Analysis of EEG Signals and Facial Expressions to Detect Drowsiness and Fatigue using Gabor Filters and SVM Linear Classifier

N Mohammed Abu Basim
PG Scholar,
ME Mechatronics
Karpagam College of Engineering
Coimbatore-32

P Sathyabalan, Ph.D.
Professor
Dept. of Mechanical Engineering
Kumaraguru College of Technology, Coimbatore-49

P Suresh, Ph.D.
Professor
Dept. of Mechanical Engineering
Karpagam College of Engineering, Coimbatore-32

ABSTRACT
More sophistication in vehicle's state of art technologies in driver assistance systems and stringent laws implemented by the governments did not stop any of the road accidents in the developing countries like India. The report shows that India contributes nearly 9.5% of the total 1.2 million road accidents globally. Among that, nearly 60-70% of road accidents are due to manmade faults like attention-less driving, usage of mobile phones while driving, intoxication of alcohol or any other drugs. The proposed system is designed based on the ground breaking concept known as "humanizing technology" which monitors the physiological changes especially in human brain and facial expressions of the driver and get processed using Gabor filters and SVM linear kernel classifier. The system can crisscross autonomously whether the ignition should get initiated or not. This type of system not only helps the drivers from the accidents, but also a great paradise for pedestrians.

Keywords
Driver assistance systems, road accidents, manmade faults, humanizing technology, physiological changes, facial expressions, Gabor filter, SVM linear kernel

1. INTRODUCTION
Long drive is the ample cause for drowsy and fatigue related accidents. Fatigue driving has main inference for transportation system safety. Analyzing the biological signal and facial expressions of a driver while driving, provides the possibility to detect mental fatigue. Mental fatigue is an aggregate process and is associated with an aversion for any effort, reduced efficiency and reduced cerebral performance. The major symptoms of mental fatigue are a general sensation of lethargy and inhibition. It is recognized as a principal safety issue in the transportation and is four times more probable to be a provider to work place impairment than drugs or alcohol. It is necessary to evolve and develop a precise and non-invasive real-time system for monitoring driver's mental fatigue to reduce road accidents.

2. RELATED WORKS
Articles related to driver drowsiness detection have been reviewed. Variations of physiological features like EEG, heart rate and pulse rate, eyelid movement, gaze, head movement and behaviors of the vehicle, such as lane deviations and steering movements are indication of drowsiness. **[1]** Presented preprocessing and classification techniques for efficient EEG-based brain–computer interfacing (BCI) and mental state monitoring applications. Very recent machine learning and adaptive signal processing techniques help in analyzing the EEG on a single-trial basis for two applications mainly for mental state monitoring and for BCI to be feasible without the need for subject training. [2] Enlightened the basics of EEG measurements which is commonly used in medical and research areas. The main purpose is to help with orientation in EEG field and with building basic knowledge for performing EEG recordings. [3] Presented a basic description of quantitative electroencephalography (EEG) in the context of neural-therapeutic application. Issues associated with spectral analysis of human EEG were discussed. [4] Offered the analysis of EEG signals based on BCI. The authors examined the human EEG data to control machines using their thoughts, in association with normal, voluntary and imagery of hand movements were studied using EEGLAB, a signal processing toolbox under MATLAB. [5] introduced a two-stage procedure based on SVM for the automatic detection of epileptic spikes in a multi-channel EEG signal. In the first stage, a modified non-linear digital filter is used as a pre-classifier to classify the peaks. In the second stage, the peaks falling into the first group are aimed to be separated from each other by a SVM that would function as a post-classifier. [6] Provided the first wide-ranging survey of all BCI designs using EEG recordings put out erstwhile to January 2006. The resulting research questions were based on various signal processing components, algorithms and techniques used in BCI. [7] presented an AI based system which could detect early onset of fatigue in drivers using heart rate variability (HRV) as the human physiological measure. **[8]** Designed a computational stress signal predictor system based on SVM, GA and ANN to predict the stress signal from a real-world data set which comprised of physiological and physical sensor response signals for stress over the time of the meditation activity.[9] proposed an automatic recognition of alertness and drowsiness from EEG by an ANN. The algorithm designed should work on recordings which were not used for the training of the same subject. 3 ANNs are selected for the study. Linear network with Widrow-Hoff (WH) algorithm, non-linear ANN with Levenberg-Marquardt (LM) rule and Learning Vector Quantization (LVQ) neural network. [10] Recommended a drowsiness warning system based on the fuzzy logic images analysis. Position of the eyes and the duration of eyelid closure is calculated based on the images taken. Hue, Saturation and Intensity of the image is given more importance than RGB. Blinking time and eye lid closure duration were used by the drowsiness detection system. [11] Designed a real time wireless BCI system for drowsiness detection which based on 2 approaches: Physical & Physiological signals. The developed algorithm is based on

