Vision based Eye Closeness Classification for Driver’s Distraction and Drowsiness Using PERCLOS and Support Vector Machines: Comparative Study between RGB and Grayscale Images

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Abstract. Driver inattention and drowsiness are part causes of road accidents in Malaysia. Based on statistics from the Royal Malaysian Police (2016), deaths from road accidents amount is 7,512 in 2016 compared to 6,706 in 2015, which is the highest number of deaths recorded. Hence, an assistant system is needed to monitor driver’s condition like some car manufacturers introduced to their certain models of car. The assistant system is a part of main system known as advanced driver assistance systems (ADAS) are systems developed to enhance vehicle systems for safety and better driving. The system is expected to gather accurate input, be fast in processing data, accurately predict context, and react in real time. Suitable approach is needed to fulfil the system expectation. This paper describes the drowsiness and driver in attention detection and classification using computer vision approach. Our approach aims to classify driver drowsiness and inattention using computer vision. We proposed a technique to classify drowsiness into three different classes of eye state; open, semi close and close. The classification is done by using feature extraction method, percentage of eye closure (PERCLOS) technique and Support Vector Machine (SVM) classifier. We examined and analysed the Grayscale and RGB images using mentioned techniques.

1. Introduction
Feeling abnormally sleepy or tired during the day and may lead to additional symptoms, such as forgetfulness or falling asleep at unsuitable times [1] and inappropriate situation [2]. Referring to recent provisional data provided by Royal Malaysian Police (2016), deaths from road accidents amount to 7,512 in 2016 compared to 6,706 in 2015, which is the highest number of deaths recorded over previous years [3]. Drowsiness might be caused due to lack of sleep, fatigue, medication consuming, or routine related with vehicle driving [4]. It leads to a significant decline in driver’s abilities of perception and vehicle control, which leads to fatalities. This will threaten safe driving. According to [5], technology that can detect and mitigate distraction is needed to play a central role in maintaining safety by providing drivers with feedback and alerts. Either eye measures or driver performance measures, numerous solutions to detect distraction or drowsiness have been developed. As mentioned in [6], several car manufacturers have developed a number of systems that could detect distraction or drowsiness. To address this problem, a technique to determine and classify whether the driver is drowsy or not using computer vision is proposed in this paper.
2. Previous Work

There were several methods for detecting distraction has been proposed previously. Various works done by various researchers could use different method or approach to detect and measure distraction. Craye in [7] classified distraction detection method into 4 main approaches which involve the usage of physiological sensors, measurement of driver performance, computer vision and visual analysis, and hybrid system which consist of combination of two or more different main approaches. Author in [7] highlighted the physiological sensors approach is suitable to be used as a ground truth for studies, and do not represent a realistic solution for inattention monitoring. Besides, driver performance approach is also correlated with driver inattention monitoring. However, both physiological sensors and driver performance are affected by external factors such as road type, weather conditions and driver experience. Alternatively, computer vision and hybrid system are considered as the most popular and efficient approaches to assess driver inattention and drowsiness. Several techniques have been discussed and one of them is on the measurement of PERCLOS (Percentage Eye Closure) [8]. Eye-closure has a high correlation with drowsiness, and many researchers have developed methods to detect the same. In [4] and [9], they introduce a method to classify eyes and detect eye closure using the concept of Principle Component Analysis (PCA) and Eigen-eyes. Corresponding to [9], template matching, using skin colour and Viola-Jones algorithm are three major techniques used for face and eye detection. The authors in [10] clearly mentioned that no matter what way is adopted, the matching time would increase drastically with the numbers and the dimensions of the used templates and input images.

3. Methodology

Referring to Section 2, computer vision approach is selected to assess driver inattention and drowsiness in this work. Figure 1 shows three different classes of eye state images used to determine driver inattention and drowsiness. We define them according to the degree of eye closeness (PERCLOS) which are open (a), semi close (b) and close (c). The latter two (semi close and close) classes are considered as distraction or drowsiness.

![Figure 1. Classes of eye state.](image_url)

We take a set of M training images belong to each class. Half (50%) of the input images for each class were used as the training images while another half (50%) were used as testing images. We use a function model to train each class of image. The classifier contains the number of classes and the class labels for the input images. The function trains a Support Vector Machine (SVM) multiclass classifier. In this paper, two experiments have been conducted. First experiments (Experiment A) was conducted by using five sets of RGB images (1920x1080) of the eye state images wearing glasses, belong to each category (Refer Figure 2). All images are taken using webcam. Each set of eye state images belongs to one person for each class and five sets of training images containing 50 sets, 40 sets, 30 sets, 20 sets and 10 sets consecutively. Figure 2 shows the example of query images of training set for Experiment A: ((a), (b), (c)).

