A Driver Fatigue Monitoring and Haptic Jacket-Based Warning System

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Abstract

Driver fatigue is a major factor in most traffic accidents. This issue has increased the urgency for in-vehicle collision avoidance systems relying on proper driver fatigue detection and warning technologies. Computer vision approaches have been of much interest due to their non-invasive nature for detecting drowsiness. In addition, increased effort has been dedicated to the design of safety systems that warn drivers of various types of collisions. How these systems alert the sleepy drivers when integrated, however, is a crucial component to their effectiveness. A nonintrusive method is proposed in this thesis as a feasible solution to accurately detect fatigue levels and perfectly produce timely warnings. Fatigue progression over time is quantified to more accurate fatigue levels according to reliable PERCLOS measurements in a continuous LBP + SVM based eye state recognition process. Given the quantized fatigue levels, a novel haptic jacket-based alerting scheme is provided to safely convey varying criticality signals. Drivers would have the option to customize haptic jacket settings for the preferred type of feedback perception. This thesis reviews existing approaches, details the proposed system, and finally presents system performance evaluation and usability studies.

Dedicated to my husband Navid

and my parents

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Chapter 1 - Introduction

1.1 Background and Motivation

Driving is a process that involves situation awareness of the environment, decision making, and the performance of actions. In this process, the most complicated stage is the situation awareness. In a complex and dynamic driving environment, attention demands result from information overload, complex decision making and the performance of multiple tasks. Direct attention is needed not only to perceive and process the available cues but in the later stages of decision making and reaction as well. On the other hand, sleep is an active state of the brain and is involuntary. A renowned sleep scientist, Allan Hobson [1], phrases the central role of the brain in sleep (by rephrasing Abraham Lincoln's famous declaration about government): *sleep is of the brain, by the brain, and for the brain*. The brain controls itself so as to produce sleep. We can fall asleep and never even recognize how difficult we try to stay awake or to sleep. We may be able to try not to sleep or to sleep long, but it does not belong to our free-will, to govern sleep or wakefulness. The brain's own electrical activity changes in response to signals from networks of brain cells.

Driving and sleepiness form an incompatible and dangerous combination. **Fatigued driving** refers to "being unintended to perform driving task at hand". During long periods of driving or as a result of driver's initial conditions, motivation for steering declines, reaction time extends, short-term memory deteriorates, attention drops, important signals are ignored, and decision errors and short-term failures of memory occurs. In extreme case, a microsleep as a short period in which driver loses consciousness comes on which can have fatal consequences. However, facing with work-related and personal responsibilities, countless people are cutting back on sleep and hence driving drowsy or fatigued.

How fatigue progresses over time could be a useful knowledge for development of fatigue recognition systems. Many studies have shown that driver fatigue happens periodically instead of linearly increase. In fact, with a general tendency towards increased fatigue, there are time intervals during which drivers struggle with fatigue causing their alertness decrease [2]. The process of falling asleep at the wheel in a fatigue episode could be characterized by gradual decline in alertness from a normal state leading to a state of fuzzy consciousness followed by the onset of sleep. Figure 1 displays fatigue progression over time while driving until approaching the sleep onset.

Figure 1: The process of falling asleep at the wheel

1.1.1 Cause and Type of Experienced Fatigue

The European Transport Safety Council (ETSC) study [3] shows that the level of fatigue or sleepiness (sleepiness is the outside exhibition of fatigue) is a function of the amount of activity in relation to the brain’s physiological waking capacity. Several factors can influence this physiological waking capacity and, hence, lower the fatigue threshold. The main causes of fatigue are described as:

- Sleep debt or poor sleep,
- Internal body clock (circadian rhythm), and
- Time-on-task (long working hours).

These factors have cumulative effects and a combination of any of these can greatly increase the risk of fatigued-related crashes.

1.1.1.1 Sleep Debt

Sleep debt is the accumulated lack of sleep resulting from poor sleep habits. Even the loss of one hour of sleep time for several days can negatively influence our daily life. Sleep deprivation slows driver's reaction time to sudden driving conditions happening on the road. A questionnaire study participated by 154 truck drivers for evaluating the relationship between prior sleep, work, individual characteristics and drowsiness found out that the prior sleep effects contributed the most to sleepiness while driving [4].

1.1.1.2 Circadian Rhythm

Fatigue is linked to the circadian rhythm acting as an internal biological clock and controlling normal sleep/wake cycles. Therefore, it has a direct effect on alertness, mood, motivation, and performance. The human body has a greater need for sleep at certain times in the 24 – hour cycle. First peak occurs in the middle of night sleep (most commonly at night between 2 – 4 am) and second sleepiness peak occurs during mid-afternoon, in 12 hours after the first sleepiness peak. People driving during these hours are at an increased risk of driver fatigue.

1.1.1.3 Time on Task

Prolonged activity inevitably leads to physical and mental fatigue. Researchers have related the duration of activity, or the so called time-on-task, to fatigue symptoms. Studies show that after just four hours of non-stop driving, drivers' reaction times can slow up to 50 percent, so the risk of crashes doubles during this time and the risk increases more than eight-fold after just six hours of non-stop driving. Figure 2 displays the percent of fatigue driving crashes and its relationship with number of hours driven [5].

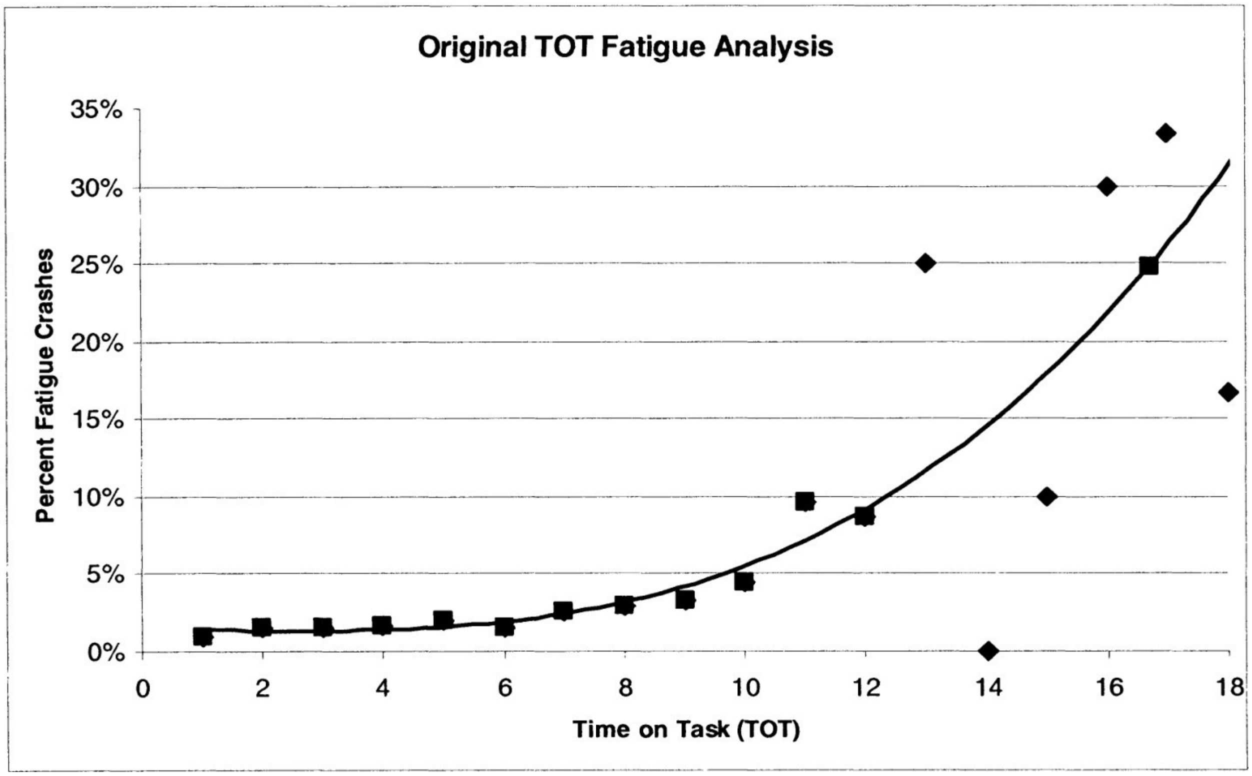


Figure 2: Relationship between number of hours driven and the percent of crashes related to fatigue driving [5]

Drowsiness-related crash scenarios appear to be quite unique. Fatigue or drowsiness-related crashes tend to occur after midnight or in the afternoon with vehicles traveling at high speeds. Among fatigue-related accidents, crashes caused by fall-sleep-drivers are more common and serious in terms of injury severity. Often time drivers do not perform any maneuvers to prevent a crash before the crash happening.

1.1.2 Who Drives While Fatigued?

Populations of drivers that are at risk of crashes due to fatigue driving include:

- young male who are more likely to be sleep deprived and drive at night;
- drivers with sleep disorders who suffer from chronic sleep deprivation;
- drivers under the influence of medication side effects which intensify sleepiness;
- night or rotating shift workers who are more likely to lack quality sleep;

- Commercial vehicle operators who are likely to experience fatigue after spending long hours monotonous driving.

1.1.3 Significance of the Problem

Studies show that $25\% - 30\%$ of driving accidents are fatigue related [6]. The US National Highway Traffic Safety Administration (NHTSA) estimates that drowsy driving causes more than $100{,}000$ crashes each year resulting in $76{,}000$ injuries, 1500 deaths and an estimated $\$12.5$ billion in diminished productivity and property loss [7]. These numbers represent $1 - 3\%$ of all police reported crashes and approximately 4% of fatalities. The National Transportation Safety Board (NTSB) confirmed fatigue as the main reason for 52% of 107 single-vehicle accidents involving heavy trucks, whereas only in nearly 18% of the cases the driver admitted to falling asleep [8]. Federal Highway Administration (FHWA) also concluded that more in-depth investigations would yield higher percentages of fatigue-related crashes than those indicated in samples of police accidents reports. In a 2006 survey with 750 drivers in the province of Ontario, nearly 60% of the drivers admitted driving while fatigued or drowsy, and 15% reported falling asleep while driving during the past year [9] [10]. In Australia, approximately 6% of crashes may be attributable to driver drowsiness and fatigue. In England, up to $16 - 20\%$ of police reported vehicle crashes are related to driver fatigue.

Researches show that if drivers get a caution one second earlier than accidents, about 90% accidents can be prevented. Therefore, developing technologies for detecting driver fatigue is essential to accident prevention.

1.1.4 Challenges in Driver State Estimation

The difficulty in determining the incident of fatigue-related accidents is due to the difficulty in identifying fatigue as a causal or contributing factor in accidents [11]. Unlike alcohol-related crashes, no blood, breath, or other objective test for sleepiness behind the wheel currently exists, which investigators could give to a driver at a crash scene. Driver impairment is usually masked by the increased arousal following the crash and hidden from the investigating officer. Even in some cases, resulting crashes might be attributed to other causes. For example, a police officer may report a crash as the result of driver running a red light, whereas the crash has actually occurred because of driver's inattentiveness due to sleepiness. As a result, sleepiness as a contributing factor in roadway accidents is underreported in crash databases that are based on police accident reports. From drivers' side, almost all drivers rate their driving ability as superior. This over confidence makes them underestimate the reaction time required and the risk involved. An overwhelming majority of the drivers who have nodded off while driving reported that they were startled awake by a crash. Failing to recognize fatigue warning signs can seriously increase the chances for falling asleep or nodding off while driving. To assist the driver with the problem of drowsiness, an on-board device that monitors driver's attention level in real time and provides interactions that make sense for the driver is vital.

1.1.5 Fatigue Warning Indicators

Fatigue can often affect driving ability long before drivers even notice they are getting tired. In an attempt to avoid having accidents, most tired drivers will try to fight against sleep with different durations and sequences of the physiological events that precede the onset of sleep. The National Sleep Foundation suggests a list of signs that can be used to decide on when the driver is no longer in conditions of continuing driving. These signs could be categorized as physical and cognitive signs as the followings:

Physical Signs

- Frequent and long eye-blinks, difficulty keeping eyes open, repeated yawning and head nodding off at the wheel;
- Lazy steering, varying vehicle speed for no reason, a drifting vehicle that wanders over road lines;
- Slowdown of breathing and heart rate, decline of muscle tone and body temperature, Electromyogram (EMG) shift to lower frequencies and higher amplitude, increase of electroencephalogram (EEG) alpha waves.

Cognitive Signs

- Difficulty focusing and daydreaming, trouble remembering the last few miles driven;
- Increased risk-taking, slower reaction and responses;
- Misjudging traffic situations.

1.1.6 Driver Fatigue Assistance Systems

A general overview of a fatigued driving assisting system could be as the followings: The driver assistance system includes two major components as presented in Figure 3. The first component is a driver state sensor that gathers and processes information from multiple variables including driving performance and infers the drowsiness level. The second component is a countermeasure system that delivers an alert to the driver based on the current drowsiness level. Feeling the warnings, the driver will make certain decisions, such as taking a short nap, to return to the normal alert state. The driver assistance system will continuously monitor the driver drowsiness level. The higher the detected level of drowsiness, the more aggressive the delivered warnings.

Both components are critical to the success of driver assistance systems. Assistance would be impossible without a reliable and valid assessment of driver drowsiness levels from the driver state sensor. Similarly, drowsiness problem cannot be mitigated if effective countermeasures are not provided to the driver. Moreover, if the alert signal is confusing or annoying, the drivers will not comprehend it.

Individual differences could be a challenge in this process making several drowsiness measures capable of detecting a high level of drowsiness in some individuals, but fail to do so in other individuals. Human factor researchers, in this regard, try to identify measures that can reliably detect driver drowsiness in a vast majority of individuals.

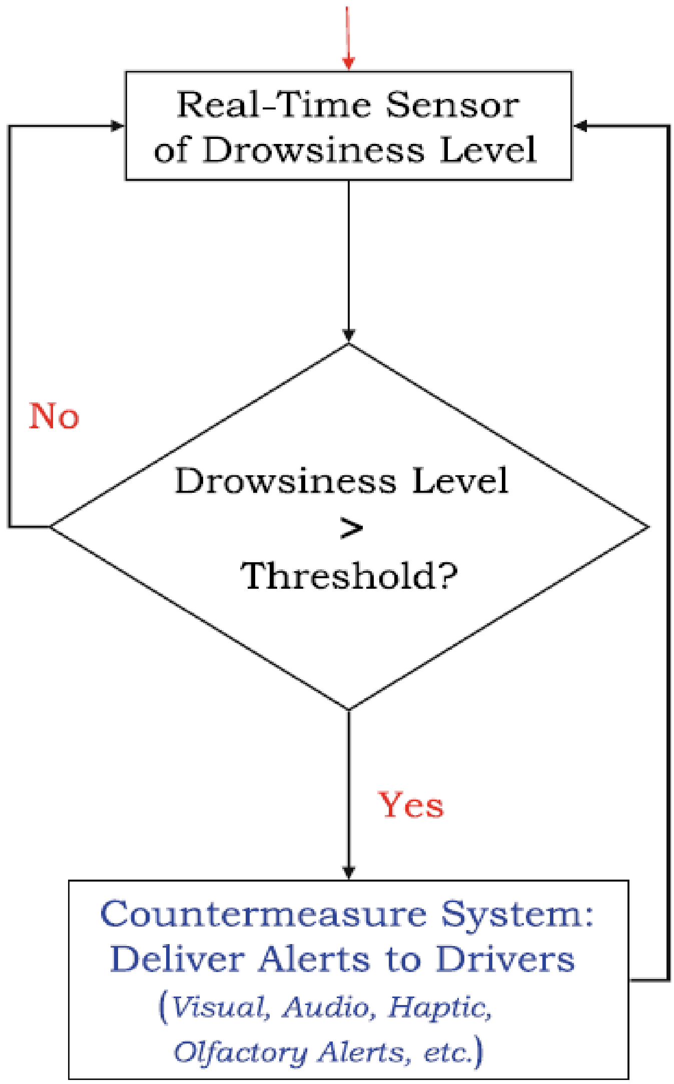


Figure 3: A closed-loop driver assistance system for driver drowsiness mitigation

1.2 Research Problems and Objectives

Deciding whether the driver is paying sufficient attention to traffic is a complicated study. In the last decade, monitoring systems based on various techniques have been developed for fatigued driving detection followed by alarm signals to alert the driver. However, finding an efficient way to constantly detect fatigue has been one of the most important issues to find out.

Visual cues resulted from changes in facial expressions are of significant importance in reflecting one's level of fatigue. In fact, there are limited but specific facial expressions particularly around the mouth and eye regions representing the fatigue state. How to efficiently extract and track these features for a real-time decision making on fatigue is challenging though. Eye closure data obtained from eye state detection is an example method suggested for fatigue estimation. However, besides the challenge of various shapes of eyes, the two main problems of the previous eye state detection methods are the high computational time and the initialization procedure.

In the next stage, how to translate the measured fatigue data to the warning signals is a major design challenge. It should not be too sensitive to slight changes causing nuisance nor too insensitive resulting in lack of information. In that context, setting the correct warning threshold to trigger the warning signal can be complicated. If too many warning signals go off, they will cause annoyance and information overload.

Warning effectiveness is another challenge in developing an acceptable collision avoidance warning systems. Warning modality based on the selected communication channel (audio, visual or touch) is one of the aspects contributing to this concept. Another contributing factor is the warning strategy in continuously controlling driver's state. To date, the majority of research on tactile collision warnings has considered the sudden single-state issuance of warning signals. However, this warning strategy may conversely lead to an unwanted hazardous situation after startling the sleepy driver. Furthermore, previous studies attempted to present warning signals when the driver is already in a critical driving condition such as approaching the edge of roadway, lane departure or about to hit the lead vehicle. Thus, the driver cannot take an early action to resolve the problem.

The objective of this thesis is to develop an amenable, noninvasive driver assisting system to both make a valid assessment of driver's fatigue levels based on the extracted visual cues and to immediately provide the driver with specific haptic warning types before a dangerous situation arises.

Specifically, the goal of the proposed system is to locate and track driver's face and eyes to compute a drowsiness index using an existing reliable ocular measure that would model fatigue progression and then taking it as the system's warning parameter to translate fatigue data to warning signals.

This research objective applies the haptic warning modality and continuously conveys graded signals to responsive body parts according to the detected fatigue level. Drivers would have their own preferred signal perception type and the system does not dictate any warning setting.

1.3 Research Contributions

This thesis presents a real-time, nonintrusive method as a feasible solution to detect driver fatigue levels and produce timely warning that could prevent accidents. Some contributions are included in the proposed system, which are as follows:

- Adaptation of the LBP Histogram feature extraction method followed by SVM classification for an efficient, computationally simple eye state recognition used for PERCLOS calculation.
- Developing a fatigue analysis algorithm to estimate gradual fatigue progression over time from early stages. A fatigue episode is, therefore, quantized into 4 levels based on PERCLOS thresholds, resulting in a more accurate inference of fatigue criticality.
- Incorporation of a previously developed Haptic Jacket scheme as the warning interface which is equipped with vibrotactile actuators in specific portions corresponding to responsive body parts for perfectly conveying different criticality levels made by the aforementioned fatigue analysis algorithm.
- Driver's preference and control is embedded in the system through haptic jacket customization to support both what they want and what they need.

