# Correlation Analysis between the EEG Parameters and the Parameters derived from ECG and Steering Wheel related Signals for Driver Drowsiness Detection

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## Abstract

Physiological signals such as Electroencephalography (EEG), Electrocardiography (ECG) and nonphysiological signals such as steering wheel related parameters have been investigated for drowsiness detection in previous researches. EEG has been deemed as a reliable way to detect drowsiness; while the accuracy of using ECG or steering wheel related parameters for drowsiness detection is not as high as that of EEG's but they have the advantages of low cost and non-intrusive.

This work is devoted to find out the possibility to enhance the accuracy of drowsiness detection based on the ECG and steering wheel related parameters. The correlation between EEG and ECG parameters and the correlation between EEG and steering wheel parameters for drowsiness detection are analyzed. If strong correlation between them are found it is possible to use the ECG and steering wheel related parameters to represent the EEG parameters which means the accuracy of drowsiness detection based on ECG and steering wheel parameters can be improved. Several parameters were chosen for the correlation analysis, the EEG parameters are the alpha, beta and theta band power, the ECG parameters are heart rate, Heart Rate Variability (HRV) parameters and a parameter derived from Detrended Fluctuation Analysis (DFA), and the steering wheel related parameters are four variables derived from steering wheel movement, all of these parameters are most commonly used parameters for driver drowsiness detection in the literature. The results of the analysis showed that neither the ECG parameters nor the steering wheel related parameters have strong correlation with EEG parameters. Parameters composed of combination of ECG signal parameters and steering wheel related parameters also did not show strong linear correlation with EEG parameters, however close nonlinear relationships have been found by artificial neural network methods, the promising results have largely increased the possibilities to build driver drowsiness detection system inexpensively and intrusively.

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# 1. INTRODUCTION

Driver drowsiness is considered to be an important cause which leads to serious traffic accidents. The National Highway Traffic Safety Administration (NHTSA) conservatively estimates that 100,000 police-reported crashes are the direct result of driver fatigue each year, resulting in an estimated 1,500 deaths, 71,000 injuries and $12.5 billion in monetary losses, also National Sleep Foundation (NSP) reported that 51% of adult drivers had driven a vehicle while feeling drowsy and 17% had actually fallen asleep.[1-2]. Recent studies presented evidence that driver sleepiness accounts for 6% of crashes, 15% of fatal crashes, and 30% of fatal crashes on rural roads [3]. And Williamson and Feyer [4] affirmed that sleep-deprived drivers are just as dangerous as drunk drivers. Due to the severity of drowsiness driving, it is necessary to keep the driver alert and remind the driver when he or she is in a drowsiness state.

## 1.1 Review of Drowsiness Detection Techniques

A number of efforts have been reported in the literature on the development of drowsiness detection systems for drivers. These drowsiness detection methods can be categorized into several major approaches.

### 1.1.1 Physiological Signal based Drowsiness Detection

This approach is to measure the physiological changes of drivers from biosignals, such as the Electroencephalography (EEG), Electrocardiography (ECG) and electromyelography (EMG). The EEG signal may be one of the most predictive and reliable measurements since it reflects directly human brain activity. Mervyn et al. verified that the classification by a support vector machine (SVM) method was highly successful in distinguishing EEG of normal wakefulness from light drowsiness, with an accuracy of over 99%[5]. Aleksandra et al. proposed a neural network method for classifying alert vs. drowsy states from 1 s long sequences of full spectrum EEG recordings in an arbitrary subject. A match of mean 94.37 ± 1.95% was obtained between the output of the neural network and expert human assessment [6].Therefore, EEG parameters have been used to detect drowsiness by many researchers.

Although EEG monitoring is a reliable method to detect drowsiness, it has some disadvantages. For EEG collection, the electrodes attached to the head may cause discomfort to the driver, also the device used to collect EEG signal is usually very expensive. Compared with drowsiness detection using the EEG signal the advantage of an ECG-based approach is that it can collect the ECG signal with easily wearable sensors. Since RR (time duration between two consecutive R waves of the ECG) series recordings are simple, inexpensive and are feasible with single lead ECG recordings (a good R peak recognition even in presence of a noisy trace) [7], some researches are interested to use, exclusively, ECG for sleep-wake staging. Mourad et al. have built automatic sleep-wake stages classifier based on ECG; seven features were extracted from the RR series by three methods to classify drowsiness and alert. The overall detection accuracy reached 78.05% [8]. Ayumi et al. used a pattern recognition method called Loss-based Decoding ECOC (LD-ECOC) to classify the drowsiness level based on ECG signal. As a result, they obtained a high accuracy (88.78%) [9].

### 1.1.2 Facial Features based Drowsiness Detection

Facial features detection is another reliable approach for drowsiness detection, since people experiencing fatigue show some easily observable visual behaviors from the changes in their facial features like the eyes, head, and face [10], so in order to capture these visual behaviors and approach involving image processing technique has been proposed. Luis M. Bergasa et al. [11] developed a nonintrusive prototype computer vision system for the real-time monitoring of a driver's vigilance. The system works robustly at night and for users not wearing glasses, yielding an accuracy percentage close to 100%. However the visual detection method requires video camera fixed in the vehicle, offering again a method which is expensive and inconvenient.

### 1.1.3 Vehicle Based Drowsiness Detection

This approach is to measure the driver operation and vehicle behaviors, such as the lane deviation and steering wheel movement. Compared with the physiological signals, the drowsiness detection methods based on steering wheel related parameters have several advantages, it is unobtrusive and the cost of data collection is much lower than that of physiological signals. Researchers had tried to find the feasibility and reliability of using steering wheel related parameters as a method for drowsiness detection. Jens Berglund [12] has combined 17 independent variables that best explain the sleepiness level of the driver which is then extracted using multiple regression analysis with forward selection. The final system uses six different models to predict the sleepiness level of the driver. The performance of the final system showed promising results. The system can correctly classify the drivers in approximately 87% of the cases. The number of occasions when the system classify the driver as sleepy when he/she is still alert is very low, approximately 0.7%. King et al. [13] developed functions in the time, frequency, and phase domains to quantify changes in steering wheel input, the algorithm based on these functions identified 12 drivers before a lane breach occurred, and only two drivers were not captured until a lane breach greater than 15 cm occurred. These data and the algorithm demonstrate the potential for a steering-based fatigue detection algorithm.

## 1.2 Purpose Statement

The literature review indicated that the most reliable drowsiness detection methods (EEG based) are high-cost and complex, on the other hand the unobtrusive and low cost methods are less accurate, however if strong correlation between EEG parameters and ECG parameters are found or strong correlation between EEG parameters and steering wheel related parameters can be explored, it is possible to represent the EEG parameters by ECG and steering wheel related parameters, as a result the accuracy of drowsiness detection based on these non-intrusive, easily implementable and low cost methods can be improved.

# 2. METHODS

There are mainly two parts for this chapter, the first part will introduce the experiment design and procedures and the second part will first process the EEG, ECG signals and steering wheel movement, then the parameters used for drowsiness detection are extracted.

## 2.1 Experiment Design

A driving simulator was used by the drowsiness detection system employed in this study. The simulator has a screen to display a “virtual reality” driving environment, a real-size driver seat and a steering wheel. The virtual reality driving environment is a straight boring highway with little traffic, which is designed using UC-Win Road (Forum 8, Japan), the whole driving simulator is shown in Figure. 1.

Nine volunteers with driver licenses participated in this experiment. Each person was required to undergo a one hour driving simulation test, they drove from 12:00PM to 1:00PM; their ECG signals and steering wheel movements were collected, at the same time, their EEG signal was recorded using a forehead mounted EEG measurement device called WaveRider 2cx with single channel. The EEG signal obtained from the forehead non-hairy channels can give accurate estimation of the changing level of driving performance, comparable to that using the EEG features of the whole-head recordings [14]. Figure.2 shows the EEG signal collected from one of the subjects. ECG signal was first collected by a PVDF sensor attached to the wrist of the participant, after going through the conditioning circuit the desired ECG signal was sampled using a data acquisition card PCI6221 at 200Hz sample rate then the ECG signal was sent to the computer. An illustration of the ECG signal collected from one subject is shown in Figure.3. The steering wheel angle data was collected using an encoder fixed in the steering wheel at a 100Hz sample rate, the angular resolution was 0.01 deg, the steering wheel angle readings were also sent to the computer. The schematic diagram of this drowsiness detection system is presented in Figure. 4.

