CLASSIFYING OPTIC NERVE DISEASE FROM THE PATTERN ELECTRORETINOGRAPHY SIGNALS

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Abstract: In this study the Pattern Electroretinography (PERG) signals derived from evoked potential across retinal cells of subjects after visual stimulation were analyzed using Artificial Neural Network (ANN) with 54 healthy and 41 diseased subjects. ANN was employed to PERG signals to distinguish between healthy eye and diseased eye. Supervised network examined was a competitive Learning Vector Quantization network. The designed classification structure has about 94.7% sensitivity, 96.7% specifity, 5.26% false negative, 3.22% false positive and correct classification is calculated to be 96%. Testing results were found to be compliant with the expected results that are derived from the physician's direct diagnosis. The end benefit would be to assist the physician to make the final decision without hesitation.

Introduction

Noninvasive clinical electrophysiological and psychophysical measurements allow an assessment of the health of almost the entire length of the visual system. An understanding of each test and their interrelationships assists the diagnosis of a number of diseases. This is facilitated by the layered nature of the visual system and the assignment of electrical potentials from specific tests to particular cell layers. [1,2]

The pattern electroretinogram (PERG) is a retinal biopotential that is evoked when a temporally modulated patterned stimulus of constant total luminance (checkerboard or grating) is viewed. It receives clinical and research attention because it can provide information about inner retinal cells and the macula. It was first recorded in 1964 when Riggs and his associates used the technique to record from a local retinal area. If a subject gazes at a reversing pattern such as a checker-board, the total quantity of light entering the eye remains constant as the pattern reverses, but in the region of the retinal image, there are repetitive changes in illumination. PERG is derived from the evoked potential across retinal cells after visual stimulation such as the checker-board. The PERG is measured by an electrode embedded in a contact lens, which is placed on the subject's left cornea. By using a reference electrode attached to the ipsilateral ear, the summed response (differential between the corneal electrode and reference electrode) from the entire retina is obtained by Tomey→Primus 2.5 Electrophysiological Device [1-4].

Reporting of PERG results should include representative three waveforms with appropriate amplitude and time calibrations (Figure 1). The first, small, cornea-negative wave arises with a delay of about 35ms and is called N35; the second; a major positive wave, peaks at about 50ms (P50) and the last is followed by a negative wave through at 95ms (N95) [1-3].

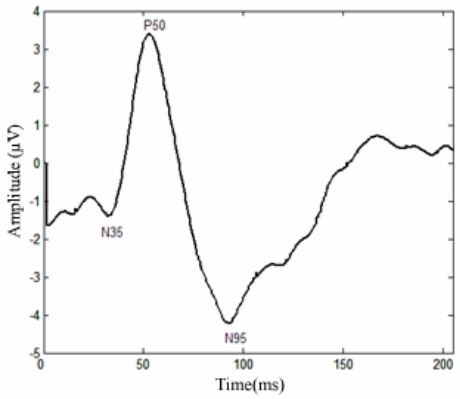

Figure 1: Normal PERG with the components labeled

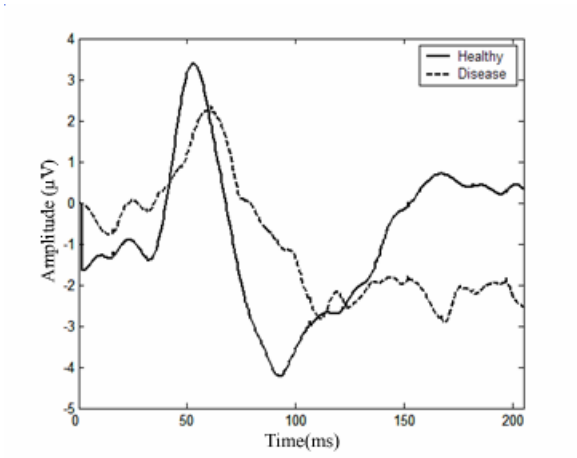

Figure 2: PERG responses samples of two different person's eye.

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For the basic PERG the stimulus consists of a checker-board. The computer records the PERG response samples over a period of 204 ms. The time progression of these frames forms a contour, which is examined by a medical expert to determine the presence of eye diseases [1]. The PERG receives clinical and research attention in both neurological and ophthalmological diseases these ocular hypertension, glaucoma, optic neuritis, optic antrophy and amplyopia [5]. However the PERG signal has a small amplitude, typically in the region of 0,5-8 μV depending on stimulus characteristics [4].

For the PERG, amplitude measurements are made between peaks and troughs: The P50 amplitude is measured from the trough of N35 to the peak of P50. In some patients the N35 is poorly defined; in these cases N35 is replaced by the average between time zero and the onset of P50. The N95 amplitude is measured from the peak of P50 to the trough of N95. It should be recognized that measuring in this way; N95 includes the P50 amplitude [4].

