Driver Hypo-Vigilance Detection based on Eyelid Behavior

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Abstract

Driver face monitoring system is a real-time system that can detect driver fatigue and driver distraction using machine vision approaches. In this paper, a new algorithm is proposed for driver hypo-vigilance detection based on eye-region processing and without explicit eye detection stage. In this method, horizontal projection of top half-segment of facial image is used to extract symptoms of fatigue and distraction. Percentage of eye closure (PERCLOS) and eyelid distance changes during time are used for fatigue detection; and eye closure rate is used for distraction detection. The novelty of our method is in adaptive feature extraction using spatio-temporal processing without explicit eye detection. Processing rate of proposed method is more than 5 frames per second.

Keywords: Driver Hypo-Vigilance, Fatigue Detection, Distraction Detection, Eyelid Behavior.

1. Introduction

The main reason of about 20% of all road crashes is driver hypo-vigilance [1]. Driver hypo-vigilance includes driver fatigue (drowsiness) and driver distraction (inattention).

Four approaches exist for hypo-vigilance detection:
(1) methods based on bioelectric and nervous signals
(2) methods based on driver steering motion
(3) methods based on driver face monitoring
(4) hybrid methods

In this article, after a short review on previous works, a new method for feature extraction in driver face monitoring systems will be presented.

2. Related Works

In driver face monitoring systems, fatigue detection is usually based on percentage of eye closure (PERCLOS) [2,3,4,5,6], eyelid distance, eye blink speed [2,6] and head nodding [3,4]. Many researchers have developed face-based monitoring systems to detect driver fatigue, but number of researches about distraction detection is less than fatigue detection. Distraction detection is usually based on eye blink rate [2,4], gaze movement [2,4] and head rotation [2,3,4,6].

Ji et al [2] have presented a prototype system for driver vigilance estimation. They have used active infrared (IR) illumination system that it has been synchronized with CCD sensor to capture frames. In this system, eye detection is based on IR reflections from pupil. Percentage of eye closure (PERCLOS), eye closure speed, eye closure duration, eye blink frequency, head orientation and gaze movement have been monitored by system to estimate driver vigilance.

Moreno et al [3] have proposed a FPGA-based system for fatigue and distraction detection in IR illumination. In this system, driver fatigue is detected by eye closure and driver distraction is detected by head rotation. Eye detection and eye closure detection is based on edge detection using Sobel filtering.

Bergasa et al [4] have developed a driver face monitoring system using active IR illumination system. Eye detection and eye tracking are based on pupil reflections in IR spectrum. For eye tracking, tow Kalman filters were used for each eye. Six features have been extracted from facial image: percentage of eye closure (PERCLOS), eye closure duration, blink frequency, nodding frequency, face pose and gaze movements. A fuzzy classifier has been used to estimate driver vigilance level.

Lalonde et al [5] have implemented a real-time GPU-based driver face monitoring system for eye blink detection. In this system, eye detection, eye tracking and blink detection is based on SIFT (Scale Invariant Feature Transform) feature points in IR illumination. Because of implementation on GPU (Graphical Processing Unit), processing speed of this system is about 25 frames per second.

Batista [6] have proposed a color-based driver face monitoring to extract head rotation, PERCLOS and eye
closure speed. The first stage of proposed system is face modeling and feature point extraction. Feature points are located on important points on facial image (such as eye corners, eyebrows, nose, mouth corners, etc). Face detection and feature points detection is based on color and geometrical model. Eye closure and head rotation are detected based on changes in location and value of feature points.

3. The System

Proposed system is a driver face monitoring system that it can detect driver hypo-vigilance (both fatigue and distraction) by processing of eye-region. Flowchart of our system is shown in Figure 1. After image acquisition, face detection is the first stage of processing. Then symptoms of hypo-vigilance are extracted from facial image. However, an explicit eye detection stage is not used to determine eye-region in face, but all of extracted features are related to eye-region (top half-segment of face). Finally, we used some simple threshold to estimate driver hypo-vigilance. Applying face detection algorithm for all frames is computationally complex. Therefore, after face detection for the first frame, face tracking algorithms is used to track driver face in other frames of sequence.

3.1. Face Detection and Tracking

We used Haar-like features and boosted decision tree for face detection, like Viola and Jones [8] algorithm. Face detection algorithm was trained by about 3000 faces and about 300000 non-faces.

For face tracking, full search method is used to find the best match region of driver face image in new frame. Center of search region is placed in last center of face image and size of search region is changed according to size of face image (about 1.5 times bigger than size of face image). Matching degree of facial image and sub-windows of search region is computed by correlation. However, face tracking by full search method and computing correlation coefficient is very computationally complex, but full search method is more accurate than other tracking methods such as 3-step search and 2-D logarithmic search; and correlation is more reliable than Sum of Absolute Difference (SAD) and Sum of Squared Difference (SSD).

