# EEG Based Hearing Threshold Perception Classification Using Multilayer Perceptron Neural Network

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***Abstract-*** *An acoustical stimulation can cause an EEG signal known as an auditory evoked potential to emerge from the scalp of the brain. The click-sound stimuli excited at three distinct frequencies were heard and the auditory evoked potential (AEP) signals that arose while hearing them were recorded in this study. The recorded AEP signal was used to extract the spatial and temporal characteristics of four different bands. The individual's hearing frequency perception response was then connected to the retrieved information, and neural network models for the left and right ears were created. The constructed neural network model's maximum classification accuracy in differentiating a person's hearing frequency perception response has been observed to be 94.5 percent.*

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

## I. INTRODUCTION

EEG is a non-invasive clinical tool that can be used to diagnose brain disorders and has applications in both physiological research and medicine. From babies to adults, vital brain functions can be observed using EEG waves. The amount of hearing capacity is reflected in the somatosensory stimuli connected to the visual and auditory [1, 2, 3]. When an auditory input is provided in a time-locked fashion, the brain produces an EEG signal called an AEP. The reproducible positive or negative peaks, latency, amplitude, and behavioural association are all components of the AEP signal. AEPs have a substantially lower amplitude than EEG signals [4, 5]. The AEP response reveals a person's level of auditory proficiency. The earliest phase (0–12 millisecond) of AEPs is made up of auditory brain stem responses (ABRs).ABRs are made up of Jewett waves, which are a collection of waves and peaks. The Roman numerals I–VII are used to identify the ABR waves or peaks. Clinically relevant waves are typically thought to be I, III, and IV [6]. The peak components of the perceived signal were found to have significantly increased, according to Picton et al. [7]. Furthermore, it has been noted that the perceived signal's peak evoked peak was closer to 450 msec. The level of a subject's hearing perception was indexed using the discovered signals dependent on the condition of the stimuli. For the AEP recordings of people with normal hearing and those with impaired hearing, Shangkai et al. [8] computed the AR models.The ability to distinguish between normal and pathological hearing perception is provided by the hearing thresholds estimated using AR models. The estimated hearing threshold derived using a parametric model and the audiologist's evaluation accord well. By employing auditory evoked potential, Maryam Ravan et al. [9] showed that machine learning algorithms can be utilised to categorize specific subjects. The greedy technique was used to choose the evoked potentials' wavelet coefficient characteristics. Several machines learning methods, including the multilayer perceptron, support vector machine, and fuzzy C means clustering, were used to categorize the retrieved characteristics.

From the captured auditory evoked potential signals, Sriraam extracted time domain and frequency domain features to distinguish between target stimulus and non-stimulus hearing perception. For subjects with normal hearing, a classification accuracy of 65.3% to 100% has been reported. The click-sound was aroused at three frequencies in this study: 500 Hz, 1000 Hz, and 2000 Hz, with a fixed acoustic stimulus intensity of 25 dB. The AEP signals that were generated during this perception were recorded. From the collected AEP signals, four distinct energy bands' spatio-temporal characteristics were extracted, correlated to the subjects' hearing frequency perception level, and a network model was created. Figure 1 displays the block diagram of the proposed EEG-based hearing frequency perception level detection system.

