DROWSINESS DETECTION FOR DRIVER ASSISTANCE

By

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DROWSINESS DETECTION FOR DRIVER ASSISTANCE

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Abstract: This thesis presents a noninvasive approach to detect drowsiness of drivers using behavioral and vehicle based measuring techniques. The system accepts stream of driver's images from a camera and steering wheel movement from G-27 Logitech racing wheel system. It first describes a standalone implementation of the behavioral based drowsiness detection method. The method accepts the input images and analyzes the facial expressions of the driver through sets of processing stages. In order to improve the reliability of the system, we also proposed a comprehensive approach of combining the facial expression analysis with a steering wheel data analysis in decision level as well as feature level integration. We also presented a new approach of modeling the temporal information of facial expressions of drowsiness using HMM. Each proposed approach has been implemented in a simulated driving setup. The detection performance of each method is evaluated through experiments and its parameter settings were optimized. Finally we present a case study which discusses the practicality of our system in a small-scaled intelligent transportation system where it switches the driving mechanism between manual and autonomous control depending on the state of the driver.

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INTRODUCTION

1.1. Motivations

Drowsiness is one of the main causes of severe traffic accidents occurring in our daily life. According to the US National Highway Traffic Safety Administration, approximately 100,000 crashes occur in US each year due to drivers' drowsiness resulting in an estimated 1,550 deaths, 71,000 injuries and $12.5 billion losses [1]. Another report [2] states that the US government and businesses spend an estimated $60.4 billion per year on accidents related to drowsy driving and it also costs the consumer about $16.4 billion in terms of property damages, health claims, lost time and productivity due to drowsy driving. In 2010, the National Sleep Foundation (NSF) reported that 54% adult drivers had driven a vehicle while feeling drowsy and 28% had actually fallen asleep[3]. The German Road Safety Council (DVR) claims that one in four highway traffic fatalities are a result of momentary driver drowsiness [4].

The tremendous casualties, injuries and property damages caused by drowsiness call for a notable initiative in developing an effective system that can detect drowsiness and take proper measures before accidents could occur. The U.S. Department of Transportation has also progressed in the making of intelligent vehicles in an effort to prevent such accidents [2]. With the increasing interest towards intelligent transportation systems, the development of robust and practical drowsiness detection system is a crucial step. Many researches are being conducted with the aim .

of finding drowsiness detection techniques that are not only affordable for public use but also capable of real-time detection with appreciable accuracy.

Motor companies like Toyota, Ford, Mercedes-Benz and others are also currently employing car safety technologies to prevent accidents from happening when the driver is getting drowsy. This trend is expected to make the cars smarter and significantly reduce the accidents caused by drowsiness of drivers. Adhering to these endeavors, our research is motivated by the statistical significance of accidents due to drowsiness and provides an improved and systematic approach to drowsiness detection.

1.2. Challenges

While the ongoing researches have shown promising advancements, there are still core challenges yet to be addressed. They have used behavioral or physiological changes of the driver and sensing the various responses of the vehicle to the driver's actions as ways of detecting drowsiness. While each method has its own merits and attributes, it also has drawbacks that pose a challenge in making it practical and efficient.

Behavioral measures pertain to the visual information of the driver and are highly affected by the lighting condition, the quality of the measuring device and other external factors. Physiological changes include variation of pulse rate, brain waves or electric signals of body muscles. While such measures could potentially give accurate indication of fatigue, they are highly affected by artifacts. Vehicle based measures such as vehicle speed, steering activity and lane deviation are highly affected by external factors and are unreliable to effectively detect drowsiness of drivers. One obvious possibility to remedy this issue is to improve the measuring devices and processing methods which many researchers have been trying to deal with. Another possible method is not only improving the measuring methods but also combining them in a complementary way to increase their reliability as a unit on which only little has been done.

Another main challenge is in setting a criterion as to how to define the critical events of interest when accepting the input data. For vehicle based measures, for example, these events may include steering movements with little or no corrections and frequent macro corrections (both could indicate drowsiness). In behavioral measures, such events that could indicate drowsiness could include muscle movements in the detected face as whole, the eyes region or the mouth region. Another subtle challenge that goes hand in hand with defining the input parameters is specifying the optimum time window to state the drowsiness of the driver as early as a critical event has been detected. This can only be evaluated through experimentation and there exists an unavoidable tradeoff between speed and accuracy of prediction. On one hand, if the time window is too short, the system may be merely detecting "noise," and may therefore generate excessive number of false positives. On the other hand, if the time window is too long, the system may be too slow to be of any practical use.

In our thesis, we have proposed a novel approach of drowsiness detection and addressed the different challenges through sensor integration, parameter optimization, feature selection and modeling.

1.3. Contributions

Our main objective is to come up with noninvasive, cost effective and efficient drowsiness detection system that can easily be implemented in driver monitoring systems of actual vehicles. We have primarily implemented behavioral based drowsiness detection method through facial expression recognition. Many of the previous research works and commercially available behavioral measuring methods mainly focus on eye closure and not on other facial expressions. While notable results can be achieved through the analysis of eye closure, including other facial motions and behavioral changes could give more reliability to the system which our research focuses on.

In an effort to further increase the reliability of the behavioral based drowsiness detection system, we integrated it with a vehicle based analysis of steering wheel movement in independent as well as comprehensive approaches. Many of the previous works have mainly focused on developing a drowsiness detection method using one of the two approaches and not so much has been done on their integration. Our thesis presents a systematic approach of developing an integrated drowsiness detection algorithm, implementing it and assessing its effectiveness in various virtual driving scenarios. We explore different ways of integration and input processing techniques and optimize the different system parameters to maximize the accuracy and speed of detection. By accepting stream of images of the driver's facial movements and the car controller data including the steering wheel activity, the system can determine the status of the driver as drowsy or non-drowsy.

We have also proposed a new method of modeling the dynamics of facial expressions of a driver during drowsy and non-drowsy episodes. The facial expression based drowsiness detection method initially proposed uses a single frame based static classifier which does not consider the temporal information of the sequences of frames. This method uses dynamic classifier to model the temporal information of the sequences of frames and gives decision according to the transition of facial expression in the sequences of frames.

The system gives decision in real time and hence can easily be integrated with car safety systems to alarm the driver, undertake safety measures or switch between manual and autonomous driving. We first implemented the algorithm in a simulated driving setup and evaluated its performance through experimental results. Later, we implemented the system as client application connected to a server equipped with indoor localization and racing wheel system. The server is connected to RC cars that can be controlled manually using the racing wheel system as well as autonomously by generating commands from the server based on a designed trajectory. Our system gives a real-time decision of the state of the driver to the server and the server will switch the control between manual and autonomous driving according to the decision. The experimental results from the implementation are satisfactory and have shown the practicality of our system.

The remainder of this thesis is organized as follows:

Chapter II. Presents a comprehensive review on various literatures of previous and current works on drowsiness detection, relevant findings and successful methodologies that have been implemented in drowsiness detection systems.

Chapter III. Describes the overall approach and the algorithm procedures of behavioral based drowsiness detection system through facial expression recognition.

Chapter IV. Presents steering wheel analysis based drowsiness detection system and the integration of the facial expression recognition with steering wheel data analysis in decision level as well as feature level for an improved and more reliable drowsiness detection system.

Chapter V. Gives a detailed explanation of Hidden Markov Models and drowsiness detection using HMM based dynamic modeling.

Chapter VI. Describes the experimental setup and the experimental results for each of the methods proposed, evaluated their classification accuracies and compared their performances.

Chapter VII. Presents a case study of the application of the system in an intelligent transportation test-bed.

Chapter VIII. Summarizes the work that has been done in this research and provides a projection of what could be done in the future to improve the system.

CHAPTER II

RELATED WORK

The end applications of many of the researches that have been done on drowsiness detection are mainly focused on car safety systems and monitoring of driver's state of fatigue. These driver assistant systems have been implemented through different sensors that indicate the driver's behavioral or physiological change while driving or the change in measure of the various responses of the vehicle. In recent years, researchers have conducted experiments and implemented various techniques in order to determine drowsiness of drivers in real-time scenarios[5]. These techniques can be categorized in to four major groups:

1. Vehicle based measuring techniques
2. Physiological measuring techniques
3. Behavioral measuring techniques
4. Hybrid techniques

2.1. Vehicle based measuring techniques

Real time drowsiness detection has been implemented using different detection techniques analyzing various types of input data. In this approach, the driver's drowsiness is measured through analyzing the different controller signals of the vehicle such as steering wheel movement, the pressure from the gas and brake pedal, speed of the vehicle, change in shift lever and the deviation from lane position [6, 7]. The measured data is constantly monitored and any data variation that crosses a specified threshold indicates a significantly increased probability that the driver is drowsy. The measurements of these signals are obtained from sensors attached to the vehicle. These measurements are generally taken in controlled environments with a simulated driving setup because conducting such experiments in real life scenarios is unsafe and could lead to accidents.

Among the vehicle-based metrics that have been used to determine drowsiness, steering wheel movement has been widely shown by researchers to give better detection capability [6, 8-10]. The steering angle is constantly measured by a sensor and the change in angle movement is monitored if it is within or exceeds the specified threshold. In normal driving, the driver makes many small adjustments of steering wheel (between 1 – 5 degrees) to keep position within the lane and few large adjustments (between 6 – 10 degrees) during lane change or at a road curvature[6]. When the driver is drowsy, on the other hand, the driver anticipates making lane adjustments by making many large steering wheel movements and less small adjustments. This leads to a significant and unpredictable variation in steering wheel movement which can be analyzed to determine the state of the driver. Steering wheel movement has been adopted by major car companies such as Nissan and Renault to detect fatigue [11]. However, it works in very limited situations because it is more dependent on the geometric characteristics of the road than the kinetic characteristics of the vehicle.

The other vehicle based metrics have similar limitations as steering wheel movement in accurately detecting the drowsiness of the driver. The measured data from these metrics does not fully differentiate between normal and drowsy driving as it depends on the nature of the road, the traffic and the vehicle. Moreover, the deviation in normal driving analyzed from the vehicle based measurements may not necessarily be caused by drowsy driving. Similar measurements could be read from a driver with a lack of experience or other driving impediments unrelated to drowsiness. Generally, drowsy driving is bound to show certain signal variations in the vehicle based measurements that can easily be analyzed and detected, however, the detection of such variations in measurements may not necessarily come as result of drowsiness. This makes vehicle-based measurements poor predictors of performance deter because of drowsiness.

2.2. Physiological measuring techniques

The second approach makes use of the measurement of physiological activities of the human body such as brain wave (Electroencephalogram - EEG), heart rate (Electrocardiogram – ECG), electric signals from muscle cells (Electromyogram – EMG) or eye movement (Electrooculography – EOG) [12-14]. The electrodes are attached to the specific parts of the body according to the measuring technique and the electric signal is measured and analyzed to determine the drowsiness state of the driver.

Physiological signals are weak and can easily be distorted with noise. To minimize the noise, researchers have used different techniques to preprocess the raw data. Patel *et al.* [15] used band pass filters and thresholding to remove noise from the input ECG data in the low and high frequencies. After preprocessing stage, the output data is analyzed in frequency domain by using Fast Fourier Transforms (FFT) and important features are extracted for classification. Fu-Chang *et al.* [16] performed similar experiments on EEG data to determine drowsiness of a driver. They used Independent Component Analysis (ICA) to segregate and localize mixed EEG data to distinct brain activities. From the preprocessed data, features are extracted in frequency domain using FFT and classified using a Self-organizing Neural Fuzzy Inference Network. Hu and Zheng [17] also implemented drowsiness detection system by making use of EOG data. They initially identified the eye blinks from the recorded EOG data and extracted the eye lid movement parameters as features to be classified using Support Vector Machines (SVM).

The main attribute of physiological measuring techniques is that they are able to determine the decrease in level of alertness ahead of time before the actual drowsiness episode starts. Humans do not naturally get drowsy in an instant and there is gradual decrease in response or activity of the various body parts which eventually lead to drowsiness. For example, in EEG analysis, the change in signal power at the alpha range (8 – 12Hz) and indicates early sign of drowsiness [6]. Physiological measuring techniques can measure such changes at the early stages and the person can be alerted or the proper safety measure can be taken before accidents could occur. The measured signals are also reliable to detect drowsiness as their correlation with the alertness of the driver is quite accurate and they are usually independent of the external factors such as the nature of the road, the type of vehicle or the traffic. Hence, they have a more accurate drowsiness detection capability than vehicle based and behavioral measuring techniques. However, the main limitations behind these techniques are:

- They are not practical for everyday use as it would require the driver to always wear the sensing devices which causes discomfort.
- Physiological signals are generally very weak and can easily be contaminated by artifacts that are caused by muscle movements of different body parts.
- They need intricate hardware systems to sense, amplify and preprocess the signal for analysis. The hardware cost of such systems is too high to be used commercially.

2.3. Behavioral measuring techniques

The third approach makes use of computer vision techniques to detect the changes in driver's behavior such as facial expressions, head movements, eye closure or constant blinking and yawning [18]. These and other changes in patterns of behavior of a driver are manifested when the person is feeling drowsy. Behavioral measuring techniques take the visual information of the driver in real time, process the information and determine the state of the driver based on the level of presence of the changes in the driver's behavior.

Among the computer vision-based approaches, researchers have mainly focused on the analysis of blinks and the percent of closure (PERCLOS) of the driver's eyes to determine the drowsiness of the driver [19-22]. According to the study by the Federal Highway Administration, PERCLOS had been found to be the most reliable measure of drowsiness among many other measuring techniques [23]. Initially, stream of images of the driver are obtained from video sources such as webcam, digital video camera or infrared camera. The next step is preprocessing the images to detect the face and eyes of the driver. The output from the preprocessing stage will be used to extract certain features needed to determine the changes in behavior of the driver. Li *et al*. [24] performed successive image filtering techniques such as image subtraction, morphologically closed operations and binarization, and finally counted the number of pixels around the eyes region to detect eye closure. Liu *et al*. [21] extracted simple features from the temporal difference of consecutive image frames and used them to analyze the rules of eyelid movement during drowsiness. Garcia *et al.* [25] have also presented a non-intrusive approach to drowsiness detection. They used an IR illumination system and a high resolution camera to accept a stream of images and perform face and eye detection. They applied filters on the eyes region and performed horizontal and vertical projections of the pixel values of the detected eye area. The vertical projection corresponds to the eye height which is used to evaluate the PERCLOS. Zutao and Jiashu [22] initially performed face and eye detection and tracked the eye pupils using non-linear Kalman and mean-shift tracking. They also performed vertical and horizontal projections of the pixels around the eyes region. Since the eye ball color is much darker than the surrounding, they calculated the pixel values in the vertical projection to determine the percentage of eyelid closure. Flores *et al.* [26] computed the binary, gradient and logarithm image of eyes region, obtained random samples around the region and used an elliptic shape to represent the eyes. They then used an SVM classifier [27, 28] to decide whether the eyes are closed or not.

One of the main factors affecting the performance of PERCLOS based systems is the ambient lighting condition. Using a webcam could be appropriate in day time or when there is sufficient light to clearly see the eyes of the driver but could perform poorly when there is limited lighting condition. On the other hand, a camera with infrared technology might work well during the night but perform poorly in the daylight since the retinal reflections of infra-red cannot be obtained in the presence of ambient sun light reflections [16]. Moreover, mere analysis of eye closure may not be enough to predict drowsiness as the driver may not necessarily close his eyes throughout the drowsy episodes especially during the early stages. A drowsy driver usually does not go to deep sleep immediately rather alternates between nodding off and opening his eyes. The opening of the eyes in such transitions can empirically be misinterpreted as being awake if eye closure is the only parameter being analyzed. Hence, in recent years, some researchers are considering other facial movements in addition to eye closure such as eyebrow raise[29], yawning[30] and head or eye position orientation[31, 32].

In developing facial expression based drowsiness detection systems, the initial and profound task is identifying and representing facial behaviors systematically. Gu and Ji were among the first to present the idea of recognizing facial behaviors, such as facial expressions, orientation and gaze in a systematic approach [33]. These facial expressions were represented by single or a combination of individual muscle movements called action units. These action units have been carefully coded with a unified description method of expression called Facial Action Coding System (FACS) [34]. They adopted a dynamic Bayesian Network in order to capture the spatio-temporal representation of the facial expressions and detect fatigue. Vural *et al.* [18] employed machine learning methods to analyze facial movements during drowsy episodes. These facial motions include blinking, yawn motions, eye-gaze, eyebrow raise and other movements that are represented by action units of FACS[35]. They trained SVM classifiers for each action units with a training dataset which is coded by certified FACS coders. Finally, they employed and compared

Adaboost and multinomial ridge regression to classify the action unit outputs and predict drowsiness.

