Prediction of Driver Fatigue

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ABSTRACT

This paper describes a Prediction of driver-fatigue monitor. It uses remotely located charge-coupled-device cameras equipped with active infrared illuminators to acquire video images of the driver. Various visual cues that typically characterize the level of alertness of a person are extracted in real time and systematically combined to infer the fatigue level of the driver. The visual cues employed characterize eyelid movement, gaze movement, head movement, and facial expression. A probabilistic model is developed to model human fatigue and to predict fatigue based on the visual cues obtained. The simultaneous use of multiple visual cues and their systematic combination yields a much more robust and accurate fatigue characterization than using a single visual cue. This system was validated under real-life fatigue conditions with human subjects of different ethnic backgrounds, genders, and ages; with/without glasses; and under different illumination conditions. It was found to be reasonably robust, reliable, and accurate in fatigue characterization.

1. INTRODUCTION

HE EVER-INCREASING number of traffic accidents in the United States that are due to a diminished driver's vigilance level has become a problem of serious concern to society. Drivers with a diminished vigilance level suffer from a marked decline in their perception, recognition, and vehicle-control abilities and, therefore, pose a serious danger to their own life and the lives of other people. Statistics show that a leading cause of fatal or injury-causing traffic accidents is due to drivers with a diminished vigilance level. In the trucking industry, 57% of fatal truck accidents are due to driver fatigue. It is the number one cause of heavy truck crashes. Seventy percent of American drivers report driving fatigued. The National Highway Traffic Safety Administration (NHTSA) estimates that there are 100000 crashes that are caused by drowsy drivers and result in more than 1500 fatalities and 71 000 injuries each year in U.S. With the ever-growing traffic conditions, this problem will further increase. For this reason, developing systems that actively monitoring a driver's level of vigilance and alerting the driver of any insecure driving conditions is essential for accident prevention,

Mathematical models of alertness dynamics joined with ambulatory technologies:

1)These technologies use mathematical models to predict operator alertness and performance at different times based on interactions of sleep, Circadian, and related temporal antecedents of fatigue.

2) Vehicle-based performance technologies:

These technologies detect the behavior of the driver by monitoring the transportation hardware systems under the control of the driver, such as driver's steering wheel movements, acceleration, braking, and gear changing .

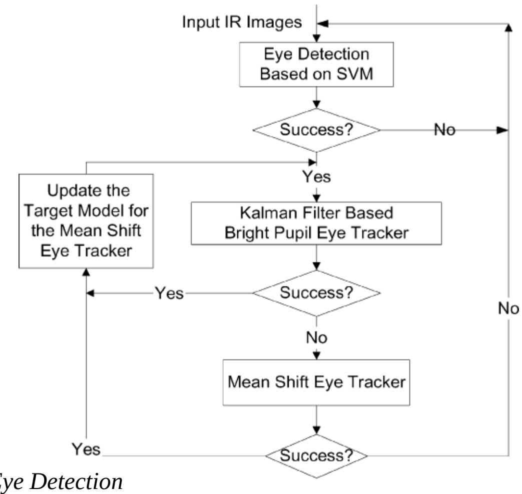
3) In-vehicle, online, operator-status-monitoring technologies:

2. EYE DETECTION AND TRACKING

Fatigue monitoring starts with extracting visual parameters that typically characterize a person's level of vigilance. This is accomplished via a computer vision system. The system consists of two cameras: one wide-angle camera focusing on the face and another narrow-angle camera focusing on the eyes. The wide-angle camera monitors head movement and facial expression while the narrow-angle camera monitors eyelid and gaze movements. The system starts with eye detection and tracking. The goal of eye detection and tracking is for subsequent eyelid-movement monitoring, gaze determination, facial-orientation estimation, and facial-expression analysis. A robust, accurate, and real-time eye tracker is therefore crucial. In this research, we propose real-time robust methods for eye tracking under variable lighting conditions and facial orientations, based on combining the appearance-based methods and the active infrared (IR) illumination approach. Combining the respective strengths of different complementary techniques and overcoming their shortcomings, the proposed method uses active IR illumination to brighten subject's faces to produce the bright pupil effect. The bright pupil effect and appearance of eyes (statistic distribution based on eye patterns) are utilized simultaneously for eyes' detection and tracking. The latest technologies in pattern-classification recognition (the support vector machine) and in object tracking (the mean shift) are employed for eye detection and tracking based on eye appearance

A. Image-Acquisition System

Image understanding of visual behaviors starts with image acquisition. The purpose of image acquisition is to acquire the video images of the driver' s face in real time.