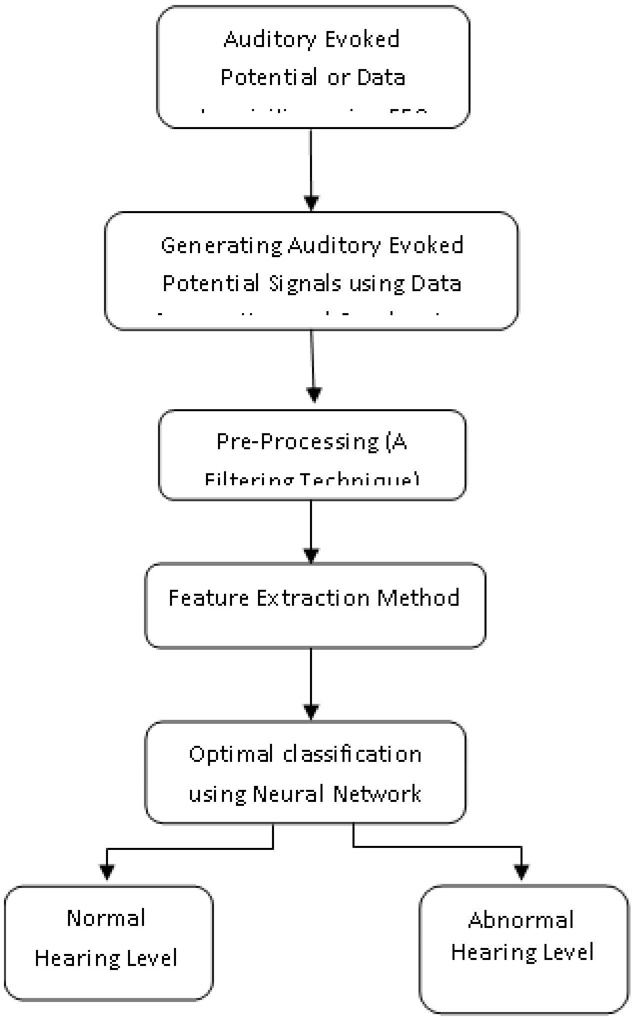



Figure I shows a technique for detecting the amount of hearing frequency perception based on EEG.

The structure of this essay is as follows. The suggested approach for the AEP hearing frequency perception response procedure is explained in Section II. The development of a neural network model and an analysis of its performance are presented in the next section. Findings and a conclusion complete the paper.

## II. RELATED WORK

The majority of researchers have used different neural networks and algorithms for their EEG data collecting systems. Auditory evoked potential signals were produced utilizing feed forward neural network with backpropagation algorithm as part of a classification approach for the hearing threshold[1].The K-Nearest Neighbors algorithm was used to classify the acquired feature sets after two different types of AEP signals were gathered [2]. The upper and lower hearing threshold components of an individual were extracted using the Autoregressive (AR) pole tracking technique, which records the position of the poles [3]. In clinics, the method of determining a person's threshold level makes use of a multilayer feed forward neural network and the Levenberg-Marquardt algorithm (LM) to create final results[4]. To combine an EEG-based auditory attention detection (AAD) paradigm with an acoustic noise reduction technique, Tom Francart has presented a solution employing the beamforming algorithm[5]. A machine learning system that uses the Multilayer Perceptron Algorithm to automatically classify different types of hearing loss[6]. Auditory evoked potential signals (AEP) were suggested as a method for intelligently assessing the level of hearing ability [7]. Neetha Das has presented an EEG-based auditory attention detection (AAD) paradigm based on the multi-channel Wiener filter[8] using Multilayer Feedforward Network. Using the Levenberg-Marquardt algorithm, the hearing capacity of various age groups is measured [9]. According to Kamalraj Subramaniam's research, participants with hearing loss have a higher gamma band power value than participants with normal hearing [10].

## III. AEP HEARING FREQUENCY PERCEPTION PROTOCOL

### A. Experiment setup:

A straightforward experimental setup has been developed and suggested in order to gather the auditory evoked EEG signal from the brain. A mindset-24 EEG amplifier and an audio metric booth SM960-D are part of the experimental equipment. According to EN ISO 389-7:2005 standards, the audiometric booth was calibrated. A single earphone was utilized, albeit the test ear varied depending on the subject's preference.

In order to ensure adequate electrical conductivity between the skin and the electrodes, the subjects were asked to wash their hair the night before the EEG recordings and to refrain from using hair products. Prior to the trial, the volunteers were required to have enough sleep. The individual was lying comfortably within the audiometric booth during the trial. Five participants with normal hearing took part in this experimental study. The individuals were all between the ages of 22 and 25. All of the participants were postgraduate students at the University of Malaysia Perl. Each individual was in good health and not using any medications.

