

A Semi-Automatic Control Mechanism for Automobile Driver Assistance

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Abstract: *Monitoring driver fatigue, inattention, and lack of sleep is very important in preventing motor vehicles accidents. A visual system for automatic driver vigilance has to address two fundamental problems. First of all, it has to analyze the sequence of images and detect if the driver has his eyes open or closed, and then it has to evaluate the temporal occurrence of eyes open to estimate the driver's visual attention level. In this paper we propose a visual approach that solves both problems. The main objective of the project is to build a robust real-time system to monitor the loss of attention of the driver. The percentage of eye closure has been used to indicate the alertness level.*

Keywords: Driver's alertness, attention monitoring, Support Vector Machines (SVMs), Haar features, Boosting, AdaBoost, Gaussian mixture model

1. Introduction

According to the U.S. National Highway Traffic Safety Administration, approximately 4,700 fatalities occurred in motor vehicles in the year 2000 in the US alone due to driver inattention, driver fatigue, and lack of sleep. Of these about 3,900 were from inattention and about 1,700 were from drowsiness, fatigue, illness, or blackout. Automatically detecting the visual attention level of drivers early enough to warn them about their lack of adequate visual attention due to fatigue or other factors. A system for classifying head movements and eye movements would be useful in warning drivers when they fell asleep. It could be used to both gather statistics about a driver's gaze and monitor driver visual attention.

This paper describes a framework for analyzing video sequences of a driver and determining the visual attention of the driver. The system does not try to determine if the driver is daydreaming and thus not paying adequate attention to the road, which is an example of cognitive under loading. In this case the driver is looking straight ahead and appears to be fully alert. The proposed system deals with the strictly measurable quantifiable cues like eye blink rate. The system collects data with a single camera placed on the car dashboard. The system focuses on eye blinking, two important cues for determining driver visual attention, to make determinations of the driver's visual attention level.

2. Previous Work

Much terminology has been introduced in the driver vigilance and attention monitoring fields. In particular lays a terminology groundwork, and there are others who use similar terminology. In our paper similar terminology is used. Visual attention refers to whether the driver is visually looking forward and alertness/drowsiness refers to whether the driver is fatigued and possibly fighting against sleeping bouts, micro sleep, or other similar conditions. Work on driver alertness, has yielded many systems. However, it is

becoming clear that more than alertness needs to be monitored. With new technologies becoming more a part of everyday life, drivers need to be careful to make sure they are paying adequate visual attention to the road. Therefore methods must be developed which monitor both drowsiness and visual attention. In the case of a decrease in visual attention, the driver may be fully awake, yet still not paying adequate visual attention to the road. Relying solely on determining if the eyes were open would not be enough in the event the driver was not drowsy, but was instead simply looking off centre for a while. In this case the eyes would be open, yet the driver could possibly have allowed visual attention level. More than eye closure metrics must be used in this case. Detecting rotation can play an important part in detecting a decrease in visual attention. Various classes of systems have emerged to determine driver drowsiness and attention levels. Some systems rely on external car behaviour like the distance to roadway lines. Others are trying to use infrared beam sensors above the eyes which detect when the eyelids interrupt the beam and the system will measure the time that the beam is blocked, thus providing eye closure information. Another class that has emerged is the one in which data is acquired from visual sensors. An important aspect of these systems is that unlike infrared beams and the necessary hardware the user must wear, these are simple to install and are non invasive. To monitor driver visual attention or alertness a head tracking method must be developed. Several researchers have worked on head tracking, and the various methods each have their pros and cons. Among more recent methods to track facial features Huang and Marianu present a method to detect the face and eyes of a person's head. They first use multiscale filters like an elongated second derivative Gaussian filter to get the pre-attentive features of objects. Then these features are supplied to three different models to further analyze the image. The first is a structural model that partitions the features into facial candidates. After they obtain a geometric structure that fits their constraints they use affine transformations to fit the real world face. Next their system uses a texture model that measures colour similarity of a

