Classification of Human Concentration in EEG Signals using Hilbert Huang Transform

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***Abstract* — The electroencephalogram (EEG) is an important technique that allows people to study brain signals. Classifying whether a person is concentrating or not is almost impossible with our naked eye. Thus, a system that could accurately distinguish these two categories is highly valued. Previously, the study to determine a mental state of concentration and non-concentration is based on the Fourier Transform. In this study, we employed Hilbert Huang Transform (HHT) to extract important features for this mental classification task. HHT consists of two step: (1) Using EMD and (2) Hilbert Transform. The EMD will decompose the signal into a collection of Intrinsic Mode Functions (IMF). Then Hilbert Transform is employed to obtain the IMF to compute the power spectrum to extract important features based on different subbands i.e. gamma, beta, alpha, theta and delta. An Extreme Learning Machine (ELM) is then used as a classifier to distinguish the two mental states. Four different sets of investigations were performed using the existing FFT and three investigated the HHT framework including single IMF, two and three IMFs. The results showed that the HHT with single IMF offers slight improvement compared to the existing FFT.**

Keywords — Electroencephalogram, Extreme Learning Machine, Hilbert Huang Transform

I. Introduction

EEG was discovered in the year of 1921 and since then has become one of the most emerging scientific fields as researchers are now able to investigate and evaluate the fluctuation of human brainwaves. EEG refers to a current that flows during the synaptic excitations of the dendrites of many pyramidal neurons in the cerebral cortex of the brain. Upon excitation of the neurons, small currents go through the dendrites and emit measureable electromagnetic waves[1]. These waves are used as EEG signals and are needed to be amplify by a computer system in order to be analyzed. EEG signals are non-stationary signals as its frequency change with time. EEG signals can be subdivided to into five different sub-bands namely delta, theta, alpha, beta and gamma based on their frequency range. The sub-bands of the brain waves can be tabulated as in Table 1.

The state of concentration is one of the most important human mental states as it indicates the power of focusing one's attention or mental state on a certain task or object. Many studies have been carried out and discovered that human brain waves undergo a significant change when a person is in a state of concentration compared to a relaxed state. EEG signals have been used as a research teaching tool to compare students' attention and inattention behaviors which influences learning outcome[2].

TABLE 1: FREQUENCY BANDS AND THE CORRESPONDING BRAIN STATE[2]

Activity	Frequency (Hz)	Brain State
Delta	0.5-3	sleep/ unconscious
Theta	4-7	emotional pressure/ consciousness interruption/ deep physical relaxation
Alpha	8-13	calm consciousness
Beta	14-30	conscious / alert
Gamma	31-50	peak performance

Previous studies using EEG signal also helped to detect the decrease of human attention while performing a task to determine the human consciousness[3]. It has proven that EEG signals undergo distinguishable changes between the state of concentration and non-concentration. Apart from that, based on past studies on human concentration, it was proven that mental activities such as attention or concentration are closely related to alpha and beta bands[4][5]. The EEG's information of concentration are not only important for evaluation performances (teaching methods or workers) but can also be extended to control robots based on the measurement of concentration level[6]. The development of new technologies that allow humans to interface or control other devices by using thought will undeniably bring many benefits and advantages to the society such as increased quality of life and aid those who are handicapped.

The existing methods were based on linear and stationary assumption such as Fast Fourier Transform[7]. Meanwhile, Wigner distribution was designed for linear but non-stationary systems. This study was to classify two mental states of the human brain in the form of concentration and non-concentration. This investigation proposed Hilbert Huang Transform (HHT) to extract important features of both concentration and non-concentration in the human brain's EEG signal. These features were used as input in the Extreme Learning Machine (ELM) to classify the results between both mental states. Thus, Hilbert-Huang transform (HHT) was an empirically based data-analysis method which was adapted to produce a physically meaningful representation of data from non-linear and non-stationary systems, especially for the time-frequency-energy representation[8]. The Extreme Learning Machine (ELM) was utilized as a classifier in this research to distinguish whether the brain signal refers to a person concentrating or not. ELM is a simple yet efficient learning algorithm of a single layer feedforward neural network (SLFN)[9]. ELM is designed to overcome several issues in back-propagation learning algorithms such as trivial factor, time consumption, human intervention as well as local minima.

This research presents a method of distinguishing the state of concentration and non-concentration of the human based on important features extracted from the signals during the feature extraction process. This is in addition to the normal classification method. This study proposed HHT to determine the features of EEG signals by using Empirical Mode Decomposition (EMD) to produce several numbers Intrinsic Mode Functions (IMF).

The activeness and reaction of the human brain towards a particular stimulus may vary from person to person. Therefore, it is very difficult to obtain fairly similar brain signals from every subject even though a similar technique was used to induce concentration. The response of different subjects to a similar concentration induction technique may be different. Therefore, it was assumed that all the subjects were able to indulge in the state of concentration based on the given procedure.

II. Related Work

Several researches were carried out for the analysis and classification of EEG signals for many purposes such as education, industrial and medical. Basically, the analysis of EEG signals can be broken down into three steps which are preprocessing, feature extraction and classification.

A. Preprocessing

Previous research on the brain signal reference concept using cross correlation for brain computer interface stressed the importance of converting an EEG signal from the time domain to frequency domain as many of the popular approaches for analyzing brain signals are in frequency domain[10]. Another study proposed that it is necessary to perform segmentation and filtration on raw EEG signals to remove unwanted signals and make the data more processable in their research on the problems related to segmentation of EEG signals upon the fluctuation of frequency components[11]. Mitul Kumar Ahirwal and Narendran D. Iondhe[12] in their work to analyze the power spectrum of EEG signals for estimating visual attention utilized the FIR filter of second order in EEG signal filtering in the range frequencies between 0.1Hz to 60Hz and Notch filter to remove power line interference in the channels spectrum at the frequency around 50Hz. Artifacts present in the signals were cut off manually from the signals in all channels at once.

