

EEG Based Detection of Conductive and Sensorineural Hearing Loss using Artificial Neural Networks

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Abstract

In this paper, a simple method has been proposed to distinguish the normal and abnormal hearing subjects (conductive or sensorineural hearing loss) using acoustically stimulated EEG signals. Auditory Evoked Potential (AEP) signals are unilaterally recorded with monaural acoustical stimulus from the normal and abnormal hearing subjects with conductive or sensorineural hearing loss. Spectral power and spectral entropy features of gamma rhythms are extracted from the recorded AEP signals. The extracted features are applied to machine-learning algorithms to categorize the AEP signal dynamics into their hearing threshold states (normal hearing, abnormal hearing) of the subjects. Feed forward and feedback neural network models are employed with gamma band features and their performances are analyzed in terms of specificity, sensitivity and classification accuracy for the left and right ears across 9 subjects. The maximum classification accuracy of the developed neural network was observed as 96.75 per cent in discriminating the normal and hearing loss (conductive or sensorineural) subjects. From the neural network models, it has been inferred that network models were able to classify the normal hearing and abnormal hearing subjects with conductive or sensorineural hearing loss. Further, this study proposed a feature band-score index to explore the feasibility of using fewer electrode channels to detect the type of hearing loss for newborns, infants, and multiple handicaps, person who lacks verbal communication and behavioral response to the auditory stimulation.

Keywords: EEG, Auditory Evoked Potential, Power Spectral Density, Neural Network.

1. Introduction

Hearing loss is the most prevalent sensory disability in the world. Over 275 million people in the world are differentially hearing ability level enabled. Hearing impairment survey was conducted in different countries, where as 0.5 per cent of newborns have onset of sensorineural hearing disorder [1][2]. Universal newborn hearing screening test consists of transient evoked oto-acoustic emissions (TEOAE) and automated auditory brainstem response (AABR). Auditory brainstem response (ABR) is an electrical potential signal emanated from the scalp of the brain by presenting a sound stimulus to assess the functioning of auditory neuropathy by using electroencephalography [3]. TEOAE machine mostly detects outer hair cells dysfunction (conductive hearing loss) where as AABR test was also able to detect neural conduction disorders (sensorineural hearing loss) [4]. AEP response reflects the neural processing of hearing ability level of an individual. Auditory brainstem responses (ABRs) comprise the early portion of (0-12 millisecond) of AEPs. In clinical application, the most predominant presence or absence of peak V in response to the perceived sound stimulus which determines the objective measure of hearing [5][6].

Delgada et al [7] have proposed the complete automated system for ABR response identification and waveform recognition. The analysis portion was divided into: (i) peak identification and labeling, (ii) ABR interpretation. When the threshold level was above 20 dB hearing loss, the subjects were flagged as having a form of hearing loss. When the peak intensity level was greater than 4.40 ms the subjects were flagged as having hearing pathologies. The accuracy measure of peak V was reported as 80-94 per cent for high threshold levels (50–100 dB) whereas performance of 60 per cent was observed at near threshold levels (30-40 dB). Robert Boston et al [8] proposed an expert decision support system for interpretation of brainstem auditory evoked potential response and improved the performance accuracy. The

prototype system consists of 36 rules. 13 rules were framed in order to find the presence of a neural response and 10 rules to identify a peak as peak V. 20 ABR recorded waveforms were tested with system; the rule-based expert decision system identifies 13 ABR waveforms. This proposed rule based system was not as effective in identifying ABR waveform when no response was present. Nurettin et al [9] automated recognition of ABR waveform to detect the hearing threshold of a person was proposed. In this method, amplitude values, discrete cosine transform coefficients, discrete wavelet transform coefficients were extracted from the ABR waveform classified using support vector machine and a classification accuracy of 97.7 % was reported. Jose Antonio et al [10] constructed and developed an EEG auditory evoked potential data acquisition system (EEG-ITM03) and used to determine the hearing impairment of a patient. The EEG- ITM03 can be used under non-noise controlled conditions. AEP data from their corresponding channels are acquired and processed the signal to identify the presence/absence of hypoacusia.

