

Research Article

Enhancing Visual Evoked Potentials Detection with Use of Computational Intelligence Tools

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Received 28 October 2010; Revised 7 March 2011; Accepted 8 March 2011

Abstract The analysis of evoked potentials (EPs) in the electroencephalogram (EEG) is usually inspected visually and demands subjective interpretation of the results. This paper aims at combining an statistical criterion based on the magnitude square multiple coherence (MSMC) estimate with computational intelligence methods in order to estimate the EPs detection rate (DR) using only portions of the frequency spectrum. Thus, networks were used to predict the DR in EEG signals of 15 normal subjects during stroboscopic stimulation. The algorithms were designed to receive the spectral information of two, four or six EEG derivations as the input and DR as the output. Our best result shows that the artificial neural networks can estimate DR with correlation coefficient of 0.97 compared with MSMC, even when a reduced amount of spectral information from the data is available.

Keywords detection; evoked potential; coherence; neural networks; neurofuzzy networks

1 Introduction

The electroencephalogram (EEG) is the signal resulting from the continuous record of the electrical brain activity of cerebral cortex [15]. The EEG is recorded by electrodes placed on the scalp and these electrodes are distributed according to established patterns. The most used is the 10–20 system, where 20 electrodes are attached in the scalp [15].

Whenever an external stimulation is applied, such as stroboscopic flashes, clicks or electrical shocks, responses are expected to occur in the cortex, with stronger amplitudes in areas physiologically related to the stimulation (i.e. visual, auditory or somato-sensory cortex). For example, Figure 1 shows the EEG signal recorded from two

electrodes, O1 and O2, which are located above the primary visual cortex. Since these evoked responses exhibit very small amplitude in comparison with that of the spontaneous EEG, averaging techniques are often necessary to reveal them. One of such is the coherent average of the EEG triggered by the stimulation signal, which leads to an estimate of the cortical response and is called the evoked potential (EP) [14].

In the clinical practice, the EP wave-shape has been used in the evaluation of brain function, since the amplitude and latency of the EP may change due to some pathologies or even during anesthesia or different mental states [18]. In addition, alterations in the evoked potential may indicate the presence of lesions [18].

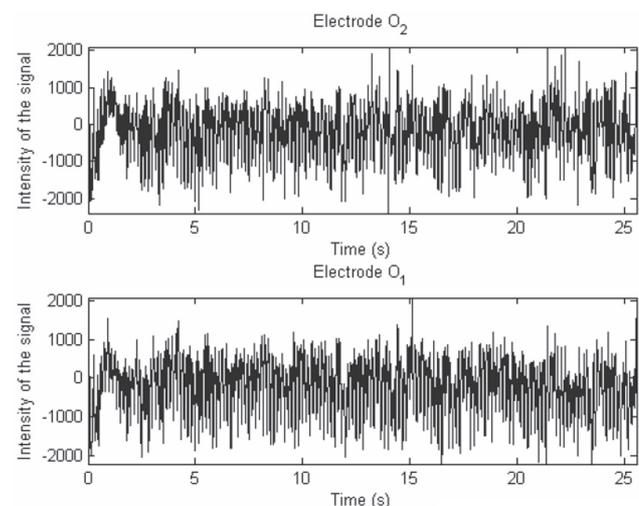


Figure 1: EEG signal recorded from electrodes O1 and O2, which are located above the primary visual cortex.

In some other applications, the morphology of the evoked response is not the crux point, but one is rather interested in assessing whether there is or not response to the stimulation. This is the case of newborn auditory screening or even in monitoring spinal cord surgeries. For such cases, a statistical criterion that allows testing the null hypothesis of lack of evoked responses is necessary [22].

Many techniques have been developed in order to statistically test the presence or absence of response [16]. These techniques are called objective response detection (ORD) and multivariate objective response detection (MORD). These tests consist of a comparison between a detector and a statistical threshold, since the latter comes from the null hypothesis (H_0) which assumes that the analyzed signals have no significant response. The ORD and MORD techniques most used are as follows: spectral F test (SFT) [25], magnitude squared coherence [5,14], phase synchronization measure [25] and magnitude-square multiple coherence [15].

Visual evoked responses, which are the focus of this work, are usually elicited by three types of stimuli: checkerboard, specific pattern of stimulus and flash. Each kind of stimulation leads to different response patterns, for example, the signal resulting from stroboscopic (flash) stimulation differs from that produced by checkerboard pattern reversal stimulation [18]. The visual potential is used in clinical practice and may have different forms, such as checkerboard patterns, sine wave gratings, bar gratings, small light spots and random dots. Furthermore, there are visual evoked potentials generated with diffuse light, colored light, eye movements, and so on [18].

