EEG-Based Auditory Cortex Detection Using Neuro-Fuzzy And Wavelet Fractal Features

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Abstract- *The auditory evoked potential (AEP), also referred to as an EEG signal, is transmitted from the scalp of the brain by audio stimulation. AEP response reflects the auditory ability level of an individual. In this study, repetitive clicks at 256 Hz were stimulated at various stimulus intensities of 80 dBHL to record AEP signals in both the ears of a normal and abnormal subject. To determine the hearing threshold level, the AEP responses of subjects with normal hearing and those with defective hearing were subjected to fixed acoustic stimulus intensities. To identify the individual's hearing threshold, the obtained variables were correlated to neural network models. The neural network model that was developed allowed for the distinction of a person's hearing frequency perception response with a maximum classification accuracy of 94.5 percent.*

Keywords- EEG, auditory evoked potential, hearing perception, auditory stimuli level, neural network.

I. INTRODUCTION

The human brain is a complex and difficult organization that spans time and space. Because of an increase in the elderly population and stress in daily and social life, the number of patients with nervous system impairment is increasing. To overcome these issues, it is necessary to use a real-time interpretation of the brain signal (brain wave) by connecting the human brain to the machine, or a fusion technique for enhancing human ability by inputting and modulating external information. Fuzzy logic and neural networks, among other model-free techniques, have offered an alluring alternative over the past three decades for modelling complex systems that must account for non-linearity and imperfect information encountered in the real world. Fuzzy reasoning has two distinct meanings.

Hearing loss has been the most prevalent sensory impairment on the globe. Over 275 million people throughout the world experience various hearing-related problems. Transient Evoked Otoacoustic Emissions (TEOE) and Automated Auditory Brainstem Response (AABR) are used in the universal new born hearing screening test. EEG is used to evaluate the functionality of auditory nephropathy utilizing the AABR, an electrical potential signal that is emitted from the scalp of the brain by presenting a sound stimulus. EEG is a non-invasive technology that includes placing many electrodes on the scalp to record the electrical activity of the brain. Any electrophysiological reaction to a physical stimulus is known as an evoked potential and is measured by the EEG. AEP signal is an electrical potential signal elicited from the brain while an auditory stimulus is presented in a time-locked manner. The recorded AEP signals have a lower signal-to-noise ratio than recorded EEG signals. To boost the signal-to-noise ratio of the AEP signal, it is necessary to average several single trials to define the AEP waveform.

In this project, the recordings were made at a sampling rate of 256 Hz per second for a total of 10 seconds. 2560 data points will be collected over ten seconds. Each ear undertakes five trials, with a minute of rest in between each trial. 500, 1000, 2000, and 4000 Hz were the average hearing threshold values. For each of these values, the EEG signals were recorded. Figure 1 depicts the block diagram of an EEG-based hearing ability level assessment system.

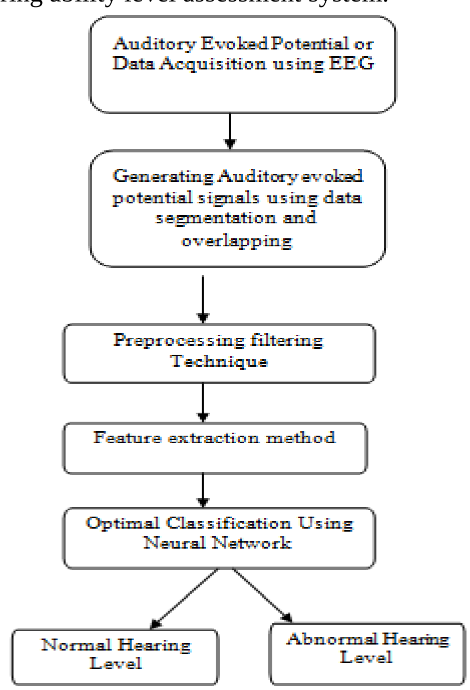

Figure 1.EEG-based hearing ability assessment system

To detect or estimate the hearing threshold levels, click, chirp, and tone burst stimuli are frequently utilized. Other types of stimuli can be used to elicit AEP signals. A catalyst in the ear results in the synchronized firing of the AEP is affected by the auditory nerve. The AEP directly depends upon the relationship between the stimulus duration and the duration of response.