Figure.1 Driving simulator

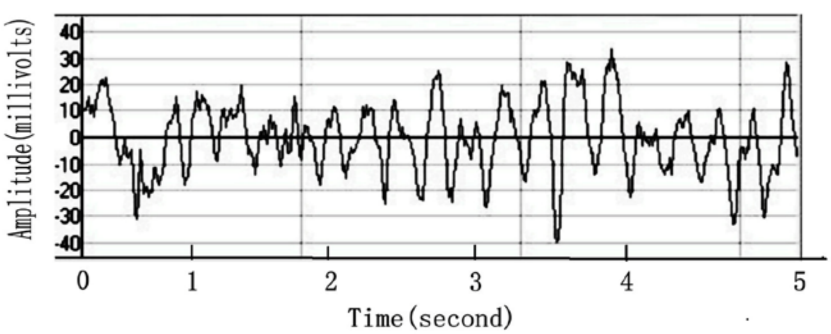



Figure. 2 Illustration of EEG signal

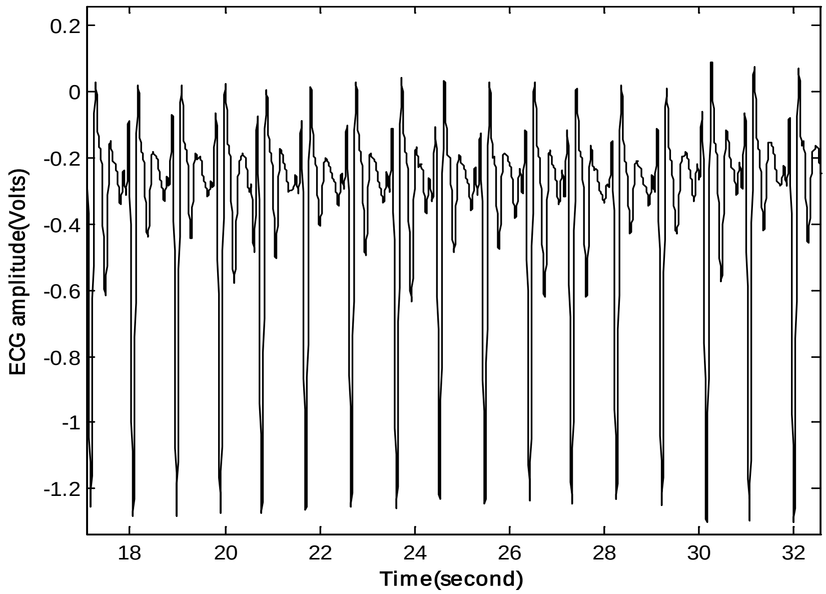



Figure. 3 Illustration of ECG signal

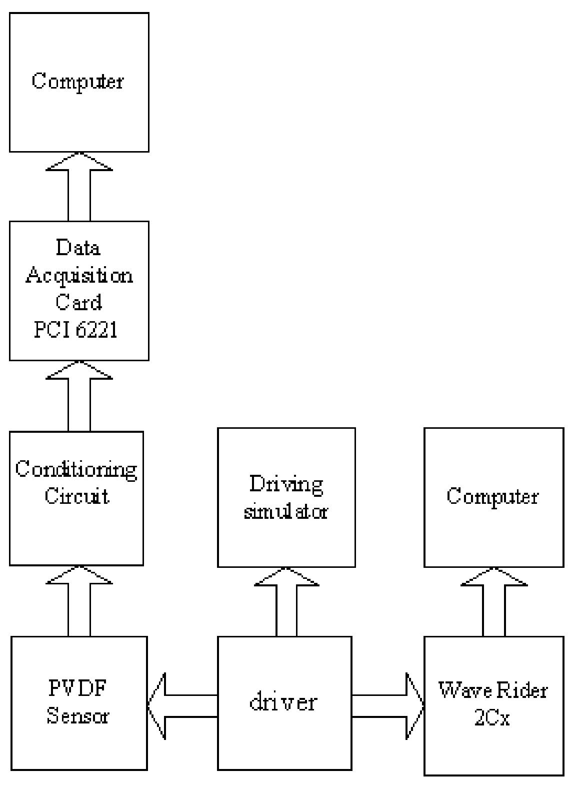



Figure. 4 Schematic diagram of the experiment

## 2.2 Signal Analysis

This section details the selection and extraction of the parameters used for drowsiness detection from each of the EEG, ECG raw data and steering wheel angle inputs. Since the correlation analysis is based on these parameters, this step is the prerequisite procedure for the next chapter.

### 2.2.1 EEG parameters

Several EEG parameters have been used for drowsiness detection, for example, Makeig and Jung have reported that EEG power spectra at theta (4-7Hz) band and alpha (8-11Hz) band are associated with human drowsiness [15] [16], Horne and Baulk [17] established correlations between the alpha and theta EEG power and the incidents (a car wheel crossing the lateral lane marking) in a simulated driving task. Klimesch[18] showed that the EEG beta band is related to alertness level, and as the activity of the beta band increases, performance of a vigilance task also increases, so the parameters used in this study are selected among them. The parameters this study adopted are alpha, beta and theta band power, since these parameters have been used in researches which had showed its high accuracy.

The procedures of calculating these parameters are as follows: first, alpha, beta and theta band power are computed every two seconds by the software supplied with the WaveRider 2Cx. The results are saved in txt file, and then the average power in each band is calculated by a 150 point window with an overlap 75%.

### 2.2.2 ECG Parameters

Heart Rate Variability is acquired by analyzing R wave to R wave interval (RRI) derived from an ECG. From spectrum of HRV signals, the research here obtained Low-Frequency (LF) components between 0.04Hz and 0.15Hz, and High-Frequency (HF) components between 0.15Hz and 0.45Hz. LF components are influenced by both the sympathetic nerve and parasympathetic nerve which correlates with wakefulness characteristics and HF component is influenced by a parasympathetic nerve which correlated with sleepy characteristics. The ratio of LF power over HF power is commonly used as indicators of sleepiness level [9].

A five minutes ECG data window with 75% overlap of free motion artifacts was chosen for the HRV analysis. Peak detection algorithm was implemented in Matlab to identify a QRS complex for extraction of RRI. The QRS complex is a name for some of the deflections seen on a typical ECG. It is usually the central and most visually obvious part of the tracing. The heart rate was derived from RR interval (RRI). Then the RRI signal is evenly resampled at 4Hz, and the power spectrum estimation of the evenly sampled RRI was performed in three algorithms, lomb-scargle periodogram estimation (LOMB), fast fourier transform (FFT) and autoregressive estimation (AR). Although many papers on the subject of HRV contain attractively drawn AR spectra, it is simply not possible to know from a single AR spectrum if the model order was adequate to capture the important frequency components of the ECG [ 19 ], so all the three different algorithms are used to guarantee important frequency components are all included.

Besides LF/HF Ratio, the method of detrended fluctuation analysis (DFA) has also been proved that it can be used to differentiate a drowsiness state from an alert state [8], the analysis procedure is described in [20]. The RRI time series were summed up and the trend was removed by a fluctuation function called F (n), n is a scaling factor, then a graph representing log (F (n)) versus log (n) is depicted. The slope of this graph is a scale-independent marker; it can be used to discriminate between sleep stages as shown in Figure. 5 [8], from the figure it is shown the steep slope indicate that the driver is alert, on the other hand, the flat slope indicate that the driver is drowsy.

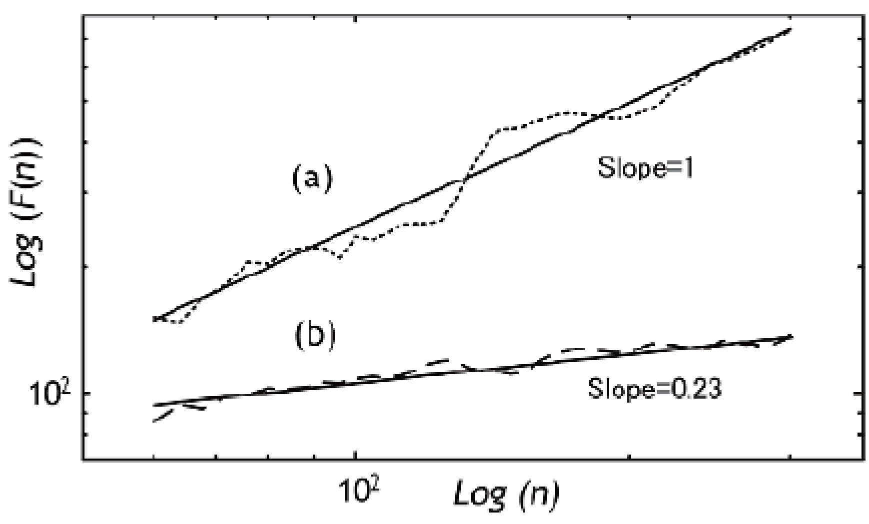



Figure. 5 Plot of Log (F(n)) vs. Log (n) with 60 <n <300 for (a) 5 minutes RR of wake stages expressed in dot lines, and (b) 5 minutes RR of sleep stages expressed in dashed lines. Solid lines represent linear fit slope to the fluctuation functions.

In additional, the heart rate is also adopted here as another parameter for drowsiness detection, since big fluctuations can be observed when the driver becomes drowsiness [21].

### 2.2.3 Steering Wheel related Parameters

Four parameters are chosen for correlation analysis.

The first parameter is proposed by King et al. [13] who suggested a method to indicate sleepiness where the basic idea is to plot the wheel angle, θ, against the wheel angle velocity, ω, in the same graph. Both variables are plotted against their own mean value to show the direction in which the steering wheel is moved. Data clustered around the origin indicates an alert driver while a more spread out spectrum indicates a sleep deprived driver. To separate the two an ellipse is defined around the origin and as long as the samples are within the ellipse the driver is still alert. If the samples are outside the ellipse this is believed to be an indicator of sleepiness, the principle is shown in Figure. 6. The formula of this parameter is as follows:

$$Dist = \sqrt{(a \times \theta)^2 + (b \times \omega)^2} \quad (1)$$

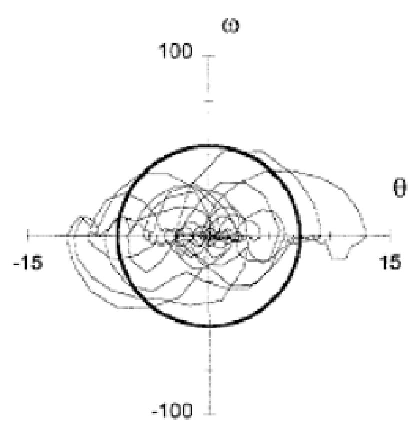



Figure. 6 Illustration of the principle of variable ellipse

The second parameter is a variable called Amp_D2_Theta (Amplitude Duration Squared Theta) proposed by King et al. [13] could be used to indicate driver sleepiness. This variable is defined as the area between the steering wheel angle, θ, and the mean of θ multiplied with the time the steering wheel angle is on the same side of the mean of θ, an illustration of the principle of this variable is shown in Figure. 7. This variable could formally be written as:

$$Amp\_D2\_Theta = K \cdot \sum_{j=1}^{J} A_j \cdot t_j \quad (2)$$

K is scaling factor, $A_j$ is the area of the jth block, $t_j$ is the time of the jth block.

The third parameter is the standard deviation of the steering wheel angle (SDEV) which could be used to predict driver sleepiness [22]. A problem with this variable is that any road curvature will make a significant contribution to the steering wheel angle. Kircher et al. [23] suggests subtracting the mean value for each mile of road from the steering wheel angle to reduce this problem.

