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Drivers Drowsiness Detection Using Machine Learning

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ABSTRACT

Driver drowsiness is one of the most significant causes of motor vehicle accidents. There is an annual increase in the number of fatalities and fatal injuries worldwide. Driver fatigue is one of the leading factors of automobile accidents. It is a serious road safety issue. If drivers were alerted before they became too sleepy to drive safely, some of these collisions could be avoided. In order to reliably detect drowsiness, it is necessary to provide opportune warnings of drowsiness. To date, slumber detection methods have been ineffective due to their failure to account for individual differences. On the basis of the type of data employed, slumber detection can be conveniently divided into intrusive and non-intrusive methods. During the survey, non-intrusive methods detect drowsiness by measuring driving behavior and occasionally ocular features, with camera-based detection systems being the most effective and therefore useful in real-world driving scenarios. By detecting drowsiness in the motorist, road accidents can be prevented. This paper describes a machine learning method for detecting fatigue. Face detection is used to identify the driver's eye regions, which are then used as templates for eye tracking in subsequent frames. The monitored eye's images are used to detect drowsiness in order to generate warning alarms.

1. Introduction

Drowsiness is one of the leading causes of automobile accidents. If the driver's fatigue can be predicted at an early stage and he or she is alerted of it, the number of accidents can be reduced. In this paper, a system for detecting driver fatigue using machine learning is proposed. In the initial stage, frontal face detection and eye detection are detected separately. High frame rates are the result of three major contributions of the object detection framework. This paper's first contribution is a new image representation known as an integral image, which enables extremely rapid feature evaluation. It employs a set of characteristics that resemble Haar Basis functions. In order to compute these features very quickly at multiple dimensions, the integral image representation is introduced for images. A few operations per pixel are required to compute the integral image from an image.The second contribution is a method for constructing a classifier using AdaBoost and a limited number of significant features. To ensure rapid classification, the learning process must focus on a small number of essential features and exclude the vast majority of available features. This feature selection is accomplished by modifying the AdaBoost procedure in a straightforward manner.

2.LITERATURE REVIEW

The developed system is a real time system. It uses image processing for eye and face detection. HAAR based cascade classifier is used for face detection. An algorithm to track objects is used to track the eyes continuously. In order to identify the drowsy state of the driver, the PERCLOS algorithm issued [2]. The paper focuses on developing a non- intrusive system which can detect fatigue and issue a warning on time. The system will monitor the drivers eyes using a camera. By developing an algorithm, the symptoms of driver fatigue can be detected early enough to avoid accident. When the signs of fatigue have been identified output in the form of sound and seat belt vibration is provided to alert the driver. Warning will be deactivated manually rather than automatically. This paper uses a faster algorithm than PERCLOS. This system will detect drivers fatigue by the processing of the eye region. After image acquisition, the first stage of processing is face detection. If eyes are blinking visual, non-visual, and vehicular features into one. The last idea is to develop wearable hardware such as smart watches in order to detect drowsiness

3.METHODS AND MATERIAL

Tools & Image Processing Methods

Open CV:
OpenCV (Open-Source Computer Vision) is the Swiss Army Knife of Computer Vision, it has a wide range of modules that can help us with many Computer Vision problems, but perhaps the most useful part of OpenCV is its architecture. and memory management. It gives you a framework in which to work with pictures and videos however youwant, using OpenCV algorithms or your own, without worrying about allocating and reallocating memory for your pictures. optimized and can be used for real-time video and image processing The highly optimized image processing function of OPENCV is used by the author for real-time image processing of live video streaming from the camera.

DLib: Dlib is a modern C toolkit with algorithms and tools for machine learning to create complex C ++ software to solve real problems. It is used in a wide variety of fields in both industry and academia, including robotics, embedded devices, cell phones, and large, high-performance computing environments. Lib's open source licenses allow you touse it in any application for free.The author uses the open source Dib library for the CNN (Neural Networks) implementation. The author uses highly optimized prediction functions and detectors ofpreviously learned face shapes to detect facial features.

EAR (Eye Aspect Ratio)

The numerator of this equation calculates the distance between the vertical landmarks of the eye, while the denominator denotes. calculates distance between the horizontal eye reference points weighting the denominator accordingly since there isonly one. The aspect ratio of the eye is roughly constant when the eye is open, but quickly drops to zero when you blink.When the person blinks, the aspect ratio of the eyes drops dramatically and approaches zero. As shown in Figure 2, the aspect ratio of the eyes is constant, then quickly drops to zero and then increases again, suggesting that a singleblink has occurred.

4.Algorithm Steps

Step 1 – Take image as input from a camera.

Step 2 – Recognize the face in the image and create a region of interest (ROI).

