Driver Drowsiness Monitoring Based On Yawning Detection

By
Shabnam Abtahi

A Thesis
Presented to Faculty of Graduate Studies and Research
In partial fulfillment of the
Requirements for the degree of

Masters of Applied Science
in Electrical and Computer Engineering
University of Ottawa

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final version, as accepted by examiners. Also, I authorize the University of Ottawa to lend this document to other institutions for the purpose of scholarly research.

Shabnam Abtahi

I further authorize the University of Ottawa to reproduce this document by photocopying or by any other means, in total or in part, at the request of other institution or individuals for the purpose of research

Shabnam Abtahi

Abstract

Driving while drowsy is a major cause behind road accidents, and exposes the driver to a much higher crash risk compared to driving while alert. Therefore, the use of assistive systems that monitor a driver's level of vigilance and alert the fatigue driver can be significant in the prevention of accidents. This thesis introduces three different methods towards the detection of drivers' drowsiness based on yawning measurement. All three approaches involve several steps, including the real time detection of the driver's face, mouth and yawning. The last approach, which is the most accurate, is based on the Viola-Jones theory for face and mouth detection and the back projection theory for measuring both the rate and the amount of changes in the mouth for yawning detection. Test results demonstrate that the proposed system can efficiently measure the aforementioned parameters and detect the yawning state as a sign of a driver's drowsiness.

Acknowledgements

I would like to express my deep and sincere gratitude to my supervisor Dr. Shervin Shirmohammadi for giving me the opportunity to work on this project and also for his support and assistance with the research.

Besides my supervisor, I would like to thank Dr. Behnoosh Hariri for all her guidance, patience and kindness throughout this project.

I would also like to thank all my friends and relatives for participating in collecting image and video datasets.

Last but not least, I would not have been able to achieve any of my success if not for the support of my parents, Nastaran and Ghasem and my sisters, Maryam and Yasaman. Their constant encouragement and love keeps me motivated.

Table of Contents

Table of Figures

Table of Tables

List of Acronyms and Definitions

NHTSA	National Highway Traffic Safety Administration
HRV	Heart Rate Variability
LF/HF	Low Frequency/High Frequency
BP	Back Propagation
FBP	Fast Back Propagation
s-FCM	spatial Fuzzy C-Means
BP ANN	Back Propagation Artificial Neural Network
CUs	Computational Units
ARM	Advanced RISC Machine
CWT	Continuous Wavelet Transform
DWT	Discrete Wavelet Transform
DTW	Dynamic Time Warping

Chapter 1 - Introduction

Driver fatigue not only impacts the alertness and response time of the driver but it also increases the chances of being involved in car accidents. National Highway Traffic Safety Administration (NHTSA) analysis data indicate that driving while drowsy is a contributing factor to 22 to 24% of car crashes, and that driving while drowsy results in a four- to six-times higher near-crash/crash risk relative to alert drivers [1]. The near crash/crash risks of driver drowsiness may vary based on time of day or ambient lighting situations. Drowsiness is slightly increased when there is no high roadway or traffic demand and also in the darkness. A higher probability of drowsiness-related baseline epochs was identified during free-flow traffic densities, on divided roadways and areas free of roadway junctions. Drowsy driving denotes a situation when the driver is in a state of mental and physical fatigue, which includes decreasing mental alertness and a sensation of weariness and reduction in eye scanning behaviors [2]. A severely drowsy driver will exhibit extended incompetence to safely perform a driving maneuver, be unaware of the vehicle's turning radius, perform driving maneuvers under the incorrect assumption that it is safe, experience eye lid closures and have difficulties keeping his/her head in a lifted position, minimal body/eye movement and repeated yawning [1]. When the driver is impaired by fatigue, his/her ability levels, driving behaviours, proficiencies and decisions are adversely affected and, in these situations, the high accident rate is due to the fact that sleepy drivers fail to take correct actions prior to a collision [3]. An important irony in driver's fatigue is that the driver may be too tired to realize his/her own level of drowsiness. This important problem is often ignored by the driver. Drowsy driving is a serious issue in our society not only because it affects those who are driving while drowsy, but because it puts all other road users in danger. Therefore, the use of assisting systems that monitor a driver's level of vigilance is crucial to prevent road accidents. These systems should then alert the driver in the case of drowsiness or inattention.

1.1 Motivation

A common activity in most people's life is driving; therefore, improving driving (making driving safe) is an important issue in everyday life. Even though the driver's safety is improving in road and vehicle design, the total number of serious crashes is still increasing. Reducing the number of car crashes would benefit millions of people around the world. Most of these crashes result from impairments of the driver's attention. There are four major types of attentional impairments that affect driver's reaction, and include alcohol, aging, distraction and fatigue. Approximately 40% of deaths from crashes in U.S. highways can be attributed to alcohol. Aging results in slower response to hazards. Drivers' distraction is increasing as vehicle technologies such as navigation systems, cell phones and the internet become more advanced. Compared with the above three impairments, fatigue is often cited in accidents since drivers tend to adopt risky strategies to drive at night [1]. The U.S. National Highway Traffic Safety Administration has reported that driving while drowsy is one of the reasons behind road accidents, and exposes the driver to a much higher crash risk compared to driving while alert [2]. Based on the Ontario Ministry of Transportation's Driver's Handbook, drivers' abilities are affected by drowsiness and fatigue long before they notice that they are getting tired. All of the above are therefore motivations to design and implement an assistive monitoring system in order to detect drivers' drowsiness and fatigue.

1.2 Objective

The goal of this research is the use of assistive systems that monitor a driver's level of drowsiness. The detection system in general may determine both driver related features (physiological data) and vehicle related features (driving performance data). This requires computing relevant measures to predict the onset of drowsiness. After the detection of drowsiness, the system alerts the driver to take appropriate preventive action in order to avoid serious car crash. The objective of this research is to develop an accurate and reliable system to detect a driver's drowsiness based on his or her yawning. The system will alert the drivers in the case of sleepiness when a number of yawning situations increase in a short period of time. Three different methods were developed in order to find the best way that has high accuracy and reduce the probability of having insufficient alertness. A brief explanation about each method for detecting drivers' drowsiness and subsequently alerting them will be discussed in section 1.3.

1.3 Drowsiness Detection Methods

Many special body and face gestures are used as signs of driver fatigue, including yawning, eye tiredness, eye movement and falling head, which indicate that the driver is no longer in a proper driving condition. Accordingly, to detect driver drowsiness, a monitoring system is required in the car. The aim of using this system is to reduce the number of accidents due to drivers' fatigue and hence improve the transportation safety. A great variety of methods for fatigue detection has been proposed by other researchers and will be discussed in Chapter 2 -. Three separate methods were implemented in this research in order to find the best and reliable method, which will be briefly described in this section and the detailed explanation of each method will be discussed in Chapter 3 -.

1- The first method is focused on color segmentation of the driver's facial characteristics. The first step in this method is to determine the face region in order to remove the background and clarify the search area. This step will be done based on analyzing the skin color properties in RGB, YCbCr and HSV color spaces. In the next step, the eyes and mouth will be located by utilizing the specific formula for each component based on the color segmentation. The eye component will be used as a reference point to confirm the location of the mouth. The mouth component will be located in the form of a white area in the lower half of the face in the center of the eyes' location. The geometrical properties of the white area will be changed when the mouth position changes from normal to yawning condition. In this case, the height of the mouth becomes greater and the system will propose this condition as an instance of yawning.

2- In the second method, the yawning condition will be detected by applying an active contour model. In the first step of this method, the face area will be located using the same technique as method one, by applying skin color segmentation in the video frames. In this method the result of face detection based on skin color properties will be three face candidates. The correct face candidate will be selected after matching the face template with each candidate. The template was the combination of ten faces' images, to which the Daubechies wavelet was applied. After locating the face area, the mouth will be detected by using the mouth map formula in the lower half of the face. The active contour model will be utilized in this part to detect the area around the mouth. As the mouth becomes wider and wider to change the form from normal to yawning the snake contour model will continuously get the shape of the mouth. By counting the number of pixels in the snake contour and following the routine of the yawning condition, the system will be programmed to alert the driver when necessary.

3- The last and most reliable method in this development is based on using the concept of the Viola-Jones face detection algorithm, which is already implemented in OpenCV. This theory uses a large number of faces to train the classifier with the features resulting from integral images. Then, the Adaboost algorithm will be utilized to select the most important features of the face. The important features will create the cascade of the classifiers, which decides whether the face is detected or not. The mouth location will be located by using the same concept as face detection. After finding the mouth area, the histogram of the mouth will be found in the first frame and will be assigned as a reference histogram for yawning detection. The histogram in the next frames will be found and compared with the reference histogram and the back projection theory will be applied. In this theory, the histogram differences will be determined and it will be changed when the mouth goes into the yawn state. As the differences between the reference histogram and next frames' histogram become greater, the system will alert the driver. This method was programmed on an APEX board, produced by CogniVue Corporation, which has a camera that can be used in the car and will produce realistic conditions for an in-car scenario.

Detailed information for each theory will be discussed in Chapter 3 -and the result for each method will be given in Chapter 5 -

1.4 Research Contributions

This thesis presents an assistive system that monitors a driver's level of awareness and alerts the driver in case of sleepiness. The system will be installed in the car in front of the driver to monitor his/her face during driving.

Several contributions are included in this new system, which are as follows:

- Analysis of the characteristics of driver drowsiness and its detection using three different methods
- Design and development of a drowsiness detection system based on Viola-Jones theory features
- Construction of a large dataset of actual driver videos and images in different environments and conditions including various face poses, illumination, facial expression, age, facial hair, weather conditions, etc.
- Proof-of-concept and performance evaluation as validation of the design and theory
- Porting and re-implementation of the proposed method to an actual in-car smart camera system: CogniVue Corporation's APEX platform, which has a limited instruction set and resources. The system was successfully demoed at the 2011 ACM/IEEE International Conference on Distributed Smart Cameras, and the technology was transferred to CogniVue Corp.

1.5 Research Publications

- S. Abtahi, B. Hariri, S.Shirmohammadi, "Driver Drowsiness Monitoring Based on Yawning Detection", Proc.IEEE International Instrumentation and Measurement Technology Conference, Binjiang (Hangzhou), China, May 10-12, 2011
- B. Hariri, S. Abtahi, S. Shirmohammadi, L. Martel, "Vision Based Smart in-Car Camera System for Driver Yawning Detection", Proc. ACM/IEEE International Conference on Distributed Smart Cameras, Ghent, Belgium, August 23 - 26, 2011

1.6 Thesis Outline

The majority of this thesis presents the design and evaluation of the driver monitoring system to evaluate drivers' fatigue. It reviews existing approaches related to the topic, details different methods and the final proposed system, and finally presents a set of results and associated evaluations.

The remainder of this thesis is structured as follows:

Chapter 2 - Literature Review provides information on existing approaches about driving drowsiness detection

Chapter 3 - Proposed Systems specifies three different methods for the design of the drowsiness detection system in detail

Chapter 4 - Dataset Collection presents the procedure of collecting the required dataset for testing the methods

Chapter 5 - Results and Discussion presents the evaluation results for all three implemented methods, which were discussed in section 3

Chapter 6 - Conclusion and Future Work summarizes and concludes the thesis, while outlining venues for future research

Chapter 2 - Literature Review

Driver drowsiness is a major cause of road accidents. Therefore, much research has been done in order to develop precise monitoring systems to increase transportation safety and decrease the number of deaths caused by fatigued drivers. The methods for assessing driver drowsiness are generally related to the measurement of the driver's state, driver performance and a combination of the driver's state and performance. For each method, different criteria must be analyzed, for example yawning, head position and eye closure can be studied in a driver's state measurement, while lane tracking and tracking distances between vehicles are involved in the studies of a driver's performance. Based on the result of different researches, the most accurate technique towards driver fatigue detection is dependent on physiological phenomena like brain waves, heart rate, pulse rate and respiration. But these techniques are intrusive and require the attachment of some electrodes on the driver, which are likely to cause annoyance to him/her. Therefore, to monitor the driver's vigilance, different techniques of computer vision can be used, which are natural and non-intrusive. These techniques focus on observable visual behaviours from changes in a human's facial features like eyes, head and face [4].

2.1 Driver's Performance

The objective measure of how the vehicle is being controlled by the driver is a key component of the driver's performance. These measures are the least invasive way of detecting driver state since there are no direct interactions with the driver. But on the other hand, these measures are a direct result of the driver's input to the vehicle's control, such as steering, throttle and brake. Vehicles are gradually equipped with systems for detecting driver metrics; therefore these measures are particularly suitable. The driver metrics consist of lane position, headway and steering wheel angle. Driver performance can be influenced by many factors, such as experience, distraction and driving conditions; therefore, driving performance is not necessarily closely correlated with driver state. A number of studies about the driver's performance have been done by other researchers, which have mainly employed lane tracking and also tracking of the distance between the driver's vehicle and the car in front.

Tuncer et al. proposed an assistant system to track a lane, which will be activated for those drivers who are not able to perform a good job of lane keeping [3]. In order to develop the lane keeping controller system, a series of robust, parameter space based and velocity scheduled control design techniques were carried out, using the Control of Mechatronics Systems toolbox. For lane detection and lane tracking, a camera based image processing algorithm is required, which will use offline and real time hardware-in-the-loop simulations. In order to process the video frames coming from an in-vehicle camera pointed towards the road ahead, a PC is used that detects and computes the tracking of the lane, which it does by carrying out the fitting of composite Bezier curves to the curved lanes. In the next step, a dSpace microautobox is used to obtain the lane data from the PC and the Carmaker vehicle data from the dSpace compact simulator. It will then calculate the required steering actions and send them to the Carmaker vehicle model.

In the drowsiness detection method proposed by Pilutti et al. [5], driver assessment is determined in the context of a road departure warning and intervention system. In this method, the vehicle lateral position is used as the input and steering wheel position as the output in order to develop a system that will be updated during driving. The driver's performance will be determined by analyzing the changes in the bandwidth and/or parameters of such a model.

2.2 Driver's State

2.2.1 Physiological

Any physical changes that occur within the body during the onset of fatigue are considered to be physiological measures, which are a direct measure of fatigue. In general, different physiological measures have been used in attempts to detect tiredness, such as heart rate and body temperature. The electroencephalogram is another physiological concept that has become widely accepted as key for determining a person's state with respect to sleepiness and wakefulness. An electroencephalogram offers an objective degree of sleepiness that can be obtained in real time; therefore, it is one of the most promising tools for detecting driver state of fatigue. Electroencephalogram was the emphasis of the literature review of physiological measures because it is viewed as the most precise physiological measure of drowsiness.

The activity in the brain can be determined by electroencephalographic measurements. The brain's level of alertness will be changed by electrical activity, which allows the detection of sleepiness and different stages of sleep. In the paper proposed by Picot, a fatigue detection system is based on brain and visual activity [6]. A single electroencephalographic channel is used in order to monitor the brain activity for drowsiness detection. The measurement of electrical activity of the brain—electroencephalographic—will be determined by placing the electrodes on the scalp. Electroencephalographic data can be analyzed where rhythmic activities are calculated in several physiologically significant frequency bands in the frequency domain. In order to detect drowsiness, any change in α, θ and β will be analyzed in electroencephalographic data, for example, an increase of the α and θ activities and a decrease of the β activity. α and θ are linked to relaxed and eyes closed states and β is linked to active concentration. The main goal of the electroencephalographic based detection system is to detect important variations of activity in the appropriate frequency ranges. Visual activity is detected through blinking detection and characterization. Cascading decision rules are then used to merge both brain and visual information according to a medical scale of drowsiness evaluation. Merging detection systems allows the fatigue detection system to detect three levels of drowsiness: “awake,” “drowsy” and “very drowsy.”

Furman et al. [7] method analyzed driver fatigue condition by using an electrocardiography based approach. For their experiment, electrocardiography, electroencephalography, electromyography, eye movement and video of ten participants were recorded while they were asked to alternately undergo a Maintenance of Wakefulness Test or a Driving Simulation Test every two hours. In the falling asleep condition, the Heart Rate Variability (HRV) in the very low frequency range decreases consistently a few minutes before complete sleep occurs. The results obtained by their experiments suggested that derived parameters in the time and time-frequency domains may offer a suitable device for monitoring drivers' drowsiness.

According to Shan and Bowlds’ technique, a pulse wave sensor is used to detect a driver’s drowsiness [8]. The mentioned sensor measures heart pulse wave from the driver’s palm. The technique next employs an adaptive filter to cancel the measurement noise produced by the change of the gripping force. The sensor, along with the adaptive filter, is provided a clear heart pulse wave for later heart rate variability analysis. By utilizing the power spectrum density of the subjects’ heart rate time series, the low frequency to high frequency (LF/HF ratio) can be measured. The result of the LF/HF ratio indicates decreasing trends as drivers go from awake to drowsy.

Hayashi et al. proposed another method of driver drowsiness detection by pulse wave analysis with a neural network [9]. Since the biological signal such as pulse wave sharply reflects a human's mental condition, this method is used to measure the driver's awareness condition. In order to reduce noise signals by the driver's movement, the sensor measuring the pulse wave was attached on a driver's wrist. Three indexes from the obtained pulse wave will be evaluated, such as sympathetic nerve activity and parasympathetic nerve activity, from Heart Rate Variability analysis and will be given as an input to the neural network to determine the driver's state of drowsiness.

2.2.2 Behavioural Features

The ability of the driver to drive can be determined by the way he/she is behaving while behind the wheel. Behaviors indicative of tiredness or other unsafe driving situations such as distraction take the form of yawning, blinking, eyes closure, head movements, use of mobile devices and eye glance patterns.

The first step towards drowsiness detection based on behavioural features is to detect the driver's face. In this case, the search area for any facial feature will be reduced to the face region. There are numerous techniques towards face detection processing; images containing faces have been developed in different research categories such as face recognition, face tracking, pose estimation and expression recognition. To build a system that will be able to analyze the information included in face images, a robust and efficient face detection algorithm is required. The objective of face detection is to recognize all image regions that contain a face without considering its position, orientation and lighting conditions.

2.2.2.1 Face Detection

For face detection itself, several approaches have been used in the related literature. Knowledge based methods [10] try to encode human knowledge about the characteristics of a typical face, such as the relationships between facial features, and use them as a way to detect faces in an image.