The last parameter considered is the number of steering wheel direction reversals which could also be used to indicate driver sleepiness [6]. Reversals less than 0.5 are considered as noise.

All four of these parameters are averaged by a five minutes window with a 75% overlap.

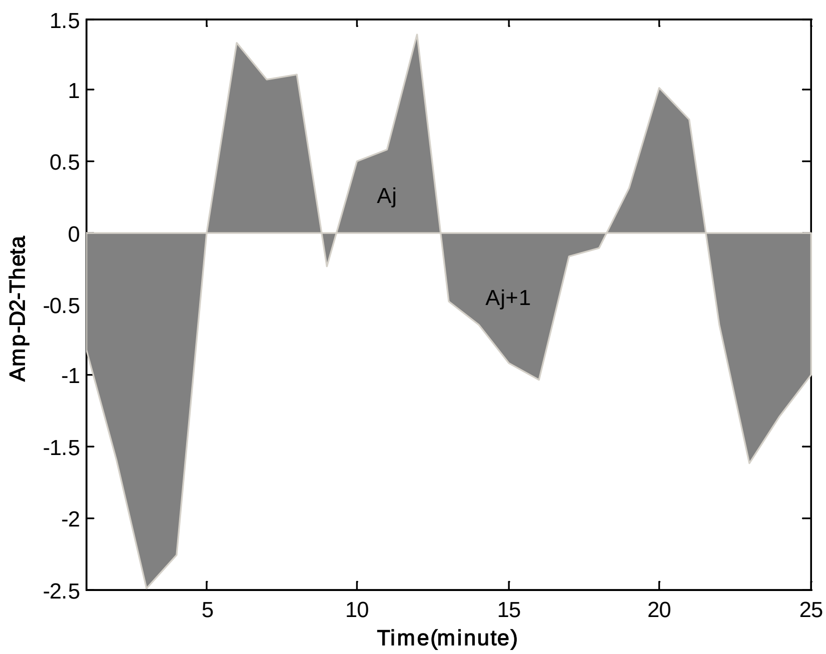


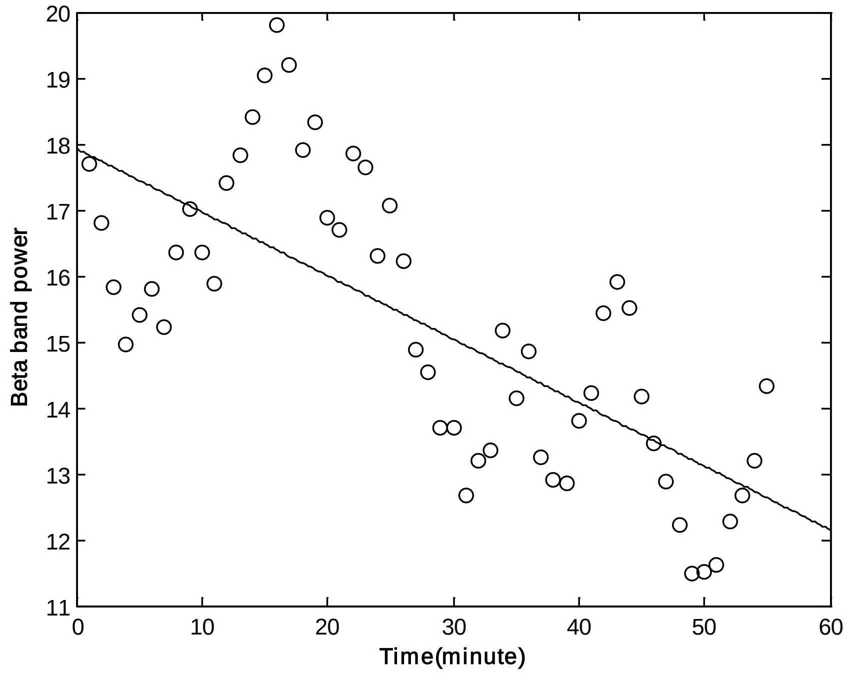

Figure. 7 Illustration of the principle of variable Amp_D2_Theta

# 3 CORRELATION ANALYSIS

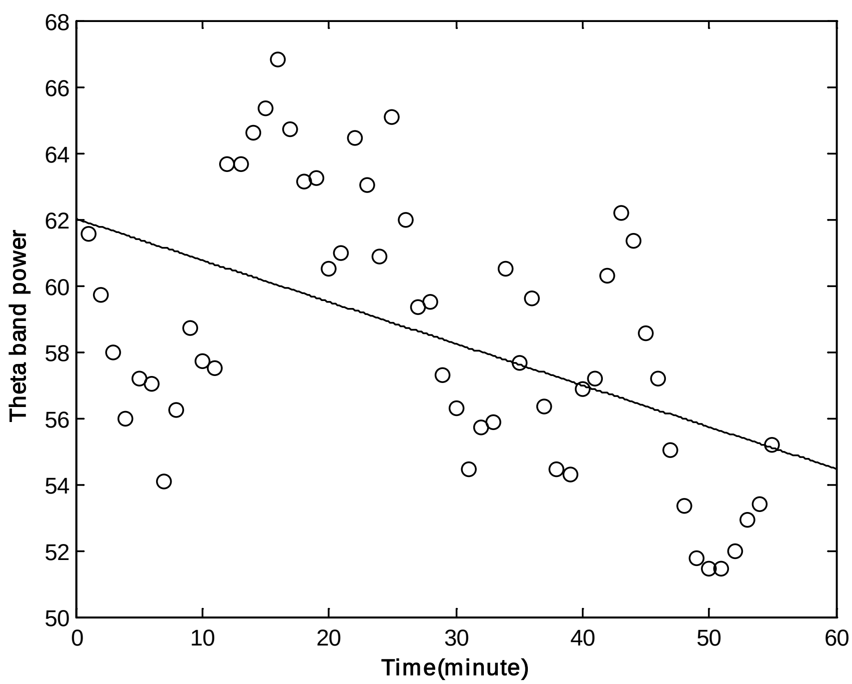
There are mainly four sections in this chapter. The first is devoted to finding the correlation between EEG parameters and ECG parameters, the second finds the correlation between EEG parameters and steering wheel related parameters, the last two analyzes the correlation between EEG parameters and combined parameters derived from the various ECG parameters and steering wheel related parameters.

## 3.1 Correlation Analysis between EEG Parameters and ECG Parameters

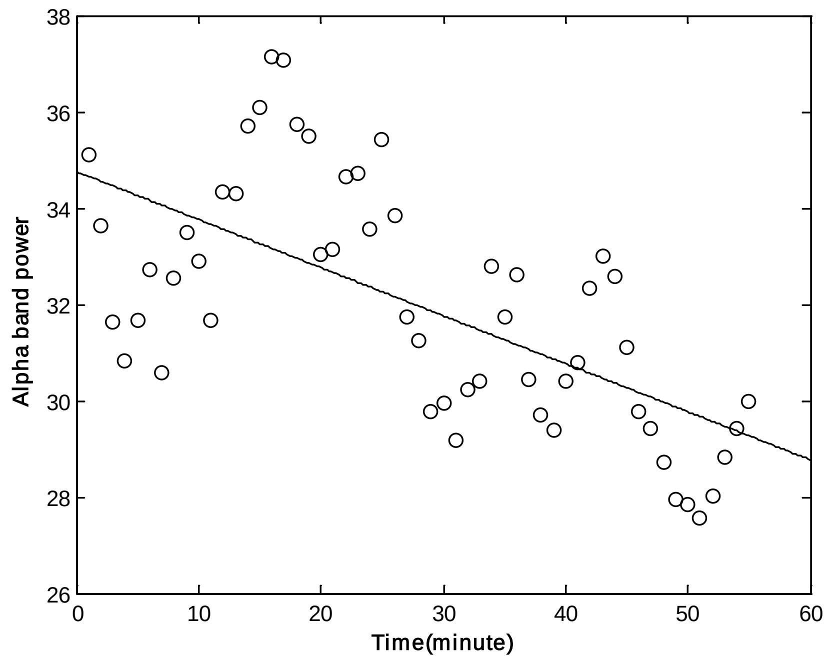
Firstly figures of each of the various parameters used here are shown. Figure. 8 (a) to (c) shows the changes in beta band, theta band and alpha band power of Subject 1. It is demonstrated that despite some fluctuations, the whole trend of beta, theta and alpha band power all keeps decreasing over time, however it is difficult to tell the changing of drowsiness degree based on these three parameters, because each of them can only partially explain the drowsiness degree, an index called $(\alpha+\theta)/\beta$ [24] can be used to check the changing of drowsiness degree. The value of this index is shown in Figure. 7 (d), it is shown that the index value keeps increase which is a sign of the driver becoming drowsier. However not every subject followed this pattern, the indexes of subject 3 and 4 kept increasing over time. The reasons are as follows, although all the subjects participate in this test in the afternoon, they did not have a sleep deprivation the day before the simulation, so when the simulation started generally they were in different physiological states (drowsy or alert), some of the subjects feel sleepy only five minutes after the simulation starts, and when they finished the simulation they did not feel sleepy at all while some of the other subjects feel sleepy in the middle and some did not feel sleep until the end of the test. However sooner or later, for all the subjects there was a surge in this index signifying an increased stress aimed to overcome the feeling of drowsiness. Since the aim is to find high correlation between these parameters no matter the driver is drowsy or alert. These subjects are eligible for the experiments.



