An EEG Based Vehicle Driving Safety System Using Automotive CAN Protocol

Renji V.Mathew [1], Jasmin Basheer [2]

[1]*PG Scholar*, [2]*Assistant Professor, Department of ECE, SBCE, Alappuzha, Kerala, India.*

Abstract — *A real-time drowsiness detection system in vehicles using single channel EEG dry sensor is described. Drowsy driving is a severe issue that leads to traffic accidents. Sleeping can be identified by the physical activities such as eye blink level, yawning, gripping force on the wheel etc. In some cases people will mentally sleep with eyes open for a short time, will leads to accidents. In this system, analysing the mental activities of human brain using EEG (Electroencephalography) based on BCI (Brain Computer Interface). Human brain consists of millions of interconnected neurons. According to the human activities unique electric brain signal will form. Drowsiness is detected by analysing the power of EEG bands. An algorithm is developed for this detection. In this work, using single dry electrode brain wave sensor (Neurosky - Mindwave) which can collect EEG based brain signals of different frequency and amplitude and it will convert these signals into packets and transmit wirelessly to next section for checking the attention level, drowsiness detection and gives the drowsy driving alert and keeps the vehicle to be in self-controlled function until awakened state. This can save a lot of lives in road transportation. The nodes in this system are implemented on ARM7 (Advanced RISC Machine) cores (LPC 2148). Communications between these nodes are accomplished through automotive CAN (Controller Area Network) protocol.*

Keywords — *ARM, BCI, Drowsiness Detection, CAN.*

I. Introduction

An embedded system is a dedicated function computer system within a larger mechanical or electrical system, frequently with real time computing constraints. Embedded systems provide variety of applications in in human life at different fields. The recent advantages in embedded systems change human lifestyle in a smart way.

Long-term, repetitious, or night time driving often lowers driving performance. As is widely assumed, drowsiness significantly contributes to automobile accidents, leading to a considerable number of traffic collisions, injuries, and fatalities in each year. Developing an effective system for detecting drowsiness is thus of priority concern for real-life driving. Such an in-vehicle system must continuously monitor the awaken state of drivers. Several bio-behavioural signatures have been developed to monitor drowsiness of automobile drivers, including eye blinking, head nodding, yawning, gripping force on the wheel and so on. But all these measuring techniques will check only the physical activities of the human. However, false alarms are likely since these physical attributes are not always accompanied by drowsiness. Related studies in recent decades have demonstrated that electroencephalography (EEG), i.e., the electric fields produced by brain activity, is a highly effective physiological indicator for assessing vigilance states. EEG is the only brain imaging modality with a high temporal and fine spatial resolution that is sufficiently lightweight to be worn in operational settings. Numerous EEG studies suggest that delta (1–3 Hz), theta (4–7 Hz), and alpha (8–12Hz) activities are highly correlated with fatigue, drowsiness, and poor task performance [1]. By using the conventional wet and wire EEG acquisition system, our previous studies explored driver brain activity changes: from alertness to drowsiness. Based on the neurological results, drowsiness monitoring algorithms were developed by using machine learning methods. The experimental results further demonstrated the feasibility of detecting or monitoring driver drowsiness using EEG signals. However, designing a user acceptable and feasible EEG device to realize the real-time monitoring system is still a challenging task. Data collection in most EEG studies requires skin preparation and conductive gel application to ensure excellent electrical conductivity between a sensor and human skin. These procedures consumes more time, uncomfortable, and also painful for participants. Additionally, the signal quality may degrade over time as the conductive gel dries out. Hence, a wearable and wireless dry-electrode EEG system must be used, capable of assessing the brain activities of participants performing ordinary tasks This study develops an EEG-based in-vehicle system for evaluating human states (drowsy and wake). EEG signals of participants are recorded via a dry-contact EEG device when they perform a sustained-attention driving task and also drowsy state. An effective system using support vector machine (SVM) is developed to model a classifying mechanism [3]. The nodes in this system are implemented on ARM cores. Communications between these nodes are accomplished through automotive CAN protocol [7]. The proposed work “An EEG based vehicle driving safety system using automotive can protocol” can overcome all the accident due to drowsy driving.

II. Objectives

There are few drowsiness detections systems existing currently, which works according to physical parameter measurements mostly according to image processing techniques. The disadvantage of image processing technique is the detection possible only in eye close state. Also in existing system the lack of self-control mode if drowsiness is detected, only warning signal is given to the driver to become alert.