B. Eye Detection

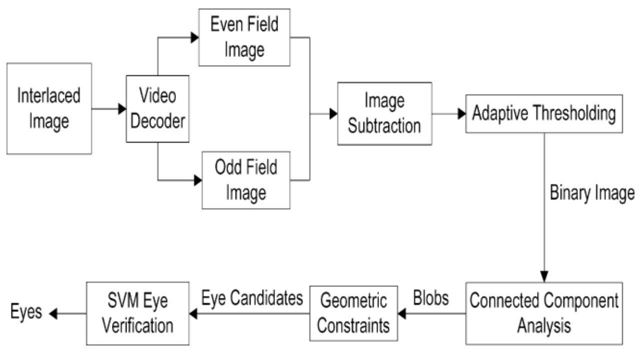
Eye-tracking starts with eyes detection. Fig. 6 gives a flowchart of the eye-detection procedure. Eye-detection is accomplished via pupil detection due to the use of active IR illumination.

Specifically, to facilitate pupil detection, we have developed a circuitry to synchronize the inner and outer rings of LEDs with the even and odd fields of the interlaced image, respectively, so that they can be turned on and off alternately.

The interlaced input image is deinterlaced via a video decoder, producing the even and odd field images.

C. Eye-Tracking Algorithm

The detected eyes are then tracked frame to frame. We have developed the following algorithm for the eye tracking by combining the bright-pupil-based Kalman filter eye tracker with the mean shift eye tracker. While Kalman filtering accounts for the dynamics of the moving eyes, mean shift tracks eyes based on the appearance of the eyes. We call this two-stage eye tracking. After locating the eyes in the initial frames, the Kalman filtering is activated to track bright pupils. The Kalman filter pupil tracker works reasonably well under frontal face orientation with open eyes. However, it will fail if the pupils are not bright due to oblique face orientations, eye closures, or external illumination interferences. Kalman filter also fails when sudden head movement occurs, because the assumption of smooth head motion has been violated. Therefore, we propose to use.



3. EYELID-MOVEMENT PARAMETERS

Eyelid movement is one of the visual behaviors that reflect a person's level of fatigue. The primary purpose of eye tracking is to monitor eyelid movements and to compute the relevant eyelid-movement parameters. Here, we focus on two ocular measures to characterize the eyelid movement. The first is Percentage of eye closure over time *(PERCLOS)* and the second is average eye-closure speed *(AECS).* PERCLOS has been validated and found to be the most valid ocular parameter for monitoring fatigue The eye-closure/opening speed is a good indicator of fatigue. It is defined as the amount of time needed to fully close or open the eyes. Our previous study indicates that the eye-closure speed of a drowsy person is distinctively different from that of an alert person. The cumulative eye-closure duration over time, excluding the time spent on normal eye blinks, is used to compute PERCLOS. To obtain a more robust measurement for these two parameters, we compute their running average (time tracking). To obtain running average of PERCLOS measurement, for example, the program continuously tracks the person's pupil shape and monitors eye closure at each time instance. We compute these two parameters in a 30-s window and output them onto the computer screen in real time, so we can easily analyze the alert state of the driver.