1.4 Research Publications

The following two papers have been published during working on thesis experiments:

N. Azmi, A.S.M.M. Rahman, S. Shirmohammadi, and A. El Saddik, "LBP-based driver fatigue monitoring system with the adoption of haptic warning scheme, "in *IEEE International Conference on Virtual Environments Human-Computer Interfaces and Measurement Systems (VECIMS '2011),* Ottawa, Canada, September 2011, pp. 24-27. [95]

A.S.M.M. Rahman, N. Azmi, S. Shirmohammadi, and A. El Saddik, "A novel haptic jacket based alerting scheme in a driver fatigue monitoring system, "in *IEEE International Workshop on Haptic Audio Visual Environments and Games (HAVE '2011),* Jiangxi, China, October 2011, pp.112-117. [94]

1.5 Thesis Outline

The remainder of this thesis is organized as follows:

Chapter 2 – Overview of Fatigue Detection and Warning Methods presents an overview of approaches taken by a variety of driver fatigue detection and warning systems including types of warning information to better understand the research motivation.

Chapter 3 – Vision-Based Fatigue Detection Techniques focuses on the existing methodologies for fatigue detection through ocular measures and face monitoring. Some selected techniques are also further explained.

Chapter 4 – Proposed System specifies the implementation of different modules involved with real-time fatigue detection and warning stimulation, specifically regarding feature extraction to train the SVM classifier for eye state recognition, accurate fatigue level estimation from eye closure data, haptic jacket adaptation for haptic stimulation, and the haptic jacket features.

Chapter 5 – System Validation details conducted validations and experiments to evaluate performance, accuracy and user acceptance of the system.

Chapter 6 – Conclusion & Future Work summarizes and concludes the thesis, while outlining some hints for future research.

Chapter 2 - Overview of Fatigue Detection and Warning Methods

To increase traffic safety and to reduce the number of traffic accidents, numerous universities, research centers, and governments (Europe Union, etc.) are contributing to the development of driver assisting systems by driver state analysis using different technologies. Generally, driver state refers to overall physical and functional characteristics indicating features such as distraction, fatigue, attentional capacity, and mental workload. Figure 4 shows possible inputs to a driver state measurement system based on both overt and covert measures [12].

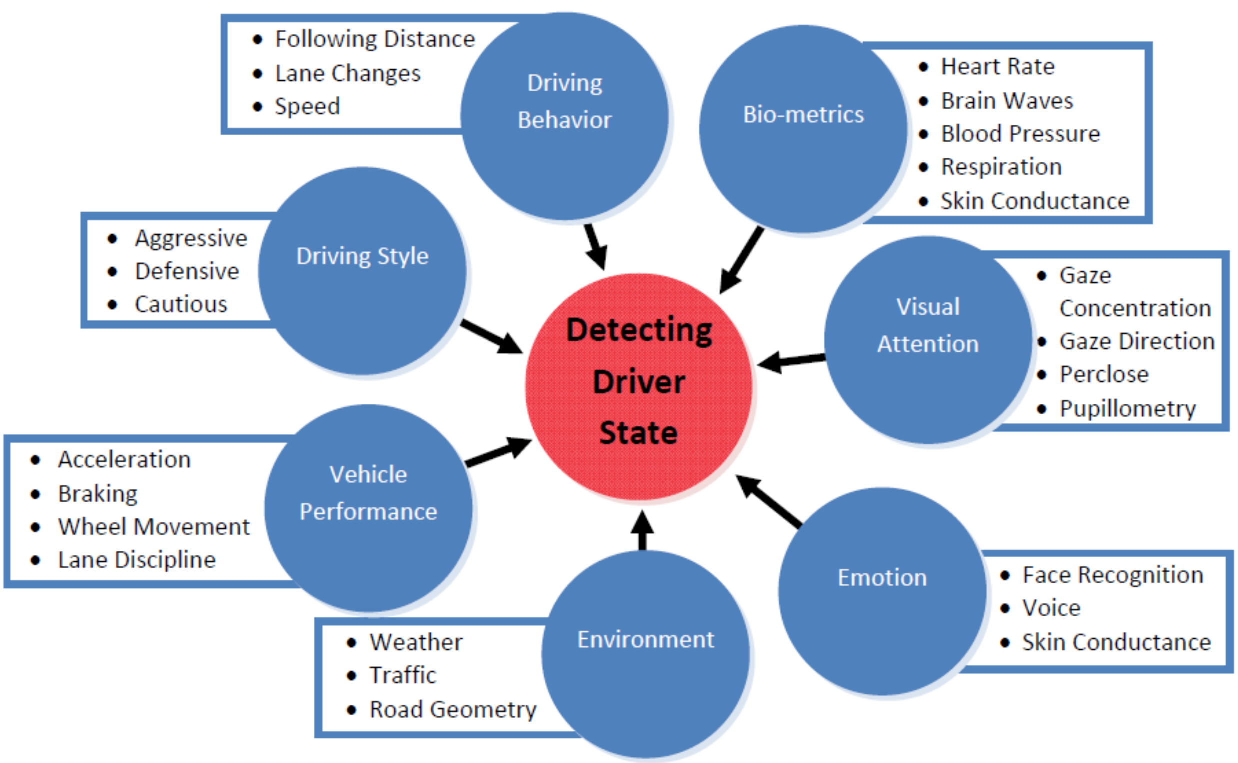


Figure 4: Domains from which inputs for an integrated driver state detection system might be drawn [12]

2.1 Fatigue Detection and Prediction Technologies

Drowsiness detection methods can be classified in terms of their specific techniques [13]. These techniques mainly focus on changes of physiological signals, driver performance and ocular measures. These approaches are presented and discussed in detail in the followings.

2.1.1 Detection by Physiological Signals

This method is based on the fact that such physiological signals as pulse rate, EEG (electroencephalography), ECG/EKG (electrocardiogram) and electrodermal activity show different patterns at different human-vigilance levels. With the onset of fatigue, body temperature, heart rate, blood pressure, respiration rate and adrenalin production are lowered.

One of the most valid indexes of driver alertness is electroencephalography (EEG). The spectral analysis of an EEG that shows the transition from wakefulness to sleep can be described as a shift toward slower EEG frequencies. In other words, changes in theta, alpha, and beta frequencies are associated with brief periods of sleepiness (microsleep) and the onset of sleep [1] [14] [15] [16] [17] [18].

2.1.1.1 EEG of Sleep

EEG is a neurophysiologic measurement of the electrical activity of the brain by recording from electrodes placed on the scalp. The resulting traces are known as an EEG and represent an electrical signal (postsynaptic potentials) from a large number of neurons. The EEG is capable of detecting changes of an electrical activity in the brain on a millisecond-level, and measures brainwaves of different frequencies within the brain. EEG signals are categorized by their frequency ranges, and each range is named by Greek letters [1] [14]. *Beta* rhythms are the fastest, greater than $14\ Hz$, and represent an activated cortex. *Alpha* rhythms are about $8-13\ Hz$ and are associated with quiet, waking states. *Theta* rhythms are about $4-7\ Hz$ and occur during some sleep state. *Delta* rhythms are quite slow, less than $4\ Hz$, often large in amplitude, and are a sign of deep sleep. Table 1 summarizes these EEG signals.

Table 1: Characteristics of EEG Signals

EEG signal	Signal frequency	Characteristics
Delta	$1-3\ Hz$	deep sleep
Theta	$4-7\ Hz$	NREM Stage I
Alpha	$8-13\ Hz$	quite, waking states
Beta	$>14\ Hz$	an activated cortex

Sleep can be categorized into distinct states according to the EEG signals. Rapid eye movement (REM) sleep and non-REM (NREM) sleep are two types of sleep [1] [14]. Although the progression of EEG waves has been divided into discrete stages, it is actually gradual and continuous. During a normal night, we slide through the stages of NREM, into REM, then back through the NREM stages, repeating the cycle about every 90 minutes. REM sleep is an active period of sleep marked by intense brain activity. This stage is also referred to as paradoxical sleep since brain activities during REM are comparable to those during wakefulness. Brain waves are fast desynchronized, similar to those in the waking state. Most dreams occur in REM sleep. NREM sleep is characterized by a reduction in physiological activity. As it gets deeper, the brain waves measured by EEG get slower with greater amplitude, breathing and heart rate slow down, and blood pressure drops.

The changes in EEG during fatigue progression are distinct enough to reliably identify sleepiness, although the simultaneous use of EOG (electrooculogram) is strongly recommended. The followings are some examples of detection devices based on physiological measures [18].

The *ABM Drowsiness Monitoring Device (DMD)* records EEG via telemetry to detect drowsiness. The system requires an operator to wear a baseball cap containing disposable electrodes. It gives an auditory alert when EEG-determined drowsiness indicator exceeds a threshold. The *EEG Based Algorithm to Detect Different Levels of Driver Fatigue* uses delta, theta, and alpha activity of the EEG to detect “early, medium, and late” sleepiness. The

Engine Driver Vigilance Telemetric Control System 3rd Generation (EDVTCS) measures electrodermal activities and reactions. Operators are required to wear watch-type sensors. The system activates an auditory alarm when alertness falls below the critical level.

The most accurate technique for monitoring human vigilance level is based on physiological features. However, the biggest drawback associated with the EEG, as an on-road drowsiness detection device, is the difficulty in obtaining recordings under natural driving conditions, which makes it an unrealistic option for detection of fatigue. Electrode-based collection of these parameters while driving is intrusive and causes annoyance to the driver.

2.1.2 Detection by Driver-Vehicle Data

A change in the mental state can induce a change in driving performance. Driver-vehicle data including steering angle, brake input, and speed can be chosen to help drowsiness detection of drivers [19] [20]. The most frequently measured parameter is the frequency of steering wheel movements, which decreases as the driving period grows. Conversely, when a subject is distracted by a rich environment, steering wheel movements are often frequent. SWRR (Steering Wheel Reversal Rate) can be obtained by continuing on oscillation numbers of the steering wheel when the amplitude is lower or equal to a certain maximum value from 5 to 10 degrees. On high vigilance periods small amplitudes of steering wheel movements are frequent, whereas great corrections happen during low vigilance states [21]. The underlying presumption is that an alert driver makes a comparatively large number of fine-steering adjustments to cope with the driving task and makes a relatively few number of large-steering ones, except when deliberately changing lanes to pass other vehicles.

SDLP (standard deviation of lateral position) or standard deviation of steering wheel movements increases rapidly after the first 30 minutes of driving. Standard deviation of the steering wheel is more affected by road curvature [22]. Lane tracking variability is increased in prolonged wakefulness [23]. Drivers who lose alertness will, due to lapses in information processing, cause their vehicle to wander somewhat within the traffic lane, possibly to leave the lane or to go off onto the road shoulder. A fatigued driver permits himself to face situations requiring changes in speed more frequently. Standard deviation of vehicle speed increases after 3 hours of driving [21] [23]. In another case, drivers suffering from loss of alertness will more likely follow a vehicle ahead in a risky short distance and in high closure rates.

A task focusing on measuring operator's reaction time called Psychomotor Vigilance Task (PVT) shows noticeable differences between alert and drowsy drivers [24] [25]. PVT measures the latency between a visual stimulus and a motor response (e.g., pressing a button) and is a very sensitive measure of fatigue based on night work and sleep loss studies.

In [26], the pressure distribution on the seat of male subjects was measured during simulated long-term driving, and the results showed that there was a relationship between changes in the load center position (LCP) and driver reported subjective fatigue. The algorithm for deriving a fatigue index was calculated on a time interval of 10 minutes, which was a considerable delay.

Attentive and inattentive driving in car-following situations is distinguished in [27] by analyzing the vehicle following distance and steering angle. Localized energy analysis of the steering-wheel angle dynamics and vehicle tracking is performed in [28] to detect driver fatigue. A trend of localized energy increase is then found with driving time. The chaos theory is used in [29] to describe the dynamics of steering-wheel motion and estimate driver fatigue. An energy analysis in addition to a Gaussian mixture model was adopted in [30] to identify the driver state based on two driving behavior signals: 1) forces on the pedals and 2) vehicle velocity. Steering-wheel position, accelerator pedal position, lane boundaries, and upcoming road curvature are adopted in [31] to infer driver status. Vehicle dynamics and driving performance data such as vehicle position, velocity, and acceleration, as well as throttle and brake pedal positions were considered to model normal driving. The results showed that the accuracy varied among individuals.

Table 2 shows some sleep detection devices based on driver-vehicles performances.

Table 2: Sleep Detection Devices Based on Driver-Vehicle Performance [18]

Name of device	Description
APRB / ACARP Device for Monitoring Haul Truck Operator Alertness	Uses secondary tasks to estimate alertness via an auditory and visual reaction time task. Used in mining industry trucks.
DAS 2000 Road Alert System	Measures drivers' acceleration, braking, gear-changing, lane deviation and distances between vehicles.
FMD-Fatigue Monitoring Device	Auditory and visual reaction time test. Response pads on steering wheel. Used in mining trucks.
Roadguard	Is a secondary task comprising a reaction task. Only operates when vehicle is in top-gear.
Safety Driver Advisor	Learns normal driver steering movements and detects deviations from normal. Comprise a driving time measure, a dashboard display of recommended rest-break times and a monitor of erratic steering behavior. Recommended driving time is 2h for day, 1h for night.
SAMG-3Steer	Monitors normal corrective movements of steering wheel.
Stay-A-Wake	Monitors speed and steering behavior.
SAFETRAC	Uses measurement of lane deviation and steering movements.

These techniques characterize the vigilance states of drivers by comparing the reactions of the drive-vehicle system with a pre-determined threshold. However, this threshold is difficult to define because of the considerable inconsistency in the reactions of driver-vehicle systems in the beginning stage of drowsiness. Another limiting factor on performance-based measures is that decline in performance capacity may occur prior to changes in driver performance. This phenomenon can be attributed to drivers' skills and the ability of more experienced drivers to compensate during a routine driving task, despite their diminished capacity.

2.1.3 Computer Vision-Based Methods

Computer vision is a prominent technology in monitoring the human behaviour. In recent years machine learning applications to computer vision had a revolutionary effect in building automatic behavior monitoring systems. Drowsiness, fatigue and sleepiness cause changes in facial appearance. The visual cues that typically reflect a person's level of fatigue include slow eyelid movement, smaller degree of eye openness, yawning, and frequent nodding. By taking advantage of these visual characteristics, as fatigue symptoms, computer vision is the most feasible and appropriate technology available to supervise fatigued drivers faces.

Most of the existing vision-based methods followed by the techniques employed in the proposed system are explained in detail in the next chapter.

2.2 Fatigued Driving Warning

Alerting the drowsy driver is the most critical issue in an automatic driver assisting system. Alert signals should be as non-intrusive as possible in order not to startle the operator causing an accident. An overview of currently available countermeasures techniques for fatigue mitigation is provided in this section.

2.2.1 Modalities of Information Presentation

There are three possible sensory modalities through which the continuous warning feedback could be offered to the drowsy driver: the visual channel, the auditory channel, and the haptic channel. Driving is predominately a visual task that requires constant scanning of the roadway. It has been acknowledged that drivers normally suffer from visual overload [79]. Even smallest notifications could distract the driver, taking their attention from the road at the wrong time. Nevertheless, one solution could be designing enhanced displays to present enhanced continuous feedbacks through the visual channel. For example, ambient lighting is a good suggestion as a continuous peripheral indication of the danger that the driver is encountering. However, the direction from where the hazard is coming may still be unclear and may cause nuisance and distrust. Furthermore, visual signals are not perceived when driver's eyes are closed. Researchers, instead, have thought of potential use of a variety of non-visual displays. The majority of works have focused on the development of in-vehicle auditory signals and displays [80] [81]. Auditory alerts possess an attention taking quality. They also perform well at conveying urgency to the driver so that they can decrease reaction time to crash threats. On the other hand, auditory warnings must be presented loud enough to be distinguished with the background noise. In addition, for the fatigued driving warning application, a suddenly issued auditory signal could surprise the driver leading to a more dangerous situation. Therefore, the haptic channel seems to be the least intrusive one in providing continuous signals.

2.2.1.1 Types of Haptic Feedback

Haptic feedback can be broadly divided into two modalities: vibrotactile and kinaesthetic. Vibrotactile feedback stimulates human subcutaneous tissue, while kinaesthetic feedback concentrates on the gross movement of the human body. An acceptable silent mode of alerting a drowsy driver is tactile vibration feedbacks.

2.2.1.1.1 Advantages of Tactile Feedbacks

Skin constitute the largest portion of our senses, while is little used during driving [79]. Accordingly, tactile warning signals have a number of potential advantages compared to other warning modalities:

- First, skin stimulation is a potential communication channel for warning signals delivery without overloading limited cognitive resources of the driver [82]. Indeed, it has been claimed that a person does not need to "look out" for tactile warning signals since the tactile stimuli are automatically attention capturing, resulting in a faster response.
- Second, tactile signals have the advantage of being unaffected by the background noise level. This is in contrast with the auditory warning signals, where ensuring their correct audibility over any possible background road noise and/or the sound of car stereo is a real challenge.
- Thirdly, in contrast to the more commonly used auditory warning signals, tactile displays allow information delivery specifically at the operator. With this advantage, in terms of privacy, passengers are not required to be aware of or distracted by any tactile warning being delivered to driver's body.

- Finally, tactile warning signals are much easier to localize in the spatially confined car interior rather than auditory warning signals [83] [84] [85].

Thus, tactile cues are capable of effectively interacting with drivers by presenting directional signals. Some studies have considered the application of tactile displays and warning signals (e.g. [86]). As an example of potential tactile influences over other types of warning signals, we can refer to [87] in which presenting a counterforce (consisting of an increase of $25\ N$) on the gas pedal when drivers were too close to the vehicle ahead of them could lead to a safer driving compared to using visual or auditory warning signal for communicating the same warning information.

2.2.2 Vibrotactile Safety Drowsy Driver Warning Systems

While research interest in the adoption of tactile warning signals in vehicles emerged more recently, there are already a number of commercial vibrotactile safety systems available in the market, such as the lane departure warning systems designed in certain models of Citroen and BMW cars [88][89]. Moreover, according to the Denso Corp., one of the world's largest automobile parts manufacturers, all new cars will be equipped with some sort of tactile generating device as a standard by the year 2020.