### B. AEP data acquisition:

The most fundamental clinical audiology approach is the assessment of hearing sensitivity to pure tones. Each threshold run was preceded by an initial familiarization exercise to make sure the listener could recognize the tone and comprehend the challenge. The behavioral hearing threshold thresholds for the right and left ears must be established separately. All individuals' left and right preoperative pure tone hearing thresholds were measured for three fixed frequencies (500 Hz, 1000 Hz, and 2000 Hz) and varied stimulus intensities (from 20 dB to 70 dB). In order to make sure the subjects could hear and perceive the appropriate sound stimulus, the mean hearing threshold values for the frequencies were computed. The average threshold was recorded by each participant, with standard deviations of 20.52.4 dB for the right ear and 222.5 dB for the left ear. Using an EEG amplifier called the Mindset-24, auditory evoked potentials were captured using an active listening paradigm. The left and right mastoid were utilized as reference electrodes, and electrodes were inserted at the T3, T4, T5, and T6 regions using the 10-20 electrode placement system (Standard placement Nomenclature, American Encephalographic Association) [11]. The chosen temporal region affects how well some memory processes and hearing perceptions stand [12]. To verify the subject's proper data has been obtained, the subjects' EEG signals were originally recorded with their eyes closed and opened for 60 seconds.

Impulsive click sounds at frequencies of 500 Hz, 1000 Hz, and 2000 Hz were presented to the individuals at a constant stimulus intensity level of 25 dB. The subjects were exposed to stimuli and frequencies while listening to various sound levels through earbuds. The subjects were exposed to the auditory stimulus (click sound) through earphones after manually pressing a button to create the click sound. For 10 seconds, auditory evoked potentials were captured in order to capture the contribution of overlapping AEPs from earlier stimuli. AEP signals were captured for 10 seconds at 256 Hz sample rate. Given that the interest frequency of the input signals is below 100 Hz, 256 Hz has been chosen as the sampling frequency to satisfy the sampling condition. The subjects were instructed to mentally count the click sound without speaking, and they were then asked to report at the end of the experiment. Subjects were urged to pay attention and respond accurately for five trials while reaction times and accuracy of detection were tracked. If the participants properly counted the number of click sounds, the trails were accounted for in the AEP database.

### C. Hearing frequency perception feature extraction

The recorded raw AEP signals were first divided into frames, each of which contained 256 samples with a 50% overlap. In order to enhance the combinations of data representation of feature set with adequate accuracy, frame overlapping was used. After segmentation, 17 frames were obtained as each AEP signal trailed for 10 seconds with a total of 2560 samples captured. After segmenting the data, four electrode positions were used to extract the delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–40 Hz) frequency bands using a Chebyshev Infinite Impulse Response Filter. The pass band of the Chebyshev second order filter is monotonic, and the only place where ripples are present is in the stop band, where there is a sharp roll off to the input AEP signals. Figure 2 displays the channels T3, T4, T5, and T6's filtered delta, theta, alpha, and beta for a typical frame. The filtered band signals are then used to obtain the temporal energy entropy band characteristics using Equation (1).

$$E = \sum_{n}^{N} x(n) \ln(x(n))^2 \quad (1)$$

where
E is the energy entropy,
x( n) is the nth sample of the filtered signal.
n= 0, 1, 2, ... , N-l, are the discrete time indices

There are four temporal energy elements in a segmented frame of the filtered signal. A feature set of 16 features was created by combining the four channels' temporal entropy features. A data set of 1275 feature samples has been created using the total of five trails for five subjects and the segmentation of each single trail into 17 frames. The corresponding auditory perception frequencies for these feature samples were then assigned. The filtered band data were positively Fourier converted in this spectral feature extraction technique, and Equation (1) was used to derive the matching spectral energy entropy. An individual's frequency-based hearing perception level is represented by 1275 data samples in the extracted spectral energy entropy feature set, which is then correlated with the individual's hearing frequency perception level (HFPL).

## IV. HFPL CLASSIFICATION USING NN

The most widely used neural network architecture, the multilayer perceptron (MLP), gets its computing power from a massively parallel distributed topology. [13]. Two distinct neural network models were created using time-frequency domain features to distinguish between the frequency associated hearing perception levels of the right and left ears of a normal hearing person. Both neural network models comprise two output neurons to categorize the three hearing frequency perception levels and 16 input neurons reflecting the AEP properties. There are 1275 samples in the master data set. The remaining 510 samples (or the remaining 40% of the master data samples) were used for testing after the neural network had been trained with the first 765 samples (or

60% of the master data set samples). The training samples are chosen at random from the total samples in order to create a generalized neural network. The data sample is normalized using the binary normalization procedure between 0.1 and 0.9. Using the log sigmoid function, the two output neurons and the 12 hidden neurons are triggered. The neural network model underwent training with a 0.0001 tolerance and testing with a 0.1 tolerance. During the training sessions, the mean squared error (MSE) halting criterion was applied. The MLP is trained using the Levenberg-Marquardt (LM) algorithm for each weighted sample.

