Signal Processing in Human-Computer Interface

by

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Abstract

Low efficiency of the common Human-Computer Interface (HCI) such as keyboard and mouse are exposed when operations become more and more complex. It's needed to study on advanced HCI like Brain-Computer Interface (BCI) to improve efficiency and develop new functions. BCI has potentials to be applied in driving systems and is usually used to detect the drowsiness of drivers. Once the driver is detected as being drowsy, a driving assistance system will alert him/her or the car becomes semi-autonomous.

In the field of drowsiness detection, bio signal processing with a 10-20 System is the common method. Unfortunately, this method is not very accurate because of the limitation of the unknown knowledge about brain waves and judgement error on the true value of drowsiness state as well as the influence of many factors such as age, alcohol and drug. In this thesis, we studied a probabilistic neural network (PNN) based on Lempel-Ziv Complexity, Approximate Entropy, and a rational band feature. Experimental results indicate that 82% accuracy was achieved by using this PNN model for predicting the human drowsiness. We also investigated the eye movement analysis and alcohol influence on the drowsiness.

Keywords: Human-Computer Interface, Bio signal processing, Drowsiness detection, EEG analysis, Alcohol and drug influence

Chapter I Introduction and Literature Review

1.1 Problem Statement

Researchers proposed a wide variety of drowsiness detection methods through all kinds of data sources, which can be categorized into physiological methods, vehicle data-based methods and behavior-based methods [1]. The difficulty levels to apply these methods are various, so are the rates of accuracy. For example, vehicle data-based method is the easiest to implement, because it only needs an embedded system to record and analyze the steering wheel movements, gas pedal movements, etc. But there are many factors could affect its reliability, such as personal driving habits and especially road conditions.

This thesis proposes a method of combining behavior-based methods and physiological methods. Behavior-based methods usually record head movements, face deformations or eye movements based on computer vision techniques [2]. This method is limited by personal habit. Besides, when eyeglasses reflect the light, it also decreases the accuracy. But with the development of physiological sensors, it is possible to record signals of a subject's certain movement. Computer can detect the similar signal pattern when you do the same movement repeatedly. I recorded some signal patterns of drowsiness movements, such as yawning and longer eye closing. If the program receives the signals similar to the drowsiness pattern, it returns an S value stand for the similarity. If S value is big enough, it alters the subject. Another function is to extract 3 features of the brain waves. After extract these features, use a

probabilistic neural network PNN to train them. Import features and their corresponding drowsiness states for the network to implement pattern recognition.

1.2 Drowsiness: Introduction

1.2.1. Definition of Drowsiness

Drowsiness is a state of strong desire for sleep, or sleeping for unusually long periods [3]. Mostly, it refers to feeling abnormally sleepy during the day time. It can be accompanied by lethargy, weakness, and lack of mental agility. Drowsiness may lead people to fall asleep in wrong place or wrong time, such as working, reading and even driving. As a result, it increases the risk for workers and drivers to have accidents.

1.2.2. Drowsiness during driving

Because driving needs full concentration, it sometimes leads to drowsiness especially during long distance driving. Drowsiness increases the reaction time at emergencies and heavy drowsiness even causes an intermittent long time eye-closing. According to the latest study of the Foundation for Traffic Safety with data from 2009-2013, it is estimated that driver drowsiness causes approximately 328000 crashes, which lead to 6,400 deaths and 109,000 injuries each year [4].

1.2.3. Reasons of Drowsiness

There are 5 main reasons that cause drowsiness:

No enough rest and disorder life habit.

Illnesses, such as stroke and delirium.

Injury, such as concussion and other head injury.

Lack of nutrition, such as low sodium and low blood sugar.

Drug and alcohol.

1.2.4. Drug Influence

The impacts of different drugs in the past studies are summarized below.

Benzodiazepines: Benzodiazepines are a class of psychoactive drugs which are useful in a variety of indications such as alcohol dependence, seizures, anxiety disorders, panic, agitation, and insomnia. It can decrease Alpha wave band and Beta wave band.

Marijuana/ Hashish/ THC: These drugs are mostly used as medicinal drugs during chemotherapy to reduce untoward effect. Alpha wave band increases after take them. Long term will lead drug addiction. Patient feels fevered and dizziness.

Lysergic acid diethylamide (LSD-25): LSD is widely used as pharmaceuticals and as psychedelic drugs. It decreases Alpha wave band and increases Beta wave band and fast activity from a normal background. LSD can cause pupil dilation, reduced appetite, and wakefulness. The side effects of this powerful drug may cause convulsions, fears, anxiety, wanting to harm others at higher doses.

Barbiturate: Barbiturate is a drug that acts as a central nervous system depressant which is used as anxiolytics and hypnotics. It increases activities in low frequency band. With high does, the high frequency bands are inhibited and the low frequency bands predominate. It also

decreases voltage and electric pattern.

Caffeine: Caffeine is a central nervous system (CNS) stimulant. It is the most widely consumed psychoactive drug all over the world. Caffeine can reduce physical fatigue and to prevent or treat drowsiness. Clinical experiments show caffeine leads an Alpha wave band to increase frontally while Theta wave band is reduced.

Cocaine: Cocaine is a strong stimulant mostly used as a recreational drug. Its mental effects include loss of contact with reality, an intense feeling of happiness, and agitation. With lower to moderate doses, Alpha wave band and Beta wave band are increased. With increased doses, there is a desynchronization of the EEG and high frequency band predominates. The Alpha wave band increase frontally is seen during the euphoric phase of the subjective report. Besides, cocaine causes epileptic. Abuse will decrease Delta wave band and slower alpha wave band to destroy dopamine system.

General comments:

Above 6 kinds of psychoactive drugs can be classified by stimulants and depressants. Benzodiazepines and Barbiturate belong to depressants. Marijuana/ Hashish/ THC, Lysergic acid diethylamide, Caffeine and Cocaine are considered as stimulants.

Stimulants are used to make people stay awake and reduce pains during treatment. Most of them have effects of increasing high frequency bands and decreasing low frequency bands.

Depressants are used as anxiolytics and hypnotics. They can increase low frequency bands and decreasing high frequency bands.

1.3. Drowsiness Detection Methods

To prevent drowsiness is to keep operators' health and safety. So, drowsiness detection has become a popular subject. There are 3 kinds of methods to detect drowsiness during driving.

The first one is to analyze images of subjects' face or eyes during driving, and then compare the result to normal pattern. Another method is to obtain subject's EEG and analyze it to determine the drowsiness degree. The last one is to record wheels' movements, and the pressure on steering wheel. Because when people are awake, the number of turning movements is greater than that during drowsiness and the pressure is also higher.

1.3.1. Face Activity Analysis Method

Face activity analysis method is a non-contact method, because it only needs camera and embedded processor, which don't contact drivers. Hence, it's more convenient than EEG analysis method with respect to drivers. According to experiments, facial expression that includes 17 facial muscle activities can show the degree of drowsiness well [5]. Among the 17 facial muscle, eye activities are the most stable and meaningful features. Usually, to obtain videos of meaningful facial muscle activities, a camera is set on the dashboard. Subjects are asked to drive on a monotonous loop to stimulate driver drowsiness. After images data collection, there are usually 3 steps to detect the drowsiness. Firstly, recognize degree of eye openness by Orthogonal Locality Preserving Projection (OLPP) method. Secondly, lots of degree of eye openness in a short time can show many meaningful results including PERCLOS (percentage of eyelid closure over the pupil over time reflects slow eyelid closures rather than blinks), closing/opening duration, average opening/closing speed, blink rate (BR).[6] Compare them to normal pattern to calculate the drowsiness degree. Lastly, use machine learning to let

program analyze the amount of results and adjust the way to evaluate a new driver. But these methods have low tolerance for degraded image resolution because of their high dependence on accurate shape fitting. Whereas in real driving environment, many factors may affect the image quality captured by cameras such as bumps of vehicle, bad illumination and light reflected from driver's glasses.

1.3.2 EEG Analysis Method

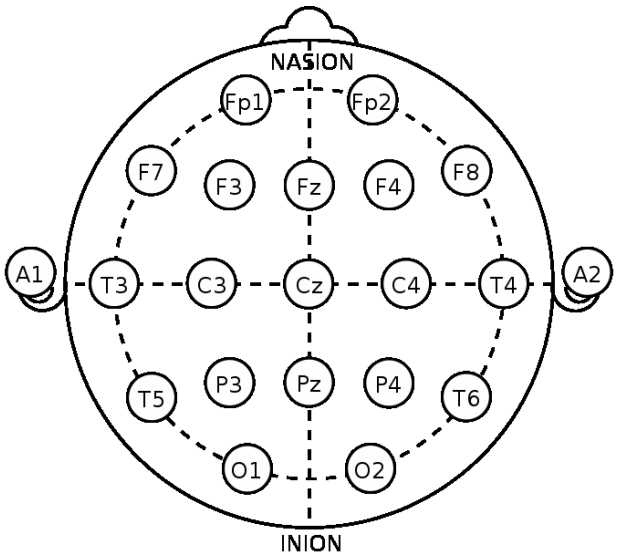
Usually, EEG analysis method is more accurate than facial image analysis. This method is based on bioelectricity signals produced by billions of neurons in the brain. Neural function depends on electrical events within the plasma membrane of neurons. Different activities produce different signals. EEG has 4 major brainwaves Delta waves, Theta waves, Alpha waves and Beta waves.

Delta – frequencies below 4 Hz, during sleep in adults, in temporal region during wakefulness and generalized maximal anterior during drowsiness in normal elderly

Theta – 4 Hz to less than 8 Hz, in children and young adults during wakefulness, during drowsiness in adults

Alpha – 8 to 13Hz, Alpha brainwaves are dominant during quietly flowing thoughts, and in some meditative states.

Beta – above 13 Hz, Beta activity is closely linked to motor behavior and is generally attenuated during active movements.



