Jurnal
Teknologi

Full Paper

CLASSIFICATION OF HEARING PERCEPTION LEVEL USING AUDITORY EVOKED POTENTIALS

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Article history
Received
1 June 2015
Received in revised form
13 August 2015
Accepted
29 September 2015

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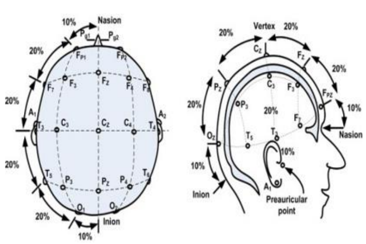
Graphical abstract



Abstract

An auditory loss is one of the most common disabilities present in newborns and infants in India. A conventional hearing screening test's applicability is limited as it requires a feedback response from the subject under test. To overcome such problems, the primary focus of this study is to develop an auditory loss assessment system using auditory evoked potential signals (AEP). The AEP responses of fourteen normal hearing subjects to auditory stimuli (20 dB, 30 dB, 40 dB, 50 dB and 60 dB) were derived from electroencephalogram (EEG) recordings. Box counting fractal method is applied to extract the fractal features from the recorded AEP signals. Feed forward and feedback neural networks are employed to distinguish the different hearing perception levels. The performance of the proposed auditory loss assessment system found to exceed 80% accuracy. This study indicates that AEP responses to the auditory stimuli to the normal hearing persons can clearly distinguish the higher order auditory stimuli followed by the lower order auditory stimuli and it can be used to estimate the level of hearing loss in the patient.

Keywords: EEG, auditory evoked potential, hearing perception level, feed forward network, feedback network

1.0 INTRODUCTION

Auditory evoked potential (AEP) can be observed as an electroencephalogram (EEG) signal elicited from the brain while an auditory stimulus is presented in a time-locked manner. AEP response reflects the neural processing of hearing ability level of an individual. AEP signal consist of reproducible positive or negative peaks, latency, amplitude and behavioural correlation [1]. Depending upon the latencies, AEP can be subsequently divided into short (0-12 milliseconds), middle (8-50 milliseconds) and long latency evoked potentials (50-300 millisecond) [2]. Most of the researchers mainly focused on the analysis of auditory brainstem response (ABR), the early portion (10-12 msec) of AEP signal. ABR signal comprised of seven peaks (I-VII), of which pre-dominant presence or absence of peak V essentially determines the hearing ability level [3, 4]. Early researchers have developed different techniques to detect the ABR peak V using spectral energy [5], matched filter [6], spectral analysis [7] and wavelet analysis [8].

The major difficulties encountered in identifying the ABR peak V are 1) At least 1000 to 2000 trials are necessary in order to realize the structure of a waveform with defined peaks, hence the task of averaging the ABR waveform becomes difficult and consumes more time; 2) it is quite complex to segregate the associated ABR peak IV and peak V; 3) it is also very difficult to search and identify the individual peaks of the ABR for abnormal hearing subjects, because of pathology of the auditory nerve. Further, it has also been reported that is finding the ABR peak V is difficult when the stimulation intensity level is below 30 dB, the defined five peaks are no longer visible [9]. Consequently, the identification of peak V appears to be quite difficult, and the level of confidence declines in the objective measure of hearing threshold.

Gao and Murray [10] postulates a new objective AEP measurement that measures the EEG signal after an onset of the stimulus. The auditory stimuli were presented bilaterally with monaural acoustical stimulus to the ears. EP signals were recorded from 1.5 ms to 10 ms, and contain 145 data points. The measured AEP signal comprises of different structures or characteristics for normal and abnormal hearing subjects. The estimated AEP hearing threshold values by parametric modeling techniques discriminate the normal and abnormal hearing subjects.

Sudirman and Seow [11] have collected the EEG signal from two normal hearing subjects with the mean age of 21.5 years. The subjects were exposed to sound stimuli with modulated frequency levels 400 Hz, 500 Hz, 5000 Hz, and 15000 Hz. The gamma rhythm values are higher than other rhythms and it shows the relationship between the frequency perception and the brain response. AEP data has been recorded using 16 channels EEG for 10 seconds from eight participants. A click stimulus was used to evoke the potential response.

AEP signals were used to differentiate the hearing perception based on the target and the non-target stimulus.