This research is concentrated on the diagnosis of optic nerve disease through the analysis of PERG signals with the help of an Artificial Neural Network (ANN) that will not only simplify the diagnosis but also enable the physician to make a quicker judgment about the existence of optic nerve disease more confidencely. An ANN can determine its conditions and adjust itself to provide different responses by using inputs and desired outputs, which are provided to the system. The most important thing about an ANN is that it works as an expert system which will eventually help the physicians on the decision making process about the existence of the optic nerve disease.

An ANN is a mathematical model consisting of a number of highly interconnected processing elements organized into layers, the geometry and functionality of which have been resembled to that of the human brain. The ANN may be regarded as possessing learning capabilities in as much as it has a natural propensity for storing experimental knowledge and making it available for later use [6-8]. By virtue of its parallel distribution, an ANN is generally robust, tolerant of faults and noise, able to generalize well and capable of solving nonlinear problems. Operation of an eye, either optic nerve disease or healthy, may be regarded as an inherently nonlinear system due to the absence of the property of frequency preservation as required by the definition of a linear system [9]. Application of ANNs in the medical field include diagnosis of myocardial infarction [10], electrocardiogram analysis [11], differentiation of assorted pathological data [12, 13], EMG analysis [14], EEG recognition [15] and ERG classification [3]; however neural network analysis of PERG signals is a relatively new approach.

In this study, the PERG responses have been sorted into two classes (see Figure 2); healthy and diseased. In order to do this classification, an ANN composed of Learning Vector Quantization network (LVQ).

As a result of this grouping, a trained expert can make a classification based on the features found in the PERG frames. Our primary research motivation was to advance the research of optic nerve disease, and develop a novel decision making system for identification of eye diseases.

Material and Methods

The Tomey Primus 2.5 electrophysiology unit was used for transient PERG recording in the Ophthalmology Department of Erciyes University Hospital. Representative PERG signal waves for each group are seen in Figure 2.

Electrophysiological PERG signals were acquired from patients and healthy volunteers. The test group consisted of 95 people composed of 54 healthy and 41 diseased (optic neuritis) subjects.

The recording electrodes should consist of a corneal contact lens electrode which supports the eyelids and reference electrodes placed centrally on the forehead or near each orbital rim. The ground electrode can be located on the forehead or ear. Skin electrodes should have a resistance of 10kΩ or less measured at 30-200 Hz. The electrodes should be cleaned after use with each patient. It is recommended that all reports contain measurements of P50 and N95 amplitude and P50 latency (the peak of N95 is often rather broad precluding accurate latency measurement of this component). Whenever practical, reporting of PERG results should include representative waveforms with appropriate amplitude and time calibrations. Because of the small amplitude of the PERG signal averaging is always necessary. For the transient PERG the analysis period should be 150 ms or greater [4].

All data which was recorded from any patients were used as input of the ANN. PERG signals are sampled at a proper frequency levels and then grouped in certain number of data points. After recording, to obtain optimum result we have composed feature vector from value of differences of P50-N35 and N35–N95 for input ANN.

The system consists of four parts: (a) measurement of PERG signals, (b) neural network inputs were selected, (c) classification using LVQ network, (d) classification results.

The ANN chosen was a supervised competitive network which was implemented in the The competitive network used was a LVQ network.

LVQ is a method for training competitive layers in a supervised manner. A competitive layer will automatically learn to classify input vectors. However, the classes that the competitive layer finds are dependent only on the distance between input vectors. An LVQ network has a first competitive layer and a second linear layer. The competitive layer learns to classify input vectors. The linear layer transforms the competitive layer's classes into target classifications defined by the user [17].

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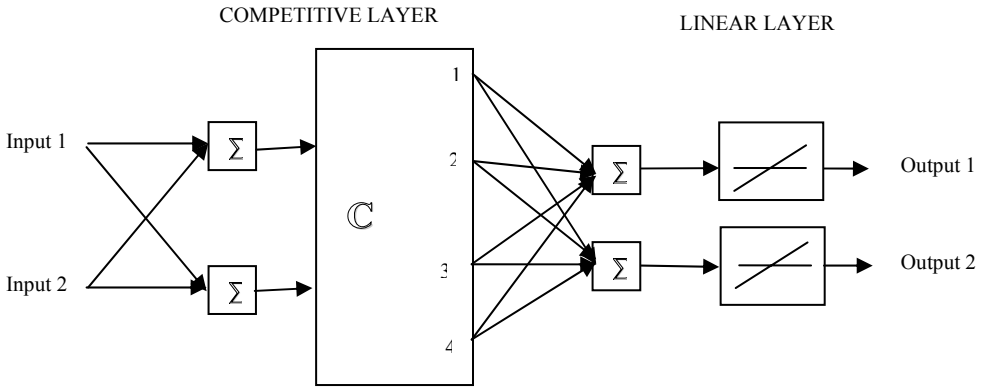

Figure 3. Structure of ANN

The advantage of the LVQ networks compared to statistical methods of classification is that the last demand first a good comprehension of the parameters involved in order to define the classification rules, while the former explore and understand unknown environments by simply presenting to them input and output patterns [7, 15].