Here is an EEG 10-20 System. The letters used are:

F: Frontal lobe, T: Temporal lobe, C: Central lobe, P: parietal lobe, O: Occipital lobe, Z refers to an electrode placed on the mid-line.

10-20 System is an international standardized system so that different studies could be compared to each other. This system is based on the relationship between the location of an electrode and the underlying area of a scalp. The "10" and "20" refer to the fact that the actual distances between adjacent electrodes are either 10% or 20% of the total front–back or right–left distance of the skull.[7]

First, a subject needs to be set in a very quiet room with noiseless EEG detection tools. After some time, subject will feel drowsy. We can classify drowsy periods by Alpha signal power spectrum changes [8]. Alpha waves highly occur on the occipital lobe when subjects close their eyes. But EEG signals are hard to collect because it's very weak. Normally the potential is very low and human body also produces many other electrical signals including ECG, EOG and EMG. So, before extract EEG signals, EEG should be filtered with 0.5Hz to 60Hz.[9]

The advantage of using EEG to detect drowsiness is accuracy. The EEG signal reflects very well the loss of alertness, so is appropriate to detect drowsiness.[10] Here is an example of

“awake state” and “drowsiness”[11].

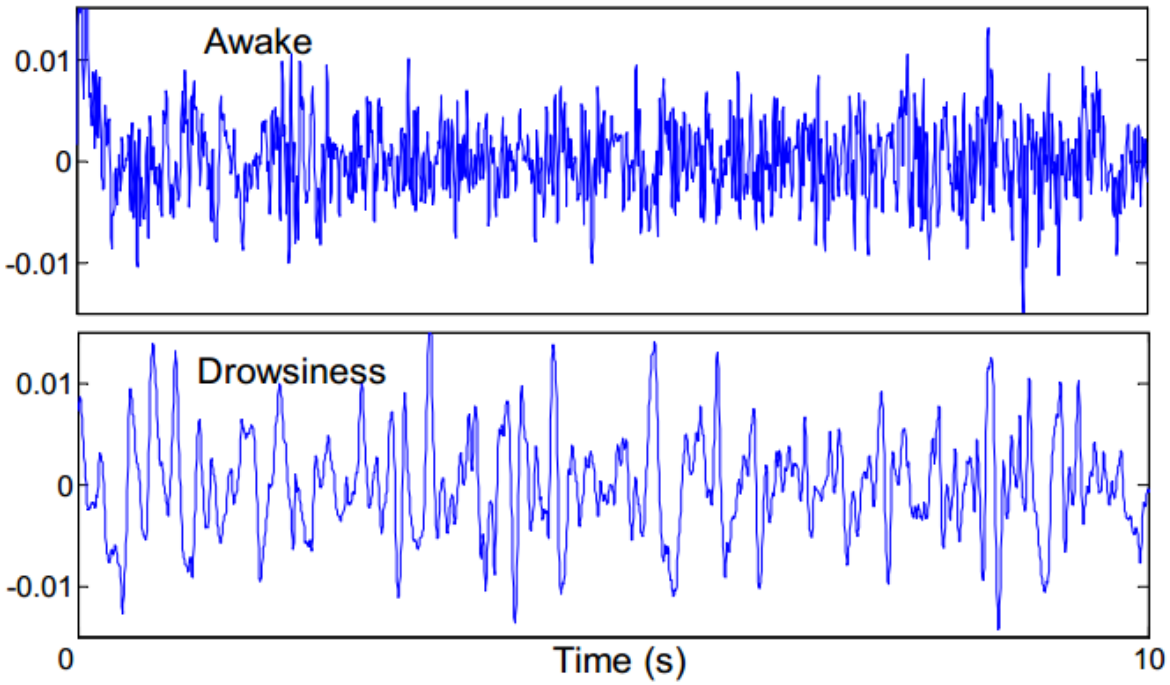


Figure 1 Frequency of awake signal is higher than frequency of drowsy signal

Chapter II Human Computer Interface

2.1 Human Computer Interface Introduction

With the development of computers, Human Computer Interface (HCI) is the tool which connects us with computer. It is widely believed that as the computing, communication, and display technologies progress even further, the existing HCI techniques may become a bottleneck in the effective utilization of the available information flow. For example, keyboard and mouse are the main mode of HCI. These devices are very familiar to human but their low efficiency is exposed when operations become more and more complex.

In recent years, many tremendous new HCI technologies emerged. The most interesting one is Brain-Computer Interface. Brain-Computer Interface has a 10-20 system to collect users' brain waves. Brain waves patterns are different when people imagine different things. These patterns are the input of Brain-Computer Interface. Brain-Computer Interface platform converts these patterns to the computer orders to implement complex operations, if a programmer wants to build a controller to control a subject's movement, Usually it takes several hours to several days if he only uses a basic programming language. But with a Brain-Computer Interface platform, it can be implemented in a few minutes. Programmer records his neutral state without thinking anything. This is the basic state of his brain. And then he could imagine subject movements in his brain and choose the corresponding operations. The controller is implemented when all movement patterns are imported.

The Brain-Computer Interface platform is an advanced HCI. It uses brain waves as input which can carry far more information than keyboard and mouse. It saves a lot of time and increases happiness in programming. This new technology may resolve the interaction bottleneck in the future.

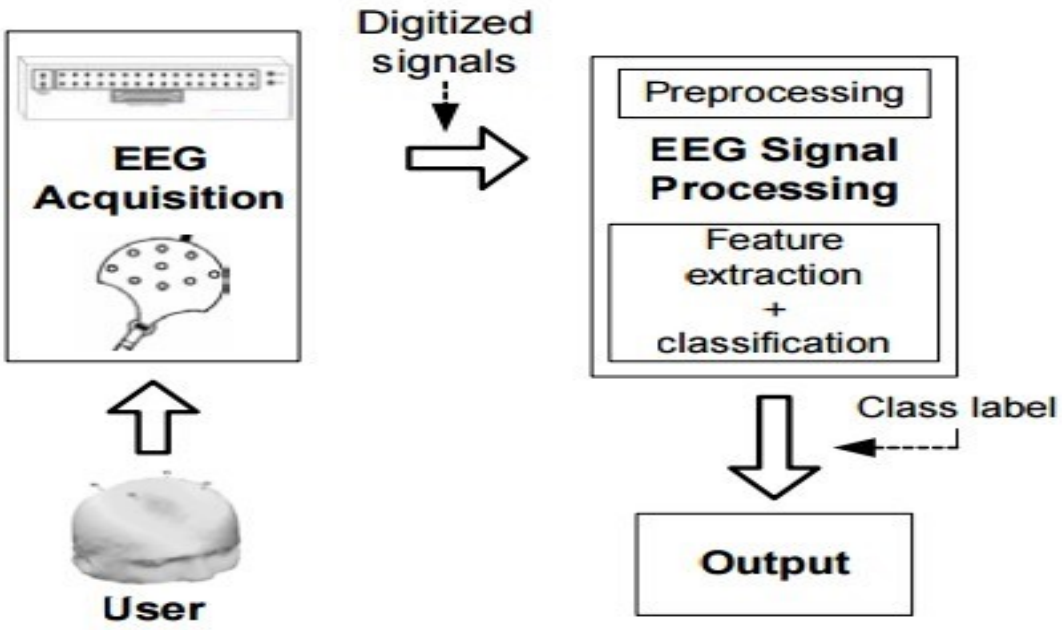


Figure 2 BCI system

2.2. Hardware of OpenBCI: Introduction

OpenBCI is an open source brain-computer interface platform. Open-BCI was created by Joel Murphy and Conor Russomanno, after a successful Kickstarter campaign in late 2013. Open-BCI boards can be used to measure and record electrical activity produced by the brain (EEG), muscles (EMG), and heart (EKG), and is compatible with standard EEG electrodes. Because of an open license and modular architecture, it can implement different communication channels in the serial or parallel hybrid mode. [12]

Hardware: The Open-BCI 32bit Board uses the ADS1299, an IC developed by Texas

Instruments for bio potential measurements. The Open-BCI uses a microcontroller for on-board processing — the 8bit version (now deprecated) uses an Arduino-compatible ATmega328P IC, while the 32bit board uses a PIC microcontroller — and can write the EEG data to an SD card, or transmit it to software on a computer over a Bluetooth link.

In 2015, Open-BCI announced the Ganglion board with a 2nd Kickstarter campaign. It costs $100 (1/5 the cost the 32bit board). It has 4 input channels for measuring EEG, EMG, and EKG, and is also Bluetooth enabled. [13]

OpenBCI belongs to brain computer communication devices. It has 3 parts, EEG gathering system, EEG signal processing system and output system. EEG gathering system is usually an EEG 10-20 System with 30 electrodes which stick on scalp.[14] After acquisition, EEG is transferred to the processing system. In this system, EEG is preprocessed and classified by different frequency. Each class of brain wave corresponds to a mental activity (MA). At last, classification result is sent to output system. There are 3 keys of good BCI operations. (1) Extract the right features from EEG. (2) Use the appropriate classification strategy. (3) Let the subject do the right MA so that BCI can gather the meaningful data.[15]

Chapter III Technical Approach

3.1. Eye Movement Analysis

3.1.1. Introduction

This method records bio signals when a subject blinks his eyes. Make the bio signals during waking status as the normal pattern. Compare the subject's bio signals with his normal pattern and use a specific algorithm to calculate the drowsiness degree.

3.1.2. Experimental Settings

Preparation: Set a subject in a quiet room. Turn off all kinds of electrical devices because their electrical signals may affect the bio signals. Attach two gold electrodes to the area above the subject's eyes for recording eye-blink bio signals. Stick two BIAS electrodes on two ears.



