EEG Different Frequency Sound Response Identification using Neural Network and Fuzzy Techniques

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Abstract— **Electroencephalographic (EEG) technology has enabled effective measurement of human brain activity, as functional and physiological changes within the brain may be registered by EEG signals. In this paper, electrical activity of human brain due to sound waves of different frequency, i.e. 40 Hz, 500 Hz, 5000 Hz and 15000 Hz, is studied based on EEG signals. Several signal processing techniques, i.e. Principle Component algorithm, Discrete Wavelet Transform and Fast Fourier Transform, are applied onto the raw EEG signal to extract useful information and specific characteristics from the EEG signals. This research has shown that the characteristics of EEG signals differ with respect to different frequency of sound waves, and hence the EEG signal can be identified with suitable characterization algorithm using artificial intelligent techniques, such as Artificial neural network, fuzzy logic and adaptive neuro-fuzzy system.**

Keywords— **EEG, sound wave, signal processing, artificial intelligent.**

I. Introduction

When listening to sound waves or tones of different frequencies, our brain will react differently and produce EEG signals with different qualities/characteristics. In recent years, a lot of research had been carried out to understand the characteristics of EEG signal. It is demonstrated in the work by Ragi *et al.*[1] that sounds containing enhanced inaudible high frequency component (HFC) has modulatory effect on human acoustic system. Besides, Husheng Lu *et al.* [2] confirmed the characteristic of EEG and the location in brain when a person is exposed to different rhythm music. In the research, it is shown that when listening to music, the low frequency spectrum (lower than 10 Hz) was restrained obviously, where as the high-frequency composition of EEG signal had obvious enhancement. The quicker the rhythm, the higher the characteristic frequency emerging was in the EEG signal. The most significant EEG signal enhancement was noticed around the area of Temporal lobe and Parietal lobe.

To analyze and categorize the EEG signal accurately, eventually analysis is to be done on clean EEG signal. However, EEG data captured over the scalp usually contain artifacts or noise. These artifacts or noise maybe caused by the instrument or biological response, e.g. eyes movement, certain concentration or distraction etc. In order to analyze and classify the EEG signal correctly, the EEG signals need to be processed, and the artifacts to be filtered. Lin *et al.*[3] in his work proposed Independent Component Analysis for artifact filtering, where as Shaker [4] proposed Wavelet Transform for EEG characteristic extraction and classification.

Artificial Intelligent (A.I.) techniques were used in EEG signal classification as A.I. technique is much simpler than conventional modeling method for highly non-linear signal like the EEG signal. Subasia *et al.* [5] and James *et al.* [6] applied artificial neural network and fuzzy logic technique for classification of normal and epileptic EEG signal. In this paper, an algorithm based on artificial neural network, fuzzy logic and combinational of the two methods mentioned above, i.e. adaptive neuro-fuzzy system, is designed for classification of EEG signal with respect to different frequency of sound waves. Performance of the different type of classification algorithm is compared in the last section of this paper.

II. Methodology

A. Experiment Setup

EEG machine in Medical Electronic Laboratory, Universiti Teknologi Malaysia is used in this study. The complete set of EEG machine includes the laptop with Neurofax EEG-9100 software, together with the EEG Electrode-Cap Electrode System I and EEG acquisition set. The Electrode Board Adapter is used to connect the Electro-Cap to EEG acquisition. The EEG machine is to be setup in a quiet environment as the purpose of the recording is to measure one's brain response when hearing to certain frequency of sound waves. Noisy environment will defeat the purpose mentioned. Besides, as the EEG acquisition is very sensitive to electric and magnetic field, the EEG machine should be isolated from other wiring or other electrical system that might generate electric and magnetic field unintentionally.

Monotone sound waves of 40 Hz, 500 Hz, 5000 Hz and 15000 Hz are collected to be played through speaker of personal computer, with the speaker placed 20 cm in front of subjects. 5 subjects, male and female, range from 22 – 27 years old are selected to perform the experiment. The subjects chosen are adults with good hearing ability. The subjects should have short hair but not bold. Prior to the EEG signal recording, the subjects are asked not to put any oil on their hair and keep their hair dry. Besides, the subjects are required to have enough rest before the experiment is conducted. During the experiment, the subjects are required to sit still with their eyes closed throughout the experiment to prevent the artifact as eyes blinking, muscle movement etc.