candidate with the face model, which includes variation between facial regions, symmetry of the face, and colour similarity between regions of the face. The texture comparison relies on the cheek regions. Finally they use a feature model to obtain the location of the eyes. Their method uses Eigen-eyes and image feature analysis. Then they zoom in on the eye region and perform more detailed analysis. Their analysis includes Hough transforms to find circles and reciprocal operations using contour correlation. Shih, Wu, and Liu propose a system using 3D vision techniques to estimate and track the 3D line of sight of a person using multiple cameras. Their approach uses multiple cameras and multiple point light sources to estimate the line of sight without using user-dependent parameters, thus avoiding cumbersome calibration processes. The method uses a simplified eye model, and it first uses the Purkinje images of an infrared light source to determine eye location. When light hits a medium part is reflected and part is refracted. The first Purkinje image is the light reflected by the exterior cornea. Then they use linear constraints to determine the line of sight, based on their estimation of the cornea center. Terrillon use Support Vector Machines (SVMs) to solve the pattern recognition problem. SVMs are relatively old, but applications involving real pattern recognition problems are recent. First they do skin colour-based segmentation based on a single Gaussian chrominance model and a Gaussian mixture density model. Feature extraction is performed using orthogonal Fourier-Mellin moments. Then they show how, for all chrominance spaces, the SVMs applied to the Mellin moments perform better than a 3-layer perceptron Neural Network.

In a lip colour based approach is used to find the lip colours. They also use dynamic thresholds and a voting system to robustly find the lips. Then the 3D mouth height is computed, which allows the system to determine if the mouth is open or not. The method is stereo based, and relies on images being well lit in a controlled environment. In the above feature point extraction method is evaluated for accuracy. This differs from the approach proposed in our paper because they rely on a well lit image, which makes lip identification much easier than with our unconstrained day time driving illumination conditions. In a method is presented which tracks the head and estimates pose. It relies on 2D template searching, and then 3D stereo matching. A 3D model is then fit and minimized using virtual springs, which is simpler than the least squares fit approach. Manual initialization is required to build the facial feature model, which can be a cumbersome burden.

3. The Overall Algorithm

An overview of the algorithm is given below. In the following sections each step is discussed in detail.

- Viola jones algorithm is used for face detection of driver.
- Local features extraction is done using Gaussian Mixture Model.
- Detection of eye blinking and eye closing.

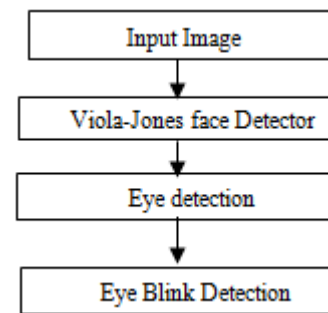


Figure 1: System Block Diagram

4. Viola-Jones Face Detector

This algorithm has three major contributions/phases they are feature extraction, classification using boosting and multi-scale detection algorithm. For feature extraction and feature evaluation rectangular features are used, with a new image representation as their calculation is very fast. The classifier training and feature selection using a slight variation of a method called Ada Boost. A combination of simple classifiers is very effective. The features are of four basic types. They are easy to calculate. The white areas are subtracted from the black ones. A special representation of the sample called the integral image makes feature extraction faster.

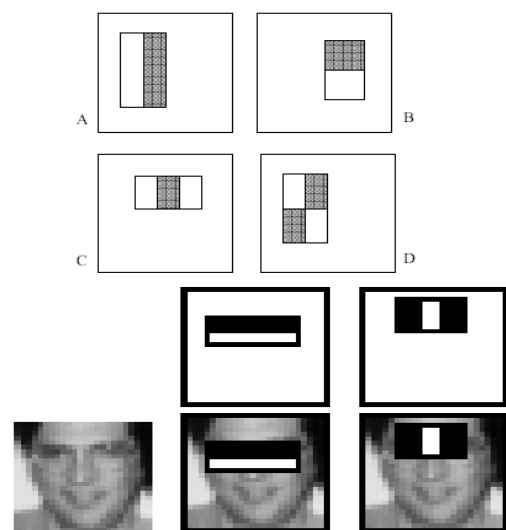


Figure 2: Examples of Haar features

The integral images are summed area tables where there presentation that means any rectangle's values can be calculated in four accesses of the integral image. The fast computation of Pixel Sums is done.