In the context of awakening the drowsy driver, the most successful commercial implementation of a tactile display in vehicles is their use in warning drivers when they cross a lane boundary. In 2004, Citroen started to offer a Lane Departure Warning System (LDWS) as an optional extra in its C4 hatchback and C5 saloon cars [88][89]. This device alerted potentially drowsy drivers by sending vibrations to their buttocks should they begin to slowly cross a lane boundary. The implemented vibrotactile signals in these LDWSs are spatially informative, mimicking the effect of rumble strips impact: if the car veers to the right, the right side of the seat base vibrates and vice versa. Another driving study [90] showed that steering wheel vibration could also be effective in warning drivers of their lane departure situation. Vibrating the steering wheel or delivering a pulse-like steering torque signal to the steering wheel [91] was found to be more effective than an auditory alert, especially in case where no advance training about the meaning of the warning signals was provided for drivers. Practically, drivers could react more than half a second faster following either the vibrotactile or torque warning signals than following the auditory alerts, when the warnings were unexpected.

Capturing the attention of the distracted driver is another area for which tactile warning signals have been developed. Intelligent collision warning systems particularly were designed to avoid front-to-rear-end (FTRE) collisions [86] [92] [93]. FTRE collisions are one of the most common causes of crashes among drivers; especially among those who are distracted for example because of using their cell phones while driving.

Our proposed warning style is based on vibrotactile interactions through a previously developed haptic jacket interface [99] [94]. Previously, by calculating various fatigue levels of the operator, we leveraged armband-based multi-level haptic feedback scheme [95]. However, it was not possible to have the customizing option to wear the armband in different manners and users often forgot to wear it during the experiments.

Chapter 3 - Vision-Based Fatigue Detection Techniques

To identify drowsiness through ocular measures, it is necessary to follow three main steps:

- Face localization,
- Tracking the face and its components in the subsequent frames,
- Estimating the cues, and then the state of the driver.

In the field of computer vision, detecting a specific object in an image is a computationally expensive task. Fatigue monitoring systems track the changes in visual cues by face detection and facial features extraction as the major steps.

3.1 Face Detection and Facial Feature Extraction

Face detection and its feature extraction could be addressed using either feature-based approaches, without machine learning, or appearance-based approaches, with machine-learning inside. These approaches are further explained bellow.

3.1.1 Feature-Based Approaches

The advantage of feature-based approaches is that they make an explicit use of face knowledge: local face features and their structural relationship. For example, the geometric positions of 34 fiducial points are used as facial features in [32] to represent facial images. Then, the facial movements in image sequences can be evaluated by measuring the geometrical displacements of facial feature points between the current frame and the initial frame. In another approach, shapes and locations of facial components such as eyes, mouth and eyebrows are extracted to represent face images through facial geometry analysis [33] [34]. Another study for face representation suggests Action Unit (AU) detection through tracking facial fiducial points and then classifying calculated features [35]. It has been concluded that the facial representation based on tracked facial points is well suited for facial expression analysis. Recently, that study is extended to a fully automatic AU detection system in which feature points are automatically localized in the first frame. Afterwards, AdaBoost is applied to select a subset of most informative spatiotemporal features to recognize AU temporal segments. In some existing works [36] [37], optical flow analysis has been used to model muscle activities or estimate displacement of feature points. Flow estimates are, however, sensitive to non-rigid motion, motion discontinuities and varying lighting.

The feature-based approaches are usually applied for one single face detection. However, good quality images are required and algorithms are computationally expensive. Furthermore, the disadvantage of geometrical feature-based representation is the dependency on accurate and reliable facial feature detection and tracking, which is not easily accomplished in many situations.

3.1.2 Appearance-Based Approaches

On the other hand, appearance-based approaches extract features to follow facial appearance changes mainly based on texture analysis. In practice, these approaches have proven to be more efficient and robust than feature-based approaches. Many appearance-based approaches have been proposed to deal with facial expression recognition (FER) problems. A survey of this body of research can be found in [38]. Generally, image filters such as Gabor wavelets are applied either to the whole face area or specific face regions to extract appearance changes of the face. With these methods, multiple faces can be detected in even low resolution images.

Related works have mostly focused on using Gabor-wavelet representations [39] [40] [41] due to their superior performance resulted in high recognition rate for facial actions. However, convolving face images with a bank of Gabor filters for extracting multi-scale and multi-orientational coefficients is both time and memory intensive, and demands heavy computations. Compared to Gabor wavelets, Local Binary Pattern (LBP) features can be extracted faster in a single scan through the raw image. Time and memory costs of the two feature extraction processes are compared in [42] as presented in Table 3. The results show that a facial expression recognition (FER) system using LBP histograms allows for very fast feature extraction whereas the other method requires a high computational cost in extracting a large set of Gabor wavelet coefficients.

Table 3: Comparison of Time and Memory for Extracting Features [42]

Methods	Memory (feature dimension)	Time (feature extraction time)
LBP	2478	$0.03\ s$
Gabor	$42{,}650$	$30\ s$

Furthermore, extensive experiments on the Cohn-Kanade database show the efficiency and effectiveness of the LBP features for facial expression discrimination. Additionally, experiments on face images with different resolutions prove the robustness of LBP features to low-resolution images, which is critical for real-world applications where only low-resolution input is available. This texture descriptor is further explained in section 3.5.

3.1.3 Viola–Jones General Object Detection Framework

Recent progresses in face detection are mostly made based on the cascade detector framework proposed by Viola and Jones [43], which provides a fast and robust face detection system. Its OpenCV implementation allows researchers to train their own classifiers. Three major components contributing to the cascade face detector are: 1) an over-complete set of local features that can be evaluated quickly, 2) an AdaBoost-based method to build strong nonlinear classifiers from weak local features, and 3) a cascade detector architecture that satisfies the real-time detection speed.

Haar-like features are widely used in face searching along with AdaBoost learning algorithm for training purposes to have accurate face detection. Some of these training data are available in the Intel Open Source Computer Vision (OpenCV) library [44], where it is possible to find XML descriptions of the cascades of classifiers for frontal or partially rotated faces.

Besides face detection, the Viola –Jones algorithm and the relative trained classifiers from OpenCV library could be applied to detect any object such as face components, more importantly eyes and mouth, as those reflecting changes in facial expressions. In this thesis, the algorithm is applied for face and eyes localization using the already trained classifiers from OpenCV library.

Many studies using image processing approach and computer vision techniques to detect fatigued driving have been reported in the literature. It is believed that monitoring eyes and mouth obtains fatigue symptoms early enough to prevent an accident.

3.2 Mouth Detection

Estimating the position of the mouth is one of the approaches in fatigue detection research. Mouth opening degree varies in different driving states of normal, talking or dozing. Accordingly, Fisher classifier has been used in [45] to extract the mouth shape and position. Then, the mouth region's geometry character is considered as the feature value, and all these features are put together to make up an eigenvector as the input of a three-level back-propagation (BP) network, then the output is obtained among three different spirit states. In another attempt [46], a gravity center template is used to extract the mouth area. Then, they used Gabor wavelet to get the corners of the mouth. Linear discriminant analysis (LDA) was also used to classify mouth into two states: 1) normal and 2) yawning. In another work [47], a back-propagation artificial neural network (BP ANN) is used to estimate the following three mouth states from lip features: 1) normal; 2) yawning; and 3) talking. They used a facial action coding system (FACS) to code facial expressions and then employed machine learning to discover which facial configurations were suitable for fatigue detection, with 31 facial actions applied to predict drowsiness. Yawning could be detected by the openness of the mouth represented by the ratio of mouth height to width. The ratio is used to represent mouth openness in [48], and yawning is detected when the ratio is above 0.5 in more than 20 frames.

Mouth features and yawning frequency are important cues of drowsiness. However, it appears that drivers yawn less often in critical moments before falling asleep, not more often [49]. In addition, most people are used to hide their mouths opened during yawning, which negatively affect detecting and tracking the mouth in consecutive frames.

3.3 Head Position

Head-nodding frequency, slouching frequency, and posture adjustment frequency have been derived from changes in head position in [50]. Facial orientations are divided into five clusters in [51] as frontal, left, right, up, and down, depending on eyes position and the center of the face. In a similar approach in [52], a coarse estimation of 3D face pose is obtained based on positions of pupil and nostril. Face orientation is determined in [53] using an eigenspace algorithm to map seven pupil features (inter-pupil distance, sizes of the left and right pupils, intensities of the left and right pupils, and ellipse ratios of the left and right pupils). The face orientation is then quantized into the following seven angles:

1) $-45°$;
2) $-30°$;
3) $-15°$;
4) $0°$;
5) $15°$;
6) $30°$;
7) $45°$.

A headband with IR reflective markers is employed in another study [54] to estimate the 6-degree-of-freedom head pose with an average error of $0.2°$. The head position sensor system MINDS (Micro-Nod Detection System) proposed by ASCI is conceptually designed to detect microsleep events occurring in association with head nodding by assessing the x, y and z coordinated of the head through conductivity measurements [55]. Driver's head is tracked in real time. The signal is correlated with head position of the driver, and the software detector extracts head motion behavior associated with driving while drowsy. However, microsleeps could also occur without any obvious head nodding event.

3.4 Why Eyes?

Among all visual cues, most of the fatigue-related information can be directly obtained from driver's eyes. Actually, the shape of eyes changes under fatigue state: eyes become bigger when the spirit is vigorous; smaller while dozing and completely closed when the driver is sleeping. The eye blink frequency increases beyond the normal rate in the fatigued state. In addition, microsleeps as short periods of sleep lasting for 3 to 4 seconds are the good indicator of fatigue. When the eyes are closed due to drowsiness, visual inputs to the driver are temporarily halted. Therefore, designing a system only based on eye features is reliable enough to properly detect driver's sleep onset.

3.4.1 PERCLOS

PERCLOS (PERcent eye ClOSure) is a measure of driver alertness as reliable as EEG [59]. The measure is the percentage of eyelid closure over the pupil over time and reflects slow eyelid closures rather than blinks. In a 1994 driving simulator study, the PERCLOS drowsiness metric was established as the proportion of time (%) in a minute when the eyelids are 80% or more closed [60]. For instance, if the eyelids are $80 - 100\%$ closed for a total of 6 seconds within a one-minute time window, PERCLOS would be $6/60$ or 10%. The metric was highly correlated with other physiological signs of drowsiness and was an effective criterion for drowsiness prediction algorithms. PERCLOS was found as an indicator of sleepiness onset and was connected to poor performance in visual tasks. The authors point out "...it seems obvious that if a driver's eyelids are closed, the ability to operate a vehicle would be greatly hampered" [60]. Based on this research, the US NHTSA and FHWA consider PERCLOS to be among the most promising real-time measures of alertness for in-vehicle drowsiness-detection systems.

In terms of video coding, eye closures with a duration over $300 - 500\ ms$ are typically coded as slow eyelid closures and entered in the PERCLOS calculation. Normal eye blinks are eye closures with duration under $300 - 500\ ms$. PERCLOS values do not seem to vary significantly with a different closure value in this range and human factor researchers may pick a value as threshold anywhere between $300 - 500\ ms$.

High PERCLOS values appear to be directly linked with crashes. Thresholds for decision making about drowsiness, are usually set at PERCLOS values between 0.05 and 0.15. As an example, in [61], two PERCLOS thresholds have been defined for driver drowsiness: 8% and 15%. For a PERCLOS measurement of over 15%, the driver is considered as “drowsy”, and if PERCLOS is between $8-15\%$, the driver is declared as “likely drowsy”. Subsequent research works have adopted the same threshold values.

Main technologies that have been used to driver sleepiness are the analysis of video imagery during daylight illumination and infrared reflectance devices during driving at night.

3.4.2 Systems for Daylight Illumination

Video imagery systems for driver fatigue detection rely on calculating ocular measures such as PERCLOS from captured video frames. One commercial example of these systems is Driver State Sensor (DSS) device developed by SeeingMachines [62]. DSS is a robust, automatic and nonintrusive sensor platform that uses face tracking techniques to deliver information on driver fatigue and distraction. DSS is located on the dashboard in cars and measures the drowsiness state using eyelid opening and PERCLOS. A snapshot of the system is displayed in Figure 5.

Figure 5: Driver State Sensor (DSS) device developed by SeeingMachines [62].

Another system developed by the SeeingMachines company is called FaceLAB. In this system, the 3D pose of the head and the eye-gaze direction are exactly calculated. FaceLAB can also monitor eyelids and output eye open state and blink rates and accordingly estimate driver's fatigue level.

PERCLOS, blink frequency, eye closure duration (ECD), nodding frequency, fixed gaze, and frontal face pose were normalized and used as inputs to fuzzy inference system (FIS) for fatigue detection in [52]. Various linguistic terms and their corresponding fuzzy sets were distributed in each of the inputs using induced knowledge based on the hierarchical fuzzy partitioning (HFP) method. Then consistent, less redundant and interpretable fuzzy rules were automatically generated based on a fast prototyping algorithm. Fixed gaze, PERCLOS and ECD were determined to be the three crucial cues for driver fatigue detection with 98% accuracy.

Some other methods have also been used for fatigue detection. Gabor features representation of the face is used in [63] for fatigue detection. After the face is located, Gabor wavelets are applied to the face area to obtain different scale and orientation features of the face. Then, features on the same scale were fused into a single one to reduce the dimension. Finally, the AdaBoost algorithm was used to extract the most critical features from the dynamic feature set and construct a strong classifier for fatigue detection.

A real time tracking kernel for stereo cameras is developed in [68] to estimate face pose and face animation, including the movement of the eyelid, eyeball, eyebrow, and mouth, for driver inattention detection.

A Bayesian Network (BN) was employed in [57] to infer fatigue from gaze information. Mixture Gaussian model is used in [58] to model the "normal behavior" statistics from the eye closure duration (ECD) and frequency of eye closure (FEC) for each subject to identify anomalous behaviors. The blinking waveform is analyzed in [65] to obtain three factors as fatigue signs: 1) the length of a blink; 2) the closure rate; and 3) the blink rate. These factors were then weighted using a multiple regression analysis for each individual to calculate the drowsiness level. Driver fatigue is detected in [50] using fuzzy logic to fuse four cues: 1) PERCLOS; 2) head-nodding frequency; 3) slouching frequency; 4) posture adjustment frequency.

3.4.3 Systems Using Infrared Illumination

A popular method for locating eyes involves the use of the “bright-pupil” effect produced by near-IR light. Many researchers have applied IR illumination techniques in image acquisition systems for three purposes: to minimize the impact of different ambient lighting conditions, to allow the bright-pupil effect to be produced, and finally due to the invisibility of the near-IR illumination to the driver causing no interference with driving. A camera equipped with a two-ring IR illuminator was first adopted in [52], [53] and [54] to acquire a driver image. The ring sizes were calculated such that turning on the inner ring would obtain a bright-pupil image, while turning on the outer ring would result in a dark-pupil image. To ensure that images with and without bright pupils were interlaced, a controller was designed to synchronize the IR illuminator with the image frame rate. Digitally subtracting a dark-pupil image from a bright-pupil image yielded a difference image in which pupils appeared to be the brightest regions in the image. By searching the entire image, the pupils were detected as the two located bright blobs that satisfied certain constrains. The need for the synchronizer was eliminated in [66] by obtaining the pupil location from a single image. First, pupil candidates were obtained through Sobel edge detection, and then, SVM classifier with Gaussian Kernel identified them. In another work [67], a round-template two-value matching algorithm was proposed for locating bright pupils, which had an accuracy of 96.4% but consumed $1011\ ms$ on a $\mathrm{PIII}\ 800-\mathrm{MHz}$ computer.

The “bright pupil” effect benefits the eye extraction and tracking process. However, it is only useful under some limited lighting conditions that cannot be satisfied in real driving scenarios where sunlight can interfere with IR illumination causing the “bright pupil” effect not appear clearly.

In an attempt [52], the following three main illumination challenges were investigated, as shown in Figure 6: 1) artificial light from elements outside the road (such as street lights); 2) vehicle lights; and 3) sunlight. The “bright pupil” effect will disappear under these conditions leading to eye detection failure. Sunlight and reflections from glasses, for instance, could cause 30% drop in inattention detection performance.

(a) (b) (c) (d)

Figure 6: Effects of external lights on the acquisition system. (a) Out-of-the-road lights effect. (b) Vehicle lights effect. (c) Sunlight effect. (d) Sunlight effect with filter [52].

Generally, the “bright pupil” effect is not robust, regardless of how the hardware is adjusted, specially in daytime or when wearing glasses. Even under constrained conditions, the IR reflection in pupils varies by individual. Even with the same driver, the intensity depends on head position, gaze point, and openings of the eye. Pupils are also occluded when the eyes are closed. Therefore, more reliable real-time eye detection algorithms are preferred over the “bright-pupil” effect.

As described in the previous sections, possible solutions are eye tracking approaches without relying on “bright pupil” effect. Many studies have concentrated on image processing approaches to estimate driver’s physical parameters such as gaze, face pose, and mouth activity. In recent years, the most successful ones have been texture-based methods and machine learning. These appearance (texture)-based methods perform well in situations where the IR-based system does not, such as where the driver is wearing glasses, and is also able to work with sunlight and track the eyes under fast illumination changes. In addition, the system would clearly understand the difference between open and closed eyes instead of loosing tracking.

Overall, a majority of drowsy driver detection systems are based on indices of eye activity. Table 4 summarizes these sleep detection devices [18].

Table 4: Sleep Detection Devices Based on Eye Activity [18]

Name of device	Description
Alert driver	Monitors eye droop, pupil occlusion and eye closure via a camera. Uses image neural nets, fuzzy logic to locate subject's eyes. Is also model-based.
CoPilot	Detects percentage of time eyes are closed over a specified time interval (PERCLOS systems) via infrared camera
Expresseye	Measures fixation, gaze control, and saccadic eye movement to a target. Uses infrared light corneal reflection technique
EyeHead	Measures eye position, head position, and eye to point of fixation distance. Uses a magnetic head tracker
Eye-Gaze System	Measures gaze-direction via corneal reflection technique. Also measures pupil diameter, blinking, and eye fixation
Eyeputer	Records eye movements via corneal reflection technique
FaceLAB 4.5	Measures eye-gaze and closure. Uses PERCLOS fatigue assessment scale
IM-Blinkometer	Detects blinks using a piezoelectric adhesive disk attached to canthus of the eye
MTI AM eye	Detects eye blinks. Measures ratio of closed to open eyes to detect sleepiness. Uses infrared reflectance
Nissan Drowsy/Inattentive Driver Warning	Uses image processing to monitor eyelid movements
OptalertTM	Uses infrared oculography to detect eyelid movements during blinking and eye closure. The system is being further developed to measure intersaccade interval
PERCLOS	Detects eye closure using infrared, retinal-reflectance device. Measures duration of blinks and eye closures, and proportion of time eyes closed over a specified time interval
Photo Driven Alert System	Worn on ear and measures blink rate
SafetyScopeTM	Ocular system in quantifying sleepiness
SmartEye	Detects head position and point of gaze via image processing
Toyota Driver Drowsiness Detection and Warning System	Detects eyelid movement using camera mounted on rear-view mirror
Vehicle Driver Anti-Dozing Aid (VDAD)	Measures eye closure and head movement via infrared reflectance. Developed by US military

Most of the previous approaches detect eyes in their open state, while for the fatigued driving case a method is required for eye detection in different eye states during both alert and drowsy states.