However, the analysis of the EEG using evoked responses is subjective and qualitative. This assessment depends on the experience of professionals who are carrying out the analysis. An alternative to evaluating the EP is the use of quantitative and statistical techniques, such as the ORD technique [15]. ORD technique has been identified as one of the most efficient ways for the analysis of EEG during rhythmic stimulation [5,6,25]. These techniques can be implemented both in time and frequency domains, but the literature commonly presents analysis in the frequency domain [15]. In this domain, the coherence is the technique which has been used as a powerful tool in the analysis of the EEG during periodic stimulation [5,14,22,25].

According to Miranda de Sá et al. [16], the magnitude-squared coherence (MSC), which calculates the coherence between the stimulation signal and the EEG, can be estimated by considering only the EEG signal. MSC is used efficiently to measure and compare the strength of responses from cerebral regions at distinct frequencies and for distinct subjects with varied ages [17].

Recently, Miranda de Sá et al. [15] and Felix et al. [6] proposed the estimate of the magnitude-square multiple

coherence (MSMC) between the stimulation and N different EEG signals so as to increase the detection rate for a fixed signal length.

In this work it is argued that the estimate of detection rate—which is associated with the strength of the EP [17]—of evoked responses can be determined by using only some frequency bands of signal spectra. Thus, the detection rates of EPs were evaluated by combining MORD techniques and artificial neural networks (ANN) [8] or Neurofuzzy Networks [26].

The ANN is constituted by neuron structures based on the human neural system that mimics the learning procedure of the biological neuron [8]. There are many applications of ANN to EEG signals [4,7,12,19] such as EEG processing [23] and evoked potential identification [9,11]. Applications of ANN in EEG signals involve a specific approach, according to the required analysis. When analyzing sleep waves, for example, the RNA is frequently used for the classification of sleep-wake cycle states of newborns [4]. Another example is the monitoring of anesthesia depth using ANN [23] in which the EEG of patients can provide information about the central nervous system. In this case, the ANN is used for monitoring the alterations in EEG. Furthermore, dynamic neural networks are used for identification of visual evoked potentials [11]. The objective of ANN in this analysis is the identification of features in the visual evoked responses. Other applications can be cited such as brain computer interface [7] and artifact detection in EEG [4].

Neurofuzzy networks are also implicated in biologic systems [2,26], as for example analysis in EEG [1,20]. According to [2], features extracted for auditory evoked potentials can be used for automatic closed-loop control of general anesthesia using fuzzy systems. Moreover, the Neurofuzzy systems can be used for the classification of EEG spikes [1], which are important tools in epilepsy diagnosing. Another example is the determination of sleep stages in EEG using fuzzy systems [20].

This paper proposes an alternative system to EP detection using computational intelligence techniques. The algorithms consider the energies only in some spectral bands of the EEG during intermittent photic-stimulation as the inputs and the detection rate obtained by MSMC as the output. Thus, we are analyzing an alternative way to estimate the detection rate of EPs by improving the detection power of MORD techniques.

2 Materials and methods

2.1 Magnitude squared multiple coherence (MSMC)

Coherence function between two signals: $x(n)$ and $y(n)$, is defined by [3]

$$\gamma_{xy}(f) = \frac{S_{xy}(f)}{\sqrt{S_{xx}(f)}\sqrt{S_{yy}(f)}}, \quad (1)$$

where $S_{yx}(f)$ is the cross power spectral density (PSD) and $S_{xx}(f)$ and $S_{yy}(f)$ are their individual PSDs. The coherence function can be perceived as the spectrum of cross correlation between signals. It indicates the linear dependency between harmonics of signals, and it provides synchronization between the series in the frequency [14,21]. The analysis of synchronization has been widely used for the analysis of EEG signals. Among the applications, we can mention the evaluation of synchronization between different brain regions or assessments pathologically [21].

Taking the square of absolute value of equation (1) we obtain a real number given by [3]:

$$\gamma_{xy}^2(f) = \frac{|S_{xy}(f)|^2}{S_{xx}(f)S_{yy}(f)}. \quad (2)$$

When we estimate equation (2) for ergodic signals we have the following estimative [3]:

$$\hat{\gamma}_{xy}^2(f) = \frac{|\sum_{i=1}^M X_i^*(f)Y_i(f)|^2}{\sum_{i=1}^M |X_i(f)|^2 \sum_{i=1}^M |Y_i(f)|^2}, \quad (3)$$

where * indicates the complex conjugate, $X_i(f)$ and $Y_i(f)$ are Fourier Transform of the i th windowed epochs and M is the number of epochs used in the estimation.

