Fatigue Detection in Drivers using Eye-Blink and Yawning Analysis

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Abstract *Colossal loss of lives and economic resources has given rise to the need to develop an active safety system that can prevent road accidents by warning drivers of their poor driving conditions, thus, the emergence of driver monitoring system, especially in automation system of future vehicles. This research work proposes an approach to test driver's alertness through hybrid process of eye blink detection and yawning analysis. The system counts the number of left and eye blinks as well as yawning detected, and compared with a threshold after which an alarm is triggered to show that fatigue had been detected. The algorithm was implemented in MatLab 8.10 (R2013a) using the detection accuracy, sensitivity, specificity as metrics for performance evaluation. The developed algorithm gave detection accuracy rate of 85.7%, sensitivity rate of 75%, precision rate of 60% and specificity rate of 88.24%.*

Keywords *Fatigue detection, Yawning Eye-blink, Support Vector Machine, Adaboost*

I. INTRODUCTION

Fatigue in drivers is a major cause of road accidents with several thousands of casualties each year because of drivers falling asleep behind the wheel. Risk of death or serious injury is projected to be greater in sleep related accidents than in any other type of accident [1]. National Highway Traffic Safety Administration (NHTSA) an agency of the Executive Branch of the US government submitted that driving while drowsy is a contributing factor of 22 to 24 percentages of car crashes [2]. This record shows that car accidents caused by fatigue drivers is four to six times higher than near crash or crash relative to alert drivers as fatigue drivers fail to take correct actions prior to a collision [3]. This is because fatigue impact the alertness and response time of the driver thus increasing the chances of getting involved in car accidents.

Drowsiness and fatigue often affect drivers' ability long before he notices or sense tiredness. He might be too tired to realize his level of in-attentiveness. Sometimes, drivers are aware of feeling sleepy and make a conscious decision whether to stop and rest, or continue driving while trying to fight off sleepiness and stay awake. At this state, many employ a range of strategies to help fight off sleepiness and stay awake, most of which are ineffective. The driver face monitoring system is a real-time system that investigates the driver physical and mental condition based on intelligent image of driver face images.

The challenges of driver face monitoring system are how to measure fatigue and how to measure concentration. There is no precise definition for fatigue, hence no measurable criterion or tool. However, there is a relationship between fatigue and some symptoms including body temperature, electrical resistance of the skin, eye movement, breathing rate, pulse rate, brain activity and yawning. The most accurate techniques are based on physiological measures such as brain waves, heart rate, pulse rate [4], but these techniques are intrusive in nature as they require drivers to wear sensors. In comparison, methods based directly on observable visual behaviours are less intrusive, but face the challenge of choosing the right number and combination of parameters for accurate detection [4]. The driver state can be estimated from eye closure, eyelid distance, blinking, yawning, head rotation and gaze direction as one of the first and most important symptoms of fatigue is said to appear in the eye [5]. Hence, eye closure detection is the first symptom used to measure fatigue in a driver face monitoring system.

Notable work has been done in this area by combining visual parameters like closure duration, blinking frequency, nodding frequency, face position, fixed gaze and yawning to monitor the fatigue and vigilance level. There also exists a hybrid approach for detecting fatigue which combines driver's state and vehicles performance to predict the driver's fatigue [6]. These methods are not intrusive, but are subject to several limitations such as the system not working with people who have dark skin since the algorithm is based on binarization which does not work for dark skinned people [7]. Another limitation from some of the works includes its sensitivity to changes in lighting condition. This research work proposes a new approach to solving driver's drowsiness through the hybrid process of eye blink detection and yawning analysis, rectangular histogram of oriented gradients (RHOG) and using

SVM (Support Vector Machine) to classify feature vectors to detect yawning as well as eye blinks.

II. METHODOLOGY

The proposed hybrid method adopted AdaBoost face detection algorithm for face, eye and mouth region detection. Discriminative features were extracted from the detected face components using Rectangular Histogram of Oriented Gradients (RHOG), while a two-level cascaded support vector machine (SVM) was used for classification. The complete frame work for detection and classification is shown in Figure 1.

Face detection was performed using the AdaBoost face detection algorithm that uses sets of cascades of classifiers that were already trained with many faces and mouths [8]. The same algorithm was also used to detect face components such as left eye, right eye and mouth region. Having detected a face in one frame, the detected face was used as a template for tracking in subsequent frames except the system losses track of the face and then goes back to the face detection phase to re-detect the face. Histogram of Oriented Gradient (HOG) was used to extract features from the detected parts namely the left eye, right eye and the mouth. The images detected (the left eye, the right eye and the mouth) were divided into smaller regions (cells). Histogram of gradient was computed for successive orientation within each cell and the combined histogram entries were used as the feature vector to describe the object. The computed gradients were normalized by grouped into larger spatially connected blocks. This helps to provide robust illumination invariance for the images (of drivers) extracted from video frames.