B. EEG Data Recording

EEG data recording is carried out for the 5 subjects. The subjects are then exposed to sound waves of different frequencies, starting from 40 Hz, followed by 500 Hz, 5000 Hz and 15000 Hz of sound waves. The subjects are exposed to tones with same frequency for at least 15 seconds for EEG data recording, but only the last 10 seconds of data will be used for analysis. The sampling frequency set in this study is 500 Hz. Neurofax outputs EEG data for all 20 channels. However, only the channels from Temporal lobes are of interest (T3, T5, T4, T6), as the study is focusing on human auditory perception or human brain response towards different sound wave frequencies.

The EEG signal from Neurofax is saved as ascii files to easier processing and visualizing. However, in order for Matlab to process the data, the data is to be saved as .txt file. For every set of EEG data, the last 5000 samples (last 10 seconds of EEG signal) are saved in .txt format using Microsoft Excel.

III. EEG Signal Processing

A. EEG Signal Filtering using Principle Component Analysis (PCA)

The raw EEG signal is affected by noise/artefact. Hence, filtering of the EEG signal is needed before further analysis on the EEG signal.

Principle component analysis (PCA) can be used for noise filtering of the EEG signals. The concept of PCA is to generate a new set of variables, called principle components. Each principal component is a linear combination of the original variables, and is orthogonal to each other. For most of the system, the most of variance in the data is along the first principal component, followed by second component which is perpendicular to the first principal component, and so on. The full set of principal components is as large as the original set of variables.

With the same assumption towards EEG signals, PCA is applied onto the raw EEG signals (4 channels) to obtain much more simplified signals with less noise. Wavelet Toolbox from Matlab provides wavelet-based multivariate principle component analysis, with the function name "wmspca". By selecting the numbers of retained principal components, simplified signals can be reconstructed.

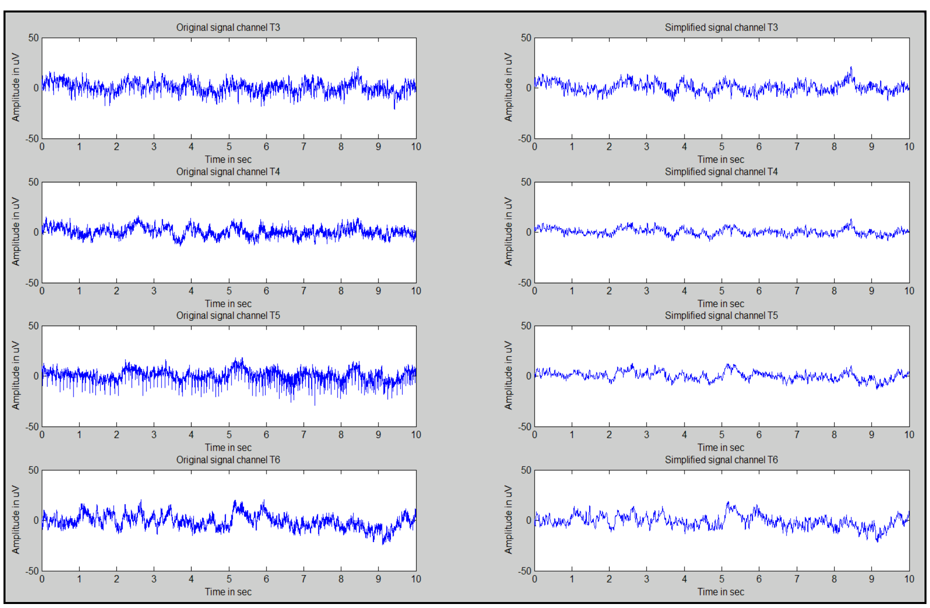

Figure 1 Original EEG (left) at different channels comparing to the simplified EEG signal (right) using multiscale PCA.