Taking $x(n)$ as identical events in all epochs (e.g. visual stimulus) and $y(n)$ the EEG signal from the scalp, equation (3) can be simplified and denoted as the magnitude square coherence, MSC(f), [17,25]

$$\text{MSC}(f) = \frac{|\sum_{i=1}^M Y_i(f)|^2}{M \sum_{i=1}^M |Y_i(f)|^2}. \quad (4)$$

The multivariate extension of the coherence concept leads to magnitude squared multiple coherence (MSMC), where the coherence function is calculated with signals of several electrodes [15].

The MSMC is a technique that uses multiple coherence between the stimulation signal, $x[k]$, and N EEG derivations ($y_N[k]$, $N = 1, 2, \dots$) [15]. It must be mentioned that such a technique is independent of the shape of the stimulation signal and only needs the N available EEG signals to be estimated. Thus, the MSMC of $x[k]$ can be estimated as

$$\text{MSMC}(f) = \frac{V^H(f)\hat{S}_{yy}^{-1}(f)V(f)}{M}, \quad (5)$$

where

$$V^H(f) = \left[\sum_{i=1}^M Y_{1i}(f) \quad \sum_{i=1}^M Y_{2i}(f) \quad \dots \quad \sum_{i=1}^M Y_{Ni}(f) \right], \quad (6)$$

$$\hat{S}_{yy}(f) = \begin{bmatrix} \hat{S}_{y_1y_1}(f) & \hat{S}_{y_1y_2}(f) & \dots & \hat{S}_{y_1y_N}(f) \\ \hat{S}_{y_2y_1}(f) & \hat{S}_{y_2y_2}(f) & \dots & \hat{S}_{y_2y_N}(f) \\ \vdots & \vdots & \ddots & \vdots \\ \hat{S}_{y_Ny_1}(f) & \hat{S}_{y_Ny_2}(f) & \dots & \hat{S}_{y_Ny_N}(f) \end{bmatrix} \quad (7)$$

and $Y_{Ni}(f)$ is the Fourier Transform (FT) of the i th window of the $y_N[k]$ signal, H superscript is the Hermitian form of $V(f)$, \hat{S}_{yy} is the auto-spectrum matrix estimate and M is the number of windows used in FT calculations of each signal.

According to [15], the critical values are

$$\text{MSMC}_{\text{crit}} = \frac{F_{\text{crit},\alpha,2N,2(M-N)}}{\left(\frac{M-N}{N}\right) + F_{\text{crit},\alpha,2N,2(M-N)}}, \quad (8)$$

where N is the number of signals, M is the number of segments used in the estimation, $F_{\text{crit},\alpha,2N,2(M-N)}$ is the critical value for the F -distribution with $2N$ and $2(M-N)$ degrees of freedom for a significance level α . This threshold is used for calculating the detection rate of the EP. When peaks of the frequency of stimulation and its harmonics are above the critical threshold, we say that there was a detection of VEP.

2.1.1 Detection rate

This section illustrates the detection rate estimation obtained by MSMC. Consider impulse train with fundamental frequency at 20 Hz and a white noise added. This resultant signal was computationally generated with 256 Hz sampling frequency and the number of windows and derivations was $M = 12$ and $N = 5$, respectively. Figure 2 shows MSMC calculated using equation (5) and the critical value (black line) obtained by equation (8) (significance level at 5%).

Detection rate was obtained by counting the number of harmonics of the fundamental frequency that were higher than the critical value and divided by the total number of harmonics. In this case, as sampling frequency is 256 Hz and the fundamental frequency is 20 Hz, there is a total of $\text{fix}(128/20) = 6$ harmonics in the spectrum. Thus, it can be seen by analyzing Figure 2 that the detection rate is 83.33%, since five of the six possible harmonics were significant.

This result is obtained according to following steps: (1) calculation of coherence, (2) calculation of critical value, (3) calculation of the number of harmonics in the coherence spectrum and (4) comparison of coherence values higher than the critical values in the harmonics. Note that the whole spectrum, value by value, must be evaluated in order to estimate the detection rate in this case.

2.2 Neural network

The artificial neural network is the structure that contains neurons similar to the neural human system. Figure 3 shows the multilayer perceptron composition used in this paper which contains hidden layers. In this example, the network contains some neurons in the input layer, three neurons in the hidden layer and one neuron in the output layer. The input layer receives information presented by signals or parameters analyzed and the output layer provides a response for the system. In this paper, neural networks