Eye closure behavior and its impact on appearance changes during a fatigue episode could also be extracted through feature extraction methods explained in section 3.1. More recently, local binary pattern (LBP) was proposed as a powerful images texture descriptor, and was applied for facial expression representation. This operator is further described in the following section.

3.5 Local Binary Patterns (LBP)

Ojala et al. introduced LBP as a means of encoding local gray-level structure for texture description [69]. LBP features were then introduced to represent faces in facial image analysis. The idea of using LBP for face description is motivated by the fact that LBP can efficiently encode texture features of the face micro-patterns which has been effective information for both face recognition and facial expression recognition applications [70] [71]. A comprehensive study on using LBP for facial expression recognition can be found in [42].

The derived binary numbers, called LBP codes, codify local primitives including different types of curved edges, spots, flat areas, etc, as shown in Figure 7.

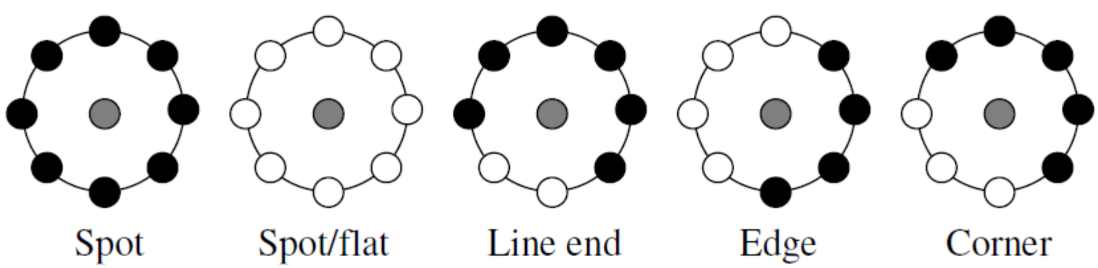


Figure 7: Examples of texture primitives which can be detected by LBP (white circles represent ones and black circles represent zeros) [42].

The LBP operator is defined as an ordered set of binary comparisons of pixel intensities between the central pixel and its surrounding pixels. Basically, LBP applies a 3×3 mask over the entire image. In each step of sliding and shifting, the value of the central pixel is set as threshold for neighbour pixels changing them to a binary unit: 0 or 1. Then, binary units are arranged clockwise resulting in an 8 bit integer LBP code on the 8 pixels around the central one. An illustration of the basic LBP operator is shown in Figure 8 and the corresponding equation is shown below.

$$LBP_{P,R}(x, y) = \sum_{p=0}^{7} s(g_p - g_c)\, 2^p \qquad (4.1)$$

Where g_c corresponds to the grey value of the center pixel, g_p to the grey value of the 8 surrounding pixels and function $s(k)$ is defined as:

$$s(k) = \begin{cases} 1 & if \quad k \geq 0 \\ 0 & if \quad k < 0 \end{cases}$$

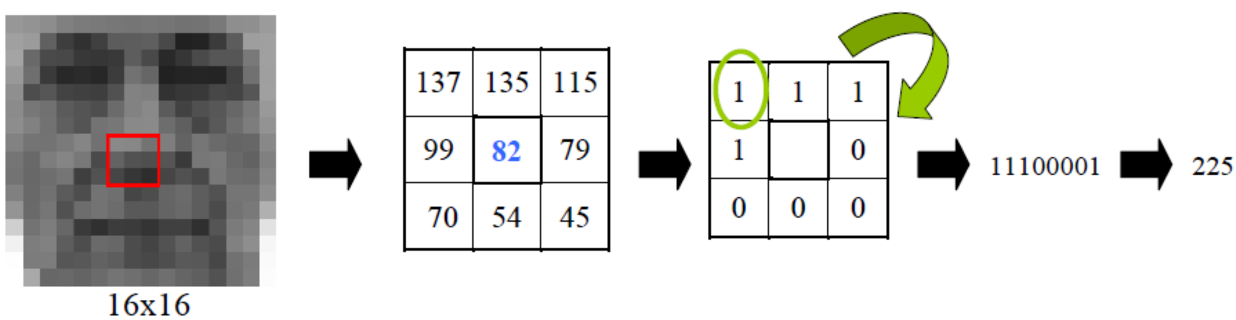


Figure 8: LBP labelling: binary label is read clockwise starting from top left neighbour

The binary-valued image patch, called LBP map, is used as a local image descriptor.

The LBP has been extended to multiresolution analysis [72], color texture analysis [73] and spatio-temporal texture analysis [74]. Some of the applications for the LBP and its extensions include visual analysis, image retrieval, motion detection, remote sensing, biomedical image analysis, and outdoor scene analysis.

3.5.1 LBP Histogram

A descriptor for texture analysis is a 256-bin histogram, H_i, of the local binary pattern. After labelling an image with the LBP operator, a histogram of the labelled image $f_l(x, y)$ could be calculated as in Equation 4.2.

$$H_i = \sum_{xy} l(f_l(x, y) = i), \quad i = 0, 1, \dots, n - 1 \tag{4.2}$$

Where n is the number of different labels produced by the LBP operator and $l\ (A) = 1$ when A is $true$ and similarly, $l\ (A) = 0$ as A is $false$. The LBP histogram, calculated over the entire LBP image, is consisted of bins each of which accumulates the total number of corresponding codes and hence represents image characteristics by its micro patterns such as edges, spots and flat areas.

The basic histogram, computed over the entire LBP map image, can be extended into a *spatially enhanced histogram* which is capable of encoding both appearance and spatial relations of face regions. As the n face regions have been determined, a histogram is computed independently for each of the regions. The resulting histograms are combined to form a spatial enhanced histogram. The size of the enhanced histogram is $n \times k$, where k is the length of a single LBP histogram. This histogram provides an effective face description on three different levels of localization: the labels for the histogram contain patterns information at the pixel level, the labels summed over a small region provide information at the regional level, and the regional histograms are concatenated to build a global texture feature of the face. It should be noted that when extracting the facial features using the histogram-based methods, despite the example in Figure 8, the regions are not restricted to be rectangular, of the same size or shape, and it is not necessary to cover the entire image either. They could be, for instance, circular regions located at the fiducial points.

3.5.2 LBP Properties

Facial appearance of the same person can vary largely due to illumination variation. Especially, driver's face is exposed to frequent illumination variations during daylight driving. Conversely, LBP features are invariant to monotonic gray-level transformations caused by illumination variation. In this context, a related study has investigated face recognition rates for faces under varying illuminations before and after applying the LBP operator [75]. Figure 9 displays one person's images taken in different illumination conditions and the resulted LBP texture patterns. Also, Figure 10 shows the same idea for faces of three persons under two example illuminations.

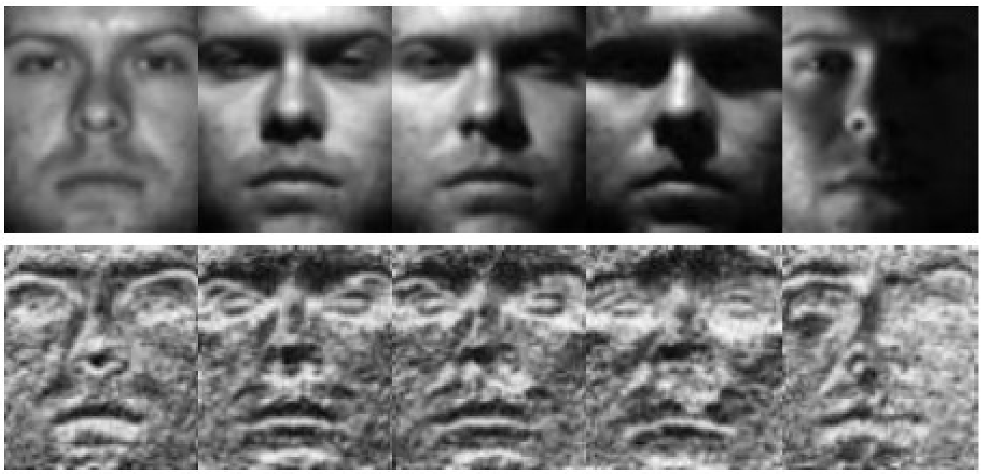


Figure 9: Applying LBP on one person's face images under various illuminations [75]

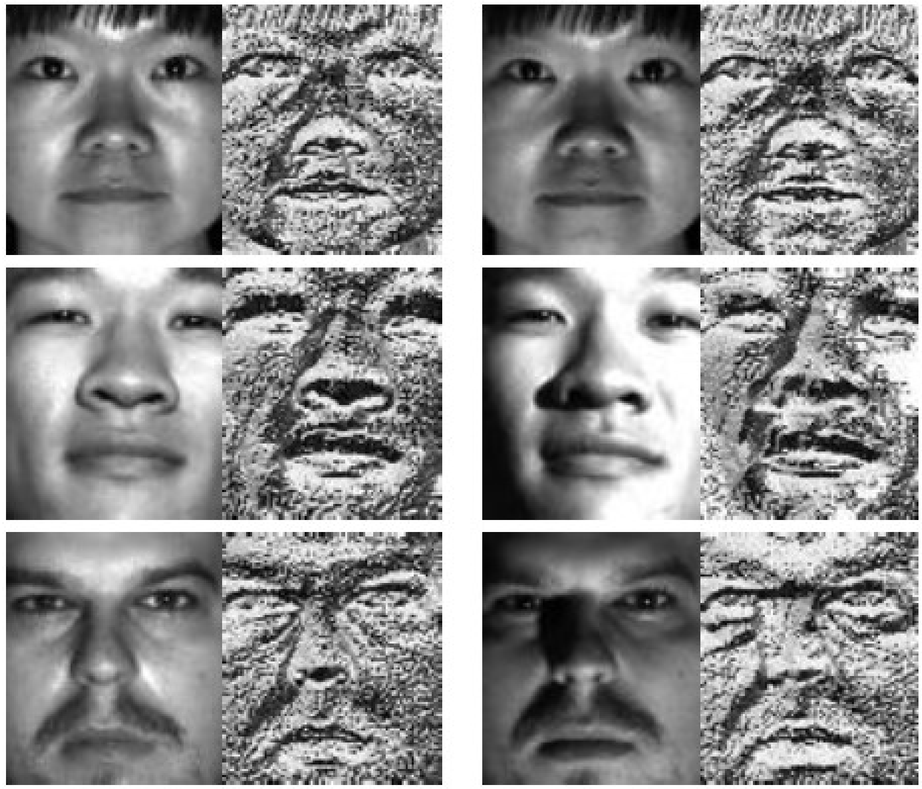


Figure 10: Applying LBP on three person's face images under various illuminations [75]

The database in [75] is created based on images of 30 persons with 10 images under different illumination conditions per person. Experiments confirm that the LBP operator can improve the recognition rate significantly when used to smooth the various illumination conditions.

Another important property of LBP features is their computational simplicity and the ability to codify all image pixels through a single scan. This key property would allow researchers to implement simpler feature extraction algorithms with faster processing time which is helpful in real-time applications. LBP features have been proved to be robust to low-resolution images, which is critical in real-world applications. Additionally, it has shown excellent performance in comparative studies in terms of both speed and discrimination performance.

3.6 Classification

The goal of a classifier is to compare the extracted features of a face image with those of the template and report the match degree in terms of some match or similarity measure. Basically, the last part of an expression recognition system involves the classification task. In this stage, the extracted facial features are used for classification. In this thesis, the output of the LBP feature extraction module, representing eye behavior, is considered as the input to the classification module that would identify eye states in each frame.

3.6.1 Dataset

Classification task is dependent on a dataset created from a portion of the extracted features. This dataset is then used to train the classifier so that it would be able to recognize the desired expressions in other images, both in the same dataset with which it was trained and the new ones. Computer vision-based expression analysis systems can extract the data in several formats, ranging from low-level inputs such as raw pixels to higher level inputs such as facial action units or basic facial expressions. If the database is large enough, low-level inputs are suitable to detect a particular expression or a particular state, and it actually helps to avoid intermediate representations such as Facial Action Coding System (FACS) [76]. On the other hand, when the dataset is relatively small, higher level representation of the image is beneficial. For the fatigue detection purpose, large sets of data from different subjects are not easily accessible since capturing spontaneous fatigue behaviour is a challenging task. Hence, using higher-level inputs might increase the system performance. Therefore, in this thesis local binary pattern histograms (LBPHs) are selected as the feature vectors representing eye region expressions and used as the input to the automated fatigue detector.

3.6.2 Support Vector Machines (SVM)

SVM is a pattern classification algorithm that finds the optimal linear decision surface between two hypotheses based on the concept of structural risk minimization. The decision surface is a weighted combination of elements of training samples, namely support vectors. These elements characterize the boundary between two classes.

Therefore, this classifier is naturally defined as a two-class discriminant classification. A considerable advantage of SVM over the traditional neural networks is its better generalization performance even with a small dataset [77]. In this context, maximal margin decision boundary can achieve optimal worst-case generalization performance. SVM is originally designed to solve problems where data is separable by a linear decision boundary. Nevertheless, using kernel functions, it is also potential to deal with problems that are not linearly separable in the original space (e.g. [78]). Some commonly used kernels are Gaussian Radial Basis Functions (RBFs), polynomial functions, and sigmoid polynomials.

Since eye state recognition is a two-class problem, SVM is selected in this thesis as the classifying function. The classification problem in this thesis is deciding about the eye state either as open or closed among a dataset consisted of eye features representing various eye states, which is not linearly separable. Therefore, the RBF kernel is selected due to its better boundary response allowing for extrapolation and an overall better performance.

Chapter 4 - Proposed System

4.1 Requirements

Developing automatic driver drowsiness detection and warning system by means of facial expression tracking requires solving four questions:

1. How to define features of drowsy expression,
2. How to capture the features from the driver's recorded face video,
3. How to estimate driver's drowsiness index from the features, and
4. How to re-alert the sleepy driver based on the estimated fatigue level.

Our approach to solving these problems is explained in this chapter.

4.2 Architecture Overview

We propose a collision avoidance driver assisting system for both driver fatigue detection and fatigue driving warning. The main idea behind our approach is to automatically detect eye states specially during fatigue driving conditions and to re-alert the driver. A video camera monitors driver's face continuously. Captured video frames are then provided to the image processing module to extract certain facial features. Corresponding warning signals will re-alert the driver in case these features confirm driver's fatigue state. The general architecture of the system is shown in Figure 11. The main stages are: face detection, eye localization and tracking, eyes region feature extraction, eye state recognition, fatigue estimation through fatigue level analysis and finally warning feedback generation.

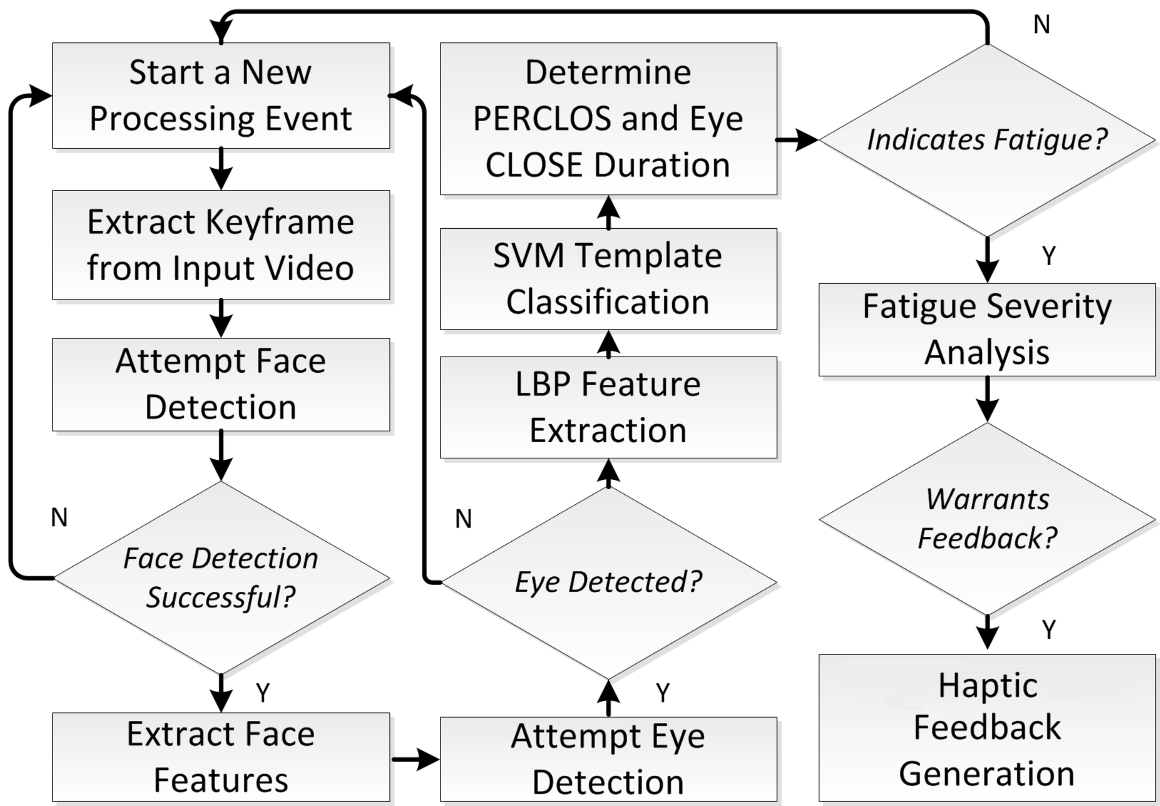


Figure 11: A flowchart based overview of the warning system to the fatigue driver.

4.3 Image Processing Functional Requirements

The image processing part of the system, dealing with monitoring driver's eyes to estimate fatigue levels, must essentially perform the following functions:

- Detecting driver's face in all input frames,
- Provide the eye location for both eyes,
- Representing eye state using a feature extraction method.

4.3.1 Face Detection

The first part of the fatigue monitoring system is the module for face detection. Face detection unit receives a video frame from the video capture unit and uses a cascade of classifiers that work with haar-like features to detect the face with the idea of Viola-Jones face detector [43]. The implementation is done using OpenCV library with decision tree classifiers that were trained with human faces.

OpenCV provides a number of object detection functions. In detail, a dataset in the form of XML file called *haarcascade_frontalface_alt2.xml* is loaded in the memory. This file contains information about human faces. After the file is loaded, a function named *cvHaarDetectObject* is called to find rectangular regions that are most likely faces in each frame coming in real time, and the function returns those regions as a sequence of rectangles. The size of rectangles that represent faces is measured, and the largest one is considered as the user's face. Based on this technique, OpenCV detects images that contain faces.

The main advantage of the Viola-Jones face detector algorithm is its very high detection rate for faces in the frontal orientation considering that the nominal face orientation while driving is frontal. If the face orientation is in other directions (e.g., down or sideways) for an extended period of time, the driver is either fatigued or inattentive. Moreover, the algorithm is so efficient and quick, as mentioned before, that could be used for real-time applications. During the face detection procedure, the classifier trained for face detection searches for a face in the image. In case no face is found, further processing is cancelled and system returns related error message.