The features are extracted from sub windows of a sample image. The base size for a sub window is 24 by 24 pixels. Each of the four feature types are scaled and shifted across all possible combinations. In a 24 pixel by 24 pixel sub window there are ~160, 000 possible features to be calculated. The learning with many features is done. We have 160, 000 features – how can we learn a classifier with only a few hundred training examples without over fitting? The Idea is to learn a single simple classifier then classify the data and look at where it makes errors, then reweight the data so that the inputs where we made errors get higher weight in the

learning process. Now learn a 2nd simple classifier on the weighted data, combine the 1st and 2nd classifier and weight the data according to where they make errors, Learn a 3rd classifier on the weighted data and so on until we learn T simple classifiers, final classifier is the combination of all T classifiers. This procedure is called "Boosting" which works very well in practice.

The boosting with single feature perceptrons in Viola-Jones version of Boosting is simple classifier. At each stage of boosting given reweighted data from previous stage, train all K (160, 000) single-feature perceptrons, Select the single best classifier at this stage, Combine it with the other previously selected classifiers, Reweight the data, Learn all K classifiers again, select the best, combine, reweight, Repeat until you have T classifiers selected, Hugely computationally intensive.

The detection in Real Images Here in this project we are going to detect the faces first and then the eyes are detected in the real images. So it is divided into two main divisions like face detection, eyes detection. In face detection the basic classifier operates on 24 x 24 sub windows. The scaling is done by first Scale the detector (rather than the images), the features can easily be evaluated at any scale and Scale by factors of 1.25 to detect the location we need to move detector around the image then a real face may result in multiple nearby detections post process detected sub windows to combine overlapping detections into a single detection. In Training in this paper, 24x24 images of faces and non faces (positive and negative) are taken. For eyes detection first by using the Viola Jones based face detection we detect the face location. Then the approximate positions of the eyes are extracted using the Haar wavelets. The exact positions of the eyes are extracted using the local feature extraction. For local feature extraction these joint position of features extracted from the Haar wavelets are modeled using a mixture of Gaussian trees which is in turn known as a Gaussian mixture model.

5. Gaussian Mixture Model

Mixture Models are a type of density model which comprise a number of component functions, usually Gaussian. These models are also amenable to effective methods for on-line adaptation of models to cope with slowly-varying lighting conditions. They are a semi-parametric alternative to non-parametric histograms (which can also be used as densities) and provide greater flexibility and precision in modelling the underlying statistics of sample data. This model is an extension of the single tree proposed in and improves the ability of the model to capture pose variation, with mixture components corresponding approximately to frontal views and views facing somewhat to the left or right. Using tree-structured covariance enables efficient search for the feature positions using distance transform methods. Let the conditional density for a pixel belonging to multi-coloured object be a mixture with M component densities:

$$p(\mathbf{x}|\mathcal{O}) = \sum_{j=1}^M p(\mathbf{x}|j)P(j) \quad (1)$$

Where a mixing parameter $P(j)$ corresponds to the prior probability that pixel was generated by component j and

where. Each mixture component is a Gaussian with mean and covariance matrix, i.e. in the case of a 2D colour space:

$$p(\mathbf{x}|j) = \frac{1}{2\pi|\Sigma_j|^{\frac{1}{2}}} \exp^{-\frac{1}{2}(\mathbf{x}-\mu_j)^T \Sigma_j^{-1} (\mathbf{x}-\mu_j)}$$