The goal of the feature invariant approaches [11] [12] is to find structural face features, such as eyebrows, eyes, nose, mouth and hairline, which persist under various poses, viewpoints or lighting and use those features to detect faces. Such features are mostly extracted using edge detectors. For example, Sirohey proposed a method to identify the face from a cluttered background based on segmentation [13]. The Canny edge detector and heuristics are used as an edge map to remove and group edges. Then, the ellipse is fitted to the boundary between the head region and the background and the face will be detected. Another method of face detection based on locating facial features is developed by Graf et al. [14]. In this method, the morphological operations will be applied to find the areas that have high intensity with certain shapes. Based on the prominent peak value of the image histogram, the adaptive threshold will be chosen to create binarized images. Then, the connected component in the binarized images will be evaluated as candidates for the facial features in order to determine the face location. Han et al. proposed a method of face detection based on a morphology technique to perform eye analogue segmentation since eyes and eyebrows are the salient and relatively stable features in the human face [15]. The located eye-analogue will be used to search for the potential face regions with a geometrical combination of eye, nose and mouth. A trained backpropagation (BP) neural network will get all potential face images and verify the face location.

The texture of human faces [16] or human skin color [17] [18] have also proven to be effective features that can be used towards face detection. In the method proposed by Ying et al. [19], they considered skin color as the most important feature that can be separated from other parts of the background by using the maximal varieties variance threshold. Saxe and Foulds developed a face detection system that uses histogram intersection in the HSV color space to highlight the skin region [20]. In their method, an initial patch of skin color will be used to initiate the iterative algorithm. In order to detect skin color, the method presents a control histogram, which will be applied on different patches in the image and the current histogram for comparison. Then, the threshold value will be assigned to be compared with the result from histogram comparison to analyze the skin region.

Template matching methods [21] [22] store several standard patterns of different faces to describe the face as a whole or the facial features separately, and compute the correlations between an input image and the stored patterns in order to determine the degree of similarity of the pattern to a face.

Craw et al. [23] proposed the following method: the frontal view face is detected based on template matching. The extracted edges from Sobel filtering will be grouped together to locate the face. Then, the same procedure will be repeated to find other facial features such as eyes, mouth and nose in the candidate face. Another method of face detection is described by A. Samal et al. [24] based on using silhouettes as templates for face localization. Principal component analysis is utilized to collect a set of face silhouettes, which are represented by an array of bits. Then, the Hough transform and eigen-silhouettes will be used for face localization.

In appearance based methods, the face models are learned from a set of training images, which include the representative variability of facial appearance. Such methods can take advantage of neural networks, which are applied in many pattern recognition problems, Support Vector Machines, Naïve Bayes Classifiers or Hidden Markov Models as tools to evaluate the matching of the pattern to the training database.

Tsai et al. proposed a method of face detection using eigenface and neural networks [25]. In this method, the eigenface algorithm is utilized to find the face regions candidates. The neural network with the backpropagation (BP) algorithm is then used to examine the face candidates. In this system, the input vector of the neural network is the projection weights of the face space. At the end, template based face verification is used to confirm the face region from the output of the neural network. Another method of face detection based on BP neural network and Bayesian decision is described by Liu et al. [26]. The first step in their method is to extract possible faces from the images by applying a skin color algorithm. In the second step, the BP neural network model is utilized to determine whether the human face exists in the region based on the output of the skin color model. At the end, the Bayesian decision theory will be used to classify the face or non-face pattern and also to improve the correct rate of face detection.

Shavers et al. used the concept of support vector machines to develop a face detection system [27]. The λ coefficients that correspond to support vector machine support vectors are calculated from a set of training images, which consist of face and non-face images. The system will simply determine the support vector machine's detection rate for the simplest kernel function and will be able to decide whether the image presented to the system is a face or non-face image.

El-Khamy et al. describe a method of human face recognition by the use of a neural network algorithm and statistical feature extraction [28]. The edge of the face image is detected by applying a Sobel filter in the preprocessing step. Then, the two-dimension black and white image will be transformed to a one-dimensional vector. Finally, seven features will be extracted based on the statistical analysis. The fast back propagation algorithm will be used in the recognition step.

Ruan and Yin [29] proposed a fast face detection method by using two different approaches of skin color information and linear support vector machines. In the first step of their method, the information about skin color related to the YCbCr color space will be extracted from the image and exclude the background region from the images. Then the sample features from the skin region will be transferred to the support vector machine classifier for training and classifying. The linear support vector machine will be used to separate non-face regions from the remaining regions.

Current state of the art face detection systems are mostly based on the use of classifiers. The most famous and commonly used face detection scheme in this category is the Viola-Jones face detection algorithm [30]. It is able to efficiently detect neutral frontal faces as it has been trained with a large database of faces. Detailed information about this method will be explained in section 3.3.

Erdem et al. combined two methods of face detection for more accurate and reliable results [31]. The first method is the Haar feature based face detector, which was developed by Viola and Jones [32]for gray scale images and the second method is a skin color filter, which provides complementary information in color images. In their method, the image is passed through a Haar feature based face detector, which has a high number of false detection and low number of missed faces. Then, the skin-color post-filtering method is used to eliminate many of these false detections.

2.2.2.2 Eye Closure

Different methods of driver's fatigue detection are implemented by other researchers specifically focussed on changes and movement in the eyes. These techniques analyze changes in the driver's direction of gaze, eye closure and blinking rate.

As people become drowsy, their blinking patterns change. Sigary proposed a method of hypo-vigilance detection by processing of the eye region and without an explicit eye detection stage [33]. In order to extract symptoms of fatigue and distraction, a horizontal projection of the top half segment of the facial image is required. For drowsiness determination, the percentage of eye closure and eyelid distance changes over time.

Another drowsiness detection method based on eyelid movement was proposed by Liu et al. [34]. In their method based on the eyelid changes from a temporal differences image, the fatigue situation will be analyzed. The number of white pixels can be used for the fatigue judgement criterion in the first step. Then, the number of pixels with positive change in the three level difference image and the number of pixels with negative change between current frame and previous frame will represent eyelid movement from open to closed, which will be useful as an indicator of drowsiness.

Omidyeganeh et al. [35] used a method of fatigue detection by applying the Structural Similarity Measure to find the eye location. In their method, structural similarity measure value will be evaluated between -1 and 1. When two images are the same, the max gained value will be 1 and when there are some differences, the result will be -1. Then the horizontal and vertical projection will be applied on the eye region to determine the amount of eye closure and align the detected eye region.

Tabrizi and Zoroofi [36]proposed a non-intrusive and simple way of fatigue detection by determining whether the eye is open or closed. In their algorithm the three steps were analyzed, such as determining eye regions by eye map and locating pupil center by the center of mass of the eye region image and the last step is refining the pupil center and detecting the iris boundary. In order to analyze eye state for determining the drowsiness stage, a chromatic based algorithm has been used, which has a better detection rate for closed eye.

The paper presented by Arimitsu [37] discussed the method of awakening drivers based on seat belt vibration as a stimulating device. The seat belt motor retractor produces the vibration stimulus, which was composed of pulsation tension. The key components that determined the awakening effect of the stimulus are magnitude, duration and repetition rate of the additional tension. The driving simulator is used to measure the driver's drowsiness by detecting changes in the driver's eye movements measured by electrooculography. Any changes in facial expression of the driver observed by the examiners through a video camera, subjective evaluation and lane deviation are also useful to determine fatigued drivers.

2.2.2.3 Yawning

Azim et al. [38] propose a yawning detection system that relies on eye closure duration measured by information about eye state and yawning analysis based on mouth condition. Face detection by use of the Viola-Jones theory [32] was the first step in their method to eliminate the frame region in the face area to reduce the search area. The state of eye closure is used to determine the vigilance and fatigue level of the drivers, which also depends on choosing the best candidates from the bright blob in the upper half of the face in which the size, intensity, position and distance are considered. The mouth is detected by using spatial fuzzy c-means (s-FCM) clustering in the extracted mouth window from the face region. For analyzing the drowsiness of the driver, the width to height ratios of eyes and mouth are used as inputs for the support vector machine for classification. The support vector machine determines the state of driver drowsiness based on closed or half open eyes in several consecutive frames with or without yawning condition at the same time. The alarm is generated after the system concludes that the driver is in a critical condition and must rest.

In order to find the state of driver drowsiness, Yufeng et al. [39] proposed a method focused on finding the face in the first step. This step can be determined by using the difference in images between two images in a sequence of images. The adaptive threshold method can be used to segment the moving area that the face and head outline are in for this localization. The location of the chin and the nostril area are determined in the next step based on considering the location of the chin in the lower half of the face region. The directional integral projection will be used to find the midpoint of the nostrils. The yawning state is determined based on calculating the distance between the chin and the location of the midpoint of the nostrils.

Driver's fatigue is detected in the proposed method of Saradadevi et al. [40] based on tracking mouth condition and recognizing yawning. In their method, the cascade of classifiers proposed by Viola-Jones [32] was used in order to find the mouth location. A cascade of boosted classifiers of simple Haar-wavelet features on different scales and positions is calculated by canny integral image. The Adaboost learning algorithm is then utilized to select the combination of features and find the mouth location. The support vector machine is then applied to produce a prediction model for the target value of data instances in the testing model. The support vector machine trains the mouth and yawning images by transforming data to the support vector machine software and conducts scaling on the data by using the Radial Basis Function Kernel.

The support vector machine supports the method to find the yawning condition and alert the driver in case of drowsiness.

In the method proposed by Ying et al. [41], driver fatigue and drowsiness are determined by monitoring the changes in the state of the mouth and eyes' positions. In terms of face detection, their method considers the skin color as the most important feature that can be separated from another part of the background by using the maximal varieties variance threshold. Mouth location will be found by applying horizontal and vertical projection in the face area considering the color red as a key component for this method. In order to find the state of the driver's alertness level, a BP neural network consisting of the main characteristics of the mouth and eyes is required. The driver's lips and eyes' features will be added to the mentioned neural network as an input to train it in order to be able to recognize between the normal position and yawning and also the closed eyes' conditions. Derived results from the neural network show if the driver is in a state of decreased alertness.

The robust and reliable method of face detection based on the Viola-Jones theory [32] has been used by Wang and Shi [42] in order to limit the mouth search area to the face region. The mouth region will be located based on multi-threshold binarization in intensity space and also using the Gaussian model in RGB color space. The lip corner will be found by calculating the integral projection of the mouth in the vertical direction. The two lines running through the lower and upper lip boundaries resulting from the integral projection represent the mouth openness. In this method, the yawning stage will be determined by finding the degree of mouth openness in terms of the aspect ratio of the mouth bounding rectangle. A large mouth openness over a predefined threshold for a continuous number of frames means that the driver is in a state of drowsiness.

Two cameras are used in the proposed method of Li et al. [43] to detect driver's fatigue in real time. In their method, one low resolution camera was installed in the car to supply the driver's head position and one high resolution camera to locate the mouth region in each frame. Skin color as a significant feature of face was used to detect the driver's face location based on its exclusive characteristic in the Cb and Cr color space. Haar-like features were used to locate the mouth in each frame and the historical position of the mouth was used to track the mouth in a series of frames. In order to determine the yawning condition, the ratio of mouth height and width was studied.

In the method studied by Fan et al. [44], the driver's face was detected by using a Gravity-Center template. Once the face is located, the information about facial organs can be located roughly. The horizontal grey projection is used to detect the mouth's left and right corners. Similarly, the vertical corner of the mouth will be found by applying the vertical grey projection on the face. Gabor wavelet is used in the next step to detect mouth image features. At the end, the linear discriminant analysis is taken as a classifier to detect yawning.

Jimenez et al. [45]described a new method of fatigue detection in drivers based on the percentage of closing eyes and detection of yawning and nodding. After finding the face region by using the Viola-Jones theory, the eye and mouth will be located based on the candidate region of interest in the face area. After converting the image into gray scale, the threshold that was assigned by using the histogram of each eye location will be applied on the area. The eye state will be determined by analyzing the histogram of white sclerotic and identifying the shape of eye upper curvature compared to the eyebrow. The yawning condition is detected first by threshold calculation after histogram analysis by seeking the maximum concentration of pixels. When the amplitude ratio of the mouth doubles its minimal size, the yawning situation is found.

Rongben et al. [46] in their method for fatigue detection analyzed the driver's vigilance based on mouth condition. In the first step of their development, the interest of area for the mouth was selected by finding the face location using color analysis. In order to detect the mouth, skin and lip pixels segmentation by Fisher classifier was applied. Then, lip features were extracted by connected component analysis. Kalman's filter was used to track the mouth in the video frames. Three different mouth conditions, such as normal, yawning and talking state, were represented as an output of BP ANN by analyzing the mouth region's geometric features in order to make up an eigenvector as the input of a BP ANN.

According to the method of Alioua et al. [47], drowsiness and fatigue conditions can be determined by microsleep and yawning detections, respectively. Local Successive Mean Quantization Transform is used at the beginning to detect face location. Then, the face is split up according to Sparse Network of Winnows classifier. The Circular Hough Transform will be applied on the eyes and mouth extracted regions in order to determine the yawning situation. The yawning condition is detected if the large dark area with a circular form that shows the mouth is widely open.

The fatigue detection system developed by Narole et al. [48] relies on the driver's eyes and mouth conditions. After finding a face region by skin color segmentation, the eye and mouth area can be detected by a thresholding and segmentation process. For this purpose, the lip pixels can be identified by using the Red/Green ratio, which has different values for skin and for lips. At the end, the neural network along with genetic algorithm are used to detect the driver's drowsiness.

Chapter 3 - Proposed Systems

To detect the drowsiness of drivers, the most important element is a reliable system to monitor the driver and determine whether he/she is fatigued. Even though drowsiness is a concept that is understood by anyone, it is a very complex task to quantify it.

Within the literature of drowsy driver research, drowsiness is frequently detected and rated based on subjective, physiological, behavioral and performance based measurement. This section proposes three implemented methods of drowsiness monitoring system based on yawning detection in order to reach the goal of having a reliable and robust system. These three methods are implemented and tested separately to get the accurate and real time system.

The first method focuses on fatigue detection in terms of color segmentation for finding face and mouth location and the geometrical properties of mouth condition for determining the occurrence of yawning condition.

The second method locates the face area based on template matching and color segmentation. The mouth area is acquired by color condition and actively applying a contour model, which will be helpful to detect yawning condition since it has the nature of flexibility to get the form of the mouth area.

The last method, which as will be shown later is more robust and accurate than the other two methods, detects the face and mouth based on the Viola-Jones theory. The yawning condition is determined by applying back projection theory and comparing the histograms of the mouth in the first frame with the following frames.

Each method of drowsiness detection is discussed in detail below. Figure 1 – Yawning Detection Algorithmshows the general algorithm of drowsiness detection system.

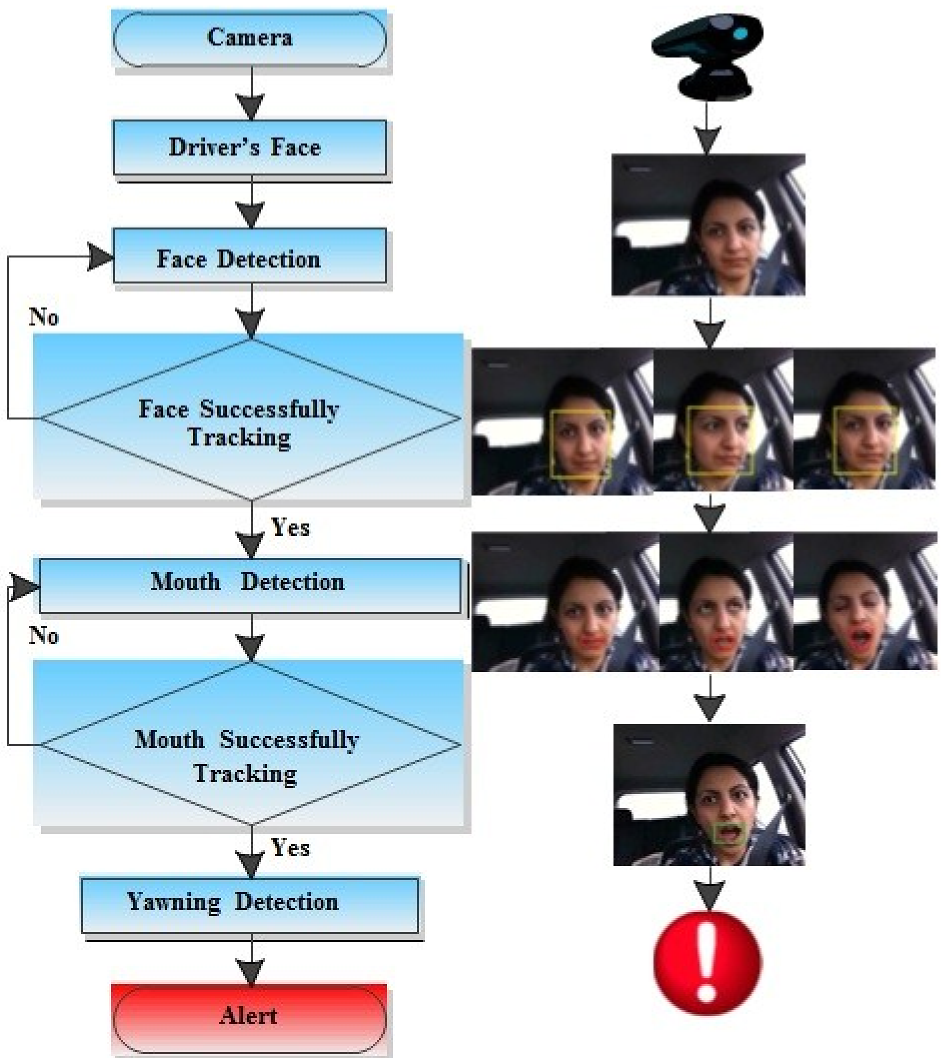


Figure 1 – Yawning Detection Algorithm

3.1 Color Segmentation

The driver fatigue detection procedure consists of different phases to properly analyze changes in the mouth of the driver. These phases are categorized the same as shown in Figure 1 – Yawning Detection Algorithmand each phase will be introduced in detail in the following sections:

3.1.1 Face Detection

Given a single image, the goal of face detection is to identify all image regions that comprise a face regardless of its position, orientation and lighting conditions. Such a problem is challenging because faces are non-rigid and have a high degree of variability in size, shape, color and texture [49]. It is basically assumed that the camera is installed inside the vehicle facing the driver at a fixed angle. Therefore, the problem of relative camera-face pose is less challenging in our case while head position might still vary from driver to driver. There is also a great deal of variability among faces including shape, color and size. The presence of facial features such as beards, moustaches and glasses can also make a great deal of difference. The other important factor consists of the lighting conditions. These are mainly affected by the environment light, which can change depending on the weather conditions and time.