B. Feature Extraction

A feature refers to a distinctive or characteristic measurement, transform or structural component extracted from a segment of pattern. The feature can then be used to represent the original pattern with minimum loss in information. A feature vector is a set consisting all the features used to describe a pattern and which help to reduce the dimensional space needed for pattern representation. Feature extraction is a process to draw out a feature or feature vector from a pattern vector[13].

In Mitul Kumar Ahirwal and Narendra D. Iondhe's research on power spectrum analysis of EEG signals for estimating visual attention, they utilized Independent Component Analysis (ICA) to separate 32 channels into components and Principle Component Analysis (PCA) to minimize all components into a single component[12]. ICA is a method to determine underlying factors or components from multivariate statistical data. This technique tends to looks for components that are statistically independent and non-Gaussian. It is a very robust method but can only extract sources that are combined linearly. PCA has very low level of noise sensitivity, low demand for capacity and memory as well as high efficiency as processes take place in a smaller dimension. However, in PCA, covariance matrix can be difficult to be evaluated in an accurate way and it is unable to capture even a simple invariance unless training data provides this information.

EMD is a method for analyzing non-stationary and nonlinear data such as analog as well as digitized signals, representing time-varying or spatially varying physical quantities. This decomposition converted the signal into several IMFs, which provide useful information in both time and frequency domains [14]. These IMFs can be converted through the Hilbert transform resulting in local energy and instantaneous frequency[15]. Such representations would be ideal for nonlinear and non-stationary data analysis.

C. Features

The generation of control signals based on concentration detection proved that the beta band rises and theta band declines during concentration and therefore, the power ratio between beta band and theta band can be utilized as a parameter in determining a state of concentration[5]. The index of concentration was used to determine one's concentration state based on the number of occurrences whereby the index of concentration was higher than the threshold[4].

On appraising human emotions using time frequency analysis based on alpha band features, the researchers utilized both linear (power, standard deviation and variance) and non-linear (entropy) statistical features for the classification of discrete emotions in order to analyze the nature of the characteristics of different EEG patterns[16].

D. Classification

EEG-based classification system of a passenger's motion sickness level by using feature extraction and selection technologies briefly introduced several classifiers such as Gaussian Maximum Likelihood, K-Nearest Neighbor and Support Vector Machine. Gaussian Maximum Likelihood classifier is one of the most common techniques used in statistical classification[17]. It belongs to the parametric model which was made up of mean vector and covariance matrix for a normal distribution. One of the downsides is that the covariance matrix may be singular or near-singular resulting in an inaccurate estimation[17].

The K-Nearest Neighbor classifier is an approach that assigns a point that is unknown to the class most common among its k nearest neighbors. This approach has two advantages which are its execution time and difficulties in handling high dimensional data[17].

The SVM classifier is also one of the most famous learning algorithms which is used for classification and regression issues. This classifier is designed by solving a constrained optimization problem[17]. This classification method is used to separate EEG signals into categories based on the obtained features from the feature extraction process. The SVM is able to produce accurate and robust classification, find the optimal separation hyperplane, and deal with high dimensional data. However, it requires both positive and negative examples as well as a good kernel function.

Huang et al.[18][19] developed a new learning algorithm known as ELM by adjusting the parameter of the network iteratively. This algorithm initially chooses the input weights and hidden layer biases randomly. Then, it will determine the weight of the outputs analytically without the need of complex iteration[18][19]. The learning speed of ELM is very fast. Besides, ELM tends to have a better generalization performance for feedforward neural network as it not only tends to achieve the smallest training error, but also the smallest norm of weight. ELM is different from tradition gradient-based learning algorithms which work for differentiable activation functions only. Single layer Feedforward Neural Network with non-differentiable activation functions can be trained by using ELM. Traditional gradient-based learning algorithms face issues like improper learning rate, local minimum, overfitting and many more but ELM on the other hand is able to achieve straightforward solutions without such trivial issues[19].

III. TECHNIQUE USED

This section describes the theories of the techniques used in this research. Basically, this research involves the use of HHT and ELM.

A. Hilbert Huang Transform and Feature extraction

A1. Hilbert Huang Transform

The first step in getting HHT is to EMD; this method consists of the decomposition of a time series into a finite number of components known as IMF. IMF is an oscillation mode embedded inside the data[15][20]. Each component needs to follow certain conditions: (1) the mean value of the two envelopes defined respectively by local maxima and local minima must be zero and (2) the number of extrema and the zero-crossing must be either equal or differ at most by one [15][20]. The extraction of IMFs by original signal is called the sifting process. The proto IMF can be expressed from the mean of the upper and lower envelope $m_1(t)$ as follows:

$$h_1(t) = x(t) - m_1(t) \tag{1}$$

$h_1(t)$ is proto IMF because it does not necessarily satisfy the rigorous constraints that define an IMF. Therefore, the sifting process is applied again on $h_1(t)$:

$$h_1(t) - m_{1\,1}(t) = h_{1\,k}(t) \quad (2)$$

Where $m_{11}(t)$ is the mean of the upper and lower envelopes of $h_1(t)$. This process is generally reiterated k times until eventually $h_{11}(t)$ obtained as:

$$h_{1(k-1)}(t) - m_{1k}(t) = h_{1k}(t) \quad (3)$$

The iteration of k allows $h_{1k}(t)$ to satisfy the stoppage criterion of the sifting process[21]. Once the first IMF $c_1(t)$ finish extraction from the original signal x(t), the residual part r(t) will be obtained:

$$x(t) - c_1(t) = r_1(t) \quad (4)$$

Thus the $r_1(t)$ can be treated as new time series to be sifted to get next IMF. This whole process will be continued until the residue $r_n(t)$ is a monotonic function with only single extremum. The originated signal x(t) can be represented as the sum of all IMFs with adding residue such as[21]:

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \quad (5)$$

Obtain IMF component then is possible to apply Hilbert Transform to each component as:

$$H[x(t)] = x * \frac{1}{\pi t} = y \quad (6)$$

The marginal spectrum represent accumulated energy over entire data span[7], can define as:

$$h(w) = \int_0^T H(w,t)dt \quad (7)$$

B. Feature Extraction

In this study, two types of features experimented were performed: (1) the signal data was preprocessed into several subbands of gamma, beta, alpha, theta and delta then directly converted into the FFT power spectrum. (2) The same preprocessed method was also used but the feature was extracted using HHT. The decomposition of EMD produced several numbers of IMFs from five different subbands which were gamma, beta, alpha, theta and delta. Each subbands consist of four to nine numbers of IMFs produced. IMFs provide a useful means to analyse both the time and frequency domains simultaneously. By using FFT, the IMFs can be converted to the frequency domain to compute the power spectrum of each IMF. Each subband have a number of features extracted according their number of IMFs. This feature also needs to be selected to be used in the classification process.

C. Classification

Extreme Learning Machine (ELM) was used in this research as a classifier to distinguish whether the brain signal refers to a person concentrating or not. ELM is a feedforward neural network typically used for the regression and classification with a single hidden node[18][19]. The basic model structure of ELM is as shown as below[9]:

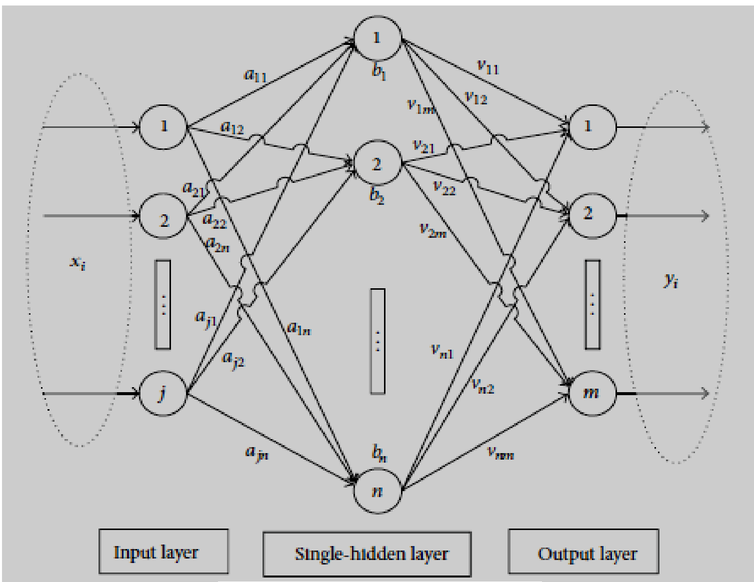

Figure 1. The model structure of ELM.

Based on the model structure as shown in the fig.1, the ELM model consists of j input layer nodes, n hidden layer nodes, m output layer nodes as well as the hidden layer activation function g(x) [9].

For N distinct sample whereby $x_i \in R_N \, x \, R_J \, , y_i \in R_N \, x \, R_m$ (i = 1, 2,…., N), the hidden layer's output can be expressed by equation (8) while the output layer's output can be expressed by equation (9) [12].

$$h = g(ax + b) \tag{8}$$

$$h(x_i)V = y_i \, , where \; i = 1, 2, \quad , N \tag{9}$$

Equation (8) can also be expressed in a simpler term as follows:

$$HV = Y \tag{10}$$

whereby,

$$H = \begin{bmatrix} g(\vec{a}_1, b_1, \vec{x}_1) & g(\vec{a}_1, b_1, \vec{x}_2) & \cdots & g(\vec{a}_n, b_n, \vec{x}_N) \\ g(\vec{a}_2, b_2, \vec{x}_1) & g(\vec{a}_2, b_2, \vec{x}_2) & \cdots & g(\vec{a}_n, b_n, \vec{x}_N) \\ \vdots & \vdots & \ddots & \vdots \\ g(\vec{a}_n, b_n, \vec{x}_1) & g(\vec{a}_n, b_n, \vec{x}_2) & \cdots & g(\vec{a}_n, b_n, \vec{x}_N) \end{bmatrix} \tag{11}$$

$$V = \begin{bmatrix} v_1^T \\ v_2^T \\ \vdots \\ v_n^T \end{bmatrix}_{nxm} \tag{12}$$

$$Y = \begin{bmatrix} y_1^T \\ y_2^T \\ \vdots \\ y_N^T \end{bmatrix}_{Nxm} \tag{13}$$

where $a_i = [a_{i1}, a_{i2}, \cdots, a_{in}]^T$ represents the weights that connect the ith input nodes and the hidden layer, b_j represents the bias of the j^{th} hidden node while $v_j = [v_{j1}, v_{j2}, \cdots, v_{jn}]^T$ represents the weights that connect the jth hidden node and the output layer. The output of the neural network is represented by H. The user of ELM need to set the input weights a_{ij} and the bias of the hidden layer b_j. The output weights V can be computed via a series of linear equations transformation[9].