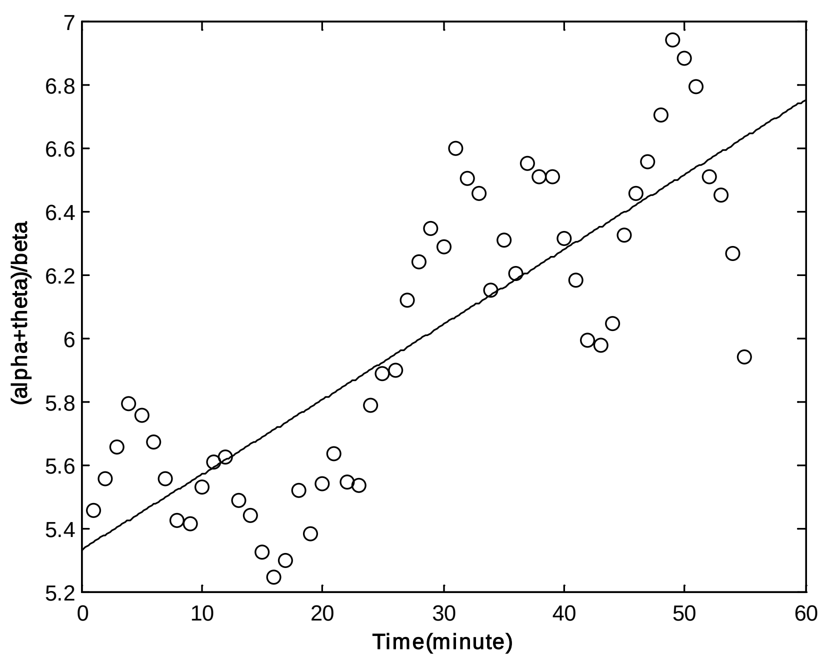

(a)




(b)



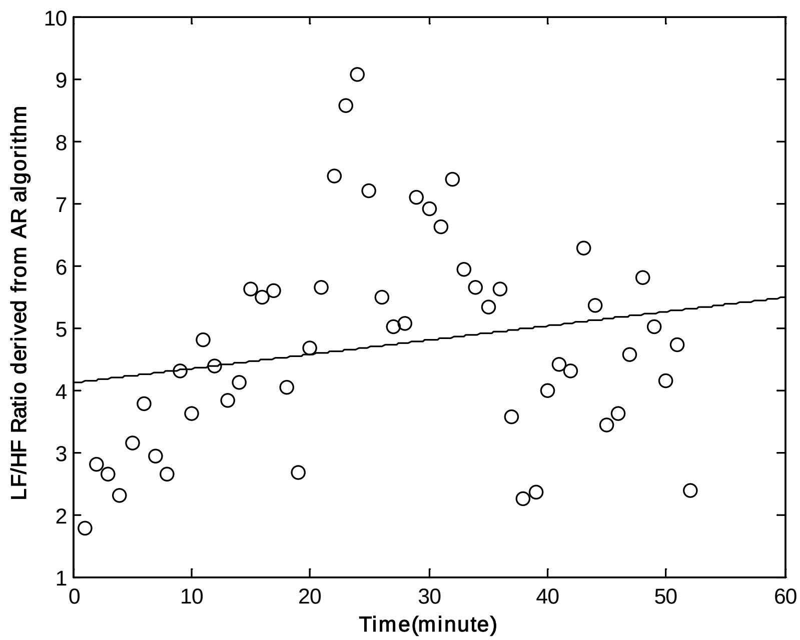

(c)



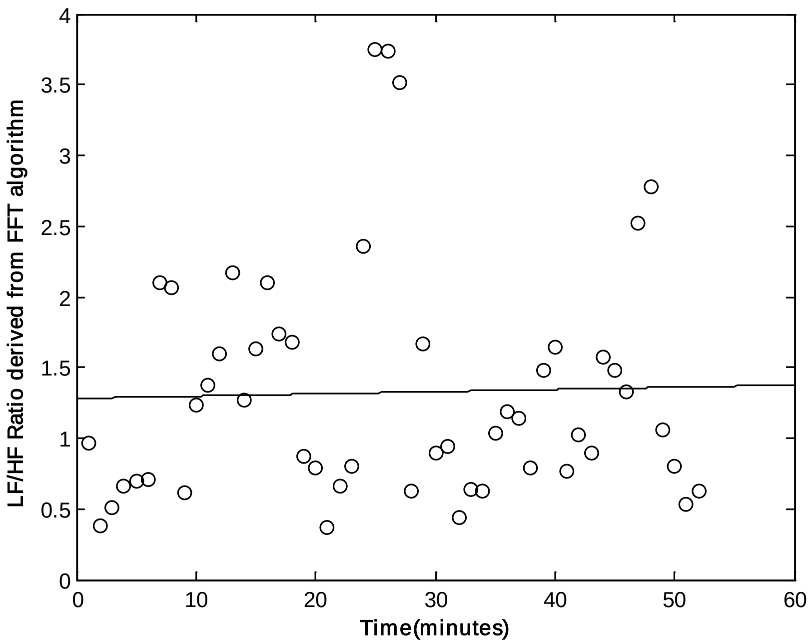

(d)

Figure. 8 (a) to (c) beta, theta and alpha subband power changing over time, (d) index $(\alpha+\theta)/\beta$ (from Subject 1)

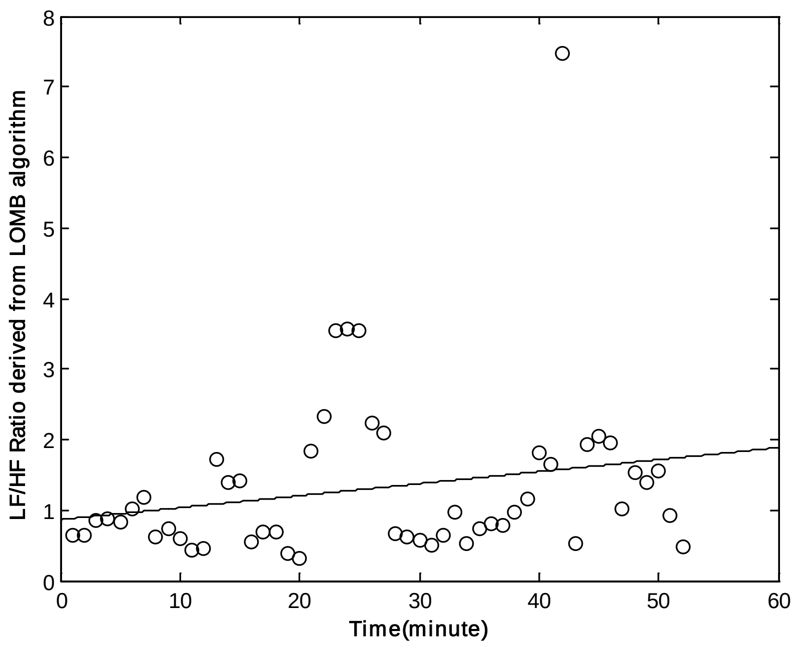
After observing the variation of EEG parameters over time, the LF/HF ratios based on three different algorithms, AR algorithm, FFT algorithm and LOMB algorithm are shown in Figure. 9 (a) to (c). It is demonstrated that the LF/HF ratios are different when computed on different algorithms. The purpose is to find out the one which correlates most closely with EEG parameters. The index derived from DFA is shown in Figure. 9 (d), there exist some fluctuations in the figure which means the subject became drowsiness during the test, while judging from the regression line, the whole trend of changing is not very obvious.



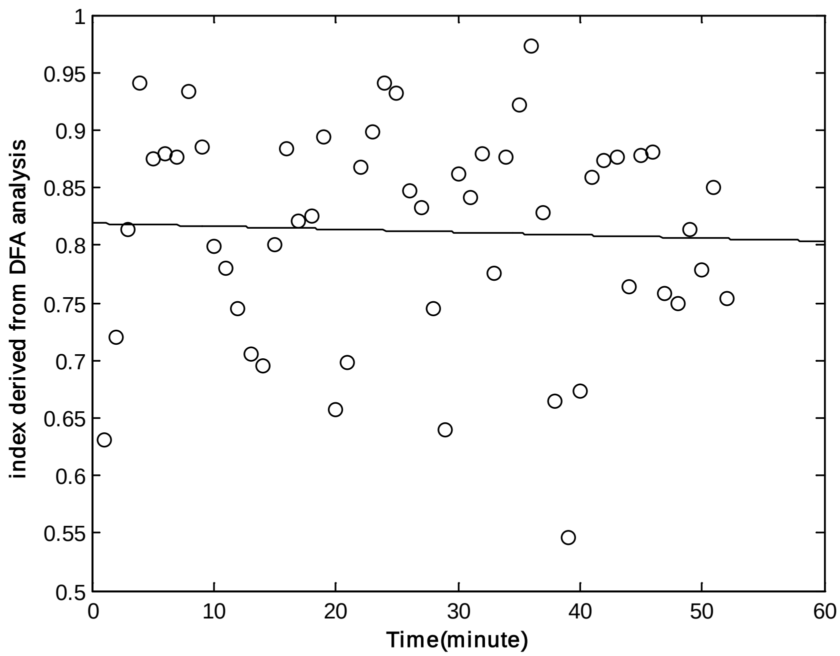

(a)


LF/HF Ratio derived from FFT algorithm
Time(minutes)
0
0.5
1
1.5
2
2.5
3
3.5
4
10
20
30
40
50
60

(b)


LF/HF Ratio derived from LOMB algorithm
Time(minute)
0
1
2
3
4
5
6
7
8
10
20
30
40
50
60

(c)




(d)

Figure. 9 (a) to (c) LF/HF ratio changing over time (Subject 1), three ratios are derived from the lomb-scargle periodogram, AR and FFT algorithms respectively. Figure. 9 (d) Index was derived from a DFA analysis

Compared with the index $(\alpha+\theta)/\beta$, the trends of LF/HF ratio are opposite, while it is difficult to tell the relationship between EEG related band power and the ECG parameters only based on the comparison of the changes of the whole trends, as a result a linear correlation coefficient between the alpha, beta and theta band power numbers and ECG parameters are calculated.

The relationships between the three frequency bands of EEG and the ECG parameters are summarized in Table 1. The index numbers 1 to 3 indicates the correlation with the beta, theta and alpha band power respectively. Here s present the parameter derived from detrended fluctuation analysis. ccF represent the LF/HF ratio calculated based on FFT algorithm. ccH is the heart rate, ccf represent the LF/HF ratio calculated based on lomb algorithm, ccm represent the LF/HF ratio calculated based on AR algorithm. For example s1 represent the correlation coefficient between the parameter derived from detrended fluctuation analysis and beta band relative power.