## V. RESULTS

The recorded AEP signal was used to derive the spatiotemporal energy entropy properties of four different bands. Two network models (one for the right ear and the other for the left ear) were created based on the retrieved temporal data and the individuals' hearing frequency perception levels. The network weights were initialized to 0.5 to 0.5 and normalized during training. Five different sets of randomized weight values were used to train the network in each trail, and their corresponding epoch and classification accuracy were noted. There were five of these trials, and the combined findings, including the minimum, maximum, mean, minimum, and mean classification accuracy of temporal energy entropy, are provided in Table I. According to Table I, the right ear's categorization accuracy for hearing frequency perception is 75.2%, whereas the left ear's is 72.7%. Additionally, it can be seen that the right ear models' minimum and maximum classification accuracies are 67.6% and 75.2%, respectively. The minimum and maximum classification accuracy for the left ear network models are also observed to be 67.4% and 72.7%, respectively. For both the right and left ear models, the highest mean classifications are 73.6% and 72.2%, respectively. The trained right ear network models' minimum and maximum epochs were found to be 126 and 300, respectively. The minimum and maximum epochs are seen to be 175 and 360 correspondingly for the left ear network models. The right and left ear network models' total mean epochs are observed to be 200 and 260, respectively.

TABLE I. CLASSIFICATION OF TEMPORAL ENERGY ENTROPY FEATURE USINGMLP

| Trail No | Ear | Epoch | | | Classification Accuracy | | |
|---|---|---|---|---|---|---|---|
| | | Min | Max | Mean | Min | Max | Mean |
| | | | | | | | |
| 1 | R | 179 | 230 | 204.5 | 69.4 | 72.6 | 70.5 |
| 2 | R | 193 | 200 | 196.5 | 67 | 69.1 | 68.1 |
| 3 | R | 157 | 300 | 228.5 | 70.5 | 74.9 | 72.9 |
| 4 | R | 130 | 198 | 164 | 71.2 | 72.5 | 71.5 |
| 5 | R | 120 | 234 | 177 | 72 | 75.9 | 73.5 |
| | | | | | | | |
| 1 | L | 195 | 245 | 220 | 68.1 | 71.5 | 69.9 |
| 2 | L | 173 | 230 | 200 | 67.3 | 68.6 | 67.5 |
| 3 | L | 218 | 300 | 250 | 66.1 | 69.4 | 67.3 |
| 4 | L | 290 | 350 | 300 | 71.6 | 72.8 | 72.6 |
| 5 | L | 230 | 370 | 290 | 70.1 | 72.4 | 71.3 |

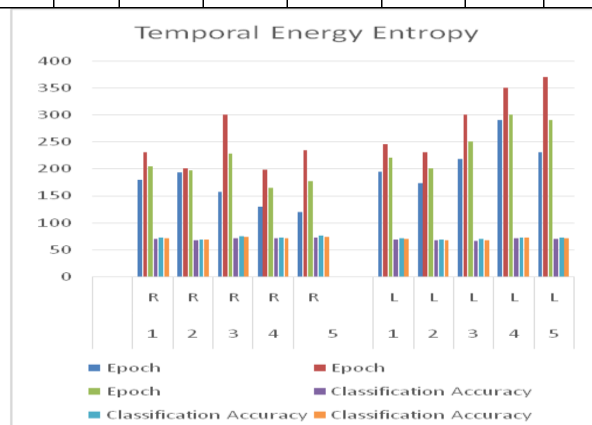
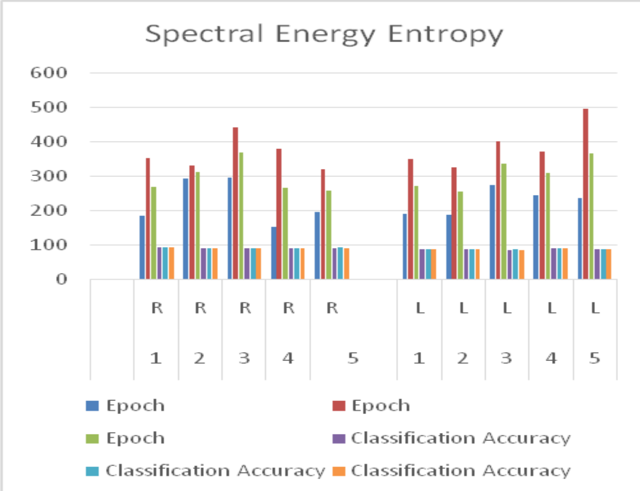