6. Eye Blink Detection

Eye patches are extracted using the positions which are the output of the Gaussian mixture model. Then we need to plot the properties of the extracted eyes and compared with the properties of the eyes stored. The detection of blinking and the analysis of blink duration are based solely on observation of the correlation scores generated by the tracking at the previous step using the online template of the user's eye. As the user's eye closes during the process of a blink, its similarity to the open eye template decreases. Likewise, it regains its similarity to the template as the blink ends and the user's eye becomes fully open again. This decrease and increase in similarity corresponds directly to the correlation scores returned by the template matching procedure. Close examination of the correlation scores over time for a number of different users of the system reveals rather clear boundaries that allow for the detection of the blinks. As the user's eye is in the normal open state, very high correlation scores of about 0.85 to 1.0 are reported. As the user blinks, the scores fall to values of about 0.5 to 0.55. Finally, a very important range to note is the one containing scores below about 0.45. Scores in this range normally indicate that the tracker has lost the location of the eye. In such cases, the system must be reinitialized to relocate and track the new position of the eye.

7. Experimental Results

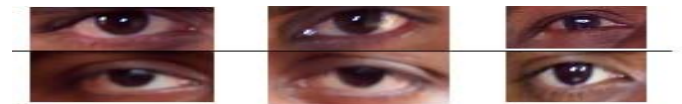


Figure 3: Open eye



Figure 4: Closed eye



Figure 5: Open eye output

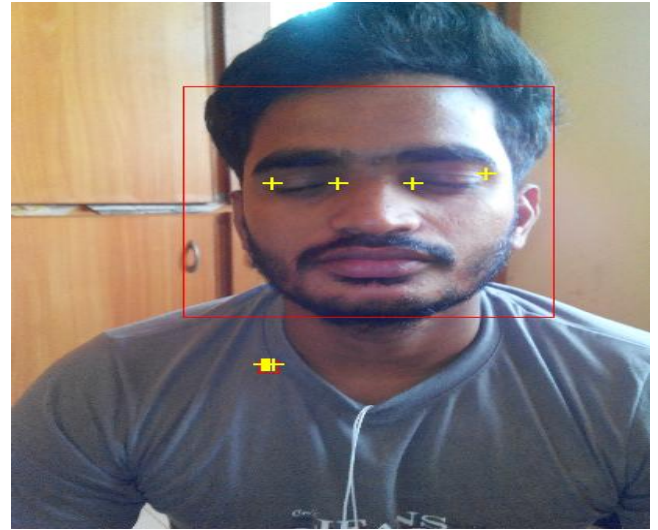


Figure 8: Closed eye output

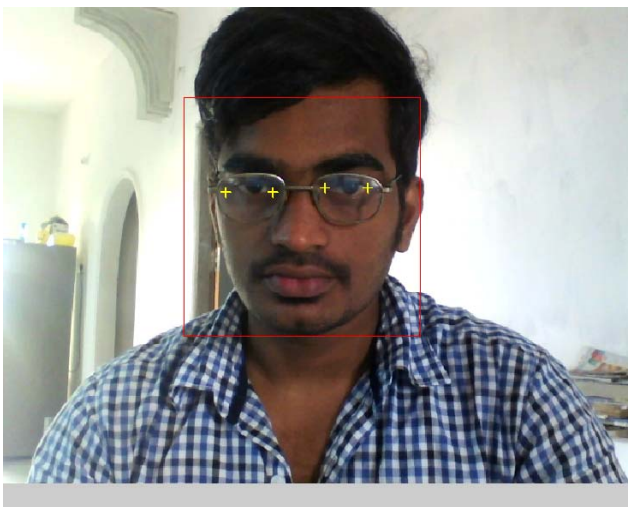


Figure 6: Open eye output wearing spectacles



Figure 9: Closed eye output wearing spectacles

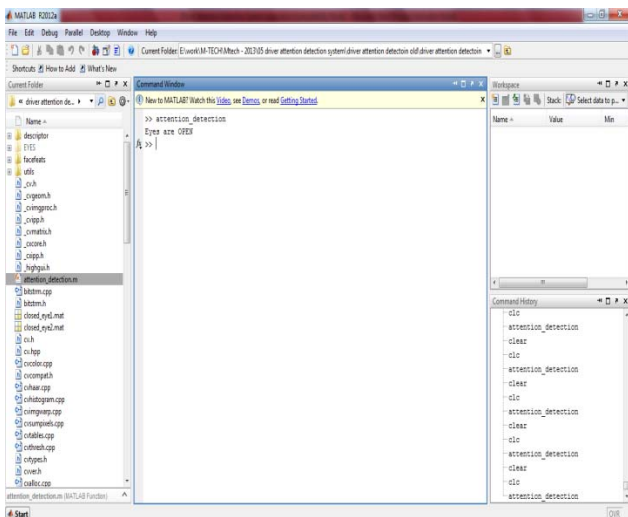


Figure 7: Control Signal output for open eye

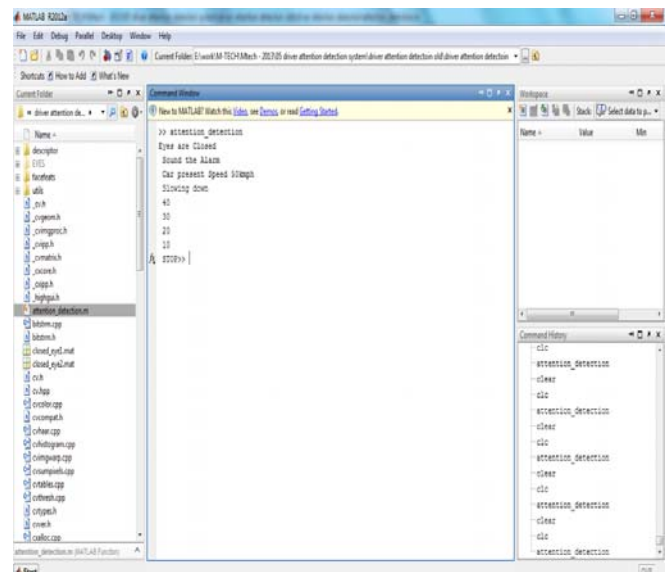


Figure 10: Control Signal output for closed eye

8. Conclusion and Future Scope

