Driver Drowsiness Detection Using Naive Bayes and Svm Classifiers

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Abstract- *In this work, eye condition based driver drowsiness system has been explored in which first face of the person has been segmented out from a video frame and then location of both eyes has been extracted as a rectangular patch which contains the iris, sclera and eyelid pixels of the eye region. Further texture features has been taken using improved local binary patterns. Texture features contains the histogram of the MLBP image produced of the eye region. A number of frames has been selected for the training purposes in which SVM and Naïve Bayes classifiers has been applied for classification of test eye regions which provides the decisive information about opening and closing of an eye. Experimental results shows that both classifiers gives effective results when proposed texture feature extraction based on variants of local binary pattern has been applied as compared to the existed LBP based feature extraction. In comparison to Naïve Bayes classifier, Support vector machine classifier gives high accuracy in the actual classification of test eye patches. SVM provides about 96% accuracy in true classification of the eye patch condition*.

Keywords- Naïve bayes, SVM, drowsiness detection, feature extraction, LBP etc.

I. INTRODUCTION

Driver drowsiness is a significant factor in a large number of vehicle accidents. Drowsy driving increases the risk of causing an accident four to six times, compared with alert driving. In fact, at least 15–20% of all vehicle accidents have been estimated to be sleepiness related [1]. Drowsiness can result from sleep-related or task-related fatigues [2]. The term fatigue refers to a combination of symptoms such as impaired performance and a subjective feeling of drowsiness [3]. Author in [4] grouped the methods of fatigue driving detection into five categories:

- Subjective report measures;
- Drivers' biological measures;
- Drivers' physical measures;
- Driving performance measures; and
- Hybrid measures.

Among these approaches, drivers' physical measures have advantages such as being cost-efficient, non-intrusive, and real-time. The development of technologies for detecting or preventing drowsiness at the wheel is a major challenge in the field of accident avoidance systems [5]. Diverse techniques have been developed for monitoring driver drowsiness.

These techniques can be generally classified into three main categories [6].

1) The first category includes methods based on biomedical signals, like cerebral, muscular and cardiovascular activity [7]. Usually, these methods require electrodes attached to the driver's body, which will often cause annoyance to the driver. Also, long time driving would result in perspiration on the sensors, diminishing their ability to monitor accurately.
2) The second category includes methods based on the driver's performance, by monitoring the steering wheel movement, accelerator or brake patterns, vehicle speed, lateral acceleration, lateral displacement and other signals recorded by CAN [8]. The advantage of these approaches is that the signal is meaningful and the signal acquisition is quite easy. However, these systems are subject to several limitations such as vehicle type, driver experience, geometric characteristics and condition of the road. Since these procedures require a considerable amount of time to analyze user behaviors, they do not work with the so called micro sleeps, i.e., when a drowsy driver falls asleep for a few seconds on a very straight road section without changing the vehicle signals.
3) In the third category, computer vision uses natural and non-intrusive techniques for monitoring driver's drowsiness from the images captured by cameras placed in front of the user. These approaches effectively measure physical changes of the driver such as sagging posture, leaning of the driver's head and the open/closed states of the eyes. Different kinds of cameras and analysis algorithms have been

reported in the literature for this approach: methods based on visible spectrum camera [9]; methods based on infra-red (IR) camera [6] and methods based on stereo camera.

II. LITERATURE SURVEY

Jaeik Jo et. al. [10] proposed a driver drowsiness detection method that can be used to warn drivers of the onset of drowsiness reliably. The proposed method has three advantages over previous methods. First, it fuses information from both eyes in order to correctly classify eye state even when one eye has not been properly localized or is obstructed. Second, the method calculates a userspecific threshold for eye state classification in order to improve accuracy across a wider range of drivers, including those with small eyes or high blinking frequency. Third, the method learns the particular driver's blinking pattern by fusing two drowsiness measurements (PERCLOS and ECD) over an initial (normal) driving period.

Arun D Panicker et. al. [11] proposed a new method using ISPA for open-eye detection to be used in vehicle driver drowsiness monitoring. The performance of the proposed ISPA method is satisfactory and it could be extended for night time system using an IR camera with no or a little modification. The ISPA method is proven to work efficiently in low-resolution images for many eye postures. This method yields excellent results on images with varying illumination and complex backgrounds.