Many of the researches on behavior based drowsiness detection system used frame based classification techniques that give decision based on the spatial features extracted from one input image frame. While this is essentially sufficient for some scenarios where there is definite separation of behavioral changes during drowsy and non-drowsy episodes, it lacks efficiency in situations where there is non-uniform change in transition between drowsy and non-drowsy episodes which actually is the case in most real life scenarios. Moreover, analysis of image sequences gives more accurate description of facial expressions and frame based classification approaches do not utilize all the information available in image sequences. The dynamic Bayesian network in Gu and Ji's work consists of a first-order HMM along with the Bayesian network to capture the temporal dynamics of the facial movements during drowsiness across consequent frames in a specific period of time[33]. Yin *et al.* [36] have also implemented dynamic drowsiness detection system using multi-scale Gabor features from image sequences. To account for the temporal aspect of human fatigue, they applied Local Binary Pattern (LBP) operators to the multi-scale image sequences and divided them into region sequences. They computed the histogram of each LBP region sequences and concatenated them as dynamic features. By applying Adaboost weak learning algorithm [37], they selected the most important features and constructed a strong cascaded classifier to detect fatigue. Generally, there is still a challenge in extracting dynamic features of facial expressions for drowsiness detection and there have only been few researches done on this area thus far.

2.4. Hybrid Systems

All the measuring techniques discussed have their own advantages and limitations. Vehicle-based measures are nonintrusive but lack reliability. Physiological methods are reliable and accurate but are intrusive. Behavioral methods are more reliable than vehicle based measures but are affected by the ambient light. Hence it is wise to fuse the information from different measuring techniques in a comprehensive manner that makes the best use of their advantages. However, there are only few existing works on drowsiness detection by fusing different measuring techniques. Among the pioneer researches conducted, the idea of integrating vehicle based and behavioral detection methods was presented in the Advanced Driver Fatigue Research project report by A. Eskandarian *et al.* [38] for the U.S. Department of Transportation. They preprocessed and formed vectors using 15 seconds of steering wheel data. They also implemented eye tracking to record the pupils' diameter and formed a vector of eye closure data of 15 seconds. Then they concatenated the two vectors and trained an Artificial Neural Network (ANN) to determine the state of the driver. Cheng et al. [39] also combined behavioral measures and vehicle based measures and concluded that the reliability and accuracy of the hybrid method was significantly higher than those using single sensors.

CHAPTER III

DROWSINESS DETECTION BASED ON FACIAL EXPRESSION RECOGNITION

Inspired by the previous researches of behavioral measuring techniques, we developed a real time drowsiness detection system that incorporates facial expression changes instead of only eye closure. It makes use of a computer vision approach to track the face of the user through time and detect the facial motion and appearance changes occurring during drowsiness.

When a driver gradually feels drowsy, he/she manifests various behavioral changes that can be analyzed and regarded to attest that the person is feeling drowsy. The behavioral changes can include frequent blinking, prolonged eye closure, head tilting to a certain direction, eyebrow rising in an effort to keep the eyes wide awake and seldom occurrences of jaw drop and yawning. Our primary objective is to come with essential features that can clearly show these behavioral changes on the face of the driver from a set of training videos recorded during drowsy and non-drowsy episodes. We used data-driven feature selection technique to isolate the most important features clustered around the face region manifesting the behavioral changes. We chose a classification method that can analyze the cluster of selected features in real time and classify them with appreciable confidence.

In this thesis, we addressed the optimization of the different parameters and settings of the functional blocks of the system. We started with considering different regions of interest of the driver's visual information that we can use to extract and cluster the essential features for classification. We proceeded to choosing different ways of setting the threshold to select features that classify the training images with the minimum error. We also used different classification methods and optimized their parameters for better classification accuracy.

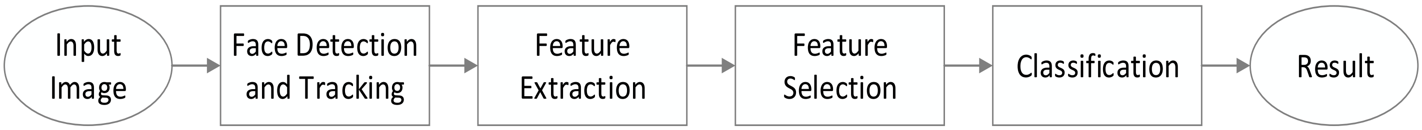

Figure 1. . The system diagram of drowsiness detection using facial expression.

The general block diagram of the system is shown in Figure 1. It accepts streams of input images from a camera in front of the driver at a rate of 15 frames per second. It uses OpenCV's library to accept each frame and store it in an image structure that can easily be used for further processing [40]. The stream of image frames then goes through four main image processing stages:

- Face detection and tracking
- Feature extraction
- Feature selection
- Classification

3.1. Face Detection and tracking

In this stage, we automatically identify the location and size of the face of the user in the captured image frame. We similarly perform face detection on the sequences of incoming frames and use an effective tracking algorithm to locate the face and record its changes in position over time. The recorded face locations will later be used to select the face region and extract essential features for further processing.

Figure 2. Procedures of localizing the face region

The procedures for localizing the face region from the input image are shown in Figure 2. Originally, depending upon the light intensity of the environment, the captured image from the camera may have a very small range of contrast between the driver's face and the background. Once the grayscale of the image is obtained, the system normalizes the brightness level and increases the contrast of the image through histogram equalization. Next, it uses Viola-Jones robust real time face detection algorithm [41] implemented in OpenCV to detect the face of the user. Among the various techniques which have been proposed for face detection, this algorithm is better suited for real time face interactive applications because of its low false positive rates and low computational complexity. According to our experiment, however, using the face detector alone is not reliable to effectively localize the face when the driver's head rotates to a certain angle or suddenly moves to a certain direction which frequently happens when the driver is drowsy. Hence we implemented Camshift tracking algorithm [42, 43] to track the face of the driver under different circumstances where the face detector fails to detect. The final face region is determined according to the outputs from both face detector and tracker.

In Camshift tracking, we initially perform face detection and use the color information of the detected face region as a template for the tracking of consecutive frames accepted from then on. It first creates the color histogram of the detected face and calculates the probability that each pixel belongs to the face region (face probability) based on the histogram. It recalculates the face probability of each pixel for the new sequences of frames and estimates the face location that covers the area with the highest concentration of pixels with high face probabilities.

When the next frame is captured, we perform face detection and Camshift tracking in separate threads. This is because Camshift generally looks for a region having the same color makeup as the detected face and it may include the neck and other unnecessary regions having similar color makeup as the face region. Therefore, the region tracked from the Camshift will be adjusted according to the size of the final face region from the previous frame and the size of the detected face from the face detector if the face is detected as shown in Figure 3. The final face region is then passed to the next processing stage to extract features.

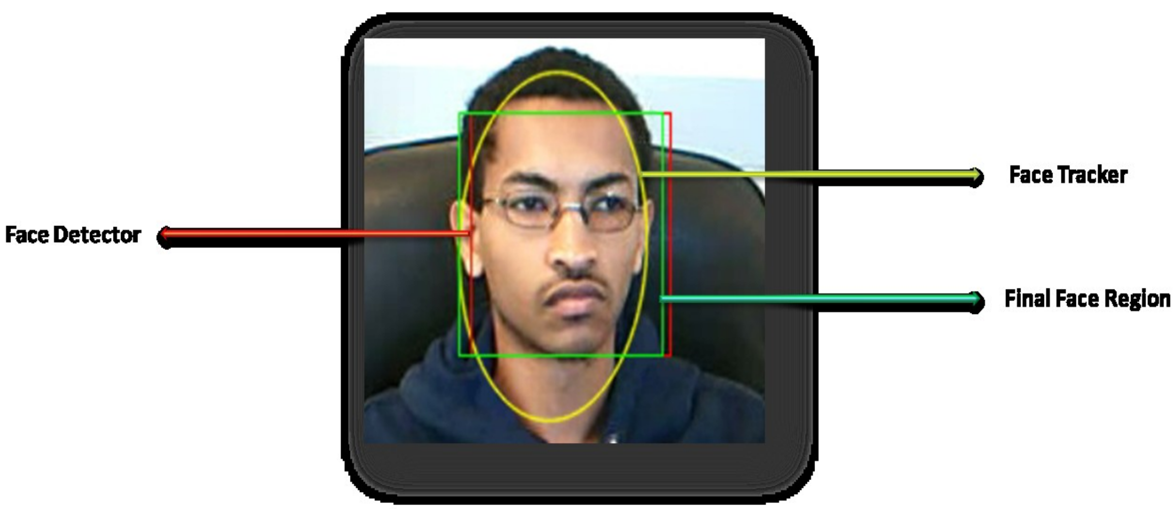

Figure 3. Face Detection and Tracking

3.2. Feature extraction

The grayscale of the input image is passed to Matlab engine along with the locations of the detected face. We have used two approaches of using the input image for feature extraction:

- Crop the detected face of the user
- Crop the region where the eyes are most likely located

The input image is reshaped to a fixed size and its Gabor features are extracted through Gabor Wavelet Decomposition [44, 45]. We preferred Gabor wavelet features for detection because they can represent changes in surface textures such as wrinkles, bulges and changes in feature shapes and they are relatively more robust to illumination changes and random head movement.

3.3. Feature Selection – Adaboost weak learning Algorithm

The facial features from the Gabor decomposition are too many to be used for classification in their entirety and hold a lot of redundant information. Hence we used the Adaboost weak learning Algorithm [46] to select the most important features for classification.

Adaptive boosting is an algorithm for constructing a "strong" classifier as linear combination of "weak" classifiers $h_j(x)$.

$$f(x) = \sum_{j=1}^{T} \alpha_j h_j(x) \qquad (1)$$

Where, α_j is calculated from the training error ε_j of the j^{th} weak classifier as:

$$\alpha_j = \frac{1}{2} \ln\left(\frac{1-\varepsilon_j}{\varepsilon_j}\right) \qquad (2)$$

The weak classifier used here is a simple threshold function $h_j(x)$ consisting of only one feature $f_j(x)$ [47].

$$h_j(x) = \begin{cases} 1 & if \;\; p_j f_j(x) < p_j \lambda_j \\ -1 & otherwise \end{cases} \tag{3}$$

where λ_j is a threshold and p_j is a parity to indicate the direction of the inequality.

We compute the threshold value in two different ways:

- *Averaging:* It can be computed as the average of the mean value of the positive samples and the mean value of the negative samples on the j^{th} feature response:

$$\lambda_j = \frac{1}{2}\left(\frac{1}{m} \sum_{p=1}^{m} f_j(x_p \mid y_p = 1) + \frac{1}{l} \sum_{n=1}^{l} f_j(x_n \mid y_n = 1) \right) \tag{4}$$

- *Searching-maximum:* We can also choose a threshold among the j^{th} feature of all the samples that maximizes separation between the classes:

$$\lambda_j = \max\left(\arg\min\left\{S^+ + (T^- - S^-), S^- + (T^+ - S^+)\right\}\right) \tag{5}$$

Where S^+ is the number of positive samples below threshold, S^- is the number of negative samples below threshold, T^+ is the total number of positive samples and T^- is the total number of negative samples.

Algorithm: Adaboost (Schapire and Singer, 1999)
Input: N training samples with labels (x_i, y_i), $i = 1,2,\cdots,N$ with m positive $y_i = 1$ and l negative $y_i = -1$ samples
Initialize: the weights of training samples : $$w_i^1 = \begin{cases} 1/2m, \text{ if } i \text{ is a positive sample} \\ 1/2l, \text{ if } i \text{ is a negative sample} \end{cases}$$
Do for $t = 1,\cdots,T$ 1. Normalize all weights 2. For each feature j, train a weak classifier h_j with error $\varepsilon_j = \sum_{i=1}^{N} w_i^t \lvert h_j(x_i) - y_i \rvert$ 3. Choose h_t with the lowest error ε_t 4. Update the weights: $w_i^{t+1} = \frac{w_i^t exp\{-\propto_t y_t h_t(x_i)\}}{C_t}$ where $\propto_t = \frac{1}{2} ln\left(\frac{1-\varepsilon_t}{\varepsilon_t}\right)$ and C_t is a normalization constant
Output: Final strong classifier $$H(x) = \begin{cases} 1 & \text{if } \sum_{t=1}^{T} \alpha_t h_t(x) > 1/2 \sum_{t=1}^{T} \alpha_t \\ -1 & \text{otherwise} \end{cases}$$

Table 1. Adaboost Algorithm

3.4. Classification

At this stage, the selected features from the Adaboost are classified to a state of either drowsy or non-drowsy by using different classification methods. The cascaded linear classifier built from the weak classifiers selected in the Adaboost feature selection can be used as one classification method. We have also chosen Support Vector Machines (SVM) as another classifier as it has been successfully used in a wide variety of data classification and pattern recognition applications [48]. We evaluated the classification accuracies of each method and compared their results for the different feature extraction and selection parameters. Each classification method gives an output for the set of selected features extracted from a single frame. However, when giving a final decision of the state of the driver, we consider a set of such classification outputs from sequence of frames of predetermined window size. This helps make the system more robust and reliable.

i. Adaboost

We linearly combine the weak classifiers working on each selected feature to get a strong classifier and obtain the classification output $H(x)$ as follows:

$$H(x) = sign\left(\sum_{j=1}^{T} \alpha_j h_j(x)\right) \quad (6)$$

For a final decision, we calculate the mode of the classification outputs of sequences of frames and declare the state of the driver based on the majority of the outputs as shown in Figure 4.

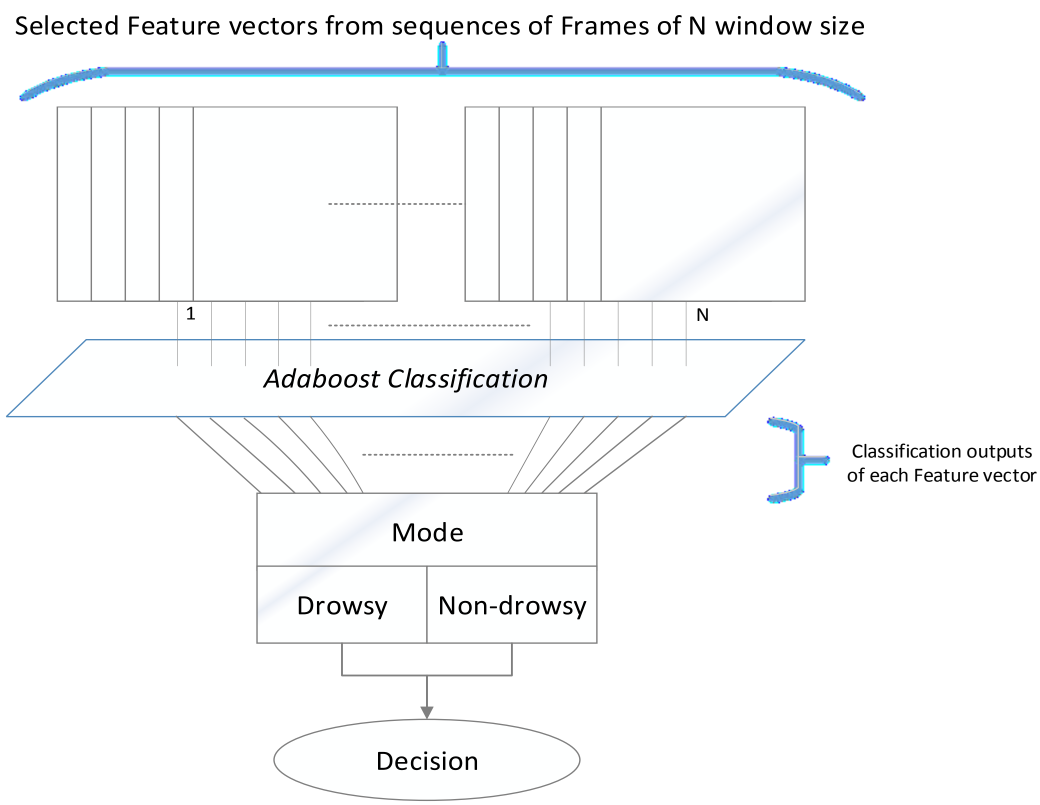

Figure 4. Classification Decision for N feature vectors using Adaboost

ii. Support Vector Machines (SVM)

We are essentially dealing with a two-class classification problem (drowsy or non-drowsy). We chose SVM as it is generically used for binary classification problems and has attributes that make it a perfect fit to our problem.

- SVM does not depend on the dimensionality of the input space
- It is less prone to over-fitting
- It always gives an optimum global solution during training.

We feed the selected features to the SVM for nonlinear classification by using Radial Basis Function (RBF) kernel method [49]which proved to have a gain in performance over the linear combination of the Adaboost weak classifiers. The RBF kernel maps the training feature vectors nonlinearly in to a high-dimensional feature space. In this space, an optimal separating hyper-plane is constructed by the support vectors corresponding to the centers of the RBF kernels in the input space.

When giving the final decision of the state of the driver based on sequences of frames, for each classification output, we first calculated the point distance from the separating hyper-plane. Next we used sigmoid function $S(d)$ to convert the distance to a class probability as shown in Figure 5.

$$S(d) = \frac{1}{1+e^{-d}} \qquad (7)$$

Where d is the point distance from separating hyper-plane

The output obtained from the sigmoid function ranges from 0.5 to 1 because its input is distance which is positive. The output will be assigned as a class probability for the class output of the SVM for each feature vector. The class probability for the complement class of each feature vector will then be the sigmoid output subtracted to one. For example, if a given feature vector is classified as drowsy by the SVM classifier, then we first obtain the class probability for drowsy P_d from the sigmoid output of the calculated point distance. The class probability for the non-drowsy P_n of the feature vector then becomes $P_n = 1 - P_d$. Then, for a final decision, we calculate the average of both drowsy and non-drowsy class probabilities for sequences of such feature vectors and declare the class with the larger average as the state of the driver.