The procedure of computing the output weights V using ELM can be broken down into three steps as follows[9]:

1. The input weights a_{ij} and the hidden layer biases b_j are set by randomly selecting numerical values between 0 and 1.
2. The calculation of output matrix H.
3. The calculation of output weights V with the formula as follows:
   $V = H^{*}Y,$

whereby H^{*} is the generalized inverse matrix of the output matrix H [12].

IV. METHODOLOGY

This section discusses the experimental procedure of this research from data acquisition to classification. The classification process with ELM was carried out through FFT and HHT feature method and the testing accuracy of both cases were compared.

The following Fig.2 depicts the workflow of the research from raw data acquisition to classifying the processed data into the category of concentration and non-concentration.

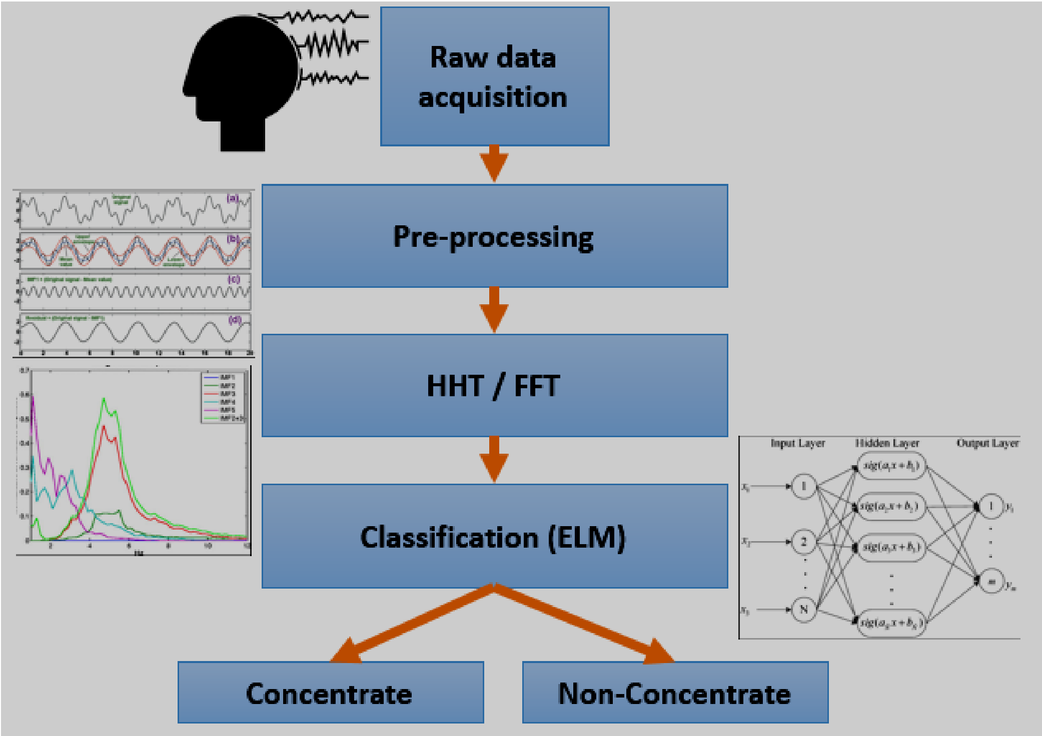

Figure 2. Workflow of the project

A. EEG Signal Detection Device

In this research, a highly portable mobile sensor known as Neurosky Mindwave Mobile was used to collect raw brain signals. This device consists of a single dry sensor. The sensor s is located at fp1 location of the International 10-20 System. A person's mental state and activeness are governed by different parts of the brain in the forehead region. Therefore, observing EEG signals in this region is sufficient enough to tell whether a person is concentrating or not[2]. The sampling frequency of the device is 512Hz.

B. Data Acquisition

All the subjects participated in this experiment voluntarily and were healthy with no hearing impairment and had never participated in any EEG related training before. The experiment was carried out in a silent room with all parameters such as lighting and fan speed fixed. The experiment was carried out on one subject at a time. The subjects were briefed about the purpose of the research and the experimental procedures before the experiment was conducted.

As the experiment began, the subject was given five seconds of rest. This period prepares the subject for the upcoming tasks. Next, the subject was be required to perform back calculation from 100 to 0 for 60 seconds. Backward calculation is a form of concentration exercise which can induce concentration on the subject[22]. For the next 60 seconds, relaxing music was played and subjects were required to relax their minds with their eyes closed. The whole experiment lasted for 2 minutes and 5 seconds per subject.

C. Preprocessing

Basic preprocessing was carried out on the raw data which were sampled at the sampling rate of 512Hz. The 2nd order Butterworth bandpass filter with lower cutoff frequency of 0.1Hz and higher cutoff frequency of 60Hz[12] was used to remove unwanted EEG signals. The notch filter was also used to remove 50Hz frequency due to noise of the power current device. The filtered signals then underwent segmentation. Segmentation of 5 seconds per sample were carried out on the 125 seconds long signals per subject to obtain 25 samples per subject as shown in the Fig.3.