Feng You et. al. [12] Propose a non-intrusive night-monitoring system for fatigue driving. First, they combine template matching with a validation process to achieve fast, robust eye detection. Second, a Gabor filter is used to locate the corners of the eyes, and a gray-level integration projection method is applied to calculate the height of an open eye. Finally, they calculate eye-blinking frequency and assess the fatigue level of the driver.

Hu Shuyan et. al. [13] constructed a SVM drowsiness detection model with all the features. The dataset is firstly divided into three incremental drowsiness levels, and then a paired t-test is done to identify how the parameters are associated with drivers' sleepy condition.

Faisal Mohammad et. al. [14] developed the Drowsy Driver Scleral-Area (DDSA) app using a Haar cascade classifier and dedicated JAVA code image processing software applied over a masked region surrounding the eye. The app was able to quantify the area of the white sclera that represented the state of eye opening. Manual adjustments provided a fine-tune feature to account for inter-subject differences.

Rami N.Khushaba et. al. [15] proposed a new feature projection method in order to reduce the dimensionality of the extracted features from a combination of EEG, EOG and ECG channels. The proposed UFNPA considers the fuzzy nature of the input data while preserving the local discriminant and geometric structure of different data points. To avoid the singularity problem, the UFNPA utilized singular value decomposition to produce a set of statistically uncorrelated features that proved its effectiveness across different datasets and classifiers.

III. PROPOSED WORK

The system module of the proposed system is shown in Figure 1. First of all, frames have been extracted from the captured video. Next eye region has been localized using cascade object detector. The cascade object detector uses the Viola-Jones algorithm to detect people's faces, noses, eyes, mouth, or upper body. Next a set of features are extracted from each eye patch to help discriminate between open and closed eye patches and used to build a Feature vector. For classification SVM and Naïve bayes classifiers has been used. The steps used are explained below.

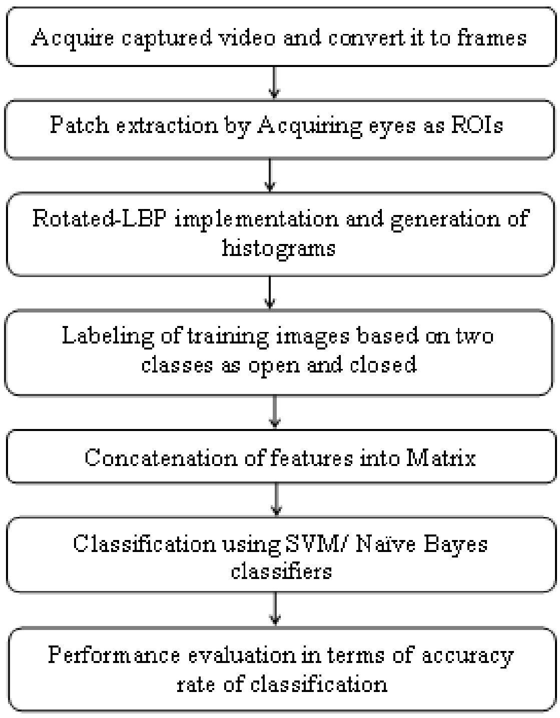

Figure 1: system module

Texture feature extraction using LBP

The local binary pattern is a powerful gray level invariant texture primitive. The histogram of the binary patterns computed over a region is used for texture description [16]. The operator describes each pixel by the relative gray levels of its neighboring pixels; see Figure 2 for an illustration with 8 neighbors. If the gray level of the neighboring pixel is higher or equal, the value is set to one, otherwise to zero.

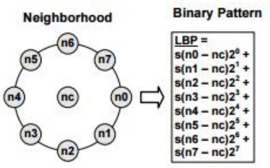

Figure 2: LBP evaluation [16].

The LBP operator takes 3 $\times$ 3 surrounding of a pixel and

1. Generates a binary 1 if the neighbor is greater than or equal to the centre.
2. Generates a binary 0 if the neighbor is less than the centre.

