Classification with the Neural Network Application of Basic Hearing Losses Determined by Audiometric Measuring

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ABSTRACT: *Pure tone audiometer is used to determine a person's hearing threshold level at different frequencies.The hearing test provides an evaluation of the sensitivity of a person's sense of hearing and is most often performed by an audiologist using an audiometer. There are different types of hearing loss, depending on which part of the hearing pathway is affected. In this study, air and bone path audiograms belong to conductive, sensorineural and mixed hearing losses and their subgroups were obtained. A specialist will always try to localize where in the hearing pathway the problem lays, so as to be able to classify the hearing loss as belonging to one of the groups. This is most important in determining the appropriate treatment. In our study, ANN that was an expert system was improved to classify of these hearing losses. With 98,75% correct classification satisfactory classification results were obtained, which were consistent with diagnostic results by clinical doctors.*

Keywords: Audiogram, Neural networks, Signal classification

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1. Introduction

Pure tone audiometry is used to identify hearing threshold levels of an individual, enabling determination of the degree, type and configuration of a hearing loss[1].

Most audiograms cover the limited range 100Hz to 8000Hz (8k) which is most important for clear understanding of speech, and they plot the threshold of hearing relative to a standardised curve that represents 'normal' hearing, in dBHL. A typical audiogram was shown in Fig. 1.

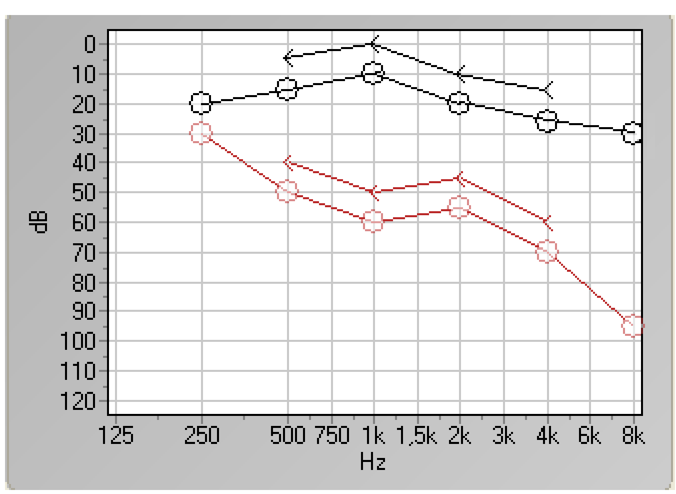


Figure 1. A typical audiogram comparing normal (black) and presbyacusis hearing loss(red).
o: air path, <: bone path conductive

Hearing impairment covers both degree and content of hearing loss. In the literature, audiogram information was rather used to evaluate various hearing losses. Horst et all were studied with audiograms of patients with Menie're's disease. They were investigated some correlation between hearing loss and audiogram fine-structure[2]. Job et all, a Windows software system has designed with graphical displays of audiograms. In their study, an audiometric pattern classification is done for each audiogram using discriminant factorial analysis[3].

In following restricted lesion of the cochlea, sensorineural hearing loss (SNHL) were been operated with audiograms [4,5]. Kim et all were purposed to audiologically evaluate the otologic problems in children with Turner Syndrome[6].

In this study, audiogram curves belong to basis hearing losses were trained by LM neural network structure. Basis hearing losses were contained conductive hearing loss which happens when there is a problem conducting sound waves through the outer ear, tympanic membrane or middle ear, sensorineural hearing loss that is a type of hearing loss in which the root cause lies in the vestibulocochlear nerve, the inner ear, or central processing centers of the brain and mixed hearing loss which is used only when both conductive and sensorineural hearing losses are present in the same ear[7].

Conductive, sensorineural and mixed hearing loss were leaved to three sub-groups respectively according to formation causes. Conductive hearing loss covers cerumen in hearing loss, serous otitis media (SOM), otosclerosis, sensorineural covers presbyacusis, acoustic trauma, congenital hearing losses and mixed type covers chronic otitis media, improved otosclerosis, traumatic causes[8,9]. ANNs (Artificial Neural Network) which are computational models of the brain have been used in a number of different ways in medicine and medically related fields to support clinical decision-making such as classification of various diseases [10,11]. In recent years, many researchers are using ANN for classification of biologic signals. For example automatic recognition of electroencephalography [12], ultrasonic Doppler signals analysis [13].