the calculation of Mahalanobis distance which is tested using Virtual Reality based driving mode. **[12]** Proposed a system based on eyelid parameters for drowsiness detection. SVM was used as a classification technique. Karolinska Drowsiness Score KDS is used for scoring the driver's drowsiness level and developed for the quantification of sleepiness in active situations. Karolinska Sleepiness Scale KSS was used for rating of the subjects sleepiness based on points 1-9.1-extremely alert, 9-very sleepy, great effort to keep it alert, fighting sleep. **[13]** Reviewed the effects based on EEG and ECG assessment of mental fatigue in a driving simulator. EEG power spectral density for 5 brain regions (frontal, central, parietal, occipital and temporal) were analyzed. It is found that theta increases in the frontal, central and occipital regions, while alpha rhythm increased in the central, parietal, occipital and temporal, whereas beta rhythm decreased in the frontal, central and temporal. [14] Reviewed the published papers related to neurophysiological measurements like EEG, EOG, and heart rate in pilots/drivers during their driving tasks. The brain activities of the driver/pilots were analyzed during drive performance based on the aspects of the brain activity which could be related with the important concepts of mental workload, mental fatigue and situational awareness. [15] Proposed a new system based on eye states and its parameters for drowsiness detection. The method uses feature level fusion for both eyes. Initial period of driving of an individual was noted to calculate the baseline probability. Based on opening and closing of eyes at any movement, which uses individual classification threshold.

3. PROPOSED ARCHITECTURE

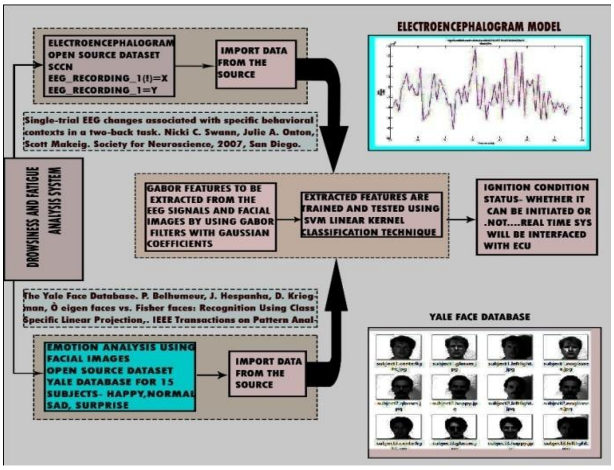

Fig. 1

3.1 Electroencephalagram EEG

Electroencephalography is a medical imaging technique that reads electrical activity of the scalp generated by brain structures which is defined as electrical activity of an alternating type recorded from the surface of the scalp after being selected up by metal electrodes which are known as sensors and conductive media usually gel solution. The EEG database used in the proposed prototype system doesn't provided the actual drowsiness or fatigue data instead used the open source data from the reference mentioned in the figure 1. 2 subjects' EEG data were analyzed among 15 subjects.. These data were extracted and analyzed properly to suit for the design of the system by using certain thresholds regarding drowsiness.