The eight neighbors of the centre can then be represented by an 8-bit number.The problem of variations to rotations in LBP arises due to the fixed arrangement of weights. As the weights are aligned in a circular manner, the effect of image rotations can be countered by rotating the weights by the same angle while computing the descriptor. Since the angle of the rotation cannot be known, we propose an adaptive arrangement of weights based on the locally computed reference direction. The reference direction should be such that if an image undergoes a rotation, it should also undergo a rotation by the same angle. In our experiments, we have tested different choices of the reference direction, such as the gradient, weighted difference between the pixels, etc. The best results were obtained with what we call, the Dominant Direction. The Dominant Direction is defined as the index of the neighbouring pixel whose difference from the central pixel is maximum

$$D = \underset{p\in(0,1\ldots p-1)}{\arg\max} |g_p - g_c| \tag{1}$$

The proposed reference quantizes the dominant directions into P discrete values. The proposed descriptor is computed by rotating the weights with respect to the Dominant Direction, hence, the descriptor is called Rotated Local Binary Pattern. Since the dominant direction is taken as the reference in the circular neighbourhood, the weights are assigned with respect to it [31]. Thus, the MLBP operator is defined as

$$MLBP_{R,P} = \sum_{P=0}^{P-1} s(g_p - g_c).2^{\mathrm{mod}(p-D,P)} \tag{2}$$

where mod indicates the modulus operator. In the above definition, the weight term $2^{\mathrm{mod}(p-D,P)}$ depends on D

IV. CLASSIFIER TRAINING

1. Support Vector Machines

The foundations of Support Vector Machines (SVM) have been introduced by Vapnik et al [17] for binary classification. The simplest form, given data points represented as p-dimensional vectors, the SVM classifier tries to find a hyperplane which separates these points into two-class data with maximal margin (maximizes the distance between the margin and the nearest data point of each class). The margin is defined as the distance of the closest training point to the separating hyperplane [17]. Figure 3 shows two-class data which can be separated by many liner classifiers, but only one is considered that maximize the margins (the green line) and the linear classifier is known as a maximum margin classifier.

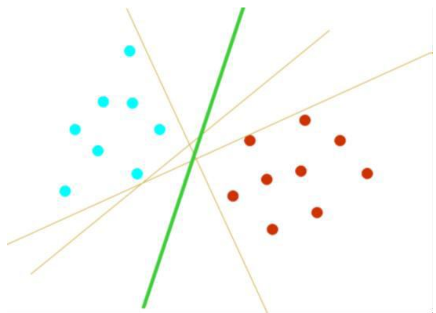
Figure 3: Optimal separating hyperplane [17]

2 Naïve-Bayes

Naive Bayes Classifier Naive Bayes is a classifier method which is introduced by Thomas Bayes. This method learning from data and predict class which each class have probability [18]. Bayes theorem is shown in Eq. (3)

$$P(A/B) = \frac{P(B/A)*P(A)}{P(B)} \tag{3}$$

where $P(A)$ and $P(\mathrm{B})$ are probabilities of observing A and B . $P(\mathrm{B}/\mathrm{A})$ is the probability of observing event B given that A is true. Naïve Bayes equation is represented by P(A |B), A is a input vector that have feature and B is a class label. Based on information from training data, for each combination A and B, the final probability P(B | A) of model should be trained. With that model, testing data of A' can be declared by look for B' value by maximazing P(A'|B') value. Then for classification, Naïve Bayes formula can be declared as Eq. (4)

$$P(B/A) = \frac{P(Y)\prod_{i=1}^{q} P(A_i \mid B)}{P(B)} \qquad (4)$$

where P(B| A) is probability data for A vector in Y class. P(Y) is initial probability of Y class.

V. RESULTS AND DISCUSSIONS

A. Classification Accuracy

This section provides definitions and some results for tests that detect the presence of a condition (a test result is either "positive" or "negative", which may be "true" or "false").

Definition 1: A true positive test result is one that detects the condition when the condition is present.

Definition 2: A true negative test result is one that does not detect the condition when the condition is absent.

Definition 3: A false positive test result is one that detects the condition when the condition is absent.

Definition 4: A false negative test result is one that does not detect the condition when the condition is present. condition present absent positive true positive false positive Test negative false negative true negative Let TP denote the number of true positives, TN the number of true negatives, FP the number of false positives, and FN the number of false negatives.