Sudirman et al [11] investigated EEG based hearing ability level identification using artificial intelligence. AEP signal was recorded for 10 seconds and collected from temporal lobes (T3, T4, T5, and T6) of the brain. The signals were analyzed using FFT. The extracted features were trained using gradient descendant algorithm with momentum. The feed-forward neural network was used to classify the hearing level based on brain signals. Emre et al [12] have used the continuous time wavelet entropy features of auditory evoked potential to characterize the relative energy in the EEG frequency bands. Continuous time wavelet entropy gives detailed information of EEG response of brain which determines hearing perception level of a person. Maryam Ravan et al [13] demonstrated that machine learning algorithms can be used to classify individual subjects using auditory evoked potential. The wavelet coefficients features of the evoked potentials were selected using greedy algorithm. The extracted features were feed into various machine learning algorithms such as multilayer perceptron neural network, support vector, fuzzy C means clustering. Sriraam extracted appropriate features from the recorded auditory evoked potential signals to differentiate the hearing perception based on target stimulus and non-stimulus. Applied two time domain features, spike rhythmicity, autoregression Levinson method and two frequency domain features, power spectral density (AR Burg method), power spectral density (Yule-Walker method) have a classification accuracy of 65.3–100 % for normal hearing subjects [14]. In most of the previous research works, the hearing threshold levels of the normal and abnormal hearing were determined using defined peaks (V) by recording the AEP signals bilaterally with monaural stimulation. In order to realize the structure of the AEP waveform with defined peaks, it requires 750-1000 trails which are time consuming. Further, the accidental movement of the subjects may mislead the interpretation of peak IV and V. References to a human expert were always needed in difficult cases. Further, the accuracy of the threshold determination depends on the relevance of the stimulation intensities. To identify and interpret the peak V in the AEP waveform for near threshold level (25-30 db) becomes fallible. Hence most of the researchers analyzed the complete waveform of AEPs instead of identifying the defined peaks. The hearing frequency synchronized with near hearing threshold level (25 dB) stimuli have not been analyzed by previous the researchers [11-14].

In this paper, AEP signals emanated while perceiving the click-sound excited at frequency of 1000 Hz with fixed acoustic stimulus intensity of 25 dB are recorded with infrequent shifts in intensity levels of the normal hearing, conductive or sensorineural hearing loss subjects. Power spectral features and spectral entropy features of gamma band were extracted from the normal hearing and abnormal hearing subjects. The extracted spectral features were then associated to the auditory perception and feed forward and feedback neural network models for left and right ears were configured. The feature based score index for 19 electrode channels were computed and their potential significant electrode channels were selected. The block diagram of the proposed EEG based hearing loss detection system was shown in Figure 1.

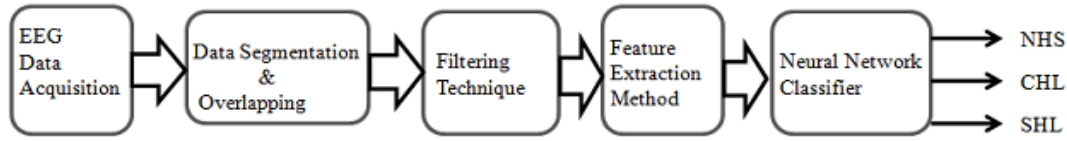


Figure 1. Block diagram of EEG based hearing loss detection system
 NHS- Normal hearing subject; CHL-Conductive hearing loss; SHL- Sensorineural hearing loss

This paper is organized as follows. Section II explains the proposed method of AEP data acquisition and its feature extraction method. In section III, the neural network models along with its performances are described. Section IV illustrates the results obtained from the feature classification. Finally, the paper is concluded with concluding remarks.

2. AEP Data Acquisition and Method

2.1. Experiment Paradigm

In order to collect the auditory evoked EEG signal from the brain, a simple experimental set up has been formulated and proposed. The experimental setup includes a mindset-24 EEG amplifier and an audio metric booth SM960-D [15]. The audiometric booth was calibrated as per EN ISO 389-7: 2005 standards. Although the test ear varied among the subjects depending upon their preference, a single earphone was used. The subjects were requested to wash their hairs the night before the EEG recordings and requested to avoid using hair chemicals or hair oils, in order to maintain good electrical conductivity between the skin and the electrodes. The subjects were required to have enough rest before the experiment was conducted. While conducting the experiment, the subject was seated comfortably inside the audiometric booth. For this experimental study, 3 normal hearing subjects, 3 conductive hearing loss subjects, and 3 sensorineural hearing loss subjects were participated. For abnormal hearing subjects, the protocol was explained to them with the help of a sign language interpreter. A written consent was obtained from all the subjects prior to the testing. All the subjects were healthy and free from any medication.