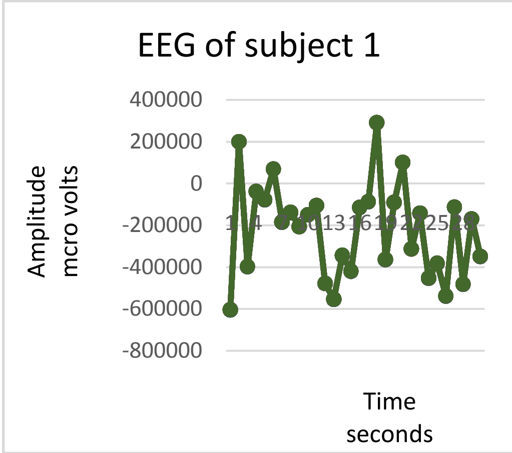

Fig. 2

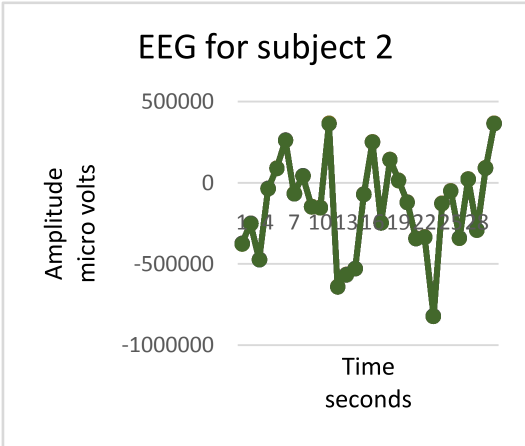

Fig. 3

3.2 Facial Expressions

It is an easy task for a human to identify the facial expressions, but a machine to identify is not easy. Understanding the emotions in the cognitive science is considered as the central problem. In order to overcome this, it is necessary to study the human behavior. Darwin identified six universal expressions for man and animals such as anger, disgust, fear, happiness, sadness and surprise. It is also considered that these expressions are partly responsible for the theory of evolution. This shows that all humans have the capacity to express and perceive these emotions and their respective facial expressions [16]. The frontal muscle is also known as epicranius, serves only for the purpose of facial expressions. The corrugator supercilii is a pyramidal muscle found on the medial end of the eyebrow, below the frontalis and above the orbicularis oculi, is considered as frowning muscle, usually help in the expression of suffering. Orbicularis oculi is a muscle in the eyes that closes the eyelids, helps in closing the eye, no other muscles have the tendency to accompany this purpose. The procerus muscle is also known as pyramidal nasi muscle which helps in pulling the part of the skin between the eyebrows downwards and assists in flaring the nostrils, which mainly contributes to the expression of anger. The levator labii superiori salseque nasi is also known as Otto's muscle, helps in dilating the nostril and elevating the upper lip that, enables ones to snore. The levator labii superioris helps in retracting the upper lip during depression and everting it during sadness. The depressor anguli oris is used in the facial expressions, where it dampens the corner of the mouth which is associated with frowning.

Quadratus menti is the facial muscle of the mouth which depresses the lower lip. Paul Ekman and W.V. Friesen in 1970 proposed Facial Action Coding System FACS, a method used to analyze the facial behaviors [17] [18]. The image database is extracted from the source mentioned in the figure 1. For this work, only 4 basic expressions (happiness, surprise, sad and normal/neutral) have been taken and analyzed for the purpose of convenience.

Fig. 4 The Yale Face Database contains 165 GIF images of 15 subjects (subject01, subject02, etc.). There are 11 images per subject, one for each of the following facial expressions or configurations: center-light, w/glasses, happy, left-light, w/no glasses, normal, right-light, sad, sleepy, surprised, and wink.

3.3 Gabor Filters

When the signals are of different frequencies, we filter them. As filtering eliminates certain information care should be taken when using the selected methods to retain the information. In order to find the expectancy of the response based on the stimulus onset which is a form of temporal localization [19]. The Fourier transformation helps in yielding the exact information about the frequencies of the signal, but the time course of the signal is lost or sometimes it is assumed to be constant. The amplitude of the brain signal is extracted and statistically analyzed. Measuring the peak amplitude leads to errors and attempts made to attain accuracy by integrating the signal over time introduce temporal covering which gets mixed with spreading caused by filtering. The technique works by choosing a time function, or window, that is essentially nonzero only on a finite interval.

