**Driver Drowsiness Detection Based on Face Feature and PERCLOS**

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**Abstract.** Driving vehicles are complex and require undivided attention to prevent road accidents. Fatigue and distraction are a major risk factor that causes traffic accidents, severe injuries, and a high risk of death. Some progress has been made for driver drowsiness detection using a contact-based method that utilizes vehicle parts (such as steering angle and pressure on the pedal) and physiological signals (electrocardiogram and electromyogram). However, a contactless system is more potential for real-world conditions. In this study, we propose a computer vision based method to detect driver’s drowsiness from a video taken by a camera. The method attempts to recognize the face and then detecting the eye in every frame. From the detected eye, iris regions for left and right eyes are used to calculate the PERCLOS measure (the percentage of total time that eye is closed). The proposed method was evaluated based on public YawDD video dataset. The results found that PERCLOS value when the driver is alert is lower than when the driver is drowsy.

1. **Introduction**  
Driving activities require full attention and a large amount of brainpower. Moreover, driving requiring proper coordination of movement of the hands and feet, shifting gears while watching other vehicles. Lack of attention can be fatal for drivers, pedestrian, and economic activities. Therefore, it is important for a country to have solid rules and regulations to maintain safety in land transportation. Besides, the complexity and road characteristics can influence driver’s attention. For example, in Indonesia, the current road infrastructure is far from optimal in a sense the number of vehicles produced and sales is not proportional with regards to road infrastructure [1]. This is true especially for big cities such as Jakarta, Jambi, and Surabaya. It is estimated that in 2020, traffic fatality in Indonesia may reach 40,000 per year [1].

Let the government remains responsible to control the vehicle growth and poor infrastructure. Besides these road characteristics, drivers violating traffic law (extreme speeding, drinking, and traffic light offense) also held largely responsible for vehicles accidents. Even with sufficient road infrastructure and excellent driving personalities, accidents are still unavoidable.

According to [2], there is a strong relationship between fatigue and safety risks in driving. Fatigue may be influenced by health and sleep-related problems. Extreme fatigue can lead to driver drowsiness which has been regarded as the culprit of road accidents and may lead to severe injuries, and a high risk of death. In this regard, drowsiness is referred as the decrement or loss of alertness that led the driver to fall asleep while driving.
Naturally, fatigue can reduce attention, lessen the information received, and decrease the ability to provide a response or the ability to assess a condition. This situation may lead to inaccurate decision making while driving. The worst-case scenario can happen when the driver is drowsy and thus fall asleep, losing control of the vehicle. To prevent the occurrence of this scenario, we need to monitor driving activities by detecting whether the driver is drowsy or not. Such system could be used to generate some warning alarms to alert the driver or send a signal to family relatives or friends. Indeed, detecting driver’s drowsiness is challenging due to the variety of ambient illumination and condition of the driver (sleep apnea, talking, yawning, wearing attributes like glasses).

This study aims to develop a drowsiness detection method based on a video based on face feature. This requires the method to recognize the presence of a face and subsequently the eye of the driver for each frame. The detected eye is used to measure the state of the eye closed. By using a predetermined threshold, the drowsiness can be recognized by measuring the percentage of total time that eye is closed.

2. Related Works
There are several approaches have been proposed to measure the state of drowsiness driver while driving. According to [3], these approaches can be categorized into three categories as the following:

1. Vehicle-based metrics – These metrics are measured based on vehicle signals including steering wheel angle, pressure on acceleration pedal, and lane position signals.
2. Physiological metrics – The body signal of the driver can be used to detect drowsiness. These metrics include an electrocardiogram, electromyogram, electrooculogram, and electroencephalogram signals.
3. Behavioral metrics – By attaching a camera within the vehicle, the driver’s behavior can be monitored. The behavior metrics include eye closure, eye blinking, head pose, and yawning.

The vehicle-based and physiological metrics are contact-based method whereas sensors need to be attached to vehicle or driver’s body. This is not an easy task to be done in real-world setting and not maybe uncomfortable for the driver itself. Therefore, a noncontact-based method like behavioral metrics is more flexible and suitable for the real-world environment. Most behavioral metrics is measured based on facial feature analysis. Furthermore, they can be divided into three kinds: appearance-based, template-based, and feature-based methods. Appearance-based methods require a huge amount of data for training classifiers while template-based methods require expensive computational cost due to model matching process. In contrast, feature-based methods can monitor driver drowsiness state in a more direct way. The features can be measured based on eye state estimation, mouth state estimation, and head pose analysis. Different ambient light conditions like poor lighting and driving at night can interfere drowsiness detection process. In general, any kind of object detection schemes, such as boosting [4], neural network [5], and support vector machine [6], can be used to extract facial features.