In this paper, a simple hearing perception level protocol using AEP signals have been proposed to determine the inter-hearing perception level of the normal hearing subjects. The normal safe hearing level of a human subject ranges from 20 dB to 80 dB. In the experimental study, the AEP signals are stimulated at four distinct hearing frequency levels (1000 Hz, 2000 Hz, 4000 Hz, and 8000 Hz) and along with different sound intensity levels (20 dB, 30 dB, 40 dB, 50 dB and 60 dB); the corresponding hearing perception levels have been unilaterally recorded with monaural acoustical stimulus. Higuchi fractal feature vectors were extracted from the recorded AEP signals, whereas previous researchers have not explicitly used this fractal feature for any hearing perception analysis. Feed forward and feedback neural network models for the left and right ears were developed. The block diagram of AEP based hearing ability level assessment system is shown in Figure 1.

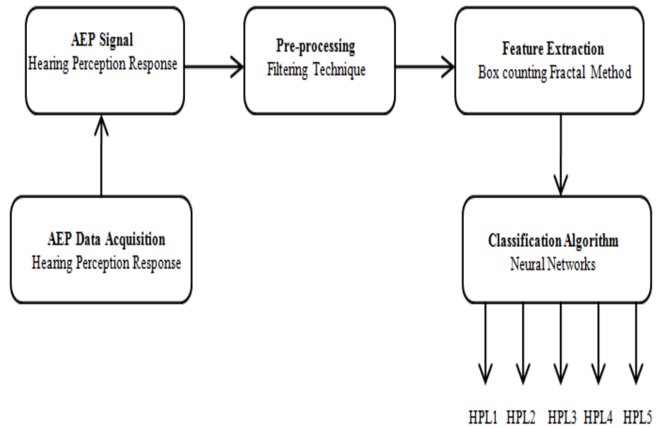


Figure 1 An intelligent hearing ability level assesment system

2.0 MATERIALS AND METHODS

2.1 Subjects

A participant selection criterion plays an important role in minimizing the confounding variables. Fourteen subjects were participated in the experimental study. The normal hearing group (NHG) consisted of fourteen normal hearing subjects (NHG: fourteen males; age 25.4 ± 3.6 years). The experimental procedure and the protocols were explained to NHG with help of research scholars. Participants with external ear pathology, a neurological disorder, or who were under the period of certain medications were excluded from the study. A written consent was obtained from all the subjects prior to proceeding with the experiments. All the subjects were healthy and free of any medication.

2.2 Behavioral Audiometry Test

To record the auditory evoked EEG signal from the normal hearing subjects, a simple hearing perception level protocol was formulated and proposed in this study. The experimental study involves a two-fold procedure to acquire the AEP data from the subjects. First, the subjects were allowed to participate in the hearing screening test and the hearing threshold values were determined using the behavioral pure-tone audiometric test [12].

Behavioral pure tone screening audiometry test was conducted in a soundproof booth at the acoustic research lab, Universiti Malaysia Perlis, Perlis. A SM960-D diagnostic memory audiometer was used to perform the diagnostic behavioral pure tone audiometry. A pure tone stimulus was presented through headphones. Behavioral pure tone stimulated at 1 kHz, 2 kHz, 4 kHz and 8 kHz at various stimulus intensities range from 70 dB to 20 dB in the left and right ear.

2.3 AEP Based Hearing Protocol

The EEG signals were recorded using the Mindset-24 EEG amplifier portable biosignal acquisition system (nineteen EEG bipolar channels; filters: 0.5-100 Hz; data acquisition: A/D converter with 12-bit resolution and sampling frequency range: 128 Hz, 256 Hz, 512 Hz, meets IEC 60601-1 standard for research purpose) [13, 14]. Using 10-20 electrode positioning system (Standard Positioning Nomenclature, American Encephalographic Association), electrodes was placed (temporal) over the locations T3, T4, T5 and T6. The left and right mastoid was made as the reference electrodes [15]. The EEG signals were initially recorded from the subjects with their eyes closed and also in the open position for 60 seconds. Subsequently, the signals were investigated manually in order to ensure that the data recorded were in appropriate manner [16]. The experimental setup for AEP data collection is shown in Figure 2.