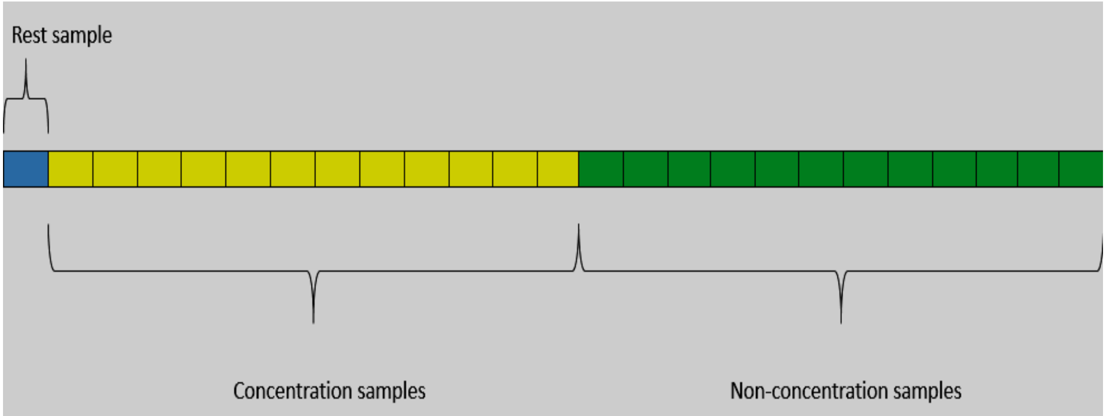

Figure 3. Segmentation of filtered data

The rest of the samples were removed as it was not required in the research. From the five subjects, 60 samples of concentration and 60 samples of non-concentration were obtained.

Next, each sample were multipled into separated filtered data of several subbands which were the gamma, beta, alpha, theta and delta band as shown in Fig.4. Then, each data also went through down sampling from 512Hz into 128Hz to have better resolution EEG data scale because the EEG of the normal human brain is in the range of 0.5Hz and 32Hz[14]. During the gamma band, there were several noises and those higher than gamma band also had noise for EEG signal data samples.

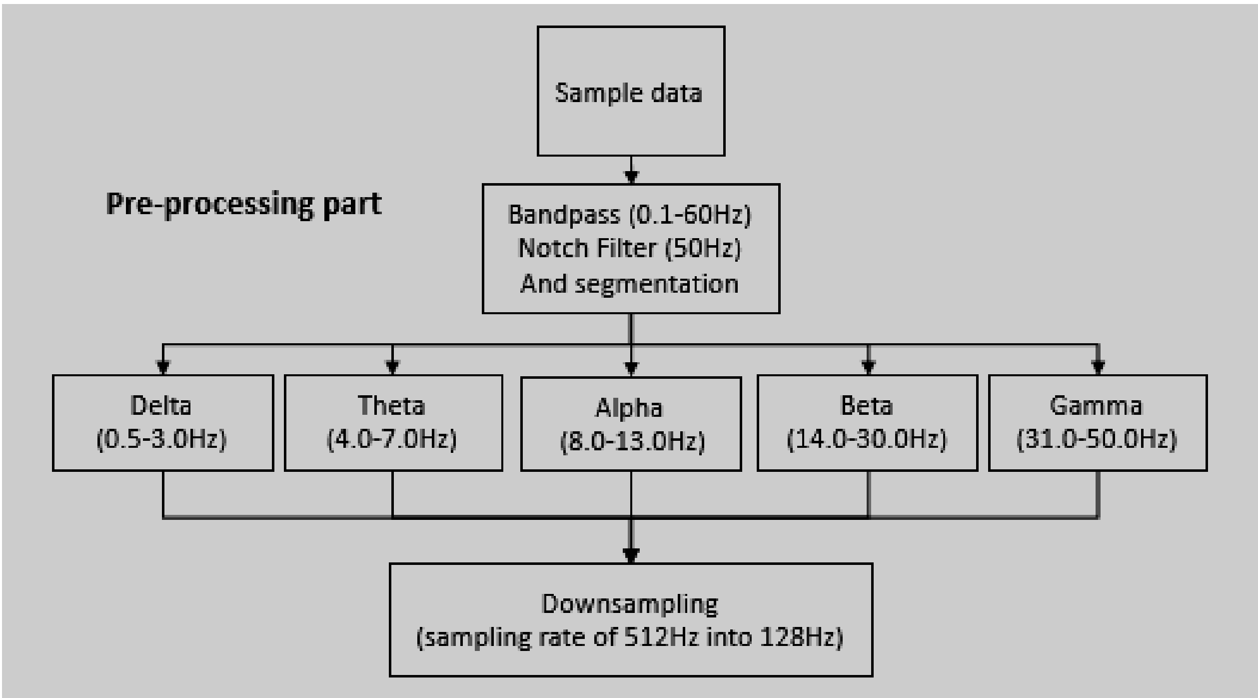

Figure 4. Preprocessing design of this study

D. Feature Extraction

The decomposition of EMD produced different numbers of IMF from each subband. The table below shows the different subbands of the signal produced by EMD.

In Figure 5 is shown from power spectrum can determine the different concentrate EEG giving higher spike at alpha band and non-concentrate EEG at delta and theta band. From figure 6 and figure 7 the decomposition of EMD, the number of IMFs were selected from 1st IMF only, 1st and 2nd IMFs and also 1st to 3rd IMFs.

TABLE 2. THE NUMBER OF IMFS PRODUCED FROM DECOMPOSITION OF EMD FROM DIFFERENT SUBBANDS.

Frequency Range (Hz)	Frequency Band	Frequency Bandwidth (Hz)	number of IMFs (concentrate data)	number of IMFs (non-concentrate data)
0 .5– 3	Delta	4	4 - 5	4 - 5
4 – 7	Theta	4	7-8	7-8
8 – 13	Alpha	6	7-8	7-8
14 – 30	Beta	16	8-9	8-9
31 – 50	Gamma	20	8-9	8-9
0.1 - 50	Actual sample	50	9-12	9-12

The higher value of IMFs has lower data frequency and was almost considered each other as a noise from the data sample itself. All IMF samples were treated as a new signal. The power spectrum of all IMFs were computed for all samples (concentrate and non-concentrate) which produced 5 to 15 distinctive features of each samples. The total data from all samples have 60 samples for concentration and 60 samples for non-concentration. 40 samples were used as training and 10 samples were used for testing from both categories.

