Automatic Detection and Classification of Hearing Loss Conditions Using an Artificial Neural Network Approach

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Abstract. The auditory dysfunction is one of the most frequent disabilities, this condition can be diagnosed with an electroencephalogram modality called auditory evoked potentials (AEP). In this paper, we present a machine learning implementation to automatically detect and classify hearing loss conditions based on features extracted from synthetically generated brainstem auditory evoked potentials, a necessity given the scarcity of full-fledged datasets. The approach is based on a multi-player perceptron, which has demonstrated to be a useful and powerful tool in this domain. Preliminary results show very encouraging results, with accuracy results above 90% for a variety of hearing loss conditions; this system is to be deployed as hardware implementation for creating an affordable and portable medical device, as reported in previous work.

Keywords: Hearing loss · Diagnostic · BAEP · Latency · Neural Networks

1 Introduction

The auditory dysfunction is one of the most frequent disabilities and it's usually caused either by genetic characteristics or prenatal factors or by infections that cause damage to the auditory pathways. According to data in the national survey of the demographic dynamics of 2014 (INEGI), 6% of the population (7.2 million) have a disability, of which 33.5% has auditory issues. Therefore, detecting this condition in the early stages, can mitigate the consequences. Several of these problems can be diagnosed using an electroencephalogram modality called auditory evoked potentials (AEP), a study which is usually performed on non-cooperative and/or on pediatric patients. The use of Artificial Neural Networks (ANNs) has shown to be effective in the field of medicine where they have been used to detect various diseases [1, 2]. Given that such systems can help in the diagnosis of diseases such as hearing loss, a great deal of research has been carried in this domain, which have aimed at investigating the use of ANNs to detect hearing loss in neonatal patients [6]. The ANN extracts features in the frequency domain to determine whether or not a hearing condition is present.

Such tools are increasingly necessary for estimating auditory levels in order to assess the degree of hearing loss in pediatric and handicapped patients.

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Current technologies could exploit reliable measurement techniques such as EEG, developing an intelligent model for estimation auditory levels. In this paper, we undertake such an approach for proposing a system for automatically detecting a classifying various hearing loss conditions. Several related works have been proposed the automatic or semi-automatic evaluation of hearing loss conditions [13]. Some of these include the Raleigh test, the Watson's U2 test, the Kuiper's test, the Hodges–Ajne's test, the Cochran's Q-test, and the Friedman test. For a more detailed study, the reader is directed an excellent survey in the topic [14].

The present work is not based on the frequency domain, but we use a multilayer perceptron (MLP) trained with time-domain measurements of BAEP signals, since it makes our architecture simpler to implement. For instance, we take into account the absolute values of BAEP features such as the amplitudes and latencies. These are the features used by doctors to assess the severity of various hearing loss conditions and makes the results more intuitive. This article presents a diagnostic model based on a multilayer perceptron (MLP), with synthetic data simulating patients of 6, 12 and 24 months of age, as it will be described later in the article.

This paper is organized as follows: in Sect. 2, we describe the use and characteristics of the BAEP signals. In Sect. 3 we explain the proposed system based on the MLP architecture. In Sect. 4, we delve into the obtained results and in Sect. 5 we conclude the article, pointing at future extensions and other possible directions.

2 Neurophysiological Signal Present in BAEP

The electroencephalography is a non-invasive technique widely used in the diagnosis of many neurological diseases and problems associated with brain dynamics [16]. These signals are indicators of the cerebral electrical activity that can help to interpret several brain conditions. Therefore, understanding the characteristics of the BAEP signals, used as the foundation of this work, is vital. The next section will be devoted to this purpose and to provide more context to their use in hearing loss conditions.

2.1 Auditory Evoked Potential

When an auditory stimulus is provided to the human brain, there is a potential peak referred to as auditory evoked potential (AEP) in the auditory cortex, from which on can assess the auditory capacity of a patient, through the analysis of these evoked responses. Thus, AEP is a modality of electroencephalography that represents variations of voltage in a sensitive nerve pathway after or during extrinsic acoustic stimulation, which captures and the neuroelectric activity generated as responses to a stimulus.