Definition 5: Sensitivity measures the ability of a test to detect the condition when the condition is present. Thus, Sensitivity = TP/(TP+FN).

Definition 6: Specificity measures the ability of a test to correctly exclude the condition (not detect the condition) when the condition is absent. Thus, Specificity = TN/(TN+FP).

$$Accuracy = \frac{TP - TN}{TP - TN + FP - FN}$$

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TP - FP}$$

Results for existed and proposed methods has been shown in tabular form and also graph comparison has been provided below

Table 1: Sensitivity, specificity, and accuracy values using local binary patterns

Classifier used	Sensitivity	Specificity	Accuracy
SVM	85.046	85.543	85.475
Naïve Bayes	84.112	88.971	88.303

Table 2: Sensitivity, specificity, and accuracy values using modified local binary patterns

Classifier used	Sensitivity	Specificity	Accuracy
SVM	96.261	95.976	96.015
Naïve bayes	85.046	93.144	92.030

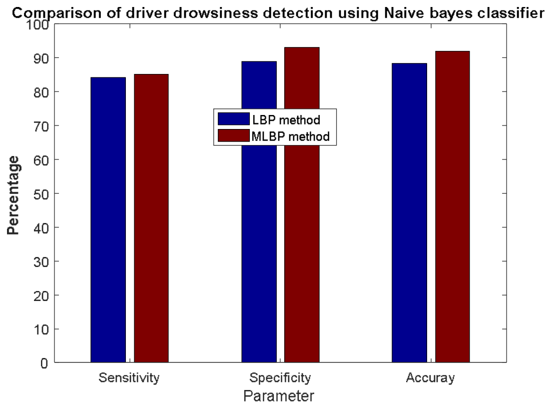

Figure 4: Comparison of driver drowsiness detection using Naïve bayes classifier

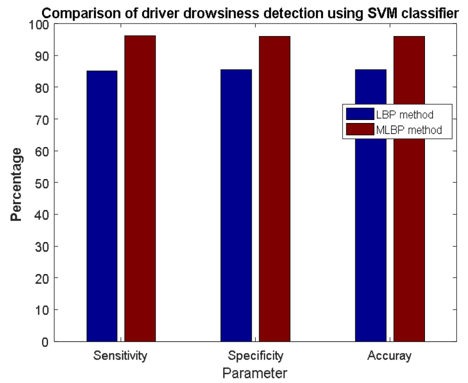

Figure 5: Comparison of driver drowsiness detection using SVM classifier

All eye patches obtained after extraction are tested based on local binary pattern texture features and proposed modified LBP features. As a classifier, Naïve Bayes and SVM classifiers have been used which shows effective results when proposed feature extraction method has been tested as compared to existed one.

VI. CONCLUSION

Quantifying drowsiness, however, has proven to be difficult. While a passenger in a vehicle may be able to assess the state of the driver's drowsiness, an objective real-time fatigue detection system has not yet been fully realized . Previous methods used a variety of physiological indicators such as brain wave patterns, heart rate monitoring, and steering grip force as part of the detection system. Although these studies have provided some quantitative information regarding driver fatigue, they were not particularly successful in applying their techniques in real world driving environments. For example, brain wave pattern detection is invasive, since electroencephalography (EEG) requires electrodes to be placed on the scalp. Also, electrodes placed over clothing to detect heart rate provided relatively noisy data compared to direct contact electrodes. Similarly, steering grip pressure has not been shown to be a reliable indicator of fatigue. Therefore, a great emphasis has been placed on technological development of two approaches: non-invasive vehicle assist systems and real time face/eye detection software. In this work, face/eye driver drowsiness detection system has been proposed based on spatial texture features using modified local binary patterns. Local binary patterns work in 3*3 neighborhood basis and detect the texture changes in the image. In this work, rotation invariant LBP has been used instead of basic LBP which gives high accuracy rates when these features are tested based on machine learning classifiers. Two classifiers named as SVM and Naïve Bayes has been tested on the collected dataset of features from the frames of a video of fatigued driver. It has been concluded that SVM is more effective as compared to Naïve Bayes which gives almost 96% accuracy in true classification of tested eye data in classification of drowsiness and non-drowsiness condition of an eye.

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