Figure 2 Experimental setup for AEP data collection

3.0 BOX COUNTING FRACTAL FEATURE

Fractal Dimension (FD) is a descriptive quantitative measure that provides a single non-integer value (fractional) and quantifies the characteristics of a signal. One of the main characteristic of fractal feature is that it presents invariance under time and/or space translations. Box-counting method employs the self similarity property to compute the FD values and it is the most commonly employed method used to compute the FD values. In this method, the signal is completely covered with collection of square boxes and the numbers of square boxes are then counted [17].

The AEP signal X^j obtained from the j^{th} channel is divided into *F* number of frames and written as

$$X^j = \left[X_1^j, X_2^j, X_3^j, \ldots, X_i^j, \ldots, X_F^j\right] \quad (1)$$

Further, each frame of the AEP signal consists of 256 samples and the ith frame can be represented as:

$$X_i^j = \left[x_i^j(1), x_i^j(2), x_i^j(3), \ldots, x_i(r), \ldots x_i(256)\right] \quad (2)$$

where,

X_i^j is AEP signal corresponding to the i^{th} frame of the j^{th} channel.

The FD can be estimated mathematically using box counting method using the following relationship,

$$FD_{BC} = -\lim_{r \to 0} \frac{\log_2(N(r))}{\log_2(1/r)} \quad (3)$$

where,

$$N_r = \sum_m (n_r(m)) \quad (4)$$

N(r) is the total number of boxes of size *r* required to cover the AEP signal.

The value of n_r (m) from the difference between the maximum and minimum amplitude values of the data divided by the radius.

$$n_r(m) = \left[\frac{max(X_i^j) - min(X_i^j)}{r(m)}\right] \quad (5)$$

where,

r (m)- is a radius by changing a step size of *k* for $\{r \in 2^k \; k = 1,2,3,\ldots \log_2(L) - 1\}$

4.0 NEURAL NETWORK CLASSIFIERS

Artificial neural network (ANN) provides us with a new tool for designing an intelligent machine that can learn, recognize and controls the decision-making process. In general, neural network is an information processor; a single neuron performs the computation of its weighted inputs and yields an output through a non-linear activation function [18]. In this study, an intelligent hearing ability level assesment design with feed forward model multilayer perceptron neural network (MLPNN) and feedback model Elman neural network (ENN) classifers are investigated to find suitable neural network architecture for a hearing perception level assessment system. The neural network models are configured based on selection of activation function, hidden neurons learning rate and momentum factor. In this experiment a five class intelligent hearing ability level assessment system is designed using MLPNN and ENN classifiers. Using Higuchi fractal features, eight different neural network models are developed for the left and right ears in distinguishing the five hearing perception levels (20 dB, 30 dB, 40 dB, 50 dB and 60 dB) for four distinct hearing frequencies. In order to classify AEP dataset the each network is modeled with 4 input neurons, 3 output neurons. Table 1 shows the configuration of MLPNN and ENN models. The master dataset consists of 350 samples for the left and right ears. 60% of the data (210 samples) is used in the network training and the performances of the classifier are observed for remaining 40% of the data (140 samples). In order to develop a generalized neural network model, the training samples are selected randomly from total samples.

The results of the MLPNN classifier for left and right ears for four distinct hearing frequencies are shown in Table 1; the Table 2 displays the performance of the network classification of the AEP signal into the five hearing perception levels.

Table 1 Configuration of MLPNN and ENN models

NN	Hidden neurons	Input activation function	Output activation function	Learning rate	Mean square error (MSE)	Learning algorithm
MLPNN	15	log sigmoid	log sigmoid	0.8	0.001	Levenberg Marrqdt
ENN	21	log sigmoid	log sigmoid	0.7	0.001	Gradient descent BP algorithm with an adaptive learning rate

Table 2 Classiifcation of hearing perception levels using MLPNN

Hearing Frequency Level (Hz)	Ear	#Epoch Min	Max	Mean	Classification Accuracy Min	Max	Mean
1000	L	3500	4200	3850	**65.71**	**69.28**	**67.49**
2000	L	3850	4185	4520	67.14	72.85	69.99
4000	L	4000	4574	4287	69.28	75.00	72.14
8000	L	3900	4659	4280	**71.42**	**78.87**	**75.14**
1000	R	4462	4686	4850	**65.71**	**71.42**	**68.56**
2000	R	4530	4641	4752	69.28	72.85	70.93
4000	R	4756	4853	4950	70.00	77.14	73.57
8000	R	4850	5025	5200	**72.85**	**80.17**	**76.51**