Preoperative threshold search for the subjects were unilaterally recorded with mono-aural click stimuli of different frequencies: 500 Hz, 1000 Hz, 2000 Hz, and 4000 Hz at inter stimulus intensities range from 20 dB to 70 dB. Hearing frequency range and sound intensity range were selected in accordance with conventional pure-tone audiometric test [16]. Five audiometric test records have been recorded for each subject. The mean threshold values were calculated in order to ensure that subject was able to receive and perceive the specified sound stimulation. The subject with mean threshold hearing level ($\mu \leq 25$ dB) has been categorized as normal hearing subject. The subject with mean threshold hearing level ($\mu > 25$ dB) has been categorized as conductive hearing loss subject. The three subjects, with conductive hearing loss have reported the mean threshold value of 50 dB, 60 dB, and 65 dB respectively. The three subjects, with sensorineural hearing loss have profound congenital hearing loss.

Auditory evoked potentials with active listening paradigm were recorded using Mindset-24 EEG amplifier. The 19 channel (FP1, FP2, F7, F3, FZ, F4, F8, T3, T5, C3, CZ, C4, T4, T6, P3, PZ, P4, O1 & O2) electrodes were placed using 10-20 electrode positioning system (Standard Positioning Nomenclature, American Encephalographic Association) and the reference electrodes were on left and right mastoid [17]. The EEG signals were initially recorded from the subjects with their eyes closed and opened for 60 seconds in order to ensure the subject's appropriate data has been recorded [18].

The subjects were exposed to impulsive click sound with frequency of 1000 Hz with fixed acoustic stimulus intensity of 25 dB. Stimuli and frequencies were synchronized with sound levels and presented through the earphones to the subjects. The auditory stimuli (click sound) were produced by pressing a button manually and presented to the ear using an earphone. The

auditory stimuli were presented unilateral to the ears. The experiment was repeated for five trails and with an inter-trail rest for a minute to the subjects. AEP signals were recorded for 10 second with a sampling frequency of 256 Hz. To meet the sampling criterion, the sampling frequency of 256 Hz has been selected, since the input signals frequency of interest lies below 100 Hz. To conduct AEP response test, a type of special attention or cooperation from the normal hearing and abnormal hearing persons were not expected. Figures 2-4, show the sample EEG data recorded from the normal hearing, conductive hearing loss, and sensorineural hearing loss subjects.

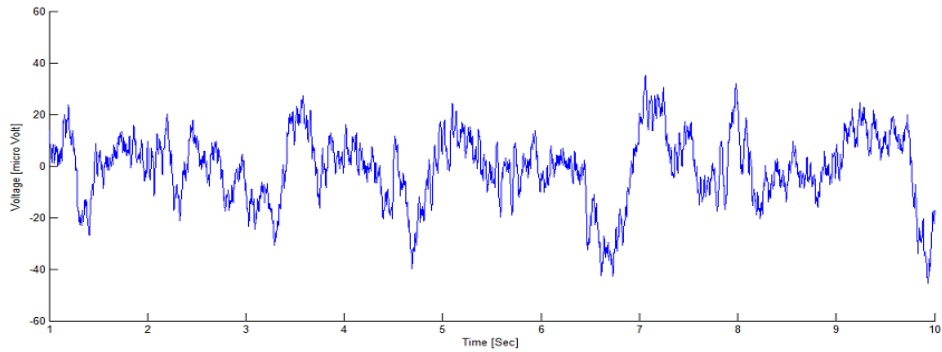


Figure 2. A typical example of raw EEG data recorded from normal hearing subject

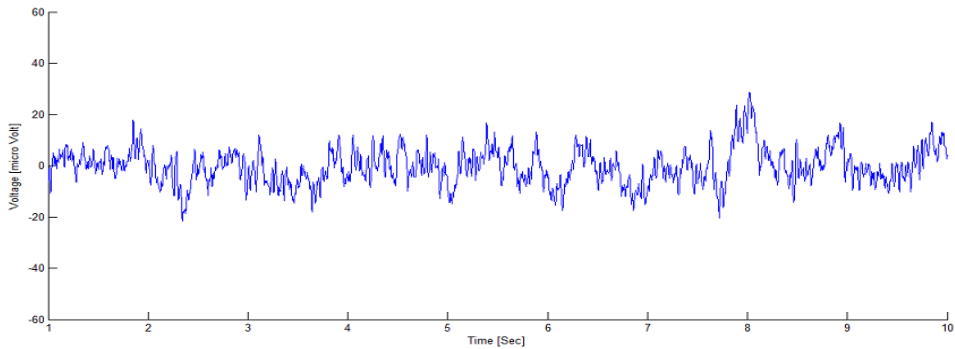


Figure 3. A typical example of raw EEG data recorded from conductive hearing loss subject