Figure 1 shows the original EEG signal vs. the simplified EEG signal using multiscale PCA. it is obvious that the main components of the EEG signals are retained but noise with higher frequency is eliminated.

B. EEG Feature Extraction Using Discrete Wavelet Transform (DWT)

In order to extract useful information from the EEG signals, Discrete Wavelet Transform (DWT) is applied onto the simplified EEG signals after wmspca. DWT is able to reveal features related to transient nature of the EEG signals.

The concept of DWT is to analyze the signal at different frequency bands, by decomposing the signal into a coarse approximation and detail information. Basically, the decomposition of the signal into different frequency bands is obtained by consecutive high-pass and low-pass filtering. The signal is decomposed simultaneously using a low-pass filter and a high-pass filter. The concept of DWT is illustrated in Figure 2.

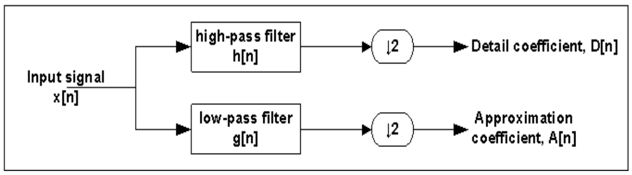

Figure 2 Decomposition of input signals using DWT

Selection of suitable number of wavelet and the number of decomposition level is very important in DWT. In this study, assumption is made where frequency components range 4-60 Hz is important for EEG signal analysis. Hence, level of decomposition chosen is 6. The extracted wavelet coefficients provide a compact representation that shows the energy distribution of the EEG signal in time and frequency.

Using the "dwt" function from Matlab Wavelet Toolbox, the decomposed EEG signals are obtained as in Figure 3. To further decrease the dimensionality of the extracted feature vectors, statistic over the set of wavelet coefficients was used for further analysis. In this study, information from sub-band 3-6 is calculated for further analysis.