At the present time, develop information about electronic audiologist's is becoming increasingly important. The audiologist is must to have serious an experience to present ideal rehabilitation and diagnose hearing loss. Thus, options presented her/his have to be objective and pointed.

Our aims with this study, elimination of inaccuracy determinations based on inexperience and to reach the easily right diagnosis have provided.

2. Material and Method

The audiogram data belong to various hearing losses were obtained in Erciyes Hearing Center in Kayseri (using Madsen Itera Audiometer interacusticus AZ 26). Audiograms were drawn using Audibel Hearing software and acquiring standard pure tone threshold audiogram ISO-1964.

Every group was contained from forty patient subjects. Control group is consisted from forty healthy subjects. Thus, total hearing loss groups (9 groups) and normal subjects were formed 40x10 = 400 data. The acquired audiogram information is 10 frequency data formed both air and bone path conductive. In this study, we present a method to classify subjects belong to basic hearing loss according to changes in audiogram curves using ANN. MATLAB software was used for implementation of ANN (MATLAB version 7.0 with Neural Networks toolbox).

2.1 Artificial Neural Network for Classification of Audiogram Curves

The ANN has been used in a lot of different ways in biomedicine recently. The advantages of ANNs are that they are able to generalize, adapting to signal distortion and noise and that they are trained by example and do not require precise description of patterns to be classified or criteria for classification [10-15].

In this study, Levenberg-Marquartd (LM) training algorithm in the feed forward multilayer perceptron was used. In this type of analysis the learning process is supervised, which means that for all data of the training set a desired output is provided. The weighting is attributed randomly at first and is continuously updated on the basis of the error calculated as the difference between the neural output and desired output, and the process ends when the error reaches its minimum level [10]. Essentially, the Levenberg-Marquardt algorithm is a least–squares estimation algorithm based on the maximum neighborhood idea.

As seen figure An ANN consists of three layers: an input layer, an output layer, and one or more hidden layers. Each layer is composed of a predefined number of neurons. The neurons in the input layer only act as buffers for distributing the input signals a_i to neurons in the hidden layer. Each neuron j in the hidden layer sums up its input signals a_i after weighting them with the strengths of the respective connections w_{ij} from the input layer, θ is the bias term (or threshold) and computes its output value y_j of the neuron as a function f of the sum:

$$y_j = f\left(\sum_i W_{ij} a_i + \theta\right) \tag{1}$$

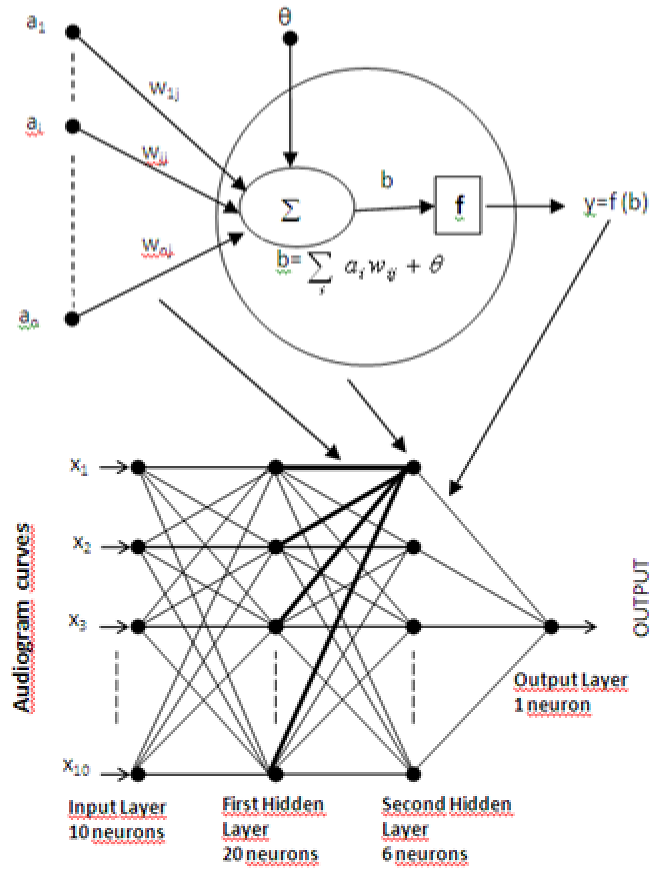


Figure 2. Structure of ANN network for audiogram classification

where *f* is the activation function that is necessary to transform the weighted sum of all signals impinging onto a neuron. The activation function *f* can be a simple threshold function, a sigmoid, hyperbolic tangent, or radial basis function. The output of neurons in the output layer is similarly computed [10-15].

Training a network consists of adjusting the network weights using the different learning algorithms. A learning algorithm gives the change $\Delta w_{ij}(t)$ in the weight of a connection between neurons *i* and *j* at time *t*. For the Levenberg-Marquardt learning algorithm, the weights are updated according to the following formula

$$w_{ij}(t+1) = w_{ij}(t) + \Delta w_{ij}(t) \qquad (2)$$

with

$$\Delta w_{ij} = \left[J^T(w)J(w) + \mu I\right]^{-1} J^T(w)E(w) \qquad (3)$$

where *J* is the Jacobian matrix, μ is a constant, *I* is a identity matrix, and *E(w)* is an error function [10-15].

During supervised learning, the ANN was trained on input vectors and the target output vectors with which it is required to associate the input vectors. With sufficient training, the ANN should be able to classify correctly previously unseen input vectors.

In our study, audiograms which were recorded from any patients were used as input of the ANN. This input vectors set belong to a subject are contained from ten data that are six air and four bone path conductive data. During the learning, it was trained on input vectors and the target output vectors with which it is required to associate the input vectors. The number of the output units is one. Samples with target outputs healthy and basic hearing loss patients are given the target numeric values of (1) and (2), (3) … respectively. Output vectors were determined from realized clinic findings these audiograms.

The network is iterated for single and double hidden layers (1) with combinations of one to thirty neurons in each layer. The train input data set consisted of every groups (healty and hearing loss groups, total train set: 320 subjects) 32 subjects, while the test data set was made of every groups 8 subjects (total: 80 subjects) similarly. The performance function of ANNs is mean square error. We trained ANNs until mean square error reached 0.0001.

We compared the predictive accuracy of ANNs that had different hidden layers, neuron numbers and training epochs. The best results were accomplished with the combination of double hidden layers consisting of twenty and six neurons consecutively. Sigmoid function and linear function was used in hidden layers and output layer respectively.

3. Results

In this study, firstly audiogram curves were performed general a classification between normal subjects and patients belong to conductive, sensorineural and mixed type hearing loss.

Results belong to this classification were given in Figure 2.

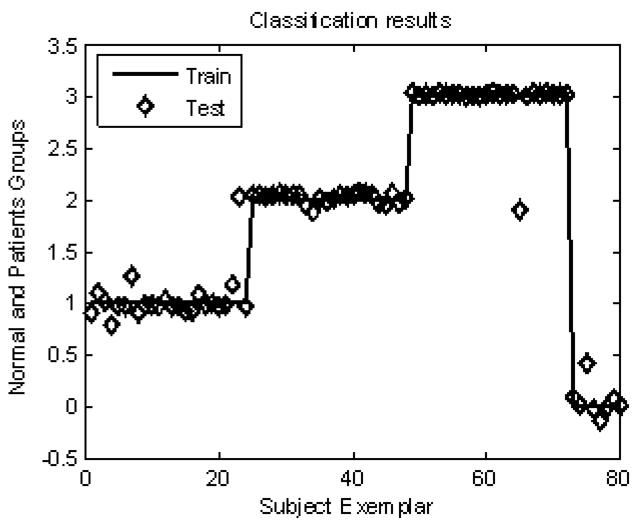


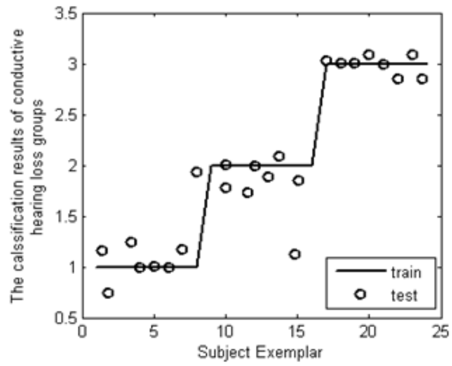
Figure 3. Classification results between normal and three basis hearing loss groups