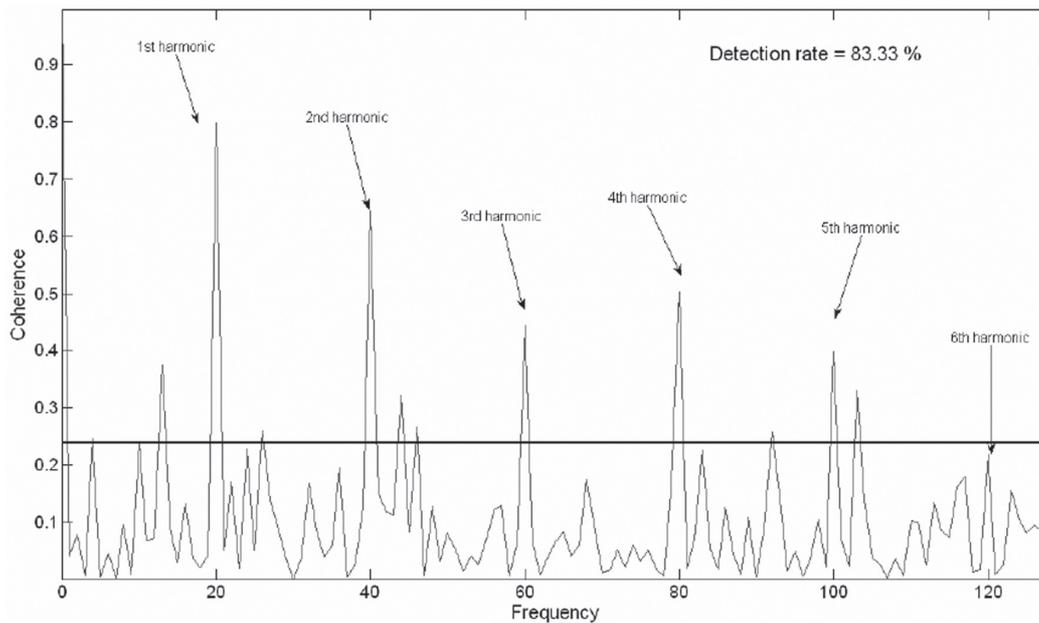


Figure 2: Detection rate obtained using MMSC. The signal was impulse train with fundamental frequency at 20 Hz and contaminated with white noise.

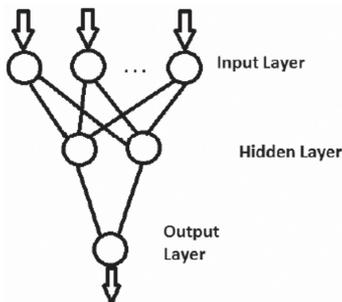


Figure 3: Multilayer Perceptron with N neurons in the input layer, 2 neurons in the hidden layer and one neuron in the output layer.

with hidden layers commonly applied to solve nonlinear separable problems have been used. Such networks are known as multilayer perceptrons (MLPs) [8].

The connections between neurons are associated with weights and in each neuron are made mathematical calculations via functions called activation functions. The activation function used in neural networks in all this work was the log-sigmoid [8].

The training of neural networks leads to learning and it is similar to the learning process of human brain. The patterns or signals analyzed are passed to the input neurons and, through functions and weights, the output is calculated. The output value is compared with the expected value and, according to parameters used in training, weights are recalculated and the output is obtained. Several training

algorithms were developed, according to the problem to be solved. The training algorithm was the well-known back-propagation method [24] with gradient descent and adaptive learning rate.

2.3 Neurofuzzy networks

The neurofuzzy training algorithms are a combination of fuzzy inference systems and the adaptive learning of neural networks. The neurofuzzy networks used in this work are now briefly reviewed.

2.3.1 Wang's neurofuzzy network

Wang [27,28] proposed this topology of neurofuzzy network where the rules are the base of the fuzzy logic system. The initial step is fuzzyfication and it uses singleton and Gaussian membership function. Then, the defuzzyfication maps the fuzzy set to a deterministic point. The mapping used in this work was the central average given by Wang [27, 28] and the inference method was the product. The training process was performed by an error back-propagation procedure.

2.3.2 Adaptive neurofuzzy inference systems (ANFIS)

ANFIS is a multilayer network based on Sugeno's fuzzy inference system [10]. The parameters of an ANFIS network can be found using two types of training algorithm: hybrid and back propagations. Both algorithms were used in this paper.

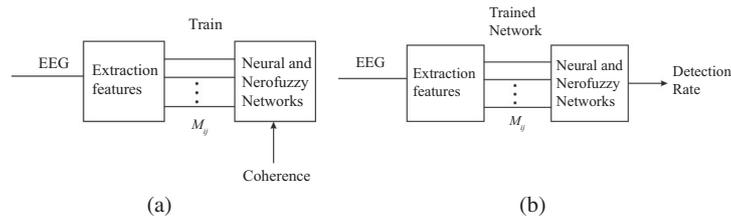


Figure 4: Block diagram (a) before training using detection rate as output and spectrum average as input and (b) after training only using spectrum average. The output is an estimation of the detection rates.