The objective of this work is to design and develop a drowsiness detection system which can overcome all the issues with existing systems. The proposed system is capable of detecting drowsiness from real time brain signal analysis, also includes a self-controlled mode of the vehicle

This work involves design and development of a prototype of drowsiness detection system which should be integrated inside the vehicles in future. The main units of drowsiness detection systems are

- Brain computer interface system
- Data processing unit
- Vehicle node 1 (Main)
- Vehicle node 2(Demo ECU)

III. Methodology

A. System Overview

On entering in to a vehicle with drowsiness detection system, driver should wear the dry electrode EEG sensor wirelessly connected with the node present inside the vehicle [16]. The display unit present in the vehicle show welcome message and instructions for wearing the sensor. After wearing the sensor the driver should blink the eye three times for starting the vehicle ie, for giving the ignition command. This will ensure that the driver don't forget to wear the sensor. Then the system checks the attention level of the driver and displays the status of that driver if the attention level is above a particular threshold the system goes to the standby mode. If the attention level is lowered for a small duration, an audible alert is given to the driver for coming back to alert state. If the attention level of the driver is again lowered then the node sends a command to the ECU to turn on the hazard signal. If the attention level is again lowered or the drowsiness is detected from the SVM based algorithm the node sends a command to the ECU to switch the engine into deceleration mode and now the vehicle goes to a self-controlled mode. In this time the signals from the proximity sensors placed in front of the vehicle guides the vehicle into a safe path until the driver come back from sleep state. The communication between the node and the ECUs are accomplished through automotive CAN (Controller Area Network) protocol [12], a vehicle bus standard which is designed to allow microcontrollers and other electronic devices to communicate with each other within a vehicle without a host computer [8]. The Fig. 1, Fig. 2 and Fig. 3 shows the architecture of the drowsiness detection system.

B. Drowsiness Detection Algorithm

In this algorithm at first the raw data is filtered by applying type 1 Chebyshav band-pass filter with cut-off frequencies 0.5Hz and 50Hz for removing artefacts. After that Fast Fourier Transform (FFT) is applied for converting it into frequency domain. A 512 point (1 second) moving window without overlapping point was applied for calculating frequency responses. Each 512 points of data are subdivided into 128 points using sub windows. Then by zero padding they were extend to 256 points in order to calculate power spectra using a 256 point FFT. The power spectra of these sub windows were converted into logarithmic scale and averaged to form a log power spectrum of each window.

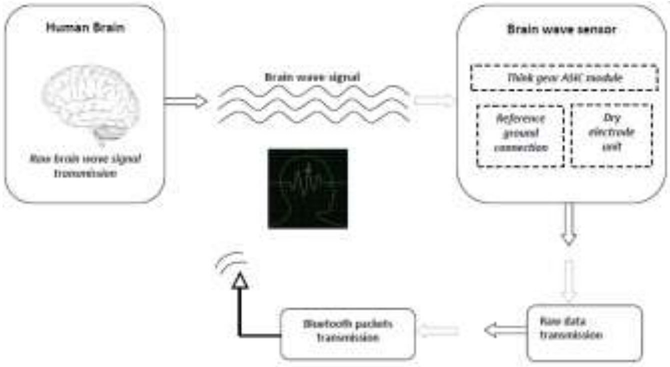

Fig. 1 Brain computer interface system.

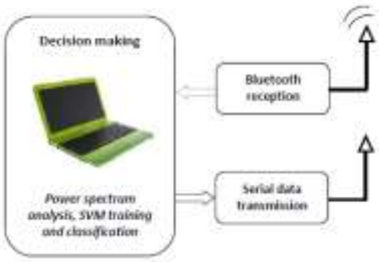

Fig. 2 Data processing unit.

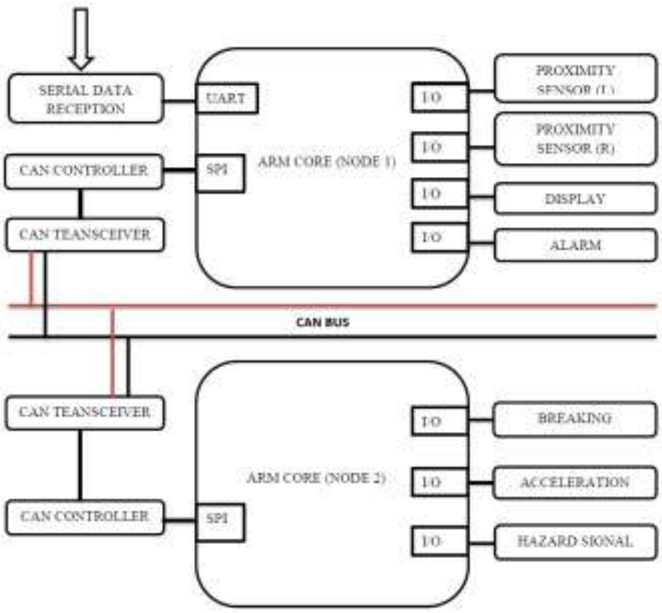

Fig. 3 ARM nodes.