Keeping all the above considerations in mind, one of the functional ways to detect the face is by detecting the skin color and texture. However, it should be noted that the detection scheme should be invariant to skin type and change in lighting conditions. Therefore, a set of bounding rules can be taken advantage of for different color spaces (RGB, YCbCr and HSV) in order to improve the detection efficiency [50]. As it is shown in the following algorithm, these bounding rules were applied with "if-AND" way. The RGB color space is used to detect skin color at uniform or lateral daylight illumination and under flashlight illumination:

$$(R > 95) \text{ AND } (G > 40) \text{ AND } (B > 20) \text{ AND}$$

$$
\begin{aligned}
&(\max\{R, G, B\} - \min\{R, G, B\} > 15) \text{ AND} \\
&(|R - G| > 15) \text{ AND} \\
&(R > G) \text{ AND} \\
&(R > B) \text{ AND} \\
&(R > 220) \text{ AND} \\
&(G > 210) \text{ AND} \\
&(B > 170) \text{ AND} \\
&(R > B) \text{ AND} \\
&(G > B) \qquad \textbf{(1)}
\end{aligned}
$$

The Cb-Cr color space is a strong determination of skin color. The following rules apply to this color space:

$$
\begin{aligned}
&(Cr <= 1.5862 * Cb + 20) \quad \text{AND} \\
&(Cr >= 0.3448 * Cb + 76.2069) \quad \text{AND} \\
&(Cr >= -4.5652 * Cb + 234.5652) \quad \text{AND} \\
&(Cr <= -1.15 * Cb + 301.75) \quad \text{AND} \\
&(Cr <= -2.2857 * Cb + 432.85) \qquad \textbf{(2)}
\end{aligned}
$$

The last space to be used is the HSV space. Hue values exhibit the most noticeable separation between skin and non-skin regions.

$$H < 25 \text{ and } H > 230 \qquad \textbf{(3)}$$

The result of face detection based on color segmentation will be discussed in section 5.1.

3.1.2 Eye Detection

After detecting the face, the location of the eyes will be detected. The main reason behind locating the eyes is to use them as a verification method in order to make sure that the location of the mouth in the face is correctly detected (using the geometrical relation between eyes and mouth in the human face).

In order to detect the eyes, the eye maps based on chrominance components are built [51] according to the following equation:

$$\mathbf{Eye\_Map} = \frac{1}{3}\left\{(C_b)^2 + (C_r)^2 + \frac{C_b}{C_r}\right\} \quad (4)$$

Figure 18 in section 5.1 shows the result of eye detection.

3.1.3 Mouth Detection

The next step towards yawning detection is to find the location of the mouth and lips. To do so, the mouth area will be segmented in the face. The strong difference between lips color and face color is used in this method. In the mouth region, the color red is the strongest component while the blue component is the weakest [51]. In this method, the mouth area is detected based on color information, after the face is located. The following equations (5) and (6) are used to generate the mouth map:

$$\mathbf{Mouth\_Map} = (C_r)^2 \times \left((C_r)^2 - \frac{\eta \times C_r}{C_b}\right)^2 \quad (5)$$

$$\eta = 0.95 \frac{\frac{1}{n}\sum_{(x,y)} C_r(x,y)^2}{\frac{1}{n}\sum_{(x,y)}\left(C_r(x,y) / C_b(x,y) \right)} \quad (6)$$

The result of the mouth map formula on the face image will be the light area on the lower half of the face, which shows the mouth region. This result will be shown in section 5.1.

3.1.4 Yawn Detection

Yawning detection is performed in two main steps: In the first step, the yawn component will be detected in the face independent of the mouth location. This component is basically the hole in the face as the result of wide mouth opening. In the second step, the mouth location will be used to verify the validity of the detected component.

After skin segmentation, the largest hole located inside the face is selected as the candidate for a yawning mouth. This hole is actually related to a non-skin area inside the face that can be related to eyes, mouth or open mouth. It can be assumed that the open mouth will be the largest of the three in a yawning state. In this way, a candidate for the yawning mouth is located. The information will be used from the detected mouth to verify the detected yawning mouth.

3.2 Active Contour Model

This approach can be summarized in the following steps: The possible area where the face is located is found based on skin segmentation. Then, the possible face candidates will be searched for around those areas. To verify the possible matching of a region to a face, the Daubechies wavelet will be first applied to the region and the first level horizontal component of the wavelet will be taken. The result will highlight the edges, which helps in removing the background noise. The vertical projection and the horizontal projection of the upper half of the region will be calculated and its similarity with the projections of a template face will be measured. The details of each step will be further explained in the following subsections. But before getting into the details, we will briefly explain the wavelet and projection methods that are used in the proposed approach.

3.2.1 Wavelet Transform

The Continuous Wavelet Transform (CWT) offers information on how to construct a time-frequency representation of a signal. This transform provides a time and frequency localization of the image. The continuous wavelet transform of a signal f(x) is determined by equations (7) and (8):

$$\mathbf{w}(\mathbf{a},\mathbf{b}) = \int_{-\infty}^{+\infty} \boldsymbol{f}(\boldsymbol{x})\boldsymbol{\varphi}^{*}_{\boldsymbol{a},\boldsymbol{b}}(\boldsymbol{x})\boldsymbol{dx} \tag{7}$$

$$\boldsymbol{\varphi}^{*}_{\mathbf{a},\mathbf{b}}(\mathbf{x}) = \frac{\mathbf{1}}{\sqrt{\mathbf{a}}}\boldsymbol{\varphi}^{*}\left(\frac{\mathbf{x}-\mathbf{b}}{\mathbf{a}}\right) \tag{8}$$

In the above equation, $\varphi*$ is the analyzing wavelet, which is called the mother wavelet. The mother wavelet will be the reference in generating daughter wavelets, which are used in the calculation of wavelet coefficients. These daughter wavelets are the translated and scaled versions of the mother wavelet. Equation (8) shows an example of a daughter wavelet where parameter “a” represents the scale and has to be positive and parameter “b” represents the translation. As can be seen from the above equation, the continuous wavelet transform is calculated by continuously shifting the mother wavelet function and calculating the correlation between the daughter wavelets and the main function. Discrete Wavelet Transform (DWT) has been proposed as an alternative to CWT and is more efficient in terms of implementation. DWT decomposes the signal in different frequency bands with different resolutions. This is achieved by passing the signal through a number of half-band high pass and low pass filters. Therefore, DWT decomposes a signal into approximate and detailed sub-bands. The approximation part of the wavelet transform is the result of the convolution of the image with a low pass filter and is more robust against noise. Daubechies functions are among the most popular filter transfer functions for DWT, which have been used for face detection.

3.2.2 Integration Projection

The integration projection is one of the most commonly used methods to extract the features in image processing. This method maps a two dimensional region into a one dimensional vector along either the horizontal or vertical direction. The one dimensional vector is the result of summing up all the pixels in a specific direction (vertical or horizontal), which then reduces the feature dimension [52]. In this case, the two dimensional intensity values within the face image are reduced to one direction. The following equations (9) and (10) give the detailed process of calculating horizontal and vertical projection:

$$\mathbf{U[i]} = \sum_{\mathbf{k-1}}^{\mathbf{N}} \mathbf{f(i,k)} \quad , \; \mathbf{1} < \boldsymbol{i} < \boldsymbol{M} \tag{9}$$

$$\mathbf{V[i]} = \sum_{\mathbf{k-1}}^{\mathbf{M}} \mathbf{f(k,j)} \quad , \; \mathbf{1} < \boldsymbol{j} < \boldsymbol{N} \tag{10}$$

Applying the wavelet transform formula on the face image in the color space will result in a gray scale image. The intensity of the pixels in the gray image is proportional to the frequency components in their neighborhoods. Therefore, the skin region of the face will turn black as there is no significant high frequency component occurring in that area. On the edge of the face where facial features occur, the pixels will get the value close to 1 since there will be a color change, i.e. from skin to eyebrow, skin to eyes or skin to mouth on the face. The vertical projection can be used on the upper half of the face to find the location of the eyes and the horizontal projection can be used on the y-axis of the whole image to get the location of the eyes and lips [53]. Applying the wavelet decomposition to the resulting projection will help remove some of the noise in the profile. The approximation result, using one dimension wavelet transform, will then smooth the x and y profile and will eliminate the noises on the vectors. The average of the x-profile and y-profile of 10 different faces with similar sizes was used to get the final template for matching the one dimensional vectors with original images. Figure 21 in section 5.2 shows the candidate faces and their wavelet transform.

3.2.3 Face Detection

As mentioned before, the first step towards face detection is to segment the possible areas where the face is located based on the properties of human skin in the RGB and YCbCr color spaces. The details of the skin color detection technique are explained in section 3.1.1. The output of the skin segmentation step will be a black and white image where the bright regions are possible locations of the face. This helps to remove a considerable amount of unnecessary details from the background. However, it should be noted that the results might still include objects in the background whose colors are close to skin color. Therefore, the output of this stage should go through further processing to remove any areas that have been falsely segmented as face region. In order to find the face candidates from the skin segmentation process, the black and white image is searched in order to find its three biggest connected components. The centroids of these components can then be considered as possible centers of the face. Figure 2 – Face candidates centroidsshows the result of skin segmentation and the centroids of the three biggest connected components, which are shown in red.

In the following step, the area around the three centroids found before will be searched in order to find the best match for the face.

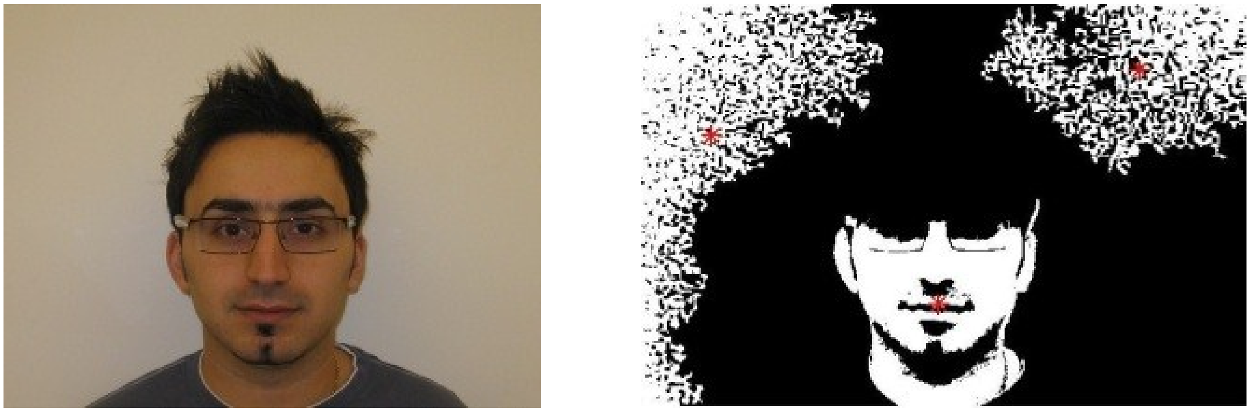
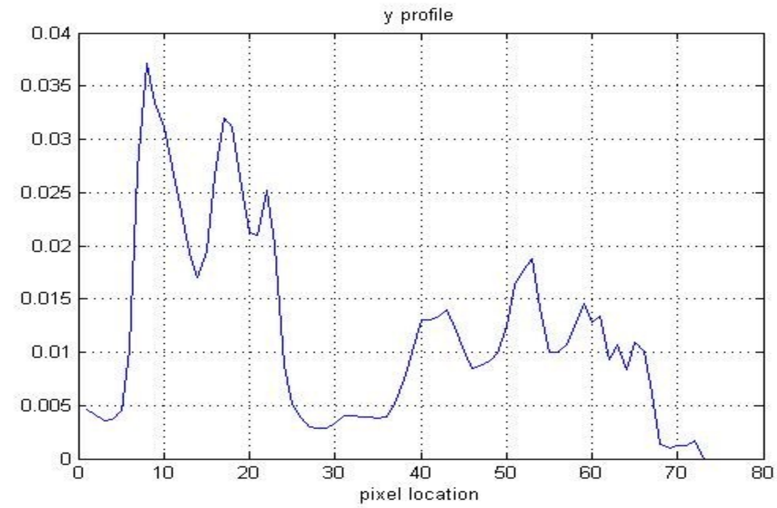


Figure 2 – Face candidates centroids

3.2.4 Face Profile Matching

Once the face location candidates are detected, template matching can be applied to the area around each candidate in order to find the exact location of the face. This step also helps to distinguish the face region from other areas such as the neck that have been segmented as skin region in the previous step. In order to find the exact location of the face, the area around the centroids from the previous step will be searched for the best match with a template face profile. The face profile is commonly defined as the horizontal and vertical projection of the face in gray scale. However, a Daubechies wavelet will be applied to the face and the horizontal component of the first level coefficients will be used as the input to the projection stage. The reason for using the vertical wavelet coefficients instead of the original image is the effectiveness of the wavelet in removing the profile noise that is caused by the change in lighting and shadows.

After applying the Daubechies wavelet on the faces, the edges are shown to be well detected and the noise level is quite low. This will be the input to the projection calculation step. After applying the wavelet to the face, the Y-profile and the X-profile of the upper part of the face are calculated. The shape of these profiles pretty much defines the feature point characteristics fFigure 3.



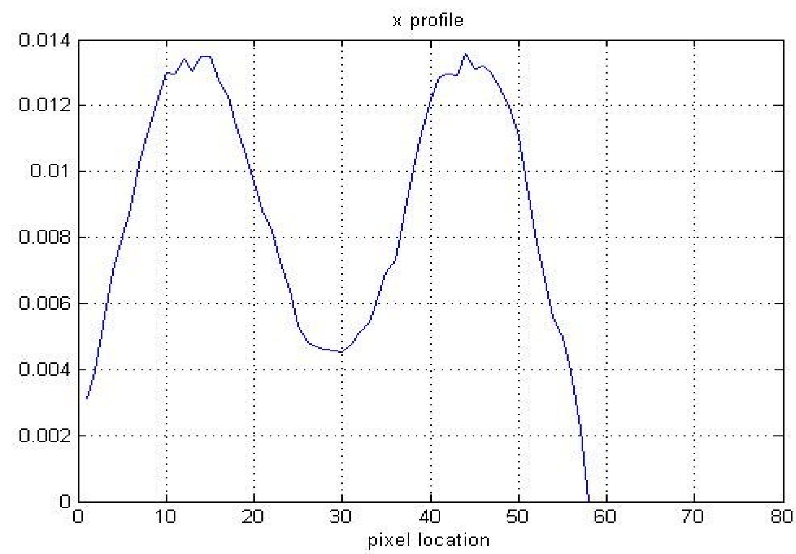


Figure 3 – Average Y-Profile and X-Profile

Figure 3 – Average Y-Profile and X-Profileshows the Y-profile and the X-profile of a sample face. As can be seen in figure 3, the Y-profile has peaks that relate to the location of the eyebrows, eyes, nose and mouth and the upper face X-profile has peaks that relate to the eyes. Therefore, the matching of these profiles to the profile of a region can be a measure of the similarity of that region to a face. The similarity measure that is proposed to use is Dynamic Time Warping (DTW). DTW is an effective technique for measuring the similarity between two

sequences independent of their shift and scaling. Therefore, it is a good similarity measurement technique for the face profiles as it can reveal the similarity of two face profiles even if the faces have different sizes or the location of the facial features slightly shift (one has a longer forehead than the other…). Prior to the start of the profile matching process, a template profile that best represents a face is required. The template profile image is found by applying the wavelet transform and integration projection to the images of a face database and averaging over the whole normalized set. The resulting projection will then be used as the template in the detection process. The face detection procedure starts by finding the x-profile and y-profile of face sized regions in the vicinity of the centroid points from the skin segmentation results. The size of the face is defined to be in a range that covers the size of all the possible faces that should be detected. The DTW distance is then calculated between the profile of the candidate region and the template profile. At the end of the template matching process, the location of the face is defined as being the region whose profile has the lowest distance to the template profile according to DTW measure.

3.2.5 Face tracking

Having found the face in one frame, the detected face can be used as a template and the program can start tracking it in the subsequent frames until the system loses track of the face and the face must be detected again. The basic idea behind the tracking process is to use a Kalman Filter to predict the next location of the face and search around the predicted location for the best match with the template face. The similar measure that is used in the template matching process is 2D correlation. The location of the face is determined as the location where the correlation is the maximum with respect to the template face. If the correlation results go below a certain threshold, the system loses track of the face. Therefore, it goes back to the face detection phase to detect the face again. This might happen in the cases when the driver moves his/her head faster than usual or turns his/her head to left or right. After the detection of the face, the mouth contour should be detected and tracked. This will be discussed in the following section.

3.2.6 Mouth Detection

After the detection of the face, the mouth region is selected at the bottom half of the face area. The first step towards mouth segmentation is the usage of the color properties of the mouth in order to highlight the mouth in the face area. In the mouth region, the color red is the strongest component compared to the green and blue components. Such a property can be exploited into defining a mouth map function that highlights the mouth area when it is applied to the face region. Section 3.1.3 explains the detailed process of finding the mouth map based on the red-difference and blue-difference Chroma components. The output of applying the mouth map to the face is a gray scale image where brighter pixels represent the mouth area. Even though the mouth area is highlighted in the output, there might be some other regions that have been falsely classified as mouth according to mouth map criteria.

Therefore, a post processing steps such as dilation, erosion and finding the biggest connected component technique can be used in the area to find the mouth location. After detecting the mouth, the active contour model will be applied in that area to find the mouth contour with a better precision. The advantage of the active contour model (snake contour model) will be utilized to extract the mouth contour. The use of the active contour model is an efficient way of segmenting the mouth after the mouth color map is applied and the mouth is highlighted in the face. The snake model is pretty useful compared to the first method in a yawning detection system for detecting the lip contours in the face, as it is quite robust against the noise that is present due to the inaccurate segmentation of the mouth in the mouth map.

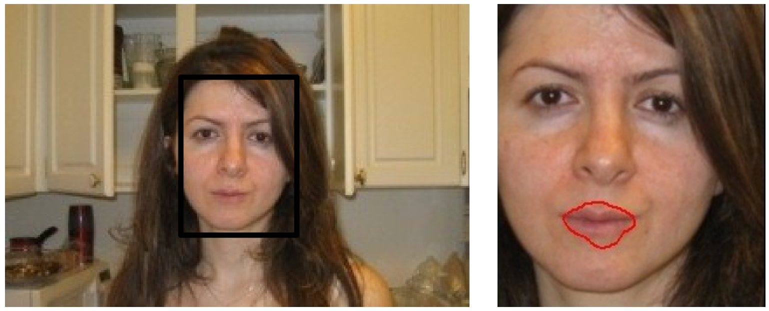


Figure 4 – An example of face and mouth contour detection

The concept of snake contours will be briefly explained in this section. The snake method aims at spline interpolation of a line around object boundaries. It starts from a set of initial points in an image and deforms in several iterations to reach the object boundaries in the image.