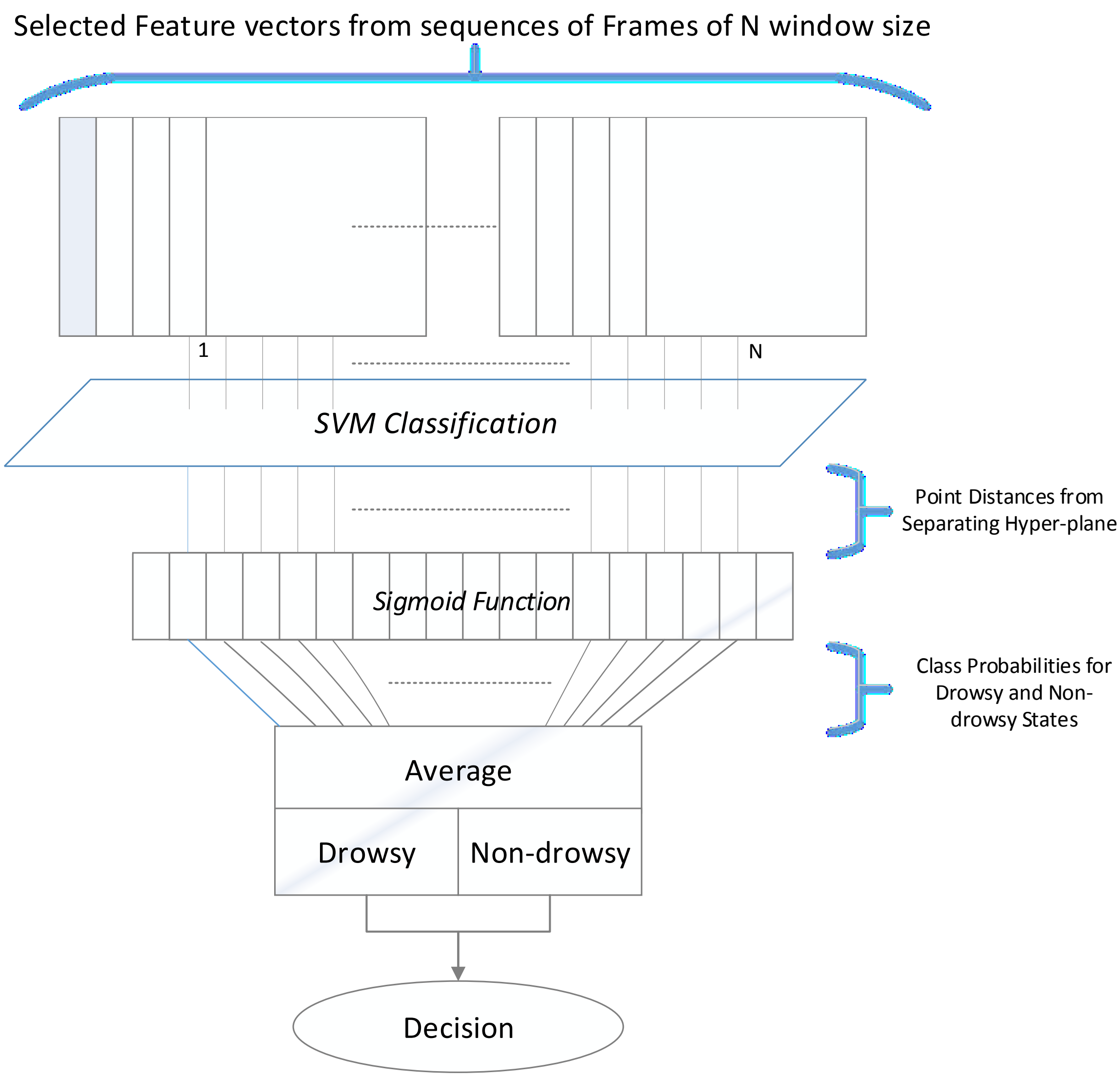

Figure 5. Classification Decision for N feature vectors using SVM

CHAPTER IV

DROWSINESS DETECTION THROUGH INTEGRATION OF FACIAL EXPRESSION AND STEERING WHEEL MOVEMENT

In this chapter, we include steering wheel movement as an additional input to the facial expression based drowsiness detection method. While the detecting facial expressions of drivers could give appreciable results in most cases, there are certain situations where the ambient light could deteriorate the quality of input images, there could be certain occlusions covering part of the face or the proposed algorithm could fail to correctly detect the state of the driver. By adding steering wheel data analysis to the proposed algorithm, we increase the system's reliability as it can properly respond in these situations. Steering wheel data analysis is independent of the ambient light, face occlusions or the limitations of the facial expression detection algorithm. Moreover, it has been shown that there is a good correlation between the steering wheel movement and the drop in the state of vigilance while driving [8, 9].

4.1. Steering Wheel Data Analysis

In an alert state, the driver tends to make small adjustments to the steering wheel angle and hence there will only be small variation. When the driver is in a drowsy state, the way he/she drives becomes unpredictable, resulting in a large change in trajectory, for example, zigzag driving and there will be a larger amplitude of movement to keep the vehicle in the center of the lane. In Figure 6, we plotted the steering wheel data with respect to time of one subject while driving in drowsy and non-drowsy states. We collected 27sec duration of steering wheel data while the driver is drowsy and 39sec duration of steering wheel data while the driver is non-drowsy. It shows that the steering wheel angles during drowsiness randomly change in large magnitudes as the time evolves. There are only small variations of steering wheel angles for non-drowsy condition. Even if there are large magnitude changes, they are not as spiked as in the case of the drowsy conditions. The steering wheel angle ranges from 0 to 250 and the wheel is neutral at 125.

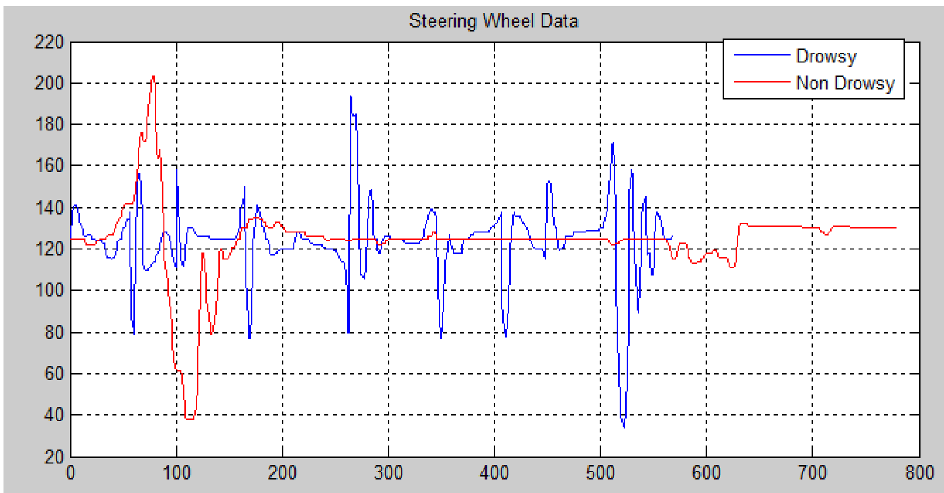

Figure 6. Steering wheel data with time increment of 50ms. The unit of Y axis is degree.

Figure 7 shows the standalone implementation of steering wheel data analysis. The system accepts the steering wheel data along with the entire car controller information at a rate of 15 packets per second and extracts the steering wheel data to a set of feature vectors for processing. As mentioned above, the steering wheel angle obtained ranges from 0 to 250 with a neutral state at 125. In order to change it to an angular measurement that ranges from -90 to 90 with a neutral state of 0, we used a normalization equation:

$$S_f = (S_i - 125) \times 90/125 \tag{8}$$

Where, S_f is the normalized steering feature vector and S_i is the input steering feature vector

After vectorization, the training set of feature vectors is used to build an SVM classifier model that categorizes incoming data to either drowsy or non-drowsy. During the real time testing, the steering wheel data is populated in a dynamic vector and passed to the SVM classifier.

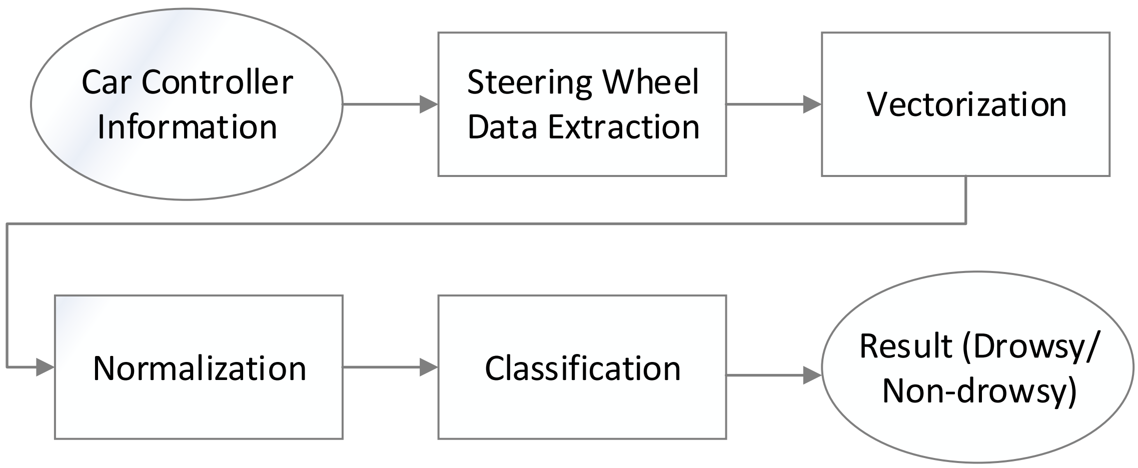

Figure 7. . Steering Wheel data analysis

Using steering wheel movement to detect drowsiness has its advantages as it performs better in certain situations where the computer vision approach does not. However, as a standalone drowsiness detection approach, it is also unreliable as it can be influenced by outside factors such as nature of the road, the vehicle, the traffic and the driver's way of driving. Hence, in this chapter, we propose optimum ways of integrating the two methods so they can complement one another.

4.2. Overall Approach

We proposed a system which implements the two well known non-invasive approaches: drowsiness detection based on facial expression and steering wheel movement, in both independent as well as comprehensive approaches. With the ultimate goal of finding a practical and unobtrusive method of detecting drowsiness of a driver, the steering wheel data analysis or the computer vision approach alone may not be sufficient to accurately determine the state of the driver, especially under different circumstances and different behavioral manifestations of the driver. Hence integrating the two sources of information will increase the detection reliability of the system and deal with situations where a single source may not give sufficient results.

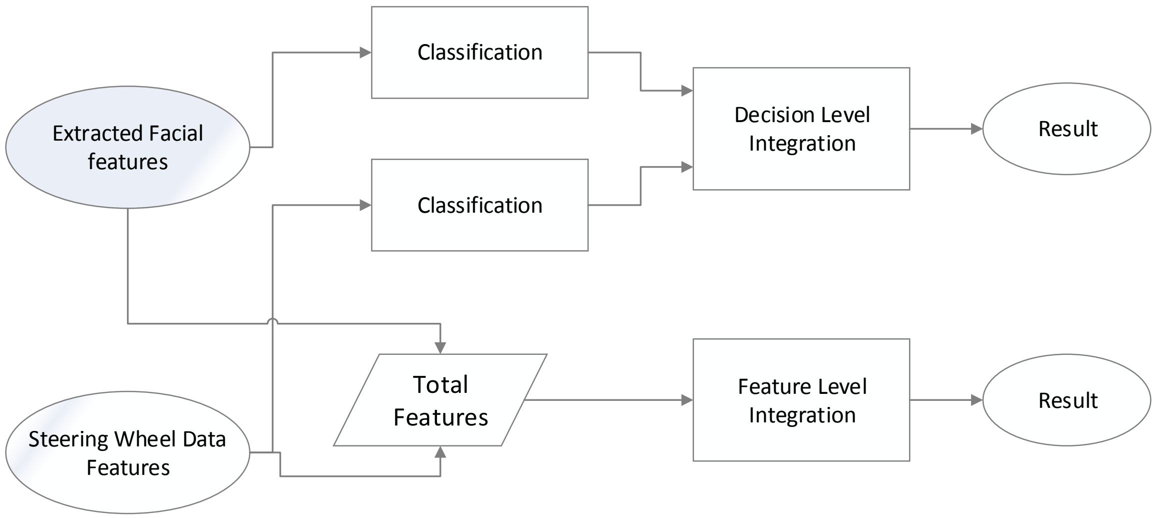

Figure 8. Overall System Diagram

The overall system diagram is shown in Figure 8. There are two main inputs to the system: the stream of driver's images and the stream of steering wheel data. The stream of images passes through processing the following stages: face detection, feature extraction, feature selection and classification. The steering wheel data pass through the feature extraction and classification stage. As for integration of these two sources of information, the final output can be obtained through data fusion at either decision level or feature level.

4.3. Decision Level Integration

One easy way of integration is at decision level where the outputs from both systems are combined using simple Boolean algebra. The final decision of the state of the user is given by calculating the mode of the classification results of sequences of images.

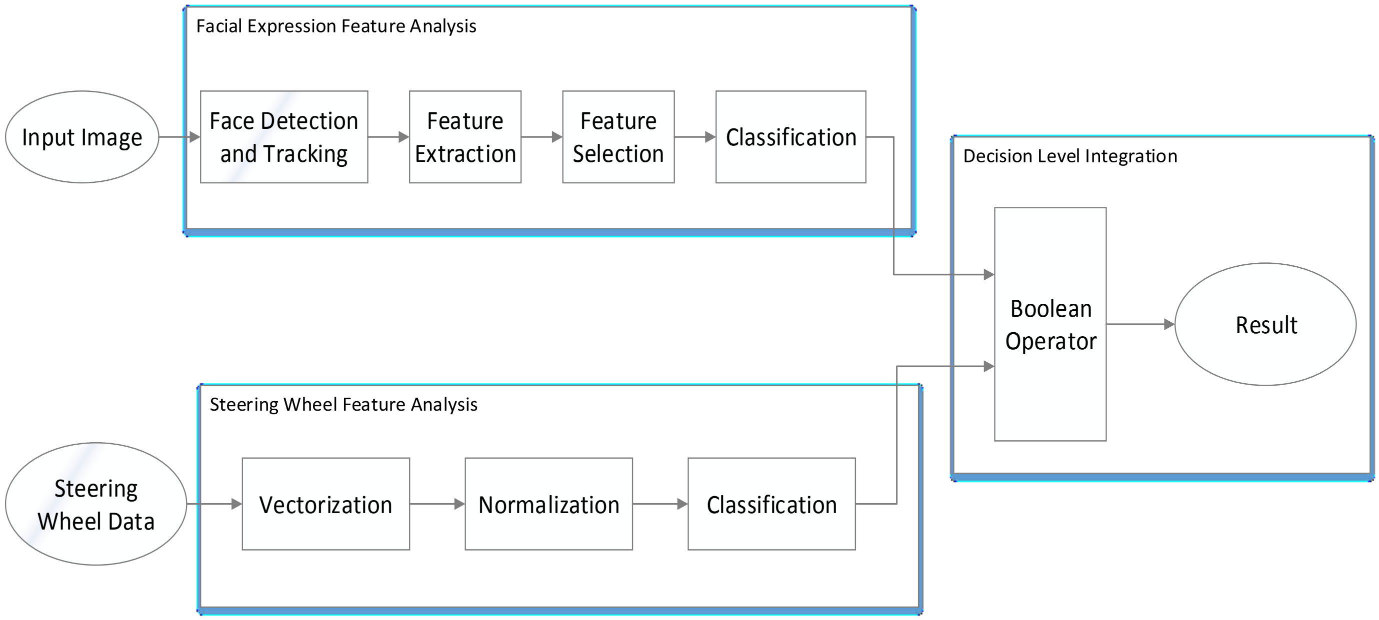

Figure 9. Decision Level Integration

This method is illustrated in Figure 9, either disjunctive or conjunctive logic can be used.

- Disjunctive Operation: $Output_{Face} \vee Output_{Steer} = Output_{Final}$ (9)
- Conjunctive Operation: $Output_{Face} \wedge Output_{Steer} = Output_{Final}$ (10)

However, this method may not necessarily enhance the performance of the detection because of the following two main reasons:

- The limitation of any of the two systems can easily be transferred to the overall output of the system. For example, if a disjunctive operator is used and one of the two systems gives an output of false positive then the overall output will also be false positive irrespective of the output of the other system.
- The combination doesn't reflect the correlation of the two inputs during drowsy and non-drowsy episodes. For example, when a driver is feeling drowsy, not only can it be seen through the person's facial expression but also in the way the person drives where he/she steers unpredictably in an attempt to keep the vehicle in the right path. If we can manage

to incorporate such variations in the steering wheel data along with the change in facial patterns as complementary inputs to one another, we can empirically get better detection outputs which is not so for this case.