4. FACE (HEAD) ORIENTATION ESTIMATION

The facial (head) pose contains information about one's attention, gaze, and level of fatigue. Facial-pose determination is concerned with computation of the three-dimensional (3-D) facial orientation and position to detect head movements such as head tilts. Frequent head tilts indicate the onset of fatigue. Furthermore, the nominal face orientation while driving is frontal. If the driver faces in another directions (e.g., down or sideway) for an extended period of time, this is due to either fatigue or inattention. Facial-pose estimation, therefore, can indicate both fatigued and inattentive drivers In our algorithm, we should have a front-parallel face to represent the initial facial model. This initialization is automatically accomplished by using the eye-tracking technique we have developed [34]. Specifically, the subject starts in the front-parallel facial pose position with the face facing directly at the camera, as shown in Fig. 11. The eye-tracking technique is then activated to detect the eyes. After detecting the eyes, the first step is to compute the distance e_{yes} between two eyes. Then, the distance between the detected eyes. The proposed algorithm is tested with numerous image sequences of different people. The image sequences include a person rotating his/her head before an uncalibrated camera, which is approximately 1.5 m from the person. Fig. Shows some tracking results under different facial rotations. It is shown that the estimated pose is very visually convincing over a large range of head orientations and changing distances between the face and camera. To quantitatively characterize one's level of fatigue by facial pose, we introduce a new fatigue parameter called *NodFreq,* which measures the frequency of head tilts over time

5. EYE-GAZE DETERMINATION AND TRACKING

Gaze has the potential to indicate a person's level of vigilance; a fatigued individual tends to have a narrow gaze. Gaze may also reveal one's needs and attention. The direction of a person's gaze is determined by two factors: the orientation of the face (facial pose). and the orientation of eye (eye gaze). Facial pose determines the global direction of the gaze, while eye gaze determines the local direction of the gaze. Global and local gazes together determine the final gaze of the person. So far, the most common approach for ocular-based gaze estimation is based on the determination of the relative position between pupil and the glint (cornea reflection) via a remote IR camera. This poses a significant hurdle for practical application of the system. Another serious problem with the existing eye- and gaze-tracking systems is the need to perform a rather cumbersome calibration process for each individual. Often, recalibration is needed even for the same individual who already underwent the calibration procedure, whenever his/her head moved. This is because only the local gaze is accounted for, while global gaze due to facial pose is ignored. The global gaze (facial pose) and local gaze (eye gaze) are combined together to obtain the precise gaze information of the user. Our approach, therefore, allows natural head.

Gaze Estimation

Our gaze-estimation algorithm consists of three parts: pupil-glint detection and tracking, gaze calibration, and gaze mapping. To produce the desired pupil effects, the two rings are turned on and off alternately via the video decoder that we developed to produce the so-called bright and dark pupil effect, The pupil-detection and -tracking technique can be used to detect and track glint from the dark images

In order to obtain the final gaze, the factors accounting for the head movements and those affecting the local gaze should be combined. Hence, six parameters are chosen for the gaze calibration to get the parameters mapping function: Ax, Ay, r, 0, g_x, and g_y. Ax and Ay are the pupil-glint displacement. the ratio of the major-to-minor axes of the ellipse that fits to the pupil. 0 is the pupil ellipse orientation and g_x and g_y are the glint-image coordinates. The choice of these factors is based on the following rational. Ax and Ay account for the relative movement between the glint and the pupil, representing the local gaze.

The use of these parameters accounts for both head and pupil movement, since their movements will introduce corresponding changes to these parameters, which effectively reduces the head-movement influence. Given the six parameters affecting gaze, we now need to determine the mapping function that maps the parameters to the actual gaze. This mapping function can be approximated by the generalized regression neural networks (GRNN) , which features fast training times, can model nonlinear functions, and has been shown to perform well in noisy environments given enough data. Specifically, the input vector to the GRNN is

$$\mathbf{g} = [\Delta x \quad \Delta y \quad r \quad \theta \quad g_x \quad g_y]$$

A large amount of training data under different head positions is collected to train the GRNN. During the training-data acquisition, the user is asked to fixate his/her gaze on each predefined gaze region. After training, given an input vector, the GRNN can then approximate the user's actual gaze. Face Top and Width Detection The next step in the eye detection function is determining the top and side of the driver's face. This is important since finding the outline of the face narrows down the region in which the eyes are, which makes it easier (computationally) to localize the position of the eyes. The first step is to find the top of the face. The first step is to find a starting point on the face, followed by decrementing the y-coordinates until the top of the face is detected. Assuming that the person's face is approximately in the centre of the image, the initial starting point used is (100,240). The starting x-coordinate of 100 was chosen, to insure that the starting point is a black pixel (no on the face). The following algorithm describes how to find the actual starting point on the face, which will be used to find the top of the face.