From the table, it can be seen that different persons each had different largest values of correlation coefficient, for Subject 1, the biggest correlation coefficient is ccF3 at 0.57; for Subject 2, the largest correlation coefficient is c3, 0.43 and for Subject 3 is ccH3 which is -0.64, then each row of the data table was checked and none of the correlation coefficient was stable. For example ccH2 is -0.72 for Subject 5, it turned out to be -0.14 for Subject 6.

Table 1 Correlation between EEG relative alpha, beta and theta power and ECG parameters

| | subject 1 | subject 2 | subject 3 | subject 4 | subject 5 | subject 6 | subject 7 | subject 8 | subject 9 |
|---|---|---|---|---|---|---|---|---|---|
| s1 | 0.44 | -0.26 | 0.22 | 0.14 | 0.07 | -0.09 | -0.05 | -0.21 | -0.01 |
| s2 | 0.42 | -0.12 | -0.38 | -0.1 | -0.13 | 0.03 | 0.12 | 0.01 | 0.08 |
| s3 | 0.47 | 0.34 | 0.43 | 0.04 | 0.13 | 0.01 | -0.16 | 0.09 | -0.14 |
| ccF1 | -0.02 | -0.13 | 0.23 | -0.09 | 0.04 | 0.17 | -0.47 | -0.04 | -0.04 |
| ccF2 | -0.15 | -0.37 | -0.26 | -0.09 | 0.04 | -0.22 | 0.43 | 0.01 | -0.01 |
| ccF3 | 0.03 | 0.57 | 0.22 | 0.19 | -0.19 | 0.22 | -0.21 | 0.01 | 0.06 |
| ccH1 | -0.21 | -0.34 | 0.44 | -0.09 | 0.77 | 0.19 | 0.30 | 0.18 | 0.56 |
| ccH2 | 0.24 | 0.39 | -0.42 | 0.5 | -0.72 | -0.14 | -0.20 | -0.22 | -0.49 |
| ccH3 | 0.12 | -0.36 | 0.31 | -0.64 | -0.12 | 0.08 | -0.02 | 0.22 | 0.25 |
| ccf1 | 0.31 | -0.32 | -0.03 | 0.12 | -0.05 | -0.19 | 0.15 | 0.29 | -0.08 |
| ccf2 | 0.20 | -0.10 | -0.17 | -0.23 | 0.17 | 0.24 | 0.13 | -0.09 | 0.13 |
| ccf3 | -0.29 | 0.36 | 0.29 | 0.24 | -0.25 | -0.23 | 0.21 | -0.01 | -0.13 |
| ccm1 | -0.41 | -0.04 | -0.19 | -0.02 | -0.09 | -0.16 | 0.43 | 0.13 | 0.10 |
| ccm2 | -0.37 | 0.09 | 0.06 | 0.13 | 0.24 | 0.13 | -0.41 | 0.02 | -0.08 |
| ccm3 | -0.36 | -0.09 | 0.05 | -0.17 | -0.33 | -0.08 | 0.23 | -0.09 | 0.03 |

Alpha level at P<0.05

## 3.2 Correlation Analysis between EEG Parameters and Steering Wheel related Parameters

After the previous correlation analysis which compared ECG and EEG parameters, this section contains a correlation analysis between EEG parameters and the steering wheel related parameters for drowsiness detection. The methods employed here are similar as in the previous section.

The correlation coefficients that were computed are presented in Table 2. The index number 1 to 3 indicates correlation coefficient computed against EEG beta, theta and alpha band power respectively. Here, ccAmpd22 represents the Amp_D2 to the theta band power. ccDist represents the Dist parameter versus the various power bands, ccSdev represents the Sdev parameter, ccSwdr represents the Swdr parameter.

From the table, it is demostrated that each different person had a different maximum value of correlation coefficient, for Subject 1, it is ccSdev3 at 0.57; Subject 2, it is ccSwdr1, 0.36 and for Subject 3 is ccSdev3 of -0.57, then each row of the data table was checked and none of the correlation coefficient were stable across the various test Subjects. For example ccSdev3 is -0.57 for Subject 1, which indicated a negative correlation relationship however, it turns out to be 0.11 for Subject 2 which indicates very weak positive correlation relationship.

Table 2 Correlation between EEG relative alpha, beta and theta power and steering wheel related parameters

| | subject 1 | subject 2 | subject 3 | subject 4 | subject 5 | subject 6 | subject 7 | suject 8 | subject 9 |
|---|---|---|---|---|---|---|---|---|---|
| Ampd2 1 | -0.04 | 0.05 | -0.04 | 0.23 | 0.12 | -0.12 | -0.01 | -0.16 | -0.20 |
| Ampd2 2 | -0.23 | -0.16 | 0.03 | -0.24 | -0.26 | 0.09 | 0.18 | 0.18 | 0.06 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Ampd23 | -0.16 | 0.16 | -0.02 | 0.21 | 0.24 | -0.05 | -0.37 | -0.17 | 0.12 |
| ccDist1 | 0.04 | 0.01 | 0.34 | 0.09 | 0.24 | 0.16 | 0.16 | 0.16 | -0.29 |
| ccDist2 | -0.12 | 0.24 | -0.40 | -0.11 | 0.11 | -0.13 | 0.28 | 0.01 | 0.16 |
| ccDist3 | -0.22 | -0.3 | 0.43 | 0.11 | -0.35 | 0.16 | -0.36 | -0.08 | 0.04 |
| ccSdev1 | -0.09 | -0.03 | -0.30 | -0.28 | -0.62 | -0.10 | 0.65 | -0.06 | -0.06 |
| ccSdev2 | 0.02 | -0.07 | 0.51 | 0.37 | 0.26 | 0.30 | -0.62 | 0.17 | -0.09 |
| ccSdev3 | 0.57 | 0.11 | -0.57 | -0.39 | 0.21 | -0.38 | 0.33 | -0.22 | 0.28 |
| ccSwdr1 | 0.25 | 0.36 | -0.17 | -0.32 | 0.42 | 0.40 | -0.06 | -0.15 | 0.56 |
| ccSwdr2 | -0.17 | -0.44 | 0.07 | 0.03 | -0.57 | -0.41 | 0.30 | 0.33 | -0.55 |
| ccSwdr3 | -0.21 | 0.29 | 0.02 | 0.31 | 0.36 | 0.34 | -0.52 | -0.39 | 0.37 |

Alpha level at $P<0.05$

## 3.3 Regression Model Building based on EEG Parameters and ECG Parameters

From the results above, it was found that there are no single ECG parameters or steering wheel parameters which show obvious linear relationship with any EEG power band; however there still exists the possibility that some various combination of these parameters may correlate favorably with some EEG band power values. The author has chosen to develop regression models to check if any such combined parameter exists.

### 3.3.1 Stepwise Regression Background Knowledge

The stepwise regression process was adopted to perform the regression model building. This is an automatic procedure for statistical model selection in cases where there are a large number of potential explanatory variables [25]. The main approaches are:

1. Forward selection, which involves starting with no variables in the model, trying out the variables one by one and including them if they are 'statistically significant'.
2. Backward elimination, which involves starting with all candidate variables and testing them one by one for statistical significance, deleting any that are not significant.
3. Methods that are a combination of the above, testing at each stage for variables to be included or excluded.

### 3.3.2 Regression Model Building

In this study, three models were built using stepwise regression; these models are built to find the relationship between alpha, beta and theta band power and the other parameters respectively, the data collected from all the nine subjects is used for the model building. For each model nine candidate parameters are available, these include the five ECG related parameters and all four steering wheel related parameters discussed above. The stepwise regression will first select the ‘significant’ parameters from these parameters using F-test with significant level 0.15, and then build a regression model based on the ‘significant’ parameters. All the parameters selection procedures for each model are shown in Figure.10 (a) to (c). all the programs are complied using C language in Matlab 7.0.

```
Initial columns included:  none
Step 1, added column 8, p=0.00142108
Step 2, added column 4, p=0.00120945
Final columns included:  4 8

ans =

    'Coeff'            'Std.Err.'        'Status'    'P'
    [       0.0115]    [       0.0107]    'Out'      [       0.2825]
    [ 3.3411e-004]    [9.4279e-004]    'Out'      [       0.7234]
    [-1.2398e-004]    [3.6365e-004]    'Out'      [       0.7335]
    [ 8.9201e-004]    [2.7204e-004]    'In'       [       0.0012]
    [      -0.0015]    [       0.0017]    'Out'      [       0.3814]
    [          NaN]    [          NaN]    'Out'      [          NaN]
    [-3.3613e-004]    [5.8791e-004]    'Out'      [       0.5681]
    [       0.0015]    [3.6534e-004]    'In'       [4.6974e-005]
    [-4.5874e-004]    [3.4907e-004]    'Out'      [       0.1901]
```

(a)

```
Initial columns included:  none
Step 1, added column 3, p=0.00137236
Step 2, added column 9, p=0.000721439
Step 3, added column 8, p=0.018823
Step 4, added column 1, p=0.042426
Step 5, added column 7, p=0.122882
Final columns included:  1 3 7 8 9

ans =

    'Coeff'           'Std.Err.'        'Status'    'P'
    [     -0.0534]    [      0.0248]    'In'       [      0.0322]
    [      0.0023]    [      0.0023]    'Out'      [      0.3047]
    [      0.0038]    [9.0542e-004]    'In'       [4.8190e-005]
    [5.6209e-004]    [7.9128e-004]    'Out'      [      0.4782]
    [      0.0028]    [      0.0041]    'Out'      [      0.4951]
    [         NaN]    [         NaN]    'Out'      [         NaN]
    [      0.0021]    [      0.0014]    'In'       [      0.1229]
    [     -0.0016]    [8.3105e-004]    'In'       [      0.0597]
    [      0.0027]    [8.2849e-004]    'In'       [      0.0013]
```

(b)