In this paper, a research project to develop a nonintrusive and autonomous driver drowsiness system based on

Computer Vision and Artificial Intelligence has been presented. This system uses advanced technologies which analyze and monitor the state of the driver's eye in real-time and for real driving conditions. It can also detect the state of driver when wearing spectacles.

To acquire the data required to develop and test the algorithms presented in this paper, several tests have been conducted and were exposed to a wide variety of difficult situations commonly encountered on roadways. This guarantees and confirms that the experiments presented here are proven to be robust and efficient for real traffic scenarios.

The system detect real time eye blink using Viola Jones object detection technique. The performance of this method was measured in different light conditions. The experiment was implemented on female and male participants; some were prescribed with eye glasses. This system easily detects the face and eye of a driver. The blinking of eye has been detected at a very high rate because independent haar classifiers are used for the left and right eyes. Most recent 100 frames of left and right eye are analysed and the average positive and negative alert were determined. The experiment was conducted for different conditions. The eyes blinks were detected more accurate for the driver without eye glasses. The positive alert without eye glasses was best recorded in after noon condition (95%) for both male and female driver. It was recorded 16% same for male and female drivers. The average performance of drowsiness detection system for male was recorded 89.35% and for the female drivers it was recorded to be 89.60%.

For future work, the objective will be to reduce the percentage error, that is, reduce the amount of false alarms; to achieve this, additional experiments will be developed, using additional drivers and incorporating new analysis modules, for example, facial expressions.

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