1. Starting at (100,240), increment the x-coordinate until a white pixel is found. This is considered the left side of the face.
2.If the initial white pixel is followed by 25 more white pixels, keep incrementing x until a black pixel is found.
3.Count the number of black pixels followed by the pixel found in step2, if a series of 25 black pixels are found, this is the right side.
4.The new starting x-coordinate value (x1) is the middle point of the left side and right side.

6. FACIAL-EXPRESSION ANALYSIS

Besides eye and head movements, another visual cue that can potentially capture one's level of fatigue is his/her facial expression. In general, people tend to exhibit different facial expressions under different levels of vigilance. The facial expression of a person in fatigue or in the onset of fatigue can usually be characterized by having lagging facial muscles, being expressionless and yawning frequently.

Our recent research has led to the development of a feature-based facial-expression-analysis algorithm. The facial features around the eyes and mouth represent the most important spatial patterns composing the facial expression. Generally, these patterns with their changes in spatio-temporal spaces can be used to characterize facial expressions. For the fatigue-detection application, in which there are only limited facial expressions, the facial features around the eyes and mouth include enough information to capture these limited expressions. So, in our research, we focus on the facial features around the eyes and mouth. In our method, the multiscale and multiorientation Gabor wavelet is used to represent and detect each facial feature. For each pixel in the image, a set of Gabor coefficients in the complex form can be obtained by convolution with the designed Gabor kernels. After detecting each feature in the first frame, a Kalman filter-based method with the eye constraints is proposed to track them. The Kalman filter is used to predict the current feature positions from the previous locations. It puts a smooth constraint on the motion of each feature. The eye positions from our eye tracker provide strong and reliable information that gives a rough location of where the face is and how the head moves between two consecutive frames. By combining the head-motion information inferred from the detected eyes with the predicted locations from the Kalman filtering, we can obtain a very accurate and robust prediction of feature locations in the current frame, even under rapid head movement.

7. FATIGUE MODELING USING BAYESIAN NETWORKS

As we discussed above, human fatigue generation is a very complicated process. Several uncertainties may be present in this process. First, fatigue is not observable and can only be inferred from the available information. In fact, fatigue can be

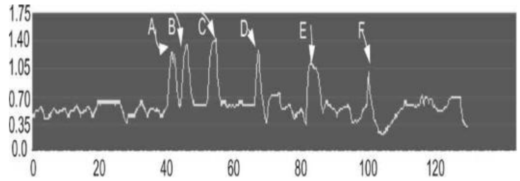
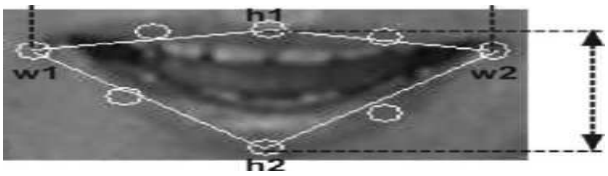


Fig. Plot of the openness of the mouth over time. The bumps *A*,

regarded as the result of many contextual variables such as working environments, health, and sleep history. Also, it is the cause of many symptoms, e.g., the visual cues, such as irregular eyelid movements, yawning and frequent head tilts. Second, a human’s visual characteristics vary significantly with age, height, health, and shape of face. To effectively monitor fatigue, a system that integrates evidences from multiple sources into one representative format is needed. Naturally, a Bayesian networks (BN) model is the best option to deal with such an issue.



BN provides a mechanism for graphical representation of uncertain knowledge and for inferring high-level activities from the observed data. Specifically, a BN consists of nodes and arcs connected together forming a directed acyclic graph (DAG).