3.4 SVM Linear Classifier

The An SVM uses a discriminant hyper plane which is used in identifying classes [20]. The selected hyper planes are the one that helps in maximizing the distances from the nearest training points which is known as “margins”. This is known to increase the generalization capabilities. SVM uses a regularization parameter C, enabling the accommodation to outliers and allow errors on the training set. It also enables the classification using linear decision boundaries and this is known as linear SVM. This classifier has been applied successfully to a relatively large number of brain computer interface problems. It also helps in creating the non-linear decision boundaries, with only less complexity by using kernel trick. The kernel generally used in EEG and image analysis is the Gaussian or Radial Basis Function RBF kernel. The corresponding SVM is known as Gaussian SVM.

4. WORKING AND RESULTS

Like most of the machine learning systems, feature extraction is needed. Here, feature extraction is done by transforming each above mentioned EEG epoch and facial expressions namely happy, sad, normal/neutral and surprise in to feature vectors. The main purpose of using the feature extraction methodology in this work is to extract the set of feature vectors which can help in differentiating the alert and drowsiness/fatigue state, based on neurophysiological variations like electroencephalogram and facial expressions. The resulted feature vectors are generated for EEG and facial expressions as shown in the figure 5, 6, 7, 8, 9, 10. The word series in the mentioned figures represents the no of subjects. For instance: series 1,2,……10 = subject 1, 2,……10. The training of SVM is essential to find the previously mentioned separating hyper lane using the training dataset.