The AEP test consists of the stimulation of the auditory path through a beep signal that stimulates most of the cochlea, i.e. the areas with frequency higher than 1,500 Hz. This mechanical stimulus is transformed by the organ of Corti into an electrical

stimulus that travels the auditory path to reach the cerebral cortex. From the moment the organ of Corti is stimulated until the arrival of the information to the cortex, approximately 300 ms pass, and this period known as latency.

The auditory pathway consists of a series of nerve stations as depicted in Fig. 1. Typically, the applied stimulus in BAEP tests goes through to nervous system, producing a signal that can be observed on top of the figure.

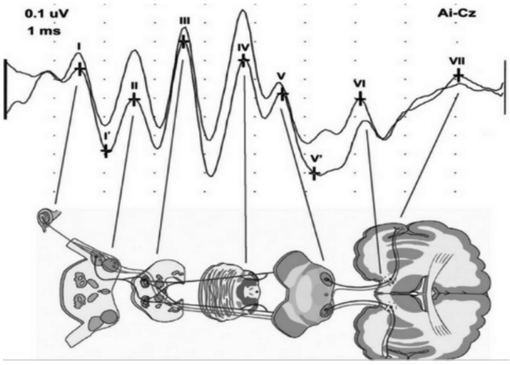

Fig. 1. The wave pattern obtained by AEP and the associated latencies (see Table 1).

The signal is composed of a series of waves, with distinct peaks and valleys. The waves are of clinical interest and can be classified as follows:

- Wave I: electrical activity of the spiral ganglion.
- Wave II: posterior part of the anteroventral cochlear nucleus and behind zone of the posteroventral cochlear nucleus.
- Wave III: anterior part of the anteroventral cochlear nucleus ipsilateral and medial nucleus of the contralateral trapezoid body.
- Wave IV: isolateral and contralateral cells of the olive superior medial.
- Wave V: cells of the lateral lemniscus and/or inferior colliculus.

The latencies of each wave are measured and categorized as I-III, I-V and III-V. The normal latencies at 80 dB for healthy adult individuals in a normal environment are [16, 17]: Wave I (1.5 ms), Wave III (3.75 ms) and Wave V (5.5 ms).

The information contained in those 5 waves are of clinical interest. The waves are presented in time limits clinically known as latencies, as we have described previously and is depicted on Fig. 1. The wave patterns formed by the acoustic stimulus are shown in Fig. 1 as well, whereas Tables 1 and 2 summarize the most important aspects of the latencies and the amplitudes, respectively.

Table 1. Mean latencies of 165 normal patients of different ages [3, 4].

Age in months	Time difference in the waves down shown in milliseconds				
		Y1:	Y2:	Y3:	Y4:
		I	V-I	I-III	III-V
0	Mean	1.58	5.18	2.77	2.43
	N	14	14.00	10.00	11.00
6	Mean	1.49	4.87	2.59	2.35
	N	17	16.00	13.00	12.00
12	Mean	1.47	4.58	2.41	2.32
	N	18	16.00	16.00	11.00
18	Mean	1.41	4.49	2.34	2.15
	N	11	11.00	10.00	7.00

Table 2. Amplitude of peaks in AEP of 50 normal patients [3, 4]

Age in months	AEP components			
	I	II	III	IV-V
1	0.54 ± 0.08	0.45 ± 0.09	0.59 ± 0.08	0.48 ± 0.06
10	0.51 ± 0.04	0.75 ± 0.15	0.86 ± 0.10	0.82 ± 0.07
30	0.35 ± 0.03	0.59 ± 0.10	0.72 ± 0.08	0.68 ± 0.07
50	0.17 ± 0.02	0.35 ± 0.07	0.40 ± 0.07	0.50 ± 0.06

Two typical patterns of the BAEP (Brain-stem auditory evoked potentials) signal are shown in Fig. 2. The recorded signals were classified as normal (a) and abnormal (b) by the physician, based on the information contained of peaks and encoded in the tables.