Step 3 – Recognize the eyes from the ROI and send them to the classifier

Step 4 – The classifier classifies whether the eyes are open or closed

Step 5 – Calculate the score to be verified. when the person is sleepy

With a webcam we take pictures as input. To access the webcam, we created an infinite loop that captures each frame. We will use the method provided by OpenCV to access the camera and configure the capture object, we will read each frame and store the image in a frame variable. In order to recognize the face in the image, we must first convert the image to grayscale, as the OpenCV algorithm for object recognition uses gray images as it is input. We don't need any color information to recognize the objects. We use a hair cascade classifier to identify faces. Then we do face recognition. Returns an array ofdetections with x, y coordinates and the height and width of the bounding box of the object. Now we caniterate over the faces. and draw contour boxes for each face.

5.Data Pre-processing

Removing Columns

We removed the following columns: Run name, frames, and event_id. These columns where identifiers and did not provide any value for classification.

We found that we should remove these columns after viewing the attributes selected by Weka. When we chose the AttributeSelectedClassifier, it ranked these columns high. This meant that even though they do not contain valuable information, the machine learning algorithms found a correlation between these columns and the run class.

It was interesting for us to note that the quality measures degraded after removing these features. It is clear that these identifiers where giving extra information to the machine learning algorithms, but we had to remove them because they were not relevantto the classification task.

Missing Values

In the case of per-event aggregate features, some of the runs did not have all the events. Therefore, we had missing value for some of the features. It appeared that those events were not significant in the classification, but we did not want to remove the events from the data. Also, we did not want Weka to try to fill those missing values for us. Therefore, after discussing with the person who we obtained the data from, we agreed that it is reasonable to put 0 for the missing values.

Features

Due to the time-series nature of data, we need to somehow aggregate the values in the time-series to generate features for this data set. This can be done in many ways. Therefore, we created 2 different set of features:

1. Per-run aggregate features
2. Per-event aggregate features

Below you can find the feature description and the experiment results for each set of features.

Per-run aggregate features

The most simple set of features is to aggregate all the values for each column in the run. For each column, we generated 4 features:

- Mean of all values in the column
- Minimum of all values in the column
- Maximum of all values in the column
- Standard deviation of all values in the column

For example, for the speed column, the mean, min, max, and std. of the speed in the run would be 4 different features. This totals to 76 features for this feature set.

The above 4 features for each column are generated based on the hypothesis of how a drowsy person“may” act. We do not have the exact answer but the hope is that the machine learning algorithms can find it out.

For example, for the speed column one could hypothesize that if a person is drowsy he may drive slower/faster in average (mean). He may have very slow/fast speeds in cases where he falls asleep (min, max). Or he may deviate from his average speedbecause of his impairment (standard deviation).

Per-event aggregate features

Each run is composed of a set of events. For example,the driver first pulls out of a driveway, then drives in an urban area, then enters the highway and so on. There are certain events where the driver is more proneto become drowsy. For example, we hypothesize that when driving in the highway or driving in the straightrural road which are more boring experiences, it is more likely to become drowsy. Also, one would hypothesize that the driver will be more likely to get drowsy in the later part of the trip when he gets close to the destination.

With the per-run aggregate features, this information is lost and not available to the machine learning algorithms. Therefore, we introduce a new set of features: Per-event aggregate features.

For this feature set, we aggregate the values per event in each column. This means that we generate these 4 features per-event per-column:

- Mean of all values in the event in column
- Minimum of all values in the event in column
- Maximum of all values in the event in column
- Standard deviation of all values in the eventin column

There are 25 total events and 19 columns. This totals to 1900 features in the dataset.

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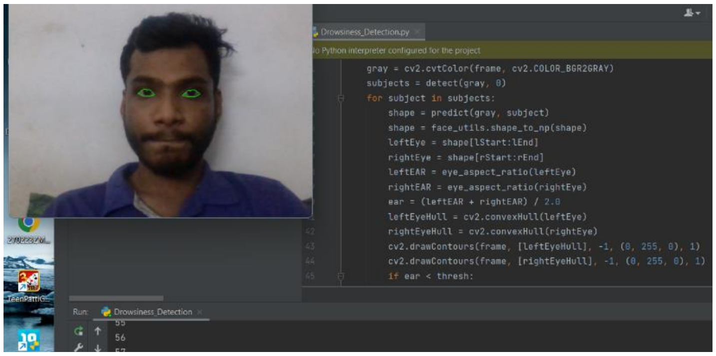
2. Results



8. Conclusions

In this study, we used supervised machine learning techniques to try to identify sleepy drivers. We had to do time-series aggregation in order to produce features because the data were time-series in nature. We made an effort to produce aggregate features at the run and event levels for each run. According to the area under the ROC curve, we discovered that the aggregate characteristics for each event produce better classifiers. When examining the chosen attributes from the dataset, the per-event aggregate features are also more useful and understandable. Additionally, for this classification task, function-based classifiers such as Logistic Regression and SMO outperformed Bayes and Trees.

9.References

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