3.2. Feature Extraction

Proposed system uses horizontal projection in top half-segment of facial image to extract symptoms of driver hypo-vigilance. Our contribution is in using a spatio-temporal structure without explicit eye detection for feature extraction. Our proposed method for feature extraction is not very sensitive to illumination, skin color and wearing glasses, because it is an adaptive method.

Horizontal projection in image $I$ is computed by equation (1):

$$HP(j) = \sum_{i=1}^{M} I(i, j)$$  (1)

Length of $HP$ is equal with height of $I$. In our proposed system, only horizontal projection of top half-segment of facial image is used, so length of horizontal projection will be equal with half height of driver face image.

In presented algorithm for hypo-vigilance detection, PERCLOS and eyelid distance changes (ELDC) are used for fatigue detection and eye closure rate (CLOSNO) is used for distraction detection. To extract these symptoms from driver face image, only horizontal projection is computed in top half-segment of facial image.

Before extracting the hypo-vigilance symptoms, system needs to be trained. Because of different eyelid behavior in different individuals, estimating driver vigilance level based on absolute values is not suitable for robust driver face monitoring systems. For example, eyelid distance in Japanese or Chinese men is lower than Mid-East, European and American men. Therefore, for developing a robust and adaptive system, normal values of each vigilance symptom must be computed in training stage. PERCLOS$_N$ and CLOSNO$_N$ are normal values of PERCLOS and CLOSNO respectively that are extracted in training stage for each individual. In addition, normal eyelid distance will be save as a horizontal projection, implicitly.
Training duration is about 1-2 minutes. In 100 first frames of training sequence, we suppose that driver eyes are usually open. So, horizontal projection of open-eyes can be estimated by computing average of horizontal projections of 100 first frames. Horizontal projection of open-eyes was named $HP_{LO}$ and it can be computed by equation (2):

$$HP_{LO} = \frac{1}{N} \sum_{i=1}^{N} HP_i$$

(2)

In equation (2), $HP_i$ is the horizontal projection of frame $i$ and $N$ is 100.

Eye closure can be detected by computing correlation of horizontal projection of current frame ($HP_i$) and $HP_{LO}$ ($CHP_i$). If correlation of $HP_i$ and $HP_{LO}$ is near to 1 (larger than $th_{CHP}$), eye is open in frame $i$, else, lower correlation between $HP_i$ and $HP_{LO}$ shows that eye is closed.

$$CHP_i = Corr(HP_{LO}, HP_i)$$

(3)

$$\begin{cases} 
\text{eye is closed} & \text{if } CHP_i < th_{CHP} \\
\text{eye is open} & \text{else}
\end{cases}$$

(4)

After computing the $HP_{LO}$ as horizontal projection of open-eyes, a copy of $HP_{LO}$ is named as $HP_0$. $HP_0$ will be updated during acquisition of new frames using fuzzy running average method [9]. In fuzzy running average method, updating $HP_0$ is dependent to matching degree (correlation coefficient) of $HP_0$ and $HP_i$. Fuzzy running average is shown in equation (5).

$$HP_i = \alpha HP_0 + (1-\alpha)HP_i$$

(5)

$$\alpha = 1 - (1-\alpha_{min})exp(-5*CHP_i)$$

(6)

In equation (6), $\alpha_{min}$ is a constant (0.8). According to equation (6), $\alpha$ changes in range [0,1].

Eye closure status is saved in a circular list ($L_{eye\_closure}$). If eye is open, the current element of $L_{eye\_closure}$ will be 1, else the current element of $L_{eye\_closure}$ will be 0. When $L_{eye\_closure}$ was full, new data replaces the oldest one. Length of $L_{eye\_closure}$ ($N_L$) must be equal with number of training frames (about 1500-3000). $L_{eye\_closure}$ is helpful for computing PERCLOS and CLOSNO, but ELDC is computed using correlation of current horizontal projection ($HP_i$) and $HP_{LO}$. $HP_{LO}$ implicitly shows the eyelid distance of driver in normal status.