Table 3 Classiifcation of hearing perception levels using ENN

Hearing Frequency Level (Hz)	Ear	#Epoch Min	Max	Mean	Classification Accuracy Min	Max	Mean
1000	L	7200	7650	7425	62.85	67.85	65.35
2000	L	7500	7924	7712	64.28	70.00	67.14
4000	L	7850	8050	7950	65.71	71.42	68.56
8000	L	8020	8300	8160	69.28	72.85	71.06
1000	R	7400	7860	7630	65.71	67.14	66.42
2000	R	7628	7920	7774	64.28	70.00	67.14
4000	R	7900	8500	8200	67.85	72.14	69.99
8000	R	8250	8750	8500	69.28	75.00	72.14

4.0 RESULTS AND DISCUSSION

In this paper, a simple method to estimate the different hearing levels using Higuchi features has been discussed. Higuchi fractal features were extracted from the recorded AEP signals. The extracted features were associated to the different hearing perception level of the various normal hearing subjects. Form Table 2, an intelligent hearing ability level assessment system using Box counting fractal feature and modeled using MLPNN for the hearing frequency level of 8000 Hz has obtained the highest mean classification accuracy of 75.14% and 76.51% for the left and right ears. Further, it can be inferred that for the hearing frequency level of 8000 Hz has obtained the highest minimum classification accuracy of 71.42%, 72.85% and highest maximum classification accuracy of 75.81%, 80.17% for the left and right ears, respectively. It is also observed for the hearing frequency level of 1000 Hz has obtained the minimum mean classification accuracy of 67.49% and 68.56% for the left and right ears. Further, it can be inferred that for hearing frequency level of 1000 Hz has obtained the lowest minimum classification accuracy of 65.71%, 65.71% and the lowest maximum classification accuracy of 69.28%, 71.42% for the left and right ears, respectively.

From Table 3, an intelligent hearing ability level assessment system modeled using ENN for hearing frequency level of 8000 Hz has obtained the highest mean classification accuracy of 71.06% and 72.14% for the left and right ears. Further, it can be inferred that the Box counting algorithm for hearing frequency level of 8000 Hz has obtained the highest minimum classification accuracy of 69.28%, 69.28% and highest maximum classification accuracy of 72.85%, 75.00% for the left and right ears, respectively. It is also observed that for the hearing frequency level of 1000 Hz has obtained the minimum mean classification accuracy of 65.35% and 66.42% for the left and right ears. Further, it can be inferred that for the hearing frequency level of 1000 Hz has obtained the lowest minimum classification accuracy of 62.85%, 65.71% and the lowest maximum classification accuracy of 67.85%, 67.14% for the left and right ears, respectively.

From the results, it can be inferred that an auditory frequency of 8000 Hz has relatively outperformed other auditory frequencies in classifying the different hearing perception levels. The acoustic structures of 8000 Hz contain higher energy components to traverse the auditory system, while compared with other acoustic structures. Further, it can be observed that the auditory frequency of 1000 Hz has made relatively less impact in classifying the different hearing perception levels while compared with other auditory frequencies. From the results, an auditory frequency of 8000 Hz stimuli quickly and more frequently reaches the activated auditory pathways. Hence, normal hearing persons can quickly perceive higher order auditory stimuli followed by the lower order auditory stimuli. From the results, it also indicates an asymmetric classification performance between the left and right ears, these significant differences are due to the inherent more active auditory stimuli perception made by the right ears compared to the left ears.

5.0 CONCLUSION

In this study, the hearing ability level assessment system using Higuchi fractal feature along with machine learning algorithm distinguishes the different hearing perception level. It also opens the possibility of devising a clinical test that can determine the hearing perception level of infants and adults. Further, the intelligent hearing ability level assessment system can also be used to help the neuro physicians in assessing the specific hearing loss and then accordingly can suggest more suitable cochlear implant designs to the hearing patients.

Acknowledgement

The authors would like to thank Brigadier General Dato' Professor Dr. KamarudinHussin, the Vice Chancellor, University of Malaysia Perlis for his continuous support and encouragement. The authors are thankful and would like to acknowledge the Fundamental Research Grant Scheme (FRGS) grant: 9003-00278 by Ministry of Higher Education, Malaysia

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