SVM (Support Vector Machine) classifier is used for classification of EEG spectra into two categories, alert and drowsy. Given set of training data, each marked for belonging to one of two categories, SVM training algorithm builds a network that assigns new examples into one category or the other. Ideally, an SVM can identify a hyper plane that separates alert and drowsy EEG signal data in its high-dimensional feature spaces. The basic concept of an SVM classifier is as follows: Each sample in a set of training samples is matched to two categories before being reflected into a high-dimensional space using the Kernel function. Subsequently, the SVM attempts to create a model and uses it to assign the samples to a category. The SVM model then constructs a separating hyper plane in high-dimensional space. On either side of the hyper plane, which divides the samples, parallel hyper planes are located. The SVM maximizes the distance between these two parallel hyper planes. A greater distance or difference between parallel hyper planes indicates a smaller total SVM error rate.

Matlab built in functions are used for training and classifying SVM. Svmtrain trains a support vector machine classifier.svmstruct = svmtrain (training, group) trains a support vector machine classifier using data training taken from two groups given by group. SVM Struct contains information of the trained classifier, including support vectors, that is used by svmclassify function for classification. Group is a column vector of values of same length as training that defines two groups. Each elements in group specifies the group the corresponding row of training belongs to. Group can be a string-array, numeric-vector, or a cell array of strings. Svmtrain treats empty strings in group as missing values and ignores the corresponding rows of training. Svmtrain(….,'kernel_function',kfun) allows user to specify the kernel function KFUN used to train the training data into kernel space. The default kernel function is dot product. KFUN can be one of the following types.

- Linear : linear kernel or dot product.
- Quadratic : quadratic kernel
- Polynomial : polynomial kernel (default order 3)
- Rbf : gaussian radial basis function kernel
- Mlp : multilayer perceptron kernel (default scale 1)

Svmclassify classifies data using a support vector machine group = svmclassify (svmstruct, sample) classifies each row of data in sample using the information in a support vector machine classifier structure svmstruct created using svmtrain. Sample must have same number of columns as the data used to train classifier in svmtrain. The group indicates the group to which each sample is assigned. Svmclassify(...,'showplot',true) plots the sample data on the figure created using the showplot option in svmtrain.

C. Nodes Working Flow Diagrams

Fig. 4 Node 1 working flow.

The working of data processing unit is as follows. The data from brainwave sensor is received by data processing unit through bluetooth communication. Then the following steps are followed.

1. Allocating buffers to store received values.
2. Get the connection id for the Bluetooth receiver connected on the computer. Using the function 'TG_Get New Connection Id'. This connection id is called ID handle.
3. Connect the connection ID handle to serial port where Bluetooth receiver is connected. (function 'TG_Connect' is used)
4. Set the serial connection for the external hardware to be controlled.
5. Wait for data packets to receive. (Function: TG_Read Packets)
6. Check whether values received. (Function: TG_Get Value Status)
7. Send a data ("A") to UART after Detecting 3 eye Blinks
8. Wait for data packets to receive. (Function: TG_Read Packets)

9. Check whether values received. (Function: TG_Get Value Status)
10. Send a data ("B") to UART when attention value is between 50 and above.
11. Send a data ("C") to UART when attention value between 40 & 50
12. Send a data ("D") to UART when attention value between 30 & 40
13. Send a data ("G") to UART when attention value less than 30 or GROUP = 2 from Drowsiness detection algorithm.
14. Go to step 8