Following is an outline for this paper. In Section II, the proposed AEP hearing perception protocol and method are described. A neural network model was developed and its performance was analyzed in the part that follows. This paper is completed with its conclusion and results.

II. AEP DATA ACQUISITION AND METHOD

A. Experiment setup:

A simple experimental setup has been developed and suggested to collect the auditory evoked EEG signal from the brain. The experimental setup includes a Mindset-24 EEG amplifier. The subjects were instructed to wash their hair the night before the EEG recordings and to avoid using hair products that could affect the electrical conductivity between the skin and the electrodes. Before the experiment began, the subjects were required to get enough rest. The individual was lying comfortably in the audiometric booth during the experiment. Twenty subjects participated in the experimental study. Ten individuals with normal hearing and ten with abnormal hearing who were in good health participated in the study.

B. AEP data acquisition:

With the assistance of research researchers, the experimental process and protocols were described to NHG and ABNHG. Before beginning with the trials, all individuals provided written consent. All the subjects were healthy and free of any medication. The behavioural hearing threshold levels for the right and left ears should be determined independently. All subjects' left and right per-operative pure tone hearing thresholds were measured for four fixed frequencies (500 Hz, 1000 Hz,2000 Hz, and 4000 Hz). 80 DbHL was the initial stimulus intensity, and it was reduced by 5 DbHL. To ensure that the subjects could hear and perceive the desired sound stimulus, the mean hearing threshold values for the frequencies were calculated. The average threshold was 20. 5 ± 2. 4 dB for the right ear and 22 ± 2 .5 dB for the left, according to all of the participants. As a result, mean threshold values were calculated to ensure that the subject was able to receive and recognize the desired sound stimulation.

C. Physiological method using EEG:

The EEG signals were recorded using the Mindset24 EEG amplifier portable bio-signal acquisition equipment (meets IEC 60601-1 standard for research; 19 EEG bipolar channels; filters: 0.5-100 Hz; data acquisition: 12-bit A/D converter with sampling frequency ranges of 128 Hz, 256 Hz, and 512 Hz. Using the 10-20 electrode placement system, electrodes were placed over the areas FP1, FP2, F7, F3, FZ, F4, F8, T3, T5, C3, CZ, T4, T6, P3, PZ, P4, O1 and O2 (frontal, occipital, parietal, temporal, and central) (Standard Positioning Nomenclature, American Encephalographic Association). The left and right mastoids were used to create the reference electrodes. The subjects were instructed to take off their eyeglasses, stop often nodding their heads, and refrain from moving their bodies in any way to diminish the effects of artifacts. An impulsive click sounds with an 80 dBHL acoustic intensity and a frequency of 500, 1000, 2000, and 4000 Hz was played for the subjects to hear. For the subjects with normal hearing, synchronized stimuli and frequencies were presented through headphones in the left and right ears with different sound intensities, and their related AEP signals were recorded. AEP signals were gathered for 10 seconds at a sample rate of 256 Hz. The same test was administered five times, each time with a one-minute inter-trial rest period. The procedure was then performed in the right ear at each frequency after recording AEP signals in the left ear. The AEP data from patients `with normal and impaired hearing were physically examined by two audiologists to improve the data's reliability and validity.

$$E= \sum_{n}^{N} x(n) \ln\left(x(n)\right)$$

where

E is the spectral entropy,
X(n) is the feature extracted EEG signal.
n = 0, 1, 2, …., N-1, are the sample points.

D. Feature Classification:

Feature extraction refers to the process of transforming raw data into numerical features that can be processed while preserving the information in the original data set. When you need to reduce the number of resources required for processing without losing vital or relevant information, feature extraction is useful. Feature extraction can also be used to reduce the quantity of redundant data in a study. The AEP signals were filtered using the feature extraction technique. To extract the optimal feature for the dataset's study, the following features are used: Auto regressive and Power.Auto-regressive models have many applications in EEG signal analysis, ranging from estimating spectral properties to rejecting artifacts and discriminating stationary signals. The amount of activity in certain frequency bands of the signal is represented by power, whereas coherence between different electrodes reflects the degree to which connections are present across brain regions.