The implemented face detection algorithm comes in the Appendix in Algorithm 1 and the obtained result is displayed and Figure 12.

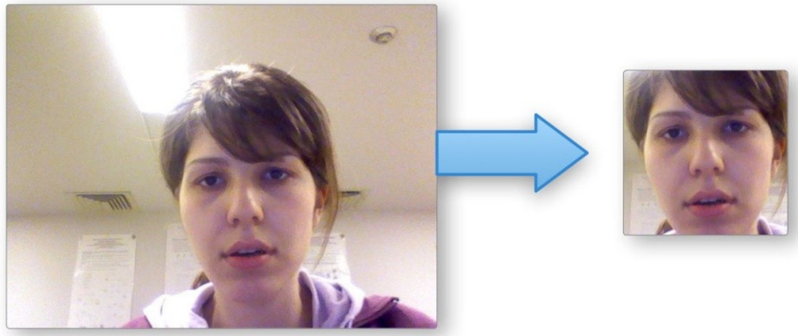


Figure 12: Face detection and cropping

If there are more faces detected in an image, the biggest one is taken by the algorithm for further processing.

A sample of the extracted faces can be seen in Figure 13.

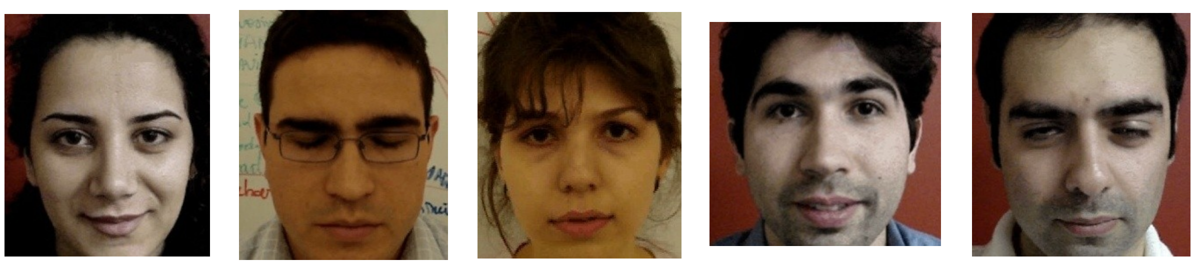


Figure 13: Output images from the face detection unit

4.3.2 Eye Detection

After successfully locating the face, parts of that containing more related fatigue expression information will be separated and investigated. Based on a previous discussion, tracking eye behavior is reliable enough for early drowsiness detection. First, regions of interest (ROI) are set and cropped based on coordinates of the face boundary box. Half of face width and two third of its height are considered as the width and height of each eye region. The eye detection classifiers for both left and right eyes are then adopted from the OpenCV library only on the left and right upper face parts to detect left and right eyes separately.

In this procedure, both XML files *haarcascade_mcs_lefteye.xml* and *haarcascade_mcs_righteye.xml* are loaded from the memory, including information about the left eye and right eyes. Then, the *cvHaarDetectObject* function is called twice to search for each eye in its cropped region. The search area of facial elements detectors is narrowed for improving the time efficiency of the algorithm. The face image with its cropped features is shown in Figure 14.

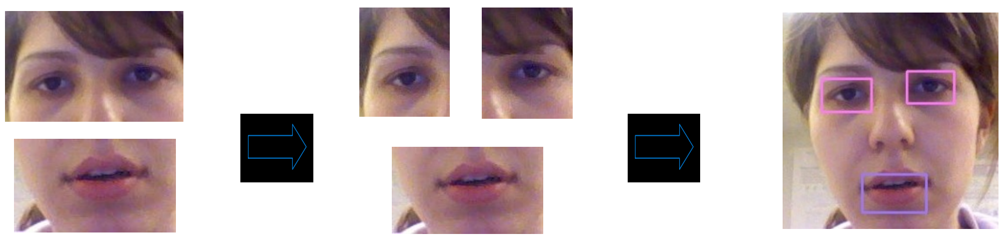


Figure 14: ROI and face components localization.

Eye detection and localization procedure is represented in Algorithm 2 in the Appendix.

Different eye states, with or without glasses, with different face distances from the camera, and with a bit face rotation were successfully detected using this algorithm (Figure 15).

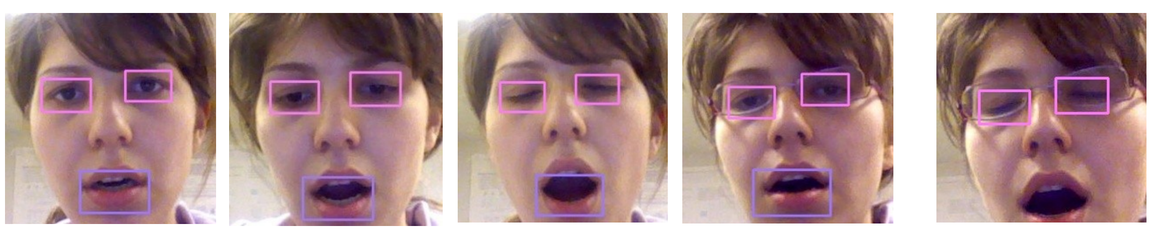


Figure 15: eye detection for open/closed, with/without glasses eyes.

After the eyes are detected, their boundaries are available, but are required to be drawn by assigning their boundary box coordinates and the corresponding width and height to a *CvRect* variable, as shown in Algorithm 3 in the Appendix.

The face ROI in this system is the face upper part which is obtained based on eye rectangles. Actually, a resized rectangle including both eye locations is considered as the face upper part for further processing.

Having locations of the face and facial landmarks, the face representation can be formed. In this work, fatigue or drowsiness is considered as a facial expression causing unique changes in the face appearance, mostly occurring in eyes region. Therefore, a facial feature extraction technique could be applied to represent these observable signs.

4.3.3 LBP Feature Representation

In order to capture fatigue expressions from driver's eyes, LBP feature extraction method is employed with its advantages in facial texture encoding. Face images can be seen as a composition of micro-patterns that can be well described by LBP texture operator. LBP can encode fine details of facial appearance by capturing small appearance details, making it suitable enough for fatigue detection through eye region expressions.

Applying the LBP operator, the input image is converted into its corresponding LBP map by sliding window technique where value of each pixel in the neighborhood is thresholded with the central pixel value. Central pixel is then encoded with LBP code (binary or decimal) and is replaced in the corresponding LBP image pixel. These binary codes are so called micro-textons, representing texture primitives such as curved edges, flat or convex areas. The LBP encoding process for the upper face part, resulting in pixel-level binary pattern descriptors, is illustrated in Figure 16.

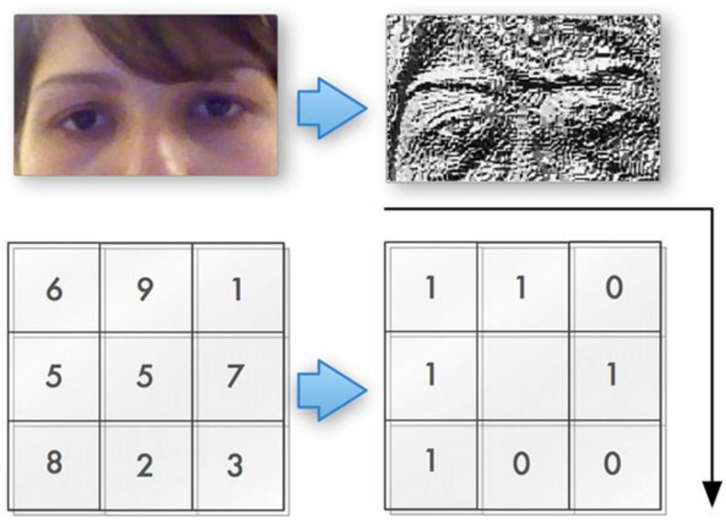


Figure 16: Face upper part LBP image.

Relying on the fact that eyes are in the upper half of the face, the search domain is limited to the upper part of the face image for fatigue detection from eyes behavior.

Based on the operator, each pixel of the region is labeled with an LBP code. The $256-$bin histogram of the labels contains the density of the region from which it is extracted, and is used as a texture descriptor of that region. Expressions are extracted from the eye region through LBP Histogram formation.

4.3.4 Eye Region Feature Extraction

Before features can be extracted, the desired face region needs to be normalized to have the same size for all input images. All upper face regions are rescaled to the same size with resolution of 90×48. In this thesis, the basic $LBP_{8,1}$ operator is used which has $2^8 = 256$ LBP patterns. Then each block in the region is scanned to obtain its LBP histogram. Feature extraction procedure from the eye region could be explained in three steps:

- Dividing the cropped upper face part into smaller sub-blocks,
- Calculating local LBP Histograms as the feature vector for each block, and
- Creating a single feature vector as the representative of the whole upper face part.

The upper part of the face is further divided into 20 smaller non-overlapping sub-blocks, considering the fact that applying the LBP operator on the whole selected part of the face would result in loosing spatial information of the texture. Another reason is that this division would enhance the region shape information. Figure 17 shows 5×4 grids of the normalized upper face region.

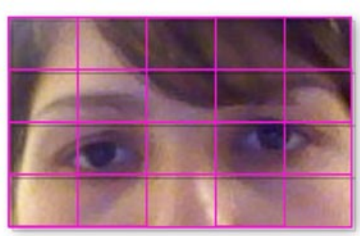


Figure 17: upper face region grids

Each sub-block is independently encoded with the basic LBP operator and subsequently the *cvCreateHist* function is called to obtain Local LBP Histograms separately from each region. These local histograms are then concatenated to each other to form the enhanced global feature vector representing the whole eye region. The shape of the global histogram is used as the feature in our system. For an eye region with 20 sub-regions, this vector consists of 20 histograms (Figure 18), each of which including 256 bins and so an eye state, or a fatigue expression, is described by 5120 features.

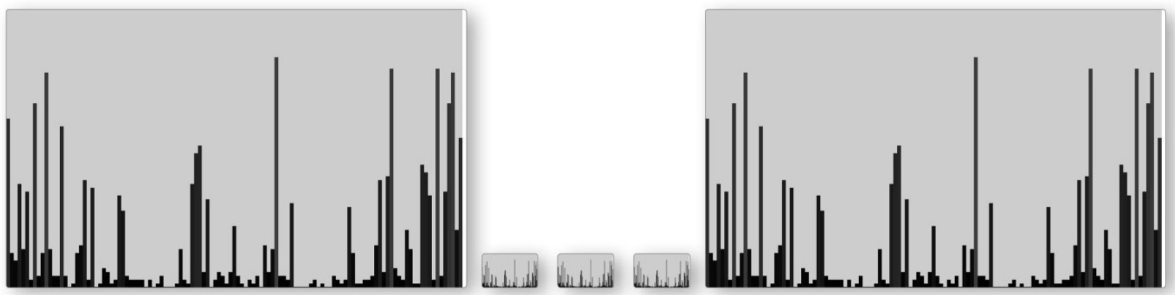


Figure 18: LBP histograms are extracted and concatenated into a single, spatially enhanced feature histogram

The one-step procedure is also illustrated in Figure 19.

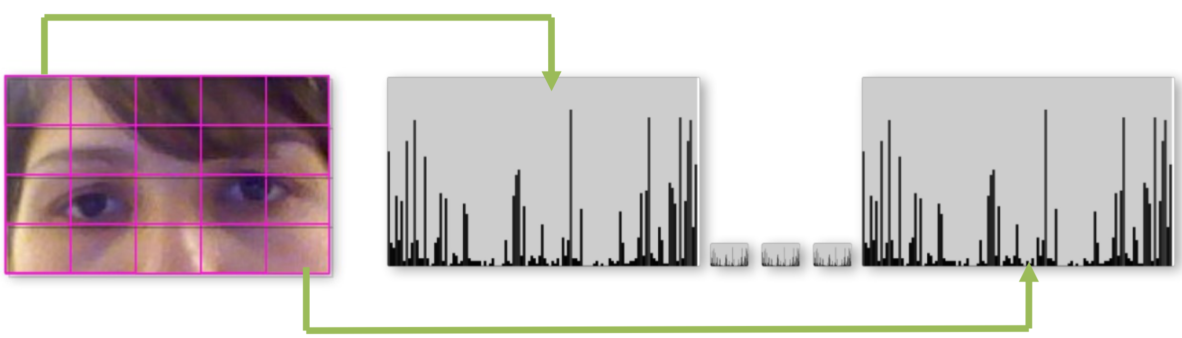


Figure 19: Feature extraction from face image using LBP operator

Consequently, every input frame would have an LBP Histogram (LBPH) as the feature vector of the eye state. These vectors are the classifier training data in the next stage.

The advantage of the proposed system over conventional methods, in the domain of facial expression recognition, is that it requires no manual operation, whereas conventional approaches require some manual operations for face cropping and selection of fiducial points on face images.

4.3.5 Eye State Recognition

In this module of the system, the method that connects the desired extracted features to the current driver's fatigue level is described. To identify fatigue through eye behavior analysis it is necessary to know its state over time and to develop an algorithm to measure the time spent in each state.

4.3.5.1 Eye States Definition

Two default eye states are considered in this work: open and closed. Eye state is defined as open if the iris and sclera of the eye (both black and white regions of an eye) can be observed. Otherwise, if the iris and sclera are not visible or even difficult to distinguish, the eye is assumed as closed. This definition matches the criteria for PERCLOS calculation where the eye closed for more than 80% is considered as closed. The defined eye states are shown in Figure 20.

Figure 20: Open and closed states of an eye

Furthermore, we found out that states of both eyes may not be completely similar in a sense that one of the eyes is more closed than the other one in the same frame. In this case, the eye state is judged based on the more closed eye state.

4.3.5.2 SVM Classification

After obtaining feature vectors of the desired regions of the face, highly involved with fatigue expressions, eyes are ready for the relative state recognition. A binary classification on LBP feature vectors of input frames would yield an efficient real-time determination of the current eye state. Therefore, and according to the previously described advantages, SVM classifier with RBF kernel is applied on the test images to distinguish between the open and closed eye states. The greatest advantage of SVM is its good performance in generalization even with small set of training data. This property is certainly helpful in the area of driver drowsiness detection, where collecting natural fatigue expressions is a challenging task. Other reasons for implementing the current module using an SVM were the binary nature of the proposed classification problem and the efficiency of SVM in working with high dimensional feature vectors.

4.3.5.3 Training and Testing sets of SVM

Training the SVM classifier requires a set of face images showing drowsiness expressions. Since there is not any facial drowsiness dataset available for the research community, we created our own dataset. To construct this training set, videos of 10 persons were collected. In each of these videos, the participants were asked to naturally express both alert and fatigue driving states. Alert state is known as open eyes with normal blinking and eye movements, while the drowsy state is consisted of higher blink frequency, longer blink durations, and micro sleeps, lasting for at least 3 to 4 seconds, as well as a small head nodding at the end. Figure 21 shows some sample images of the training data.

Eyes Open

Eyes Closed

Figure 21: The sample fatigue expression images from the training dataset

The trained classifier matches the input histogram with the closest state and outputs the corresponding class label (0 for open and 1 for closed).

System's performance is verified by measuring the accuracy rate, which is the proportion of the properly classified images to all images in the test set. For this purpose, an integer variable called true prediction counter (TP) is used during the test phase, which increments immediately after a test image state is classified as true. Then, accuracy (ACC), as the output of this phase, is calculated by dividing TP over the accumulating train data, loading from the dataset. The SVM, trained with both open and closed eye states, resulted in a successful eye state recognition rate of over 95%, after being tested with the two datasets.

4.4 Real-time Fatigue Detection

Having repeated the eye state recognition procedure continuously for all image sequences, the number of consecutive frames in which eyes are closed are visually known. Therefore, over a period of time, the simple static eye state data is converted to at least two dynamic fatigue parameters: blink duration or PERCLOS and blink rate or blink frequency.

4.4.1 Fatigue Index

As mentioned earlier in the previous chapter, PERCLOS determines the percentage of time the driver's eyes are closed. To calculate the value of PERCLOS at time t for the current frame, the following steps are considered:

1. Select a time window $[t - T, t]$ of a predefined length, T, in which the eye position has been tracked (i.e. in each input frame, the eye region is located and extracted).
2. Count the number of time intervals, n, and their durations (t_i for the i^{th} one), during which the eyes are detected as closed. This time is equivalent to the duration of eyelid closure or the continuous closed state in the time window.
3. Evaluate the following equation (Eq. (3.1))

$$PERCLOS = \sum_{i=0}^{n} \frac{t_i}{T} \times 100 \tag{3.1}$$

It is necessary to remove blinking time from the accumulator to make the measurement more accurate. As mentioned before, the duration of normal blinking is under the range of $300 - 500ms$, whereas above this range, the driver is at least experiencing slow eye closures. The processing time of our algorithm is $2f/s$, allowing us to be aware of the eye state every $500ms$. Consequently, if the eyes are detected as closed for at least 3 consecutive frames, the driver is not in a normal alert state anymore, and hence this duration should enter the cumulative PERCLOS calculation.

Subsequently, driver fatigue decision is made by applying fatigue threshold on PERCLOS.

4.4.2 Fatigue Levels Analysis

Three PERCLOS thresholds are set for fatigue analysis. In case the driver shows $3seconds$, $6seconds$ or $9seconds$ continuous eye closure over a $1-minute$ time window, the PERCLOS score crosses the defined 5%, 10% and 15% thresholds respectively. Taking into account the algorithm frame rate, $2f/s$, if, for example, the computed PERCLOS is greater than 5%, eyes have been recognized as closed for 6 consecutive frames and hence the system has reached the first safety driving limit and immediately issues a warning. The procedure for various levels of fatigue detection based on PERCLOS calculation is detailed in the following algorithm:

Various Fatigue Level Analysis

Require: Video stream from the camera monitoring the operator/* the system can proces F frames in each second in its online surveillance. */

1. Compute the PERCLOS score P_S of the operator using equation 3.1
2. **if** $P_S < n$, where n is the average PERCLOS score of the operator in normal condition **then**
3. Flush previous PERCLOS score list. Go to step 8.
4. **end if**
5. Retrieve and update the vector score list P_{S_i} for the past 60 seconds.
6. Compute the cumulative PERCLOS score of the operator $L = \sum_{i=1}^{c*n/F} P_{S_i}$, where c is the tolerance constant, and F is the number of frames that the system can process in each successive seconds.
7. **return** Approximated haptic feedback level, $h_l = trunc\left(\frac{L}{c}\right)$, where $h_l \in \{1, 3, 5\}$.
8. **return** $null$ /* Eye state open, reset warning levels. */

It has to be noted that if, for instance, the driver makes $3 seconds$ eye closure in 3 different times over the time window, it is equivalent to crossing the first level of fatigue threshold (5%) 3 times separately. In comparison, the case of $9 seconds$ consecutive eye closure over the same time window obtains a different fatigue level (15%).