The opening and closing of the eye for blink detection was achieved through a two-level cascaded SVM (Support Vector Machine). Three classes were considered: "opened eye", "closed eye" and "non-eye". Considering the three classes, the verification procedure was designed with the two-level cascaded SVM.

The lower half of the face was the target of the mouth search region. Locating the mouth in the frame, the data related to the mouth location and size was used as reference in the yawning detection stage. Yawning detection was performed in two main steps: In the first step, the yawn component was detected in the face independent of the mouth location. This component is basically the hole in the face as the result of wide mouth opening. In the second step, the mouth location was used to verify the validity of the detected component. After finding the mouth area, the histogram of the mouth was found in the first frame and was assigned as a reference histogram for yawning detection using HOG. The histogram in the

subsequent frames were found and compared with the reference histogram.

The implementation tool used was MATLAB R2012a version on Windows 7 Ultimate 32-bit operating system, Intel®Pentium® CPU B960@2.20GHZ Central Processing Unit, 4GB Random Access Memory and 500GB hard disk drive. The developed system was tested with a dataset populated purposely for this research. The dataset contains twenty-one videos of males and females in driving position. In recording the videos, a camera was installed on the dashboard of a car and several scenarios of eyeblink, yawning and a combination of the two were captured. The videos were recorded in the same location at an average of 30 seconds per subject.

The performance of the develop system was evaluated using sensitivity, specificity, detection accuracy and precision. The following parameters were used to measure or evaluate the performance of the fatigue detection system:

1. Sensitivity (Se): the proportion of actual position which is correctly identified. It is defined as ability to detect the presence of fatigue.

$$Sensitivity = \frac{TP}{(TP + FN)} \times 100 \quad (1)$$

2. Specificity measures the proportion of negatives which are correctly identified. It is defined by the ability to detect absence of fatigue.

$$specificity = \frac{TN}{(TN + FP)} \times 100 \quad (2)$$

3. Precision is defined by the proportion of the positives that corresponds correctly with the identified.

$$precision = \frac{TP}{(TP + FP)} \times 100 \quad (3)$$

4. Detection accuracy is evaluated using

$$accuracy = \frac{TP + TN}{(TP + TN + FP + FN)} \times 100 \quad (4)$$

where TP denotes True Positive, TN stands for True Negative, FP stands for False Positive, FN stands for False Negative.
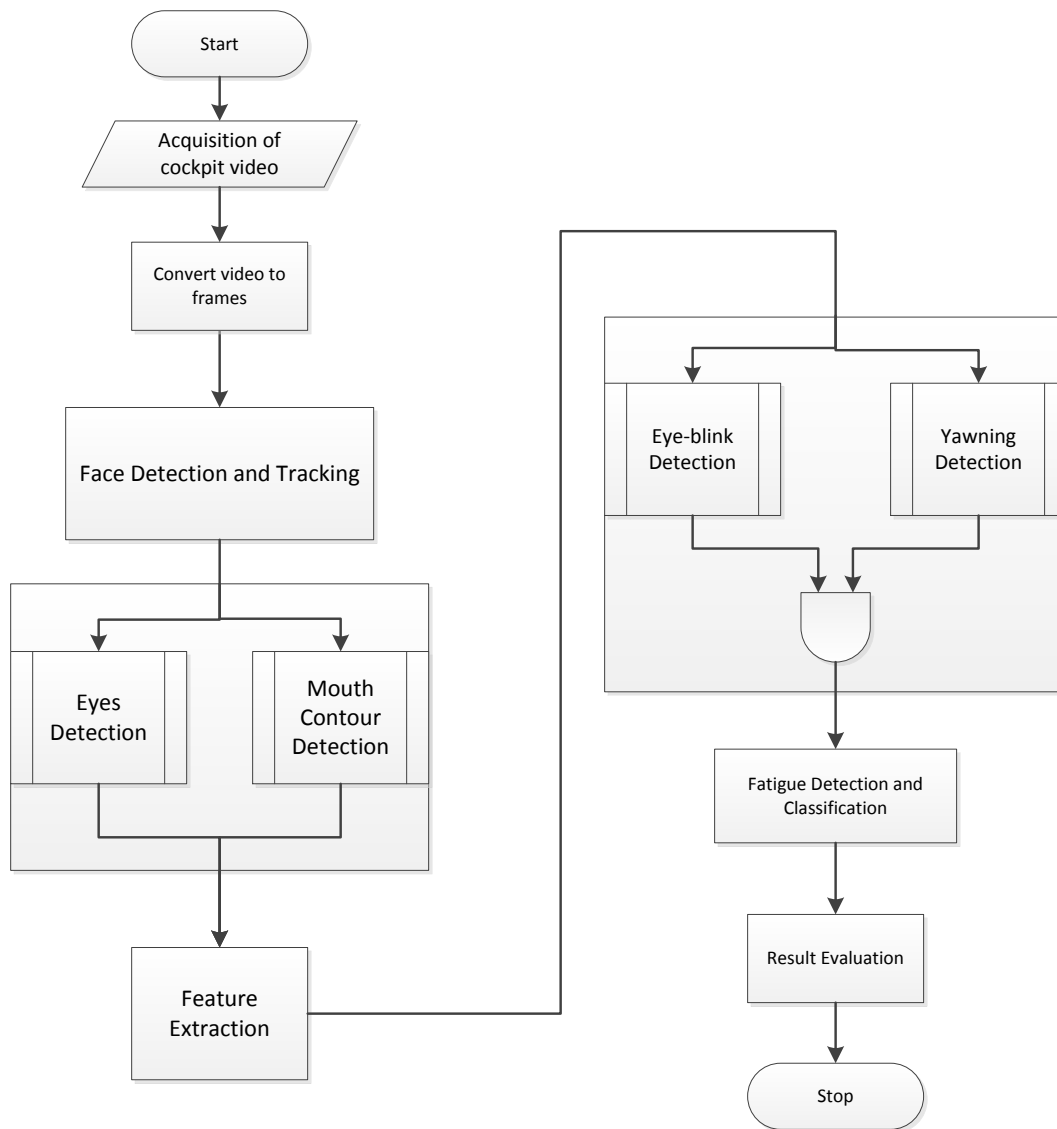
Fig. 1 Framework of the proposed system