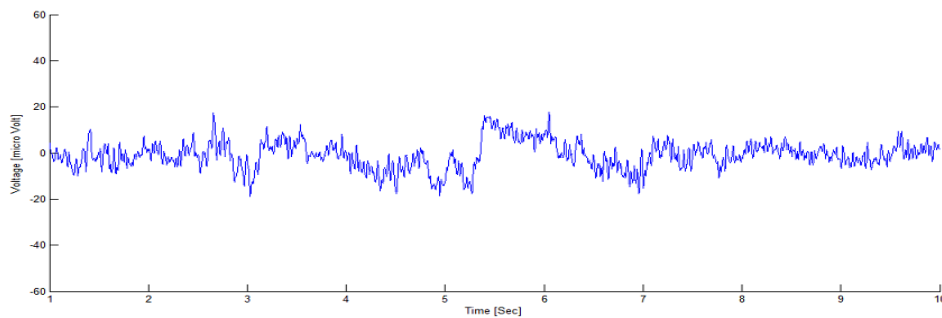


Figure 4. A typical example of raw EEG data recorded from sensorineural hearing loss subject

2.2. Statistical Analysis

Analysis of variance (ANOVA) was performed on the recorded data set to check the significant effects of electrode location within the subjects and groups of the subjects during the task of perceiving the sound stimuli (1000 Hz at 25 dB). To find the critical value from the F distribution table, the degrees of freedom of the test static, along with significance level were computed. For instance, m= 19 (electrode locations) and n= 1280 (256 data samples (1 Sec) * 5 subjects). (F (18, 24301) = 1.604; p < 0.05), F (observed value) = 61.191. The ANOVA test applied to the collected data set has yielded a confidence level of 95% and thus the validity of the experimental data set has been assured.

2.3. AEP Feature Extraction

The recorded AEP signals were first segmented into frames such that each frame has 256 samples with an overlapping of 50 % was applied to the nineteen channels of the AEP data to compute the spectrogram. Frame overlapping was made to increase the combinations of data representation of feature set with sufficient accuracy. As each EEG signal trails recorded for 10 seconds, the segmentation of 2560 samples yielded 17 frames. The segmented signals were then filtered using a Chebyshev Infinite impulse response filter to extract gamma (30-49 Hz) frequency band from nineteen electrode positions. The Chebyshev second order filter provides a monotonic pass band and contains ripples only in stop band with steep roll-off to the input AEP signals. Each segmented frame was fast Fourier transformed and consists of nineteen power spectral features. The extracted type of feature set was named as power spectral gamma-band feature PSGB19.

The power spectral band features were extracted using Equation (1),

$$E = \sum_{n=0}^{N-1} |X(n)|^2 \quad (1)$$

Where

E is the spectral power density,

$X(n)$ is the feature extracted EEG signal.

$n= 0, 1, 2, \dots, N-1$, are the sample points.

Next, spectral entropy feature of gamma-band were extracted from the recorded AEP signals. This extracted type of feature set was named as spectral entropy features of gamma band SEGB19. The spectral entropy features were extracted using Equation (4), the information entropy proposed by Shannon [19] of X is defined as

$$H(X) = -\sum_n^{N-1} P_n \log(P_n) \quad (2)$$

$n= 0, 1, 2, \dots, N-1$, are the sample points.

The power spectral density is estimated from equation (3)

$$P(\omega) = \frac{1}{N} |(X(\omega))|^2 \quad (3)$$

Where $X(\omega)$ represents the fast Fourier transform of X . From equation (2), we compute the spectral entropy as

$$H(\omega) = -\sum P_\omega \log P_\omega \quad (4)$$

As each single trail was segmented into 17 frames and then considering a sum of five trails for three subjects, a data set of 255 feature samples for normal hearing subjects have been formulated. Similarly, a data set of 255 feature samples for conductive hearing loss and sensorineural hearing loss subjects have been formulated. Power spectral features of gamma-band and spectral entropy features of gamma

band were then associated to their respective hearing threshold level of normal, conductive hearing loss, sensorineural hearing loss subjects.