The change in the shape of the snake is deformed in a way to minimize three sets of energies that are known as internal, external and constraint energies. External energies are defined by image boundaries that attract the snake towards themselves. Internal energies determine the internal energy of the spline due to stretching and bending. External energies are related to the image forces. The external source of energy from the image causes the snakes to be attracted towards lines, edges and termination points in the image. The external energy coming from the image is therefore the sum of the energies from lines, edges and termination points as defined in the following equation (11):

$$\mathbf{E_{Image} = W_{Line} E_{Line} + W_{edge} E_{edge} + W_{term} E_{term}} \tag{11}$$

Finally, the constraint energies are related to external constraint forces.

The total image energy can be expressed as a weighted combination of the three energy functions. The overall energy function minimized by the snake is defined in the following equation (12):

$$\mathbf{E_{state}} = \int_0^1 (\mathbf{E_{internal}} v(i) + \mathbf{E_{external}} v(i) + \mathbf{E_{constraint}} v(i)) di \quad \text{(12)}$$

where V is the set of points on the snake. The use of snake contours in lip reading has been previously discussed in [54] [55]. The aim of this part is to find a snake on the external lips, in which case the snake will then be updated, as the shape of the lips changes over time. Once the snake reaches the boundary of the object, it starts to settle down in the boundary and move more slowly. If the object moves slightly, the snake is able to track the motion and reside in the new boundary. In the following section, the use of snake contour patterns for detection of yawning in a video will be discussed.

3.2.7 Yawn Detection

The yawn is assumed to be modeled with a sequence of large vertical mouth openings. When the mouth starts to open, the mouth contour area starts to increase. The mouth normally opens much wider in yawning condition compared to speaking and the mouth opening cycle is longer in the yawning situation. This helps to differentiate yawning from speaking. Figure 5 – Changes in mouth contour area during yawningshows the changes in the mouth contour area in the 38 frames where a yawn is happening.

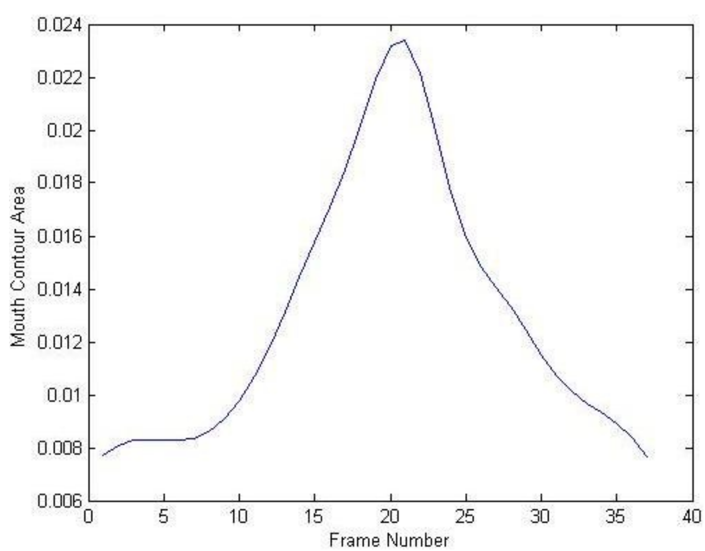


Figure 5 – Changes in mouth contour area during yawning

We have applied the active contour model to more than 50 yawning images and yawning to more than 10 videos with different characteristics. The videos have been recorded in various conditions such as different light reflection and directional lightings. The result will be discussed in 5.2.

3.3 Viola-Jones Method

The third method towards drivers' yawning detection will be explained in this section. This part will present a working system that is capable of real time monitoring of a driver to detect drowsiness based on yawning detection. The platform is an embedded real time video processing system that analyzes the video recorded by the camera installed either under the front mirror or on the dash of the car in front of the driver. The hardware and its associated cameras are based on CogniVue Corporation's APEX automotive smart camera platform. The APEX core has 96 parallel Computational Units (CUs) running in parallel with an ARM processor as the data distribution and collection unit. The computer vision software has been developed specially for this specific hardware and application, and is composed of several blocks including face detection, face tracking, mouth detection, mouth tracking and finally yawning detection based on the state of the mouth. These are the same as the previous methods, since, looking for the yawning condition in the whole frame with changing light and background condition is a cumbersome task; hence, the search space is first reduced by finding the face in video frames. In this method, the face and mouth detection technique is based on the Viola-Jones theory [32], which is a fast and robust method for object detection. The results of applying the third method on the dataset videos showed that the performance of this method is fast and can be considered as real time with high accuracy compared to the other two methods. Therefore, the C++

implementation of Viola-Jones is ported to the embedded platform and optimized to meet the real time requirement of the monitoring system. Viola-Jones takes advantage of Haar-like features that can be computed very fast using the integral image. Moreover, it uses AdaBoost for feature selection and a cascade of classifiers that help decrease the misclassification error and increase the detection time due to early rejection in the first stages. Starting from the C++ implementation of OpenCV, the code is redesigned in order to make it compatible with the parallel processing architecture of the APEX platform. The code is also simplified as much as possible to make the porting process easier while trying to preserve its functionality.

The specification of the platform will be discussed in the following section before explaining the third method in detail.

3.3.1 Platform Specification

The automotive APEX platform contains the CogniVue CV2203 highly-programmable Image Cognition Processors (ICP). It consists of an ARM 926EJTM 350MHz master processor, 34B Ops/sec low-power DSP subsystem using patented massively parallel Array Processor Unit (APU), a second 350MHz ARM 926 processor, H/W acceleration blocks, wide-bandwidth stream DMAs, internal dual 64-bit AXI data buses to/from all blocks, 16Mbyte DDR SDRAM, and 1Gbit NAND Flash. While it supports 96 parallel Computational Units (CUs) which allow heavy massive processing, and can encode/decode D1 MPEG4 video at 30fps, the platform does not support floating point operations, divisions, or numbers larger than 16 digits. These limitations cause specific design and implementation choices.

To overcome lack of floating point operation, fixed point operation was used by scaling all the floating point numbers by 2^N to discard the digits after the floating point. In this case N depends on the number of required floating point digits to maintain enough accuracy. The number 2 is selected (instead of the more intuitive 10) since scaling by powers of two has the advantage of easily shifting numbers to right and left for multiplying and dividing by 2 without using floating number operations. Both sides of all operations required scaling, so that scaling won't affect the final results.

Another layer of scaling was applied to prevent overflow in intermediate results, due to the limited number of digits per number. For example, to multiply a few big numbers and then divide them by a big number, even though the final result is less than 16 bits, there is overflow in the intermediate multiplication result. The approach was to scale those numbers down before multiplying them, and then scaled up the result.

Design and implementation for the real time performance of the system on the computationally limited hardware comes with its own set of challenges, which will be discussed in the following sections in further detail but first, the detailed explanation of the Viola-Jones theory will be given in 3.3.2.

3.3.2 Viola-Jones Theory

The method of object detection using the Viola-Jones theory is capable of processing images extremely rapidly while achieving a high detection rate. There are three main techniques involved with this model. The first technique is an integral image, which is useful for very fast feature evaluations. The second technique is a process for creating a classifier by selecting a small number of features using Adaboost. The last technique is a method of combining classifiers in a cascade structure.

In the first step, the integral image is applied on each frame in order to find Haar-like features. Since features can act to encode ad hoc domain knowledge that is problematic to learn using a finite quantity of training data and also, the feature based system operates much faster than the pixel-based, therefore, the object detection system is designed based on features rather than pixels. Three kinds of features that are reminiscent of Haar basis functions are used in the system for it to work properly. The following figure 6 shows all three kinds of features. A two rectangle feature is computed by calculating the difference between the sum of pixels within two rectangular regions. A three rectangle feature calculates the sum within two outside rectangles subtracted from the sum in a center rectangle. The last kind of feature is a four rectangle feature, which is determined by finding the difference between diagonal pairs of rectangles.

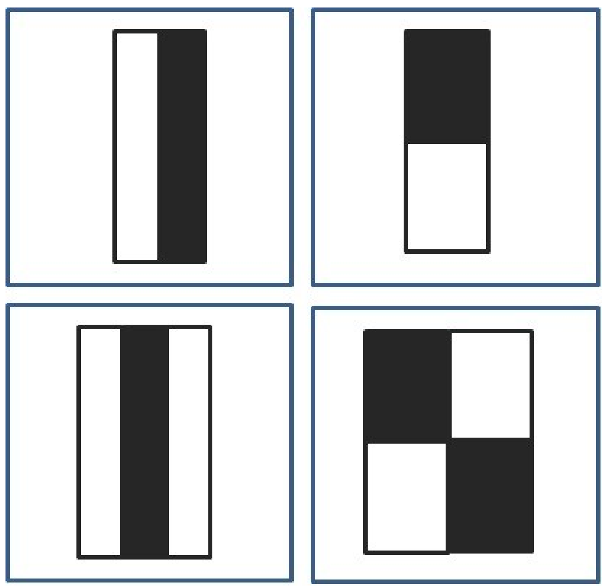


Figure 6 – Rectangle Features

In order to find the rectangle features, the concept of integral image can be used. The value of the integral image at any point (x, y) contains the sum of all the pixels above and to the left of (x, y) inclusive:

$$\mathbf{ii}(\mathbf{x}, \mathbf{y}) = \sum_{\mathbf{x}'<x, \mathbf{y}'<y} \mathbf{i}(\mathbf{x}', \mathbf{y}') \qquad \textbf{(13)}$$

where $ii(x, y)$ is the integral image and $i(x', y')$ is the original image.

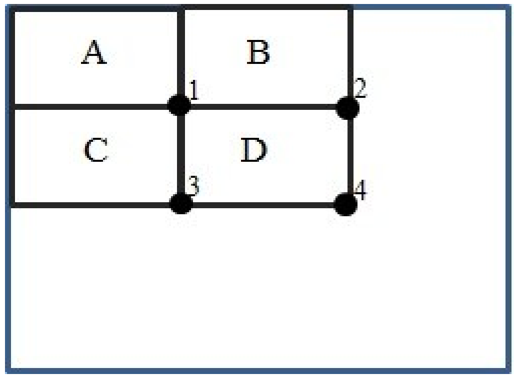


Figure 7 – Haar-like features

Furthermore, the summed area can be calculated in a single pass over the image by considering the fact that the value in the summed area at (x,y) is:

$$\mathbf{ii(x,y) = i(x,y) + ii(x-1,y) + ii(x,y-1) - ii(x-1,y-1)} \qquad \textbf{(14)}$$

After computing the summed area, any one of the Haar-like features can be evaluated in constant time at any scale or location with just four array references, which are shown in Figure 7.

$$\sum_{\substack{\mathbf{A(x)<x'<}C\mathbf{(x)} \\ \mathbf{A(y)<y'<}c(y)}} \mathbf{i(x',y') = ii(A) + ii(C) - I(B) - I(D)} \qquad \textbf{(15)}$$

In the next step, a small number of important representative features will be selected to construct classifiers. Since within an image sub-window the number of Haar-like features is very large, the learning procedure must ignore the majority of the available features, and focus on a small set of critical features that play the most important role in the classification decision. The AdaBoost algorithm is utilized in the system to select these key features and to train the classifier. In order to boost the classification performance of a simple learning algorithm, the Adaboost learning algorithm is required to combine a collection of weak classification functions to form a strong classifier. Each weak classifier can be dependent on only a single feature, therefore, selecting a new weak classifier, can be considered as a feature selection process. A large set of classification functions is combined using a weighted majority vote; however, this task is challenging to assign a large weight with each good classification function and a smaller weight with poor functions. The weight will be initialized at the beginning by $w_{1,i} = \frac{1}{2m}, \frac{1}{2l}$ where m and L are the number of negatives and positives respectively. Then the weight will be normalized by

$$\mathbf{w_{t,i}} \leftarrow \frac{\mathbf{w_{t,i}}}{\sum_{j=1}^{n} \mathbf{w_{t,j}}} \tag{16}$$

where w_t is a probability distribution. The classifier h_j will be trained for each feature, j and the error will be determined with respect to w_t.

$$\boldsymbol{\epsilon_j} = \sum_i \mathbf{w_i} \left| \mathbf{h_j}(\mathbf{x_i}) - \mathbf{y_i} \right| \tag{17}$$

The classifier with the lowest error will be selected and the weight will be updated at this stage by:

$$\mathbf{w_{t+1,j}} = \mathbf{w_{t,i}} \boldsymbol{\beta}_\mathbf{t}^{\mathbf{1-e_i}} \tag{18}$$

The final strong classifier will be determined by the following equations:

$$\mathbf{h}(\mathbf{x}) = \begin{cases} \mathbf{1}, & \sum_{t=1}^{T} \boldsymbol{\alpha}_\mathbf{t} \mathbf{h_t}(\mathbf{x}) \geq \frac{1}{2} \sum_{t=1}^{T} \boldsymbol{\alpha}_\mathbf{t} \\ \mathbf{0}, & \textbf{Otherwise} \end{cases} \tag{19}$$

where $\alpha_t = \log \frac{1}{\beta_t}$.

The last step towards face detection is to construct a cascade of classifiers that increase the detection performance while radically decreasing computation time. The main goal of this part is to ensure that simpler classifiers are constructed to reject the majority of sub-windows before using more complex classifiers in order to achieve low false positive rates. The stages of the cascade are started with a two feature weak classifier, which causes the detection performance to be far from acceptable as an object detection system. Three processing steps are required to be done for the classifier to reduce the number of sub-windows, such as: 1- estimate the feature rectangle, 2- evaluate the weak classifier for each feature and 3- combine a number of a few classifiers to build a strong classifier.

In the procedure of detecting an object, the system starts by analyzing the result of the first classifier and the positive result of this classifier triggers the evaluation of a second classifier. The second classifier is adjusted to achieve very high detection rates and the result from this classifier triggers the third one, which faces more tasks than the previous ones and the same steps will be continued for the next classifiers. A negative result at any point in the procedure will lead to the fast rejection of the sub-window. The algorithm of the detection cascade is shown in Figure 8.

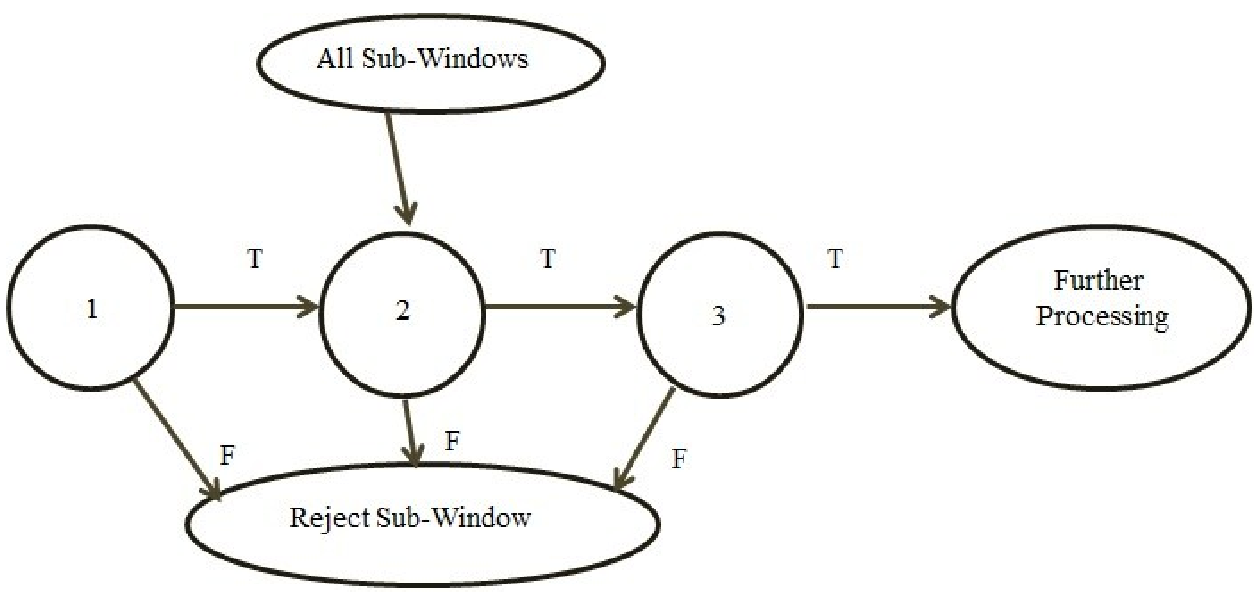


Figure 8 – Cascade of Classifiers

For the detection process, any given sub-window will go through the cascade in order to be determined by one classifier at a time, until the system decides that the window is negative or the window succeeds in each test and is positive. In the case of a positive label at the end of the cascade, the object is detected.

3.3.3 OpenCV Implementation

In the third method, the Viola-Jones theory, which is already implemented in openCV software, is used as a guideline for faces and mouth detection. The system is named the "Haar classifier" since it utilizes the Haar-like wavelets that contain adding and subtracting rectangular image areas for feature extraction before thresholding the result. For the first step of the Viola-Jones theory, OpenCV uses diagonal features as well as the other type of Haar-like features introduced by Viola-Jones to extract the face features. Figure 9 shows all types of different Haar-like features used by the classifier for face detection. The algorithm of integral image speeds up the computation of the following Haar-like features.