Fatigue Modeling With BN

The main purpose of a BN model is to infer the unobserved events from the observed or contextual data. So, the first step in BN modeling is to identify those hypothesis events and group them into a set of mutually exclusive events to form the target hypothesis variable. The second step is to identify the observable data that may reveal something about the hypothesis variable and then group them into information variables. There also are other hidden states that are needed to link the high-level hypothesis node with the low-level information nodes. For fatigue modeling, fatigue is obviously the target hypothesis variable that we intend to infer. Other contextual factors, which could cause fatigue, and visual cues, which are symptoms of fatigue, are information variables. Among many factors that can cause fatigue, the most significant are sleep history, Circadian, work conditions, work environment, and physical condition. The most profound factors that characterize work environment are temperature, weather, and noise; the most significant factors that characterize physical condition are age and sleep disorders; the significant factors characterizing Circadian are time of day and time-zone change; the factors affecting work conditions include workload and type of work. Furthermore, factors affecting sleep quality include sleep environment and sleep time. The sleep environment includes random noise, background light, heat, and humidity.

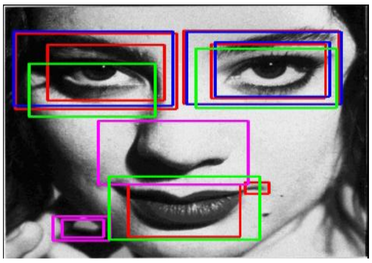
. *Construction of Conditional Probability Table (CPT)*
Before using the BN for fatigue inference, the network needs to be parameterized. This requires specifying the prior probability for the root nodes and the conditional probabilities for the links. Usually, probability is obtained from statistical analysis of a large amount of training data. For this research, training data come from three different sources. First, we obtain some training data from the human subjects study we conducted. These data are used to train the lower part of the BN fatigue model. Second, several large-scale subjective surveys , provide additional data of this type.

Fatigue Inference
Given the parameterized model, fatigue inference can then commence upon the arrival of visual evidences via belief propagation. MSBNX software is used to perform the inference and both top-down and bottom-up belief propagations are performed.

Interfacing with the Vision System
To perform real-time driver-fatigue monitoring, the visual and fusion modules must be combined via an interface program such that the output of the vision system can be used by the fusion module to update its belief in fatigue in real time. Such an interface has been built. Basically, the interface program periodically (every 0.03 s) examines the output of the vision module to detect any output change. If a change is detected, the interface program instantiates the corresponding observation nodes in the fusion module. activates its inference engine. The interface program then displays the inference result plus current time, as shown in Fig. 23. Besides displaying a current fatigue level, the interface program also issues a warning beep when the fatigue level reaches a critical level.

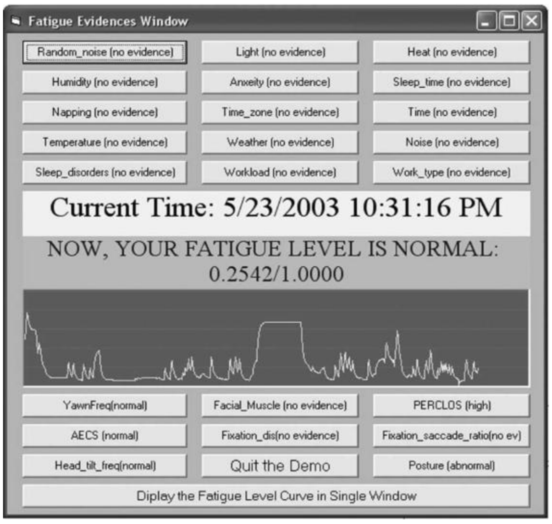
Skin detection:

Skin detection using single Gaussian distribution is one of the most known methods for skin detection. Its advantages are real-time speed, low memory requirements and main disadvantage is lower accuracy. This method is a step-up from methods that just determine the hard boundaries for skin color interval, since it uses a normal distribution of skin color regions. In order to increase accuracy of skin detection decided to use 3D classifier by counting the number of certain skin color occurrences and convolving it with Gaussian distribution afterwards. I have implemented a function that would take an input skin patch, analyze it pixel by pixel storing counts in 3D accumulator array, the size of which determine manually. After that form 1D Gaussian distribution vector of some predefined size and standard deviation and convolve it with its transpose and once again with the normal vector in order to obtain separable 3D Gaussian filter. After apply this filter to the accumulator array get normal distribution of data derived from my original skin patch. The model has to be normalized and stoed as .mat file, so it can be retrieved later and used in other methods. For the next part of my project I decided to use an improved version of skin patch, so added skin color regions from 20 other pictures found on the Internet, which resulted in 582*585 pixels picture. Furthermore decided to experiment with all the new color spaces that were mentioned in Kakumanu et al. (2007), namely perceptual color spaces (HSI, HSV, HSL, TSL), orthogonal color 5 spaces (YCbCr, YIQ, YUV, YES) and perceptually uniform color spaces (CIE-Lab and CIE-Luv).



8. SYSTEM VALIDATION

The last part of this research is to experimentally and scientifically demonstrate the validity of the computed fatigue parameters as well as the composite fatigue index. The validation consists of two parts. The first involves the validation



of the measurement accuracies of our computer vision techniques and the second studies the validity of the fatigue parameters and the composite fatigue index that our system computes in characterizing fatigue.

8.1 Validation of the Measurement Accuracy

We present results to quantitatively characterize the measurement accuracies of our computer vision techniques in measuring eyelid movement, gaze, facial pose, and facial expressions. The measurements from our system are compared with those obtained either manually or using conventional instruments. This section summarizes the eye-detection and -tracking accuracy of our eye tracker. For this study, we randomly selected an image sequence that contains 13 620 frames and manually identified the eyes in each frame. This manually labeled data serves as the ground-truth data and are compared with the eye-detection results from our eye tracker. This study shows that our eye tracker is quite accurate, with a false-alarm rate of 0.05% and a misdetection rate of 4.2%.

Further, we studied the positional accuracy of the detected eyes as well as the accuracy of the estimated pupil size (pupil axes ratio). The ground-truth data are produced by manually determining the locations of the eyes in each frame as well as the size of the pupil. This study shows that the detected eye

Positions match very well with manually detected eye positions, with a root-mean-square (rms) position errors of 1.09 and 0.68 pixels for x and y coordinates, respectively. The estimated size of pupil has an average rms error of 0.0812.

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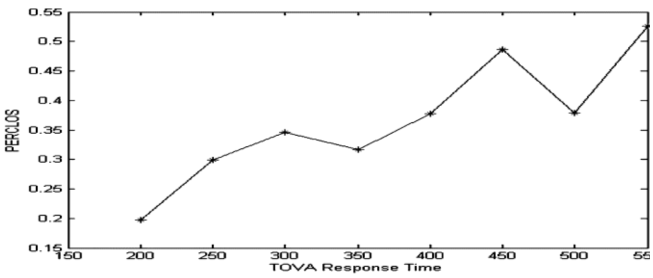
. *Validation of Fatigue Parameters and the Composite Fatigue Score*

To study the validity of the proposed fatigue parameters and that of the composite fatigue index, we performed a human subject study. The study included a total of eight subjects and two test bouts were performed for each subject. The first test was done when they first arrived in the laboratory at 9:00 PM and when they were fully alert. The second test was performed about 12 hours later, early in morning at about 7:00 AM the following day, after the subjects have been deprived of sleep for a total of 25 hours.

Plots the average response times versus average PERCLOS This figure clearly shows the approximate linear correlation between PERCLOS and the TOVA response time. This experiment demonstrates the validity of PERCLOS in quantifying vigilance, as characterized by the TOVA response time. In addition, we want to demonstrate the correlation between PERCLOS and fatigue. For this, we compared the PERCLOS Measurements for two bouts for the same individual. This comparison is shown in Fig, where it is clear that the PERCLOS measurements for the night bout (when the subject is alert) is significantly lower than the morning bout (subject is fatigued). This not only proves the validity of PERCLOS to characterize fatigue, but also proves the accuracy of our system in measuring PERCLOS. Similar results were obtained for other visual-fatigue parameters we proposed.