Figure 3 Awake eye signals with OpenBCI

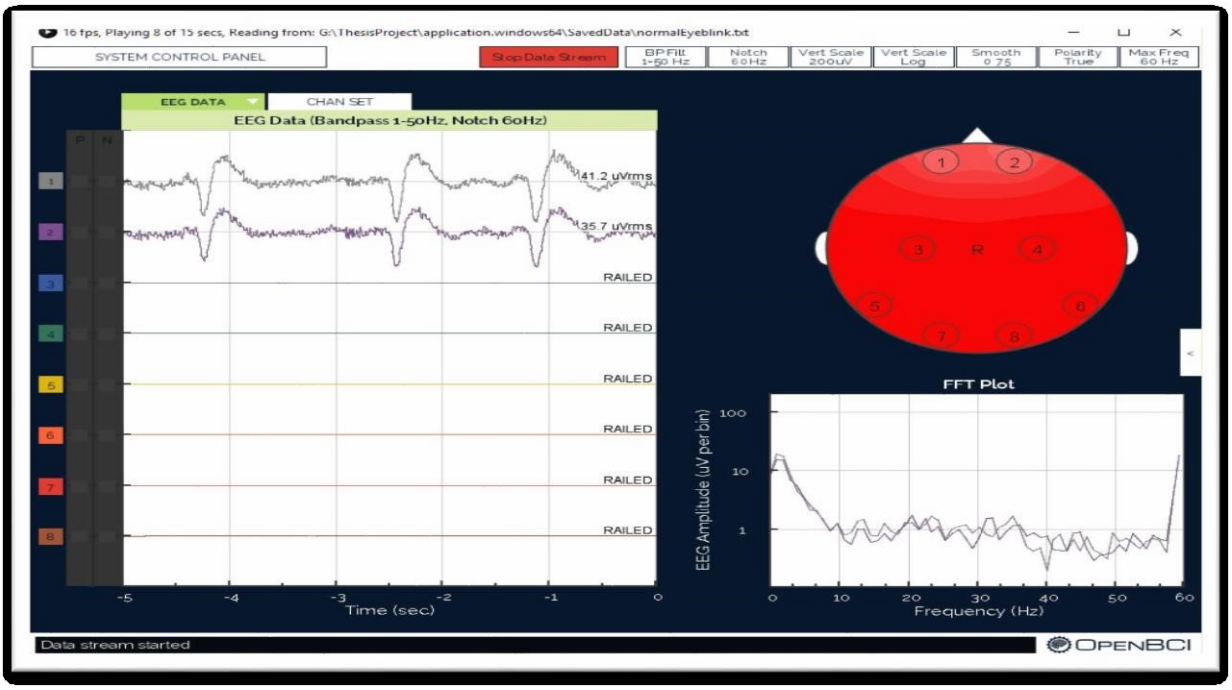


Figure 4 Awake eye signals in OpenBCI

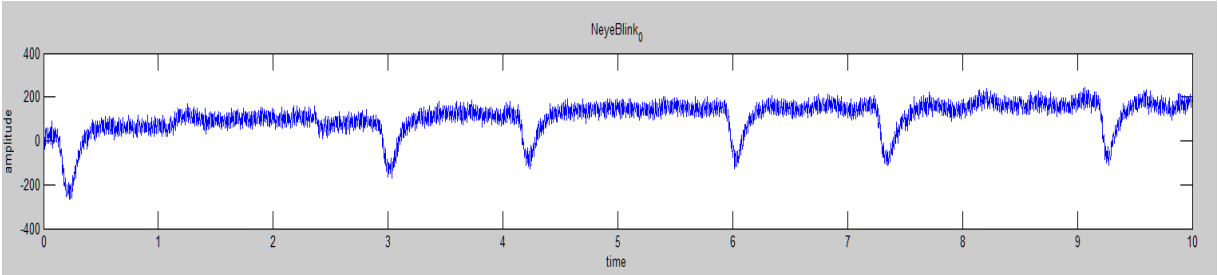


Figure 5 Awake Eye signals in Matlab plot

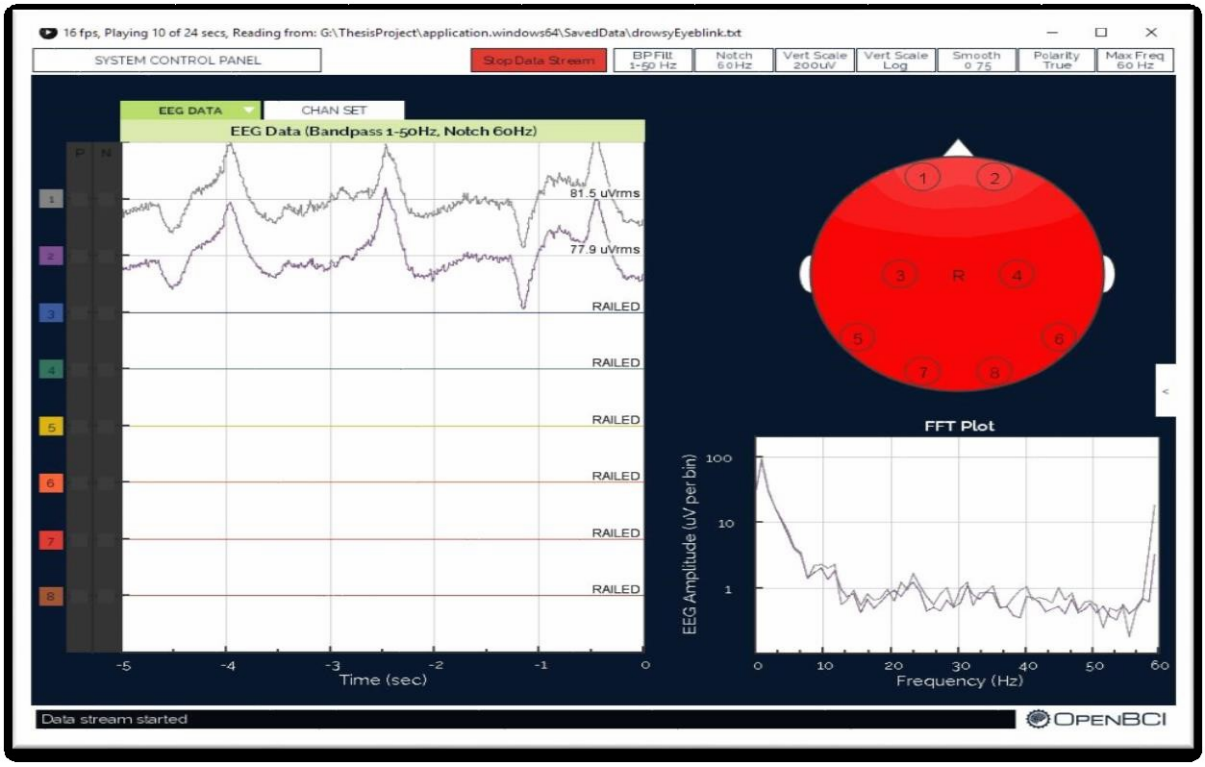


Figure 6 Drowsy eye signals in OpenBCI

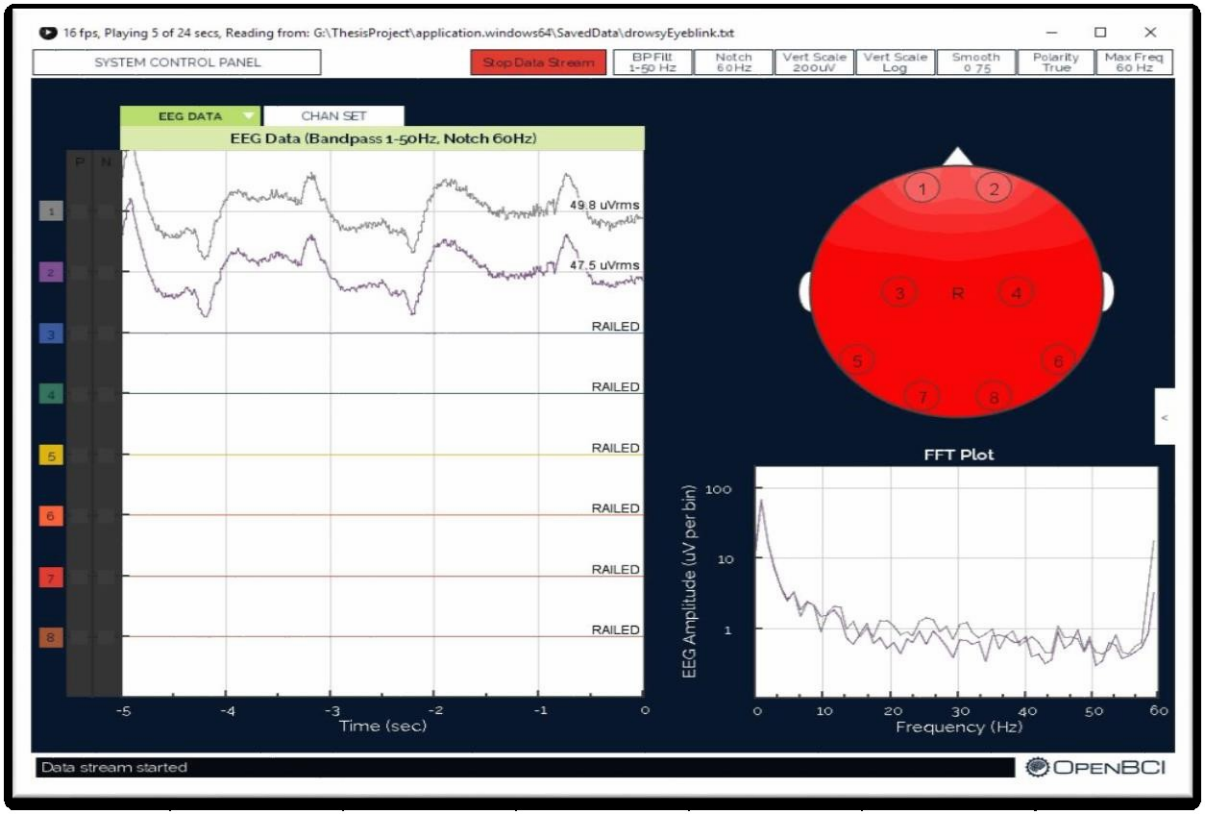


Figure 7 Drowsy eye signals in OpenBCI

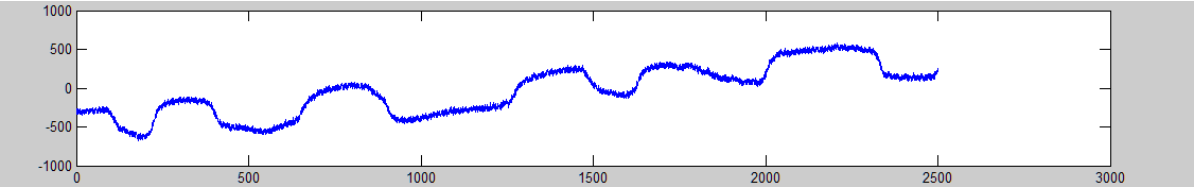


Figure 8 Awake Eye signals in Matlab plot

As shown in the above 6 images, the difference of eye signals in awake status and eye signals in drowsy status are apparent:

In normal status: shapes of vibration are similar; amplitude is stable and small

In drowsy status: shapes of vibration are irregular, amplitude is various and longer

3.1.3. Algorithm

The wave distinction comparison is a good way to detect drowsy based on eye bio signals according to these observed results. Before calculating the distinction degree of two bio waves, they must be synchronous. In other words, the wave crest (trough) positions should be the same. If they are not synchronous, the distinction degree is meaningless.