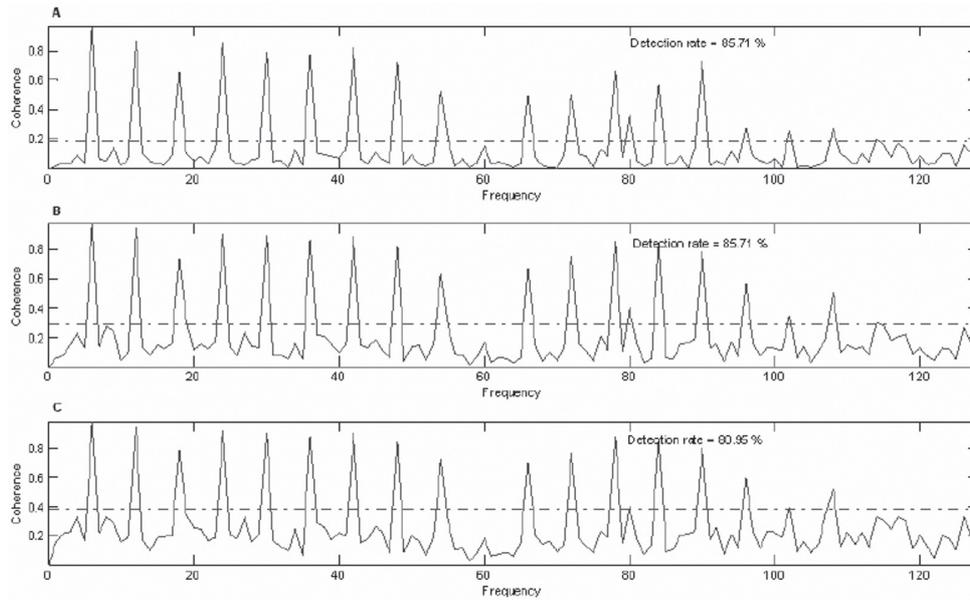


Figure 5: Multiple coherence for stimulation frequency of 6 Hz and $M = 12$ for (A) two electrodes (O1 and O2), (B) four electrodes (O1, O2, P3 and P4) and (C) six electrodes (O1, O2, P3, P4, C3 and C4).

The membership function of the input, where the fuzzyfication process occurs, is located in the first layer of an ANFIS network. The rules were associated with the probabilistic method *and* [10].

After the association of the rules, there is the process of normalization of the weights. At this stage, the maximum *or* method was applied [10]. In the defuzzification step, the relative contribution of each rule is added together and the output is calculated with Sugeno method. The method of defuzzification was the weighted average and the inference method was the probabilistic method.

2.4 Data description

The signals used here were obtained from the EEGs of 15 normal subjects (age range: 9–17 years old, mean: 13.2 years, standard deviation 2.59 years). They were recorded during visual stimulation by stroboscopic flash and using a Nihon-Koden EEG-5414K at Instituto Fernandes Figueira (IFF) Pediatric Hospital, Brazil. The subjects were stimulated at 6 and 8 Hz over a period of 25 seconds in

separated sections and the EEG without stimulation was recorded for the same period of time. The resulting signals of 16 electrodes (International 10–20 system, with reference at the ipsilateral earlobe) were then digitized at a sampling frequency of 256 Hz.

2.5 Preprocessing

In order to extract the main characteristics of the power spectrum of the EEG, the derivations O1, O2, P3, P4, C3 and C4 were chosen due to their location on the visual cortex (O1 and O2) or to their proximity to it (the remaining electrodes), where more intense evoked responses are expected thus leading to a higher detection rate. Figure 4 shows the training and simulation with EEG data.

Figure 5 shows a typical case of multiple coherence of the EEG of a subject #1 during stimulation at 6 Hz for an increasing number of electrodes. In Figure 6 the detection rate for the same subject with frequency of stimulation of 8 Hz is shown.