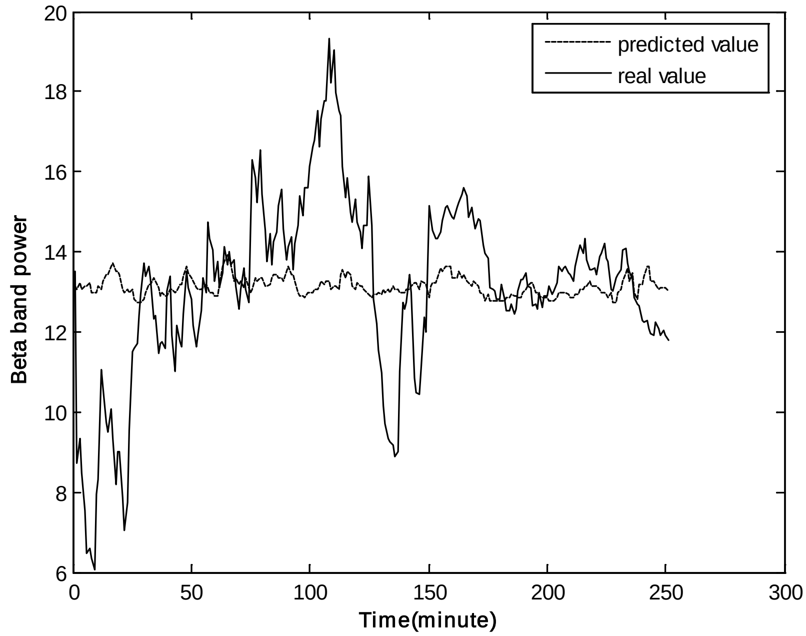
```
Initial columns included:  none
Step 1, added column 3, p=0.0012954
Step 2, added column 9, p=0.0107652
Step 3, added column 1, p=0.0623207
Step 4, added column 4, p=0.0753936
Step 5, added column 7, p=0.104599
Final columns included:  1 3 4 7 9

ans =

    'Coeff'            'Std.Err.'         'Status'    'P'
    [      0.0438]     [      0.0206]     'In'        [      0.0349]
    [     -0.0026]     [      0.0019]     'Out'       [      0.1717]
    [     -0.0035]     [8.3214e-004]      'In'        [3.0469e-005]
    [     -0.0011]     [6.1074e-004]      'In'        [      0.0842]
    [-3.1267e-004]     [      0.0034]     'Out'       [      0.9272]
    [         NaN]     [         NaN]     'Out'       [         NaN]
    [     -0.0019]     [      0.0011]     'In'        [      0.1046]
    [ 4.3925e-005]     [7.5368e-004]      'Out'       [      0.9536]
    [     -0.0023]     [8.1388e-004]      'In'        [      0.0045]
```

(c)

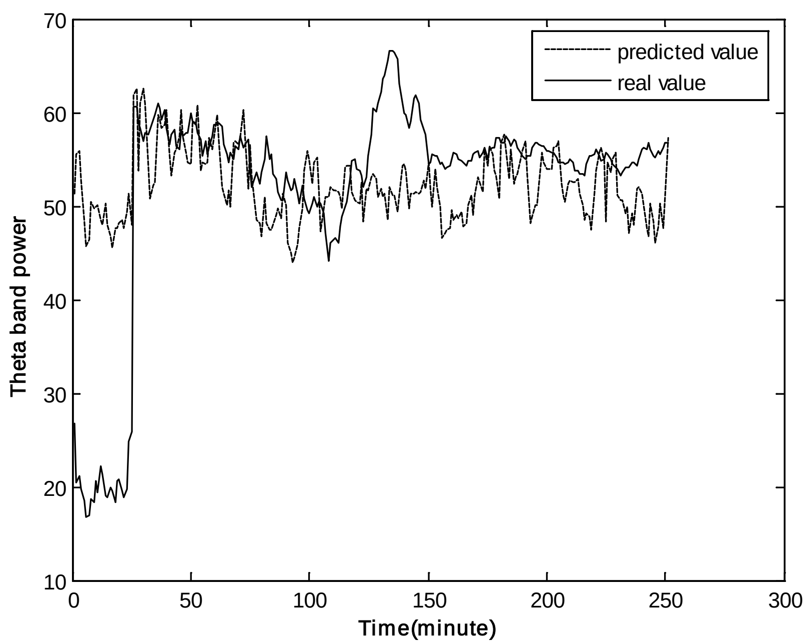
Figure. 10 (a) Stepwise parameters selection procedures for model No.1 (vs. Beta Powerband) (b) Stepwise parameters selection procedures for model No.2 (vs. Theta Powerband) (c) Stepwise parameters selection procedures for model No.3 (vs. Alpha Powerband)

After performing the parameters selection procedure, the regression models are built based on these 'qualified' parameters. For the model No.1 the qualified parameters are HR and Swdr. For the model No.2 the qualified parameters are Slope, Dist, RTm, Swdr and Sdev. For the last model the qualified parameters are Slope, Dist, HR, RTm and Sdev. The predicted value of each model and the real values of each band power are shown in Figure. 10. Then the correlation coefficients between the real values and the predicted values are also calculated for each model. They are 0.23, 0.38, 0.31 for model No.1 to 3.

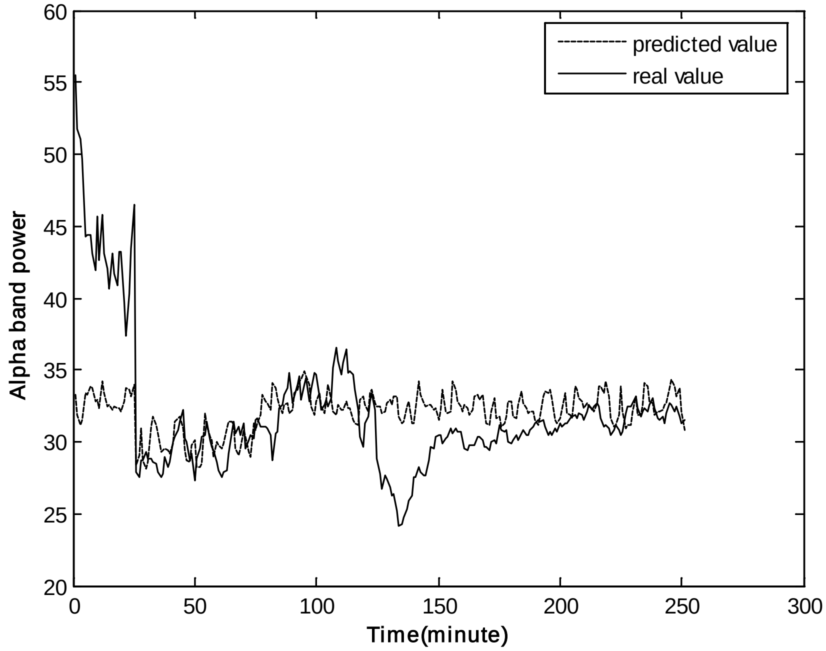
Figure. 11 (a) to (c) showed the comparison between real values and predicted values, it is obvious that the model predicted the real value poorly, since the predicted value can not follow the real value when there are big fluctuations. And from the correlation coefficient it is also shown that there is no such a combined parameters that presented strong correlation with any band power of EEG signal since the combined parameters correlate with theta band power most closely, however the correlation coefficient is only 0.38, it is not high enough to be used as the high-accuracy drowsiness predictors.




(a)




(b)




(c)

Figure. 11 (a) to (c) predicted value and real value of beta, theta and alpha band power

## 3.4 Neural Network Model Building based on EEG Parameters and ECG Parameters

From the results above, it was found that even combined parameters have not shown obvious linear relationship with any EEG power band; however there still exists chances that these parameters have close non-linear relationships, so this section is going to find out if non-linear correlation between EEG band power and ECG and steering wheel related parameters exists. The artificial neural network method is chosen to implement this task.

### 3.4.1 Artificial Neural Network Background Knowledge

An artificial neural network is a system based on the operation of biological neural networks, in other words, is an emulation of biological neural system, there are mainly three parts in an artificial neural network, one input layer, several hidden layers and one output layer, each layer has certain number neurons which are the basic components of an artificial neural network. The working principles of the artificial neural network are as follows, firstly the artificial neural network needs to be trained before using, an input is presented to the neural network and a corresponding desired or target response set at the output. An error is composed from the difference between the desired response and the system output. This error information is fed back to the system and adjusts the system parameters in a systematic fashion (the learning rule). The process is repeated until the performance is acceptable. After the training procedures the neural network should be tested with some new data (not from the training sets) in order to see its performances [26].

The back propagation (B-P) feed forward artificial neural network with three layers is adopted in this study. Back propagation is a common method of teaching artificial neural networks how to perform a given task, and in feed forward neural network the information moves in only one direction, forward, from the input nodes, through the hidden nodes and to the output nodes. There are no cycles or loops in the network [27].

### 3.4.2 Artificial Neural Network Model Building

There are totally three layers in each model, the input layers of these three models adopted the same candidate parameters used by the regression models they are the five ECG parameters and all four steering wheel related parameters; the hidden layer has ten neurons based on the number of the input. The output layers of these three models are the alpha, beta and theta band power respectively. All the parameters are normalized to the same scale from 0 to 10 for convenience. All the networks are trained for up to 100 epochs to an error goal of 0.01. The structure of the neural network models is shown in Figure. 13. The programs are implemented in Matlab 7.0 using neural network toolbox.