(1) The first step is to find the wave trough positions in each signal. Wave trough is the minimum value in each vibration and it's easy to find:

$$P = \text{index}(\min(X)) \quad (1)$$

We can get drowsy wave trough position is $P_d = P = \text{index}(\min(D))$ and awake wave trough position is $P_a = P = \text{index}(\min(A))$

(2) Get drowsy dataset T_d center on P_d and awake dataset T_a center on P_a. The size of each dataset should contain data in an eye-blink period. It's 3s approximately:

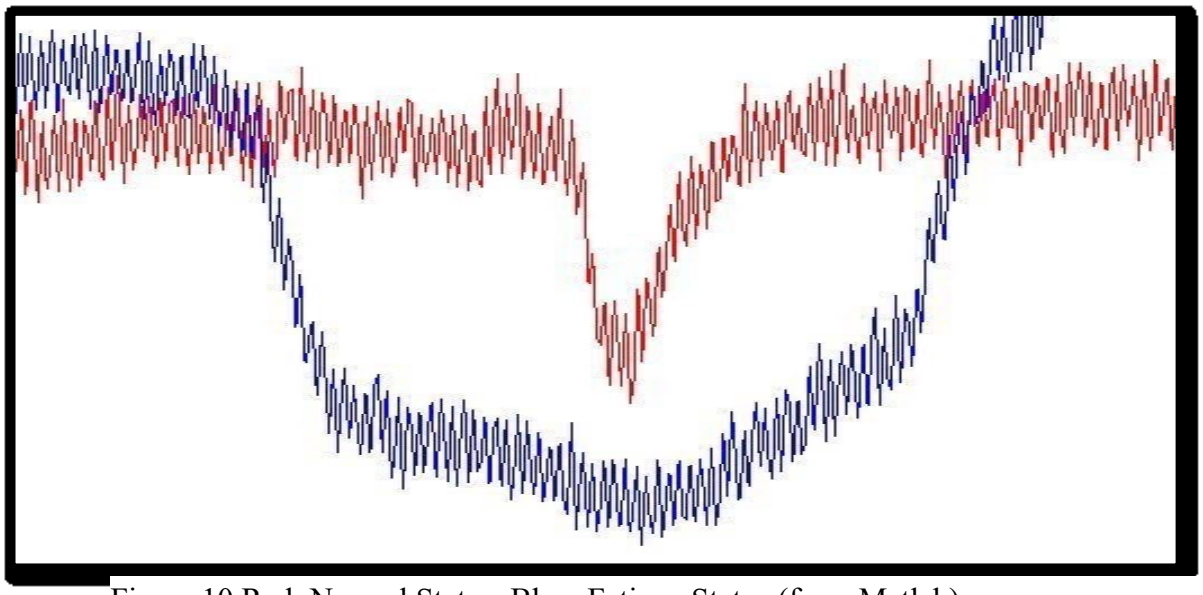


Figure 10 Red: Normal Status. Blue: Fatigue Status (from Matlab)

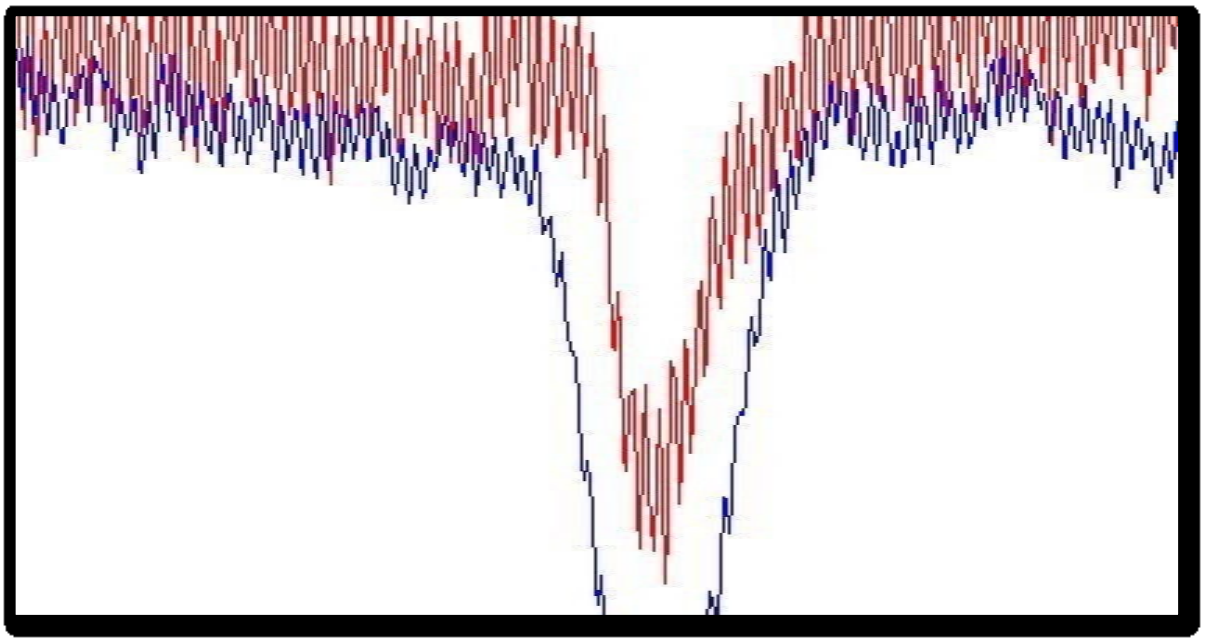


Figure 9 Red: Normal Status1. Blue: Normal Status2 (from Matlab)

(3) Calculate the distinction degree. These eye signals are in the same plane surface with the same direction, so the minimum vertical distance between the signals can describe the distinction degree. The longer distance between the 2 signals, the less distinction degree.

$$L = \mathbf{Fd}|\, T_d - T_a| \qquad (2)$$

where Fd is the Fréchet distance between two lines. The Fréchet distance is a measure of

similarity between curves that considers the location and ordering of the points along the curves.

3.1.4. Results and Conclusions

Table 1 Eye distinction degree “N” stands for normal status. “D” stands for drowsy status.

	D1	D3	D4	D5	D6	D7	D8	D9	D10
N1	259.49	380.68	520.97	510.18	333.72	273.39	378.23	288.64	241.59
N2	497.32	405.57	322.04	505.15	285.05	283.59	186.33	230.78	258.92
N3	246.05	376.31	462.52	503.87	299.29	294.67	346.16	397.50	351.34
N4	244.26	388.03	529.89	515.46	325.01	270.42	369.57	289.94	241.73
N5	394.41	402.99	561.80	498.09	309.28	276.53	352.85	339.26	291.90
N6	477.73	478.19	266.55	491.99	132.42	288.47	136.38	140.98	149.16
N7	297.86	460.62	757.76	470.16	268.38	318.95	309.83	318.33	270.25
N8	269.85	470.29	628.48	235.73	140.74	359.32	162.01	305.15	257.96
N9	273.65	417.33	559.43	522.92	316.68	279.21	360.95	288.53	241.82
N10	208.09	432.70	620.03	481.70	223.47	281.71	378.64	356.96	309.64

Table 2 Eye distinction degree “N” stands for normal status.

	N1	N3	N4	N5	N6	N7	N8	N9	N10
N1	0.00	138.74	134.58	135.36	265.39	45.44	49.76	42.66	149.55

The values in the first table are the difference between awake states and drowsy states and the mean is 350 approximately. The values in the second table are the difference between two awake states and the mean is 120 approximately. There is big difference between them. The data is collected from very awake and very drowsy states, so we define 120 as the awake state and 330 as absolutely drowsy state.

