesian5* [27] contains 300 blinks. All mentioned are recorded in a controlled environment. Another problem is no split into train, validation, and test set to minimize the possibility of over-fitting on train set or tuning parameters in a case of using the whole dataset. We present a dataset called *Eyeblink8* and the largest real-world dataset available called *Researcher's night*.

3.1 Dataset: *Eyeblink8*

This dataset contains 8 videos with 4 individuals (1 wearing glasses). Videos are recorded in a home environment. People are sitting in front of the camera and mostly act naturally with vivid facial mimics, similarly to *Talking face* dataset. There is 408 eye blinks on 70 992 annotated frames with resolution 640×480. The *Eyeblink8* dataset is publicly available[2].

3.2 Dataset: *Researcher's Night*

We introduce a new dataset which was collected during an event called *Researcher's night 2014*, which is available on demand. People were asked to read an article on a computer screen or blink while being recorded. There is sometimes more than one person in the camera field of view. We have collected 107 videos with 223 000 frames

[1] `http://www-prima.inrialpes.fr/FGnet/data/01-TalkingFace/talking\_face.html`
[2] `blinkingmatters.com/research`

of different people with a cluttered background. People are often acting naturally, wearing glasses (around 20%), touching their face, different head movements or even talking to somebody. Some of the blinks are unnaturally long, which can be considered as voluntary (people knew they are being recorded) or extended blinks. 1849 blinks were annotated which makes *Researcher's night* the biggest real-world dataset publicly available.

There are two subsets: *Researcher's night 15* and *Researcher's night 30* that are captured with 15 and 30 frames per second (fps) with resolution 640 × 480. Small deviations can occur. Each video contains different person. Dataset videos are divided into train, validation, and test set with ratio 1/4, 1/4 and 1/2. We believe this real-world dataset can help researchers to develop more precise algorithms.

3.3 The Proposed Evaluation Procedure

While listing the related work, evaluation procedure is usually not mentioned. Often the performance is evaluated using *Accuracy* without explicit formula or other metrics like *False positive rate* where the definition of *False positive* respectively *True positive* are crucial. The reported performance depends also on the threshold used to classify *True positive*. What is the *true positive* while talking about eye blink detection? Radlak & Smolka [27] consider eye blink as detected if the detected eye blink peak is between the start and end frame of the ground truth annotation. There is a difference whether the blink is annotated and detected as a single position over a video or as an interval. A distance of the positions can be thresholded to report *True positive*. While using an interval type of annotation, different metrics can be used. Inspired from PASCAL VOC challenge [9] and its object detection evaluation, we use *Intersection Over Union* (IOU) (Equation 1) metrics which penalizes difference between the intersection and union. We define blink as *True positive* if the IOU with the ground truth blink interval is larger than 0.2.

$$IOU = \frac{|A \wedge B|}{|A \vee B|} \tag{1}$$

We evaluate blink detection with *Precision*, *Recall* and *F1 score* metrics:

$$\begin{aligned} Precision &= \frac{TP}{TP + FP}, \\ Recall(TPrate) &= \frac{TP}{TP + FN}, \\ F1score &= 2 \times \frac{Precision \times Recall}{Precision + Recall}, \end{aligned} \tag{2}$$

where TP is *True Positive* count, FP is *False Positive* count and FN is *False Negative* count.

4. Eye Blink Detection Using Motion Vector Analysis

We assume the eye corners are available for each frame if face is present. While analyzing motion, it is desired to have even distribution of motion vectors. Therefore, we use Gunnar–Farneback [10] algorithm, which is a dense tracker, to estimate motion vector for each pixel within the eye region. While computing motion vector for given feature point, the Gunnar–Farneback tracker takes into consideration also the nearby motion vectors, which significantly lowers the number of outliers.

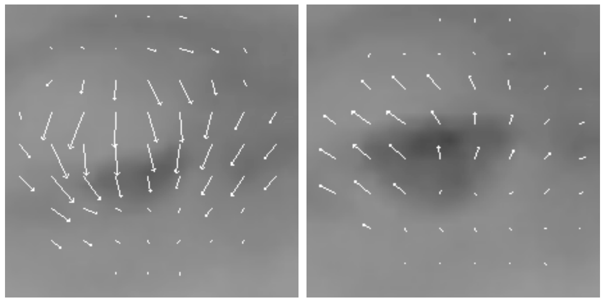

Figure 1: Visualization of motion vectors for eyelid movement down and up.