In order to quantify driver's fatigue state for a more accurate estimation, four fatigue levels are suggested, matching the ranges of the mentioned PERCLOS thresholds. These states are called as "alert", "potentially fatigued", "fatigued", and "much more fatigued". Accordingly, the driver is considered as "alert" if his/her cumulative PERCLOS score over time is below 5%. For the score range of $5\% - 10\%$ the driver is estimated as "potentially fatigued". If the driver is in the range of $10\% - 15\%$ s/he is "fatigued" and finally in the most dangerous case, when the driver makes a score of over 15%, the state of the driver is "much more fatigued". This PERCLOS Score$-$Driver State relationship, leading to fatigue level quantization, is displayed in Figure 22.

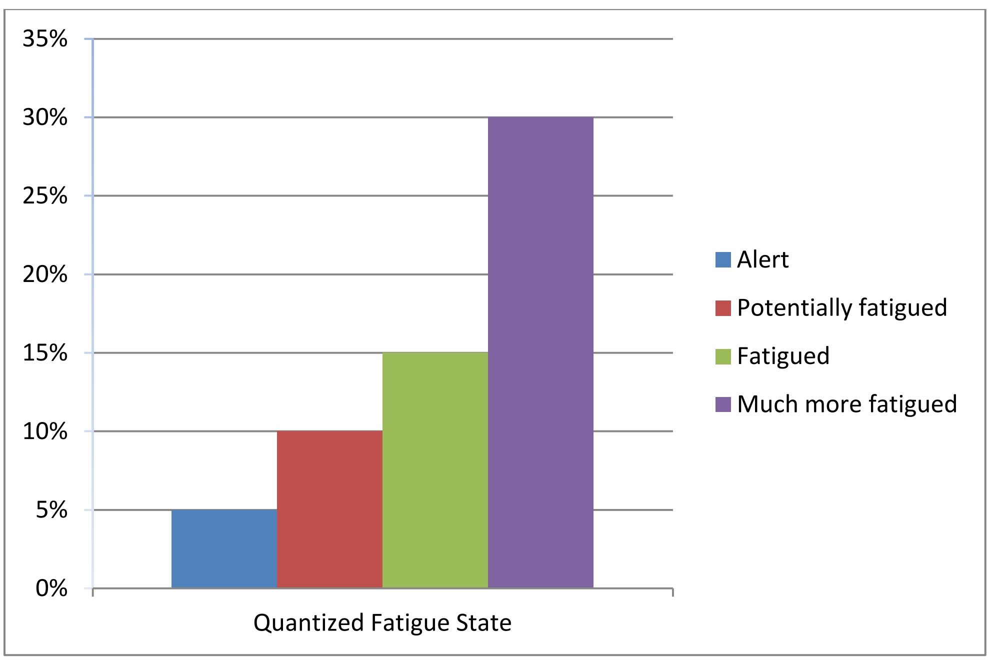


Figure 22: PERCLOS – Fatigue level relationship

We have tried to trigger an alerting feedback based on the detected fatigue severity and to make the driver aware of his/her inability to continue driving.

4.5 Feedback Generation

The second part of the proposed driver fatigue assisting systems is setting up a prototype for alarm signal deliveries. That is where the main design problem lies in related studies:

- How to present continuous warning information in an unobtrusive way?

This question could be better answered if divided into two more accurate ones:

- How to use the measured fatigue index to describe a critical warning level?
- What type of warning interface and signals to use to convey that critical level?

We suggested a practical solution for sending warning signals to the driver during fatigued or drowsy state:

- First, graded warning levels are defined to match the quantized fatigue levels in order to deliver the warning signals in a progressive manner. In fact, the obtained fatigue level is translated to the corresponding warning level.
- Second, to effectively communicate that warning level, specific portion of a previously developed haptic jacket device is taken into account to vibrate and present the corresponding haptic feedback as the warning signal.

Consequently, applying the suggested haptic feedback types, the driver is safely alerted after the fatigue state is detected.

4.5.1 Haptic Signals

Haptic alerts warn the driver approaching a crash by applying forces or generating vibrations. According to the fact that visual and auditory perceptual channels are more engaged during the driving task, warnings in the tactile modality should help the driver to have a faster reaction time. In fact, by controlling the displacement of vibrotactile stimulus on the skin, more information can be displayed to the human. More importantly, simple haptic signals would not have any negative impact on driving safety i.e. not interfering driver's attention during driving.

Considering the ability of haptic feedbacks to effectively interact with the user for warning signals delivery, a haptic prototype is adopted in our driver assisting system as the followings.

4.5.2 Haptic Jacket

The haptic jacket [99] is a suit consisting of an array of vibrotactile actuators positioned in certain locations of the jacket. Vibrotactile actuators communicate sound waves and create funnelling illusion when it comes to physical contacts with skin. A series of small actuator motors are placed in a 2D plane in the jacket and are controlled by an ATMEL MEGA128 AVR Micro-controller. The actuators are activated in a defined manner to produce touch feeling [99][100]. Configuring the Micro-controller, vibrotactile warning signals could be sent in different frequencies and intensities, corresponding to the estimated levels of fatigue.

In order to translate fatigue criticality to haptic signals, Bluetooth is considered as the communication method between the fatigue detection module and the Bluetooth-enabled haptic jacket device. The haptic interaction controller uses the Bluetooth communication channel for command transmissions. Based on this method, fatigue data, more precisely the PERCLOS threshold, is presented as the vibrotactile stimuli through the haptic jacket. Figure 23 depicts the components of the jacket in more detail.

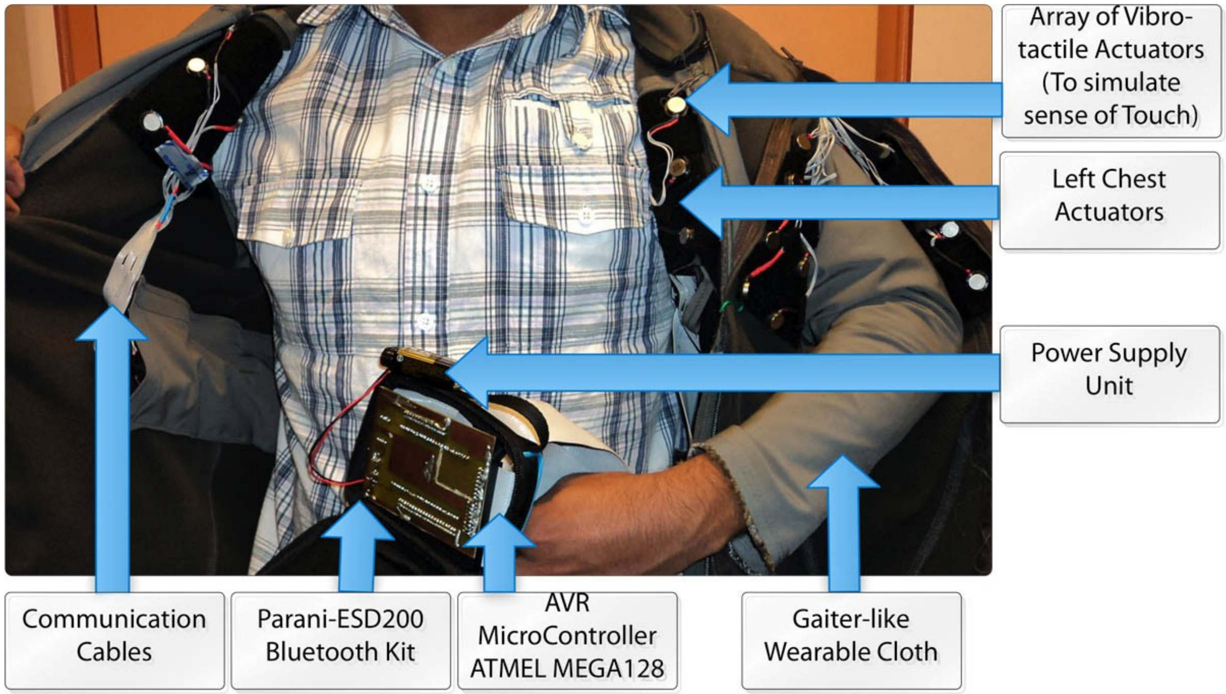


Figure 23: Haptic jacket hardware components

Perhaps, one might worry that these vibration cues would be ineffective should a driver wear thick cloths. However, recent studies have proven that tactile warning signals are transferrable through various daily clothing and even through the soles of a driver's shoes, for the idea of presenting vibration stimuli on the gas pedal [92] [97] [87].

4.5.3 Haptic Rendering Customization

Regarding what drivers would find helpful to do with the warning interface, we attempted on embedding driver's preference and control in the system. Promoting driver acceptance is presented through haptic jacket features.

4.5.3.1 Haptic Jacket Features

- The driver can select the locations on the interface from where the feedback is received.
- The driver can adjust the intensity of vibrations for corresponding fatigue levels.
- The driver is also given the option to disable the warning system should he/she find it bothersome.

4.5.3.1.1 Locations for Haptic Perception

As the default setting, three specific portions of the haptic jacket interface are equipped with actuators to signal feedbacks corresponding to the three described PERCLOS thresholds. Shoulder area is selected to express the "mild" warning type. The reason for this choice is that shoulders are less irritating for the users. In addition, since the operator would be alerted with the mild level feedback more likely compared to other levels, selection of shoulders makes vibration transfers more comfortable. As a more sensitive location, chest area is chosen for the "average" level haptic perception. Finally, taking into account the sensitive spinal reflexes and its effectiveness in conveying more urgent warnings for the sleepy driver, the backbone area is preferred for receiving the "danger" level of haptic alerts. Figure 24 illustrates the selected locations and their corresponding feedback types on both front and back view.

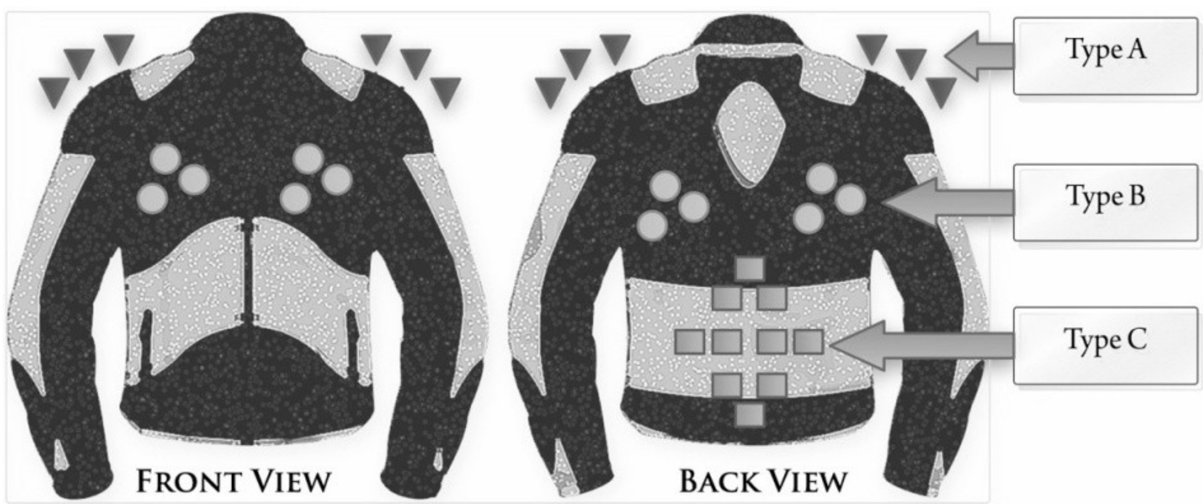


Figure 24: Depending on warning levels, different portion of haptic jacket is selected for haptic warnings delivery. Here, a) Area defined by the triangular shapes is used to provide warning $level = 1$, b) Area defined by circular shapes on the chest and back is leveraged for warning $level = 3$, and c) Spinal area with rectangular shapes is used to generate warning $level = 5$.

Besides the default settings, there is an option offered to select preferred locations for specific stimuli perception, based on individual differences in reaction. For example, the driver is able to choose just shoulder areas but with different intensities for corresponding fatigue levels, or the three defined areas with the same vibration intensity. In the former case, the intensity of warnings determine the severity of fatigue, while in the latter case warning importance would be recognized through the signalling location.

4.5.3.1.2 Warnings Intensity

The intensity of haptic feedbacks is also customizable. During the “potentially fatigued” state, where PERCLOS ranges from $5-10\%$, shoulders receive the “mild” vibrotactile warnings. If the driver is detected to have an eye closure duration equivalent to the “fatigued” state, where PERCLOS ranges from $10-15\%$, alert perception is through the chest area with the “average” haptic warning signals. Crossing the 15% threshold and staying above that, the driver is “much more fatigued” experiencing microsleeps and is highly potential to fall asleep at the wheel. For this fatigue state “danger” level warnings are selected to be sent to the backbone area.

Once the initial warning is triggered, the driver may either respond to that or not. In case of response, which is when the eye state is switched to open, the driver drowsiness level is back below the first threshold. System waits for the next eye closure to emit a haptic warning. Otherwise, in case of continuous eye closure, driver would exceed higher PERCLOS thresholds, corresponding to higher drowsiness levels, and therefore more intense warnings are issued until returning to the alert state.

4.5.4 Warning logic

A graded warning would present a degree of warning based on the severity of danger. This setting for warning delivery could be reflected in the smooth vibration transition between body parts from less sensitive to more sensitive. This is in contrast with the single-stage warning setting that produces the signal only when a certain threshold has been crossed. Graded warning allows the driver to be aware of fatigue progression from early stages of a fatigue episode rather than sensing a sudden awakening signal. Therefore, the driver would find enough time for a safe reaction or a countermeasure to mitigate the effects of fatigue. Furthermore, graded warning signals are trusted more, increasing system’s acceptance, compared to single-stage abrupt warnings.

4.5.5 Additional Specifications

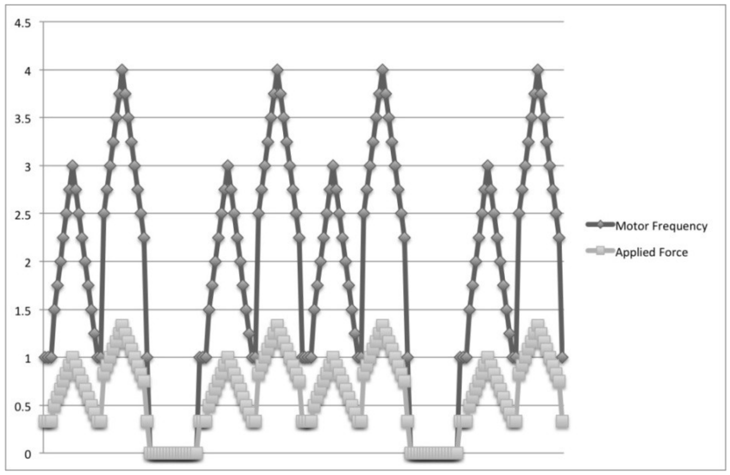
There are some other characteristics associated with the haptic jacket that enhance its performance.

4.5.5.1 Integration

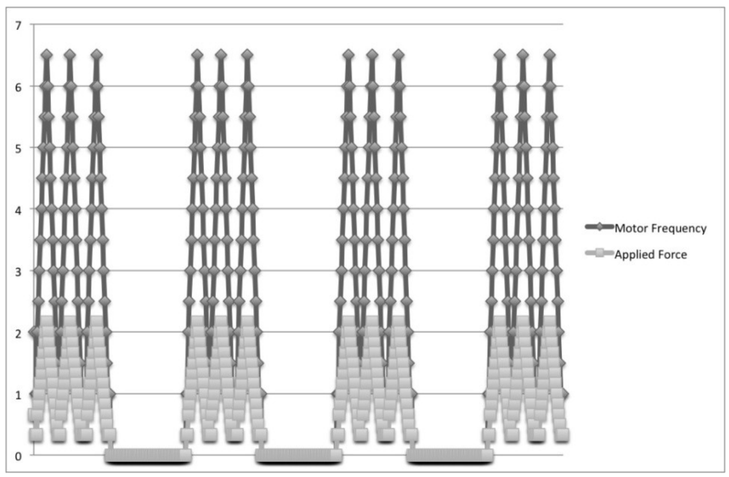
From the integration point of view, the proposed warning scheme in the form of haptic jacket is practically beneficial; compared to other in-vehicle driver assisting devices, no special method is required to add the haptic jacket to the vehicle. The wearability property of the haptic jacket, which makes it independent of the test environment, also helps to conduct the in-laboratory usability study completely close to the real in-vehicle driving situation. Other studies on driver drowsiness warnings are limited to the laboratory environment in order to have access to signal generating equipments rather than integrating them in real vehicle.

4.5.5.2 Vibration Severity Settings

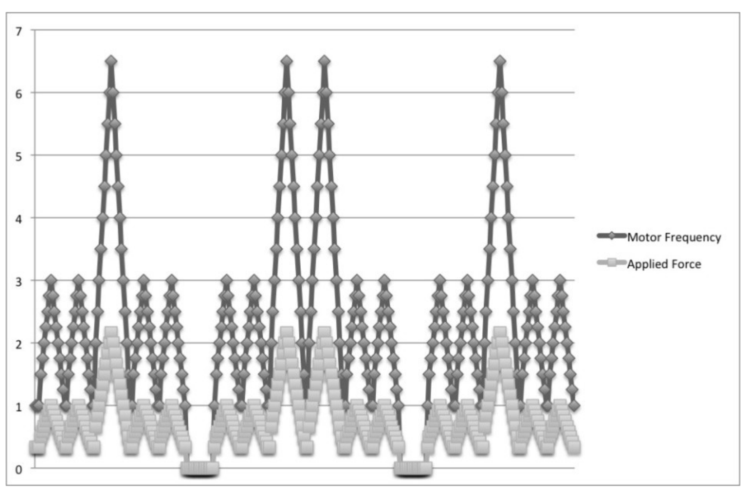
In our previous work [95], a previously developed armband with an array of actuators was employed as the interface for warning signal delivery. Three different alert levels were chosen to warn the driver about various fatigue levels, mimicking the sounds of Clap, Chopper and Ambulance respectively. The vibrotactile warning signals that were applied in that work for the armband interface could be also adapted to the haptic jacket. These three levels and their durations are shown in Figure25.



(a)



(b)



(c)

Figure 25: Haptic data type for various warning levels: (a) Clap, (b) Chopper, (c) Ambulance

For the haptic jacket, certain places of the jacket (chest, spine and shoulders) that are chosen for haptic feedbacks are of different importance in the context of fatigue severity and the driver is subsequently notified of that. For example, in order to signify very dangerous feedback, the spinal area is chosen to signal the vibrations. Nevertheless, the Clap, Chopper and Ambulance vibration alerts could be augmented with this scheme as well. As a result, not only the haptic feedback locations would inform the driver of his/her state, but the type of feedbacks also help to better infer the current situation leading to a faster reaction. This configuration is preferred for drivers who are more confident in their abilities, while more cautious drivers prefer to react sooner.

4.6 Summary

Figure 26 shows a block diagram of the overall operation of the system.