Additionally, the feature that best suits this application can be found. Various categorization algorithms will be used as well. The rates of the accuracy of various feature and classification algorithms differ. The most accurate categorization strategy will also be determined. Orthogonalized Singular Value Decomposition (OSVD) is a popular technique for decomposing a matrix into several component matrices, exposing many of the original matrix's useful and interesting properties. We can use SVD to determine the rank of a matrix, quantify the sensitivity of a linear system to numerical error, or find an optimal lower-rank approximation to the matrix. Another feature is the median skewed wavelet. A wavelet function that has been skewed using the median skewness method is called a median-skewed wavelet. A wavelet function's shape can be altered using the median skewness technique to enhance its time-frequency localization capabilities. A more accurate portrayal of the signal's energy is possible due to the modified wavelet function's skewness towards the signal's median frequency.

E. Classification of Neuro-Fuzzy:

Fuzzy logic can identify, represent, manipulate, decipher, and use fuzzy data and information that is lacking in confidence. Compared to traditional statistical modelling techniques, FL makes it significantly easier to represent non-linear data of any complexity. As a result, FL can be used to categorize non-linear and non-statistical signals, such as EEG signals, with simple observation and based on unstable and non-numerical data from the EEG signals.

The inputs are initially fuzzified, followed by inference on the fuzzy rule base, defuzzification (where the fuzzy result of the rules is transformed into a crisp output), and so on.

Three input fuzzy sets and one output fuzzy set are defined in this study to make the construction of the fuzzy system for classifying EEG signals simpler. For the system to provide the desired results, the inputs to the fuzzy system must be meaningful in order to construct fuzzy rules.

Three membership functions—neg (negative), spos (small positive), and lpos (large positive)—are defined for each of the three inputs. The result of the fuzzy system is a frequency range with low, medium, and high membership functions. 500 Hz (low), 2000 Hz (mid), and 4000 Hz (high) are the desired classification outputs, and MOM (mean of maximum) is the appropriate defuzzification technique in this study.

By examining the range of data for each input over 100 sets of data, the range of each membership function for each input is identified. The study uses a triangular membership function. The other 30 sets of EEG signals are then recognized by the fuzzy system. 24 of the 30 evaluated sets of EEG data could be correctly recognized using a fuzzy method. The identification of 2000 Hz and thus is 100% accurate, however the accuracy of the identification of the responses at 500 Hz and 4000 Hz is only 6/10 and 8/10, respectively. Due to some overlap between the two EEG responses, the classification accuracy for 500 Hz and 4000 Hz frequencies of 500 Hz and 4000 Hz is inaccurate.

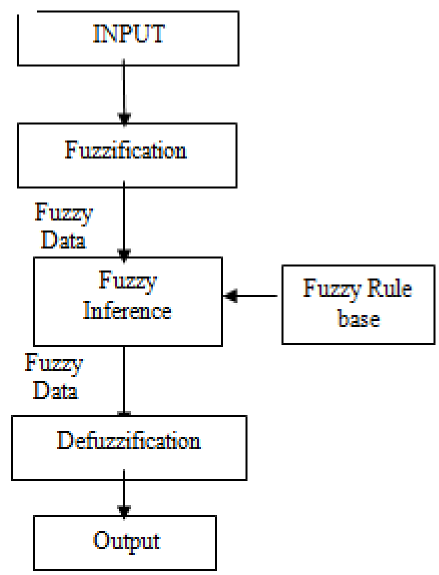

Fig 2. Operation of fuzzy

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

A fuzzy system is created by interpreting the features of the input-output model. Only fixed membership functions are examined for input membership functions to rules, rules to output membership functions, and output membership functions to a single-valued output. As a result, the membership functions selected must be capable of modeling the characteristics of the fuzzy variables. However, for non-linear and non-statistical input, such as EEG signals, it is always difficult to determine what the membership function should look like merely by inspecting the EEG data. Rather than randomly selecting the parameters associated with a given membership function, these parameters should be selected in order to tailor the membership functions to account for variations in a collection of input/output data sets. In such situations, an adaptive neuro-fuzzy inference system (ANFIS) with adaptive neuro-learning can be used.

