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AN Implementation to Detect drowsiness and Control Vehicle through BCI

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Abstract- Nowadays, human fatigue is a major reason for the traffic accidents. This accident leads to loss of lives of people and causes a lot of damage. Normally, drowsiness can be identified by several methods like image processing techniques, face recognition system, eye blinking level, and steering angle sensor and so on. But all these measuring techniques will check only the physical activities of the human. So this proposed work analyses the mental activities of brain using EEG signals based on Brain Computer Interface (BCI) Technology. When we are at drowsy or attention, corresponding signals are pass through the neurons throughout the brain that signals are extracted by using electrodes and then amplified. Further classification of above signals is done in MATLAB. By analyzing the THETA and DELTA waves the drowsy state of driver can be detected. The amplitude of theta waves are about 2 mV which is higher than alpha,delta,beta waves during first stage of drowsiness and delta's amplitude is about 1.5 mV which is higher than other classified waves during deep sleep.

Terms- Brain Computer Interface (BCI), Human fatigue, , Electroencephalogram (EEG)

1. INTRODUCTION

THE EVER INCREASING traffic accidents all over the world is mostly due to driver's poor vigilance level. About 35 percent of all serious crashes in general population is due to driver's drowsiness. According to the estimation of national highway traffic safety administration 100,000 crashes occur every week all over the world. , Although advance technology in transportation researchers ensuring safety, however the safety of a vehicle is an important task for automotive industries & researchers .Warning tones for preventing accidents is one of the design of safety systems, these warning tones for preventing accidents is an attracting in the public . In concern safety is first prior for the public, several people are dead and some are seriously injured due to drowsiness, 55- 60 % related to drowsiness causing serious accidents on the roads, falling to drowsy drivers losing their abilities in controlling vehicles.

Driving under the influences of drowsiness will cause: 1) longer reaction time, which may lead to higher risk of crash, particularly at high speeds; 2) vigilance reduction including no responses or delaying responding where performance on attention-demanding tasks declines with drowsiness; 3) deficits in information processing, which may reduce the accuracy and correctness indecision-making[9].Many factors can cause drowsiness or fatigue in driving including lack of sleep, long driving hours, use of sedating medications, consumption of alcohol, and some driving patterns such as driving at midnight, early morning, mid afternoon hours, and especially in a mo-notonous driving environment [10]. Accurate and nonintrusive real-time monitoring of driver's drowsiness would be highly desirable, particularly if this measure could be further used to predict changes in driver's performance capacity

Drowsiness can be detected by several methods. They can be divided into 2 major kinds of systems [1]. "Vehicle oriented" is the methods that analyze indirect information i.e. affected from drowsy behavior, such as steering angle, vehicle speed, or turn indicator, to indicate drowsiness of the driver. However, these driving behaviors may be different in each driver. Therefore, the disadvantage of this method is the difficulty of specifying the normal driving model and drowsy driving which can be used to detect variation in each driver's behavior. The second method is "driver oriented" [2]. This method uses physiological measurement such as eye or face movement, blink rate, or yawning. Furthermore, vital signs, like electroencephalography (EEG), electromyogram (EMG), or heart rate, are also used to indicate drowsiness. This approach is more reliable than the previous method since the physiological information depend directly with drowsiness

The driver assistive systems available in the market nowadays have been reviewed in this paragraph. In Bosch's driver drowsiness detection system [3], the level of drowsiness is determined by information from the steering-angle sensor. Ford's driver alert [4] has front and side cameras for lane detection and tracking. Fatigue detection system video camera in Volkswagen [14] monitors head movement and facial features. Toyota driver monitoring system [11] uses CCD cameras with infrared LED for eye movement monitoring.

2. Overview

An electroencephalograph (EEG) is the recorded electrical activity generated by the brain. In general, EEG is obtained using electrodes placed on the scalp with a conductive gel. In the brain, there are millions of neurons, each of which generates small electric voltage fields. The aggregate of these electric voltage fields create an electrical reading which electrodes on the scalp are able detect and record[12]. Therefore, EEG is the superposition of many simpler signals. The amplitude of an EEG signal typically ranges from about 1 μV to 100 μV in a normal adult, and it is approximately 10 to 20 mV when measured with subdural electrodes such as needle electrodes.