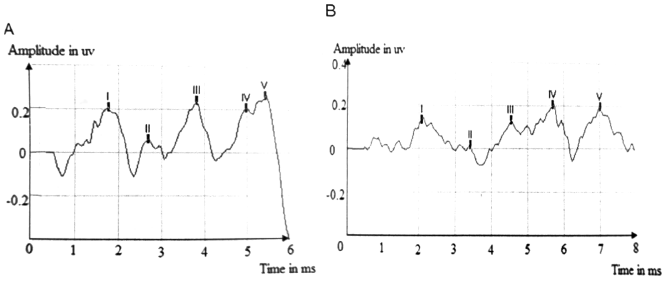

Fig. 2. Typical waveform BAEP: (A) normal patient and (B) subnormal patient [15].

The statistical differences between the age groups is important, since the amplitude of the waves change as the patient gets older. Tables 1 and 2 clearly show those

statistical differences. The mean amplitudes and the values of the BAEP components for the 5 age groups are given for stimulation with hearing levels of 80 and 60 dB in the tables.

3 Implementation of the Proposed MLP-Based Architecture

In order to implement a classification system for BAEP signals based on an MLP approach, a data set for training and testing is necessary. Unfortunately, the data collection involves certain obstacles such as the availability of samples of interest or legal restrictions in the collection and handling of patient information.

Our solution to this problem has been to generate synthetic data for training and testing [14], based on characteristics extracted from real samples as shown in Fig. 3.

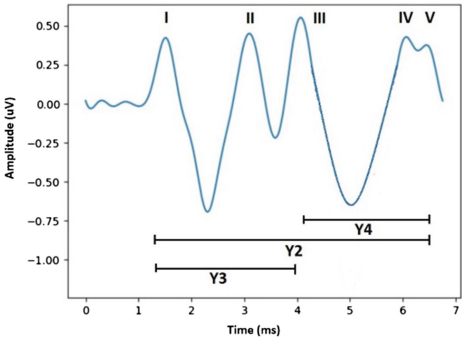

Fig. 3. A synthetically generated signal of a 6-month-old patient at 80 dB

As it can be seen, the generated signals are very similar to the real signals depicted in Fig. 2, as the values of these signals are filtered to obtain the maximum amplitude peaks in the waves I, II, III and V. Once these amplitudes are obtained, the latencies are extracted, using the temporal differences between the different peaks or waves (IV, I-III, III-V) which are subsequently used by our machine learning application.

The proposed solution is divided into two stages, the first part deals with the generation of synthetic data. The generated dataset simulates a BAEP sampled in the time domain with the objective for training and testing our MLP algorithm. The second stage deals with feature extraction (Tables 1 and 2), which are used as inputs to the MLP.

The MLP classifies the extracted data and as output provides a four-bit code according to a condition as shown in Table 3. The block diagram of the proposed solution is shown in Fig. 4, where we have a block that includes three main components. The first block retrieves the synthetically generated BAEP signal. The second block performs some preprocessing on the signal (i.e., since the sampled signal has different values it is necessary to take the values of interest from the BAEP). Once these values have been extracted, we add them to our training dataset. This dataset is then

passed to the MLP classifier, which categorizes the hearing condition and codifies its into 4 output bits, where each encoded binary value represents an ailment, as summarized in Table 3.

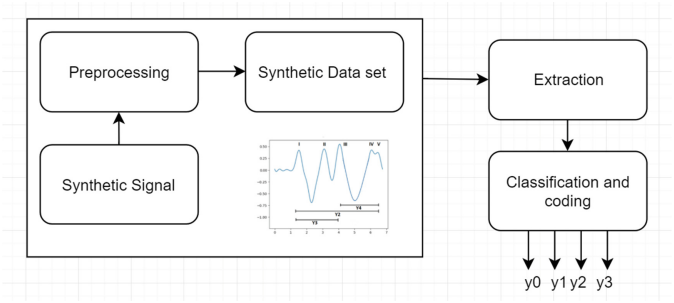

Fig. 4. Block diagram of the proposed solution.