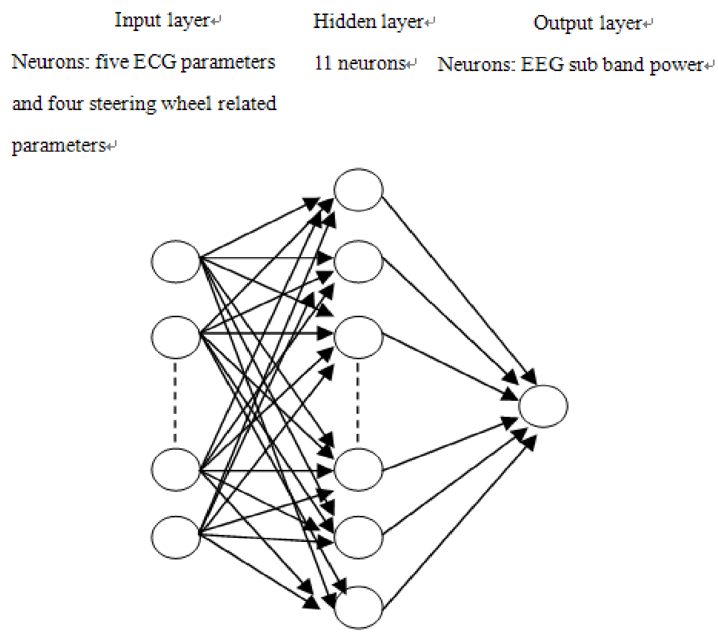
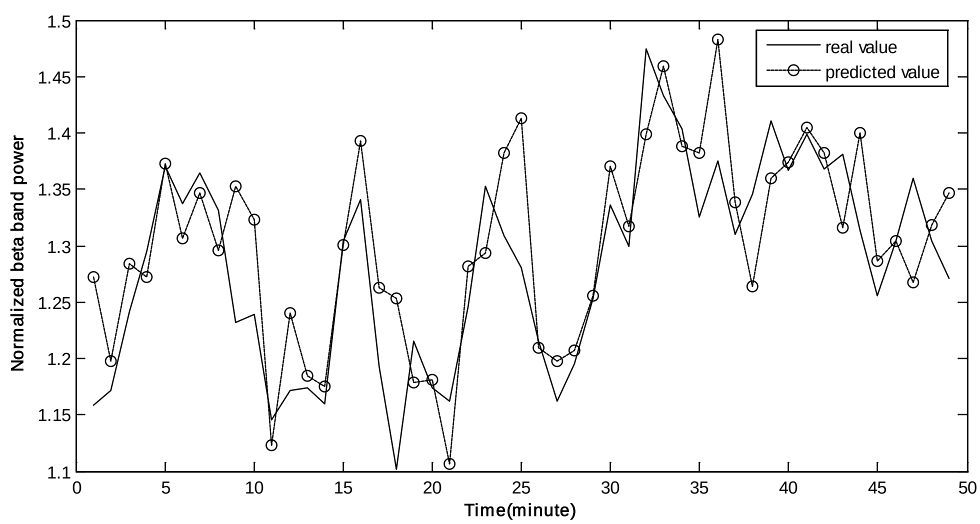
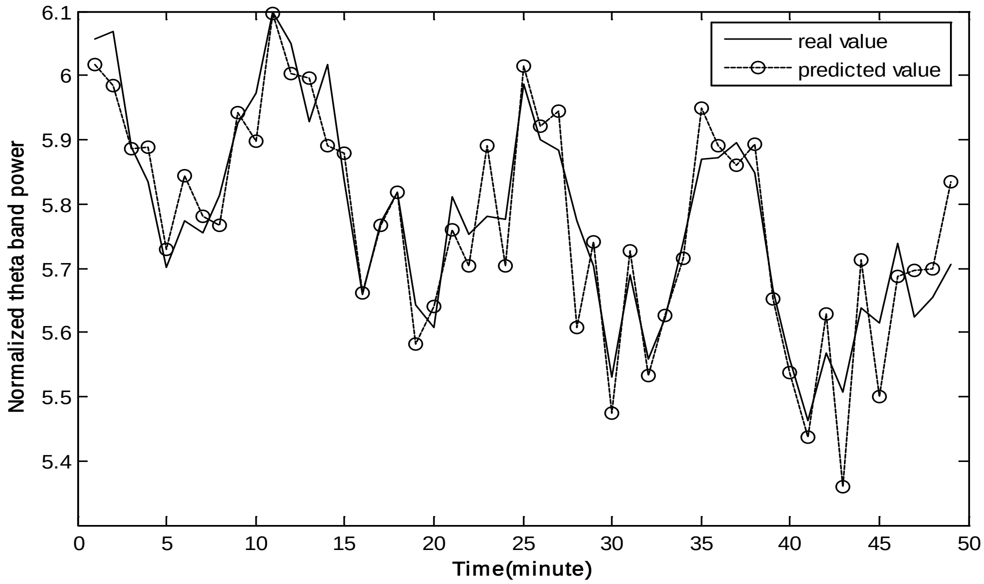



Figure. 12. structure of the three neural network used

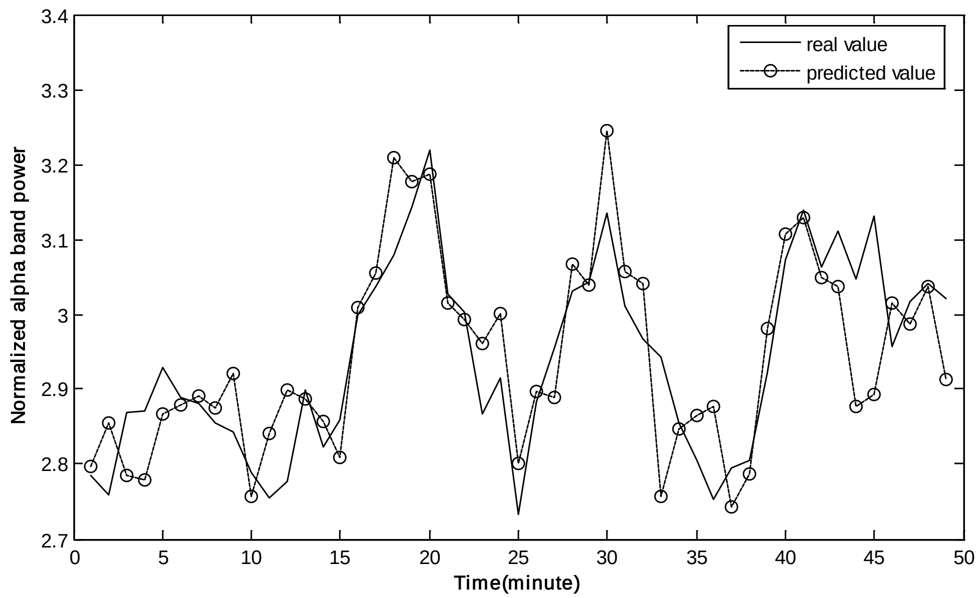
Three models were built using back B-P feed forward neural network; they are built to find the relationships between alpha, beta and theta band power and the other parameters respectively, the data collected from the eight subjects is used for the model training and the other one left is used to check the predicting performance of the model. The results of these three models are shown in Figure. 13. (a) to (c). Since only eight data sets are used for training the models, the whole training procedures of each model took less than 30 seconds which will not affect the real-time application.




(a)




(b)




(c)

Figure. 13. (a) to (c). predicted values of B-P neural network methods vs. real value of EEG beta, theta and alpha band power respectively

From the results showed above it is shown that the performance of the neural network models are much better than those of the regression models. It can predict the real value closely even when there are big fluctuations. Also the correlation coefficients of these three models are 0.78, 0.92 and 0.81 respectively which presents very promising results.

In order to check the neural network model sufficiently, another training and checking method is used here. It used all the first 37 minutes data to train the models and used each of the last 23 minute data to check each model. The correlation coefficients between the predicted values and real values (alpha, beta and theta band power) for each subject are listed in Table.3. The a, b and c in the table 3 presented the beta, theta and alpha band power.

From the table, it is shown that the correlation coefficients are pretty high which indicates the model predict each band power pretty well for each subject.

Table 3. the correlation coefficient between predicted values and real values

| | Subject 1 | Subject 2 | Subject 3 | Subject 4 | Subject 5 | Subject 6 | Subject 7 | Subject 8 | Subject 9 |
|---|---|---|---|---|---|---|---|---|---|
| a | 0.74 | 0.72 | 0.72 | 0.75 | 0.73 | 0.73 | 0.52 | 0.74 | 0.62 |
| b | 0.72 | 0.82 | 0.77 | 0.81 | 0.80 | 0.72 | 0.62 | 0.72 | 0.74 |
| c | 0.80 | 0.75 | 0.62 | 0.72 | 0.81 | 0.72 | 0.58 | 0.61 | 0.77 |

# 4 CONCLUSION

In this research, the correlation between EEG each band power and ECG parameters and the correlation between EEG each band relative power and steering wheel related parameters are presented by the correlation coefficients, which confirmed neither the ECG parameters nor the steering wheel related parameters have strong linear relationship with EEG each band power. This study also shows that the combined parameters which strongly linearly correlate with certain EEG band relative power also do not exist. However the neural network model did set up close nonlinear relationships between EEG band power and the other parameters, the promising results show that it is very possible to build high accuracy driver drowsiness detection system based on these inexpensive and intrusive methods. In order to find out the exact accuracy, the results got from the neural network still needs to be used in place of the EEG parameters and then the results obtained needs to be compared with some standard sleepiness scale.

In conclusion, from the results obtained, to detect drowsiness inexpensively and intrusively seems very feasible, on the other hand, there are still some future work can be done to improve this study.

The only requirement of this experiment is that the subjects need to have driver licenses; however, some of the other factors which may affect the results are neglected by this experiment, such as the driving experiences, the age, the physical condition and etc. The neglect of these conditions may affect the final results. For example if the subject drunk lots of coffee before the simulation, he may act differently from the subjects who did not drink any coffee.

So further research should issue the regulations for the simulation tests and also collected more detailed information about the subjects, these actions can help eliminate the uncertainty and make the results more reliable and comprehensive. The proposed information collection includes the following items: age, driving experience, driving record, physical condition (eyesight), and drug using record, all of these are potential factors that may affect the results. And for the regulations, the alcohol, caffeine, tea, and chocolate consumption should be forbidden beforehand. Traffic regulations are also needs to be made like speed limit, the legality of lane-changing, which can force the subjects follow the same driving pattern in maximum. Since results gotten in the similar conditions are more valuable than those obtained without any restrictions, these regulations are trying to make the results obtained under the most similar condition. With these regulations if some of these factors influence the results can be checked out by contrast test. For example in order to see the influence of coffee to the final results, first let subjects finish one test without drinking any coffee, at the same time let some of the other subjects did another test while keeping the other factors as similar as possible, in this way the influence of the coffee can be observed.