Based on the frequency ranges EEG signals classified into the types given below, delta wave (2-4Hz), theta wave (4-7Hz), alpha wave (7- 13Hz), beta wave (13-

30Hz) and gamma wave (30-100Hz). The characteristics of frequency range of brain signals can represent the state of person[12]. Example alpha wave appears during resting state, or eye closing. The beta waves appear during a person is active, busy or anxious thinking and active concentration. The theta waves are occurs during first stage of drowsiness.

The real-time signal processing function integrated with wireless transmission has become a trend for developing diagnosis or homecare systems because it provides a platform to build sensing and inexpensive BCI systems[7].This paper inspired me to propose a BCI system to detect driver fatigue and automatic speed control of vehicle.

3. Related Work

Considered the problem of selecting relevant features extracted from human polysomnographic (PSG) signals to perform accurate sleep/wake stages classification. extraction of various features from the electroencephalogram (EEG), the electro-oculogram (EOG) and the electromyogram (EMG) processed in the frequency and time domains was achieved using a database of 47 night sleep recordings obtained from healthy adults. Four EEG channels (C3-A2, P3-A2, C4-A1, and P4-A1), one transversal EOG and one chin EMG were registered and digitized at a sampling frequency fs=128 Hz. The EEG leads were attached onto the scalp according to the International 10-20 EEG System of electrodes placement. Multiple iterative feature selection and supervised classification methods were applied together with a systematic statistical assessment of the classification performances. The results showed that using a simple set of features such as relative EEG powers in five frequency bands yields an agreement of 71% with the whole database classification of two human experts. These performances are within the range of existing classification systems. The addition of features extracted from the EOG and EMG signals makes it possible to reach about 80% of agreement with the expert classification. The most significant improvement on classification accuracy is obtained on NREM sleep stage 1, a stage of transition between sleep and wakefulness.

In [9] the researchers analyzed the EEG data and extract features corresponding to two extreme vigilance levels: awake and sleeping and avoid the middle levels. 64 channels of signals including 4 channels of EOG are recorded. 20 channels of EEG data recorded from electrodes located at the center of the head were used. Short-time Fourier transform (FT) was used to transform the original EEG data directly to the frequency field. And a second method used the FT to transform the results of the CSP (common spatial patterns) transform to the frequency field. The EEG signals of frequency between 2Hz and 30Hz were used to analyze. Then PCA (principal component analysis) was used to reduce the dimensions. Several clustering methods such as normalized cut , soft clustering [5] and k-mean were used to cluster the EEG data. They conclude that, CSP transform could greatly increase the accuracy of the clustering of the EEG data.

In [7] EOG features, mainly slow eye movements (SEM), to estimate the human vigilance changes during a monotonous task. In particular, SEMs were first automatically detected by a method based on discrete wavelet transform (DWT), then linear dynamic system was used to find the trajectory of vigilance changes according to the SEM proportion. The performance of this system was evaluated by the correlation coefficients between the final outputs and the local error rates of the subjects. The result suggested that SEMs perform better than rapid eye movements (REM) and blinks in estimating the vigilance. Using SEM alone, the correlation can achieve 0.75 for off-line, while combined with a feature from blinks it reached 0.79.

[15] recorded 19 EEG channels signals from 10 volunteers while they were playing a virtual driving game. Recordings were band pass filtered between 0.5 and 30 Hz. Then, they extracted some chaotic features (include Higuchi's fractal dimension and Petrosian's fractal dimension) and logarithm of energy of signal. Feed forward artificial neural network (ANN) was used as a classifier to classify the two classes of vigilance; alert and drowsy (first stage of sleep). The result showed that, the ability of each feature has been evaluated and the maximum accuracy of classification was 75.5%. While the accuracy of classification with all three features for the nineteen channels was about 83.3%.

An adaptive alertness estimation methodology based on electroencephalogram, power spectrum analysis, independent component analysis (ICA), and fuzzy neural network (FNNs) models is proposed earlier for continuously monitoring driver’s drowsiness level with concurrent changes in the alertness level. Previous studies have proposed a number of methods to detect drowsiness. They can be categorized into two main approaches.

The first approach focuses on physical changes during fatigue, such as the inclination of the driver’s head, sagging posture, and decline in gripping force on the steering wheel. The second approach focuses on measuring physiological changes of drivers, such as eye activity measures, heart beat rate, skin electric potential, and electroencephalographic (EEG) activities reported that the eye blink duration and blink rate typically are sensitive to fatigue effects. Previous approaches to drowsiness detection primarily make pre-assumptions about the relevant behavior and drowsy driver detection through facial movement analysis. In other methods a drowsy driver detection system has been developed, using a non- intrusive machine vision based concepts. The system uses a small monochrome security camera that points directly towards the driver’s face and monitors the driver’s eyes in order to detect fatigue.