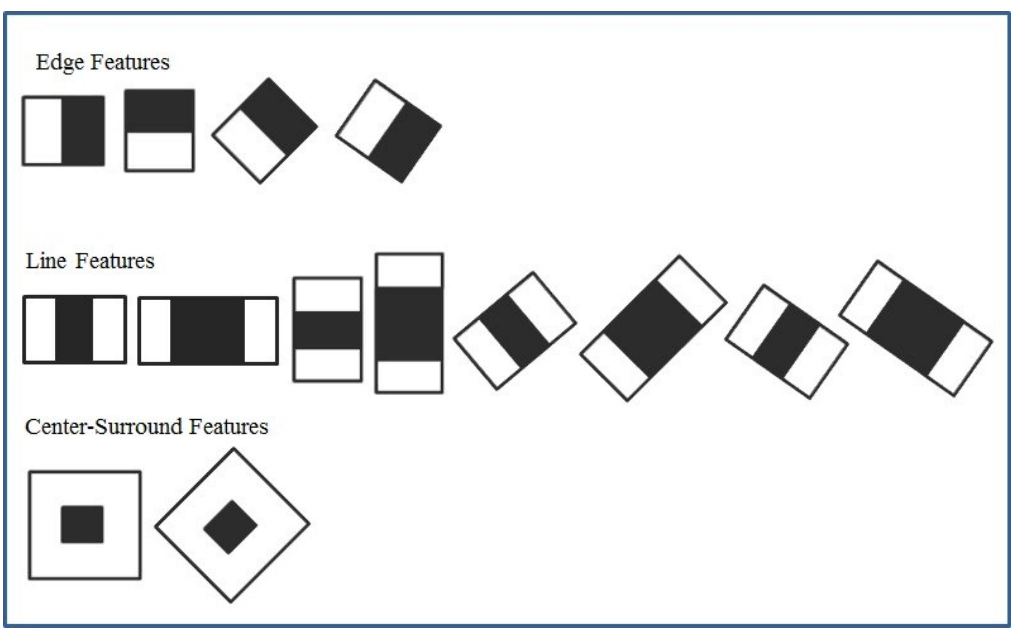


Figure 9 – Different Haar-like features used by the classifier for face detection

In the second step, for training the T weak classifiers, the boosting algorithm is required, which, in this case, is composed of decision trees with at most a few (three) levels of splits in most cases. In the final decision making procedure, a weighted vote is assigned by each of the classifiers. Each split is determined by whether the value (v) of the particular feature (f) is below or above the threshold (t).

$$\mathbf{f} = \begin{cases} +\mathbf{1}, & \mathbf{V} \geq \mathbf{t} \\ -\mathbf{1}, & \mathbf{V} < \boldsymbol{t} \end{cases} \tag{20}$$

The threshold value will be set in the first pass through the data set, which classifies the input in the best way. The resulting error will be used by boosting to determine the weight vote. Then, the feature will be reweighted low or high based on the correctness of classification.

The OpenCV face detection function was trained with a huge number of face and non-face images with a fixed size of 20*20 pixels. The Haar-like features were applied on these images and all the information about those features that have been selected using Adaboost from the set of all features was saved in an .xml file in OpenCV. In order to detect a face based on the Viola-Jones theory, the training algorithm in OpenCV uses 22 stages of classifiers with different numbers of trees and nodes. Each stage includes a number of decision trees and the number of decision trees gets larger resulting in more strong classifiers as we go to higher stages. For example, the first stage has only 3 trees but the last stage, which is stage number 22, has 212 trees. All decision trees have only a single node.

A few lines of .xml for only the first stage are shown in Appendix A. The explanation of this .xml part will be given in detail in the following part. . All other stages have the same pattern and are stored in OpenCV open source files. Line 1 indicates that the training data set are vocalized by the images of size 20*20.

Three trees are shown in the codes, each with its own properties and values. Lines 12 and 13 provide the information for the first two rectangle feature. The numbers given in line 12, <_>3 7 14 4 -1. </_>, are respectively x_0, y_0, $width_0$, $height_0$ and $weight_0$ and belong to the first rectangle, and the numbers in line 13, <_>3 9 14 2 2.</_>, are x_1, y_1, $width_1$, $height_1$ and $weight_1$ and are related to the second rectangle. Figure 10 shows the two rectangles on the coordinate system.

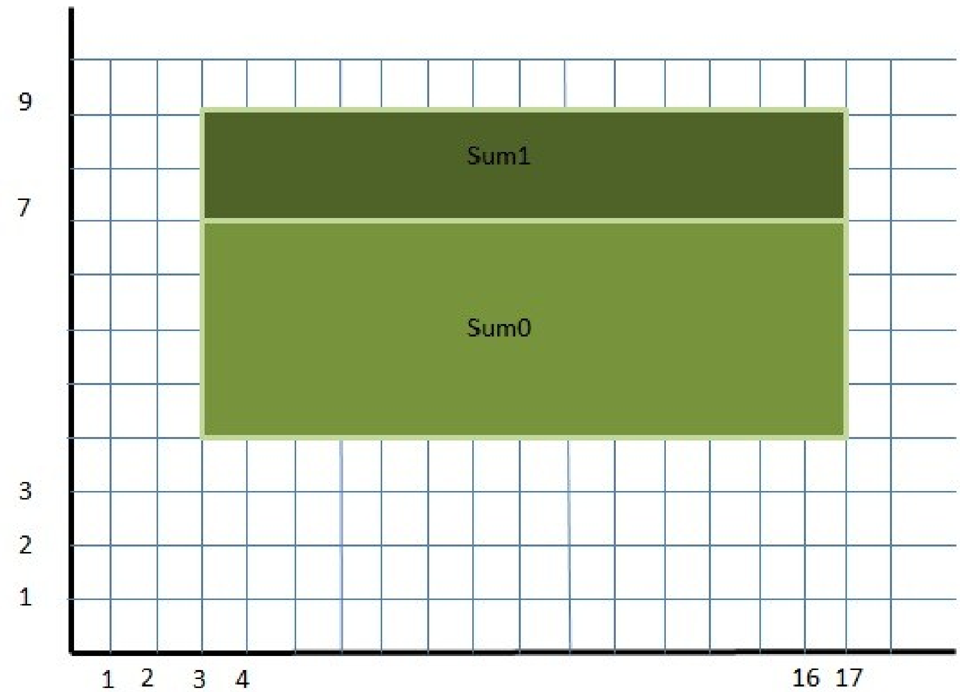


Figure 10 – Two Rectangles for the Calculating Feature

In order to find the value of the first feature, the following equation will be applied based on using the integral image:

$$\mathbf{decision\_value1} = \mathbf{sum_0} \times \mathbf{weight_0} + \mathbf{sum_1} \times \mathbf{weight_1} \qquad \textbf{(21)}$$

The result of decision_value1 will be compared to the threshold value, which is already defined in line 15.

If the result of the decision_value1 is greater than the threshold, the value saved in right_val, in line 17, will be returned and if the result from calculating decision_value1 is smaller than the threshold, the saved value in left_val, line 16, will be returned.

$$\mathbf{tree1\_feature\_result} = \begin{cases} \mathbf{right\_val}, & \mathbf{decision\_value1} \geq \mathbf{t} \\ \mathbf{left\_val}, & \mathbf{decision\_value1} < \boldsymbol{t} \end{cases} \tag{22}$$

The same procedure will be done for all the trees in each stage. After comparing the decision_result of each tree with its own threshold and returning the value, that specific value will be saved. At the end of the stage, all the values from each tree of its own will be added together. The final result of the added value will be compared to the threshold of the stage classifier, shown in line 41. If the result value is greater than the stage classifier, the voting answer to the “detected face” will be yes (+1); otherwise, the voting answer will be no (-1), which means the system could not find any faces in that area. The same algorithm will be applied on all 22 stages and the result of the “detected face” number will be added together. If the sum of the voting value becomes 22, it means all the stages are voted the face is located in that specific location but if any of the voters gives -1 as a result, the algorithm will be rejected from the location immediately and will be moved to the next location.

In the above algorithm, all trees were based on finding features by only two rectangles but in general, there are some cases that have three rectangles involved in finding the feature.

3.3.4 Face Detection

The face detection algorithm in the third method is based on the Viola-Jones technique, which is implemented in OpenCV, as was discussed in 3.3.3. The same concept as OpenCV face detection was simplified in C++ and then transported to the APEX board.

In the first step of the face detection process, all the provided data of the trained features in OpenCV will be extracted and stored in five separate files in order to use them in the algorithm to save computational time in the real time monitoring system. These files, which are the results of the training features, will be used later in the detection algorithm. In this case, the monitoring system can utilize the saved value instead of training the classifier and applying the integral image to find the features from the beginning. Each file contains one of the following groups of data: feature_coordinate, feature_threshold, feature_val, stage_classifier and feature_weight.

For the face detection process, two tasks must be considered. As was already mentioned, the Haar-like features are trained with a large number of 20*20 images but the face detection algorithm does not necessarily detect only the faces with the same size. In order to overcome this condition, the features must be scaled. In the case of having faces larger than 20*20, the feature coordinates and the feature weight of each node will be rescaled. Therefore, the first task is to search for the faces with different sizes depending on the difference between the driver's face and also their distance to the camera in the video frame. Therefore, different scale ratios of the features were used to search for the face location in the implemented code, as is shown in Figure 11. The scale ratio varies based on the size of the face that is supposed to be detected.

In order to find the table of scale ratio for different face sizes, the possible face sizes for different drivers based on the frame size were considered. For example, in the case of having a frame with the size of 480*640 and considering the distance of the driver to the camera, we assumed the largest possible face size can be 460*460 and the smallest face size can be 100*100. Therefore, by taking this information into consideration, 18 scale ratios were assigned to detect the driver's face in the videos. In order to increase the speed of the detection system and shorten the computation time required to scale the Haar-like features for different face sizes, all of the data related to each node in 22 cascades of classifiers such as x_0, y_0, $width_0$, $height_0$ and $weight_0$ will be saved in the mentioned files in 18 scales. In total, 2153 features are defined in the OpenCV face detection algorithm.

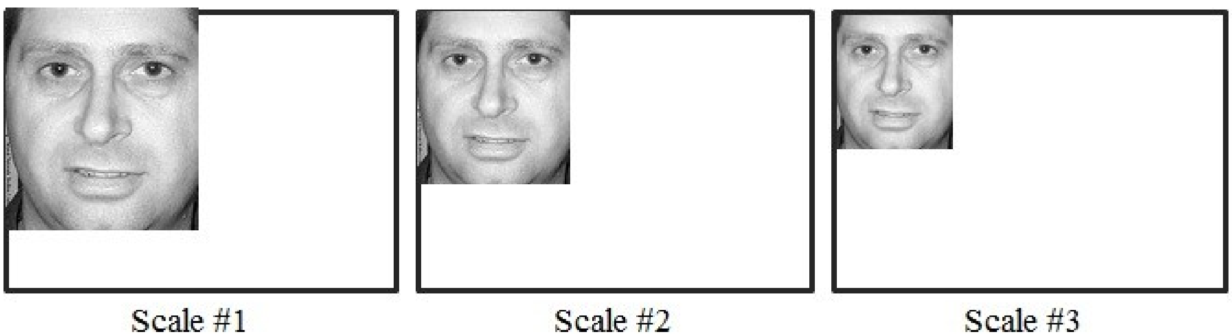


Figure 11 – Search for Face Location with Different Scale Ratios

Moreover, another task must be considered in face detection development. The algorithm starts scanning for the face from the corner of the image with the specific feature size in the beginning. If the classifiers reject the first location, the algorithm will shift the search location to the right with a specific step size. The same procedure will be applied for the whole image starting with the larger possible scale ratio and scan toward smaller scales. If the system could not detect the face with that particular feature size, the next scale for the feature will be used and the starting point from the corner of the image will be assigned until the face is detected.

Unlike the OpenCV program, in the case of detecting the face, the system will stop searching for another face since there will be only one face in the position of the driver in this scenario. Figure 12 and Figure 13 show the procedure of searching for the face in the video frames.

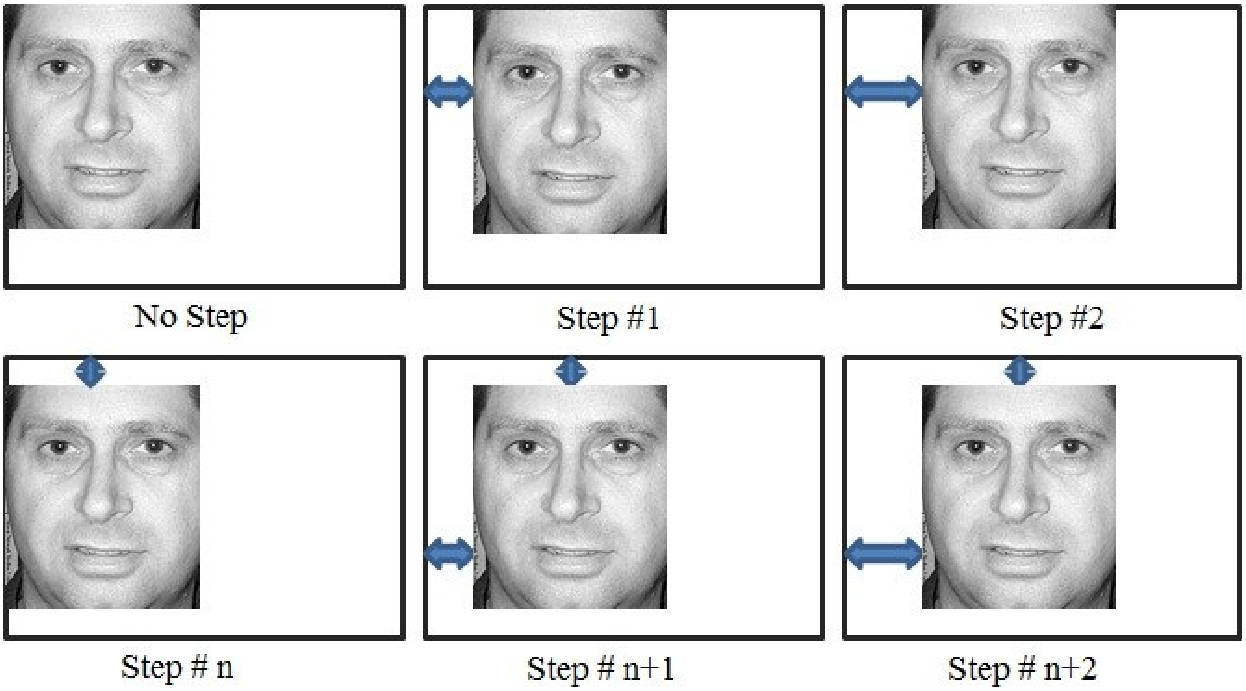


Figure 12 – Search for Face Location in an Image

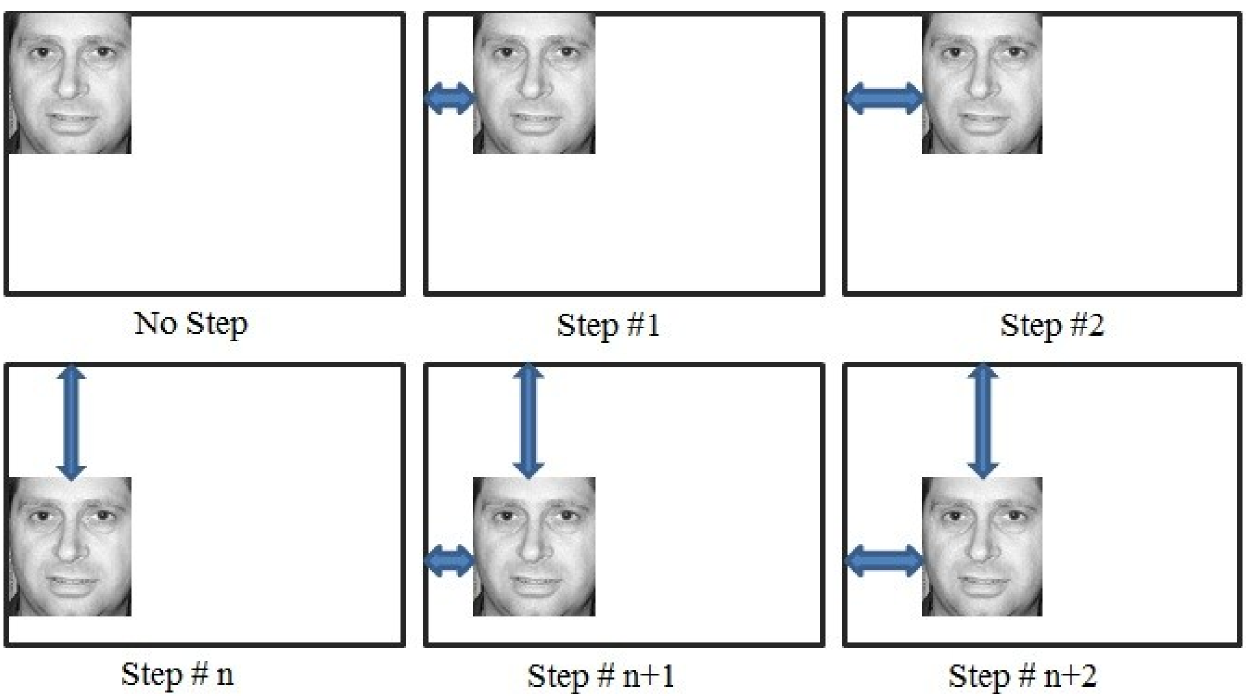


Figure 13 – Search for Face Location in an Image with Different Scale Ratios

The step size should be selected based on the face size; for example, it should be bigger for bigger face sizes in order to expedite the search process.

Since the face tracking algorithm is not fast and accurate enough in the APEX board, the face detection theory is applied on every frame to find the face location. After finding the face location in the video frames, the x and y coordinates of the left corner of the face and the size of the height and width of the face will be saved to eliminate the search area for detecting the mouth location for the next step of the drowsiness detection.

3.3.5 Mouth Detection

After detection of the face, the mouth location must be extracted. A similar procedure as the face detection will be utilized for this section. In addition to the face detection algorithm, OpenCV has a mouth detection algorithm and feature. This mouth detector is computed with 7000 positive samples.

A large number of normal mouth images in the size of 25*15 were used to train the classifier. The OpenCV mouth detector contains 16 cascade classifiers and each has a different number of trees. The first cascade in this case has 12 trees and the last cascade has 217 trees. The total number of features for determining the mouth location is 1515.

Since the result of face detection has high accuracy, for the implementation of the mouth detection algorithm in C++, the lower half of the face was the target of the mouth search region. After locating the mouth in the frame, the data related to the mouth location and size will be passed to the yawning detection part.

3.3.6 Yawn Detection

The last part of the process is to determine yawning in order to alert the driver in case of drowsiness. The first step towards reaching this goal is to calibrate the system. This function will be done by finding the location and histogram of the driver's mouth in the first frame. The term histogram is obtained by counting the number of times each color occurs in the image array. The histogram of the normal closed mouth position in the first frame will be saved as a reference for further calculation. For determining the yawning condition in this method, the back projection theory will be used. The explanation of this theory will be presented first and then the usage of this theory in the last method will be discussed.

The basic idea in back projection theory is to create a similar image giving the similarity of each pixel of the candidate object to be matched (the candidate) to the object of interest (the reference). Generally, the features used for back-projection are intensity values of the gray scale image. In order to calculate the back projection, the histogram of the reference image, in this scenario the normal closed mouth, will be computed and then the histogram of the candidate images will be compared with the referenced one. In this case, the measurement results from an image at each location over the specific region of interest should be taken to form an array. A multi-dimensional normalized histogram array is constructed by sampling from the image array. Each new image of the location of the mouth is selected and then converted into an image array over a chosen region of interest. Then, the histogram bin will be determined for each of the arrays that are related to the mouth region. The calculated new mouth histogram is compared to the reference mouth histogram. This process is repeated for the mouth region of the entire video frame. An appropriate threshold will be used to convert the gray scale image to black and white based on the back projection concept. Then, the number of black and white pixels that show the mouth area and the whole image area will be counted. In the case of having a yawning position, the number of black pixels will be increased. Therefore, by comparing the number of black pixels in each frame with the previous one, the mouth movement will be observed. If the order of changes in black pixels shows that the black pixels are increasing and decreasing within a specific number of frames and time, the yawning condition can be detected.