TABLE I. CLASSIFICATION OF SPECTRAL ENERGY ENTROPY FEATURE USINGMLP

| Trail No | Ear | Epoch | | | Classification Accuracy | | |
|---|---|---|---|---|---|---|---|
| | | Min | Max | Mean | Min | Max | Mean |
| | | | | | | | |
| 1 | R | 185 | 352 | 268.5 | 93.1 | 94.8 | 93.95 |
| 2 | R | 294 | 332 | 313 | 91.6 | 92.4 | 92 |
| 3 | R | 297 | 441 | 369 | 90.6 | 91.7 | 91.15 |
| 4 | R | 153 | 380 | 266.5 | 91.7 | 92.5 | 92.1 |
| 5 | R | 196 | 320 | 258 | 92.2 | 93.4 | 92.8 |
| | | | | | | | |
| 1 | L | 192 | 350 | 271 | 87.9 | 88.3 | 88.1 |
| 2 | L | 187 | 325 | 256 | 88.4 | 89.7 | 89.05 |
| 3 | L | 275 | 400 | 337.5 | 86.1 | 88.4 | 87.25 |
| 4 | L | 245 | 372 | 308.5 | 90.7 | 91.6 | 91.15 |
| 5 | L | 237 | 495 | 366 | 88.8 | 89.7 | 89.25 |




Dual network models were created (one for the right ear and the other for the left ear), each of which was based on the retrieved spectral features and the individuals' hearing frequency perception levels. The network weights were initialized to 0.5 to 0.5 and normalized during training. Five different sets of randomized weight values were used to train the network in each trail, and their corresponding epoch and classification accuracy were noted. Five of these trails were run, and the combined findings, including the minimum, maximum, mean, and minimum, maximum, and mean spectral energy entropy categorization accuracy, are provided in Table II. The maximum categorization accuracy of hearing frequency perception for the right ear is 94.S% and for the left ear is 91.3%, as can be seen in Table II. Additionally, it can be seen that the right ear models' minimum and highest classification accuracies are 90.4% and 94.S%, respectively. The highest and minimum classification accuracy for the left ear network models are similarly observed to be 88% and 91.3%, respectively. For both the right and left ear models, the highest mean classifications are 93.8% and 90.8%, respectively. The trained right ear network models' minimum and maximum epochs are observed to be IS4 and 440, respectively. The minimum and maximum observed epochs for the left ear network models are 188 and SOO, respectively. For the right and left ear network models, the observed average epochs are 298 and 3lO, respectively.

The analysis demonstrates that the four channels (T3, T4, TS, and T6)'s spatiotemporal energy entropy features can be used to differentiate a person's perceived frequency-based hearing perception estimate. The findings show that the classification of the characteristics of the right and left ears differs significantly. The reason for the accuracy disparities is that the right ear naturally perceives sound stimuli more actively than the left ear. Additionally, the findings from behavioral hearing threshold levels for the right and left ears of the subjects reflect the findings from EEG-based hearing perception levels for the right and left ears, and vice versa.

## VI. CONCLUSION

In this study, four different energy bands' spatio-temporal domain properties and their corresponding hearing frequency perception level of each person were recovered from the recorded AEP signal. The results show that the AEP spectral energy entropy feature outperforms the temporal features of a normal hearing person in identifying the perceived hearing frequency perception levels. The observed results support the validity of the suggested AEP hearing frequency perception response methodology for assessing frequency-based perception level for normal hearing person. The proposed procedure for estimating HFPL can be used to estimate HFPL for newborns, infants, and people with multiple disabilities who lack verbal communication and behavioural responses to sound stimulation.

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