In this study, the network architecture is shown in Figure 3. The LVQ network consists of two layers. The first layer is a competitive layer, which learns to classify input vectors into one of the subclasses. The competitive neuron whose weight vector forms the closest match with the input vector is classified as output 1. The second linear layer transforms the subclasses of the competitive layer to the output target classes so that each competitive neuron has assigned one target (output). Both the competitive layer and the linear layer have one neuron per class; thus, the competitive layer can learn up to subclasses. This is turn combined by the linear layer to form the target classes. The output neuron assigned to the winning competitive neuron also has a value of 1 while all the other output neurons have a value of 0. Depending on which neuron had a value of 1, the PERG recording was classified as healthy or optic nerve disease. The network used in this study had the following parameters: (1) 4 neurons in competitive layer, (2) 2 neurons (classes) in output layer, and (3) 100 training epochs. There were two alternative stopping rules applied during the training of this network: the number of training epochs and the error goal. Two neurons in the output layer were used: healthy and optic nerve disease [14, 15]. The train input data set consisted of 23 healthy and 22 optic nerve disease patients, while the test data set was made of 31 healthy and 19 optic nerve disease patients.

The second layer weights will have 51% (23 of the 45 in output above) of its columns with a 1 in the first row, corresponding to class 1, and 49% of its columns will have a 1 in the second row, corresponding to class 2. The second layer weights matrix says that if the competitive layer produces a 1 as the first or second element, the input vector will be classified as class 1. Otherwise it will be in class 2.

The first two competitive neurons are connected to the first linear neuron (with weights of 1), while the second two competitive neurons are connected to the second linear neuron. All other weights between the competitive neurons and linear neurons have values of 0 [15-17].

Results

After the training phase, testing of the LVQ neural network was established. The data, which has not been used as an input to the network, was applied to the network for testing the network performance.

A testing mean square error of 0.04 was observed for our optimized LVQ network with a training mean square error of 0.03. Success rate of classification was accomplished as 94-97% with the designed feature extraction and the neural network structures. The end results were classified as Healthy and Diseased. There has been 1 false classification in the negative group, while 30 subjects were correctly recognized as healthy. With a higher accuracy in the positive (optic nerve disease) group, only 1 subject were misclassified, and 18 people were accurately classified as diseased (Figure 4). The overall results point that, 96% correct classification was achieved, whereas two false classifications have been observed for the group of 50 people in total. Within these results, this network has about 94.7% sensitivity, 96.7% specifity, 5.26% false negative and false positive and is calculated to be 3.22%.

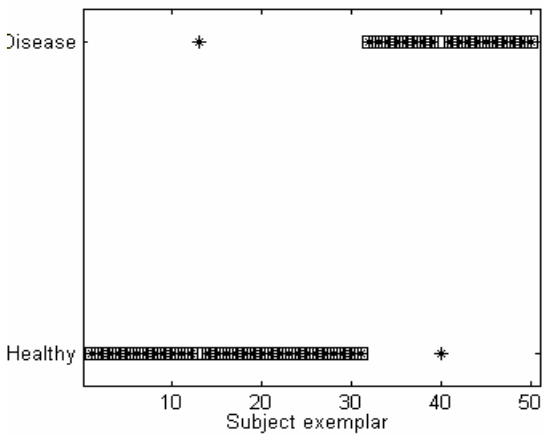

Figure 4. Output results □ Desired . Actual

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The outputs of actual network and desired network are set to vary within the range of healthy to disease. In Figure 4 is showed the output values of 31 healthy and 19 optic nerve disease subjects. It is seen in Figure 4 that the desired network output was given pattern characterized as healthy except one which has the value as disease. This means that one of 31 healthy subjects and one of 19 disease subjects were misclassified.

Discussion and Conclusion

The LVQ structure that we have built had given very promising results in classifying the healthy and optic nerve diseased eyes. We are not claiming to replace the currently used devices for PERG, on the other hand we are proposing a complimentary system that can be coupled to software of the ophthalmic electrophysiology devices. The end benefit would be to assist the physician to make the final decision without hesitation. The limitation of our proposed neural network structure is that the classification is realized based solely on the presence of abnormality with the eye. However, we are projecting to also sort out the diseased group based on the source of the ophthalmic problem.

The fuzzy appearance of the signals sometimes makes physicians suspicious about the existence of eye diseases and causes false diagnosis. Our technique focuses on this problem using ANN to decide and assist the physician to make the final judgment in confidence.

In this study, we believe that this research developed an expert system for the interpretation of the PERG signals using ANN. The stated results show that the proposed method can make an effective interpretation.

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