Chapter 4 - Dataset Collection

The face is a very non-rigid and complex structure; therefore, the appearance of a face is affected by a large number of different factors including “identity, face pose, illumination, facial expression, age, occlusion, and facial hair” [56]. As a result, to create reliable algorithms sensitive to these facial variations, a sufficiently large dataset is required that includes “carefully controlled variations of these factors.” This dataset contains static images of people in different environment and also videos of people in the driving position. To collect the dataset, the following components were configured:

1- Camera

2- Environment

3- Participants

4- Photos and Videos

Each component will be described in detail in the following sections.

4.1 Camera

To ensure a realistic setup, we worked with our industry partner CogniVue Corporation, whose APEX line of products specialize in smart in-car camera systems. Two different locations for installing the camera were considered in the video dataset collection. In the first scenario, the camera was installed under the front mirror and in the second scenarios, the camera was installed on the dash of the car. In both situations, the videos were collected using a Canon A720Is digital camera with the resolution set at 640x480 pixels and 24-bit true color (RGB) at 30 frames per second, resulting in a video that matches with the video produced by real driver monitoring systems.

Beside in-car videos, 180 images were taken to test the system in the early stages of the monitoring system development. These photos were collected randomly with different cameras.

4.2 Environment

In the dataset, the collected videos were taken in the car during day time. However, the videos were recorded in various lighting situations in order to provide a more complete dataset. The videos were recorded from early morning till sunset. Also, the weather varied from sunny to rainy, causing different lighting conditions. It should be noted that there are no faces other than the driver's face in the videos, mostly due to the angle of the camera, although there is some background movement in some of the videos, which include other people walking across the frame. It should also be noted that night time videos were not collected, because for yawning detection at night, either the lighting must be controlled in the car, in which case normal day time detection approaches would work too, or else infrared cameras must be used to overcome the extreme darkness of the image, which leads to completely different approaches of image processing and computer vision.

The photos for the image dataset were collected in different locations. The participants were asked to stand where the background is either simple or complex. A few participants were asked to stay where the background has a similar color as the face color with different lighting conditions to make the scenario more complicated and challenging for the face detection method based on color segmentation.

4.3 Participants

The participants were asked to sit in the driver's seat and fasten their seat belt to make the scenario more realistic for the video dataset. The dataset contains videos of 54 male and 44 female volunteers of different ages, ethnicities and facial characteristics. The statistics about the participants will be discussed in section 4.5. A high variety of appearances existed among these 98 volunteers in the dataset. People participated with and without glasses, men with and without beard, men with and without moustache, women with and without scarf, different hairstyles and different clothing. Similar characteristics for the participants were considered in image dataset collection, except the environment where the participants were being photographed excluded the driving scenario. Figure 14 shows a random selection of eight of the volunteers for the video and image dataset.

Figure 14 – Participants

All of the participants signed an agreement allowing their videos to be used for non-commercial and research purposes, which is attached as Appendix A.

4.4 Videos

In the first scenario three sets of videos were taken. In the first video, the person was asked to sit in the driver's seat, fasten the seatbelt and act as if driving. In the second video of the same person, she/he was asked to talk or sing while driving. This video can be used to distinguish between talking/singing compared to yawning, where both scenarios might lead to an open mouth but only yawning should be detected. In the third video of the same driver, she/he was asked to wait for a few seconds and then yawn afterwards. The videos last between 15–40 seconds. A few participants were asked to have a fourth video of their yawning while they were talking. These videos are more challenging for the researchers since the yawning happens right in the middle of talking, and so it might be more difficult to detect the former. Finally, some participants acted with and without their prescription glasses or sunglasses. After collecting 342 videos, the audio was removed to reduce size.

In the second scenario, in which the camera was located on the dash of the car, the drivers were asked to sit on the front seat and fasten their seatbelt. In this scenario, only one video was taken from each participant. The participants were asked to pretend that they were driving in normal, talking and yawning positions in a single video. The combination of these three phases was useful to improve the system in order to distinguish between these cases at the same time and detect the yawning position accurately.

4.5 Basic Videos Statistics

As mentioned earlier, volunteers of different genders, ages and ethnicity participated in our video dataset collection. Having a wide variety in participants gives a better and more reliable dataset in order to increase the accuracy of yawning detection systems. The age distribution of the participants is shown in Figure 15 and Figure 16.

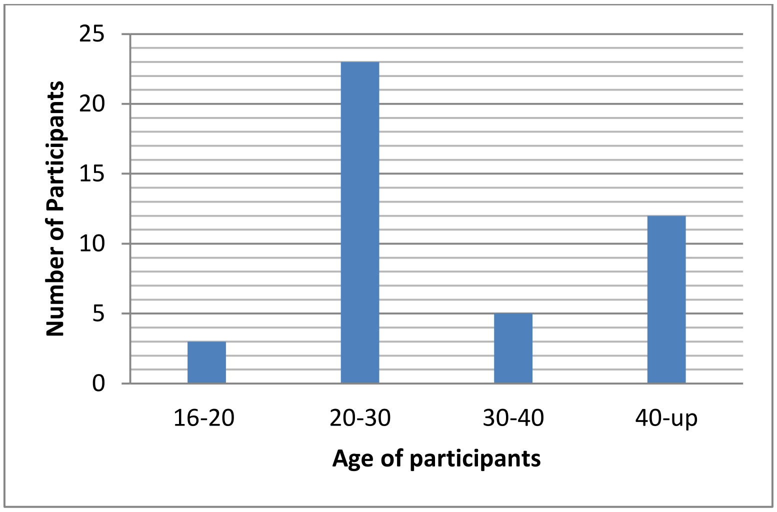


Figure 15 – Female Participants

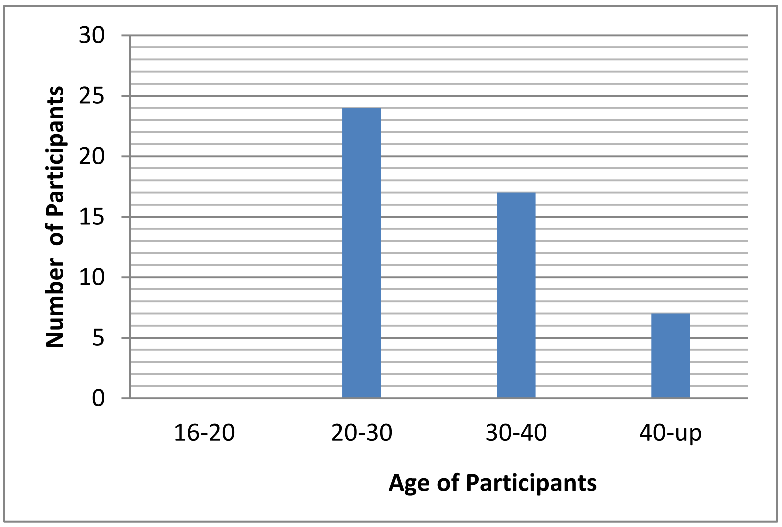


Figure 16 – Male Participants

We also included different facial characteristics. Statistically, we have videos for the following:

- Female participants:

    With prescription eyeglasses: 10 people

    With sunglasses: 10 people

Without glasses: 33 people

With scarf: 3 people

Without scarf: 40 people

- Male participants:

  With prescription eye glasses: 25 people

  With sunglasses: 5 people

  Without glasses: 28 people

  With moustache: 3 people

  Without moustache: 45 people

  With beard: 4 people

  Without beard: 44 people

In terms of ethnicity, we have people with various skin, hair and eye color, including blonde, brunette, Caucasian, African, middle-eastern and Asian individuals.

Chapter 5 - Results and Discussion

5.1 Color Segmentation

The first method towards yawning detection is based on color segmentation. This method is divided into four phases, which are face detection, eye detection, mouth detection and yawning detection. As is discussed in section 3.1.1, the face will be detected by highlighting skin color based on applying the formula on different color spaces. The result of the skin location technique is a black and white image that highlights the skin location by converting the face to white and the background and the areas around the driver to black. This background elimination reduces the subsequent errors due to false object detection in the background. The face is detected by finding the biggest white connected component and then cutting that area.

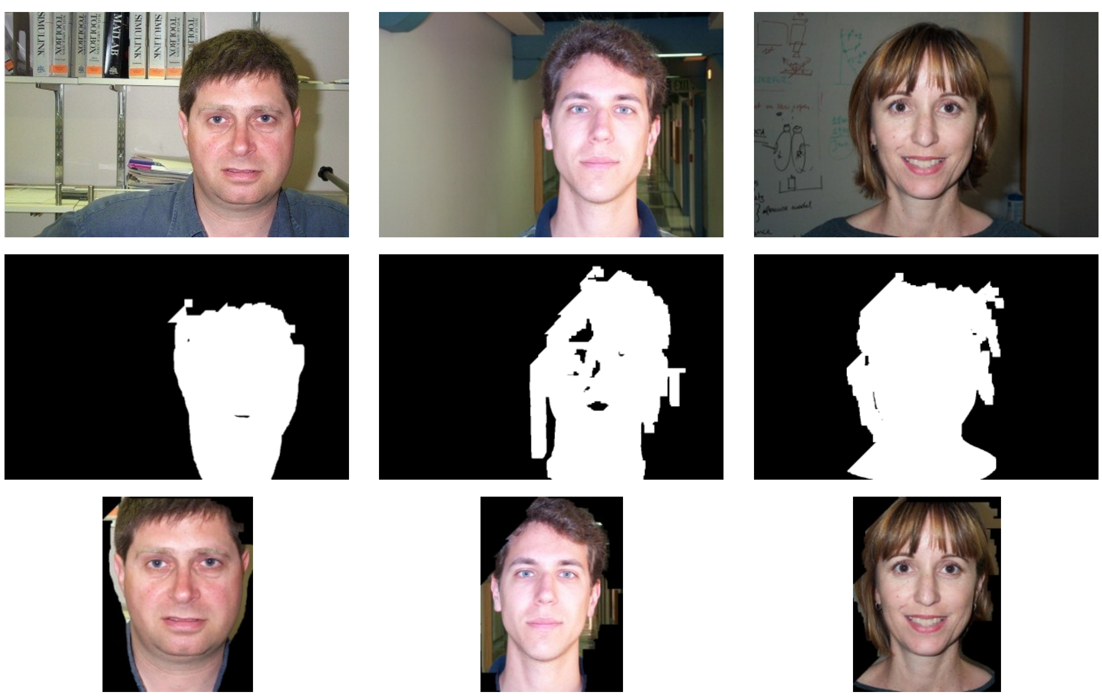


Figure 17 – Skin Detection

After finding the face area, the eye will be located in the upper half of the face. The eye map formula will be applied on the face region and it will highlight the eyes' regions. Then, the eye map image is converted to a black and white image using proper thresholding. This new image is supposed to include the eyes in white while the rest is all black. However, several pre-processing steps including erosion, dilation and finding the biggest connected components as eyes are required. Moreover, some geometrical features of the eyes will be used in the final step to reject the false detections. Therefore, the geometrical features are not used for detection and they will be used only for verification purposes. Figure 18 shows the result of the discussed technique for detecting eye location.

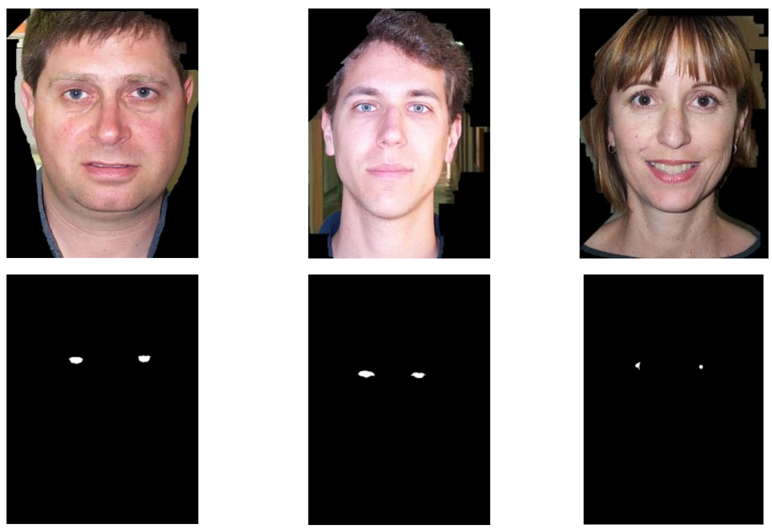


Figure 18 – Eye Detection by Applying Eye-Map

The next step is mouth detection based on the location of the eyes and considering the lower half of the face. After applying the mouth map formula, which is discussed in section 3.1.3, the result will then go through some post processing steps, such as black and white conversion, erosion, dilation and finding the biggest connected components in the same way as the eye detection scheme. The geometrical features of the face and relative location of the mouth with respect to the eyes can be exploited in this step to verify the validity of the detected mouth. The result of the mouth map algorithm after applying the pre-processing steps is shown in Figure 19.

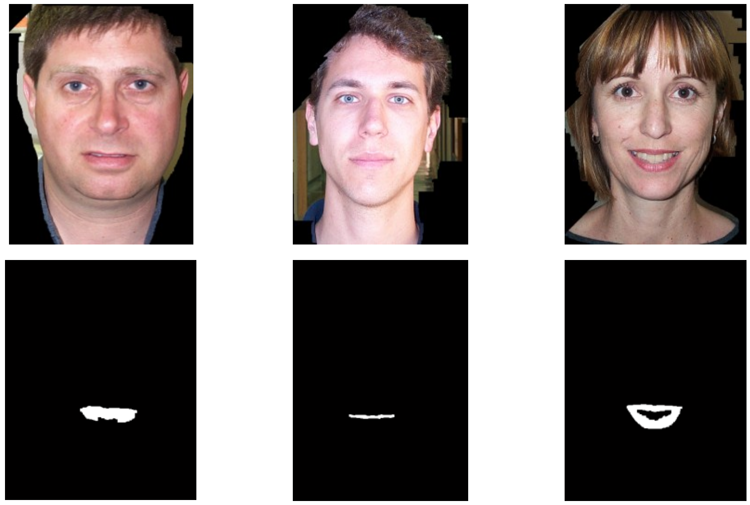


Figure 19 – Mouth Detection by Applying Mouth_Map

After locating the mouth region, the next step is to determine whether the condition of the mouth is yawning, talking or normal. As has already been discussed, the white area in the black background shows the mouth area and the form of the mouth. As the white area getting larger it means the mouth is changing into the yawning position. The verification criteria is the number of pixels located in the yawning mouth with respect to the number of mouth pixels as well as the relative location of the open mouth with respect to the lips. Therefore, if the driver is yawning, his/her mouth will be widely open so the area of the white pixels will be increased. In this case, by counting the number of white pixels compared to the number of the white pixels in the closed mouth position and also by determining the ratio of the width and height of the white area, the condition of the mouth will be determined. The result of the normal and yawning mouth condition is shown in Figure 20.

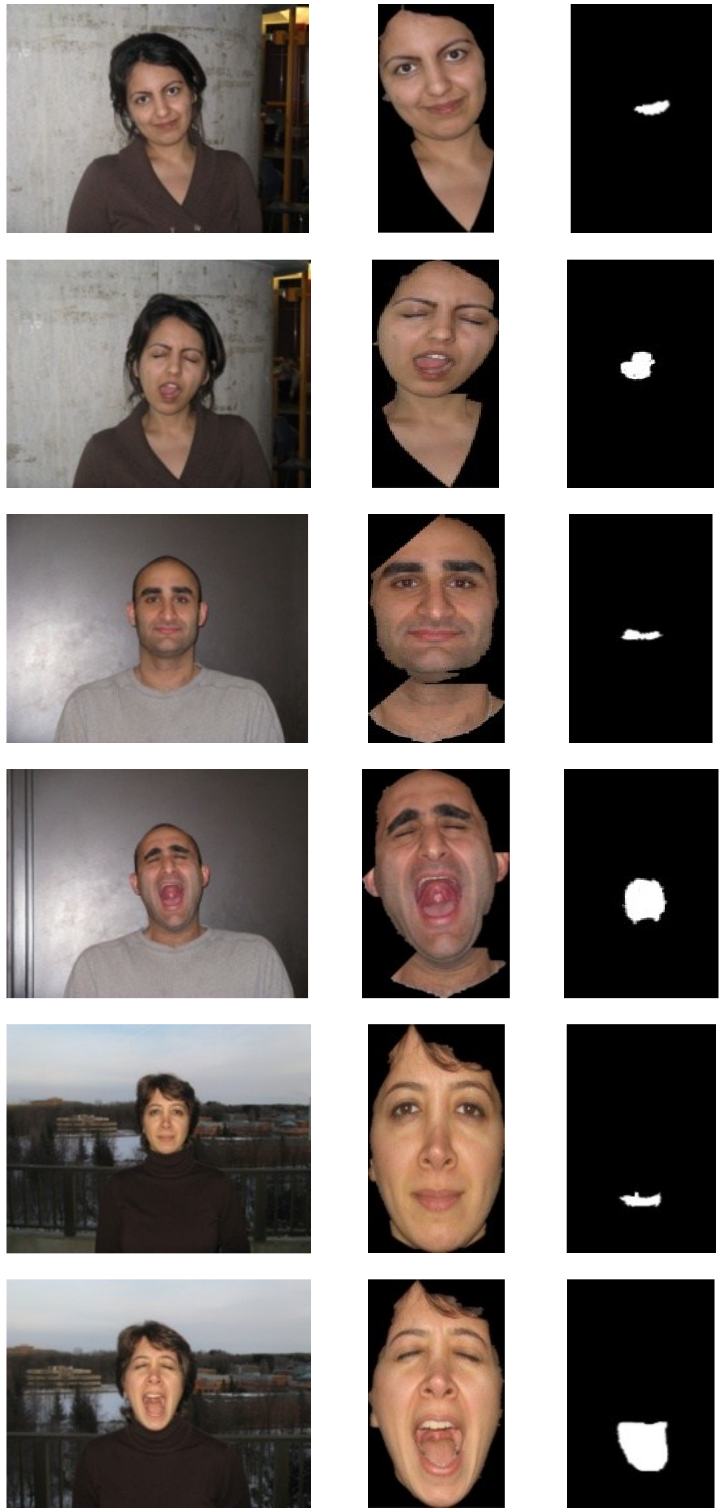


Figure 20 – Yawn Detection

Color information is an effective tool for recognizing facial areas and specific facial features if the skin color model can be accurately modified for different lighting environments. However, such skin color models are not adequately suitable where the spectrum of the light source differs significantly. In other words, color appearance is frequently not stable due to changes in both background and foreground lighting [49].