4.4. Feature Level Integration

Another method of integration is to combine the two sources of data at feature level using an SVM classifier. By using feature extraction and selection methods, we get a single vector of the most important features from the input image and then append the steering wheel data features to that vector, which can be input to the SVM classifier as shown in Figure 10.

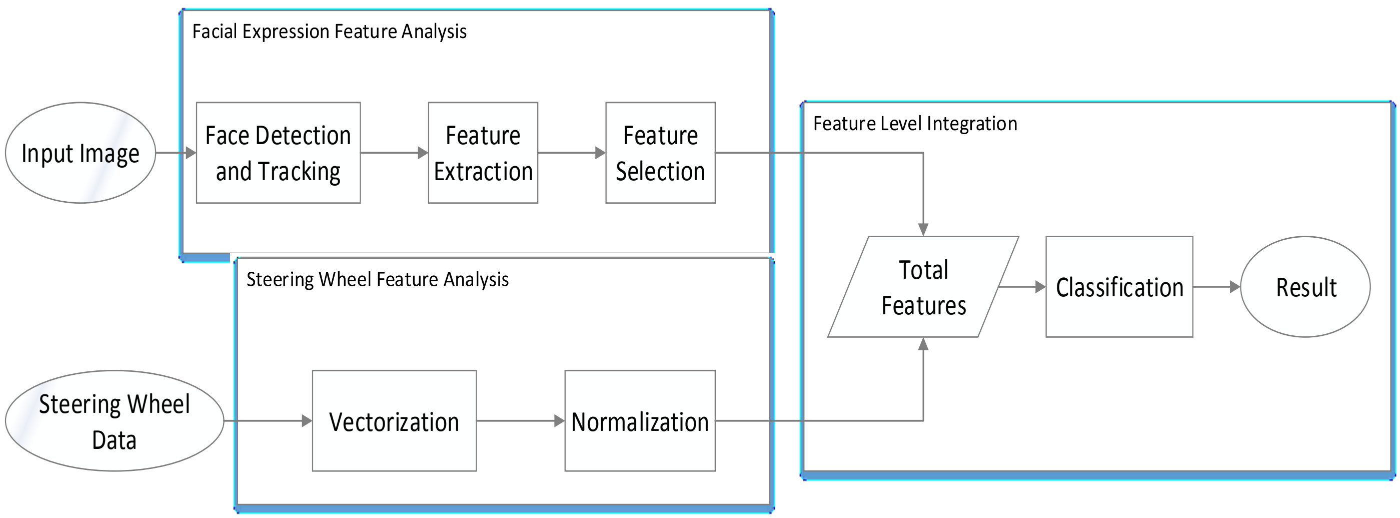

Figure 10. Feature Level Integration

For N-sized facial features $[Ff_1, Ff_2, \dots, Ff_N]$ and M-sized steering wheel features $Sf_1, Sf_2, \dots, Sf_M$, we have the concatenated feature vector as follows:

$$[f_1, f_2, \dots, f_N, f_{N+1}, f_{N+2}, \dots, f_{N+M}] = [Ff_1, Ff_2, \dots, Ff_N] \cup [Sf_1, Sf_2, \dots, Sf_M] \qquad (11)$$

In the same way as the decision level integration, the system gives final decision of the state of the driver for sequences of total feature vectors. But in this case, it first calculates the point to separating hyper-plane distance of each total feature vector in the sequence. It uses sigmoid function to convert the distances to drowsy and non-drowsy class probabilities. Finally, for a final decision, it calculates the average of both class probabilities and declares the class with the larger average as the state of the driver.

CHAPTER V

DROWSINESS DETECTION THROUGH HMM-BASED DYNAMIC MODELING

In the facial expression based drowsiness detection method proposed previously, it performs classification on frame by frame basis even if the final decision is given for a sequence of frames. The main limitation in this approach is that it does not consider the temporal sequence of the frames when it declares the state. This is because it either calculates the mode of the classification of each frame or the average of the class probabilities of each frame. The position of the frames in the sequence can be interchanged in different possible ways and the system would still give us the same final decision.

According to a psychological research [50], analyzing facial motions through sequences of frames is crucial in recognizing facial expressions. It also shows that humans are better at recognizing facial expressions from sequences of frames than individual frames. This is because facial expressions have a unique dynamic pattern of behavioral changes that can easily be recognized in time. Consequently, more researches have started to be conducted with a particular focus on modeling dynamic features to recognize facial expressions, and Hidden Markov Models has been the most widely used method in modeling the temporal dynamics [51-54] . Basing our work in these and other researches, we have proposed a method to model the dynamics of facial expressions of drowsiness in the same way as the general facial expressions have been modeled in recognition of human emotions.

In this chapter, we implement dynamic modeling approach to make use of the temporal sequences of frames to recognize the driver's expression. We model the dynamics of the driver's drowsiness by utilizing all the information available in the image sequences. We also optimize the modeling parameters and the dynamic features that capture the temporal pattern of the facial expressions indicating drowsiness.

5.1. Hidden Markov Models

Hidden Markov Models have been widely used for various dynamic classification problems and statistical modeling. The main attribute of HMM is that it characterizes an input non stationary signal as a parametric random process and the parameters can be determined or estimated in a probabilistic manner. HMM is modeled to have a set of unobservable stochastic processes (hidden states) that produce a sequence of observations. It uses the transition probabilities between the hidden states and learns the conditional probabilities of the observations given the state of the model.

Hence, an HMM model μ can be parameterized by the set of values of the hidden sates and observation symbols, the initial state probabilities, the state transition probabilities and the observation state probabilities [55].

$$\mu = \{S, K, \pi, A, B\} \qquad (12)$$

$S : \{s_1 \ldots s_N\}$: are the values of the hidden states

$K : \{k_1 \ldots k_M\}$: are the values of the observation symbols

$\pi = \{p_i : P(q_1 = s_j), 1 \le j \le N\}$: are the initial state probabilities.

$A = \{a_{ij} : P(q_{t+1} = s_j \mid q_t = s_i), 1 \le i, j \le N\}$: are the state transition probabilities.

$B = \{b_{ij} : P(o_t = k_j \mid q_t = s_i), 1 \le i \le N, 1 \le j \le M\}$: are the state observation probabilities.

q_t & o_t : are the hidden state and observation symbol at time *t*.

In modeling an HMM, there are two main problems that need to be addressed:

- *Inference:* We need to determine the probability that a given observation sequence $O = o_1\ o_2\ \cdots o_T$ is produced from a HMM parameterized by μ . This is a classification problem as we will compute the probability that a given sequence of feature vectors, which is represented by observation symbols, is produced from either the drowsy or non-drowsy HMM. We choose the model which best matches the observation sequence and hence classify the sequence as either drowsy or non-drowsy state.

- *Fitting:* We need to choose a HMM that represents a sequence of past observations well. This is a learning problem as we adjust the model parameters $\{\pi, A, B\}$ by training both models with training image sequences.

5.2. Feature Discretization

The HMM model described above is trained by a sequence of training observations and once the model parameters are optimized, it gives a probability of how likely a given sequence of observations is produced by the model. While the observation sequences in HMM are essentially discrete symbols, the input signal of our system is a multidimensional feature vector extracted from the detected face of the driver. Hence, we use the two well-known unsupervised clustering techniques: K-means and Expectation Maximization (EM), to quantize the multidimensional continuous feature vectors to discrete symbols as shown in Figure 11.

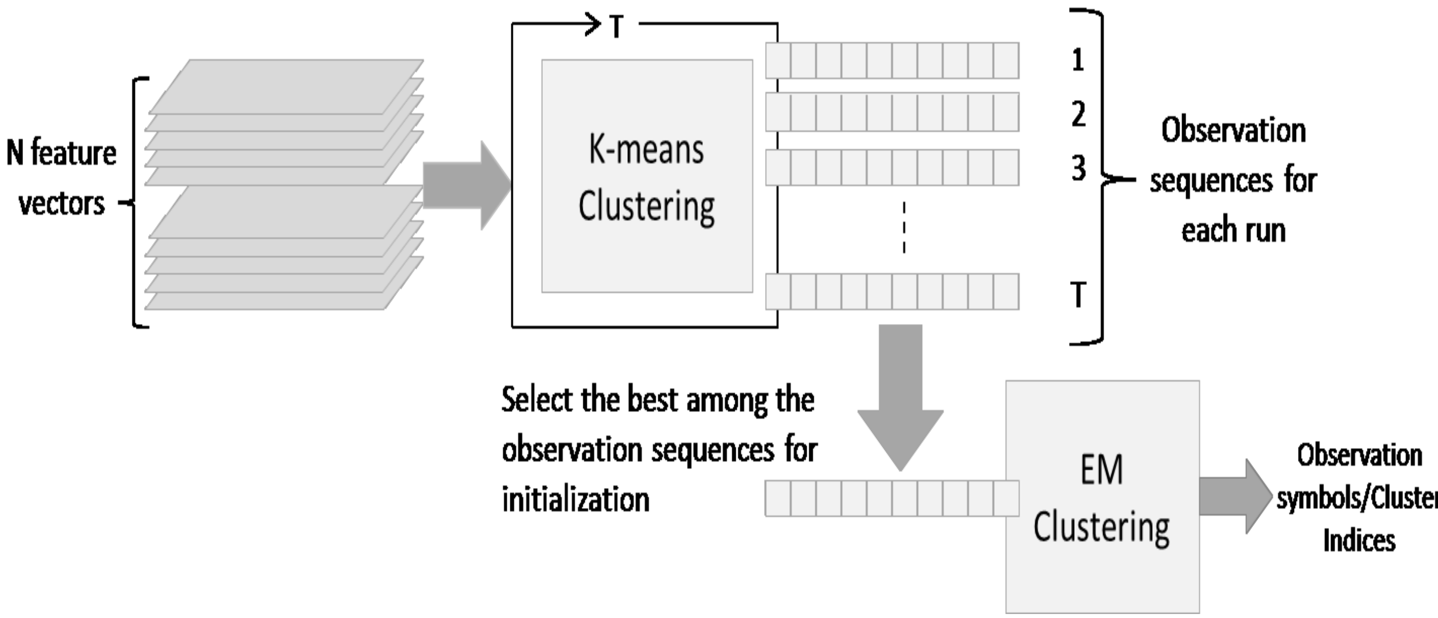

Figure 11. Feature Discretization using K-means and EM clustering

We first use K-mean clustering to cluster the N feature vectors (training data) to sequences of observation symbols. The cluster centroids are randomly initialized at first and then it iteratively adjusts their positions such that the point-to-centroid distance is a minimum. We perform K-mean clustering for T number of times as shown in Figure 11 and we use a new set of initial cluster centroid positions for each time. During each run, the sequence of continuous vectors is represented by their closest centroid indices as sequence of observation symbols. Hence, we have T sequences of observation symbols corresponding to the T runs. Among the runs, we select the one with the best sequence of symbols having the smallest within-cluster sums of point-to-centroid distances. We use the sequence of observations as initializations for the EM clustering which is better than initialization through random sampling. This is because both K-mean and EM converge to the local optimum and, hence, are sensitive to the initialization. By running the K-mean multiple times and choosing the best one to initialize EM, we minimize the random convergence that may or may not be global optimum.

The main limitation of K-means is that it fails to optimally cluster features having non-isotropic distributions. The facial feature vectors, in our case, are multidimensional continuous values that can best be modeled statistically through Multivariate Gaussian Distributions. Hence we used EM clustering which uses Gaussian mixture models to optimize the cluster centroids. After having the observation symbols, we adopted two HMM models for both drowsy and non drowsy facial expression detections.

5.3. Drowsiness Detection Using HMM models

Drowsiness is a cognitive state created through series of changes of behavioral patterns occurring through time. Such changes of facial expressions during drowsiness can be modeled just as many researchers have been modeling facial expressions to recognize human emotions. The main challenge in modeling drowsy behavioral patterns is that they have random transitions as opposed to the universal facial expressions of emotions like happy, anger, fear, sadness and surprise that have a well-defined transition going from neutral to apex. Expressions during drowsiness include, but are not limited to, frequent blinking, prolonged eye closure and sudden opening of the eyes followed by eye brow raise in an attempt to keep the eyes open, yawning, nodding and gradual head tilting to certain direction. This poses difficulty in learning the models as it includes wide variety of behavioral patterns to be considered for both drowsy and non-drowsy scenarios. In modeling the HMM for drowsy expressions, we constructed a specific model that encompasses the various transitions of expressions manifested during drowsiness. For non-drowsy expressions, a general HMM model was constructed to account for all the behavioral changes outside the drowsy expressions.

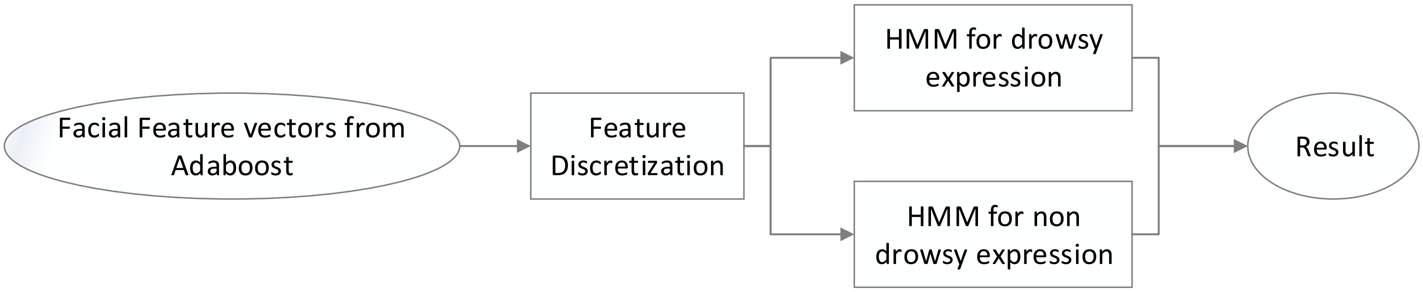

Figure 12. The system diagram of drowsiness detection using HMM dynamic modeling

The block diagram of the system is shown in Figure 12. The Gabor features selected through Adaboost are quantized to discrete observation symbols by using K-means and EM clustering. We used the same centroids to cluster the drowsy and non-drowsy image sequences and trained both models with their respective observation sequences. During training, we used Viterbi algorithm to estimate the state transition and state-to-observation probabilities of the HMMs. During testing, a given sequence of selected Gabor feature vectors are fed to both models and classified by calculating the probability of the sequences for each model.

CHAPTER VI

EXPERIMENTS AND RESULTS

In this chapter, we present the overall setup of our experiment, the procedures we have taken when conducting the experiment of each drowsiness detection method and, finally, the experimental results, comparisons and discussions.

6.1. Experimental Setup

Figure 13. Experimental Setup

The overall experimental setup is shown in Figure 13. To experiment and evaluate our proposed approach, we have set up a Logitech Communicate QuickCam STX webcam as a source of input images for the facial expression based drowsiness detection system. We placed it in front of the driver at a distance optimum enough to have a full visual of the driver's face. It captures stream of images of 320×240 pixels at rate of 30 frames per second. We have also setup a G27 Logitech racing wheel system [56] as a source of the driver's steering wheel movement for the experiment of the integrated drowsiness detection system.

In an effort to simulate the actual driving scenarios, we have used the driving simulation software Simuride [57] which is preconfigured to be easily used with the Logitech G27 racing wheel system. The software gives a visual display of the actual traffic scenes along with the car dashboard as shown in Figure 14. By using Simuride, we made the users drive in different scenarios in both drowsy and non-drowsy conditions and collected training and testing data for the analysis and evaluation of our approach.

Figure 14. Driver view in the SimuRide software.

The user interface of the application is shown in Figure 15. It shows the stream of input images of the driver from the webcam. The outputs from the face detector and Camshift tracker along with the final face region are drawn on each input image and all the information of the face region such as location and size are stated on the side. The car controller information from the vehicle including the steering wheel, gas, brake and gear are also displayed. The driver's state after processing of sequences of frames is also stated.