In this paper we used real-time wireless EEG-based brain computer interface (BCI) system for drowsiness detection. The proposed BCI system consists of a wireless physiological signal-

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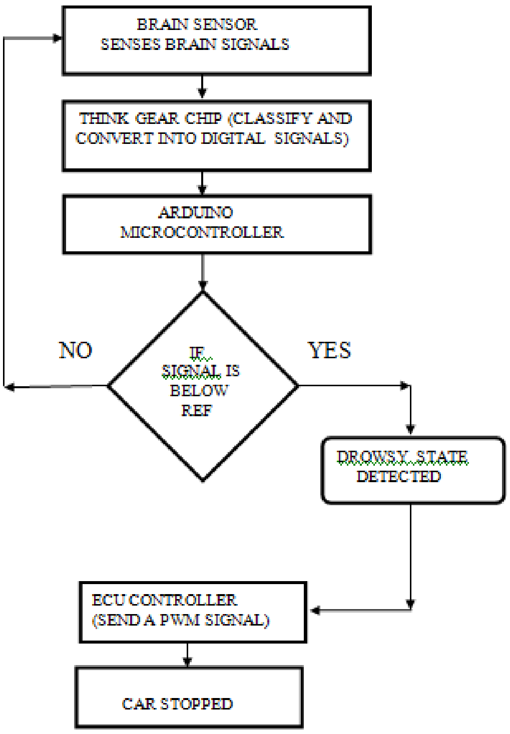
ACQUISITION MODULE USING ONLY THREE ELECTRODES. HERE THE DROWSY SIGNAL THETA AND DELTA IS MAINLY ANALYZED FOR DETECTING ONE'S DROWSINESS. AFTER ANALYZING ONE'S DROWSINESS THE CAR SPEED WILL BE REDUCED AUTOMATICALLY BY USING PWM TECHNIQUE.

4. Experimental Results

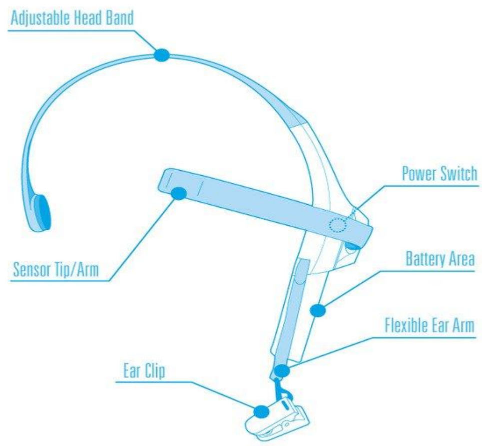
The primary object of this project is to provide a drowsiness detection system and automatic speed control system of vehicles. Only signal acquisition and processing is done here. The drowsy and attention state of the driver is analyzed by this above process.After analyzing the drowsiness of the person, the speed of the car is reduced below a particular limit and warning tone will be given to the driver simultaneously and speed also controlled .The Experiment details given below with snapshots(4.1a,b,c).



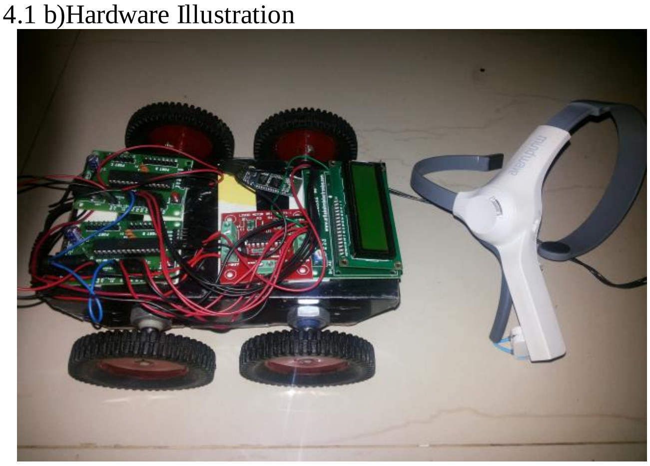
4.1 a)Hardware Model

4.1 The Brain Sensor:

The Neuro sky Mindset uses Bluetooth technology to send data to the hardware host for analysis. Since the device uses a dry-sensor, it requires no saline or gel in order to ensure proper connectivity with the surface of the forehead and noise-free EEG signals. Contact with the dry sensor electrode is achieved by the pressure of the electrode against the subject's forehead and held in place by the headset. It has proprietary filters to eliminate noise from muscle movement and electrical interference. It also includes a notch filter to eliminate 60 Hz noise from a power source. Since there are no wires attaching the electrode to an analysis device, interference due to electrode wire length is greatly reduced.