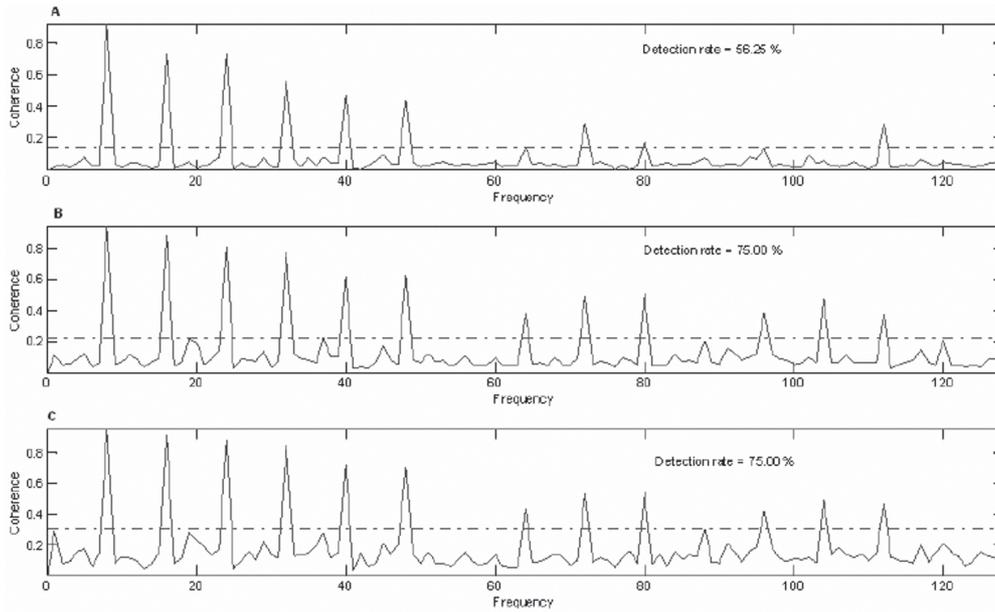


Figure 6: Multiple coherence for stimulation frequency of 8 Hz and $M = 12$ for (A) two electrodes (O1 and O2), (B) four electrodes (O1, O2, P3 and P4) and (C) six electrodes (O1, O2, P3, P4, C3 and C4).

The extraction of data features was based on the expectancy of a change of energy in the spectra around the stimulation frequencies and side bands. The Fourier Transform was then applied to the signals of the electrodes shown in Table 1. The energy at 4–5 Hz, 6–7 Hz, 8–10 Hz and 11–13 Hz were used as input to the networks.

For each subject, with and without stimulation, MSMC has been estimated from the signals of the specific electrodes and was later used for the calculation of the detection rate, as shown in Figures 5 and 6. The result is used as the output for the networks.

The input and output defined as above were used to train the networks. In the training process, 75% of the data were used whereas the remaining data was used for validation. It is worth emphasizing that overfitting was avoided as much as possible by evaluating the validation error, that is, only the network structure that showed the smaller error of validation was kept. This process is known as early-stopping.

3 Results

Figure 7 shows the neural (Figure 7(a)) and neurofuzzy (Figure 7(b)) networks performance for the validation set using two electrodes (see Table 2), that is, the comparison between the detection rate obtained using network tools and the one uses the original MSMC algorithm. In this case, the best network was neural with one hidden layer and five neurons. The mean square error and correlation coefficient (measure between the detection ratios from MSMC and the output of the networks) was 0.002 and 97%, respectively.

i	Derivations
1	O1
2	O2
3	P3
4	P4
5	C3
6	C4

Table 1: Derivations and respective numbers used in the calculation of amplitude averages as specified above.

N	Electrodes
2	O1 and O2
4	O1, O2, P3 and P4
6	O1, O2, P3, P4, C3 and C4

Table 2: Number of channels used in the detection and the electrodes associated to them, according to the order used in this paper.

The MSMC technique allows the aggregation of more signals in the detection protocol. From up to four signals (see Table 1), the detection ratio was less or equal to that obtained with two electrodes. In this case, the best network too was neural. In fact, an MLP with two hidden layers with 2 and 8 neurons, respectively, yielded to a coefficient of correlation of 0.94 when compared with the MSMC and the same set of signals. Figure 8(a) illustrates the result.