In [7], the authors utilized infrared illuminator and infrared-sensitive camera to acquire a frame of the driver. The eye was detected based on support vector machine. Then, they used Kalman filter and mean shift to track driver’s pupil. To characterize driver’s fatigue based on eyelid movement, they used the percentage of eye closure during a certain time interval (PERCLOS). They verified that PERCLOS is valid in quantifying fatigue. It was clear that PERCLOS measurement was significantly lower when the driver is alert than when driver is fatigued. Besides eye state, they also used gaze, head movement, and facial expression. However, infrared-based illuminator requires additional setting in addition to camera and thus limiting the potential of the method. Less complex instrument was used by [8]. They simply used common USB camera without any illuminator. Instead of tracking pupil, they locate face using Viola-Jones method. Then, eye was located and tracked using projection technique and unscented Kalman filter respectively. They also used PERCLOS to detect driver’s fatigue. Another eye detection that combines Viola-Jones method, template matching, and support vector machine was proposed by [9]. To detect eye state condition, they used features such as PCA-LDA, sparseness, and kurtosis. A more direct method to detect drowsiness detection was proposed by [10]. The authors used Viola-Jones
method to detect both face and eye. From the detected eye, iris contour is extracted using OpenCV function. To detect drowsiness, the also used PERCLOS metric. In summary, PERCLOS has been used as the best potential measure of drowsiness compared to other ocular metrics. However, most of these methods used their own dataset and thus it is difficult to compare their accuracy only from their reports.

Beside eye state condition, [11] used mouth state condition. The authors used a normal video camera in daylight driving without requiring additional light sources. They extract the face from video’s frame based on support vector machine method. Then, driver’s mouth was detected based on circular Hough transform. Instead of using PERCLOS, the driver’s fatigue is detected based on a high yawning frequency. In [12], a region with the maximum area within the segmented mouth region was used to classify whether a frame as yawn frame or otherwise. The Viola-Jones method was also used for mouth detection by [13]. They used projection theory to measure the rate and number of mouth changes to detect yawning. In contrast to ocular-based methods ([7], [8], [9], [10]) that using their own dataset, the methods of mouth state condition ([12], [13]) has been evaluated using public dataset i.e. YawDD dataset [14].

3. Methods
This section provides the overall stages in our drowsiness detection method as shown in Figure 1. It begins with the video input, then face detection, eye detection, iris region extraction, morphological operations, and finally PERCLOS estimation.

Input image – the input data is a video of drivers with various conditions. More detail will be explained in data collection subsection. Each frame in the video is processed one-by-one as the following processes.

Histogram equalization – since the input videos were taken from real setting. The illumination condition is changing due to the outdoor condition. Therefore, the frame within the video needs a preprocessing method for image enhancement. Histogram equalization method was used to adjust image intensities by redistributing the intensities distribution towards histogram boundaries. Each input pixel is transformed to new intensity value based on the cumulative histogram and scale factor.

Face and eye detection - to perform fast and efficient computation, we employed Viola-Jones method for both face detection and eye detection. This method used integral image representation to compute Haar-like features rapidly at many scales. The integral image at any point \((x,y)\) contains the sum of all pixels above and to the left of \((x,y)\) as follows:

\[
ii(x, y) = \sum_{x' < x, y' < y} i(x', y')
\]

where \(ii(x,y)\) is the integral image and \(i(x', y')\) is the original image. The rapid computation is achieved by constructing a cascade of classifiers which trained using Adaptive Boosting (AdaBoost) algorithm as shown in Figure 2.

Iris region extraction – from the eye image, circular Hough transform was used to isolate the iris that is darker than the other areas of the eye that has a circle shape. If Hough algorithm found iris, then edge detection method (Otsu method, Sobel, and Canny) was used to detect the boundaries of iris object. We found that Sobel is better than other edge detection methods.

Morphological filters – edges output from iris extraction contain line and curves. To measure the area of the iris, there are several morphological operations employed. First, dilation operator was used to adding more pixels to the boundaries of the iris object. This operator uses a structuring element to connect pixels of iris edges. Then, we employed flood-fill operation to fill existing holes to reconstruct a better iris shape. Since the dilation operation tends to introduce more pixel boundaries than its original shape, then we employed erode operator. This operator is the inverse of dilation operation that reduces the size of the iris area.
Figure 1. The proposed drowsiness detection method

Iris area estimation – before estimating the iris area, we ensure there is no noise or small blob existed within the iris region using Hampel identifier. Then, the area of the iris is estimated as the total number of pixels within the iris region.