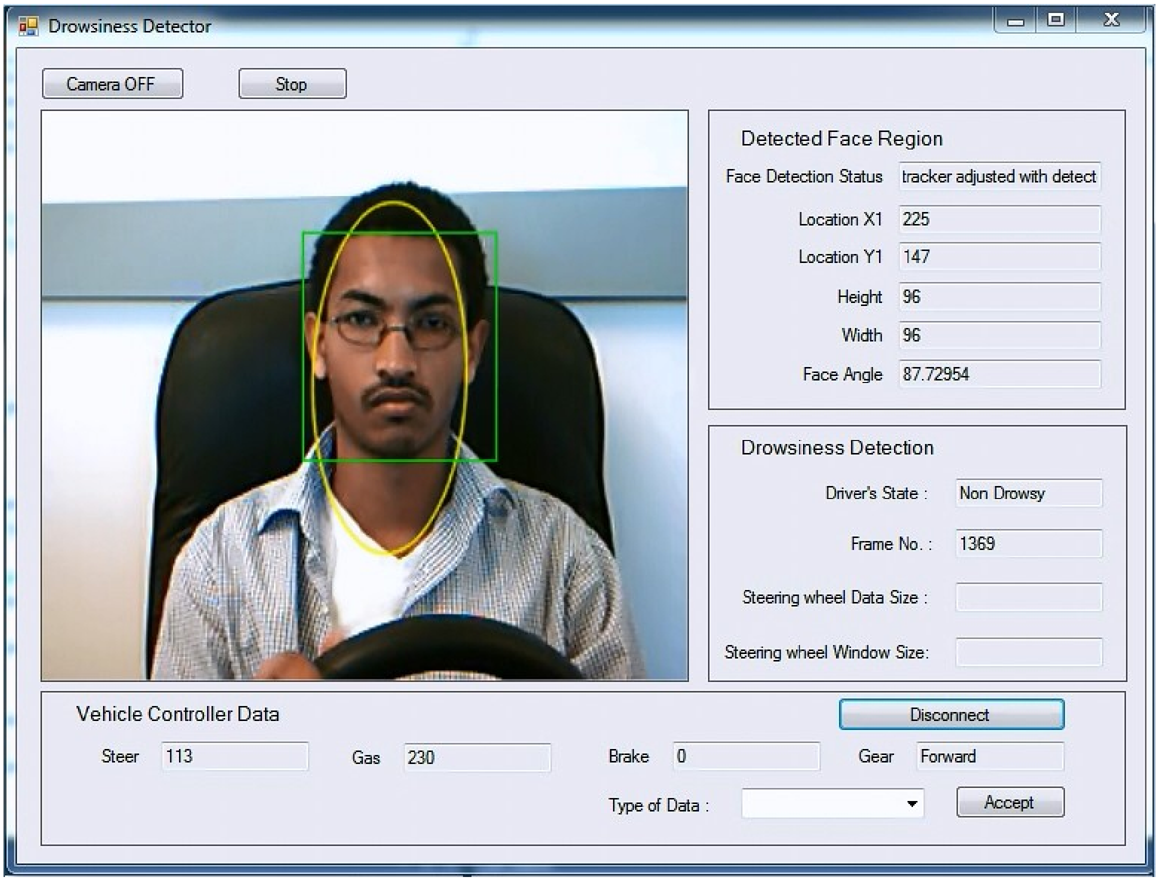

Figure 15. User Interface of Drowsiness Detection System

6.2. Experimental Procedures

In this section, we present the step by step procedure we have taken to conduct the experiments for each drowsiness detection method we proposed.

6.2.1. Facial Expression Based Drowsiness Detection

- We initially collected video data of subjects for cases of both drowsy and non-drowsy scenarios of five subjects. After collecting the videos, we reviewed the entire span on frame by frame basis and edited out unwanted sections that lead to misrepresentations of the scenario. For example, there could be a part where the driver could be wide awake when collecting a video for a drowsy episode or the driver could be yawning and getting sleepy when collecting a video for non-drowsy episode.

- During the training stage, we selected 2/3 of the image frames of the labeled video data recorded from each subject for both drowsy and non-drowsy scenarios. The remaining 1/3 of the image frames of the labeled video data were used for testing.
- For each input image, the face locations are first determined from the face detection and tracking stage. During feature extraction, the located face region is normalized to different matrix sizes depending on the choice of region of interest. If the detected face is the region of interest, the face region of each image frame is normalized to a matrix of 100×100 and if the cropped eye region from the detected face is the region of interest, the eye region is normalized to a matrix of 200×80.
- The Gabor wavelet decomposition is implemented with a 2 scales and 4 orientations filter bank which is the minimum, yet optimum, combination for our system which performs the detection in real-time.

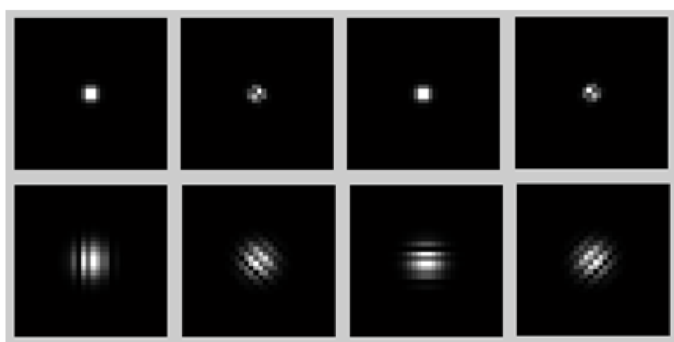

Figure 16. Gabor filter bank with 2 scales and 4 orientations.

For the case of using the detected face as the input, each input image generates a feature matrix of size 100×(100×2×4) =80000 of total features. On the other hand, when using the cropped eye region as the input, then the total features will become 200×(80×2×4)=128000 of total features.

- The total number of features obtained from the Gabor convolution is too large to be entirely used for classification and hence the need for feature selection. In the Adaboost feature selection algorithm, we have proposed Averaging and Searching Maximum threshold computations.

- During classification, we computed the average accuracy of the drowsiness detection for different number of features, choice of region of interest, threshold computation, and classification techniques (i.e. Adaboost or SVM).
- Final decision is given for 15 sequences of frames which is the same as the frame rate of the webcam used in our system.

6.2.2. Integrated Drowsiness Detection

- We initially collected the steering wheel movement of each subject along with the image frames of the driver's face for both drowsy and non-drowsy scenarios. The steering wheel data is appended to a dynamic vector in a separate thread from the one that captures the input images. However, in order to synchronize the steering wheel movement with the corresponding image frame, we selected a fixed size of steering wheel from the most recently added side of the dynamic vector on the same thread as we captured the input image.
- Next, we independently implemented the steering wheel data analysis and evaluated its detection accuracy. In a similar way as the facial expression based drowsiness detection, we selected 2/3 of the collected steering wheel vectors for training an SVM classifier with RBF kernel and the remaining 1/3 of the collected steering wheel vectors for testing the classifier. We evaluated the classification accuracy of the system for different vector sizes and determined the optimum vector size.
- For the decision level integration, we combined the outputs from the facial expression and steering wheel based detection systems with both disjunctive and conjunctive operations. We evaluated the classification accuracies for both operations by varying the

different parameter settings of the facial expression based detection system while keeping the vector size for the steering wheel data analysis constant at the optimum value.

- For the feature level integration, we added the steering wheel data vectors as additional inputs to the facial feature vectors from the Adaboost. We performed the classification in the same way we did for the facial expression based drowsiness detection method. When evaluating the classification accuracies, we kept the steering wheel data vector size constant at the optimum value and varied the different parameter settings of the facial expression part of the system.
- In each method, final decision is given for 15 sequences of frames and steering wheel vectors which is the same as the frame rate of the webcam used in our system.

6.2.3. HMM Based Drowsiness Detection

- We first recorded videos of multiple subjects in drowsy and non-drowsy scenarios. We edited out the unwanted parts of the videos in the same way we did for the facial expression based drowsiness detection method. We also performed the same procedures as the facial expression until the feature selection using Adaboost.
- Next, we quantized the feature vectors to definite indices using EM clustering of Gaussian Mixture models. We initialized the EM by running K-Means clustering for repeated number of times and choosing the best set of clusters among all.
- After representing the feature vectors with cluster indices, we trained two HMM models, one for drowsy and another for non-drowsy scenarios, by using 2/3 of the collected videos and tested the models with remaining part.
- We evaluated the classification accuracies by varying the number of facial features, the observation symbols, the hidden states and the window sizes and compared it with the corresponding results from the facial expression based drowsiness detection method.

- Final decision is given for 15 sequences of frames which is the same as the frame rate of the webcam used in our system.

6.3. Experimental Results

6.3.1. Facial Expression vs. Integration Based Drowsiness Detection

For our experiment, we used two subjects to drive in drowsy and non-drowsy scenarios and we collected the stream of images and the steering wheel data.

a. Facial Expression based Drowsiness Detection

In the training stage, we have selected 2/3 of the image frames of the labeled video data (7891 non-drowsy and 8427 drowsy images) from ten videos of five different drivers. For testing, 1/3 of the image frames of the video data recorded (3948 non-drowsy images and 4215 drowsy images) have been used. We computed the average accuracy of the detection method for different number of facial features and choices of region interest, Adaboost threshold computation and classification techniques (i.e. Adaboost or SVM). For the ease of understanding, we categorized the performance evaluation scheme to the case of Averaging and Searching Maximum Adaboost threshold computation approaches. In each case, we increased the number of features selected by the Adaboost from 10 to 300 with an interval of 10 and observed the variation in performance.

- Averaging Threshold Computation

As the number of facial features selected for classification increases, the performance saturates to the accuracy values shown in Figure 17 and 18 for the different system parameter settings. From Figure 17, we can see that the accuracy roughly increases to near-maximum at a rapid rate until the number of features reaches 100. For averaging threshold computation, the accuracy of classification using Adaboost is generally significantly lower than that of the SVM classifier with

RBF kernel for the same region of interest chosen (either eye region or detected face). Moreover, for the same classification technique chosen (either Adaboost or SVM), the classification accuracy of the system using face region as ROI is better than using the eye region as shown in Figure 17. This attests to the fact that using other facial expressions in addition to eye closure as ways of detecting drowsiness gives more reliable performance than using eye closure alone. We have obtained a maximum accuracy of 94.86% for 200 facial features selected, detected face selected as ROI and SVM classification.

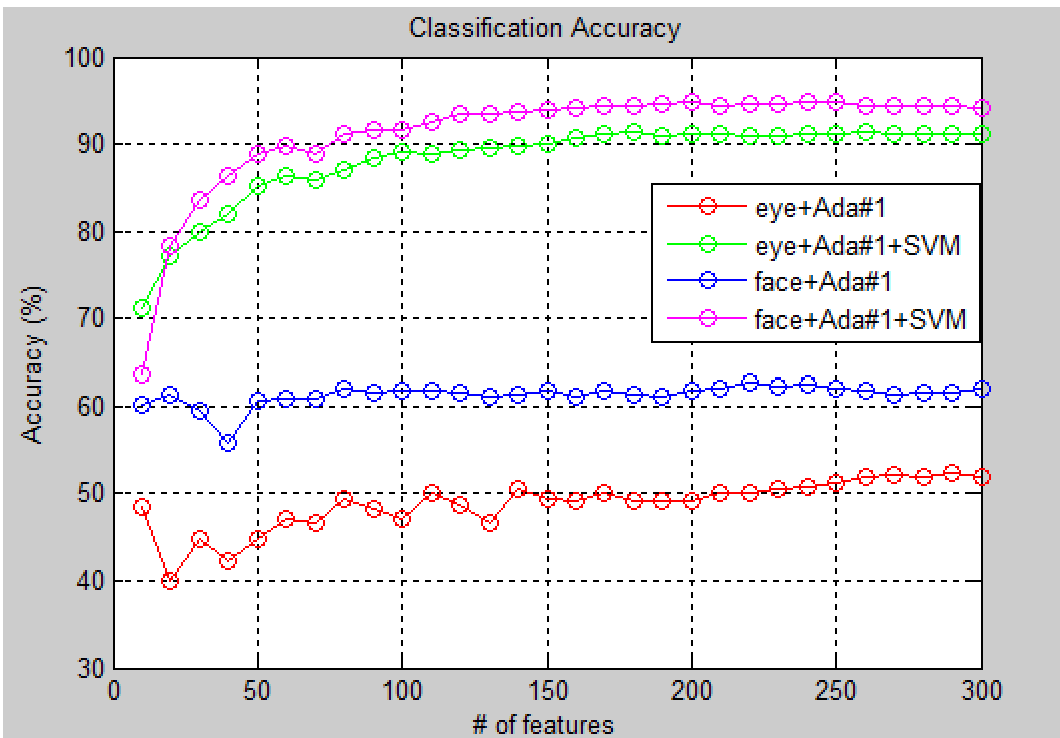

Figure 17. Classification accuracy for averaging threshold computation

- Searching Maximum Threshold Computation

Figure 18 depicts an interesting relation between the different methods of classification and choice of ROI for searching-maximum threshold computation. By using Adaboost classification method, we obtain a classification accuracy that almost remains constant which implies that the increase in number of features being added to the cascaded combination will have little significance on the detection performance. It also gives significantly lower classification accuracy as compared to SVM classification which is to be expected. Just as in the case of averaging threshold computation, using face region as ROI gives better results than using eye region. We have obtained a maximum accuracy of 92.99% for 200 facial features, face region selected as ROI and using SVM classification.

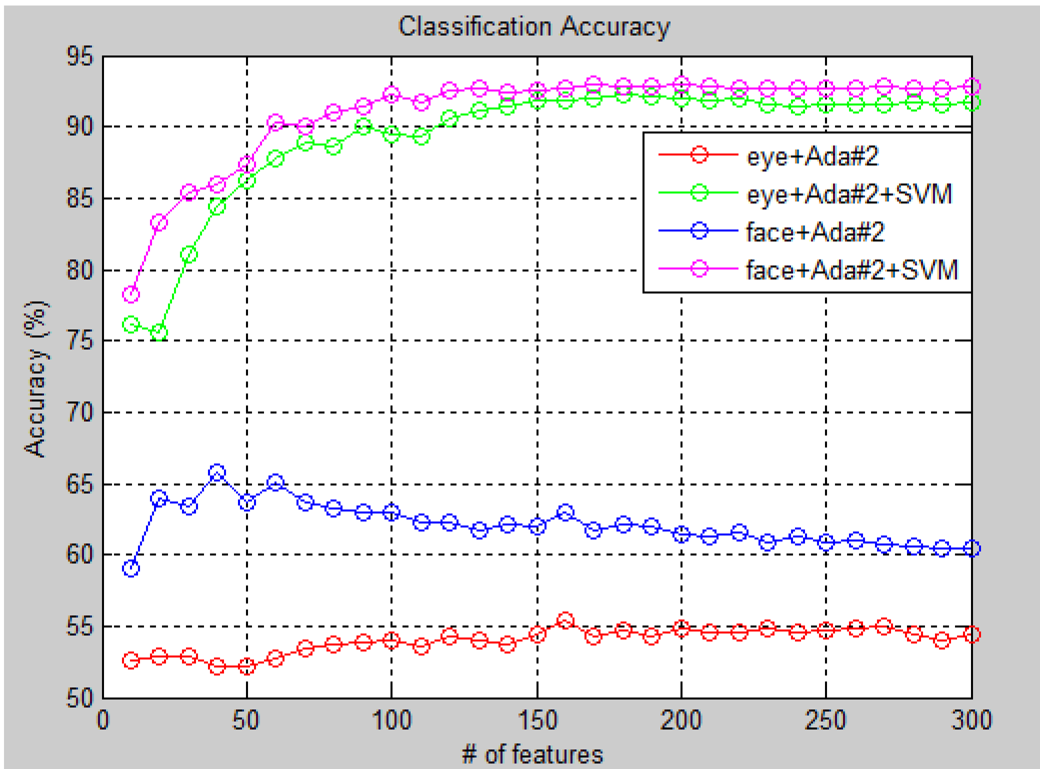

Figure 18. Classification accuracy for searching maximum threshold computation

b. Steering Wheel Data Analysis

Next, we independently implemented the steering wheel data analysis and evaluated its detection accuracy. As in the facial expression case, we used different feature vector sizes from 10 to 300 and obtained a maximum accuracy of 79.65% by using a vector size of 160 steering wheel features as can be seen in Figure 19.

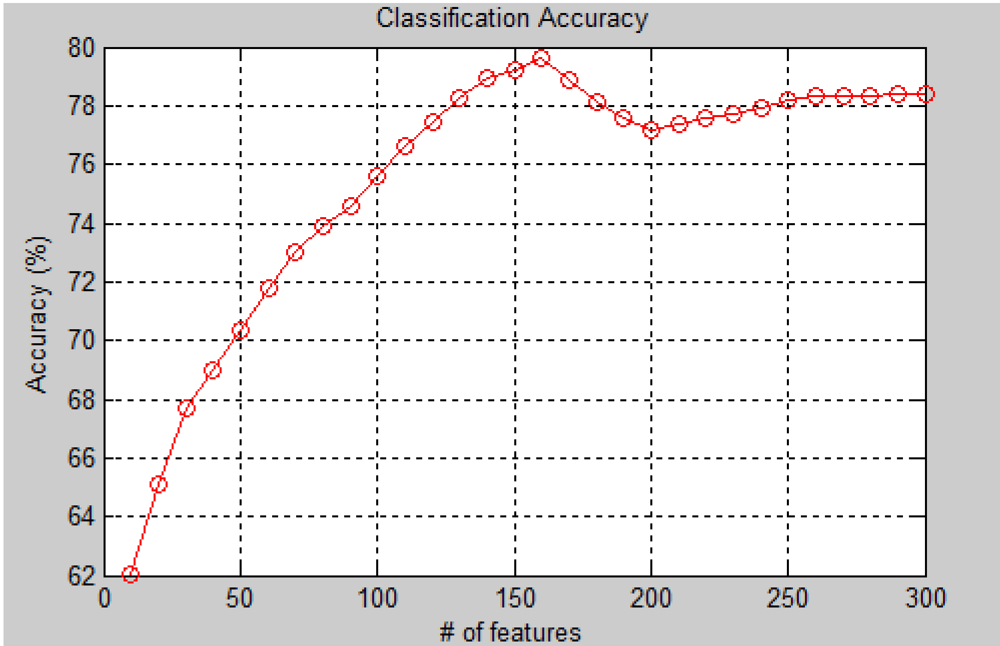

Figure 19. Classification Accuracy for Steering Wheel Data Analysis

c. Decision Level Integration

In the decision level integration of the two systems, we used disjunctive and conjunctive operations to combine the outputs of the two systems and give the final output. We have already obtained the maximum classification accuracy by using vector size of 160 features for the steering wheel data analysis. Hence keeping the same steering wheel vector size, we tuned the different parameters of the facial expression recognition and evaluated the classification accuracies as shown in Figure 20. This figure shows that by using conjunctive operation, we obtain a significant increase in accuracy as compared to its corresponding disjunctive operation. However, due to the limitations of decision level integration we discussed previously, it does not give a performance gain over the facial expression based drowsiness detection system.