5.2 Snake Contour Model

In the second method, for determining the yawning condition, the active contour model will be applied on the mouth area. As is discussed in section 3.2.3 for locating the exact face area, the template matching process with the template face profile is required. In order to find the face profile, a Daubechies wavelet will be applied to random faces. Then, the vertical and horizontal wavelet coefficient will be used instead of the original image. Figure 21 shows the result of applying the wavelet to a number of images in a face database.

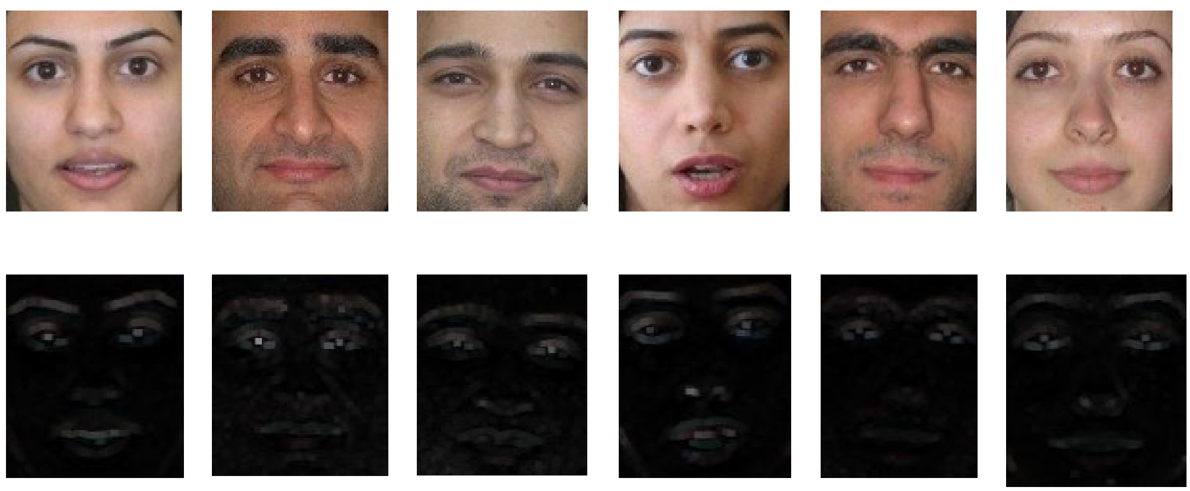


Figure 21 – Level 1 Daubechies Wavelet Transform

As is shown in Figure 21, the edges in the face profile are well detected and the noise level in this case is quite low. Therefore, the template matching will be a suitable technique for this method. The next step is to apply the mouth map formula, which was defined in section 3.1.3 on the selected faces. As a result, the middle column of Figure 22 for each face condition will be found.

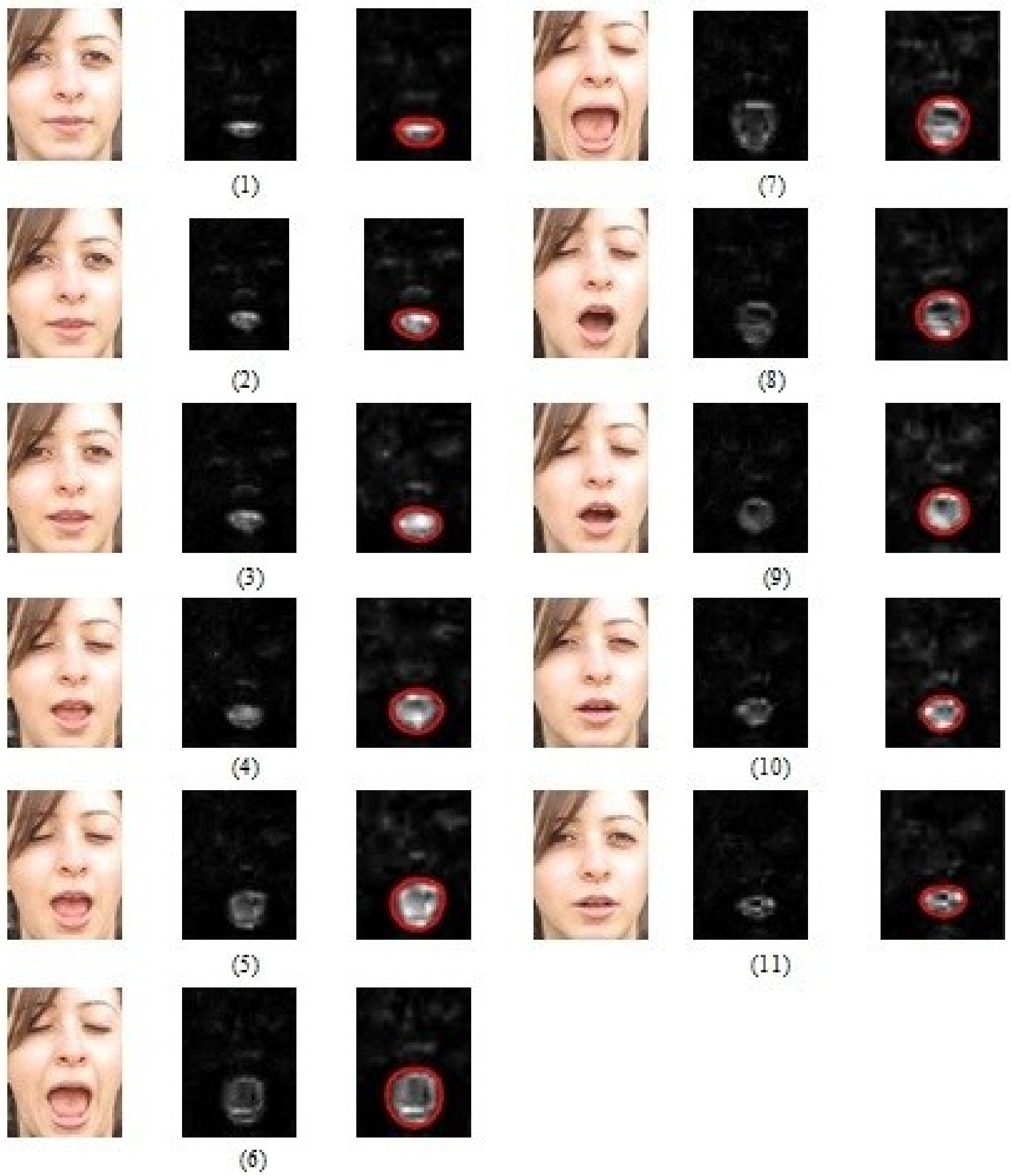


Figure 22 – Sequence of mouth contours in yawning

The faces in the random frame sequence of a video are shown in Figure 22. By using the active contour model on the mouth map, the shape of the mouth is highlighted in red. As the pattern of the mouth is getting wider in the yawning situation, the snake contour model is getting the shape of the mouth. The area in the snake contour will be computed in each frame to analyze the difference between each frame to the previous one to determine whether yawning has happened or not. If the snake follows the pattern of the yawning in a specific number of video frames

(200–400 frames), the system will alert the driver to stop driving. But this system is not able to adjust the snake when the mouth is getting narrower at the end of the yawning process therefore, this method is not suitable enough to alert the driver in the right situation. The problems about this method are the usage of color segmentation and also the low ability of snake contour model to get the shape of the mouth when it is getting narrower.

The first two methods were not sufficiently reliable since most parts of these methods are based on the usage of the color properties, which do not suffice for face and facial detection. The lighting illumination and background color have a great effect on the result of face, mouth and eye detection since they are based only on color segmentation. Therefore, the result of yawning conditions is not appropriate and accurate.

5.3 Viola-Jones Method

Compared to the other methods, the last method in this project is the most robust and accurate. The real time face and mouth detection technique is based on the Viola-Jones theory. Since this method is based on the AdaBoost algorithm and uses sets of cascades of classifiers that were already trained with a large number of faces and mouths, the result of this approach is vigorous. The AdaBoost face detection algorithm finds faces in a rapid and robust manner while the detection rate is high. The face detector is trained such that it is able to distinguish faces that are tilted up to about ±45 degrees out of plane (towards a profile view) and to about ±15 degrees in plane. However, it becomes unreliable with rotation greater than this. Figure 23 shows the result of the face and mouth detection algorithm in different driving scenarios with the camera connected to the mirror and also on the dash of the car. Therefore, both frontal faces and faces with an angle less than 45 degrees are tested. The videos of male and female drivers with different facial properties were used and the face detection results for all participants were acceptable.

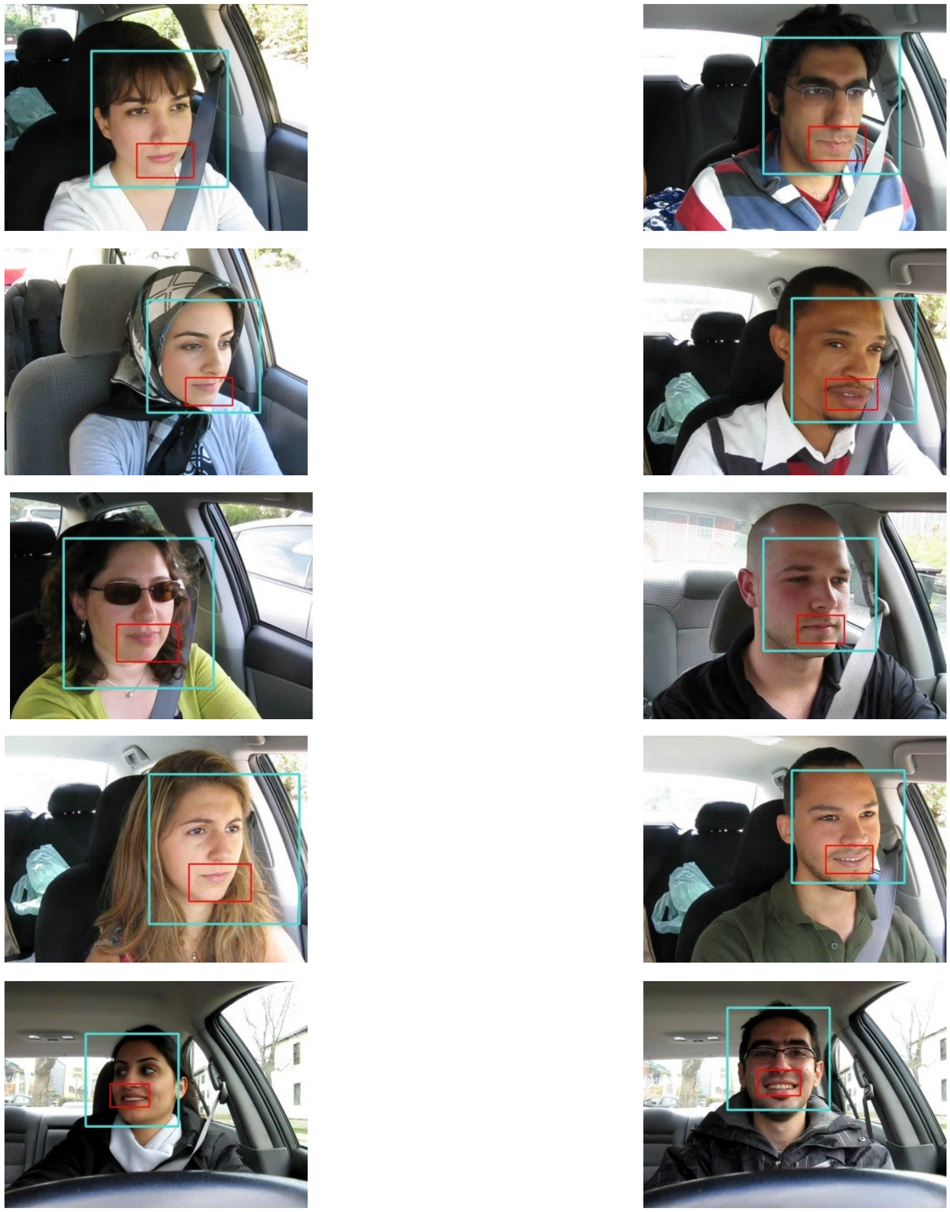


Figure 23 – Face and Mouth Detection by Viola-Jones Theory

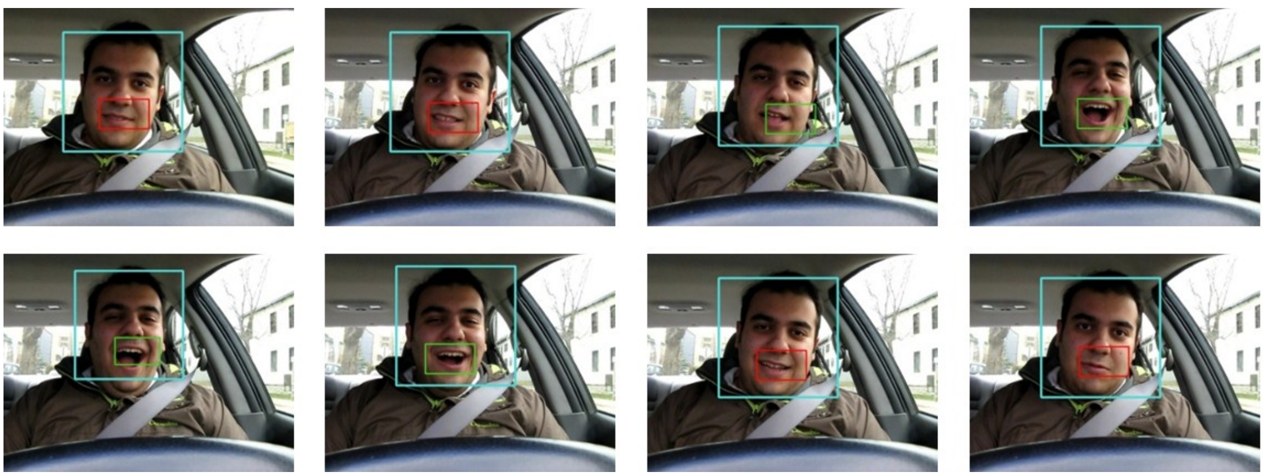
Method three based on the Viola-Jones theory works perfectly on the videos that were taken for this purpose.

This method was tested on both, PC and APEX board. On the PC, our results showed that for the videos where the camera is installed under the front mirror, the successful rate of detecting the face is about 85%, but the rate of detecting the mouth and subsequent yawning is about 40% due to the angle of the drivers' face to the camera. For the videos where the camera is installed on the dash, the face and mouth region are detected correctly and in real-time; and the success rate of detecting yawning is 95%, since the camera captures a frontal view of the drivers' face, making detection easier. The mouth detection in this scenario is 85% and the yawning detection is 60%. The result from this method is shown in figure 23.

On the APEX board, we only tested the real time demo where the camera is installed on table. The success rate of face detection in this case was 90%, although the frame rate was not fixed as it depends on the number of iterations required to locate the face, and that varies depending on the location of the face in the frame, distance to camera and face size. On average, the speed of detection for both face and mouth was 2-3 fps which is enough for yawning detection purposes. The speed of tracking was much higher, over 20 fps, although it was less reliable than detection, and during tracking the system needed to fall back to detection a lot more on APEX than on the PC. The result of the yawning detection accuracy is determined by calculating the percentage of changing the color of the frames around the mouth from red to green as the participant is yawning. Overall, the average success rate for yawning detection was 80% on APEX.

This experiment was also presented as a demo in the conference; therefore, besides the collected dataset videos, it was performed on different people who attended the conference in real time as they sat in front of the camera and pretended they were tired.

(a) Camera installed under the front mirror



(b) Camera installed on the dash

Figure 24 – Yawning Detection in Sequence of Video Frame

As is shown in figure 24, the face region is boxed in blue, while the mouth region is boxed in red. When the system determines the mouth to be in the yawning position, the area around the mouth is turned to green. Therefore, by counting the number of green boxes, the system is able to determine whether the driver is yawning or not. The implemented yawning detection system is fast in detection and also reliable and accurate in determining the driver's tiredness based on counting the number of yawns in a short period of time. When the system detects more than 4 yawns in 30 minutes, the driver will hear the alarm sound.

Before transferring the new simplified and modified codes on the APEX board, it was tested on two sets of dataset and compared with OpenCV face and mouth detection. Tables 1 and table 2 show the results of face detection, mouth detection and yawning detection in modified codes. Table 1 is based on running the code for 10 participant's video, 5 female and 5 male, in the scenario of the camera installation on the mirror.

Individual	Video type	Face Detection accuracy	Mouth Detection accuracy	Yawning Detection accuracy
Male 1	Normal	98%	92%	
	Talking/singing	100%	70%	
	Yawning	95%	75%	30%
Female 1	Normal	100%	100%	
	Talking/singing	100%	89%	
	Yawning	100%	90%	20%
Male 2	Normal	100%	82%	
	Talking/singing	100%	75%	
	Yawning	90%	80%	30%
Female 2	Normal	92%	90%	
	Talking/singing	76%	70%	
	Yawning	68%	40%	72%
Male 3	Normal	87%	80%	
	Talking/singing	95%	78%	
	Yawning	100%	70%	0%
Female 3	Normal	90%	85%	
	Talking/singing	78%	60%	
	Yawning	100%	80%	60%
Male 4	Normal	90%	70%	
	Talking/singing	80%	40%	
	Yawning	90%	32%	0%
Female 4	Normal	100%	100%	
	Talking/singing	95%	85%	
	Yawning	100%	90%	10%
Male 5	Normal	100%	10%	
	Talking/singing	45%	0%	
	Yawning	20%	0%	0%
Female 5	Normal	95%	20%	
	Talking/singing	90%	45%	
	Yawning	100%	58%	0%

Table 1 – Camera installed on the mirror

The results of the Viola-Jones method are more accurate in the case where the camera is installed on the dash of the car and recording the driver's face from the frontal view. Table 2 shows the results for 20 participant's video, 10 female and 10 male.Individual	Video type	Face Detection	Mouth Detection	Yawning Detection
		accuracy	accuracy	accuracy
Male 1	Normal/ Talking/ Yawning	100%	98%	90%
Female 1	Normal/ Talking/ Yawning	100%	85%	92%
Male 2	Normal/ Talking/ Yawning	100%	88%	70%
Female 2	Normal/ Talking/ Yawning	100%	70%	88%
Male 3	Normal/ Talking/ Yawning	100%	85%	95%
Female 3	Normal/ Talking/ Yawning	90%	55%	0%
Male 4	Normal/ Talking/ Yawning	80%	40%	45%
Female 4	Normal/ Talking/ Yawning	100%	87%	80%
Male 5	Normal/ Talking/ Yawning	82%	70%	80%
Female 5	Normal/	90%	75%	65%

	Talking/ Yawning			
Male 6	Normal/ Talking/ Yawning	100%	95%	30%
Female 6	Normal/ Talking/ Yawning	100%	70%	68%
Male 7	Normal/ Talking/ Yawning	70%	65%	0%
Female 7	Normal/ Talking/ Yawning	100%	95%	70%
Male 8	Normal/ Talking/ Yawning	100%	75%	50%
Female 8	Normal/ Talking/ Yawning	80%	78%	70%
Male 9	Normal/ Talking/ Yawning	80%	80%	50%
Female 9	Normal/ Talking/ Yawning	95%	80%	90%
Male 10	Normal/ Talking/ Yawning	98%	70%	60%
Female 10	Normal/ Talking/ Yawning	100%	95%	30%

Table 2 - Camera installed on the dash

Chapter 6 - Conclusion and Future Work

The experimental results were shown and discussed in the previous chapter. In this chapter, the conclusions of the results, as well as recommendations for future work, are given.