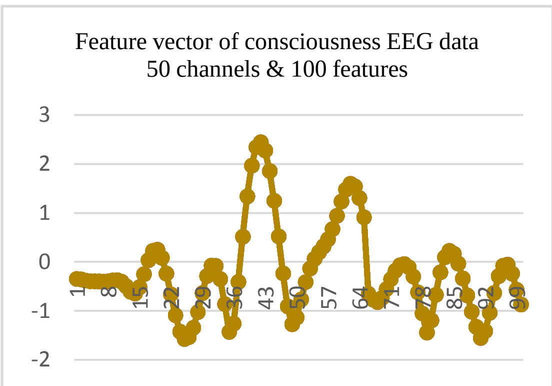

Fig. 5

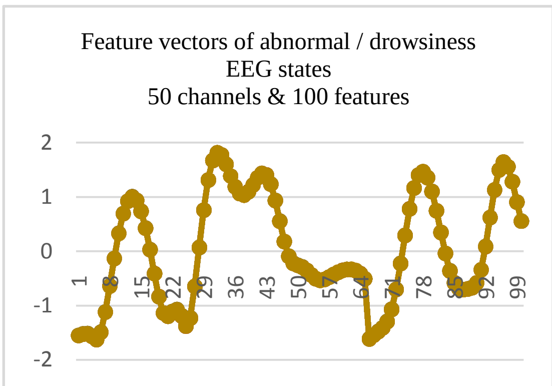

Fig. 6

Feature vectors of consciousness and abnormal EEG patterns

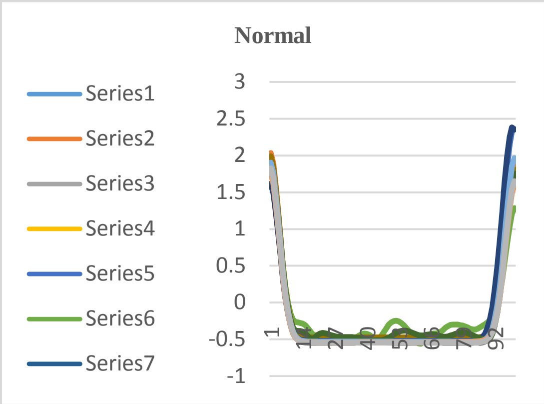

Fig. 7

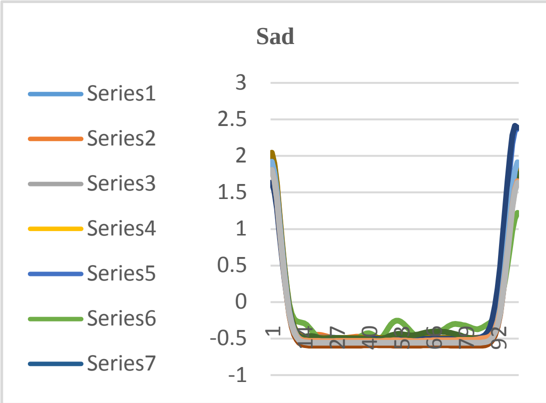

Fig. 8

Feature vectors for normal and sad expressions

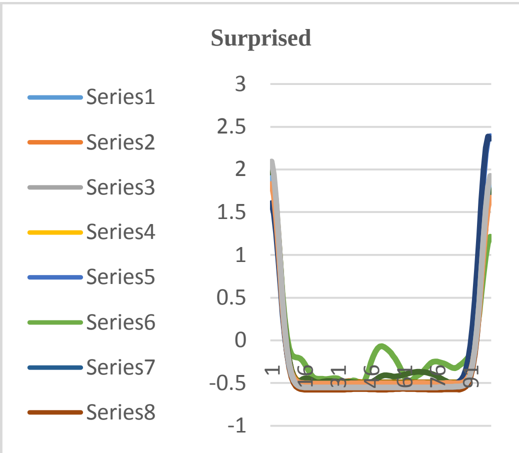

Fig. 9

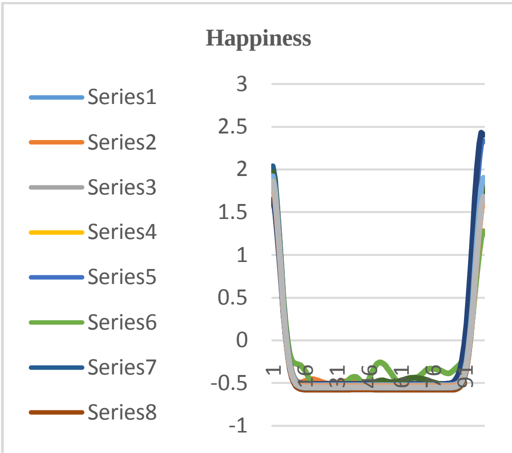

Fig. 10

Feature vectors for surprise and happiness

The figures 11, 12, 13, 14 show the working of the system. After the EEG signal gets processed by using Gabor filters. The next step is based on the analyzing of the facial expressions. After selecting the image from the database, this gets processed and finally trained using SVM linear kernel classifier, which provides the message whether the ignition can be initiated or not.