3. Feature Classification using Neural Network

The multilayer perceptron network (MLPN) was most commonly used neural-network architecture because derives its computational power through massively parallel distributed structure [20][21]. Using spectral features PSGB19 and SEGB19, two different neural network models for specific hearing frequency (1000 Hz) were developed to discriminate the hearing threshold of left and right ears of normal hearing, conductive and sensorineural hearing loss.

The neural network models have 19 input neurons representing the specific features and two output neurons to classify the normal hearing, conductive and sensorineural hearing loss subjects. The master data set consist of 765 samples. The neural network was trained with 460 samples (60 % of the master data set samples) of data and tested with the remaining 305 samples (the remaining 40 % of the master data samples). In order to develop a generalized neural network, the training samples were randomly selected from the total samples and trained. Binary normalization algorithm was used to normalize the data sample between 0.1 and 0.9. The 16 hidden neurons and the output neurons were activated using log-sigmoid function. The neural network model was trained with a training tolerance of 0.0001 and tested with a testing tolerance of 0.1. The mean squared error (MSE) stopping criterion was used during the training sessions. For each weighted sample, the MLP was trained using Levenberg-Marquardt (LM) algorithm.

The Elman network (ELN) was commonly used feedback neural-network architecture where the hidden layers were connected to input layers [20]. The feedback neural network models were configured according to the input feature vector, two output neurons to classify the normal conductive and sensorineural hearing loss subjects. In order to classify the features PSGB19 and SEGB19, the feedback neural network models were configured to have 19 input neurons representing the respective features and two output neurons to classify the normal hearing, conductive and sensorineural hearing loss subjects. In order to develop a generalized feedback neural network model, the training samples were randomly selected from total samples and trained [22]. The master data set consist of 765 samples. The neural network was trained with 460 samples (60 % of the master data set samples) of data and tested with the remaining 305 samples (the remaining 40 % of the master data samples). The 29 hidden neurons and output neurons were activated using tan sigmoid function. Binary normalization algorithm was used to normalize the data sample between 0.1 and 0.9. The neural network model was trained with a training tolerance of 0.0001 and tested with a testing tolerance of 0.1. The mean squared error (MSE) stopping criterion was used during the training sessions. For each weighted sample, the Elman network was trained using gradient descent backpropagation with adaptive learning rate algorithm.

4. Results and Discussion

First, the effects of brain rhythm on perceiving auditory frequency of 1000 Hz and their auditory response for the PSGB19 and SEGB19 features have been investigated using feed forward neural network. Table 1 shows the classification performance of MLPN using PSGB19 and SEGB19 for left and right ears at hearing frequency of 1000 Hz. Form Table 1, PSGB19 has the maximum classification accuracy of 94.45% and 96.75% for the left and right ears in distinguishing the normal hearing, conductive hearing loss and sensorineural hearing loss subjects. Further, it was observed that SEGB19 features has the classification accuracy of 92.29% and 93.45% for the left and right ears in distinguishing the normal hearing, conductive hearing loss and sensorineural hearing loss subjects.

Table 1. MLPN results using PSGB19 and SEGB19 features

Feature technique	Ear	# Epoch	Value of MSE	Sensitivity (%)	Specificity (%)	Classification Accuracy (%)
PSGB19	L	350	0.0585	273/305	278/305	94.45
SEGB19	L	420	0.0436	277/305	269/305	92.29
PSGB19	R	450	0.0287	284/305	291/305	96.75
SEGB19	R	520	0.0154	282/305	285/305	93.45

Second, the effects of brain rhythm on perceiving auditory frequency of 1000 Hz and their auditory response for the PSGB19 and SEGB19 features have been investigated using feedback neural network. Table 2 shows the classification performance of ELN using PSGB19 and SEGB19 for left and right ears at hearing frequency of 1000 Hz. From Table 2, PSGB19 has the maximum classification accuracy of 90.32% and 92.45% for the left and right ears in distinguishing the normal hearing, conductive hearing loss and sensorineural hearing loss subjects. Further, it was observed that SEGB19 features has the classification accuracy of 88.97% and 90.74% for the left and right ears in distinguishing the normal hearing, conductive hearing loss and sensorineural hearing loss subjects.