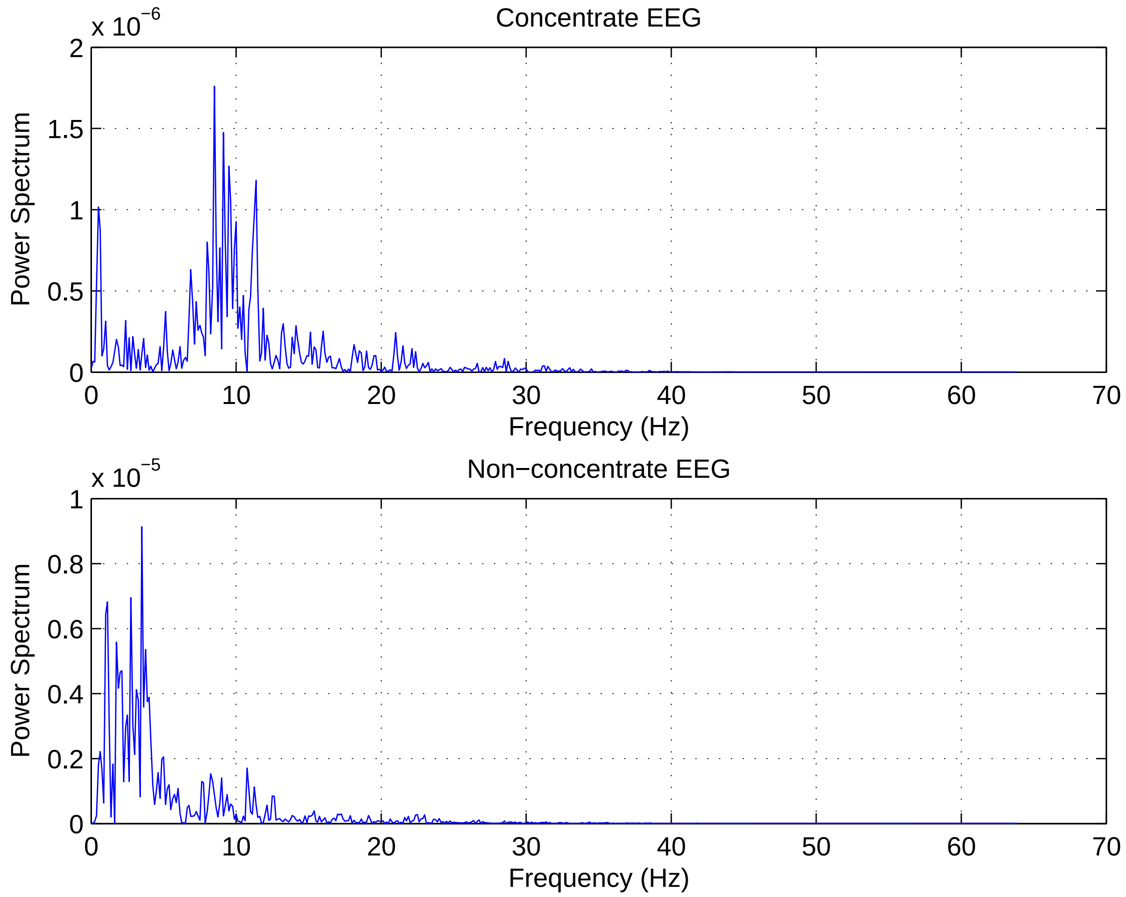

Figure 5. Power spectrum of concentration and non-concentration EEG

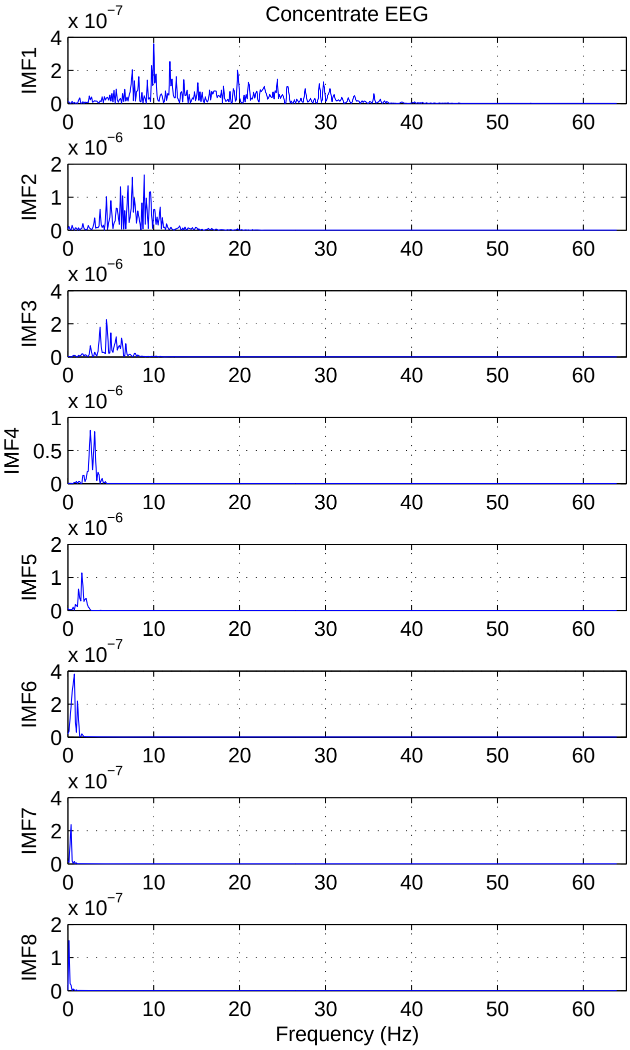

Figure 6. Power spectrum of concentration EEG by decomposition of EMD

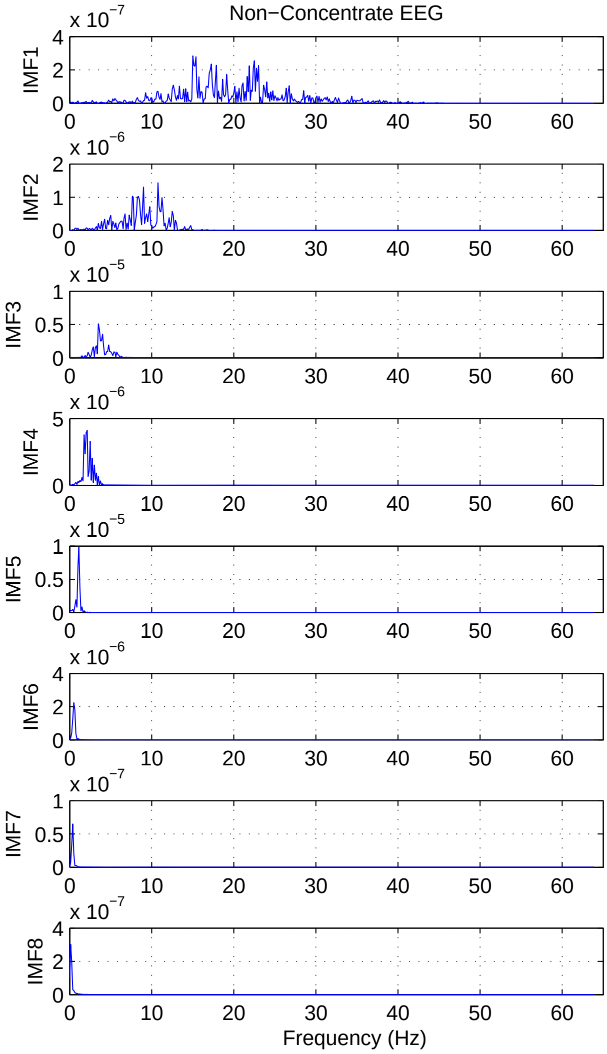

Figure 7. Power spectrum of non-concentration EEG by decomposition of EMD

E. Classification

The training samples were passed into the ELM classifier to train the model. ELM type was set to classification with sigmoidal activation function. The training samples were then passed into the ELM to test the accuracy of 10 different models. Several hidden neurons were experimented and the averages of 10 different models which gave the best testing accuracy were found. Basically, ELM created a classification that separates two different categories of data and all the parameters needed to be tuned to obtain maximum accuracy. The number of hidden nodes used was 3 to 300 but some hidden nodes were skipped as they did not have much difference between them.

V. RESULTS AND DISCUSSION

The setting of the procedure of inducing concentration on subjects is quite a challenging task. Several different procedures were tested and the one that gave the best data was chosen.

The figures 8,9,10 and 11 show the results of average training and testing of 10 ELM models by using several of the hidden nodes. The test results of using the feature with 1st IMF only have produced the highest test accuracy from other experiments that were tested. Table 3 analyse comparison result of highest test accuracy rate. The experiment also gave all data which occur overfitting reaching more than 70 hidden nodes. And also we can the different between performance from all experiment in figure 12 and figure 13