4.1 b)Hardware Illustration



4.1 c)Real time Implementation

The Neuro sky Mindset can sample data at up to 512 samples per second. In addition to the raw EEG data, the Mindset can output calculated delta (0.5 - 2.75Hz), theta (3.5 - 6.75Hz), low alpha (7.5 - 9.25Hz), high alpha (10 - 11.75Hz), low beta (13 - 16.75Hz), high beta (18 - 29.75Hz), low gamma (31 - 39.75Hz), and mid gamma (41 - 49.75Hz) waves as well as blink strength. It also outputs Neurosky proprietary attention and meditation signals that are meant to identify when a subject is paying attention or is relaxed. The attention and meditation signals will not be used for this research. These attention and meditation signals are created using data from the other frequency bands (e.g. alpha, beta, gamma, etc). These signals are not standard EEG signals, and they do not represent specific frequency bands.

- ELECTRODES
- THINKGEARCHIP
- BLUETOOTH

4.1.1.Electrodes:

The EEG recording electrodes and their proper function are critical for acquiring appropriately high quality data for interpretation. Many types of electrodes exist, often with different characteristics. Basically there are following types of electrodes:

- Disposable (gel-less, and pre-gelled types)

- Reusable disc electrodes (gold, silver, stainless steel or tin)
- Headbands and electrode caps
- Saline-based electrodes
- Needle electrodes

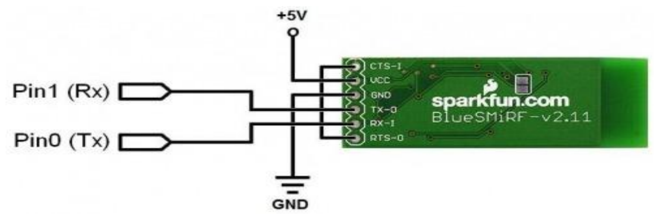
Here reusable dry electrodes can be placed close to the scalp,the contact electrodes themselves are just pieces of conductive metal.Stainless steel is typically used as the contact material,but they can be replaced with gold,silver with good conductivity.

4.1.2. Thinkgear Chip:

ThinkGear is the name of NeuroSky's single dry sensor technology that allows the measurement, amplification, filtering, and analysis of EEG signals and brainwaves. Combined with NeuroSky's proprietary eSense™ algorithms, this allows a headset to be able to measure the wearer's state of mind, and makes this information available to applications so that the applications can respond to your mental activity. the formula for converting raw values to voltage is:
[rawValue * (1.8/4096)] / 2000.
This is due to a 2000x gain, 4096 value range, and 1.8V input voltage.

4.1.3. BLUETOOTH:

The BlueSMiRF is easy to interface with an Adruino. Simply connect the power and ground pins from the device to the associated pins on an Arduino. Then, connect the two Tx and Rx pins from the device to the standard serial pins 0 or 1. This is very important as BlueSMiRF communication is fast, and must be buffered by the on-board serial chip (which only works with pins 0 and 1).



4.2.ATMEGA 328:

The Atmel 8 bit AVR RISC-based microcontroller combines 32 KB ISP flash memory with read-while-write capabilities, 1 KB EEPROM, 2 KB SRAM, 23 general purpose I/O lines, 32 general purpose working registers, three flexible timer with compare modes, internal and external interrupts, serial programmable USART, a byte-oriented 2-wire serial interface, SPI serial port, 6-channel 10-bit A/D convertor (8-channels), programmable watchdog timer with internal oscillator, and five software selectable power saving modes. The device operates between 1.8-5.5 volts. The device achieves throughputs approaching 1 MIPS per MHz.

Conclusion

The primary object of this project is to provide a drowsiness detection system and automatic speed control system of vehicles. Only signal acquisition and processing is done here. The drowsy and attention state of the driver is analyzed by this above process. After analyzing the drowsiness of the person, the speed of the car is reduced below a particular limit and warning tone will be given to the driver simultaneously and speed is controlled.

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