Table 3 Red areas are drowsiness degree>=50%

	D1	D3	D4	D5	D6	D7	D8	D9	D10
N1	259.4898	380.6757	520.9748	510.1769	333.7191	273.3934	378.2315	288.6418	241.592
N2	497.3211	405.5742	322.0405	505.1458	285.0488	283.5898	186.3275	230.7832	258.9162
N3	246.0503	376.3105	462.5237	503.8685	299.2929	294.6712	346.1567	397.5019	351.3389
N4	244.2631	388.0337	529.887	515.4611	325.0077	270.4206	369.5699	289.937	241.7348
N5	394.4122	402.9932	561.8014	498.0897	309.275	276.5319	352.8529	339.2646	291.8981
N6	477.7311	478.1935	266.546	491.9904	132.4155	288.4698	136.3779	140.9841	149.1605
N7	297.8552	460.6229	757.7627	470.1623	268.3831	318.9544	309.8311	318.3325	270.2535
N8	269.8468	470.2923	628.4796	235.731	140.7396	359.3172	162.0134	305.1473	257.9569
N9	273.6478	417.3287	559.4276	522.9182	316.6845	279.2072	360.9518	288.534	241.8152
N10	208.0921	432.6983	620.0272	481.6965	223.4651	281.7077	378.6373	356.9578	309.6399

Table 4 Red areas are drowsiness degree>=60%

	D1	D3	D4	D5	D6	D7	D8	D9	D10
N1	259.4898	380.6757	520.9748	510.1769	333.7191	273.3934	378.2315	288.6418	241.592
N2	497.3211	405.5742	322.0405	505.1458	285.0488	283.5898	186.3275	230.7832	258.9162
N3	246.0503	376.3105	462.5237	503.8685	299.2929	294.6712	346.1567	397.5019	351.3389
N4	244.2631	388.0337	529.887	515.4611	325.0077	270.4206	369.5699	289.937	241.7348
N5	394.4122	402.9932	561.8014	498.0897	309.275	276.5319	352.8529	339.2646	291.8981
N6	477.7311	478.1935	266.546	491.9904	132.4155	288.4698	136.3779	140.9841	149.1605
N7	297.8552	460.6229	757.7627	470.1623	268.3831	318.9544	309.8311	318.3325	270.2535
N8	269.8468	470.2923	628.4796	235.731	140.7396	359.3172	162.0134	305.1473	257.9569
N9	273.6478	417.3287	559.4276	522.9182	316.6845	279.2072	360.9518	288.534	241.8152
N10	208.0921	432.6983	620.0272	481.6965	223.4651	281.7077	378.6373	356.9578	309.6399

In figure 6, 50%(235) drowsiness degree is the threshold of very dangerous driving.

Accuracy is 88%

In figure 7, 60%(258) drowsiness degree is the threshold of very dangerous driving.

Accuracy is 80%

3.2. Brain Wave Analysis

3.2.1. Experimental Settings

Preparation: Set a subject in a quiet room. Turn off all kinds of electrical devices because their electrical signals may affect the bio signals. Attach 8 golden electrodes to the

area above subject's head for recording brain signals. Stick two BIAS electrodes on two ears.

3.2.2 Method

This thesis creates a new method to evaluate the drowsiness degree based on brainwaves. We extract 3 features of the brain waves: (1) Lempel-Ziv Complexity (LZ complexity) of brain waves, (2) Approximate entropy (ApEn) of brain waves, and (3) state quotient $P = (E_\theta + E_\delta) / (E_\alpha + E_\beta)$. E stands for the proportion of the band. This is an important value in common drowsiness detection. After extract these features, use a probabilistic neural network PNN to train them. Import features and their corresponding drowsiness states for the network to implement pattern recognition.

3.2.3 Algorithm

Alternating current in the United States and several other countries oscillates at a frequency of 60 Hz. Those oscillations often corrupt measurements and must be subtracted. Eliminate the 60 Hz noise with a Butterworth notch filter. Use Matlab designfilt function to design it. The width of the notch is defined by the 59 to 61 Hz frequency intervals. The filter removes at least half the power of the frequency components lying in that range.

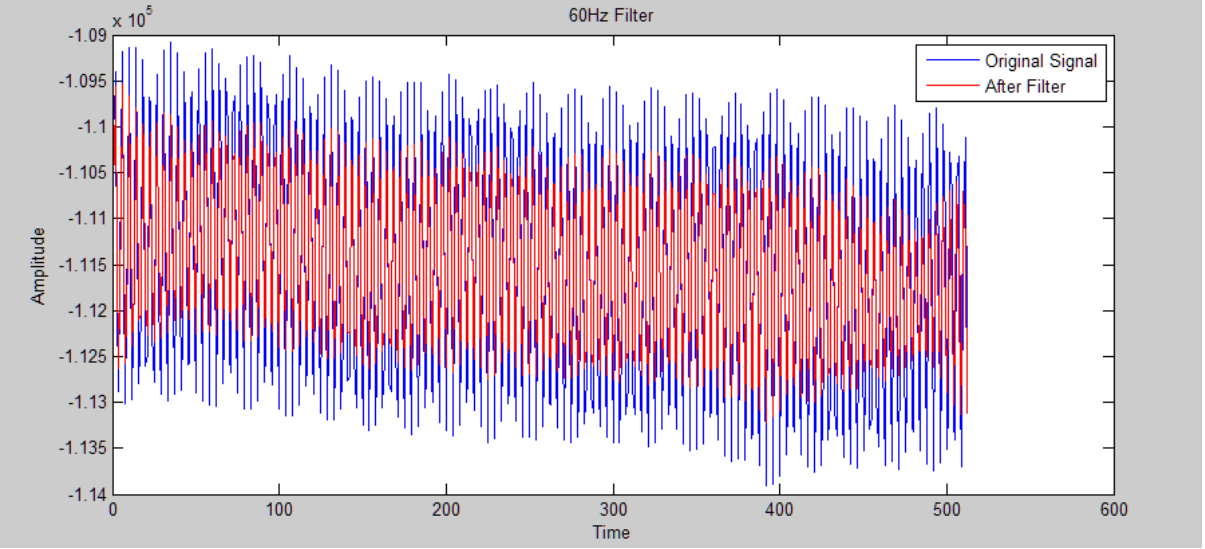


Figure 11 60Hz Filter

1. Lempel-Ziv Complexity (LZ complexity)

This complexity measure is related to the number of distinct substrings (patterns) and the rate of their occurrence along a given sequence [16]. It simplifies and shows the variations in the signal. In recent years, LZ has been used to analyze bio signals to estimate the complexity of discrete-time physiologic signals. In EEG study, LZ complexity was used to detect Alzheimer's disease [17]. It shows that the LZ complexity of different brain states is different. The LZ complexity of Alzheimer patients is lower than that of normal people. When people become drowsy in a dangerous environment, brain generates signals and releases incretion to fight against the drowsiness. Thus, these generate new brain wave patterns and lead to a high LZ complexity. So, we can treat LZ complexity as a good feature to evaluate drowsiness.

Before calculating the LZ complexity measure c(n), the signal must be transformed into a finite symbol sequence. In the context of biomedical signal analysis, typically the discrete-time biomedical signal is converted into a binary sequence. By comparison with the

threshold, the signal data are converted into a 0–1 sequence as follows:

$$P=s(1), s(2), \ldots, s(n) \tag{3}$$

where

$$S(i)=\begin{cases}0 & \text{if } x(i)<Td \\ 1 & \text{otherwise}\end{cases}, \tag{4}$$

Usually the median is used as the threshold because of its robustness to outliers. Previous studies [18] have shown that 0–1 conversion is adequate to estimate the LZ complexity in biomedical signals. In order to compute LZ complexity, the sequence is scanned from left to right and the complexity counter c(n) is increased by one-unit every time a new subsequence of consecutive characters is encountered. The complexity measure can be estimated using the following algorithm [19]:

1) Let S and Q denote two subsequences of P and SQ be the concatenation of S and Q, while sequence SQπ is derived from SQ after its last character is deleted (π denotes the operation of deleting the last character in the sequence). Let v(SQπ) denote the vocabulary of all different subsequences of SQπ. At the beginning, C(n) = 1, S = s(1) , Q = s(2) , therefore, SQ$\pi = s(1)$.

2) In general, S = s(1), s(2) ,…,s(r), Q = s(r+1), then SQπ = s(1), s(2) ,…,s(r); if Q belongs to v(SQπ), then Q is a subsequence of SQπ, not a new sequence.

3) Renew Q to be s(r+1), s(r+2) and judge if belongs to v(SQπ)or not.

4) Repeat the previous steps until Q does not belong to v(SQπ). Now Q = s(r+1), s(r+2), …, s(r+i) is not a subsequence of SQπ = s(1), s(2),…, s(r+i-1). So, increase C(n) by one.

5) Thereafter, update S = s(1), s(2),…, s(r+i-1), and Q = s(r+i+1).

The above procedure is repeated until Q is the last character. Now the number of different subsequences in P—the measure of complexity—is c(n). In order to obtain a complexity measure which is independent on the sequence length, c(n) must be normalized. If the length of the sequence is *n* and the number of different symbols in the symbol set is α, it has been proved that the upper bound of c(n) is given by

$$c(n) < \frac{n}{(1-En)log\alpha(n)} \tag{5}$$

where En is a small quantity and En→0(n→∞). In general n/ $log\alpha(n)$, is the upper bound of c(n), where the base of the logarithm is α,

$$\lim_{n\to\infty} c(n) = b(n) = \frac{n}{log\alpha(n)} \tag{6}$$

For a 0–1 sequence, α=2, therefore

$$b(n) = \frac{n}{log2(n)} \tag{7}$$

and c(n) can be normalized via b(n)

$$C(n) = \frac{c(n)}{b(n)} \tag{8}$$

where C(n), the normalized LZ complexity, reflects the arising rate of new patterns in the sequence.

Optimization:

As LZ complexity was used to analyze Electrocardiography (ECG) which has less features than EEG. Equation (4) simply converts the binary sequence by the mean of all values, but it loses the variation features of the signal. To get more variation features, we can set a value A

$$A=\frac{1}{n-1}\sum_{i=2}^{n-1} |X(i) - X(i-1)| \tag{9}$$

And then replace equation (4) with expression (10) and expression (11)

$$S1=\begin{cases}0 & \text{if } x(i)<Td\\ 1 & \text{otherwise}\end{cases}, \tag{10}$$

$$S(i)=\begin{cases}Si-1 & |Xi - Xi-1 |<A\\ 0 & |Xi - Xi-1 |\geq A \text{ and } Xi < Xi-1\\ 1 & |Xi - Xi-1 |\geq A \text{ and } Xi \geq Xi-1\end{cases}, \tag{11}$$

2. Approximate Entropy (ApEn)

Neuronal systems have been shown to exhibit various nonlinear features at some level [20]. Thus, it has been suggested to regard the EEG waveforms not as a sum of sine waves but as a chaotic pattern [21]. Therefore, it seems reasonable to apply methods from the theory of nonlinear dynamics to the EEG signal series. Entropy is a concept that addresses system randomness and predictability. Approximate entropy is a measure that quantifies the complexity or irregularity of a time series. Larger value of ApEn means more irregularity of the signal. Recently, ApEn has been used for the detection of Alzheimer's disease (AD). ApEn was significantly lower in the AD patients at electrodes P3 and P4 indicating a decrease of irregularity [22]. Besides, in an anesthetic drug effect test, with increasing enflurane (Anesthetic Drug Name) concentrations the EEG approximate entropy decreased. These two experiments showed ApEn is decreased when brain is dopey. It can be a good tool to evaluate the brain state.