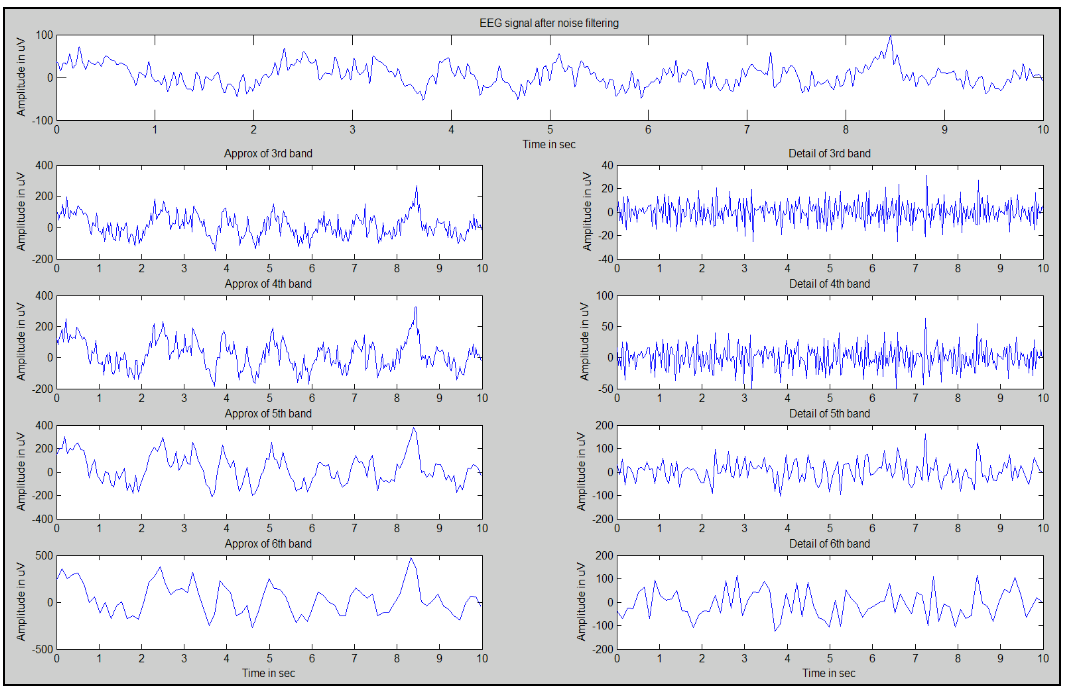

Figure 3 Detail and approximation coefficient of sub-band 3-6 of the EEG signal

C. EEG Feature Extraction Using Fast Fourier Transform (FFT)

For detail analysis in frequency domain, Fast Fourier Transform (FFT) is applied onto the EEG signal. FFT is an efficient algorithm to compute the discrete Fourier transform (DFT) and it's inverse while DFT decomposes a sequence of values into components of different frequencies. The operation of FFT is given by Equation (1):

$$X(k) = \sum_{n=1}^{N} x(n) e^{-j2\pi k\frac{n}{N}} \qquad \text{Equation (1)}$$

x(n) in Equation (1) is the discrete-time signal with n is the discrete time, X(k) is the discrete frequency representation of x(n), with k is the discrete frequency, as a result from FFT and N is the period of n to be analyzed. N chosen for FFT analysis in this study is next higher power of 2 for EEG signal with 5000 samples (10 second of data with sampling frequency 500Hz), i.e. 8192-point DFT. To obtain the power spectrum of the EEG signal, the output from FFT is multiplied with its own conjugate. The power spectrum of the EEG signals at channel T3, T4, T5 and T6 is shown in Figure 4.

To simplify the frequency domain analysis, the FFT signal obtained is subjected to logarithm of base 10, and the average of the 4 channels is obtained, and is smoothen for further analysis. Figure 5 shows the power spectrums of the smoothened EEG signal (averaging 4 channels of EEG signal) in logarithm base of 10.

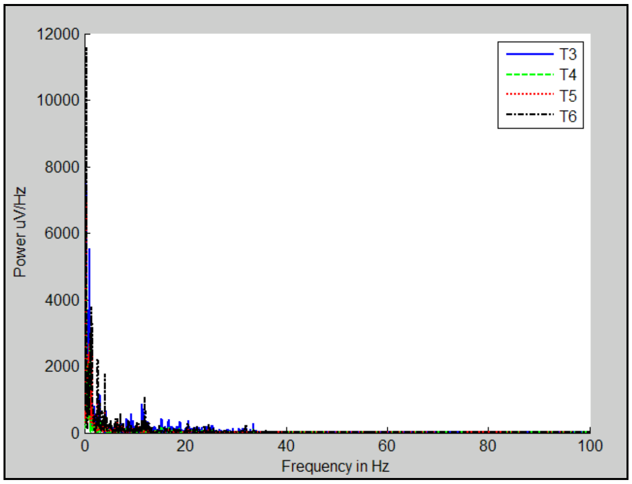

Figure 4 Power spectrum of the EEG signals at channel T3, T4, T5, T6

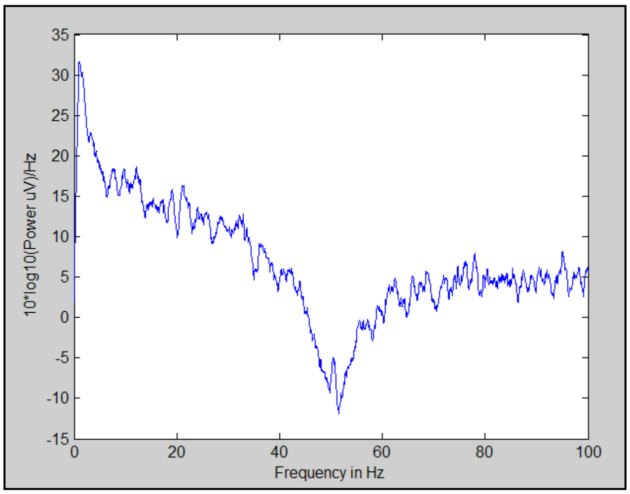

Figure 5 Smoothened power spectrum of the EEG signal

From the smoothened EEG power spectrum, statistical information can be obtained. The statistical information calculated for further analysis are the mean and max values from frequency range of 8-13 Hz, 13-21 Hz, 21-30 Hz and 30-45 Hz.

