Automatic Discrimination of Abnormal Subjects Using the Visual Evoked Potential Spectral Components

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Study of visual evoked potential (VEP) is one of the utilized methods in clinical diagnosis of ophthalmology and neurological disorders. The automatic detection of VEP spectral components is an important tool in the diagnosis of mental activity. This paper presents a novel computational approach using feedforward neural network to identify abnormal subjects from changes in spectral components. The output vector from the feedforward neural network is based on the VEP spectral components. The software was developed to identify mental state from the VEP spectral components using Matlab software package. Using this approach, it is possible to perform real-time abnormality identification accurately on personal computers.

INTRODUCTION

In recent years, a recording of visual evoked potential (VEP) has become a clear trend in brain research. It provides important insights into the functioning of the optic nerve and thereby it is useful in diagnosis of many diseases [1, 2]. Analysis of VEP using spectral response is the latest technique yet to be applied in the ophthalmology and neurological centers. In general, the clinical use of VEP is based on the peak amplitude and the latencies of the N75, P100, and N145 waves. In human beings, VEP has been helpful in diagnosing demyelination, optic nerve damage as consequence of multiple sclerosis (MS), motor neural disorder (MND), and neurotransmitter deficiencies [3]. When humans are affected by the neurological and ophthalmologic disorders, VEP recordings change in latency and the diagnosis is based on the measurement of latency directly from the signal [4, 5, 6, 7]. In certain cases, background EEG found to have effect on VEP waveforms, which in turn results in irregular peaks, and special processing techniques like averaging and interpolation have to be done to overcome these irregular peaks. These measurements become complex when background EEG amplitude is stronger and it is very difficult to locate the P100 latency value. The spectral analysis of the VEP data allows a clear-cut discrimination between normal and pathological cases [8, 9, 10, 11].

Most of the researchers are using artificial neural network (ANN) for classification of EEG signals [12, 13, 14, 15]; in this paper, we present a new ANN approach to the VEP classification. An ANN is trained to classify the subjects based on VEP spectral components. Here, we present, first, detection of abnormal subjects using VEP spectral components linked to changes in latency of abnormal subjects. Secondly, we present design of neural networks to identify abnormal subjects from changes in VEP spectral components.

MATERIAL AND METHOD

Experiments were carried with 20 normal and 40 abnormal subjects (19–32 years old, 25 females and 35 males). In the 40 abnormal subjects, there were 13 subjects having MS, 13 subjects having diminished vision, and 14 subjects having MND.

All the recordings were done in a darkened sound-attenuated room. Light emitting diodes (LED) mounted in goggles served as stimulus (rate 1.3 Hz). VEP recording was done using electrode located at Oz and FPz position. The ground electrode was attached to the ear lobe. The recorded data was converted as X-Y components and with interpolation to make 256-sample data block [16] (Figures 1 and 2). The spectral components of the recorded data were identified using Matlab signal processing toolbox functions with 95% confidence level [17]. Correlation between the resulting spectral components and patient abnormality was identified.

After identifying the correlation between spectral components and patient abnormality, using these data we trained three layer feedforward neural networks to predict patient abnormality. The feedforward neural networks had six hidden units; the weights and biases of the network were adjusted using the error back propagation algorithm [18, 19, 20]. Gradient descent was used to
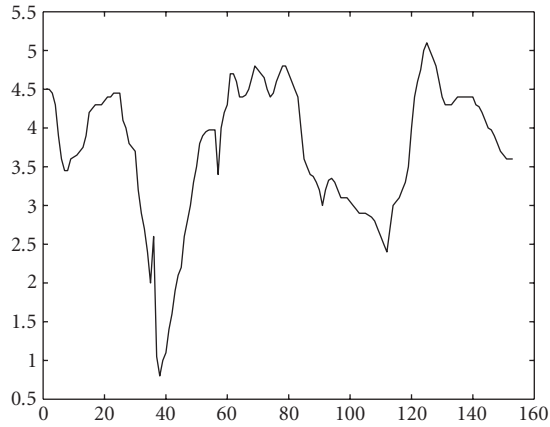
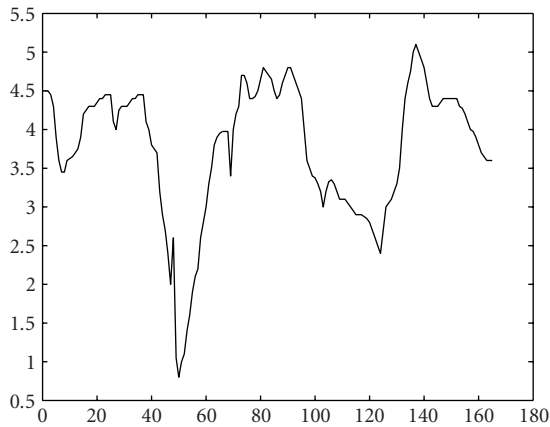FIGURE 1. Normal VEP waveform.