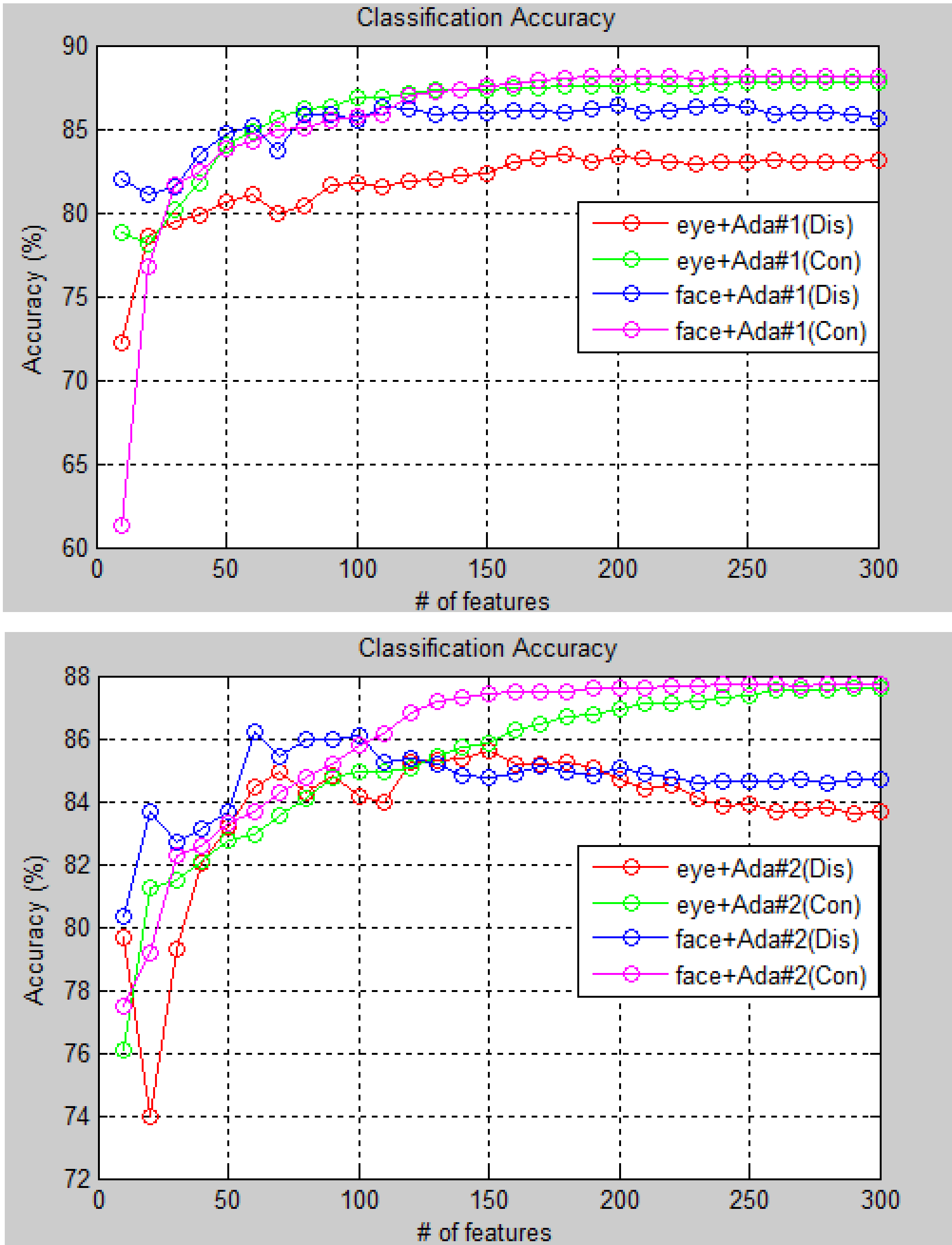

Figure 20. Classification accuracy for decision level integration

Ff = 300, Sf = 160 Face + Ada #1 + SVM(Dis)		Predicted Class	
		Drowsy	Non-drowsy
Actual Class	Drowsy	4090	55
	Non-drowsy	1095	2783

Ff = 300, Sf = 160 Face + Ada #1 + SVM(Con)		Predicted Class	
		Drowsy	Non-drowsy
Actual Class	Drowsy	3194	951
	Non-drowsy	0	3878

Table 2. Confusion matrices for decision level integration

As can be seen from the false positives and false negatives of the confusion matrices in Table 2, the disjunctive method declares the state as drowsy if either of the methods outputs drowsy. This implies that it penalizes more non-drowsy episodes than drowsy episodes and, hence, generates large false positives. The conjunctive method declares the state as drowsy only if both methods output a drowsy state and, hence, gives large false positives.

d. Feature Level Integration

For the feature level integration, we added the steering wheel data features as additional inputs to the facial features. In the same way we did for the decision level integration, we used vector size of 160 features of steering wheel data which gave us the maximum accuracy in the steering wheel data analysis and then we varied the number of facial features and the classification parameter settings to evaluate the classification accuracy of the system. Figure 21 shows that classification accuracy for the different parameter settings increases at a rapid rate until the number of facial features reaches 150 and then varies slowly afterwards. We can also infer from the graph that using the detected face region as ROI gives better classification accuracy than the eye region. This has also been true for the facial expression and decision level integration detection methods. We can also see that by integrating the two systems at feature level, there is appreciable performance gain attained over the facial expression and steering wheel data analysis. We achieved a maximum accuracy of 98.75% for 250 facial features selected with averaging threshold computation, face region used as a ROI and SVM with RBF kernel used for classification.

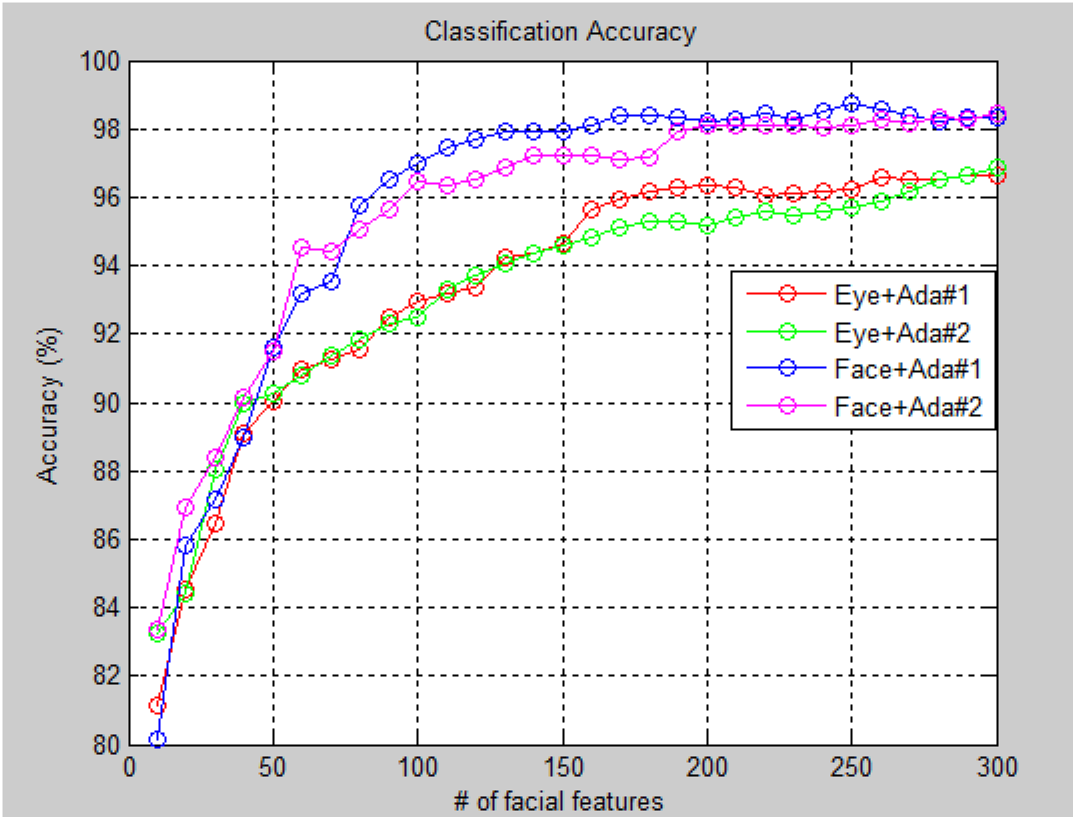

Figure 21. Classification accuracy for feature level integration

Table 3, we compare the maximum accuracies achieved by all drowsiness detection systems. It can be seen that by integrating the two inputs at the feature level, we can achieve the best accuracy.

Types of systems	Accuracy
Steering wheel analysis	79.65%
Facial expression recognition	94.86%
Decision level integration	88.15%
Feature level integration	98.75%

Table 3. . Maximum classification accuracy for facial expression vs. integrated approaches

6.3.2. Single Frame vs. HMM Based Drowsiness Detection

For this experiment, we collected a larger video data from five different subjects driving in drowsy and non-drowsy scenarios. In the training stage, we have selected 2/3 of the labeled video data (8782 non-drowsy and 9000 drowsy images). For testing, 1/3 of the image frames of the video data recorded (4394 non-drowsy images and 4504 drowsy images) have been used. By having larger data samples from many subjects, we incorporated different variations in transitions of behavioral patterns during drowsy and non-drowsy driving.

a. Single Frame Based Drowsiness Detection

We evaluated the classification accuracies for the newly collected data in the same way we did in the last section. Figure 22 depicts the variation in classification accuracies of the cases of Averaging and Searching Maximum Adaboost threshold computations respectively by varying the number of facial features from 10 to 300, choice of ROI as either eye or face region and classification technique as either Adaboost or SVM. There is a decrease in overall accuracy as compared to the previous classification results since we have a larger and more varied video data. We can also see a clear advantage of using face region as ROI instead of the eye region which is also seen in the previous classification results. In general, it shows similar characteristics as in the plots of the previous section.

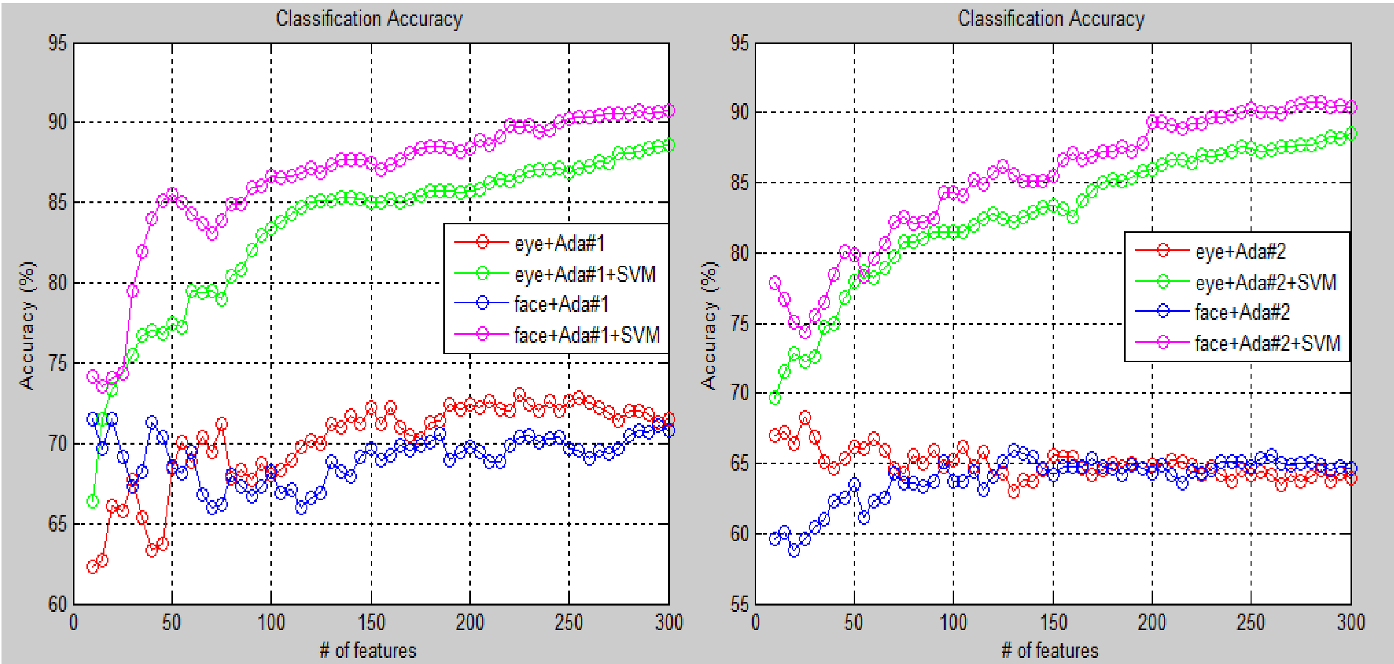

Figure 22. Classification accuracy for single frame based drowsiness detection

b. HMM based Drowsiness Detection

Next, we implemented the dynamic approach of recognizing drowsy and non-drowsy facial expressions from sequences of images. We trained two HMMs for drowsy and non-drowsy scenarios with similar sets of training image sequences. We keep the number of features at 300 which is the maximum number of features selected and the window size 15 which is the same as the frame rate of the video recorded.

We varied the number of observation symbols and the hidden states with a range of 2to 20 each and evaluated the classification accuracies for different combinations. In the sets of figures from Figure 23 – 28 shown below, we have plotted the classification accuracies by varying the observation symbols while keeping the number of hidden states constant. In each case, the classification accuracy has roughly similar pattern of variation for the different number of hidden states chosen which shows that varying the number of hidden states has less influence on the detection performance than varying the number of observation symbols.

The number of observation symbols plays a vital role in HMM modeling as it reflects the transition in the facial expression to which it is trained for. It can be seen that the classification accuracy generally increases as the number of observation symbols used increases. The number of observation symbols used is directly related to how well the clusters represent the feature vectors. By optimizing the number of cluster centers, we obtain a god separation of sequences between drowsy and non-drowsy expression which results in better detection performance. As is attested in the set figure shown below, the classification accuracy increases as the number of observation symbols increases to 8, which is the optimum number of cluster centers used, and then slowly varies afterwards.