PERCLOS measurement – PERCLOS is a percentage of the total frame that eye is closed during a certain time interval. The eye is defined as closed based on predetermined PERCLOS values. The PERCLOS measure is calculated based on the area estimation of iris. We used left iris area, right iris area, and the total of both. Three thresholds values (60%, 70%, and 80%) were tested in this study and they are referred as P60, P70, and P80. P60 means the percentage of total time that eye is closed at least 60%. Similar meaning also true for P70 and P80. The PERCLOS is calculated as follows:

\[
\text{PERCLOS} \% = \frac{\text{sum of frames when eye is closed}}{\text{interval of frames}} \times 100 \%
\]

Dataset – The proposed approach was tested using Yawning Detection Dataset (YawDD) [14]. There are two datasets; the first dataset contains 322 videos and the second dataset includes 29 videos taken from real and varying illumination conditions. It consists both male and female drivers, with and without talking, and from different ethnicities. We tested our approach using selected 50 videos from the first
dataset. This dataset was collected from 30 males and 20 females videos with different conditions as given in Table 1. In total, there are five video categories including male-normal, male-yawning, male-talking, female-normal and female-yawning and each category contain 10 videos.

Table 1. There are 50 videos used in this study

|     | male    | female  |
|-----|---------|---------|
|     | normal  | normal  |
|     | 10      | 10      |
|     | yawning | yawning |
|     | 10      | 10      |
|     | talking |         |
|     | 10      |         |

The format of input video (YawDD dataset) is 640x480 pixels and 24-bit true color (RGB) at 30 frames per second. The experiment was done on a CPU Intel Core i3-2330M, 2.20GHz with 2.0GB RAM using Matlab R2017a.

4. Experimental Results
Figure 3 shows the results of the proposed method for a frame within a video from a male driver. If the method detects a face then subsequent process continue to detect eye, iris detection using Hough transform, iris segmentation, until the measurement of the area in terms of pixel number.

![Figure 3. The results of the proposed method as explained in the method section](image)

The illustration above happens when the face is detected. It shows each area of both iris side (from the left and right eye) was extracted. Figure 4 shows the results of the sum of both iris areas for the same subject. The left figure characterizes the condition when the driver is alert while the right figure characterizes when the driver is yawning or drowsy. It shows the difference between eye blinking and the eye being closed. Eye blinking happens within short interval while closed eye happens for a longer duration. However, iris area could appear low but not because of the drowsy condition. If the head is
tilted to the side, the Viola-Jones method may not be able to detect the face as it works perfectly when the head is upright.

![Figure 4. The iris area comparison when the driver is normal (left) and yawning (right) over time](image)

This indicates that iris area cannot be used to characterize driver’s drowsiness. However, PERCLOS was found to be the better potential measure of drowsiness. In this study, we used three values of PERCLOS threshold i.e. P60, P70, and P80. Table 2 shows the results of these PERCLOS thresholds for left iris, right iris, and a pair of both iris. It is evident that the pair works better for on all video categories because the PERCLOS values of the normal drivers are lower than the yawning drivers. However, PERCLOS values tend to go higher in talking drivers. This is because drivers tend to look sideways while talking. As a result, our method was not able to detect the face and thus no iris area can be measured (high PERCLOS value). Therefore, it is very important to know whether the driver is distracted when the face was not detected in the frame. Detecting whether driver drowsy or distracted would improve the reliability of drowsiness detection.

| driver | Left Iris | Right Iris | Pair |
|--------|-----------|------------|------|
|        | P60  | P70  | P80  | P60  | P70  | P80  | P60  | P70  | P80  |
| male   | normal| 77.27 | 64.55 | 53.45 | 85.35 | 73.4 | 58.46 | 70.22 | 58.78 | 46.2 |
|        | yawning| 77.41 | 70.29 | 63.15 | 84.8  | 79.89 | 73.83 | 73.18 | 63.44 | 55.02 |
|        | talking| 89.18 | 80.12 | 65.03 | 89.02 | 86.07 | 79.14 | 83.66 | 73.74 | 60.12 |
| female | normal| 81.08 | 71.83 | 64.88 | 84.22 | 72.6  | 61.28 | 70.26 | 58.45 | 44.22 |
|        | yawning| 82.97 | 73.73 | 61.02 | 82.94 | 75.23 | 61.83 | 74.41 | 61.25 | 46.49 |

5. Conclusion
This study has presented a drowsiness detection method based on face and eye detection within a video input. PERCLOS was calculated based on the area of iris region. The experimental results suggest that the proposed method potentially can detect drowsiness based on PERCLOS as it was found that PERCLOS value is lower when the driver is drowsy (compared to PERCLOS value when the driver is alert). Better results were found when both iris region (from left and right eyes) was used to measure
PERCLOS values. The limitation of the proposed method is when the face is unrecognized. This is happens when drivers are talking or distracted and thus having tendency to rotate their face sideways. In future, a distraction detection algorithm to detect tilted face is highly demanded.

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