ANFIS, as the name implies, is a system that incorporates both A.I. techniques, neural networks, and fuzzy logic. The neural network method can learn, whereas the fuzzy system works with data that has some degree of ambiguity or uncertainty. MATLAB's Fuzzy Logic Toolbox offers ANFIS functionality, where the neuro-adaptive learning method is used for the fuzzy modelling procedure.

In this research, the ANFIS inputs are similar to the previously derived fuzzy system inputs. The outputs for those inputs are crisp numbers ranging from 0 to 1. The ANFIS output values for the intended classified output of 500 Hz, 2000 Hz, and 4000 Hz are 0.01, 0.5, and 0.99, respectively. With the assumption that the output is linear, the output classification can be derived as follows:

1. If the ANFIS result is 0.35, the recognized frequency is 500 Hz.
2. The recognized frequency is 2000 Hz if the ANFIS result is between 0.35 and 0.65.
3. If the ANFIS result is greater than 0.65, the recognized frequency is 4000 Hz.

The Fuzzy Logic Toolbox's ANFIS function is used to perform the training in order to define a better matching of membership function parameters that will enable the associated fuzzy inference system to monitor the given input-output pairs of data. Figure 3 depicts the ANFIS-generated FIS framework.

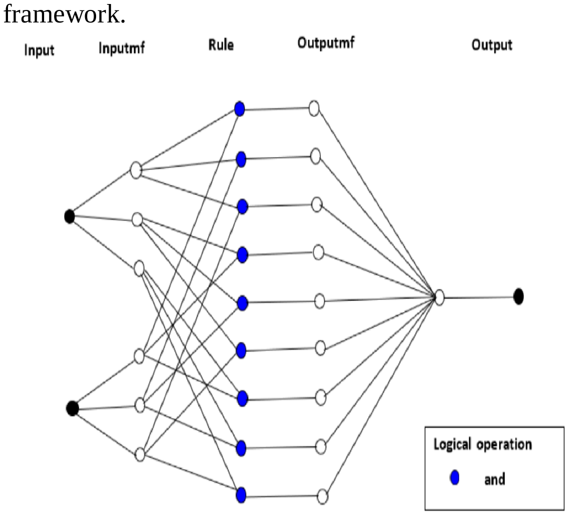

Figure 3 FIS Structure generated from ANFIS

102 sets of training data were entered into the ANFIS with goal outputs of 0.01, 0.5, and 0.99 for 500 Hz, 2000 Hz, and 4000 Hz responses, respectively.

The designed ANFIS system is then used to analyze the remaining 30 pairs of EEG signals. When tested on the 30 test data sets, the ANFIS classifier designed in this research had 100% accuracy. Allowing for some ambiguity in the ANFIS direct output, the output is then mapped to the goal frequency using the criteria.

III. CONCLUSION

According to the findings of this research, the ANFIS classifier has the highest accuracy, i.e. 100% accuracy, followed by the ANN classifier with 93.33% accuracy, and finally the fuzzy system classifier with only 80% accuracy. The fuzzy system has the lowest accuracy because its parameters are determined by a simple inspection of the DWT analysis and the power spectrum of the various frequency responses. This method contains no adaptive learning. The accuracy of the ANN classifier increases as the weights and biases of the ANN are modified based on the learning from the training data. The accuracy of the ANN can be improved further by adjusting the system's weights and biases and training the ANN with a smaller mean square error, mse, as the training objective. ANFIS combines the benefits of neural networks and fuzzy logic, where an adaptive learning algorithm is used to define the best membership functions that fit to model the input-output relationship and a certain level of fuzziness more precisely is allowed onto the inputs, which is suitable to model highly non-linear and non-statistical signals like the EEG. As a result, the ANFIS has the highest accuracy of the three classifiers in this research, reaching 100% accuracy.

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