As seen at Fig. 3, in the general classification result, ANN classification is %100 succesfully in normal subjects (0 line), conductive subjects (1 line), sensorineural subjects (2 line). As in mixed hearing loss subjects only one patient was been fault classified. False classification of only 1 subject in the total 80 test data caused 1.25% test fault while 98.75% correct classification. In such a case sensitivity is 100%, specifity is 98.25%.

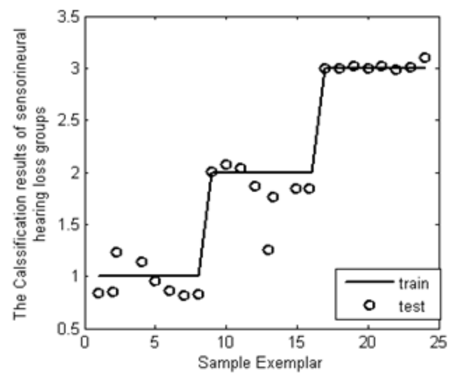
Statistical parameters (%)	*ANN (LM)*
Specifity	98.25
Sensitivity	100
Correct classification	98.75
Fault negative (normal)	0
Fault positive (patient)	1.75

Table 1. Performance results

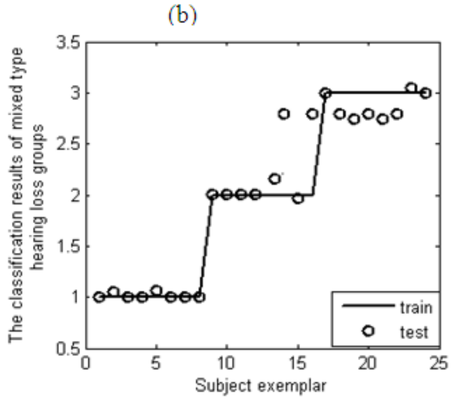
Later, hearing loss groups were separately studied more sensitively. As in Figure 4 a, b, c are respectively given conductive type hearing loss groups (1: cerumen in hearing loss, 2: serous otitis media (SOM), 3: otosclerosis) and sensorineural hearing loss groups (1: presbyacusis, 2: acoustic trauma, 3: congenital hearing loss) and mixed type hearing loss groups (1: chronic otitis media, 2: improved otosclerosis, 3:traumatic causes)



(a)



(b)



(c)

Figure 4. a:conductive type groups , b: sensorineural type groups, c: mixed type groups results

Between conductive type hearing loss groups and sensorineural hearing loos groups were realized correct classification 95.84% with false classification of only one subject. However between mixed type hearing loss groups were obtained correct classification 91.67% with false classification of two subjects.

4. Discussion and Conclusion

The ANN ensemble is recently developed technology, which has the ability of significantly improving the performance of a system where a single ANN is used. Since it is very easy to be used, it has the potential of profiting not only experts in ANN research, but also engineers' real-world applications.

In this study computer based algorithms were used to classification audiogram curves without any intervention from operator. The accuracy of the classification is high for basic hearing loss and its groups. It is hope that the classification results will aid the examination of hearing loss disorders.

This method could establish a more objective diagnostic means to improve the clinical diagnostic accuracy, efficiency and repeatability. In addition misdiagnosis caused by the subjective judgment difference could be reduced.The validity and use of our approach can be verified and applied on different patient groups.

Future work will include a study that compares the performance of the proposed classification method with that of other methods.

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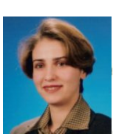

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