A robust estimate of ApEn can be obtained by using short, noisy datasets. The general procedure of estimating ApEn is described as follows:

(a) Let the original signal containing N data points be X(n)=[x(1), x(2), ..., x(N)].

(b) m of vectors X(1), ..., X(N − m + 1) are defined according to

$$X(i) = [x(i), x(i + 1),...,x(i + m - 1)]\ i = 1, 2,...,N - m + 1 \quad (12)$$

These vectors represent m consecutive x values, starting with the *i*-th point.

(c) Denote the distance between X(i) and X(j) by d[X(i), X(j)], defined as the maximum absolute difference between their respective scalar components, i.e., the maximum norm

$$d[X(i), X(j)] = \max |x(i + k - 1) - x(j + k - 1)|(\ k=1,2,...,m) \quad (13)$$

(d) For a given X(i), find the number of (j = 1, ..., N − m + 1, j =/ i) so that d[X(i), X(j)] ≤ r, denoted as Nm(i). Then, for i = 1, ..., N − m + 1

$$C_r^m(i) = Nm(i)/ (N - m + 1) \quad (14)$$

(e) $C_r^m(i)$ measures the frequency of patterns that are like the one given by the window of length *m* within a tolerance *r*.

(f) Compute the natural logarithm of each C_r^m(i) and average it over *i*

$$\varphi m(r) = \frac{1}{N-m+1} \sum_{i=0}^{N-m+1} \ln C_r^m(i) \quad (15)$$

(g) Increase the dimension to *m* + 1. Repeat steps (2)–(6) to obtain $C_r^{m+1}(i)$ and φm+1(r).

Finally, ApEn is computed based on the following formula:

$$ApEn(m, r, N) = \varphi m(r) - \varphi m+1(r). \quad (16)$$

Before computing ApEn value of the signal with length N, two parameters must be specified: *m*, the embedding dimension and *r*, a tolerance window. [23]

3. Drowsiness Degree

In the literature review, we know stimulants have effects of increasing high frequency

bands and decreasing low frequency bands while depressants can increase low frequency bands and decreasing high frequency band. We can consider low frequency bands include Delta band and Theta band appear when people are drowsy. High frequency bands include Alpha band and Beta band, which appear when people are awake.

Brain waves include 4 main bands:

Delta – frequencies below 4 Hz, during sleep in adults, in temporal region during wakefulness and generalized maximal anterior during drowsiness in normal elderly

Theta – 4 Hz to less than 8 Hz, in children and young adults during wakefulness, during drowsiness in adults

Alpha – 8 to 13Hz, Alpha brainwaves are dominant during quietly flowing thoughts, and in some meditative states.

Beta – above 13 Hz, Beta activity is closely linked to motor behavior and is generally attenuated during active movements.

So it's feasible to calculate a drowsiness degree feature by low frequency band proportion divide high frequency band proportion (i.e., a rational band feature), $P = (E\theta+E\delta)/(E\alpha+ E\beta)$.

(1) To shift data to time axis vertically can make the normalized result more accurate:

$$X(i)=X(i)-X(1) \tag{18}$$

(2) Fourier transform on data

$$Z = fft(X) \tag{19}$$

(3) Calculate normalized amplitude

$$A = 2*|Z|/Fs \tag{20}$$

(4) Calculate each band norm

$$Ex = \text{norm}(Ax),\ X = \begin{cases} [1:4] & \delta \\ [4:7] & \theta \\ [7:13] & \alpha \\ [13:40] & \beta \end{cases},$$

(5) Drowsy state bands are divided by awake state bands

$$P = (E\theta + E\delta)/(E\alpha + E\beta) \tag{21}$$

4. Build a PNN Classifier

PNN: A probabilistic neural network (PNN) is a feedforward neural network based on Bayes' rule, which is widely used in classification and pattern recognition problems. It was introduced by D.F. Specht in the 1966. This type of artificial neural network (ANN) was derived from the Bayesian network and a statistical algorithm called Kernel Fisher discriminant analysis. By this method, the probability of mis-classification is minimized.

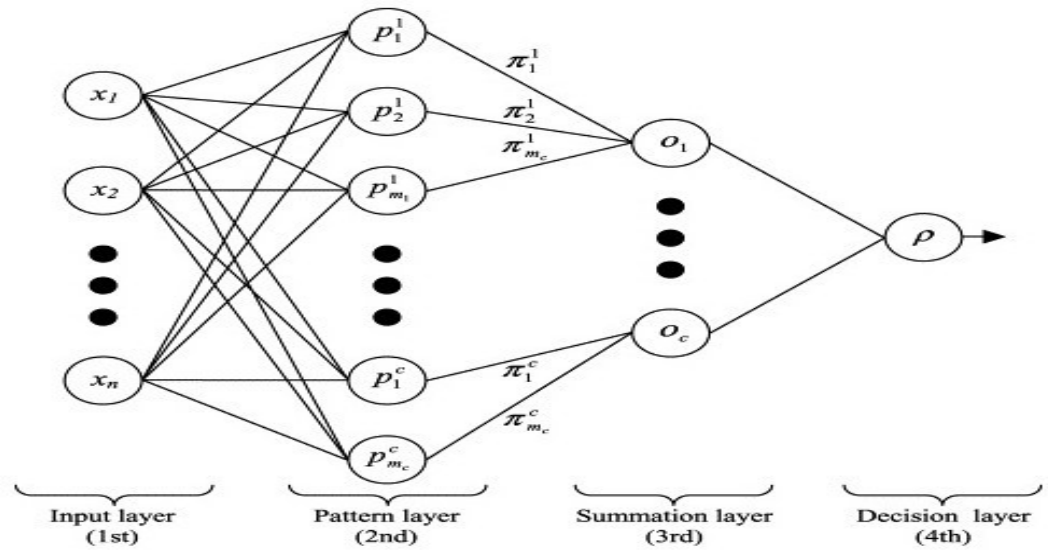


Figure 12 PNN Architecture

In Figure 12, the first layer shows the input pattern with *n* features. The number of nodes

in the pattern layer is equal to the number of training instances and the number of nodes in the summation layer is equal to the number of classes in the training instances.

The input layer distributes the input to the neurons in the pattern layer and the summation units simply sum the inputs from the pattern units that correspond to the category from which the training pattern was selected.

$$P(X \mid C_i) = \frac{1}{(2\prod)^{m/2}\sigma^m} \frac{1}{n} \sum_{i=1}^{n} \exp[-\frac{(X - X_i)^T (X - X_L)}{2\sigma^2}] \quad (22)$$

Ci is categories, X is subject, Xi is the sample of Ci, and *m* is dimension. σ is a smoothing parameter and *n* is the number of Ci. It's used in many pattern-recognition problems [24]. In medical fields, there are many methods to analyze bio signals and bio features to diagnose diseases. PNN classifier can get a very high accuracy if the features of train data are very typical and number of categories is few. In thyroid disease diagnosis PNN classifier got a 94.81% accuracy [25]. In the breast cancer diagnosis experiment, PNN classifier got a 97.0% accuracy.

In this thesis, we consider a pattern vector D with 3*24 dimensions belongs to drowsy category Cd and vector N with 3*24 dimensions belongs to normal category Cn. Use Matlab newpnn function to build a PNN classifier with them. The test data includes 30 drowsy state datasets and 24 normal state datasets.

3.2.4 Results and Conclusions

(1) LZ Complexity feature:

Before Optimized:

Table 5 Original LZ Complexity values

	1	2	3	4	5	6	7	8	mean
Drowy LZC	0.473	0.284	0.268	0.435	0.263	0.520	0.532	0.350	0.391
Awake LZC	0.522	0.485	0.330	0.351	0.492	0.433	0.444	0.441	0.437

	1	2	3	4	5	6	7	8	mean
Drows yLZC	0.422	0.348	0.524	0.358	0.265	0.336	0.277	0.441	0.371
Awake LZC	0.516	0.467	0.322	0.356	0.439	0.431	0.430	0.421	0.423

	1	2	3	4	5	6	7	8	mean
Drows yLZC	0.564	0.330	0.429	0.314	0.520	0.228	0.240	0.396	0.378
Awake LZC	0.510	0.482	0.356	0.370	0.459	0.400	0.447	0.414	0.430

Optimized:

Table 6 Optimized LZ Complexity values

	1	2	3	4	5	6	7	8	mean
Drows yLZC	0.778	0.583	0.576	0.716	0.550	0.724	0.826	0.669	0.678
Awake LZC	0.453	0.430	0.361	0.402	0.446	0.430	0.339	0.418	0.409

	1	2	3	4	5	6	7	8	mean
Drows yLZC	0.680	0.5833	0.7508	0.6684	0.5886	0.6617	0.5448	0.7029	0.6476
Awake LZC	0.418	0.4372	0.3495	0.4039	0.4372	0.4239	0.4039	0.4199	0.4118

	1	2	3	4	5	6	7	8	mean
Drows yLZC	0.7003	0.6631	0.7096	0.5793	0.7601	0.4571	0.5182	0.7268	0.6393

Awake LZC	0.4305	0.4279	0.3468	0.3973	0.4332	0.4159	0.4252	0.4186	0.4119

In LZ Complexity test, the average difference value between drowsy state and awake state is approximately 0.05. It is only 13% of the average LZ Complexity value, so it's not obvious. After optimized, the difference value between drowsy state and awake state is approximately 0.23. It is 46% of LZ Complexity value, so LZ Complexity has a typical attribute to evaluate drivers' state.