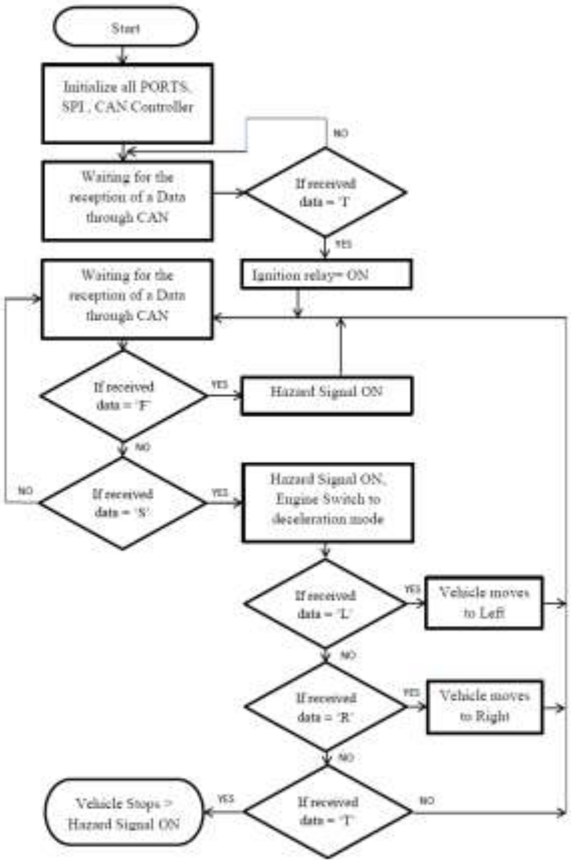

Fig. 5 Node 2 working flow.

IV. RESULTS

The power spectra of EEG recordings were converted into logarithmic scale to form a log power spectrum. Amplitude of 1sec EEG spectrum were then used for classifying. Using support vector machine training is done with alert and sleep state EEG. In the power spectrum the delta (1-3Hz) and theta (4-7Hz) power are not varied with drowsiness. Alpha (8-12 Hz) and beta (12-30Hz) power increased when the human become drowsy. The SVM classification is done using linear, polynomial, radial basic function (RBF), and sigmoid kernel functions. From the trials RBF kernel gives more accurate result.

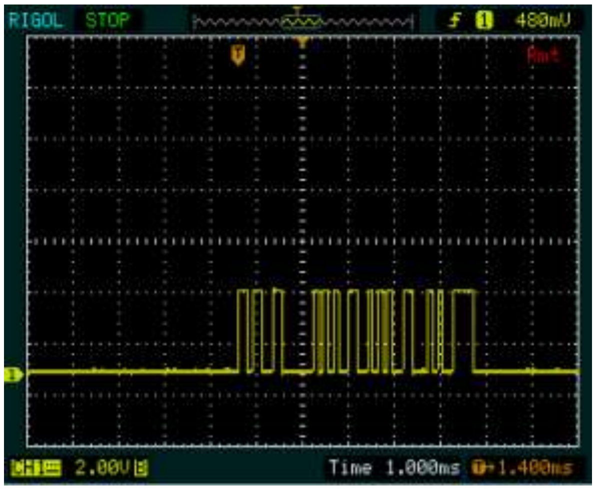

Fig. 6 CAN frame on DSO.

Fig. 7 Hardware implementation.

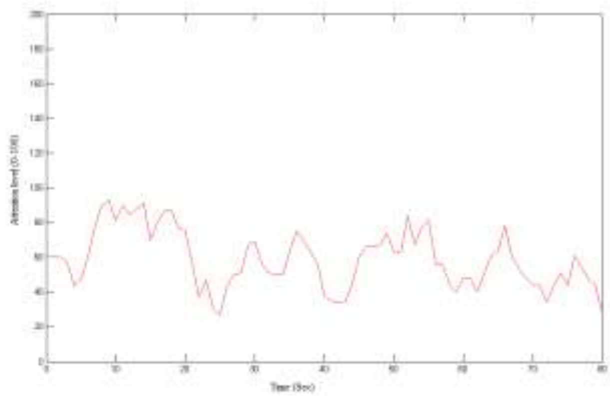

Fig. 8 Attention level of test person.

TABLE I
TEST RESULTS

Kernel function	No of trials	Successful classifications	Wrong classifi cations	Err or (%)
Linear	20	14	6	30
Polynomial	20	15	5	25
Radial Basis Function	20	17	3	15
Sigmoid	20	13	7	35

V. CONCLUSION

Different drowsiness detection methods are reviewed. Most of the techniques measures the physical activity for measuring the drowsiness. Now image processing techniques are widely used. But it has limitations. False detections are occurred frequently. Prototype of proposed work is successfully implemented and tested. The result shows the accuracy of drowsiness prediction is up-to 85%. By integrating this system, accident rate can be reduced to a large level. The complexity in live implementation is the manufacture's assistance requirement for integration. In future by using high resolution data processing we can drive the vehicle through our mind. Real-time, reliability and flexibility make CAN bus an indispensable network communication technology applied in automobile network communication field. The transfer of data from one unit to another unit is reliable and efficient as CAN bus is used as in vehicle network. Software system and hardware system are easily to be expanded and upgraded.

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