FIGURE 2. Abnormal VEP waveform (MND patient).

minimize the mean squared error between network output and the actual error rate. The neural network output vector is based on the VEP spectral components. Weights were initialized by random values and networks were run until at least one of the following termination conditions was satisfied:

(1) maximum epoch;

(2) minimum gradient;

(3) performance goal.

A group of Matlab functions were written to examine, transform, plot, and identify abnormality. For example, AND operation implementation using feedforward neural network is shown in Figure 3.

RESULTS

Using the signal processing toolbox in the Matlab software package, the spectral response of the VEP waveform for 30 patients has been computed. The spectral response shows that the peak response occurs at specific frequencies like 2, 3, 4, 5, and 6 Hz (Table 1). The important finding of

TABLE 1. Disease condition and spectral component values.

S.no	Latency in ms	Disease	Spectral components in Hz
1	100	Normal	2
2	100	Normal	2, small peak at 6
3	118	Diminished vision	3
4	120	MND	3
5	122	Diminished vision	3, small peak at 2
6	130	MS	4, small peak at 2
7	138	MS	6, small peak at 2

```
P = [0 0 1 1; 0 1 0 1];
t = [0 0 0 1];
net = newff(minmax(P), [3, 1], {purelin,
 purelin}, traingdm);
net.numInputs = 1;
net.inputs{1}.size = 2;
net.numLayers = 1;
net.layers{1}.size = 1;
net.inputConnect(1) = 1;
net.outputConnect(1) = 1;
net.targetConnect(1) = 1;
net.layers{1}.transferFcn = purelin;
net = init(net);
net.initFcn = initlay;
net.trainParam.show = 500;
net.trainParam.lr = 0.50;
net.trainParam.mc = 0.9;
net.trainParam.epochs = 5000;
net.trainParam.goal = 0.001;
[net,tr] = train(net, P, t);
p = [1;0];
a = sim(net,p);
print a;
gensim(net,−1);
if (a < 0.5) a = 0
else a = 1;
end; disp(a);
```

FIGURE 3. AND operation implementation using feedforward neural network.

this result is that there are distinct differences at the peak frequencies for normal and abnormal condition like MS, diminished vision, and MND (Figures 4 and 5).

The ANN was implemented on a personal computer using the neural network toolbox in the Matlab software package. During training period, we utilized 6 numbers of input nodes, 4 numbers of hidden nodes, 4 numbers of output nodes, logsin transfer function, GDM training method, 5000 numbers of epochs, initial and bias value, 0.9 MC value, 0.8 learning rate, and 0.0017 goal. The training error continues to decrease as the number of epochs increases (Table 2 and Figure 6). Repeated
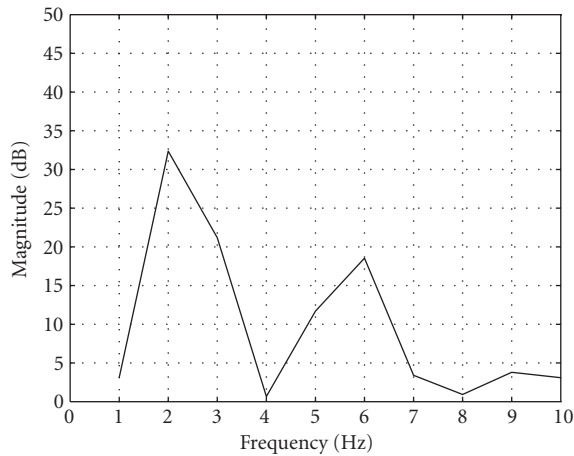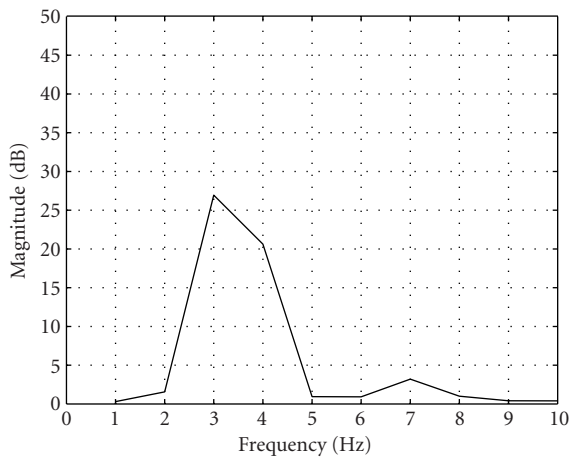
FIGURE 4. Normal VEP spectrum plot.

FIGURE 5. Abnormal VEP spectrum plot (MND patient).

TABLE 2. ANN training result.