Table 3. Global patterns of brain stem auditory evoked potential abnormalities [4]

Diagnosis	Hearing loss condition	Binary coding
Normal values	Healthy ear	0000
Prolonged latency in wave I	Distal segment of the cranial nerve VIII	0001
Prolonged latency between peaks I-III	Between cranial nerve VIII and brainstem bridge	0010
Prolonged latency between peaks III-V	Injury between the caudal portion of the brainstem and mesencephalon bridge (attack, tumor, multiple sclerosis, intracranial hemorrhage, malformation, etc.)	0011
Prolonged latency between peaks IV-V and III-V	Rostral section of the brainstem or mesencephalon bridge and vestibulocochlear nerve or brainstem bridge	0100
Wave III absent with presence of I and V	Hearing loss at mild and moderate levels	0101
Wave V absent with presence of I and III	Normal variation	0110
Wave V absent with normal of I and III	Probably auditory radiations to the primary auditory cortex	0111
Absence of waves	Severe hearing loss	1000
Excess in amplitude radius V/I	Possible hearing impairment	1001
Absence of waves except I (and possibly II)	Brain death	1010

The proposed MLP architecture is depicted in Fig. 5. The number of neurons in the input layer is 5, in order to encode a vector that includes values for age, latencies and

amplitudes of wavelengths that go from wave I to wave IV-V. The number of neurons in the intermediate layer was chosen based on an experimental test that consisted on varying the neurons of this hidden layer with 5 neurons per iteration until reaching 25 neurons within a single hidden layer. The output layer consists of are 4 neurons. The results of these experimental iterations will be discussed later in the paper.

The pathologies tackled by our approach are summarized in Table 3, which contains a description of each of the most important pathologies associated with the average variances described in Tables 1 and 2. The last column shows the associated coding that we have chosen as outputs of MLP algorithm, as will be explained in Sect. 4.

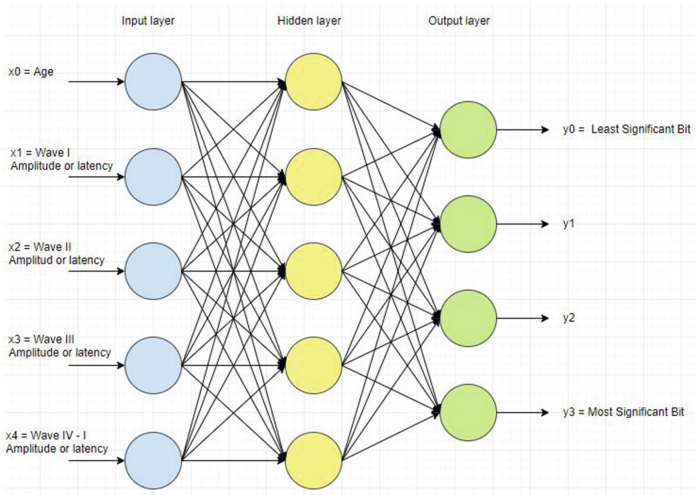

Fig. 5. Implemented MLP algorithm and its relationship with the BAEP signals

According to Cybenko's theorem, the sigmoid function [10–12] is used in the intermediate hidden layer and relu or linear regression [9] in the output layer used for convolutional networks [8] and is used in this classifier for the smallest error generated with the logistic function [7]. In order to validate the designed classifier, cross-validation is usually employed to assess the performance of machine learning models [5]. However, in our particular case, as we counted with limited dataset of synthetically generated feature vectors, we made use of use k-fold cross-validation, as is typical in such scenarios. Figure 6 shows the accuracy and loss plots in the training set; the model could probably be trained a little longer, since the trend of precision continues to increase with more iterations.

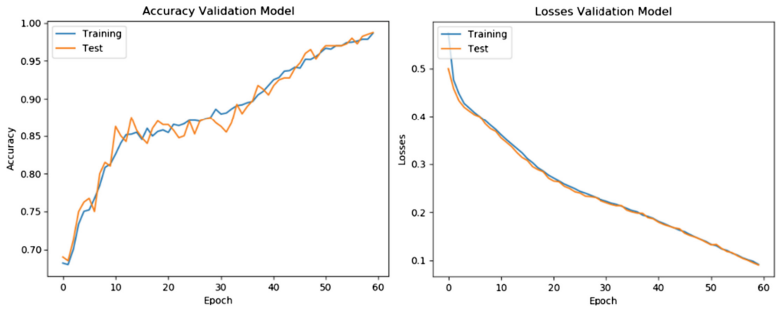

Fig. 6. Accuracy with training data and model losses with training data.

The tests on the validation set are depicted in the Fig. 7. We can see that the model has not yet over-learned the training data set. The comparison between the graphs shows that increased performance in the validation set, as we avoided overfitting.