III.RESULTS

Fatigue detection is accepted as "TRUE" when the number of left-eye blink, right-eye blink and yawning exceeds a set threshold. For verification, a manual monitoring of the videos was done and the same thresholds were used to either classify detection as "TRUE" or "FALSE". Two different threshold counts were set at two different instances as (r-eye blink, l-eye blink, yawn) at (1, 1, 1) and (2, 2, 2) respectively. Two logical combination of the counts were considered, which are AND and OR in the following manner (r-eye blink AND l-eye blink AND yawn) and (r-eye blink AND l-eye blink OR yawn. The results for the AND and OR logical combinations are as shown in Table 1, while Table 2 shows the sensitivity, specificity and accuracy results obtained.

The highest accuracy result obtained in this work is from the logical combination AND on threshold count 2, with detection accuracy, sensitivity, specificity and precision rate of 85.71%, 75%, 88.24% and 60% respectively. The result obtained from the algorithm was compared with some earlier works though with different data base and methods. When compared with [2], which was reportedly tested on both, PC and APEX board.

On the PC, their results showed that for the videos where the camera is installed under the front mirror, the rate of detecting the mouth and subsequent yawning is about 40% due to the angle of the drivers' face to the camera. For the videos where the camera is installed on the dash, the yawning detection is 60% however on the APEX board, the average success rate for yawning detection was 80%

TABLE 1: RESULT FOR FATIGUE DETECTION

Metric	AND		OR	
	(2,2,2)	(1,1,1)	(2,2,2)	(1,1,1)
TP	3	4	6	10
FP	2	5	8	2
TN	15	10	6	2
FN	1	2	1	7

TABLE 2: PERFORMANCE EVALUATION

Metric	AND		OR	
	(2,2,2)	(1,1,1)	(2,2,2)	(1,1,1)
Sensitivity (%)	75.00	66.67	85.71	58.82
Specificity (%)	88.24	66.67	53.33	50.00
Precision (%)	60.00	44.44	46.15	83.33
Accuracy (%)	85.71	66.67	66.67	57.14

TABLE 3: COMPARISON OF RESULTS WITH EXISTING WORKS

Reference	Method	Detection	No of Frames	Detection Rate (%)
Zainal, Khan and Abdullah (2014) [9]	Viola Jones and skin colour pixels detection method	Yawning and eye status	890	96.2
Abhati, Hariri and Shirmohammadi (2011) [2]	Adaboost detection Algorithm/Haar features	Yawning Detection	5,400	80
Our Method	Adaboost/HOG features/SVM	Eye Blink and Yawning Detection	2,100	96.3

IV. CONCLUSIONS

This research work has addressed the problem of detecting fatigue in drivers using a hybrid method of yawning analysis and eye blink detection. It has achieved among other things the development of a face tracking model that could extract features in a varying illumination environment. A model for feature detection was developed which uses a combination of yawning analysis and eye blink detection. Features extracted from the left eye, right eye and the mouth were used as input into the support vector machine for classification. The algorithm was implemented in MatLab 8.10 (R2013a) using the detection accuracy, sensitivity, specificity as metrics for performance evaluation.

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