In general, PERCLOS is computed as equation (7). PERCLOS shows percentage of eye closure times in last frames.

$$PERCLOS = \frac{N_L - \sum L_{eye\_closure}}{N_L}$$

(7)

CLOSNO shows eye blink rate (frequency) in a given duration. If $DL_{eye\_closure}$ is the first derivation of $L_{eye\_closure}$, CLOSNO can be computed using $DL_{eye\_closure}$.

$$DL_{eye\_closure}(i) = \begin{cases} 
L_{eye\_closure}(i) - L_{eye\_closure}(N_L) & i = 1 \\
L_{eye\_closure}(i) - L_{eye\_closure}(i-1) & i \neq 1
\end{cases}$$

(8)

$DL_{eye\_closure}$ indicates start and stop frames of eye closure events by +1 and -1 respectively. Other elements of $DL_{eye\_closure}$ are zero. Therefore, CLOSNO is computed by equation (9).

$$CLOSNO = \frac{\sum|DL_{eye\_closure}|}{2}$$

(9)

ELDC is computed based on correlation between current horizontal projection of open eyes ($HP_0$) and horizontal projection of open eyes in training stage ($HP_{LO}$) according to equation (10).

$$ELDC = 1 - Sign(Corr(HP_0, HP_{LO}), \alpha_S, \beta_S)$$

(10)

In this equation, $Sign$ is sigmoid function and $\alpha_S$ and $\beta_S$ are parameters of sigmoid function respectively. If ELDC was near to zero, distance of eyelids is normal, but if ELDC approached to one, distance of eyelids approaches to zero (eye is closed).

General form of sigmoid function is shown in equation (11).

$$Sign(x, \alpha, \beta) = \frac{1}{1+exp(\alpha(x-\beta))}$$

(11)

### 3.3. Hypo-Vigilance Detection

Driver fatigue detection is based on applying simple thresholds on PERCLOS and ELDC. If measured PERCLOS is more than 1.5*PERCLOS$_N$ or ELDC is less than 0.9, driver status is fatigue. If measured CLOSNO is less than 0.7*CLOSNO$_N$, driver status is distracted.

### 4. Experimental Results

Proposed system was tested on 4 sequences (about 20 minutes long) that contain more than 28000 frames. Sequences were captured in 3 different vehicles using a digital camera. Experiments were off-line.

Accuracy of computing PERCLOS and CLOSNO is directly dependent to accuracy of eye closure detection algorithm. Table 1 shows False Positive Rate (FPR) and False Negative Rate (FNR) of proposed algorithm for eye closure detection.

<table>
<thead>
<tr>
<th>Error rate of eye closure detection</th>
<th>FPR</th>
<th>FNR</th>
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<tbody>
<tr>
<td>normal state without glass</td>
<td>2.2% (19/871)</td>
<td>6.3% (55/871)</td>
</tr>
<tr>
<td>fatigue state without glass</td>
<td>0% (0/33)</td>
<td>54.5% (18/33)</td>
</tr>
<tr>
<td>normal state with glass</td>
<td>6.4% (5/78)</td>
<td>16.6% (13/78)</td>
</tr>
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However, proposed method has weaker results for individuals that wear glasses, but accuracy of eye closure algorithm is very good with respect to other algorithms.

Bergasa et al [4] have tested their method on 10 sequences (totally about 2 hours long) and reported 80% accuracy for eye closure detection. Our method is more accurate than Bergasa et al algorithm. The method that presented by Lalonde et al [5] could detect eye closure with 10.5% and 3% error rate for FPR and FNR respectively. This method could extract only PERCLOS feature. FPR and FNR of eye closure detection that has been presented by Batista [6] are 9.5% and 1.2% respectively. Our proposed method has very good results with respect to all of these methods.

For investigating the accuracy of ELDC, we tested our method on 9 minutes long sequence. Figure 2 shows three sample frames of this sequence that driver tends to be drowsiness. Figure 3 shows the measured ELDC from this sequence.

![Figure 2. 3 sample frames of a 9 minutes sequence that driver is drowsy. Images from top to bottom: (a) frame in t=1 min, (b) frame in t=4 min, (c) frame in t=9 min.](image)

Figure 2. 3 sample frames of a 9 minutes sequence that driver is drowsy. Images from top to bottom: (a) frame in t=1 min, (b) frame in t=4 min, (c) frame in t=9 min.

Proposed method was implemented in MATLAB R2008a and was tested on an Intel Core2 Dou 2.66 GHz with 2 GB RAM memory. Speed of proposed method is more than 5 frames per second.

5. Conclusions and Future Works

In this paper, a new adaptive method for feature extraction was proposed that is based on horizontal projection. Novelty of algorithm is in adaptive feature extraction using spatio-temporal processing without explicit eye detection stage. Accuracy of proposed method is very good for individuals that wear and do not wear glasses. The main disadvantage of our method is in face tracking, because of intensive computational complexity. For future works, we propose to use a more robust and faster algorithm for face tracking.

References