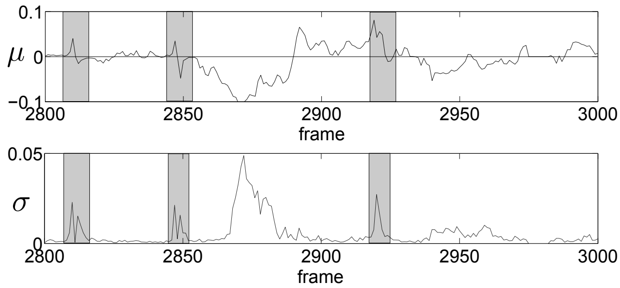

Figure 2: Curve of the vector of vertical component of the average motion vectors and its standard deviation. 3 blinks occur around frames 2810, 2850 and 2920 (the gray areas). 1 rapid head movement occurs around the frame 2880 influencing the third annotated blink.

Size of the eye region depends on camera resolution and subject distance from the camera. The eyelid trajectory (measured in pixels) increases with the region size, therefore the magnitude of motion vectors also increases. Eye region size correlates with the interocular distance (The distance between centers of the eyes.). We normalize each motion vector by the interocular distance. The eye corners are used to calculate eye centers and subsequently the interocular distance.

During head movements, all motion vectors are similar in magnitude and orientation. On the other hand, motion vectors differ in magnitude while eye blinks (Figure 1). Further, we calculate the vertical component of the average motion vector μ and the statistical standard deviation σ. We use the vertical component only because we assume that subject in front of the camera does not rotate their head significantly. The curve visualization of the vector of vertical component of the average motion vectors (individual motion vectors are already normalized) and its standard deviation is in Figure 2 where eye blinks could be observed. Peaks in σ curve could be used to detect eye blinks, but to verify or support the occurred eye blink, zero crossing in the μ curve takes place.

4.1 The State Machine

The μ and σ curves together with the Δt (the time difference between captured consecutive frames) for a given video stream are the input to the state machine. The state machine is designed manually observing the μ and σ curves of the train and validation set of the *Researcher's night* dataset. σ increases mostly during eye blink, rapid head movement or pupil movement. Eye blink is a se-

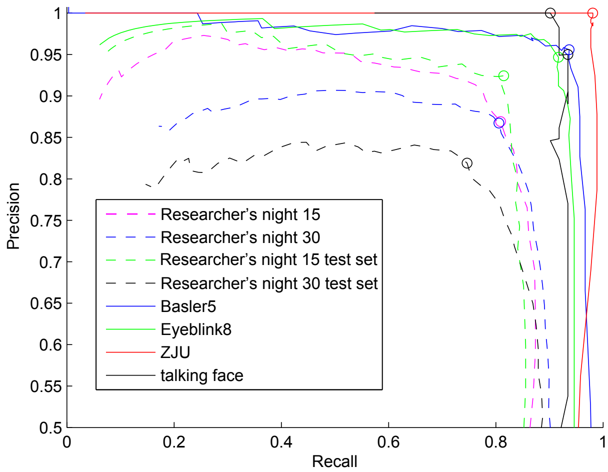

Figure 3: Evaluation of our method on all available datasets (Basler5 is old reference for Silesian5). Precision-recall curves are plotted by changing the parameter T from 0.0001 to 0.007.

quence of eye lid moving down and up (zero crossing in μ waveform), so we use this characteristics while designing the state machine. The state machine consists of the following states: the initial state (0), the eye lid moves down state (1), the eye lid moves up state (2) and the eye blink detected state (3). The major movement comes from the upper eye lid, that is why the states are named after it.

4.2 Merging Left and Right Blinks

There are two separate state machines, one for each eye. Eye blink is considered detected, if at least one of the state machines triggers the eye blink detected state. The problem is how to merge detected eye blink intervals from both eyes to acquire better precision in eye blink duration. The left and right blink is considered as one, if the intersection over union ($IOU = (A \wedge B)/(A \vee B)$, where A, B are eye blink intervals) is higher than the given threshold. In our experiments if $IOU > 0.2$, the left and right blinks are merged together (averaged) to get more precise intervals. If $IOU <= 0.2$, we assume the left and right blinks represent two independent blinks. This is important mostly while detecting incomplete or multiple blinks. Some people blink very fast twice in a row (double blink) or even four times in a row. If multiple blinks are supposed to be detected as one, different settings should take place.

4.3 Evaluation

Figure 3 shows precision-recall curves to evaluate performance over available datasets. The time constraint used as a threshold parameter in state machines for the maximum eye blink duration is 0.5 seconds. The curve has a tendency to go left at the end, because in our evaluation we assume that one frame belongs to one detected eye blink only. Because of this, individual TP and FP eye blinks influence each other.

5. Eye Blink Detection Using Recurrent Neural Network

Blink detection is a type of action recognition problem in video. The state-of-the-art methods for action recognition often use deep Convolutional Neural Network (CNN) within spatial and time domain [31, 37]. Most action recognition datasets, like UCF101 [32], consist of small videos, where only one action per video is present. Therefore, action recognition is separated from detection. The state-of-the-art results on UCF101 are achieved by combining CNN and five-layered Recurrent Neural Network (RNN) [22]. THUMOS'14 dataset [16] contains untrimmed videos which naturally merges action detection and recognition problem into one. Three-layered RNN achieves the state-of-the-art results on THUMOS'14 [38].