(2) ApEn feature:

Table 7 ApEn values

	1	2	3	4	5	6	7	8	mean
DrowsyApEn	0.0247	0.1086	0.2183	0.2156	0.2668	0.1559	0.0742	0.1104	0.1468
Awake ApEn	0.4875	0.4672	0.3808	0.3665	0.2936	0.3972	0.3732	0.5131	0.4099

	1	2	3	4	5	6	7	8	mean
DrowsyApEn	0.0247	0.0516	0.0247	0.4504	0.1741	0.2040	0.4167	0.2385	0.1981
Awake ApEn	0.4133	0.4265	0.3838	0.3317	0.2786	0.5975	0.0494	0.4452	0.3658

	1	2	3	4	5	6	7	8	mean
DrowsyApEn	0.2024	0.0683	0.0286	0.2155	0.0149	0.4207	0.1366	0.2035	0.1613
Awake ApEn	0.4378	0.4540	0.5727	0.4834	0.4643	0.5472	0.5137	0.6447	0.5147

In ApEn test, the average difference value between drowsy state and awake state is approximately 0.25. It is 86.2% of the average ApEn value, so ApEn has a typical attribute to evaluate drivers' state.

(3) Drowsiness Degree

Table 8 States quotient values

	1	2	3	4	5	6	7	8	mean
Drowsy	1.4979	1.5565	1.2336	1.8318	1.9035	2.3986	2.0647	1.1833	1.7087
Awake	0.3413	0.2571	0.7242	1.0417	0.2918	0.5725	0.7542	0.6013	0.5730

	1	2	3	4	5	6	7	8	mean
Drowsy	1.6751	0.4848	0.9892	0.4387	1.2535	0.7681	0.5969	1.5027	0.9636
Awake	1.3187	0.6543	0.6476	0.1857	1.5769	0.3075	0.2013	0.6624	0.6943

	1	2	3	4	5	6	7	8	mean
Drowsy	1.2241	2.0318	0.5734	0.6635	0.8595	2.4057	1.3471	0.4216	1.1908
Awake	0.8883	0.5033	1.1059	0.2342	2.1146	0.2445	0.7525	0.8019	0.8307

In state quotient test, the average difference value between drowsy state and awake state is approximately 0.61. It's 70.5% of the average state quotient value, so state quotient is a right feature to test drivers' drowsiness state.

(4) PNN Training Result

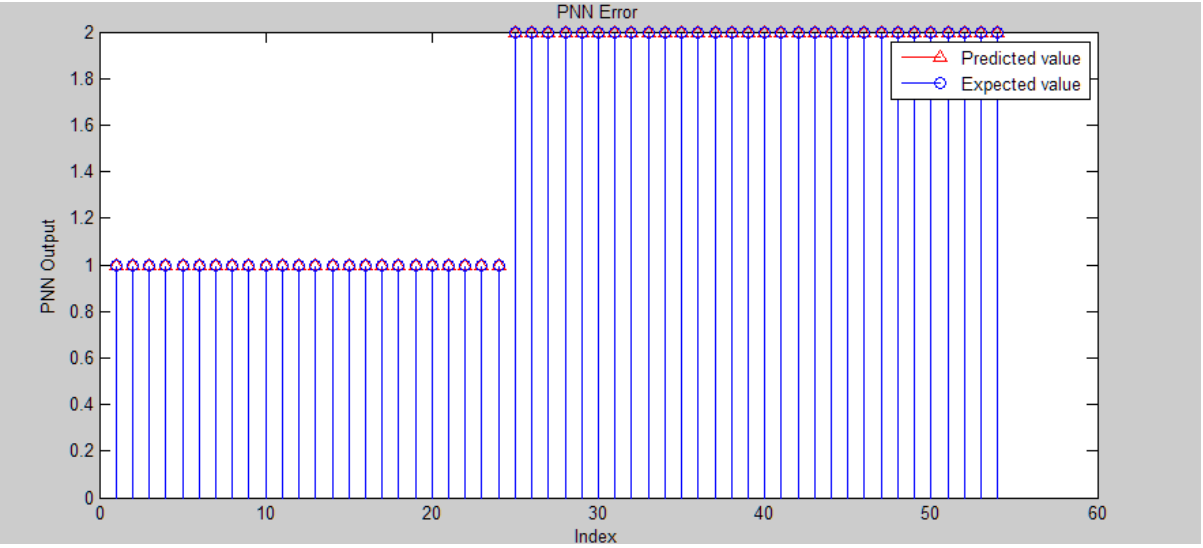


Figure 13 PNN Training

24 awake state data and 30 drowsy state data were used to build the PNN classifier. Value 1 stands for "awake state" and value 2 stands for "drowsy state". In this figure, training data are

brought back to be tested. Blue circle is expected value and red triangle is predicted value. As shown in the picture, all the predicted values are equal to the corresponding expected values. The accuracy rate is 100%, so we can think this classifier is a valid.

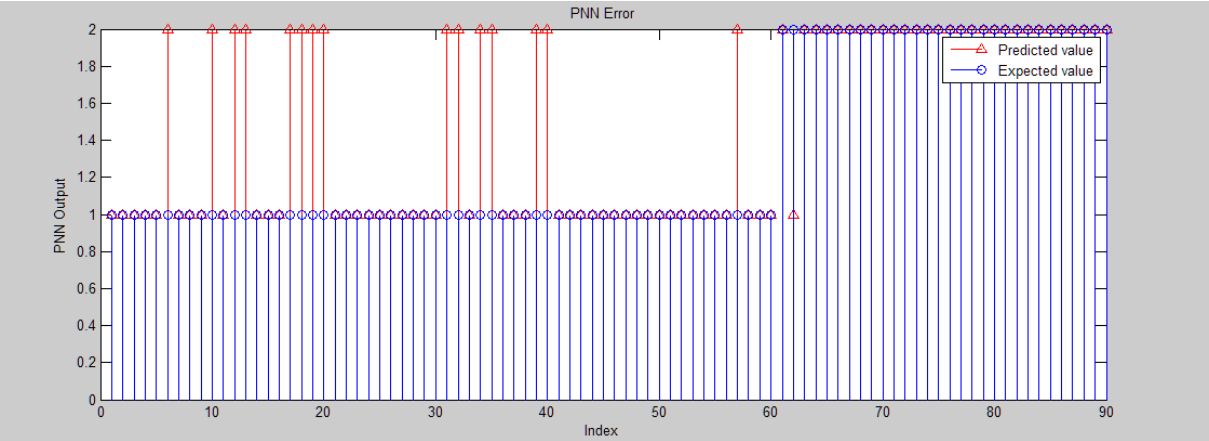


Figure 14 PNN Test Result

In this figure, 60 new awake state data and 30 new drowsy state data are tested. Value 1 stands for “awake state” and value 2 stands for “drowsy state”. 15 predicted values are evaluated wrong in awake state and 1 predicted value is evaluated wrong in drowsy state. The total accuracy rate is 82.22%

Chapter IV Comparison and Evaluation

4.1 PNN Method Compared with Single Feature Evaluation Method

Calculate the correct rate of 6 datasets including 90 signals in total with single feature.

	data1	data2	data3	data4	data5	data6	mean
LZC	72.22%	75.00%	66.67%	53.33%	70.83%	75.00%	68.84%
Quotient	58.33%	63.89%	60.00%	50.00%	62.50%	41.67%	56.06%
ApEn	66.67%	72.22%	56.67%	60.00%	66.67%	70.83%	65.51%

90 datasets runtime = 0.0013s

90 PNN runtime = 0.3175s

PNN correct rate is 82.22%

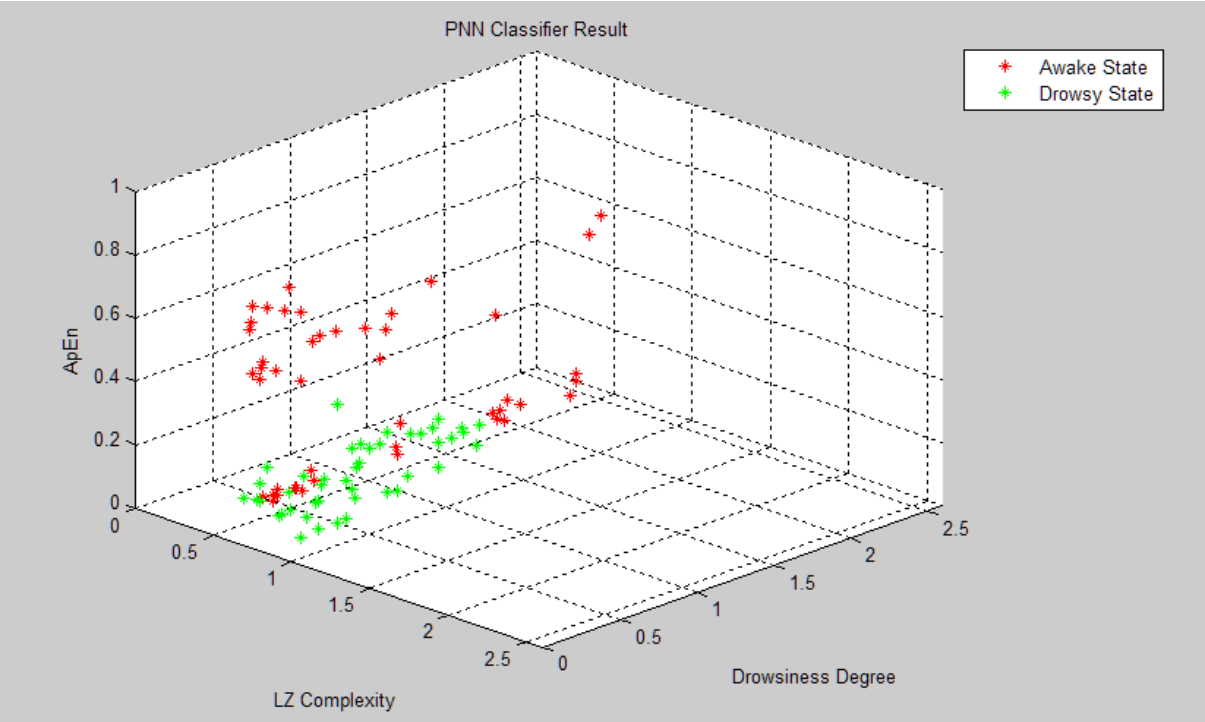


Figure 15 Result of PNN Classifier

In figure 14, red stars are awake state and green stars are drowsy state. Some red stars

have the similar X axis range with green stars and some red stars have the similar Y axis range with green because one feature of them are similar. These will lead an error in single feature evaluation.