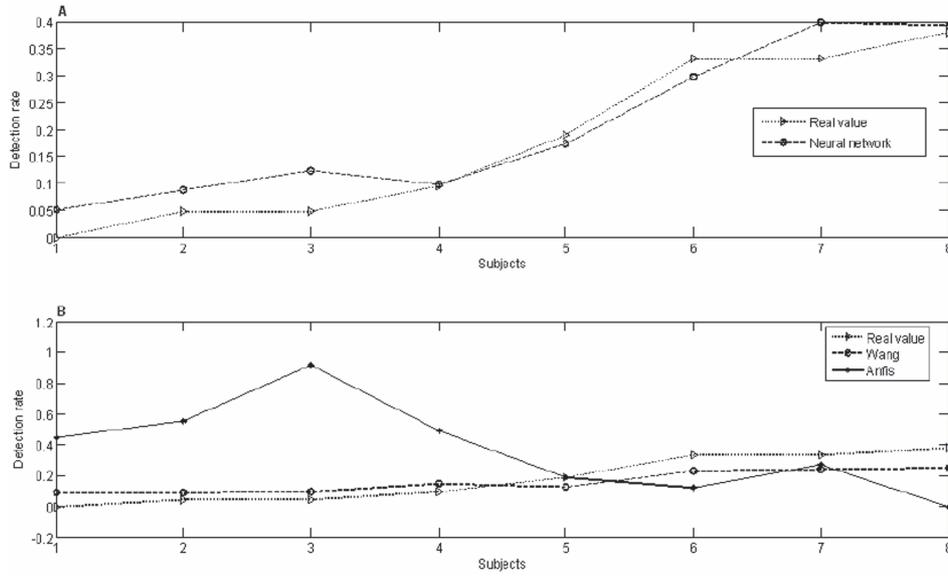


Figure 7: Comparison between the values of detection rate for the EEG of 8 subjects as part of the validation of the neural and neurofuzzy networks for two electrodes and frequency of stimulation of 6 Hz. (A) Original coherence (dotted line) and neural estimation (dashed line) by the neural network. (B) Original coherence (dotted line) and neurofuzzy estimation (dashed and continuous lines).

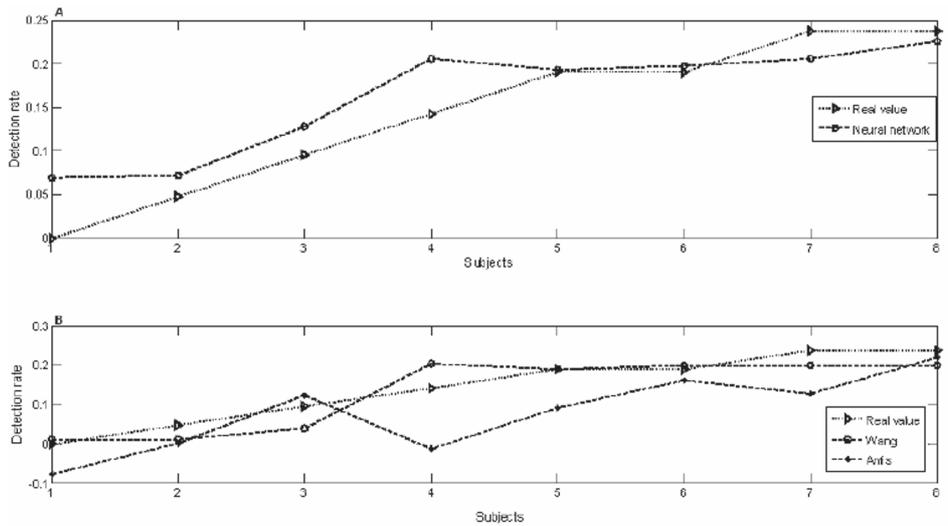


Figure 8: Comparison between the values of the detection rate for the EEG of 8 subjects as part of the validation of the neural and neurofuzzy networks for four electrodes and frequency of stimulation of 6 Hz. (A) Original coherence (dotted line) and neural estimation (dashed line) by the neural network. (B) Original coherence (dotted line) and neurofuzzy estimation (dashed and continuous lines).

Finally, the coherence for six electrodes configuration was examined. In this situation, the MLP was also better than the other tools and exhibits the coefficient of correlation of 92% with the expected output. The best neural network had one intermediate layer with nine neurons. Note that the value of the coefficient of correlation was large, however, this value was not so large as the value found for

the configuration with two electrodes. The results are shown in Figures 9(a) and 9(b) for the neural network and neuro-fuzzy network, respectively.

Table 3 displays the comparison between the mean squared errors and correlation coefficients for all three types of networks. It can be observed that the neural networks display the smallest squared error as well as the