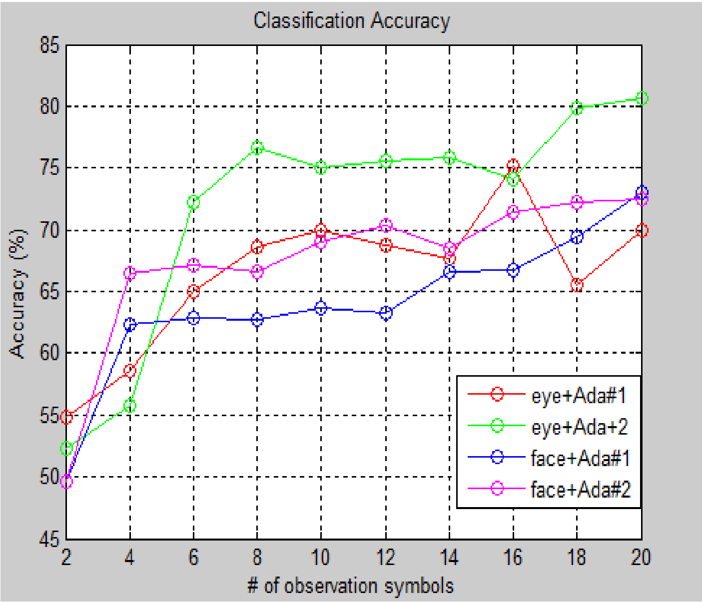

Figure 23. Classification accuracy for 2 hidden states

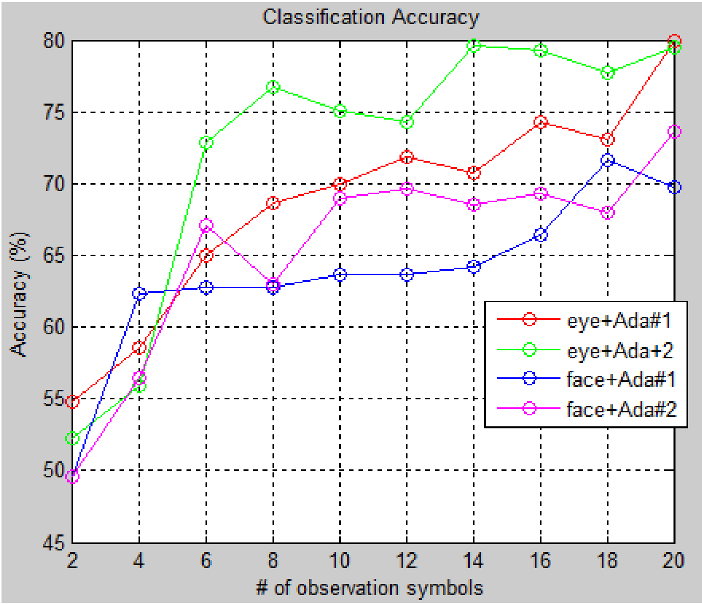

Figure 24. Classification accuracy for 4 hidden states

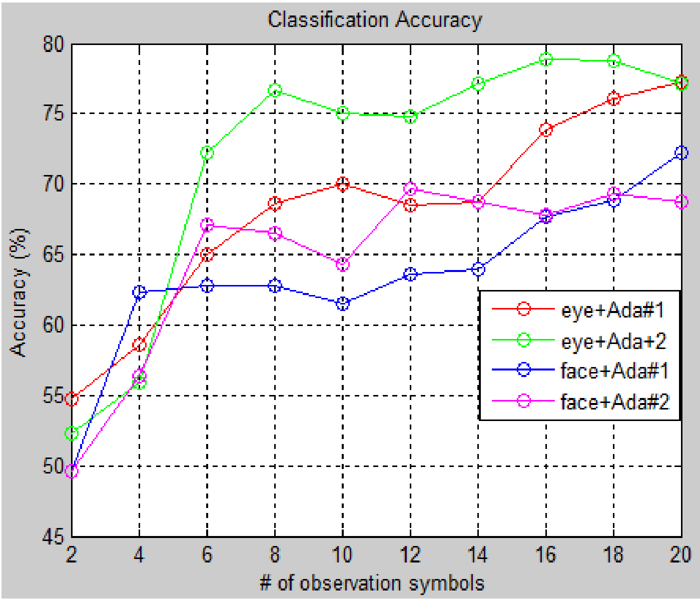

Figure 25. Classification accuracy for 8 hidden states

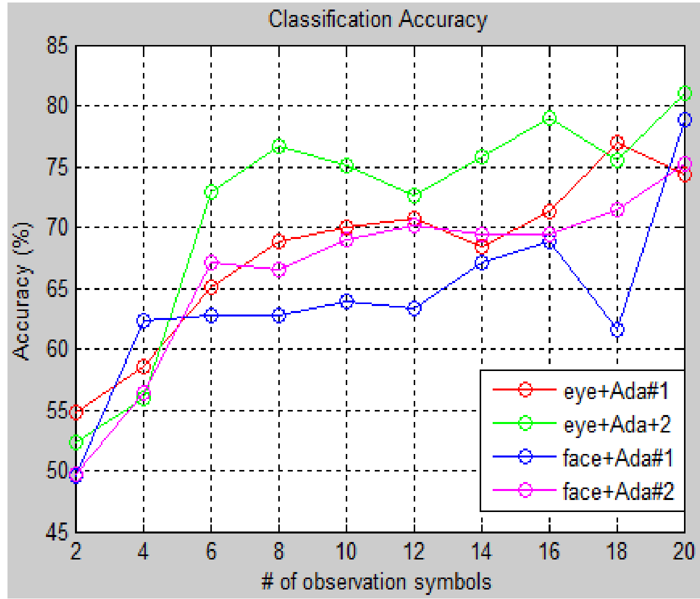

Figure 26. Classification accuracy for 12 hidden states

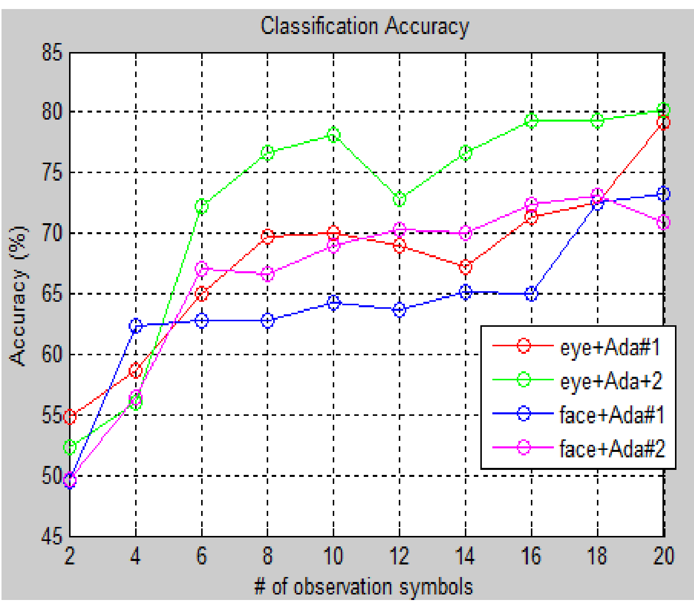

Figure 27. Classification accuracy for 16 hidden states

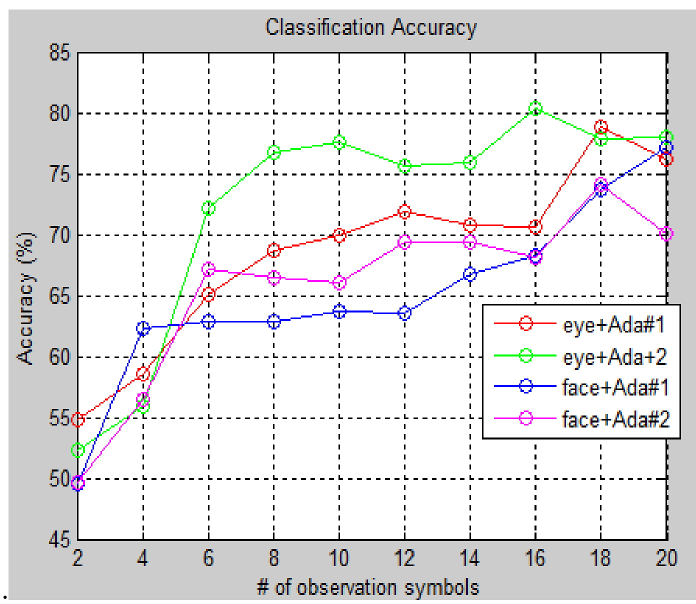

Figure 28. Classification accuracy for 20 hidden states

In Table 4, we compare the maximum accuracies achieved by the two drowsiness detection systems.

Types of systems	Accuracy
Facial expression recognition	90.76%
HMM based dynamic modeling	81.97%

Table 4. Maximum classification accuracy for single frame vs. HMM based approaches

It can be seen that the dynamic approach gives lower classification accuracy than the single frame based classification approach. In the videos we collected from the different subjects, there are various transitions of expressions that are unique for each subject which gives large variation in data when training the HMM models. Due to such data variations, the state transition and the observation to state probabilities obtained may not truly reflect the various expression transitions in both drowsy and non-drowsy scenarios. Due to the complexity of the facial expressions, the HMM models trained may not sufficiently describe the data variations. A remedy to this would be to subcategorize the expressions in to simpler, less variant actions and train multiple HMM models for each action. We also have many model parameters to optimize along with the feature extraction and selection parameters which altogether results in a decrease in classification performance of the HMM based dynamic modeling.

CHAPTER VII

APPLICATION OF DROWSINESS DETECTION IN DRIVER ASSISTANT SYSTEMS

In this chapter, we present one application of our integrated drowsiness detection system in a semi-autonomous driving mechanism which allows the car to drive autonomously when the driver gets drowsy. The research is conducted in a small-scaled Intelligent Transportation System (ITS) testbed [58] which can simulate real traffic environments, human driving experience, autonomous driving and vehicle communications. This is preferred for initial study and reliability tests while conducting ITS researches because using real vehicles poses significant cost in modifying it for the research and a fail in the experiment can have great risks to drivers, vehicles or nearby people.

7.1. Small-scaled Intelligent Transportation System (ITS) Testbed

The small-scaled ITS testbed is comprised of a set of hardware devices which includes an arena, an indoor localization system, automated RC cars, a roadside monitoring facility and a server as shown in Figure 29.

- The arena is a wooden board with dimension of 16 feet by 12 feet which can mimic real street environments. The carpet can imitate the friction from the real road and it has an intersection with cross walks, street lanes, sidewalks and turning curves at an approximate ratio of 1 to 14 (the ratio of the RC car to real car).

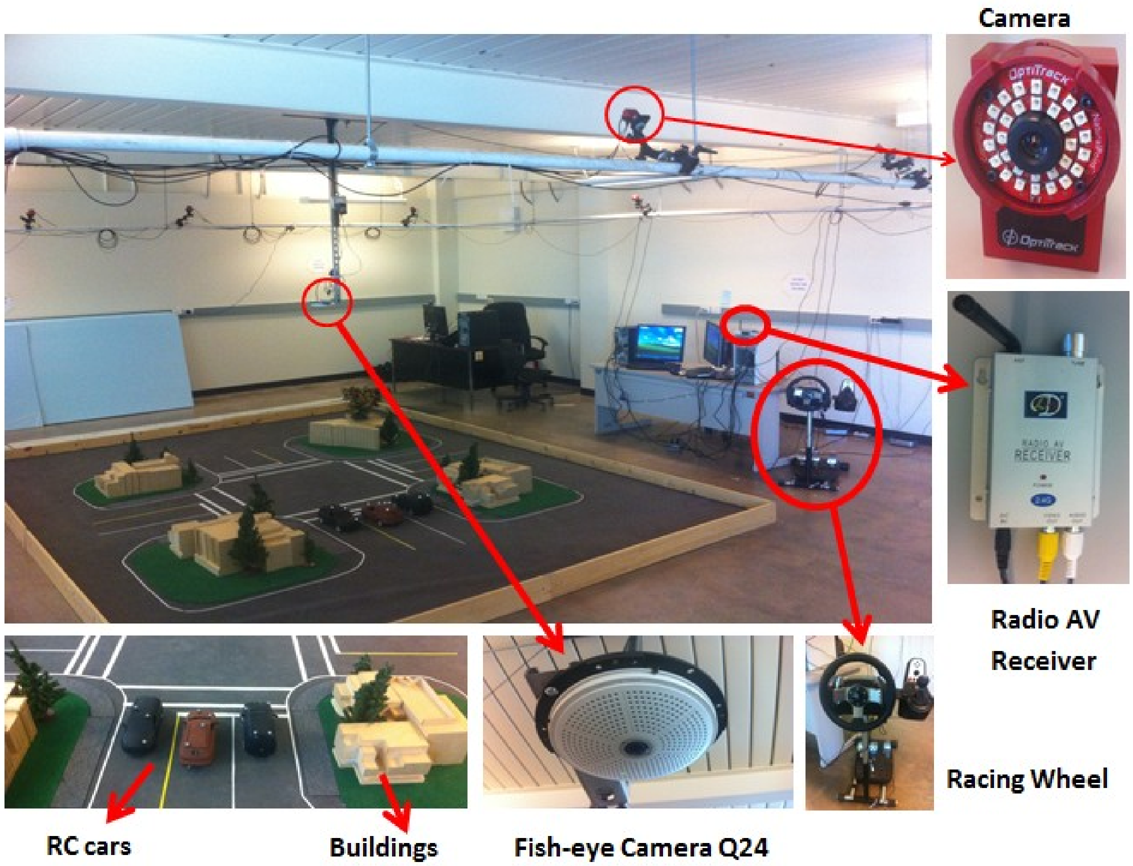

Figure 29. Overview of the ITS testbed.

- The indoor localization system is an Opti-Track system manufactured by Natural Point Inc[59]. It mimics the real world GPS system and localizes the RC cars.
- The RC cars are toys cars with modified servo motor and control parts which can be controlled either autonomously or manually. In autonomous driving, the server generates commands based on the designed trajectory and the current location of the RC car. In human or manual driving, commands are generated based on the steering data from the Logitech G27 controller controlled by the driver. In order for the driver to have real driving experience, a mini camera was placed on top of the RC car's hood and it streams the image continuously to the server. The whole human-driving setup is shown Figure 30.

Figure 30. Hardware setup of manual driving.

- The roadside monitoring facility is a fish-eye camera that can give an overview image of what is happening in the arena.
- The server is a computer that runs all software to control the devices in the ITS testbed. The indoor localization system (Opti-Track) is connected to the server via USB ports. The server runs ARENA software to collect RC cars' locations. There are two Xbee modules connected to the server. One Xbee is used to control the RC cars. The other one is used to collect data from the motion sensor. The server can also collect steering wheel data from the G27 Logitech racing wheel system. A webcam is connected to the server to capture the driver's face. The server can then send the car controller data and stream of images to the drowsiness detection system which, in this case, is a client application which can determine the driver's state and send back request to the server for proper control of the car.

7.2. Manual to Autonomous Switching Control

The driving mechanism, the server software and switching control was developed by Tran, a member in our lab. In the switching control, the driver first controls the RC car manually by looking at the video streamed from the mini camera on the RC car's hood. His facial images are captured by the webcam and sent to the client application. The overall setup is displayed in Figure 31.

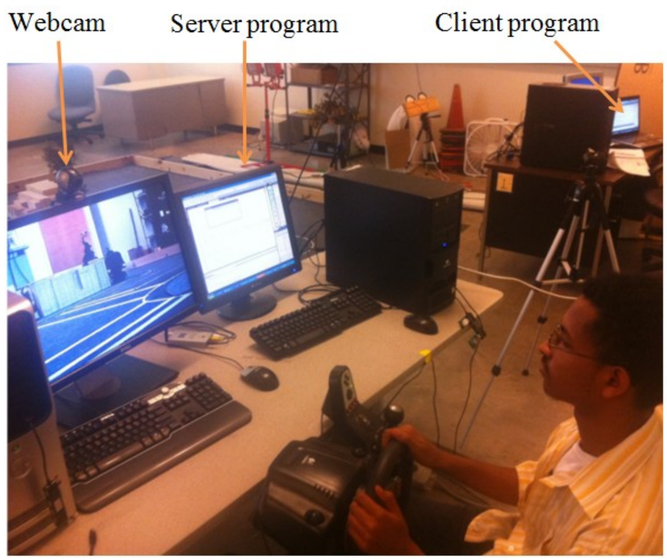

Figure 31. Manual/Autonomous switching experimental setup.

This client application always monitors the driver's state. If the driver is non-drowsy, the client sends request of keeping the driver control the RC car. If the driver is drowsy, the client can request the server to switch to autonomous driving along a predefined path of a figure eight trajectory. The results of the switching control can be displayed by plotting the RC car's locations in Figure 32. The RC car's trajectories during manual driving are plotted in blue and green curve while the trajectory during autonomous driving is plotted in red curve. The RC car was first placed at the point (-250, 1000) and manually controlled by the driver to run along the blue curve. The end of the blue curve indicates the point the driver gets drowsy and this is also the point where the server autonomously controls the RC car and starts the red curve. The end of the red curve indicates the switching point where the driver awoke and started driving manually along the green curve. We can also observe that the switching is pretty smooth since the drowsiness detection is in real-time.

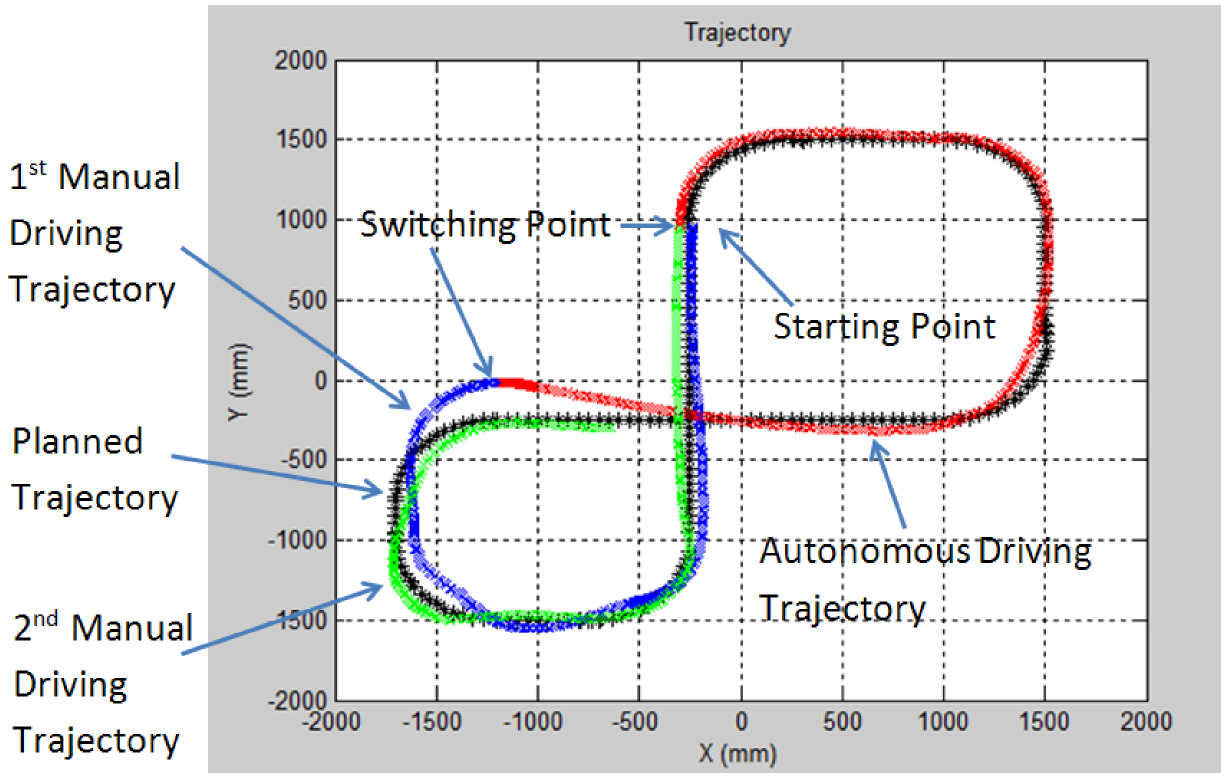

Figure 32. Trajectories of the RC car.