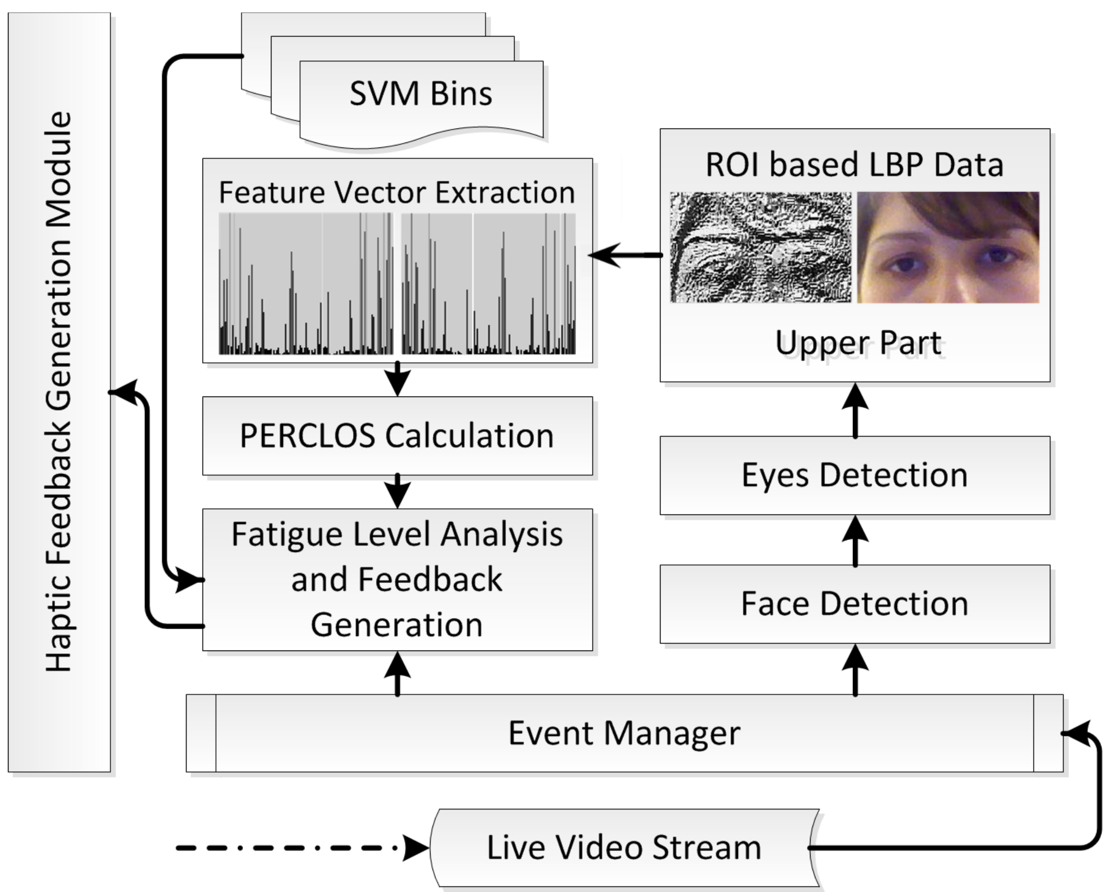


Figure 26: Schematic diagram of the proposed system

Finally, Table 5 summarizes the relationship between all defined parameters for fatigue detection and warning in one glance.

Table 5: A Summary of Defined System Variables and Their Relations

Parameters	Variations			
PERCLOS Score (P_{s_i})	5% 10% 15%			
Quantized Fatigue State	Alert	Potentially fatigued	Fatigued	Much more fatigued
Haptic Jacket Warning Locations	Shoulders Chest area Spinal area			
Intensity and Frequency	Mild Average Danger			

Chapter 5 - System Validation

Experimental results were acquired using a Sony digital video camera and a $2.66\ GHz$ CPU with $2\ GB$ RAM memory as the hardware. Video sequences were acquired at 25 frames per second with the resolution of 640×480. The proposed approach was implemented in Microsoft Visual Studio C++.

The validation consists of three parts. First part involves validating the performance accuracy of applied computer vision techniques. The second part studies validity of fatigue parameters resulting in the computed fatigue index, and finally the third part evaluates the validity of the haptic warning presentation through the suggested haptic interface.

5.1 Measurement Accuracy

In this section, some quantitative results are presented to characterize the accuracy of employed computer vision and pattern recognition techniques.

5.1.1 Test Sequences

First, recorded videos captured from 10 participants in the laboratory environment are converted into image sequences. There was no limitation on wearing glasses while recording videos. Alert and fatigue intervals are then separated for each one of the sequences followed by selection of image frames for both open and closed eyes.

5.1.2 Eye Localization

Our face and eye detectors are implemented in OpenCV using the already trained classifiers with human faces and eyes based on the Viola and Jones approach that uses haar-like features. This method of face and eye detection has been proved to be fast and effective enough for real-time eye states detection system. Various states in an image sequence of the fatigue state (open, mid-open and closed) could be successfully detected, as illustrated before.

For the eye localization study, an image sequence containing 745 frames is randomly selected, and the eyes are manually localized in each frame. The manually extracted data serves as the ground-truth data, and is compared with eye detection results of the algorithm. The study shows that the implemented algorithm is quite accurate in detecting eye position in all frames regardless of its state as open or closed, with or without wearing glasses and matches very well with manually detected eye positions. Figure 27 shows an example of eye detection and localization result during a fatigue state episode.

Figure 27: An image sequence during fatigue progression output from the eye detection module

Thus, the next experimental results on eye-state detection rely on the assumption that eye regions are located correctly in each frame.

5.1.3 Eye State Recognition

After accurately detection of eye regions, we apply our presented method to detect open/closed state of the eye. Eye state recognition performance using SVM is validated by measuring the classification accuracy. SVM is first trained with the created dataset obtained from captured videos of participants. Video frames are processed and then the classifier is trained with extracted LBPH vectors for the open and closed eye states separately. Training data consists of 300 images of each class (open and closed)—per person. Afterwards, the classification accuracy is validated by measuring the recognition rate.

Two different sources were selected as the SVM test images. 1) Some of the image sequences from the captured video frames that were used to train the classifier, 2) Some of the sadness expression sequences of the FG—NET Facial Expression database that contained the same slow eyelid closure behavior as the real fatigue image sequences. We wanted to make sure that SVM was tested on faces of persons that were never seen before during training. Therefore, we requested to have access to the FG−NET Facial Expression and Emotion Database [96]. This password-protected database contains spontaneous emotions of seven expressions (neutral, surprise, fear, disgust, sadness, happiness and anger) gathered from 18 subjects. In order to test SVM with proper states, the sadness expression which includes faces with both open and closed eye states, resembling fatigue expression, is selected. The test data consists of 250 images of the two eye states (open and closed). Sample test images are shown in Figure 28.

Figure 28: The sample sadness expression images from the FG−NET database

In the experiments, one video from our own created dataset including faces with alternate eye states is selected to test the eye state classification. The video is taken by the color video camera and lasts for one minute, containing 25 frames per second. Thus, 1500 frames are obtained after converting the video to an image sequence. The results of the test frames are summarized in Table 6, which are %96.8 and %94.78 for open and closed states respectively.

Table 6: recognition accuracy of the video test

Eye state				Recognition rate
Open		Closed		
Frame	Recognized	Frame	Recognized	
1002	970	498	472	% 95

The experimental results show that the proposed fatigue detection system using LBP features for facial information representation and SVM for classification provides 95.43 % recognition accuracy.

5.2 Validation of Fatigue Parameters

5.2.1 Fatigue Level Detection

During the experiments, users' PERCLOS score, as the most valid ocular parameter for monitoring fatigue, is evaluated when they are emulating either the alert or fatigue driving states. The subjects were asked to maintain short-period eye-closures as indicating the alert state with normal eye blinks, while longer blinks (more than 3 $seconds$) to simulate fatigue progression and the sleep onset. Continuous measurement of driver's PERCLOS score P_{s_i} over time t_i would then obtain the real-time fatigue analysis (Algorithm 5).

5.2.2 Parameter Measurement for a Test Sequence

Figure 29 depicts the parameter measured for one of the sequences. Figure 29 (a) represents the average PERCLOS score for alert state, and the scores defining different fatigue levels are depicted in Figure 29 (b). This is a representative test example with a duration of $120\ s$ where the user simulated both fatigue and alertness behavior. As illustrated, for the alert state, the graph is more stable and much lower than the fatigue one. Following the fatigue graph, at time $46 seconds$ the score crosses the minimum score boundary and remains at that level for $2\ seconds$ continuously. At this instance, we constantly flag our first haptic warning at the shoulder area of the "potentially fatigued" driver. Subsequently, at time $48 seconds$, the calculated score continues to increase beyond 10% tolerance and remains at that for $3 seconds$. Here, the average haptic warning signal is sent to the "fatigued" driver, which is the vibrotactile response at the chest area. Similarly, at the time instance $58 seconds$ the score crosses the 15% threshold for $3 seconds$. At this hazardous fatigue level, corresponding to the "much more fatigued" state, the maximum haptic signal is stimulated. The driver is immediately notified by vibrotactile stimulation at the backbone area of the haptic jacket.

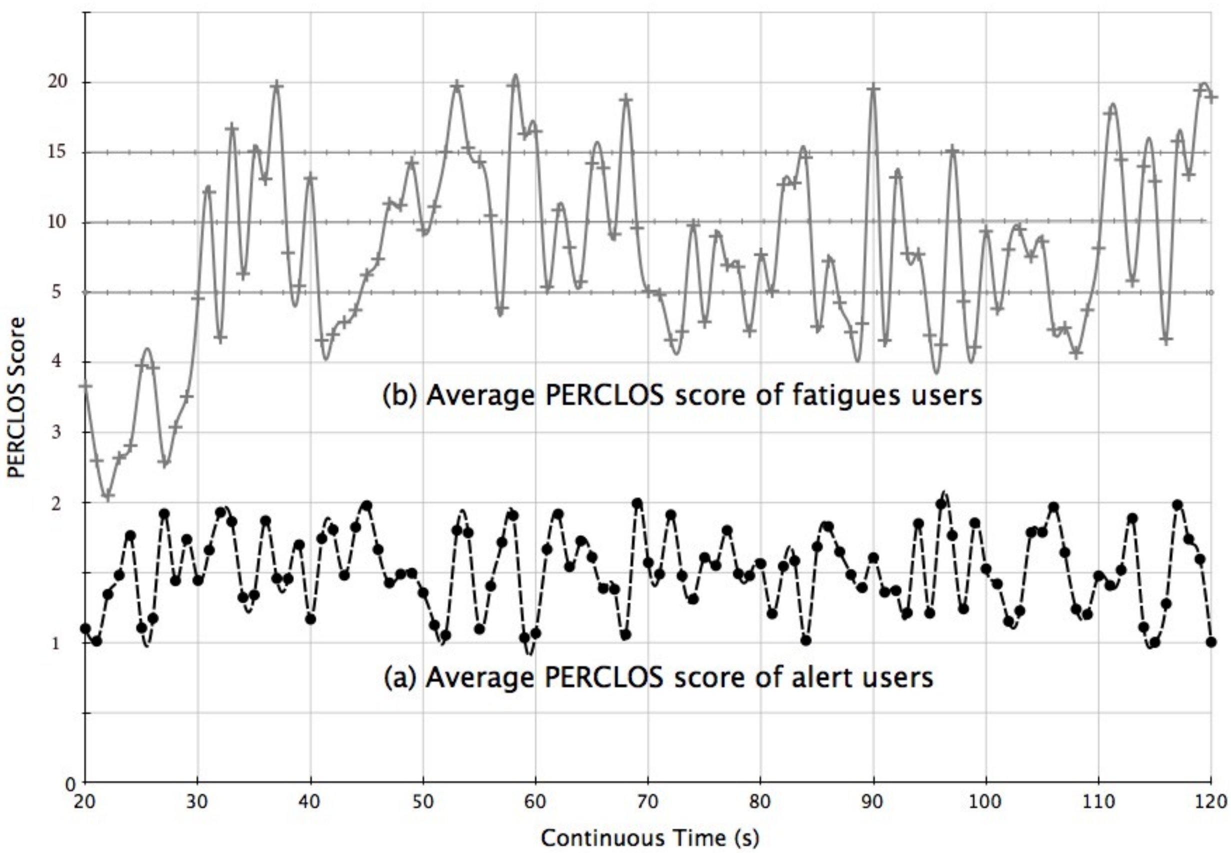


Figure 29: Eye closure monitoring over time (seconds).

Results obtained for PERCLOS were quite acceptable indicating a high correlation with detected fatigue levels. In fact, the PERCLOS score was about its respective thresholds more frequently in the "fatigued" and "much more fatigued" time interval samples than in the "potentially fatigued" and "alert" samples.

The performance was measured by comparing the system performance to results gathered by manually analyzing the recorded sequences on a frame-by-frame basis. This not only proves the validity of PERCLOS to characterize fatigue state but also proves the accuracy of the system in eye state detection and PERCLOS measurement.

5.3 Validation of Haptic Warnings

5.3.1 Haptic Feedback Perception

Performance of vibrotactile perception from the haptic jacket is evaluated through psychophysical experiments. Three different locations were empirically defined to express the urgent nature of the alarms to participants. Besides, the haptic-enabled armband that was suggested before as the warning delivery interface to alert the driver is evaluated in another run. Compared with the armband haptic feedbacks, the users have the benefit to easily distinguish the haptic feedback levels and immediately their fatigue level from haptic jacket based on particular locations of the stimuli. In the proposed system, 98.5% of the users are able to successfully distinguish between the three haptic levels. Similarly, 94.2% of them were a lot more comfortable to wear the haptic jacket instead of the haptic armband, and expressed 89% approval that this type of haptic feedback scheme is helpful in alerting the drowsy or fatigued operators.

5.3.2 User's Discomfort on the Haptic Feedback

Another attempt during the psychophysical experiment is to determine whether users are satisfied with the default haptic levels provided in the system. The evaluation consists of three trials during each participants are sent vibrotactile feedbacks from the predefined haptic jacket portions. An advantage of our vibrotactile warning scheme is that it only involves a minimal period of familiarization for users prior to testing, making them use it efficiently.

Most complaints with the default haptic feedbacks are that they sometimes cause tickles to the users. Results show that 24% of the users are not comfortable with the average haptic feedback type, perceived on their chest, due to its tickling effects. The percentage of tickle complaints from users for each type of the defined haptic rendering setups is displayed in Figure 31. According to the described default setting, the higher the warning level, the more responsive upper body part receives the haptic feedbacks. Figure 30 shows that $Level = 3$ feedback type which stimulates the spinal area is more acceptable among users due to its ability in quick warning delivery.

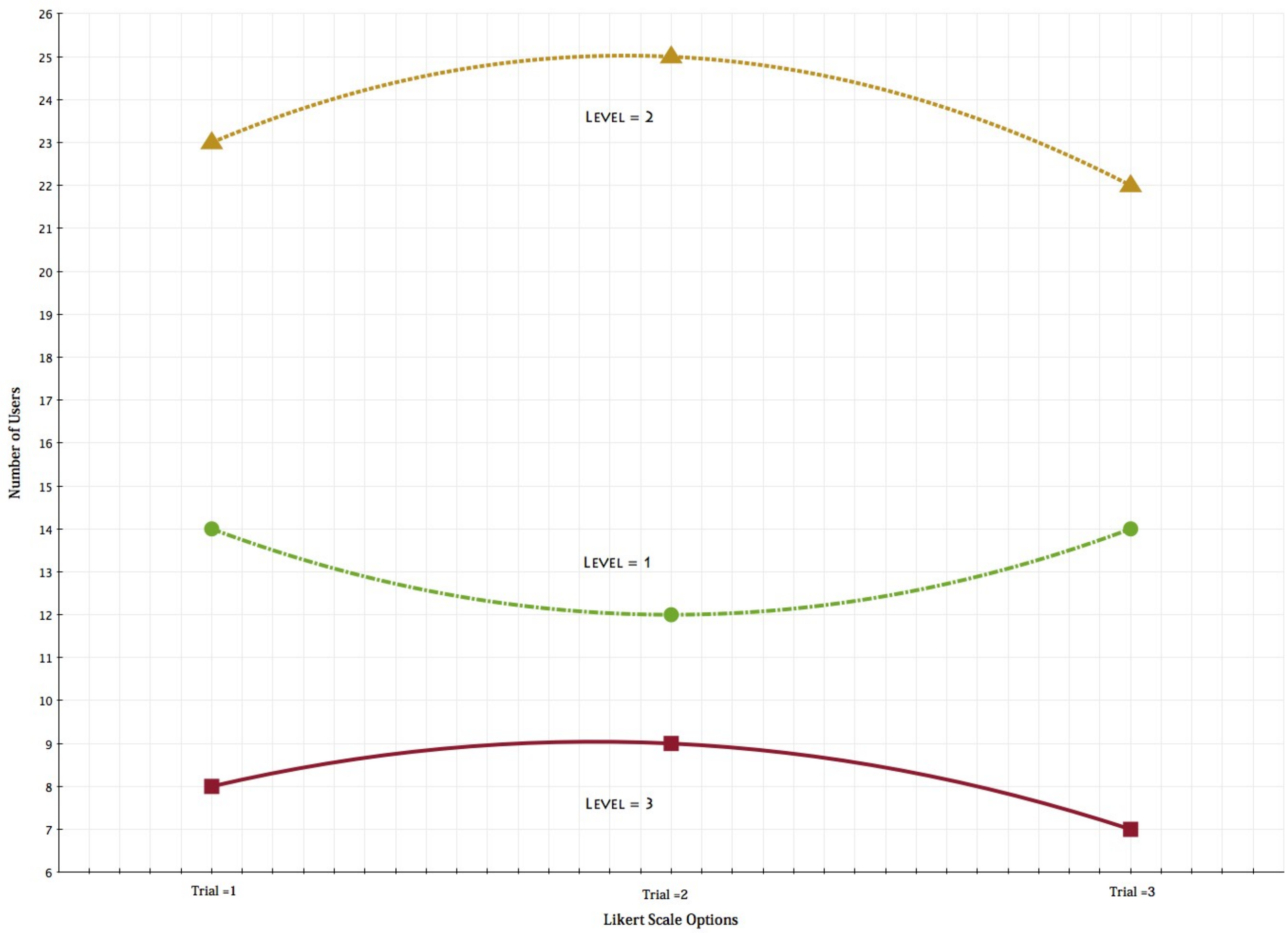


Figure 30: Number of users who are uncomfortable with the default haptic level setups

Due to tickle issues, users are provided with the option to make changes in the locations of haptic stimuli perception using the feedback controller. Accordingly, the driver is allowed to choose the jacket portion with which they feel more comfortable for tactile feedback perception. Drivers would have the chance to test various options of the location on body where they feel more responsive to the warning signals. This facility not only provides a more comfortable experience during fatigue warning deliveries, preventing driver shock and worse consequences, but it also helps the driver not to get used to a familiar feedback type; instead be surprised the next time the haptic signal is sent to a new upper body part, resulting in a more effective warning solution. Figure 31 outlines haptic rendering customization steps in a loop. First, user's preferences are taken into account by changing the settings of the MicroController (Figure 25). In the next step, haptic jacket which is updated with the new settings (2a) is ready to issue user's desired feedback type as soon as being triggered with the warning parameter (PERCLOS) (2b).