IV. EEG Signal Classification Using AI Techniques

A. Preliminary Analysis

With all the signal processing done on the EEG signals, preliminary analysis can be done on the EEG signals response when a subject is exposed to different frequency of sound waves. For the same subject, the power spectrum of the EEG signals with respect to 40 Hz, 500 Hz, 5000 Hz and 15000 Hz is shown in Figure 6. The figure shows significant difference when the subject is exposed to different frequency of sound wave (40, 500, 5000 and 15000 Hz). It is noticed that the highest power occurs for 40 Hz and 15000 Hz response, followed by 500 Hz response and the lowest power for 5000 Hz response. However, it is also noticed that the response from 40 Hz and 15000 Hz are very close to each other.

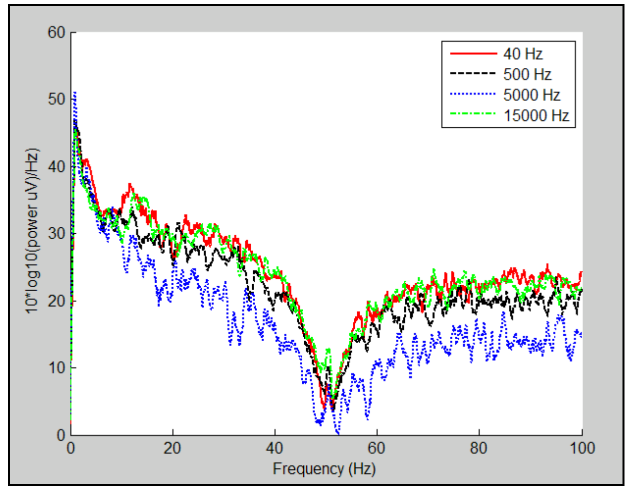

Figure 6 Power spectrum of the EEG signal (subject 1) with respect to 40 Hz, 500 Hz, 5000 Hz, and 15000 Hz

In this stidy, EEG data are collected from 5 different subjects with age range from 22-27 years old. It is noticed that the power spectrum obtained from different subjects are not exactly the same, as the natural response and hearing ability is different for each individual. However, the power spectrums from different subjects have similar pattern, where the highest power occurs for 40 Hz and 15000 Hz response, followed by 500 Hz response, and the lowest power for 5000 Hz. Hence, in order to classify the EEG signal (with respect to different frequency response), a reference per subject needs to be set. In this study, 500 Hz response for each individual is chosen as reference.

B. Artificial Neural Network as Classifier

Unlike conventional statistical analysis, artificial neural network (ANN) requires less computation power and has predictive and learning abilities. Hence, ANN is suitable for classification of highly non-linear signals like the EEG signals.

In this study, the network architecture chosen is multi-layer feedforward network with backpropagation learning algorithm, with 10 inputs and 3 outputs. The number of hidden layers is 4 with 30 neurons in each hidden layer. The neurons in all the hidden layers are modeled using tan-sigmoid transfer function, where as the output neurons are modeled using linear transfer function. The ANN designed is illustrated in Figure 7.

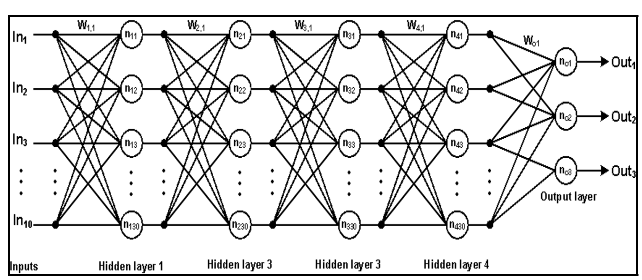

Figure 7 Structure of the designed ANN for EEG signal classification

The 10 inputs neurons are 4 inputs from DWT (mean of sub-band 3, 4, 5, 6) and 6 inputs from FFT (mean at 8-13 Hz, 13-21 Hz, 21-30 Hz, 30-45 Hz, and max at 13-21Hz, 21-30Hz), where as the 3 output neurons are vector with 3 elements, i.e. [1 0 0] represents 40 Hz response, [0 1 0] represents 5000 Hz response and [0 0 1] represent 15000 Hz response.