CHAPTER VIII

CONCLUSION AND FUTURE WORK

Our research was undertaken with a main intent to develop an unobtrusive, low cost and reliable drowsiness detection system that can easily be integrated with driver assistant systems. Among the different types of drowsiness measuring techniques that have been proposed by various researchers, behavioral measuring methods have been shown to be both practical and effective for commercial vehicle monitoring systems. Basing our grounds on the various related researches that have been done thus far; we proposed a behavioral drowsiness detection method that focuses on the variation in facial motion of a driver.

8.1. Conclusion

In this thesis, we have implemented a drowsiness detection method using facial expression recognition. We have developed efficient face detection and tracking method using a multithreaded integration of Viola-Jones face detection algorithm and Camshift tracking which are implemented in OpenCV. Gabor features can show the patterns in the muscle movements of the driver's facial expressions and have been extracted from the detected face region through Gabor filter convolutions. We have also implemented Adaboost weak learning algorithm in order to exclude a large majority of the Gabor features and focus on a small set of critical features sufficient for classification.

As effective as it can be in most situations, the proposed facial expression based drowsiness detection method can be affected by different factors and performs poorly in certain situation. In order to improve the method, we proposed two different ways of integrating it with steering wheel data analysis: decision level and feature level integration. In decision level integration, the outputs from both the facial expression and steering wheel based drowsiness detection methods are logically combined to get a final decision. In the feature level integration the facial features extracted from the Adaboost are combined with the steering wheel features and classification is done up on the combined feature vector. We have also proposed a new method of utilizing the temporal information of facial expressions through dynamic modeling. In this approach, we quantized the facial feature vectors to discrete values by using clustering techniques and developed two HMM models for drowsy and non-drowsy scenarios.

We have demonstrated the experimental results for each method proposed and optimized their parameter settings. By collecting training and testing data from different subjects, we evaluated the performance of the system under different conditions and settings. The improvement in performance due to the integration with the steering wheel data is attested through the increase in classification accuracy of the system. We have also integrated the system with a small-scaled Intelligent Transportation System and shown its applicability in switching of manual to autonomous driving during driver's drowsiness.

8.2. Future Work

In the future, there are certain improvements that can be made to the current system. It can also be conceptually expanded to include more input sources of information, new approaches of processing and better ways of decision making.

In order to reduce the influence of ambient light on the quality of input images, arranging a combination of normal and IR cameras to account for both the day and night times can make the system more robust. The Adaboost feature selection method can further be improved by employing better threshold computation methods and non-linear region based weak classifiers operating on a group of pixels. The correlation between the variation in steering wheel movement and the behavioral patterns of a driver during drowsy and non-drowsy episodes can be thoroughly studied and better ways of integrating these sources can be further explored. The performance of the HMM based drowsiness detection method can also be improved by exploring better ways of clustering the selected feature vectors and conducting further studies on modeling of drowsy and non-drowsy expressions. Currently, the system has been trained and tested using inputs from few subjects among our lab members. In order to increase the robustness of the system, collecting more training and testing data from more number of subjects will help the recognition performance.

By integrating our method with a semi-autonomous intelligent transportation system in a controlled experimental setup, we have successfully shown its practicality in driver assistant systems. The next step in the evaluation of the system is the development of a prototype system that can be deployed in an actual vehicle.

8.3. Further Research Opportunities

This research lays the foundation for further studies in the development of behavioral based non-invasive drowsiness detection systems. Such drowsiness detection systems can be very applicable not only in driver monitoring systems but also in different areas of work where the attention of the person is critical. However, many of the researches that have been conducted on drowsiness detection are focused on driver's drowsiness and prevention of car accidents due to drowsiness.

One of the main attributes of behavioral based drowsiness detection systems is that its only source of input is a camera placed in front of the user. It is noninvasive and will in no way interfere with the work of the user. This makes it an excellent choice to monitor the alertness of workers in critical sectors where due attention is required such as surveillance systems of highly secured facilities, air traffic control radar systems, maritime navigational radar systems, weather surveillance systems and so on. Another very recent path of research in relation to our system is using behavioral measuring techniques to determine the attention level of students in classrooms while the teacher is giving a lecture[60]. The feedback can periodically be analyzed and can be used by teachers to improve their teaching methods and interactions with their students.

REFERENCES

[1]. Hartman, K. and J. Strasser, *Saving Lives Through Advanced Vehicle Safety Technology:Intelligent Vehicle Initiative Final Report*. 2005, Department of Transportation: Washington, DC. p. 12.

[2]. A., E., M. A., and S. R., *Drowsy and Fatigued Driving Problem Significance and Detection Based on Driver Control Functions*. Handbook of Intelligent Vehicles: SpringerReference, ed. A. Eskandarian. 2012, Berlin, Germany: Springer-Verlag Berlin Heifelberg.

[3]. *Drivers Beware: Getting Enough Sleep Can Save Your Life this Memorial Day*. 2010, National Sleep Foundation: Arlington, VA.

[4]. Husar, P., *Eyetracker warns against momentary driver drowsiness*. 2010, Fraunhofer-Gesellschaft: Munich, Germany

[5]. Sahayadhas, A., K. Sundaraj, and M. Murugappan, *Detecting driver drowsiness based on sensors: a review.* Sensors (Basel), 2012. **12**(12): p. 16937-53.

[6]. Liu, C.C., S.G. Hosking, and M.G. Lenne, *Predicting driver drowsiness using vehicle measures: recent insights and future challenges.* J Safety Res, 2009. **40**(4): p. 239-45.

[7]. Forsman, P.M., et al., *Efficient driver drowsiness detection at moderate levels of drowsiness.* Accident Analysis & Prevention, 2013. **50**(0): p. 341-350.

[8]. Eskandarian, A. and A. Mortazavi. *Evaluation of a Smart Algorithm for Commercial Vehicle Driver Drowsiness Detection*. in *Intelligent Vehicles Symposium, 2007 IEEE*. 2007.

[9]. Eskandarian, A. and R. Sayed, *Unobtrusive drowsiness detection by neural network learning of driver steering.* Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering, 2001. **215**(9): p. 969-975.

[10]. Eskandarian, A., et al., *Advanced Driver Fatigue Research*. 2007.

[11]. Vural, E., *Video Based Detection of Driver Fatigue*, in *Graduate School of Engineering and Natural Sciences*. 2009, Sabanci University: Istanbul, Turkey.

[12]. Khushaba, R.N., et al., *Driver Drowsiness Classification Using Fuzzy Wavelet-Packet-Based Feature-Extraction Algorithm.* Biomedical Engineering, IEEE Transactions on, 2011. **58**(1): p. 121-131.

[13]. Akin, M., et al., *Estimating vigilance level by using EEG and EMG signals.* Neural Computing and Applications, 2008. **17**(3): p. 227-236.
[14]. Kurt, M.B., et al., *The ANN-based computing of drowsy level.* Expert Systems with Applications, 2009. **36**(2, Part 1): p. 2534-2542.
[15]. Patel, M., et al., *Applying neural network analysis on heart rate variability data to assess driver fatigue.* Expert Systems with Applications, 2011. **38**(6): p. 7235-7242.
[16]. Fu-Chang, L., et al., *Generalized EEG-Based Drowsiness Prediction System by Using a Self-Organizing Neural Fuzzy System.* Circuits and Systems I: Regular Papers, IEEE Transactions on, 2012. **59**(9): p. 2044-2055.
[17]. Hu, S. and G. Zheng, *Driver drowsiness detection with eyelid related parameters by Support Vector Machine.* Expert Systems with Applications, 2009. **36**(4): p. 7651-7658.
[18]. Vural, E., et al., *Machine Learning Systems for Detecting Driver Drowsiness*, in *In-Vehicle Corpus and Signal Processing for Driver Behavior*, K. Takeda, et al., Editors. 2009, Springer US. p. 97-110.
[19]. Bergasa, L.M., et al., *Real-time system for monitoring driver vigilance.* Intelligent Transportation Systems, IEEE Transactions on, 2006. **7**(1): p. 63-77.
[20]. McKinley, R.A., et al., *Evaluation of eye metrics as a detector of fatigue.* Hum Factors, 2011. **53**(4): p. 403-14.
[21]. Danghui, L., et al. *Drowsiness Detection Based on Eyelid Movement*. in *Education Technology and Computer Science (ETCS), 2010 Second International Workshop on*. 2010.
[22]. Zhang, Z. and J. Zhang, *A new real-time eye tracking based on nonlinear unscented Kalman filter for monitoring driver fatigue.* Journal of Control Theory and Applications, 2010. **8**(2): p. 181-188.
[23. Dinges, D.F. and R. Grace, *PERCLOS: A valid psychophysiological measure of alertness as assessed by psychomotor vigilance*. 1998, Federal Highway Administration: Washington, DC.
[24]. Xing, L., et al. *A new method for detecting fatigue driving with camera based on OpenCV*. in *Wireless Communications and Signal Processing (WCSP), 2011 International Conference on*. 2011.
[25]. Garcia, I., et al. *Vision-based drowsiness detector for real driving conditions*. in *Intelligent Vehicles Symposium (IV), 2012 IEEE*. 2012.
[26]. Flores, M.J., J.M. Armingol, and A. Escalera. *Real-time drowsiness detection system for an intelligent vehicle*. in *Intelligent Vehicles Symposium, 2008 IEEE*. 2008.
[27]. Cristianini, N. and J. Shawe-Taylor, *An introduction to support Vector Machines: and other kernel-based learning methods*. 2000: Cambridge University Press. 189.
[28]. Chang, C.C. and C.J. Lin, *LIBSVM: A library for support vector machines.* ACM Transactions on Intelligent Systems and Technology, 2013. **2**(3): p. 27:1-27:27.
[29]. Vural, E., et al., *Drowsy Driver Detection Through Facial Movement Analysis*, in *Human–Computer Interaction*, M. Lew, et al., Editors. 2007, Springer Berlin Heidelberg. p. 6-18.

[30]. Smith, P., M. Shah, and N. da Vitoria Lobo, *Determining driver visual attention with one camera.* Intelligent Transportation Systems, IEEE Transactions on, 2003. **4**(4): p. 205-218.
[31]. Xuetao, Z., et al. *Head pose estimation using isophote features for driver assistance systems*. in *Intelligent Vehicles Symposium, 2009 IEEE*. 2009.
[32]. Murphy-Chutorian, E. and M.M. Trivedi, *Head Pose Estimation and Augmented Reality Tracking: An Integrated System and Evaluation for Monitoring Driver Awareness.* Intelligent Transportation Systems, IEEE Transactions on, 2010. **11**(2): p. 300-311.
[33]. Haisong, G. and J. Qiang. *An automated face reader for fatigue detection*. in *Automatic Face and Gesture Recognition, 2004. Proceedings. Sixth IEEE International Conference on*. 2004.
[34]. Ekman, P., W.V. Friesen, and J.C. Hager. *Facial Action Coding System: The Manual*. 2002; On CD ROM].
[35]. Bartlett, M.S., et al., *Automatic recognition of facial actions in spontaneous expressions.* Journal of Multimedia, 2006. **1**(6): p. 22-35.
[36]. Yin, B.-C., X. Fan, and Y.-F. Sun, *Multiscale dynamic features based driver fatigue detection.* International Journal of Pattern Recognition and Artificial Intelligence, 2009. **23**(03): p. 575-589.
[37]. Freund, Y. and R.E. Schapire, *A Decision-Theoretic Generalization of On-Line Learning and an Application to Boosting.* Journal of Computer and System Sciences, 1997. **55**(1): p. 119-139.
[38]. Eskandarian, A., et al., *Advanced Driver Fatigue Research* 2007, U.S. Department of Transportation: Washington, DC. p. 1-210.
[39]. Cheng, B., et al., *Driver drowsiness detection based on multisource information.* Human Factors and Ergonomics in Manufacturing & Service Industries, 2012. **22**(5): p. 450-467.
[40]. Bradski, G., *The OpenCV Library.* Dr. Bobb's Journal of Software Tools, 2000. **25**(11): p. 120-+.
[41]. Viola, P. and M. Jones. *Rapid object detection using a boosted cascade of simple features*. in *Computer Vision and Pattern Recognition, 2001. CVPR 2001. Proceedings of the 2001 IEEE Computer Society Conference on*. 2001.
[42]. Donghe, Y. and X. Jinsong. *Face Tracking Based on Camshift Algorithm and Motion Prediction*. in *Intelligent Systems and Applications, 2009. ISA 2009. International Workshop on*. 2009.
[43]. Allen, J.G., R.Y.D. Xu, and J.S. Jin, *Object tracking using CamShift algorithm and multiple quantized feature spaces*, in *Proceedings of the Pan-Sydney area workshop on Visual information processing*. 2004, Australian Computer Society, Inc. p. 3-7.
[44]. Movellan, J.R., *Tutorial on Gabor Filters.* Tutorial paper http://mplab.ucsd.edu/tutorials/pdfs/gabor.pdf, 2008.
[45]. Oshidari, B. and B.N. Araabi. *An effective feature extraction method for facial expression recognition using adaptive Gabor wavelet*. in *Progress in Informatics and Computing (PIC), 2010 IEEE International Conference on*. 2010.
[46]. Freund, Y. and R. Schapire, *A short introduction to boosting.* Japonese Society for Artificial Intelligence, 1999. **14**(5): p. 771-780.

[47]. Shen, L. and L. Bai, *AdaBoost Gabor Feature Selection for Classification*. 2004.
[48]. Burges, C.C., *A Tutorial on Support Vector Machines for Pattern Recognition.* Data Mining and Knowledge Discovery, 1998. **2**(2): p. 121-167.
[49]. Chih-Wei Hsu, Chih-Chung Chang, and C.-J. Lin, *A Practical Guide to Support Vector Classification.* 2003.
[50]. Bassili, J.N., *Emotion recognition: the role of facial movement and the relative importance of upper and lower areas of the face.* J Pers Soc Psychol, 1979. **37**(11): p. 2049-58.
[51]. Cohen, I., et al., *Facial expression recognition from video sequences: temporal and static modeling.* Comput. Vis. Image Underst., 2003. **91**(1-2): p. 160-187.
[52]. Punitha, A. and M.K. Geetha, *HMM Based Real Time Facial Expression Recognition.* International Journal of Emergine Technology and Advanced Engineering, 2013. **3**(1): p. 180 - 185.
[53]. Cohen, I., A. Garg, and T.S. Huang. *Emotion Recognition from Facial Expressions using MultilevelHMM*. in *in In Neural Information Processing Systems*. 2000.
[54]. Xuefeng, J. *A facial expression recognition model based on HMM*. in *Electronic and Mechanical Engineering and Information Technology (EMEIT), 2011 International Conference on*. 2011.
[55]. Rabiner, L., *A tutorial on hidden Markov models and selected applications in speech recognition.* Proceedings of the IEEE, 1989. **77**(2): p. 257-286.
[56]. *G27 Racing Wheel System Getting Started Guide*. Available from: http://www.logitech.com/assets/47059/g27-racing-wheel-quickstart-guide.pdf.
[57]. *SimuRide Home Edition (HE) Driving Simulation Software manual*. Available from: http://www.aplusbsoftware.com/simuride-he.html.
[58]. Hung Manh, L., et al., *Development of a Small-Scale Research Platform for Intelligent Transportation Systems.* Intelligent Transportation Systems, IEEE Transactions on, 2012. **13**(4): p. 1753-1762.
[59]. *Optitrack: V100-R2*. 2013; Available from: http://www.naturalpoint.com/optitrack/products/v100-r2/specs.html
[60]. Montgomery, S., et al. *Engagence*. 2013; Available from: http://labs.sensorstar.com/sensorstar-hq.html.

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