Secondly, there are only nine subjects participated in the simulation tests; it is assumed that more tests will enhance the reliability of the results. Also, individualized methods are highly recommended for further study, since different people sometimes have different changing types of the parameters when they become drowsy.

At last if sleep deprivation is exerted on each subject before the simulation test, which can greatly, increases the chances that the driver becomes drowsiness, the uncertainty of the changing patterns of each parameter can be reduced a lot which can simplify the comparison between these parameters.

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# Appendix

**Code for ECG parameters**

```
function [fd, D, Alpha1, HR, RTF, LFF, HFF, RTm, LFm, HFm, RTf, LFf, HFf, NND]=procedure_mix(files)
    %first type "files=dir('*.mat')"
    filedates={files.date};
    [filenames_sorted, idx]=sort(filedates);
    k=1;
    hr=[];
    hr_t=[];
    tp(1)=0;
    stdnn=[];
    for ind=1:1:(numel(files)-5)
      val1=load(files(idx(ind)).name);
      temp1=struct2cell(val1);
      val1=temp1{1,1}(:,2);
     val2=load(files(idx(ind+1)).name);
      temp1=struct2cell(val2);
      val2=temp1{1,1}(:,2);
      val3=load(files(idx(ind+2)).name);
      temp1=struct2cell(val3);
      val3=temp1{1,1}(:,2);
      val4=load(files(idx(ind+3)).name);
      temp1=struct2cell(val4);
      val4=temp1{1,1}(:,2);
```

```
val5=load(files(idx(ind+4)).name);
temp1=struct2cell(val5);
val5=temp1{1,1}(:,2);
values=[val1;val2;val3;val4;val5];
values=values*1000;
csvwrite('100.txt',-values);
!wrsamp -F 200 -G 102.4 -i 100.txt -o 100 0
!ecgpuwave -r 100 -a mqrs -f 0 -t e
!ann2rr -r 100 -a mqrs -i s >100.rr.txt
!ihr -r 100 -a mqrs -f 0 -t e  >100.ihr.txt
!tach -r 100 -a mqrs -f 0 -t e -F 20 >100.tach.txt
rro=load('100.rr.txt');
rri=load('100.tach.txt');
hr=load('100.ihr.txt');
NN=hr(:,2);
%temp=load('100.ihr.txt');
%hr=[hr,temp(:,2)'];
%hr_t=[hr_t,temp(:,1)'+tp(k)];
%hrv_t=temp(:,1);
%hrv_r=temp(:,2);
%N=length(temp(:,1));
%tp(k+1)=tp(k)+temp(N);
!ihr -r 100 -a mqrs -f 0 -t e -x | lomb -P - >100.lomb.txt
%!tach -r 100 -a mqrs -f 0 -t e -F 4 | lomb -P - >100.lomb1.txt
%!ihr -r 100 -a mqrs -f 0 -t e -x
%a=load('100.ihr.txt');
```

```
%a(:,2)=1./a(:,2);
%csvwrite('100,ihr.txt',a);
%!lomb -P - >100.lomb.txt
!tach -r 100 -a mqrs -f 0 -t e -F 4 | memse -P -Z -b 0.03 0.15 0.15 0.4 ->100.memse.txt
!tach -r 100 -a mqrs -f 0 -t e -F 4 | fft -f 4 -P -w Welch -Z - > 100.fft.txt
%   !tach -r 100 -a mqrs -f 0 -t e -F 10 | hrfft -f 2 -P -w Welch -Z - > 100.hrfft.txt
temp2=load('100.lomb.txt');
temp=load('100.memse.txt');
temp3=load('100.fft.txt');
N=size(temp,1);
freq=temp2(:,1);
prob=temp2(:,2);
freq2=temp3(:,1);
prob2=temp3(:,2);
indl = find( (freq>=0.04) & (freq<=0.15) );
indh = find( (freq>=0.15) & (freq<=0.4) );
indl2 = find( (freq2>=0.04) & (freq2<=0.15) );
indh2 = find( (freq2>=0.15) & (freq2<=0.4) );
LFm(k)=temp(N-1);
LFf(k)=sum(prob(indl));
LFF(k)=sum(prob2(indl2));
HFF(k)=sum(prob2(indh2));
HFm(k)=temp(N);
HFf(k)=sum(prob(indh));
RTm(k)=LFm(k)/HFm(k);
RTf(k)=LFf(k)/HFf(k);
```

```
    RTF(k)=LFF(k)/HFF(k);
    HR(k)=mean(NN);
    NND(k)=std(NN,0);
    fd(k)=DFA(60./rri,30,2);
    yy = detrend(60./rri,'linear');
    yy = (yy - mean(yy)) / max(abs((yy - mean(yy))));
    [D(k),Alpha1(k)]=DFA_main(yy);
    %[Px, Prob] = lomb(hrv_t, hrv_r, freq_vect);
    %[lfhf(k) lf(k) hf(k)] =  calc_lfhf(freq_vect,Px);
    k=k+1;
end
```

**Code for Steering wheel related parameters**

```
function [Sdev, Swdr,Ampd2,Dist] = f1(srate,anglee)
%anglee=anglee.*120;
srate=0.01;
len=length(anglee);
 j=0;
 for cnt=6000:6000:len-30000 % one hour test
 j=j+1;


 %plot(time,angle1);
 %tim = time';       %output time
 %plot(tim,angle1);
 %anglee=anglee';
 angle1 = anglee(cnt+1:cnt+30000);  % caluculate variable value every 5 minutes
 temp1 = angle1([2:end 1]);
```

```
 temp1 = temp1 - angle1;
 temp1(length(temp1))=[];
 temp1 = [0,temp1'];
 velocity = temp1/srate; %output angular velocity  sample rate=0.01
 velocityAV=mean(velocity);
 angleAV = mean(angle1);
 long=length(angle1);
 %plot(tim,angle-angleAV)
 %xlabel('time')
 %ylabel('angle-angle2AV')
%------1 SDEV-----------------------------------
Sdev(j)=std(angle1-angleAV);
%------2 SWDR-------------------------------
temp6=0;
for i=1:long-1;
    if((abs(angle1(i)-angle1(i+1))>=0.5)&&(angle1(i)*angle1(i+1)<0))
    temp6=temp6+1;
    end
end
Swdr(j)=temp6;
%------ 3 Amp_D2_Theta----------------------
 k=0;sum=0;sum1=0;

 for i= 1:length(angle1)-1
     if(((angle1(i)-angleAV))*((angle1(i+1)-angleAV))>0)
         sum = sum +((angle1(i)-angleAV)+(angle1(i+1)-angleAV))/2*0.01;
```

```
        k=k+1;
      else
        sum1 = sum+sum1;
        Ampd2(j)=1/(10^4)*sum1;
        k=0;
      end
 end
 %------4 Ellips----------------
a=1;b=2.6;
Dist(j)=(sqrt((a*angleAV)^2+(b*velocityAV)^2));
 end
end
```

**Code for regression model building**

```
X=[RAlpha1', RAmpd2', RDist', RHR', RRTF' RRTf' RRTm' RSwdr' RSdev'];
stepwisefit(X, Ra', 'penter', .15,'scale','off','display','on');
x1=[X(:,4) X(:,8)];
x1=[X(:,4) X(:,8) ones(length(X(:,1)),1)];
%bb1=x1\Ra'
bb1=regress(Ra',x1)
plot(x1*bb1,'r');
hold on
plot(Ra)
corrcoef(x1*bb1,Ra)
stepwisefit(X, Rb', 'penter', .15,'scale','off','display','on');
x2=[X(:,1) X(:,3) X(:,7) X(:,8) X(:,9) ones(length(X(:,1)),1)];
```

```
bb2=x2\Rb'

figure, plot(x2*bb2,'o','color','k');
hold on
plot(Rb,'*','color','k')
corrcoef(x2*bb2,Rb)

stepwisefit(X, Rc', 'penter', .15,'scale','off','display','on');
x3=[X(:,1) X(:,3) X(:,4) X(:,7) X(:,9) ones(length(X(:,1)),1)];
bb3=regress(Rc',x3)
figure, plot(x3*bb3,'r');
hold on
plot(Rc)
corrcoef(x3*bb3,Rc)
```

**Code for neural network model building**

```
XX=[NRAlpha1; NRAmpd2; NRDist; NRHR; NRRTF; NRRTf; NRRTm; NRSwdr; NRSdev];
XX1=[Alpha12(1:len2)/max(RAlpha1); Ampd22(1:len2)/max(RAmpd2);
Dist2(1:len2)/max(RDist); HR2(1:len2)/max(RHR); RTF2(1:len2)/max(RRTF);
RTf2(1:len2)/max(RRTf); RTm2(1:len2)/max(RRTm); Swdr2(1:len2)/max(RSwdr);
Sdev2(1:len2)/max(RSdev)];
XXLIM=[min(RAlpha1) max(RAlpha1);min(RAmpd2) max(RAmpd2);min(RDist)
max(RDist);min(RHR) max(RHR);min(RRTF) max(RRTF);min(RRTf) max(RRTf);min(RRTm)
max(RRTm);min(RSwdr) max(RSwdr);min(RSdev) max(RSdev);]
net = newcf(XXLIM,[11 1],{'tansig' 'purelin'},'trainlm');
yn1 = sim(net,XX);
```

```
net.trainParam.epochs = 100;
net.trainParam.goal = 0.01;
net=train(net,XX,Rc*10);
yn=sim(net,XX1);
plot(c2(1:len2)*10);
hold on
plot(yn,'--mo');
corrcoef(yn,c2(1:len2)*10)

net=train(net,XX,Ra*10);
yn=sim(net,XX1);
plot(a2(1:len2)*10);
hold on
plot(yn,'--mo');
corrcoef(yn,a2(1:len2)*10)

net=train(net,XX,Rb*10);
yn=sim(net,XX1);
plot(b2(1:len2)*10);
hold on
plot(yn,'--mo');
corrcoef(yn,b2(1:len2)*10)
```