4.2 Alcohol and Drug Influence

4.2.1. Alcohol Influence

Experiment 1

(1) Subject consumed 2 cans beer (700ml). Record his brain waves with 10 datasets.

(2) After 30 mins, record his brain waves with 10 datasets.

(3) After 30 mins, record his brain waves with 10 datasets.

(4) After 30 mins, record his brain waves with 10 datasets.

Experiment 2

(1) Let an awake subject consumed 4 cans beer (1400ml). Record his brain waves with 10 datasets.

(2) After 30 mins, record his brain waves with 10 datasets.

(3) After 30 mins, record his brain waves with 10 datasets.

(4) After 30 mins, record his brain waves with 10 datasets.

Table 9 Number of Drowsy State in 10 datasets

	2 cans beer	4 cans beer
0min	1/10	0/10
30mins	4/10	5/10
60mins	5/10	6/10
90mins	5/10	7/10
120mins	5/10	6/10

As shown in table 9, consuming some beer leads a drowsy state. The drowsiness degree increases with the beer content and time in the first hour quickly. The effects can last more than 2 hours.

4.2.2. Caffeine Influence

Experiment 3

(1) Let a drowsy subject consumed a “5-hour Energy” (energy beverage name) which contains 230mg caffeine. Record his brain waves with 10 datasets.

(2) After 30 mins, record his brain waves with 10 datasets.

(3) After 30 mins, record his brain waves with 10 datasets.

(4) After 30 mins, record his brain waves with 10 datasets.

Experiment 4

(1) Let a drowsy subject inhale 30 puffs “Eagle Energy” (electronic cigarette name) which contains some caffeine. Record his brain waves with 10 datasets.

(2) After 30 mins, record his brain waves with 10 datasets.

(3) After 30 mins, record his brain waves with 10 datasets.

(4) After 30 mins, record his brain waves with 10 datasets.



Figure 16 Anti products

Table 10 Number of Drowsy State in 10 datasets

	5-hour Energy	Eagle Energy
0min	6/10	6/10
30mins	2/10	3/10
60mins	1/10	3/10
90mins	2/10	5/10
120mins	4/10	6/10

5-hour Energy has better effect than Eagle-Energy on relieving drowsiness. It can relieve the drowsiness quickly and effectively. But both don't have long time anti-drowsiness effects.

Chapter V Conclusion and Future Work

In this thesis, we introduced two new signal processing approaches to evaluate drowsiness degree based on bio signals. In eye blink signal analysis approach, we collect the eye blink signals when a subject is awake as the normal pattern. It's feasible to detect the drowsiness with the drowsy eye blink signal patterns based on the difference in eye blink signal voltage and periods. The accuracy rate is 80.00%. In brain wave analysis approach, we extract 3 features of brain wave signals. These features are different when subjects are drowsy or not drowsy. A pattern recognition method is applied by PNN with 3 features. The accuracy of this pattern recognition is 82.22% which is higher than that of the single feature drowsiness detection. We also tested the effects of alcohol on and some anti-drowsiness products with the PNN classifier. Alcohol leads a drowsiness increase in one hour and anti-drowsiness products can reduce drowsiness in a short time. But anti-drowsiness products effects have time limit.

It's hard to be fully drowsy when I do all the collecting operations myself, so there only "awake state" and "drowsy state". In the future, it's needed to divide drowsiness degree in more levels, such as "Awake", "Medium Drowsy", and "Very Drowsy". More levels create more categories in PNN. PNN classifier can divide patterns more detailed and more accurately.

Appendix

```
%% Load data
clc
clear
close  all
%fetch awake state data as qx.mat and awake state data to be tested as qxT.mat
NofTrainData =3; %number of training dataset = NofTrainData * LengthFiles_N
NofTestData =3; %number of training dataset = NofTrainData * LengthFiles_N

Files = dir(strcat('WakeData\\','*.mat'));
Length_NTest = length(Files);
hh=1000;
qx=[];%matrix store training awake data
for i = 1:NofTrainData;
    for ii = 1:Length_NTest;
    mov = load(strcat('WakeData\',Files(ii).name));
         mov=mov.data.X;
         nov=mov((i-1)*hh+1:i*hh,2);
         qx=[qx,nov];
    end
end

qx=qx';
%%
qxT=[];
for i = 1:NofTrainData;
    for ii = 1:Length_NTest;
    mov = load(strcat('WakeData\',Files(ii).name));
         mov=mov.data.X;
         nov=mov((NofTrainData+i-1)*hh+1:(i+NofTrainData)*hh,1);
         qxT=[qxT,nov];
    end
end

Files = dir(strcat('WakeData2\\','*.mat'));
Length_NTest = length(Files);
```

```
for i = 1:NofTestData;
for ii = 1:Length_NTest;
    mov = load(strcat('WakeData2\',Files(ii).name));

          mov=mov.data{1,1}.X;
          nov=mov((i-1)*hh+1:i*hh,1);
          qxT=[qxT,nov];
    end
end
qxT=qxT';

%load drowsy state data as pl.mat and drowsy state data under test as plT.mat
Files = dir(strcat('DrowsyData\\','*.edf'));
Length_DTest = length(Files);
pl=[];
plT=[];
for i = 1:NofTrainData;
    for ii = 1:Length_DTest;
        [hdr, record] = edfread(strcat('DrowsyData\',Files(ii).name));%%read
data
       mov = record(1,(i-1)*hh+1:i*hh);
       pl=[pl;mov];
    end
end
for i = 1:NofTestData;
    for ii = 1:Length_DTest;
        [hdr, record] = edfread(strcat('DrowsyData\',Files(ii).name));%%read
data
       mov = record(1,(i+NofTrainData-1)*hh+1:(NofTrainData+i)*hh);
       plT=[plT;mov];
    end
end
%%
Length_NTrain = size(qx,1);
Length_NTest = size(qxT,1);
Length_DTrain = size(pl,1);
Length_DTest = size(plT,1);
save step1.mat qx pl qxT plT Length_NTest Length_DTest Length_NTrain
Length_DTrain

%% Extract feature
clc;
```

```
clear;
load step1.mat
NofFeature = 3;
qxFeature = zeros(Length_NTrain,NofFeature);
for i = 1:Length_NTrain;
    qxFeature(i,1) = ComplexityA(qx(i,:));
    qxFeature(i,2) = quotient(qx(i,:),256);
    qxFeature(i,3) = approx_entropy(2,0.2,qx(i,:));

end

qxTFeature = zeros(Length_NTest,NofFeature);
for i = 1:Length_NTest;
    qxTFeature(i,1) = ComplexityA(qxT(i,:));
    qxTFeature(i,2) = quotient(qxT(i,:),256);
    qxTFeature(i,3) = approx_entropy(2,0.2,qxT(i,:));

end

plFeature = zeros(Length_DTrain,NofFeature);
for i = 1:Length_DTrain;
    plFeature(i,1) = ComplexityA(pl(i,:));
    plFeature(i,2) = quotient(pl(i,:),256);
    plFeature(i,3) = approx_entropy(2,0.2,pl(i,:));

end

plTFeature = ones(Length_DTest,NofFeature);
for i = 1:Length_DTest;
    plTFeature(i,1) = ComplexityA(plT(i,:));
    plTFeature(i,2) = quotient(plT(i,:),256);
    plTFeature(i,3) = approx_entropy(2,0.2,plT(i,:));

end
save features.mat qxTFeature qxFeature plFeature plTFeature Length_NTest
Length_DTest Length_NTrain Length_DTrain
%%
clc;
clear;
load features.mat
FeatureM=[qxFeature;plFeature];
FeatureM=FeatureM';
```

```
StateM=[ones(1,Length_NTrain),2*ones(1,Length_DTrain)];
T=ind2vec(StateM);%covert to target v
t1=clock;%time
net=newpnn(FeatureM,T);%build pnn

A=vec2ind(sim(net,FeatureM));
datat1=etime(clock,t1)
save netpnn net;


load netpnn net;
T1=[qxTFeature;plTFeature];
% T1=[qxFeature;plFeature];
T1=T1';
t2=clock;
y=sim(net,T1);
yc=vec2ind(y);
datat2=etime(clock,t2)
yc
RightState=[ones(1,Length_NTest),2*ones(1,Length_DTest)];
%RightState=[ones(1,Length_NTrain),2*ones(1,Length_DTrain)];

figure
stem(yc,'-r^')
% plot(yc,'-r^')
hold  on
title('PNN Error')
xlabel('Index')
ylabel('PNN Output')
stem(RightState)
legend('Predicted value','Expected value','fontsize',12)
Accuracy = 1-(sum(abs(RightState - yc))/(Length_NTest+Length_DTest))
sprintf('%2.2f%%', Accuracy*100)

%%
for i=1:2
    a=find(yc==i);
    if i == 1
        p=plot3(T1(1,a),T1(2,a),T1(3,a),'r*');
    elseif i == 2
        p=plot3(T1(1,a),T1(2,a),T1(3,a),'g*');
    end
```

```
    axis([0 2.6 0 2.6 0 1])
    hold on;
    grid on;
end
title('PNN Classifier')
```

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