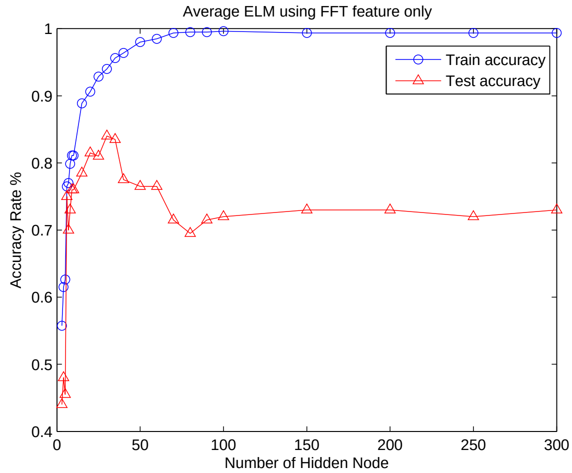

Figure 8. Average ELM result using FFT only

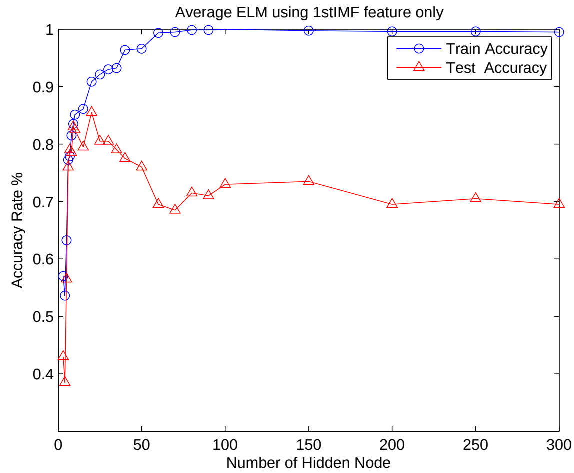

Figure 9. Average ELM result using 1st IMF only

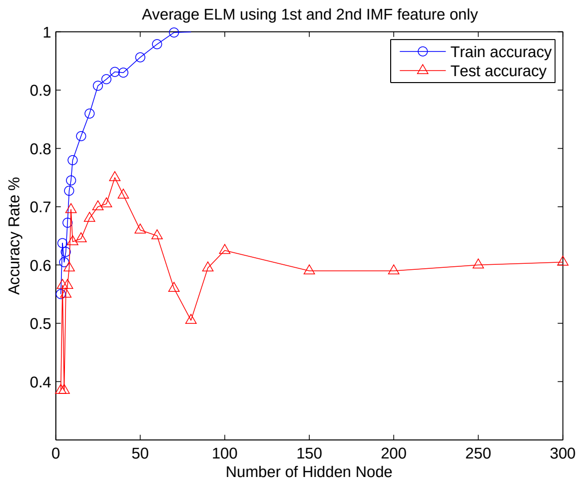

Figure 10. Average ELM result using 1st and 2nd only

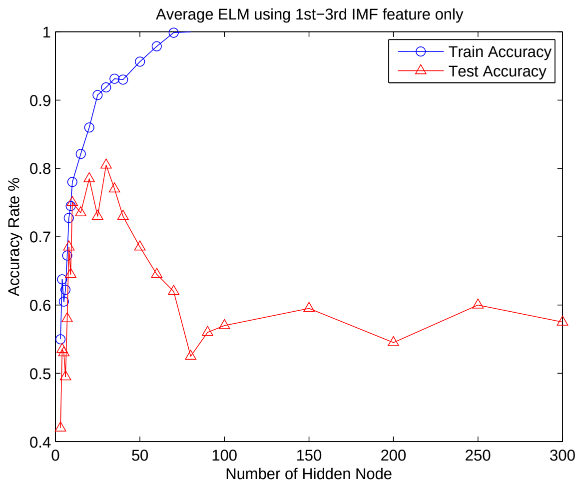

Figure 11. Average ELM result using 1st to 3rd IMF only

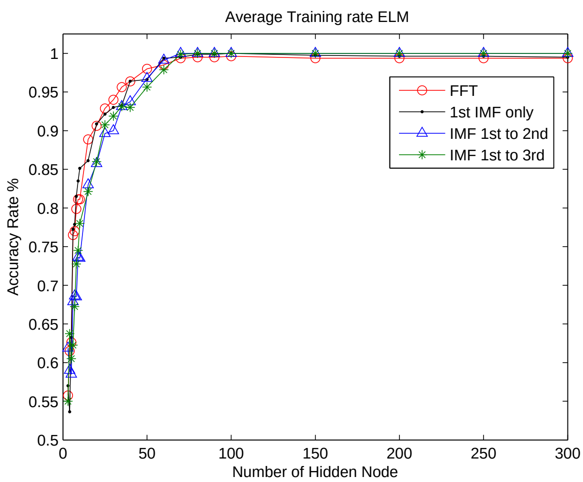

Figure 12. Average training ELM all experiment

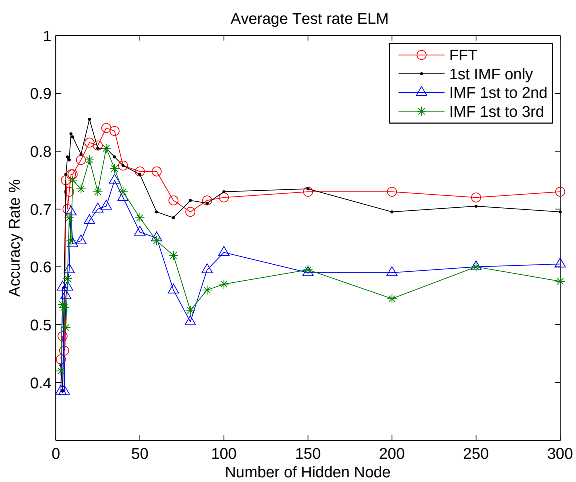

Figure 13. Average test ELM result all experiment

TABLE 3. COMPARISON OF HIGHEST TEST ACCURACY RATE BETWEEN ALL EXPERIMENT RESULTS

Testing accuracies / Investigation	FFT	1st IMF	1st and 2nd IMF	1st to 3rd IMF
Average	0.7175	0.7216	0.638	0.6297
Maximum	0.84	0.855	0.75	0.805
Minimum	0.44	0.385	0.435	0.42
Standard Deviation	0.1078	0.1152	0.1030	0.1025

The selected number of IMFs are very crucial in certain problems to differentiate a quasi-linear from a truly nonlinear system[8]. A better understanding IMF signal could lead better features to be found in which IMF would be suitable to be used among all five subbands. In addition, other than taking the power spectrum of IMF as a feature, HHT also have more types of features to be used in future experiments. These features are Instantaneous Frequency to determine the physical meaning of IMFs[20] and Marginal Spectrum which offer the compute of total energy distribution from each frequency[8].

VI. CONCLUSION

This study is to prove that HHT method have more advantages in non-linear and non-stationary signal which differ from traditional method FFT[8]. The decomposition of EMD could produce more distinguishable features if it could select only the most important part in the concentration of EEG signals and could focus more on beta and alpha bands since it was the most dominant in FFT spike found[5]. Classification with ELM provided good analysis results in different experiments with same feature used to prove that HHT have better test accuracy results and also with the lowest number of hidden nodes. The ELM could also compute the process of training and testing samples extremely fast. In the future, the need to obtain optimum IMF in extracting important features to classify a mental state of concentration will be investigated.

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