We also study the validity of the composite fatigue index that our fatigue monitor computes. Fig. plots the TOVA performance versus the composite fatigue score and clearly shows that the composite fatigue score (based on combining different fatigue parameters) highly correlates with the subject's response time.

It is clear that the two curves' fluctuations match well, proving their correlation and co variation and, therefore, proving the validity of the composite fatigue score in quantifying performance.

8.2 MONITORING PHYSIOLOGICAL CHARACTERISTICS

Among these methods, the techniques that are best, based on accuracy are the ones based on human physiological phenomena. This technique is implemented in two ways: measuring changes in physiological signals, such as brain waves, heart rate, and eye blinking; and measuring physical changes such as sagging posture, leaning of the driver's head and the open/closed states of the eyes. The first technique, while most accurate, is not realistic, since sensing electrodes would have to be attached directly onto the driver's body, and hence be annoying and distracting to the driver. In addition, long time driving would result in perspiration on the sensors, diminishing their ability to monitor accurately. The second technique is well suited for real world driving conditions since it can be non-intrusive by using optical sensors of video cameras to detect changes.

8.3 Illumination

A correct illumination scheme is a crucial part of insuring that the image has the correct amount of contrast to allow to correctly process the image. In case of the drowsy driver detection system, the light source is placed in such a way that the maximum light being reflected back is from the face. The driver's face will be illuminated using a 60W light source. To prevent the light source from distracting the driver, an 850nm filter is placed over the source. Since 850nm falls in the infrared region, the illumination cannot be detected by the human eye, and hence does not agitate the driver. Since the algorithm behind the eye monitoring system is highly dependant on light, the following important illumination factors to consider are:

1.Different parts of objects are lit differently, because of variations in the angle of incidence, and hence have different brightness as seen by the camera.

2. Brightness values vary due to the degree of reflections of the object

3. Parts of the background and surrounding objects are in shadow, and can also affect the brightness values in different regions of the object.

4. Surrounding light sources (such as daylight) can diminish the effect of the light source on the object.

8.4 Camera Hardware

The next item to be considered in image acquisition is the video camera. Review of several journal articles reveals that face monitoring systems use an infrared-sensitive camera to generate the eye images . This is due to the infrared light source used to illuminate the driver's face. CCD cameras have a spectral range of 400-1000nm, and peak at approximately 800nm. The camera used in this system is a Sony CCD black and white camera. CCD camera digitize the image from the outset, although in one respect - that signal amplitude represents light intensity - the image is still analog.

The drowsy driver detection system consists of a CCD camera that takes images of the driver's face. This type of drowsiness detection system is based on the use of image processing technology that will be able to accommodate individual driver differences. The camera is placed in front of the driver, approximately 30 cm away from the face. The camera must be positioned such that the following criteria are met:

1. The driver's face takes up the majority of the image.
2. The driver's face is approximately in the centre of the image.

The facial image data is in 480x640 pixel format and is stored as an array through the predefined Piccolos driver functions (as described in a later section).

9. CONCLUSION

Through research presented in this paper, we developed an nonintrusive prototype computer vision system for real-time monitoring of a driver's vigilance. First, the necessary hardware and imaging algorithms are developed to simultaneously extract multiple visual cues that typically characterize a person's level of fatigue. Then, a probabilistic framework is built to model fatigue, which systematically combines different visual cues and the relevant contextual information to produce a robust and consistent fatigue index.

Experiment studies in a real-life environment with subjects of different ethnic backgrounds, genders, and ages were scientifically conducted to validate the fatigue-monitoring system. The validation consists of two parts. The first involves the validation of the measurement accuracy of our computer vision techniques and the second studies the validity of the fatigue parameters that we compute in characterizing fatigue. Experiment results show that our fatigue monitor system is reasonably robust, reliable, and accurate in characterizing human fatigue. It represents the state of the art in real-time, online, and nonintrusive fatigue monitoring.

- Image processing achieves highly accurate and reliable detection of drowsiness.
- Image processing offers a non-invasive approach to detecting drowsiness without the annoyance and interference.
- A drowsiness detection system developed around the principle of image processing judges the driver's alertness level on the basis of continuous eye closures.

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