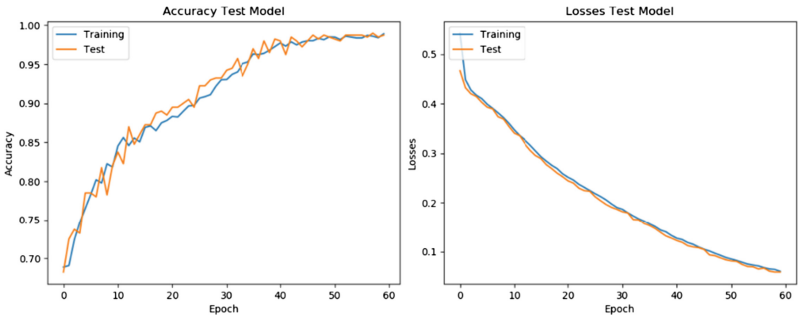

Fig. 7. Accuracy with validation data and model losses with validation data.

4 Results and Discussion

The final MLP implementation through the modification of the number of neurons in the hidden layer, and then comparing the results, gradually increasing the number of training epochs. In Table 4, we go into detail of these variations in the hidden layer of the MLP, showing the associated impact the in the model accuracy.

Table 4. Model selection method through the modification of the MLP architecture.

Neurons in the input layer	Neurons in the hidden layer	Neurons in the output layer	Epochs	Validation accuracy	Test accuracy
5	5	4	60	96.19%	96.38%
5	10	4	60	96.39%	96.91%
5	15	4	60	96.59%	97.19%
5	20	4	60	96.99%	97.79%
5	25	4	60	97.39%	98.19%

After the performance training and validation tests, synthetic signals are generated from patients of 6, 12 and 20 months of age, simulating a healthy patient. As mentioned earlier, the signals are processed in the time domain, although the signs are generated using a combination of Fourier and Wavelet transforms. The data filtered and used by our MPL algorithm, called "experimental values" are the following:

Table 5. Filtered data of the synthetic wave fed to our MLP algorithm

Age (months)	Latency wave I	Latency wave I-V	Latency wave I-II	Latency wave III-V
6	1.51	4.87	2.52	2.35
12	1.4	4.6	2.4	2.2
20	1.4	4.5	2.4	2.1

The similarity of the filtered data shown in Table 5 with respect to real data [3], can be readily observed. Therefore, this signal generation process is an important contribution of our work, but it has not been explored in detail in this paper due to space limitations.

Once the experimental values are entered into our MLP based algorithm, and the training values are compared with the experimental values.

Table 6. Output matrix, expected response by the network zeroes indicate that there are not ailments.

Y_0	Y_1	Y_2	Y_3
0	0	0	0
0	0	0	0
0	0	0	0

After the validation of the model, the perceptron makes the prediction with the experimental values, these values represent a patient without any handicaps or hearing loss conditions, therefore we show the results in Table 6 as expected from those in Table 3.

5 Conclusion

Neural network models have been used in a variety of other clinical medicine settings, but to our knowledge this is the first time it has been used to help diagnose hearing loss. The preliminary results presented in this seem rather promising, as we have obtained very good accuracies using only temporal features. It must be noted that we have undertaken such an approach due to the lack of readily available datasets containing

BAEP signals, although some works like ours are exploring the same feature generation avenue and such datasets should me made public for improving the research in this domain.

As future work, we plan to strength the signal generation process, making a more thorough study as well, to include a validation against noisy measurements. Also, we would like to carry out a comparative study using other machine learning algorithms as KNN or SVM and see how they fare in comparison with the proposed approach.

However, as explained at the beginning of this article, the rationale for this initial research is to use the proposed MLP system as a validation stage, upon which more complex feature combinations can be explored. Furthermore, we plan to integrate the MLP into an SoC FPGA for implementing a full-fledged low-cost diagnosis device and other modules are expected to produce the synthetically generation signals or in the future, to pre-process actual BAEP signals from real patients using an electronic acquisition system and the FPGA for filtering the BAEP signals and extracting the corresponding features. In this sense, the highly parallel architecture and regular architecture of the MLP or other ANNs is especially suited for implementation in reconfigurable devices and for its integration into a signal processing pipeline, which is intended as the next stage of this project.

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