6.1 Conclusion

This research analyzed three methods for detection of driver drowsiness, based on yawing action. In the first and second methods, finding the driver's face and mouth were dependent on color segmentation under different illumination conditions. Skin color information was used to detect a person's face in an image since human faces have a special color distribution. For mouth detection, the lip color was the focus of the system's detection process because the color red is held as the strongest component. However, this approach has two major problems: 1) in the case of having too bright or too dark illumination, the system fails in skin or lip color detection and 2) when the background has similar color distribution to the skin color, the system is not able to identify the differences. In the second methods besides the two mentioned problems, the active contour model was not suitable enough for yawning detection since it was not able to adjust itself with the mouth shape in most cases. In the situation when the system fails to detect face location, the mouth detection will fail accordingly since the system will search for the mouth location in the face region candidate. Due to these problems, a third method was introduced, which is based on the Viola-Jones theory. This method utilizes the face and mouth features in OpenCV xml files. For yawning detection, the back projection technique was performed. The results from this method have high accuracy and reliability, therefore, the algorithm was transferred to the CogniVue APEX board. The demonstration platform uses a small camera, which is the same as the camera that should be installed under the front mirror of a car in a practical scenario. The output of the camera will be processed in the embedded platform and the results of face and mouth tracking as well as yawning alert signal can be seen on the monitor that is connected to the system. To make the system work without a computer and only on a computationally limited embedded platform, much effort has been made in designing and optimizing algorithms and codes in order for them to work in real time and without requiring advanced hardware platforms.

6.2 Future Work

The presented technique of detecting drivers' drowsiness based on their yawning had various limitations, which may be addressed as future work. The following recommendations have been made for future research on the detection of driver's drowsiness:

- According to the statistical report from NHTSA, in general, far fewer drowsiness related baseline epochs were recognized during the daylight hours while a greater number were observed during darkness; therefore, having a hybrid system that uses data from both the infrared and visible range will be more useful and necessary.
- As having access to a database of thousands of yawning faces is not quite possible, the particular approach that is not based on classifiers is used to adapt the face detection system in this research. Due to the analysis of different methods, it is shown that when the system is trained based on a large number of samples, it will be more accurate. Therefore, training the yawning detection algorithm will be appropriate.

- In order to have the option of installing the camera on either the dash of the car or on the front mirror and also get the good results in both cases, re-training the Viola-Jones theory for these two dataset will be useful.
- Some drivers cover their mouth while yawning or they have different signs of sleepiness like eye closure or falling head; in this case, future work may consist of combining the detection of different fatigue signs.
- The algorithm was tested under two different conditions. 1) In the computer: on the collection of dataset videos, which was taken in the parked cars as is described in section 4, in the stable lighting condition and with a Canon A720Is digital camera. 2) On the APEX board: in this situation, the board with the camera attached to it was located in the lab under controlled lightning conditions. For future work, it would be better for the system to be tested with the APEX board in the real driving scenario in different lighting conditions to reduce the false detection error in the real time condition.
- In the yawning condition, the rectangle around the candidate mouth changes from red to green in the computer based condition; in the car scenario, the alarm system must alert the driver to wake him or her up in the case of having a few numbers of yawning condition in the short period of time.

Chapter 7 - References

[1] J.D.Lee, "Fifty years of driving safety research," *Human Factors:The journal of the Human Factors and Ergonomics Society,* vol. 50, no. 3, pp. 521-528, 2008.

[2] S. Klauer, T. Dingus, V. Neale, J. Sudweeks and J. Ramsey, "The impact of driver inattention on near-crash/crsh risk: An analysis using 100-car naturalistic driving study data," Springfield, Virginia, 2006.

[3] O. Tunçer, L. Güvenç, F. Coşkun and E. Karslıgil, "Vision based lane keeping assistance control triggered by a driver inattention monitor," in *IEEE International Conference on Systems Man and Cybernetics (SMC)*, Istanbul, 10-13 Oct. 2010.

[4] W. Qiong, Y. Jingyu, R. Mingwu and Z. Yujie, "Driver Fatigue Detection: A Survey," *The Sixth World Congress on Intelligent Control and Automation,* vol. 2, pp. 8587-8591, 2006.

[5] T. Pilutti and A. Ulsoy, "Identification of driver state for lane-keeping tasks," *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans,* vol. 29, no. 5, pp. 486-502, 1999.

[6] A. Picot, S. Charbonnier and A. Caplier, "On-Line Detection of Drowsiness Using Brain and Visual Information," *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans,* no. 99, pp. 1-12, 2011.

[7] G. Furman, A. Baharav, C. Cahan and S. Akselrod, "Early detection of falling asleep at the wheel: A Heart Rate Variability approach," *Computers in Cardiology,* pp. 1109-1112, 2008.

[8] S. Hu and R. Bowlds, "Pulse wave sensor for non-intrusive driver's drowsiness detection," in *Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE*, Minneapolis, MN, 2009.

[9] K. Hayashi, K. Ishihara, H. Hashimoto and K. Oguri, "Individualized drowsiness detection during driving by pulse wave analysis with neural network," in *Proceedings of the 8th International IEEE Conference on Intelligent Transportation Systems*, Austria , 2005.

[10] G. Yang and T. Huang, "Human Face Detection in Complex," *Pattern Recognition,* vol. 27, no. 1, pp. 53-63, 1994.

[11] K. Yow and R. Cipolla, "Feature-Based Human Face Detection," *Image and Vision Computing,* vol. 15, no. 9, pp. 713-735, 1997.

[12] T. Leung, M. Burl and P. Perona, "Finding Faces in Cluttered Scenes Using Random Labeled Graph Matching," in *Proc. Fifth IEEE Int'l Conf. Computer Vision*, Cambridge, MA, 1995.

[13] S. Sirohey, "Human Face Segmentation and Identification," in *Technical Report CS-TR-3176*, Maryland, 1993.

[14] H. Graf, T. Chen, E. Petajan and E. Cosatto, "Locating Faces and Facial Parts," in *Proc. First Int'l Workshop Automatic Face and Gesture Recogniction*, 1995.

[15] C. Han, H. Liao, K. Yu and L. Chen, "Fast Face Detection via Morphology-Based Pre-Processing," in *Proc. Ninth Int'l Conf. Image Analysis and Processing*, 1998.

[16] Y. Dai and Y. Nakano, "Face-Texture Model Based on SGLD and Its Application in Face Detection in a Color Scene," *Pattern Recognition,* vol. 29, no. 6, pp. 1007-1017, 1996.

[17] R. Kjeldsen and J. Kender, "Finding Skin in Color Images," in *Proc. Second Int'l Conf. Automatic Face and Gesture Recognition*, 1996.

[18] S. McKenna, S. Gong and Y. Raja, "Modelling Facial Colour and Identity with Gaussian Mixtures," *Pattern Recognition,* vol. 31, no. 12, pp. 1883-1892, 1998.

[19] Y. Ying, S. Jing and Z. Wei, "The Monitoring Method of Driver's Fatigue Based on neural network," in *International Conference on Mechatronics and Automation, 2007*, Harbin, 2007.

[20] D. Saxe and R. Foulds, "Towards Robust Skin Identification in Video Images," in *Proc. Second Int'l Conf. Automatic Face and Gesture Recognition*, 1996.

[21] I. Craw, D. Tock and A. Bennett, "Finding Face Features," in *Proc. Second European Conf. Computer Vision*, 1992.

[22] A. Lanitis, C. Taylor and T. Cootes, "An Automatic Face Identification System Using Flexible Appearance Models," *Image and Vision Computing,* vol. 13, no. 5, pp. 393-401, 1995.

[23] I. Craw, H. Ellis and J. Lishman, "Automatic Extraction of Face Features," *Pattern*

Recognition Letters, vol. 5, pp. 183-187, 1987.

[24] A. Samal and P. Iyengar, "Human Face Detection Using Silhouettes," *Int'l J. Pattern Recognition and Artificial Intelligence,* vol. 9, no. 6, pp. 845-867, 1995.

[25] C. Tsai, W. Cheng, J. Taur and C. Tao, "Face Detection Using Eigenface and neural network," in *IEEE International Conference on Systems, Man and Cybernetics*, Taipei , 2006.

[26] X. Liu, G. Geng and X. Wang, "Automatically face detection based on BP neural network and Bayesian decision," in *Sixth International Conference on Natural Computation (ICNC)*, Yantai, Shandong, 2010.

[27] C. Shavers, R. Li and G. Lebby, "An SVM-based approach to face detection," in *Proceeding of the Thirty-Eighth Southeastern Symposium on System Theory*, Cookeville, TN , 2006.

[28] S. El-Khamy, O. Abdel-Alim and M. Saii, "Neural network face recognition using statistical feature extraction," in *Seventeenth National Radio Science Conference*, Minufiya , Egypt , 2000.

[29] J. Ruan and J. Yin, "Face Detection Based on Facial Features and Linear Support Vector Machines," in *International Conference on Communication Software and Networks*, Macau, 2009.

[30] P. Viola and M. Jones, "Rapid Object Detection Using a Boosted Cascade of Simple Features," in *IEEE Computer Society Conference on Computer Vision and Pattern*

Recognition, 2001.

[31] C. Erdem, S. Ulukaya, A. Karaali and A. Erdem, "Combining Haar Feature and skin color based classifiers for face detection," in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2011.

[32] P. Viola and M. Jones, "Robust real-time face detection," *International Journal of Computer Vision ,* vol. 57, no. 2, pp. 137-154, 2001.

[33] M. Sigari, "Driver Hypo-vigilance Detection Based on Eyelid Behavior," in *Seventh International Conference on Advances in Pattern Recognition*, 2009.

[34] D. Liu, P. Sun, Y. Xiao and Y. Yin, "Drowsiness Detection Based on Eyelid Movement," in *2010 Second International Workshop on Education Technology and Computer Science (ETCS)*, 2010.

[35] M. Omidyeganeh, A. Javadtalab and S. Shirmohammadi, "Intelligent driver drowsiness detection through fusion of yawning and eye closure," in *IEEE International Conference on Virtual Environments Human-Computer Interfaces and Measurement Systems (VECIMS)*, 2011.

[36] P. Tabrizi and R. Zoroofi, "Open/Closed Eye Analysis for Drowsiness Detection," in *First Workshops on Image Processing Theory, Tools and Applications*, 2008.

[37] S. Arimitsu, K. Sasaki, H. Hosaka, M. Itoh, K. Ishida and A. Ito, "Seat Belt Vibration as a Stimulating Device for Awakening Drivers," *IEEE/ASME Transactions on Mechatronics,* vol. 12, no. 5, pp. 511-518, 2007.

[38] T. Azim, M. Jaffar and A. Mirza, "Automatic Fatigue Detection of Drivers through Pupil Detection and Yawning Analysis," in *Fourth International Conference on Innovative Computing, Information and Control* , 2009.

[39] L. Yufeng and Z. Wang, "Detecting Driver Yawning in Successive Images," in *The 1st International Conference on Bioinformatics and Biomedical Engineering*, 2007.

[40] M. Saradadevi and P. Bajaj, "Driver Fatigue Detection Using Mouth and Yawning Analysis," *IJCSNS International Journal of Computer Science and Network Security,* vol. 8, no. 6, pp. 183-188, June 2008.

[41] Y. Yang, J. Sheng and W. Zhou, "The Monitoring Method of Driver's Fatigue Based on neural network," in *International Conference on Mechatronics and Automation, 2007. ICMA 2007*, 2007.

[42] T. Wang and P. Shi, "Yawning detection for determining driver drowsiness," in *Proceedings of 2005 IEEE International Workshop on VLSI Design and Video Technology*, 2005.

[43] L. Li, Z. Li and Y. Chen, "Yawning detection for monitoring driver fatigue based on two cameras," in *12th International IEEE Conference on Intelligent Transportation Systems*, 2009.

[44] X. Fan, B. Yin and Y. Sun, "Yawning Detection for Monitoring Driver Fatigue," in *International Conference on Machine Learning and Cybernetics*, 2007.

[45] R. Jimenez, F. Prieto and V. Grisales, "Detection of the Tiredness Level of Drivers Using

Machine Vision Techniques," in *Electronics, Robotics and Automotive Mechanics Conference* , 2011.

[46] W. Rongben, G. Lie, T. Bingliang and J. Lisheng, "Monitoring Mouth Movement for Driver Fatigue or Distraction with One Camera," in *Proceedings The 7th International IEEE Conference on Intelligent Transportation Systems*, 2004.

[47] N. Alioua, A. Amine, M. Rziza and D. Aboutajdine, "FAST MICROSLEEP AND YAWNING DETECTIONS TO ASSESS," in *PROCEEDINGS of the Sixth International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design*.

[48] N. Narole and P. Bajaj, "A Neuro-Genetic System Design for Monitoring Driver's Fatigue: A Design Approach," in *First International Conference on Emerging Trends in Engineering and Technology, 2008. ICETET '08.* , 2008.

[49] M. Yang , D. Kriegman and N. Ahuja, "Detecting faces in images: A survey," *IEEE Trans. Pattern Analysis and Machine Intelligence,* vol. 24, no. 1, pp. 34-58, 2002.

[50] N. Rahman, K. Wei and J. See, "RGB-H-CbCr Skin Colour Model for Human Face Detection," in *In Proceedings of The MMU International Symposium on Information & Communications Technologies*, 2006.

[51] H. Rein-Lein, M. Abdel-Mottaleb and A. Jain, "Face detection in color images," *IEEE Trans. Pattern Analysis and Mechine Intelligence,* vol. 24, no. 5, 2002.

[52] C. Chen, "Information Fusion of wavelet projection features for face recognition," in *In: Proc. International Joint Conf. on Neaural Network*, Hong Kong, 2008.

[53] W. Miao-miao and L. Zhen, "Eyes detection based on One-Dimensional Wavelet Transform," in *International Symposium on Computational Intelligence and Design*, Hangzhou, 2010.

[54] M. Barnard, E. Holden and R. Ownes, "Lip tracking using pattern matching snakes," in *2002*, Melbourne, Australia, The 5th Asian conference on Computer Vision.

[55] G. Chiou and J. Hwang, "Lipreading from color video," *IEEE Transactions on Image Processing,* vol. 6, no. 8, pp. 1192-1195, 1997.

Appendix A –

XML Code for Stage 0 of Cascade

- 1- <size>20 20</size>
- 2- <stages>
- 3- <_>
- 4- <!-- **stage 0** -->
- 5- <trees>
- 6- <_>
- 7- <!-- tree 0 -->
- 8- <_>
- 9- <!-- root node -->
- 10- <feature>
- 11- <rects>
- 12- <_>3 7 14 4 -1.</_>
- 13- <_>3 9 14 2 2.</_></rects>
- 14- <tilted>0</tilted></feature>
- 15- <threshold>4.0141958743333817e-003</threshold>
- 16- <left_val>0.0337941907346249</left_val>
- 17- <right_val>0.8378106951713562</right_val></_></_>
- 18- <!-- tree 1 -->
- 19- <_>
- 20- <!-- root node -->
- 21- <feature>
- 22- <rects>

- 23- <_>1 2 18 4 -1.</_>
- 24- <_>7 2 6 4 3.</_></rects>
- 25- <tilted>0</tilted></feature>
- 26- <threshold>0.0151513395830989</threshold>
- 27- <left_val>0.1514132022857666</left_val>
- 28- <right_val>0.7488812208175659</right_val></_></_>
- 29- <_>
- 30- <!-- tree 2 -->
- 31- <_>
- 32- <!-- root node -->
- 33- <feature>
- 34- <rects>
- 35- <_>1 7 15 9 -1.</_>
- 36- <_>1 10 15 3 3.</_></rects>
- 37- <tilted>0</tilted></feature>
- 38- <threshold>4.2109931819140911e-003</threshold>
- 39- <left_val>0.0900492817163467</left_val>
- 40- <right_val>0.6374819874763489</right_val></_></_></trees>
- 41- <stage_threshold>0.8226894140243530</stage_threshold>
- 42- <parent>1</parent>
- 43- <next>-1</next></_>

Appendix B –

Informed Consent Form

This research project is being conducted by the research group of Professor Shervin Shirmohammadi at the School of Information Technology and Engineering of the University of Ottawa.

Purpose: This informed consent form is to make sure that you understand the nature of your involvement in this study, and to obtain your informed consent to participate in this study.

Procedure: You will be asked to sit in the driver's seat of a parked car. Three different videos have to be taken from the frontal view of your face in conditions of yawning, talking, and normal closed mouth. The entire recording session will last about 5 minutes.

Withdrawing from the study: Your participation in this study is voluntary. You may withdraw from the study at any time, by verbally informing the investigator or any of the researchers, even after signing the form. There will be no consequences following this action.

Compensation: You will not receive monetary compensation for this study.

Disclosure: You agree for the above-mentioned videos captured of you to be made available to researchers, from all over the world, for research and further study, on publically-accessible websites and for non-commercial purposes.

Confidentiality: Other than the above "Disclosure", all other information about you collected during the study will be kept strictly confidential. Your name will not be associated with the collected data in any way. The data collection will be conducted by Dr. Shirmohammadi, his graduate students, or research fellows, or his research assistant.

In closing: With your participation, you will be given a copy of this consent form. At the conclusion of the study, should you wish, you will be provided with a summary of the results. You may ask questions at any time, even after signing this consent form.

Signatures: I have read the above description of the study and understand the conditions of participation. My signature indicates that I agree to participate in the study.

Name of participant (please print name here):
____

Participant's Signature:
________________________________ **Date:**

Researcher's Signature:
_________________________________ **Date:**