In this study, 120 sets of training data are fed into the ANN with training, validation and testing ratio of 0.6, 0.2 and 0.2 respectively. During the training, the weights and biases of the neural network are adjusted iteratively to achieve the training goal, i.e. mean square error of 0.001.

The trained ANN is then used to recognize the other 30 sets of EEG signals. From the 30 sets of EEG data tested, 28 sets of EEG data are identified correctly using the ANN classifier. The accuracy of the ANN classifier is 93.33%.

C. Fuzzy Logic System as Classifier

Fuzzy logic has the capability of recognizing, representing, manipulating, interpreting, and utilizing data and information that are vague and lack certainty. Modeling of non-linear data with arbitrary complexity is much simpler with F_L as compared to conventional statistical modeling approach. Hence, F_L can be used to classify non-linear and non-statistical signals like EEG signals with only observation on the basis of imprecise and non-numerical information from the EEG signals.

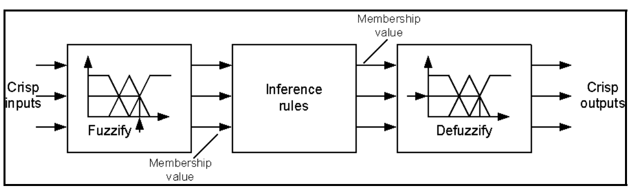

Figure 8 Operation of a fuzzy system

The operation of a fuzzy system is illustrated in Figure 8. The inputs are first fuzzified, inference then takes place on the fuzzy rule base, followed by defuzzification where the fuzzy outcome of the rules is converted to a crisp output.

To simplify the design of the fuzzy system for EEG signals classification, 3 input fuzzy sets and 1 output fuzzy set are defined in this study. The inputs to the fuzzy system must be meaningful, so that fuzzy rules can be defined for the system to match the desired outputs. The inputs to the fuzzy system are shown in Table 1.

For all the 3 inputs, 3 membership functions are defined, i.e. neg(negative), spos (small positive) and lpos (large positive). The output of the fuzzy system is frequency range, again with 3 membership functions, i.e. low, medium, and high. The desired classification output are 40 Hz (low), 5000 Hz (medium) and 15000 Hz (high), and the suitable defuzzification method in this study is MOM (mean of maximum).

The range of each membership function for every input is determined by observing the range of data for each input over 100 sets of data. Triangular membership function is chosen in the study. The fuzzy system is then used to recognize the other 30 sets of EEG signals. From the 30 sets of EEG data tested, 24 sets of EEG data are identified correctly using fuzzy system. The identification of 5000 Hz and is 100% correct, whereas identification of 40 Hz and 15000 Hz response have only 6/10 and 8/10 of accuracy. The inaccuracy for 40 Hz and 15000 Hz classification is due to some overlapping for both the EEG responses.

Table 1: Inputs of the fuzzy system

Input	Source of input
1st input (mean):	Average mean of DWT sub-band D3, D4, D5, D6 (reference to 500 Hz response)
2nd input (fftmean):	Average mean of power spectrum from different range of frequency, i.e. 8-13 Hz, 13-21 Hz, 21-30 Hz, 30-45 Hz (reference to 500 Hz response)
3rd input (fftmax):	Average max of power spectrum from different range of frequency, i.e. 13-21 Hz, 21-30 Hz (reference to 500 Hz response)

D. Adaptive Neuro-Fuzzy Inference System (ANFIS) as Classifier

A fuzzy system is designed by own interpretation of the characteristics of the input-output model. The input membership functions to rules, rules to output membership functions, and the output membership function to a single-valued output are considered with only fixed membership functions. Hence, membership functions chosen must be able to model the characteristics of the variables in the fuzzy. However, for non-linear and non-statistical input like the EEG signals, it is always hard to discern what the membership function should look like by simply looking at the EEG data. Rather than choosing the parameters associated with a given membership function arbitrarily, these parameters should be chosen so as to tailor the membership functions in order to account for the variations in a collection of input/output data sets. In such cases, fuzzy system with adaptive neuro-learning, i.e. adaptive neuro-fuzzy inference system (ANFIS) can be used.