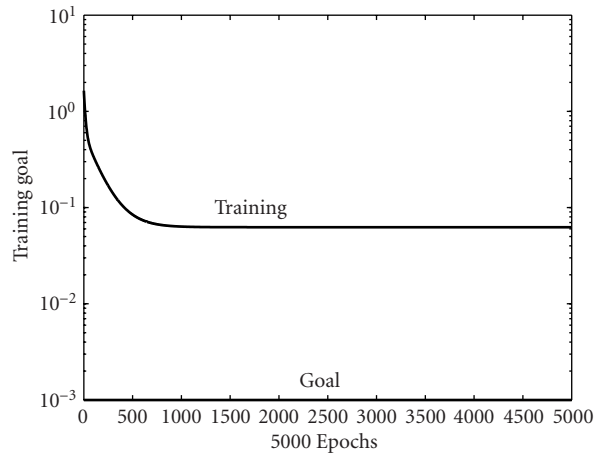| | TRAINGDM | |
Epoch	MSE	Gradient
0/5000	0.727095/0.001	0.198489/1e-010
2500/5000	0.00481211/0.001	0.00063416/1e-010
5000/5000	0.00451022/0.001	0.000414329/1e-010
Maximum	—	—

FIGURE 6. ANN training plot. Goal is 0.001.

FIGURE 7. Feedforward neural network.

experiments were performed to determine the size of the hidden layer and training sample. Our final ANN consists of 6 hidden units, which provide compromise between the mapping error and the computational time (Figure 7). Finally, we found the neural network precisely predicts the patient abnormality based on the spectral components.

DISCUSSION

All disorders analyzed in this study are found to have the common phenomenon that latency is elongated compared to normal condition. Main disorder associated with MS is demyelination of the optic nerve. Demyelination produces decreased velocity of conduction, which in turn increases the latency . For the MS condition patient, previous reports indicate that the latency will be prolonged by 10 to 30 milliseconds [3, 21]. As the severity of the disease increases, the prolongation will also increase. The present study patient with MS was found to have prolongation of
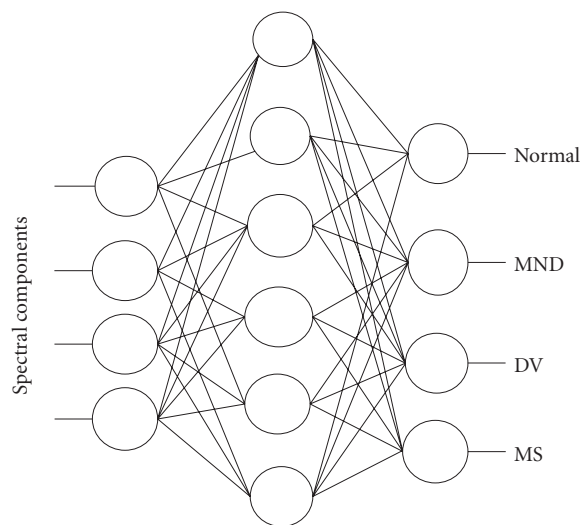
latencies by 30 to 38 milliseconds compared to normal. As the latency increases, the peak frequency is found to shift towards the higher side. As indicated in Table 1 for the 130-milliseconds peak, frequency was at 4 Hz whereas for 138 milliseconds it was at 6 Hz.

The next disorder namely diminished vision, which results either due to hereditary or degenerative condition

like MND, was found to have small increase in latency [22]. In the present work, latency is found to increase by 18 to 22 milliseconds (ie, latency of 118 to 122 milliseconds). For these waveforms, peak response is found to occur at 3 Hz. Comparatively less shift occurs in spectral response compared to MS cases where latency was increased by 30 to 40 milliseconds.

Thus the spectral response technique agrees with the pathological conditions. The further work is in progress to test this technique on more number of patients with similar disorders which will help to identify the similar ophthalmological and neurological disorders automatically without any subjective error and without any complicated processing technique like averaging and interpolation and so forth.

ANN has been used in a number of different ways in medicine and medically related fields [23, 24]. This paper examined one aspect of their use; this can be extended to many applications in medicine. At the current stage, we have tested a simple case and it can be extended to complex cases. Presently, we are testing the system on a large patient data and in future it can be implemented for routine clinical use. Using this method, it is possible to perform real-time mental state identification on personal computer. The most attractive feature of the proposed ANN-based algorithm is being virtually parameter-free, the user does not have to either initialize or select any parameter.

The combination of computer and the Matlab environment for controlling and analyzing neural network experiments has been proved to be useful in many domains. The user can alter a number of parameters and quickly see the results graphically. The application of ANN to VEP analysis may yield improvements in classification accuracy over more traditional methods. The extension of this work will even help to quantify the prognosis of the treatment.

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