Recently, RNN presents very good results on speech recognition too. Blink detection is similar to speech recognition because blinks differ in length, as different people have different speech velocity. Most classifiers could suffer from the fact that blinks vary in duration. Compared to speech recognition, blink recognition is an aligned problem, which means that each video frame can be classified to be part of a complete/incomplete or no blink. We use *Researcher's night* dataset and evaluate each eye separately, therefore the dataset has doubled in size.

RNN has difficulties to learn from long sequences because of the vanishing gradient problem [14]. Moreover, RNN trains faster on short sequences and it does not use so much memory, so the sequence size has to be as short as possible. One blink is often present on 5 to 10 frames. We use Long Short Term Memory cells [15] to overcome the vanishing gradient problem and the orthogonal initialization [30] for better convergence.

We present a method where we evaluate the power of deep learning on eye blink completeness detection while using different features. We evaluate the best performing features from the related work. We evaluate motion based and different appearance based features.

We use Gunnar–Farneback motion vectors, both vertical and horizontal direction for each pixel within the eye region which results in 610 dimensional feature vector. The size of motion vector is affected by the time, so the time between capturing the frames (Δt), motion vectors are calculated from, is used too.

Time gradients are the basic feature of *weighted gradient descriptor* [27], which, practically, is a frame difference with preserved sign. The Time gradient is computed for each eye pixel so the dimensionality is 305 elements. We further normalize the difference to domain $< -1, 1 >$. Neural network converges faster if the domain is close to zero.

Aspect eye ratio (AER) has been proven to be a useful feature [33]. We detect eye landmarks [17] to obtain distance between eye corners (Δx) and eye lids (Δy). $AER = \frac{\Delta y}{\Delta x}$.

Visual features based on Histograms of Oriented Gradients [5] achieve good performance in general. We generate horizontal and vertical gradients separately using Sobel operator over the gray-scale image. Next, the arctangent of these two gradients is computed and normalized with π to get the angle within the interval $< -0.5, 0.5 >$. The magnitude is computed using the Pythagorean Theorem. We set half of the angles to zeros. These are chosen based on the lower half of the magnitudes to suppress noise. Only angles are used as a feature, so the dimensionality is 305 elements. This feature is referred to as *Gradient Orientations.*

The most basic feature is vector of raw RGB values, which are normalized to $< -0.5, 0.5 >$ domain. There are 305 pixels and three channels, so the feature vector dimensionality is 915 elements.

5.1 Evaluation

Network classification is refined with a simple state machine which decreases the error. The state machine drops blinks of one frame length because blink should be longer at given frame rate.

RNN processes data in sequences. Features are generated for each eye separately and concatenated into one sequence. People can blink multiple times in a row. We do not merge left and right blinks because their completeness can differ. On *Researcher's night* dataset we have observed that one eye can be completely closed while the other is not. We use *F1 score* to quantify the network performance. We focus primarily on the incomplete blink detection, but we also evaluate the complete and the overall blink detection.

Blink completeness detection is a very hard problem even for humans, mostly because eyelashes or glasses cause shadows which make it harder to recognize the touch of the eyelids. Classifiers can suffer from data insufficiency. In their normal state, different people have different eye openness in normal state and different eye size. For one person, a particular motion length could mean full blink closure, while for another person with bigger eyes, it could register as an incomplete blink.

All combination of feature vectors which use *Motion Vectors* achieve the best overall blink detection *F1 score* on *Researcher's night.* Our method achieves comparable results on *ZJU* and *Silesian5* datasets. It suffers from performance on *Eyeblink8* compared to the related work, because of facial mimics and head moves (higher false positive rate). Considering that we have not retrained our model on these datasets, the results are quite satisfying. Small datasets like *ZJU* or *Silesian5* are not a good benchmark, but we report their results in order to compare with the related work.

6. Conclusion and Contribution

Two new fully annotated datasets are introduced. Both *Eyeblink8* and *Researcher's night* are real-world fully annotated datasets. *Researcher's night* is with 1849 blinks the largest dataset available. We propose an annotation which includes face and eyes corner positions, thanks to which, the performance of eye blink detection algorithms could be measured without an influence of face and eye detection methods. An application for video recording with time-stamp information was created. We also speed up video annotating by introducing the annotation tool.

We have successfully designed and evaluated two state-of-the-art methods on eye blink detection. Methods do not use initialization or calibration and many common real-world situations and variability of the eye regions are handled well. Thanks to the first method based on motion vector analysis, we were able to identify which feature could be a good input to the RNN. We have evaluated several features from the related work and evenly distributed motion vectors seem to be the best feature available. We achieve the best results on *Researcher's night* dataset. We have introduced a new problem; blink categorization into complete and incomplete ones using visual methods. We set the initial benchmark for this problem.

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