ANFIS, as derived from the title of the system, it is a system that combines both A.I. techniques, neural network and fuzzy logic. Neural network technique has the ability to learn, where as fuzzy system works on data with certain degree of vagueness or uncertainty. Fuzzy Logic Toolbox from Matlab provides the functionality of ANFIS, where the neuro-adaptive learning method is applied for fuzzy modeling procedure.

In this study, the inputs to the ANFIS is similar as the input to the fuzzy system derived previously, i.e. mean, fftmean, fftmax as described in Table 1. The corresponding outputs for those inputs are crisp values range from 0 to 1. For the desired classified output of 40 Hz, 5000 Hz and 15000 Hz, the output values set for the ANFIS is 0.01, 0.5 and 0.99 respectively. With the assumption that the output is linear, the classification of the output can be derived as following:

1. If the output of ANFIS is < 0.35, the recognized frequency is 40 Hz.
2. If the output of ANFIS is between 0.35 and 0.65, the recognized frequency is 5000 Hz.
3. If the output of ANFIS is > 0.65, the recognized frequency is 15000 Hz.

ANFIS function from Fuzzy Logic Toolbox is called to perform the training to define a better matching of membership function parameters that best allow the associated fuzzy inference system to track the given input-output pairs of data. Figure 9 shows the FIS structure generated from ANFIS.

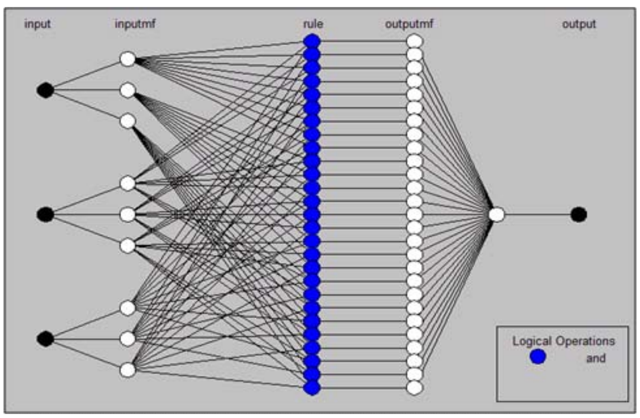

Figure 9 FIS Structure generated from ANFIS

102 sets of training data with target outputs of 0.01, 0.5 and 0.99 for 40 Hz, 5000 Hz and 15000 Hz response respectively and fed into the ANFIS for training.

The ANFIS system designed is then used to analyze the other 30 sets of EEG signals. ANFIS classifier designed in this study has 100% accuracy when tested on the 30 sets of test data. By allowing certain level of vagueness on the direct output from ANFIS, the output is then mapped to the target frequency using with the criteria.

III. Conclusions

From this study, it is noticed that ANFIS classifier has the highest accuracy, i.e. 100 % accuracy, followed by ANN classifier with 93.33% accuracy, and lastly the fuzzy system classifier with only 80% of accuracy. The fuzzy system has the lowest accuracy as the parameters of the fuzzy system are determined by mere inspection onto the DWT analysis and the power spectrum of the different frequency response. No adaptive learning is involved in this process. ANN classifier has higher accuracy as the weights and biases of the ANN are adjusted based on the learning from the training data. The accuracy of the ANN can be further improved by adjusting the weights and biases of the system and further training of the ANN with smaller mean square error, mse as the training goal. ANFIS combines the advantages of neural network and fuzzy logic, where adaptive learning algorithm is applied to define the best membership functions that fit to model the input-output relationship more precisely, and certain level of fuzziness is allowed onto the inputs which are suitable to model highly non-linear and non-statistical signals like the EEG. Hence, the accuracy of the ANFIS is the highest amount the 3 classifiers here, which reaches 100 % accuracy in this study.

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