Visual vocabulary is created by extracting feature descriptors from representative images of each class. Visual vocabulary is defined by using k-means clustering algorithm on the feature descriptors into k mutually exclusive clusters. Then, the clusters are compacted and separated by similar characteristics and each cluster centre represents a feature or visual words. The grid method is used to select feature point and Speeded-Up Robust Feature (SURF) used to extract features which have been selected. Within this step, each image from the training set is encoded. Figure 2 shows the examples of images for training set. Features are extracted from the image and use the approximate nearest neighbour algorithm to construct a feature histogram for each image. A feature vector for the image is represented by the histogram. Then, the classifier is tested and evaluated using testing set image.
confusion matrix is used to represent the analysis of the prediction. A perfect classification results in a normalized matrix containing 1s on the diagonal and an imperfect classification results in fractional value. Lastly, the image category classifier is used to predict the query images and decide its category.

Figure 2. Examples of images of training set.

Data sets of the images were trained and tested with two types of query images shown in Figure 3 which are the images of the person without glasses ((a), (b),(c)) and with glasses ((d),(e),(f)) and represent each class of eye state as mention earlier in this section.

Figure 3. Types of query images.

Second experiment (Experiment B) is repeated using the same method by using Grayscale type images which is similar to Experiment A.

4. Results and Discussion
Table 1 and Table 2 show the comparison results for Experiment A and Experiment B. In Table 1, the results are based on percentage of the classification accuracy according to each category of eye state. The first column of the table denotes the eye state: open, semi close and close. In second column, the percentage of the classification accuracy between with glasses training images versus with glasses testing images. The last column presents the percentage of the classification accuracy between with glasses training images versus without glasses testing images. For Table 2 and Figure 4, the results are based on average computational time for each experiment.
Table 1. Comparison of classification accuracy between Experiment A and Experiment B.

| Experiment | A (RGB) | Experiment | B (Grayscale) |
|------------|---------|------------|---------------|
| With glasses | Without glasses | With glasses | Without glasses |
| Open | 94.14% | 92.24% | Open | 93.00% | 93.07% |
| Semi close | 95.33% | 95.45% | Semi close | 90.13% | 93.00% |
| Close | 93.20% | 93.07% | Close | 92.80% | 93.87% |

From the results in Table 1, we can see the performance of classification accuracy between two types of testing images is almost the same at all time for both experiments. Except for open state in Experiment A, clearly, we can see the classification accuracy testing images with glasses is higher than without glasses about 1.9 % and for Experiment B, obviously in semi close state, the classification accuracy testing images with glasses is lower than without glasses about 2.87 %. In close state, the classification accuracy testing images. From the results in Table 1 for Experiment A, the average accuracy of distraction or drowsiness classification is 94.27% and 94.26% for images with glasses and without glasses respectively. Meanwhile for Experiment B, the distraction or drowsiness classification rates are 91.47% for images with glasses and 93.44% for images without glasses. These distraction or drowsiness accuracy rates were measured by averaging the accuracy rates of semi close and close classes.

Table 2. Comparison of computational time for Experiment A and Experiment B.

| Experiment | A (RGB) | Experiment | B (Grayscale) |
|------------|---------|------------|---------------|
| Number of Frame | Average Computational Time (s) | Number of Frame | Average Computational Time (s) |
| 10 | 222.9020 | 10 | 78.0373 |
| 20 | 493.0974 | 20 | 114.8722 |
| 30 | 742.8054 | 30 | 148.4608 |
| 40 | 883.3233 | 40 | 258.2315 |
| 50 | 1447.4603 | 50 | 247.0858 |

Figure 4. Comparison of Computational time for Experiment A and Experiment B.

The comparison results in Table 1 and Figure 2 clearly show the difference of average computational time between Experiment A and Experiment B. We can see the average computational time for Experiment B is faster than Experiment A which is more than 64 %.

5. Conclusion
This paper presents a non-intrusive approach for monitoring driver drowsiness and inattention based on computer vision approach. Most of previous works dealt with one type of eye condition which is without glasses. In this paper, both experiments are considering this two eye conditions which include eye with glasses and eye without glasses. Moreover, the results of the experiments show the compatibility of using one type of eye condition data training to classify two types of eye condition.
based on three classes of eye states. Besides, colour and texture feature extraction are very important for image classification. This paper has considered and analysed two different types of images such as RGB and Grayscale images. According to the experiments result, RGB image has given better results than Grayscale image in term of classification accuracy but in term of computational time, Grayscale images has given better results than RGB. In all experiments, the distraction or drowsiness accuracy were found to be always more than 90%.

This indicates that our proposed technique was able to detect and classify distraction or drowsiness of a subject with very high accuracy and fast. However, the study was limited to controlled environment such as non-volatile illumination variation and very minimum movement by the subjects. Further research and study will be conducted using the proposed technique in the condition which is similar to real driving situation.

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