Table 2. ELN results using PSGB19 and SEGB19 features

Feature technique	Ear	# Epoch	Value of MSE	Sensitivity (%)	Specificity (%)	Classification Accuracy (%)
PSGB19	L	6500	0.0045	271/305	274/305	90.32
SEGB19	L	7250	0.0086	262/305	268/305	88.97
PSGB19	R	7405	0.0055	275/305	281/305	92.45
SEGB19	R	8000	0.0090	270/305	276/305	90.74

When comparing the classification performance of the observed results of MLPN with ELN, applied to PSGB19 features, it was observed that MLPN outperformed ELN by 3% to 4% in classifying the normal hearing, conductive hearing loss and sensorineural hearing loss subjects. When comparing the classification performance of the observed results of MLPN with ELN, applied to SEGB19 features, it was observed that MLPN outperformed ELN by 2% to 3% in classifying the normal hearing, conductive hearing loss and sensorineural hearing loss subjects. From the analysis, it can be observed that the PSGB features obtained from the nineteen channels can be used to distinguish the normal hearing, conductive hearing loss, sensorineural hearing loss subjects. From the results, it was evident that AEP signals elicited from the auditory stimuli determines the functional integrity of the auditory system. From the results, it indicates that asymmetric response in the classification performance for left and right ears was reported, which shows that the significant differences may be due to the inherent more active perception of the auditory stimuli made by the right ears while compared to the left ears.

4.1. Electrode Reduction

Feature selection method is used to choose a subset of input feature vectors which can reduce the size of redundant features and able to predict the output class with accuracy comparable with the complete input feature dataset. In this study, feature selection has been proposed based on the feature PSGB19 values because it has achieved the maximum classification accuracy when compared with SEGB19 features. This study proposes feature score index, where gamma power values estimated from the nineteen electrode channels have been used as a scoring function. High score of gamma power from the corresponding channel reflects the potential channels with more discriminative information than other channels. Further, sorting 19 gamma power values in the descending order provides with the information of discriminative electrode channels capacity.

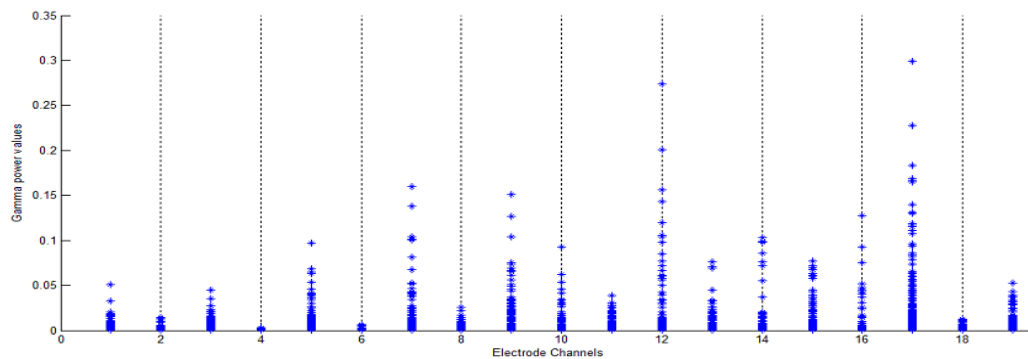


Figure 5. Gamma-power score index from nineteen electrode channels

Figure 5 displays the gamma power score index from the nineteen electrode channels. The effects of hearing processing have been found statistically that gamma power derived from brain locations reflects hearing response to the stimuli. In this study, eight potentially significant channels were selected based on their gamma power score index, P4, C4, F8, T3, T5, T4, T6, O2. As can be seen, the features derived from the temporal lobes has more involved in processing the auditory sensory responses than other regions. The selected eight channels yield the classification accuracy of 86% in discriminating the normal hearing, conductive hearing loss and sensorineural hearing loss subjects.

5. Conclusion

In this paper, spectral power and spectral entropy features of gamma rhythms were extracted from the recorded AEP signals and used to distinguish the normal hearing, conductive hearing loss and sensorineural hearing loss subjects. The result of the study concludes that gamma band feature was able to characterize the AEP signal dynamics in response to hearing states (normal, conductive and sensorineural hearing loss subjects). Feature selection method by gamma band score index was proposed which reduces electrode channel capacity in response to the auditory stimuli. Feed forward and feedback neural network models were used to classify the normal, conductive hearing loss and sensorineural hearing loss subjects. Further, it appears that a standalone hearing level system based on EEG can be designed and developed to detect the hearing loss for all including neonates, infants and multiple handicaps which helps to improve their quality of life.

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