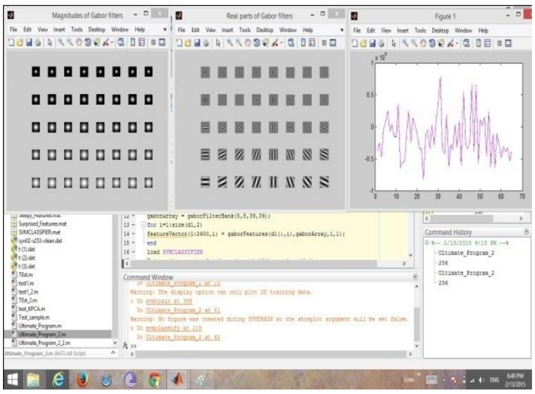

Fig. 11

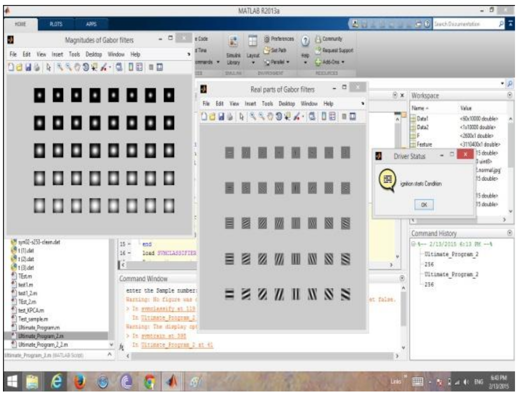

Fig. 12

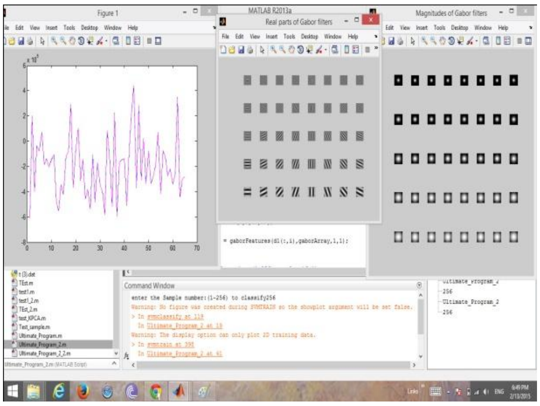

Fig.13

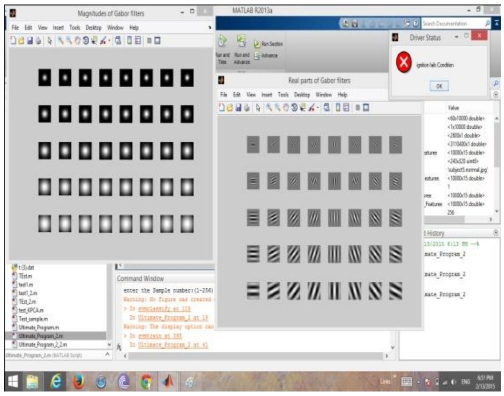

Fig. 14

Table 1 This work is completely utilized in the simulated environment using MATLAB R2013a. The working of the system can be better understood using the table, which is mentioned below. "Positive" indicates "ignition starts condition", "Negative" indicates "ignition stops condition"

2 Types of Brain waves Electroencephalogram EEG	Facial expressions			
	Happy	**Sad**	**Surprise**	**Normal**
Healthier EEG ALERT state	Positive	Negative	Negative	Positive
Abnormal EEG FATIGUE state	Negative	Negative	Negative	Negative

5. CONCLUSION

The work presented above utilized 2 top notch methodologies namely neurophysiological variations and facial expressions in analyzing the drowsiness and fatigue. Still, there are many issues remain closed like electroencephalogram used here is of non-invasive method. Our neural cortex is not a flat surface, in order to extract the data from the ongoing brain activity it is not sufficient to employ this method. There is a need to develop a system which helps in gathering the necessary data more accurately and precisely. Invasive methodologies provides higher efficiency, but it is not possible to use it in humans. Researchers are trying to rediscover the electrodes which can equalize the importance of invasive technologies. Visual topographies paved a new avenue in research regarding drowsiness and fatigue. High speed cameras, which can snap more frames in one second is one of the recent innovations which helps in designing the systems with more efficiently. Lastly, these systems are mandatory to get implemented in the countries like India which evidences a large no of fatal accidents, which not only prevent the passengers and drivers from accidents but, also a great deal for the pedestrians. In recent scenario, we are in need of the system which can communicate with the human in a more interesting way, not like programming or tuning the engine, instead techniques like via our thoughts, facial expressions or respiration. This leads to a new phenomenon known as "humanizing technology". The work presented is designed by using brain signals and facial expressions to detect drowsiness and fatigue which gets processed through Gabor filters and SVM linear classifier. This methodology is more complicated due to the selection of different algorithms and classification techniques. It can be eliminated by designing miniature universal scanning equipment with added advantages of Magnetic Resonance Imaging MRI and Computer Tomography CT scanning techniques which is embedded inside the roof of the vehicle, monitors and scan the head portion of the driver. Brain is considered as "the power house of human consciousness" which is packed inside the skull of the human head. The evolution of life starts and ends in the brain, so it is enough to look through it which can provide the best results when compared with other technologies. Care should be taken while designing the scanning equipment such that it should not contribute to any radiation side effects. This type of advanced systems will find wide applications in aerospace and automobile research especially to study and analyze the ongoing neural activities inside the brain of the pilots and drivers for the sustainable development of the human.

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