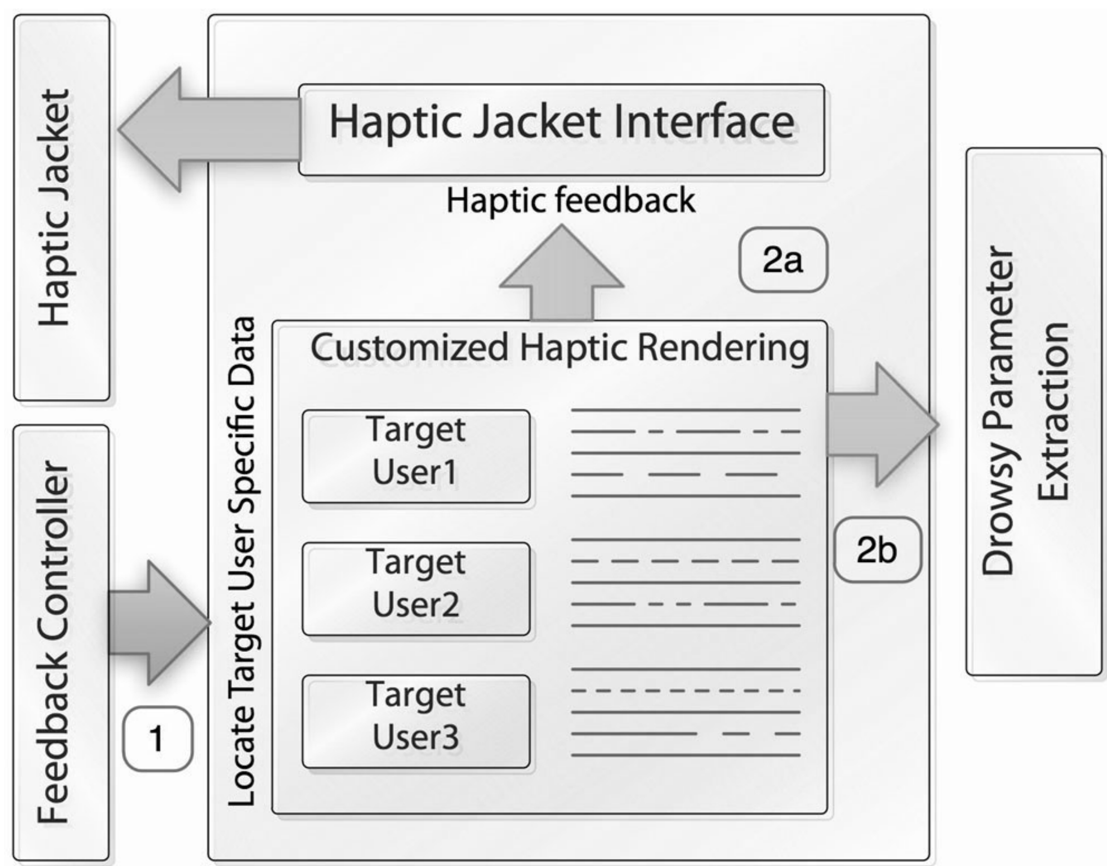


Figure 31: User customization of haptic rendering feedback loaded during the warning scheme

After performing several trails with each type of feedbacks, participants were asked about their preferences regarding the presence or absence of feedback as well as the preferred type. Results showed that users not only preferred the presence of haptic feedbacks overall, but a majority of them felt more in control when actively guided by it.

5.3.3 Usability Study

Usability tests were conducted to evaluate user's quality of experience of the proposed system. The usability tests take place at the university laboratory in a controlled environment with eight volunteers, of different age groups and academic backgrounds. The users are requested to sit in two different arrangements in front of a video camera and emulate both alert and fatigue facial behaviours separately. During the experiment, participants wear the haptic jacket that is controlled through Bluetooth communications in order to receive and experience the default haptic feedback types corresponding to expressed fatigue levels. Users' activities are monitored and noted throughout the experiment for later analysis. Afterwards, based on their interaction experience, the users are asked to rate three assertions in Likert Scale [98], with the rating range of $1-5$. The higher the rating number, the stronger the agreement is with the provided assertions. Figure 33 shows users' responses for each given assertion. The results are displayed in Figure 32.

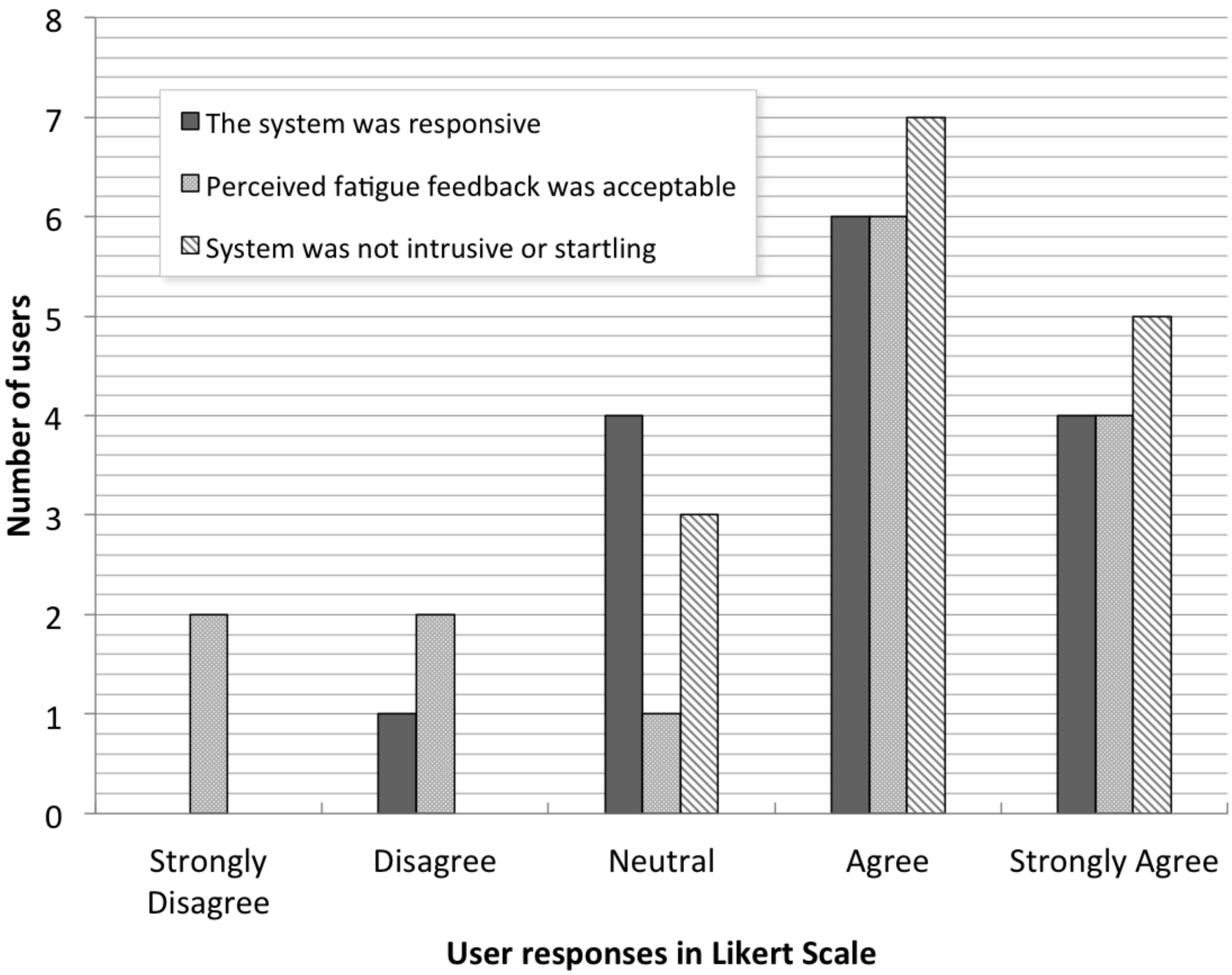


Figure 32: User responses in Likert scale.

In general, majority of the users agreed that the proposed system was responsive and performed efficiently in measuring warning levels. Amongst the participants, 6 persons are successfully able to perceive different levels of haptic feedback, and the two others confirmed that they would have no problem after getting used to it.

We are, therefore, able to conclude that haptic feedbacks, especially when customizable individually, are not intrusive or startling to the users. Overall, our user study shows that people have a good tendency of accommodating such haptic-based warning system in their driving practicing.

Chapter 6 - Conclusion & Future Work

6.1 Conclusion

Sleep deprivation while driving is a major cause of traffic accidents. To make an assessment of a driver's level of fatigue and provide a timely fashioned warning for action to be taken before the crash situation arises, an unobtrusive, automatic driver fatigue monitoring system is proposed that is capable of detecting unusual, continuous, repetitive eye closures followed by perfectly warning the driver of the dangerous situation.

To infer the fatigue state, a real-time approach for tracking eye state changes and fatigue levels over time is implemented. First, eye region is converted to feature vectors representing the eye state using an illumination invariant texture descriptor called Local Binary Pattern (LBP). Afterwards, Eye closure is determined through using the SVM classifier to distinguish between the corresponding open and closed eye states by classifying extracted feature vectors. Once the state of the eyes is collected over a period of time, it is shown how PERCLOS calculation and threshold definition is used to evaluate fatigue severity. Accordingly, driver fatigue is quantized into four levels namely "alert", "potentially fatigued", "fatigued" and "much more fatigued" during a fatigue episode. To this end, an accurate fatigue state assessment is proposed relying on the quantized fatigue levels.

The second part of the system focuses on perfectly alerting the sleepy driver through wearing the haptic jacket equipped with vibrotactile actuators. In this stage, system's warning parameter, PERCLOS, will translate fatigue levels to warning levels using the Bluetooth communication channel. In order for continuously communicating the situation criticality without causing annoyance, graded warning strategy is provided through sending haptic feedbacks to more sensitive body parts. The three selected alert locations are "shoulder", "chest" and "backbone (spinal)" areas that are stimulated in case of crossing 5%, 10% and 15% warning thresholds respectively. The logic of conveying the higher criticality level to a more reflexive upper body area would ensure less need for cognition (situation assessment and short-term planning), faster response and more corrective actions.

In order to enhance system usability, drivers' preferences are embedded in the system. Specifically, drivers would have options on selecting warning perception locations as well as adjusting the intensity (mild, average and dangerous) of vibrations for different fatigue levels. Thus, taking into account the individual differences factor through offering warning perception options, system reliability and driver trust is achieved.

Experimental results show that under laboratory conditions, the proposed system can accurately detect fatigue levels, and it can issue a warning according to detected state of eyes' open and closed, so that it meets the requirements of fatigue correction and collision avoidance systems.

6.2 Future work

This area appears promising in terms of future research due to the common everyday crashes caused by fatigued drivers, and hence automatic driver assisting systems makes them less likely to occur.

In order for monitoring driver's face at night, IR illuminations using infrared LEDs could be added to the video capturing part of the system to brighten driver's face and create the "bright pupil" effect. External sources that are the main source of noise for IR-based image acquisition systems are much limited at night, and hence their impacts are effectively minimized using the IR illuminator. Therefore, the system would work based on the proposed texture-based LBP method during day time driving and based on the "bright pupil" effect at night using a camera with the compact IR illuminator. LBP operator has been proved to improve the face and facial expressions recognition rate significantly when used to smooth the various illumination conditions. Besides applying the robust appearance-based solution, we can take advantage of IR illumination to minimize ambient lighting effects in daylight driving. For alleviating interference from light sources beyond IR light, a narrow band-pass filter, centered at the LED wavelength, could be attached between the camera and the lens. In addition, to overcome the intense sun light interference, when the power emitted by sun in the filter band hides the inner illumination, IR filters could be integrated in the car glasses.

Furthermore, a more accurate condition on direction of the driver's face would make the proposed system more suitable for real in-vehicle driver state monitoring. Camera is fixed in the central part of the dashboard to focus on driver's head for detecting visual behaviours. The proposed system is trained with the frontal face database available in OpenCV. Experiments show that faces with a little rotation degree are still detected. Hence, when the face is not detected, it is not frontal, and the driver is not following what is happening on the road. This situation could be added to the system as a sign of inattentiveness or head nodding. The criticality level is then conveyed by applying thresholds on the time duration when the driver is inattentive. Therefore, if the number of frames with not-faces is greater than a fixed threshold, an alarm signal is set off to redirect driver's eyes to the road ahead. This threshold is set such that the normal time for looking at the side view mirror is excluded. To communicate inattentiveness warning with the driver, another portion of the haptic jacket, for example arms, could be equipped with vibrotactile actuators.

Another objective for future work will be to reduce the percentage error or to improve system's recognition rate during the eye classification step. To achieve this, additional experiments will be developed, using additional drivers and incorporating new analysis modules, for example, facial expressions representing yawning and eyebrow movement analysis. Furthermore, when building real-time systems, it is also preferred to have LBP – based representation with reduced feature length. Existing LBP feature selection techniques have limitations either in feature selection ability or the computational cost. Reducing the feature vectors dimension would help to increase the algorithm's processing time up to $10f/s$, $20f/s$ and higher and hence to achieve more accurate fatigue state analysis.

As a new objective, haptic jacket can be utilized as a smart cloth, a combination of electronics and clothing textiles, equipped with both fatigue data measuring sensors and vibrotactile actuators. Consequently, physiological signals such as heartbeat, EEG, body temperature and ECG and their variations (known as the most accurate fatigue signs) could be captured via the sensors inside the jacket. Haptic jacket would then serve as an integrated in-vehicle driver fatigue detection and warning interface.

Taking fatigue driving as serious as drunk driving, the haptic jacket could be set up to be worn mandatory before starting driving, just the same as the seat belt. As an idea, it could be connected to the belt, so that the driver has to wear the jacket first and then closes the belt before start driving. Therefore, the chance to forget to wear the jacket before getting into the car or leave it somewhere is reduced.

Again with the idea of smart clothing and taking different weather conditions into consideration, active character systems including heating, cooling and active drying (in case of humidity increase) could be integrated to the haptic jacket to maintain driving quality. Haptic jacket has a great advantage over other haptic warning modalities which is interaction with the upper body part. When the driver is fatigue, muscles are relaxed and the driver tends to bend and fall asleep on the wheel. Haptic jacket is always attached to the driver and hence is able to warn the driver in any inattentiveness state.

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Appendix A –

Viola-Jones Object Detection Algorithm

The three algorithms mentioned in Chapter 3 for face and eye detection are detailed here.

Algorithm 1: Face Detection

```
FaceDetection::FaceDetection(IplImage *image)
{
char *face = "C:\\opencv\\haarcascades\\haarcascade_frontalface_default.xml";
this->faceCascade = ( CvHaarClassifierCascade* )cvLoad( face, 0, 0, 0);

bool FaceDetection::detectFace()
{
CvSeq *faces = cvHaarDetectObjects(this->image, faceCascade, buffer, 1.1, 3, 0,
cvSize(30,30));
if(!faces->total) return false;
else
{
/**get the biggest detected face**/
cvSeqSort(faces, comp_func, 0);
CvRect *r = (CvRect*) cvGetSeqElem(faces, 0);
this->face.bbox = *r;
cvClearMemStorage(this->buffer);

if(r->width>0) printf("Detected face at (%d, %d)", r->x, r->y);

} return true;
}
```

Algorithm 2: Left and Right Eyes Detection

```
char *eye_left= "C:\\opencv\\haarcascades\\haarcascade_mcs_lefteye.xml";
char *eye_right = "C:\\opencv\\haarcascades\\haarcascade_mcs_righteye.xml";
this->leyeCascade = ( CvHaarClassifierCascade* )cvLoad( eye_left, 0, 0, 0);
this->reyeCascade = ( CvHaarClassifierCascade* )cvLoad( eye_right, 0, 0, 0);
```

```
void FaceDetection::detectEyes()
{

/*left eye*/
cvSetImageROI (this->image, cvRect (this->face.bbox.x, this->face.bbox.y, this->face.bbox.width/2, (this->face.bbox.height*2/3)));
this->setCurrentROIlocation (this->face.bbox.x, this->face.bbox.y);
CvSeq *eyes = cvHaarDetectObjects (this->image, this->leyeCascade, this->buffer, 1.1, 3,0, cvSize (5,5));
cvSeqSort (eyes, comp_func, 0);
if ( eyes->total != 0)
{
CvRect *left = (CvRect*) cvGetSeqElem ( eyes, 0);
this->setAbsoluteCoordinates (*left);
this->face.lefteye.bbox = *left;

if (face.lefteye.bbox.width>0) printf ("\nLeft eye at (%d, %d)", face.lefteye.bbox.x, face.lefteye.bbox.y);

}

cvClearMemStorage (this->buffer);
cvResetImageROI (this->image);
/*right eye*/
cvSetImageROI (this->image, cvRect (this->face.bbox.x+ (this->face.bbox.width/2), this->face.bbox.y, this->face.bbox.width/2, (this->face.bbox.height*2/3)));
this->setCurrentROIlocation (this->face.bbox.x+ (this->face.bbox.width/2), this->face.bbox.y);
CvSeq *reyes = cvHaarDetectObjects (this->image, this->reyeCascade, this->buffer, 1.1, 3,0, cvSize (5,5));
cvSeqSort (reyes, comp_func, 0);
if ( reyes->total != 0)
{
CvRect *right = (CvRect*) cvGetSeqElem ( reyes, 0);
this->setAbsoluteCoordinates (*right);
this->face.righteye.bbox = *right;

if (face.righteye.bbox.width>0) printf ("\nRight eye at (%d, %d)", face.righteye.bbox.x, face.righteye.bbox.y);

} cvClearMemStorage (this->buffer);
cvResetImageROI (this->image);
}
```

Algorithm 3: Drawing the Detected Eyes Boundaries

```
// Draw eye rectanngles
CvRect leftEyeBB=objFD.face.lefteye.bbox;
CvPoint pt3, pt4;
pt3.x = leftEyeBB.x; pt3.y = leftEyeBB.y;
pt4.x=leftEyeBB.x+leftEyeBB.width; pt4.y=leftEyeBB.y+leftEyeBB.height;

cvRectangle(img, pt3, pt4, cvScalar(255,120,255), 2,8,0);

CvRect rightEyeBB=objFD.face.righteye.bbox;
pt3.x = rightEyeBB.x; pt3.y = rightEyeBB.y;
pt4.x=rightEyeBB.x+rightEyeBB.width; pt4.y=rightEyeBB.y+rightEyeBB.height;

cvRectangle(img, pt3, pt4, cvScalar(255,120,255), 2,8,0);

cvShowImage("Nilufar Window", img);
cvWaitKey(0);

cvReleaseImage(&img);
```