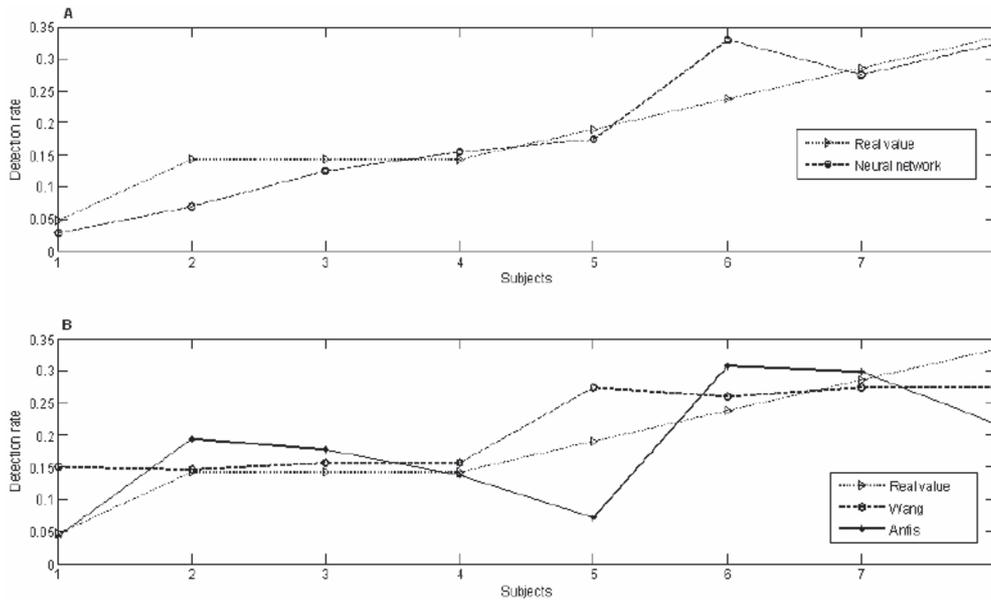


Figure 9: Comparison between the values of detection rate for the EEG of 8 subjects as part of the validation of the neural and neurofuzzy networks for six electrodes and frequency of stimulation of 6 Hz. (A) Original coherence (dotted line) and neural estimation (dashed line) by the neural network. (B) Original coherence (dotted line) and neurofuzzy estimation (dashed and continuous lines).

Parameters		Neural	Wang	Anfis
$N = 2$	C.C.	0.97	0.96	0.80
	Error	0.0020	0.0068	0.1966
$N = 4$	C.C.	0.94	0.91	0.81
	Error	0.0014	0.0014	0.0070
$N = 6$	C.C.	0.92	0.84	0.72
	Error	0.0019	0.0028	0.0044

Table 3: Errors and coefficients of correlation for the neural and neurofuzzy networks trained using data from two, four and six electrodes. C.C. stands for coefficient of correlation.

highest correlation coefficients in all the cases. In the case of two electrodes, the correlation coefficients are at the highest value for the neural networks possibly indicating the situation where the proposed methodology is more effective.

For stimulation frequency of 8 Hz, the analysis was performed with two electrodes: O1 and O2. In this case, the frequency bands applied as inputs to neural networks were the same ones used in the case where the frequency was 6 Hz. After training, the obtained coefficient of correlation was 89% and the mean squared error was 0.0058. In this particular case, the neural network has two hidden layers with two and seven neurons, respectively. The estimated values for the detection rate for 8 subjects are illustrated in Figure 10.

4 Discussion and conclusion

The application of neural and neurofuzzy tools to detect evoked responses has been presented. It has been shown that the estimate of the detection rate of subjects can be found using less frequency bands when compared with MSMC itself. Such bands were used as the input for neural and neurofuzzy networks. With its ability to generalize to new cases, the neural network has shown to adequately reproduce outputs (detection rates) for different inputs other than those shown during the training process and for different kinds of stimulation.

The best performance of the neural and neurofuzzy networks occurred when only two channels were used (evaluation with stimulus in the frequency of 6 Hz). Although further investigation is pending, preliminary results show that the level of correlation between the original detection rate and the output of the network tool decreases as the number of channels increases.

For the frequency of 8 Hz, an acceptable response obtained using a neural network was also obtained. The network used for 8 Hz validation was the same used in 6 Hz, that is, the networks were trained only once. This shows that it is only necessary to provide some specific frequency bands of the EEG signal spectra to the network so as to reliably estimate the detection rates.

The possible reason for an efficient estimation of the detection rate using part of the spectrum is the presence

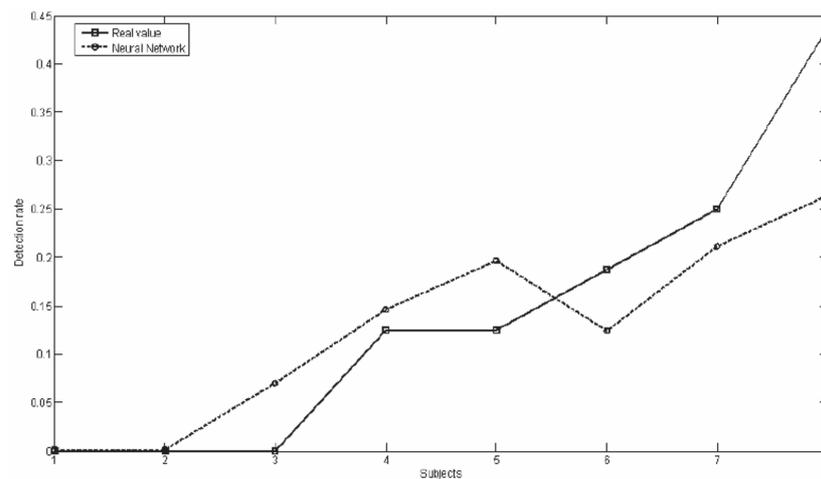


Figure 10: Values of the detection rate for the EEG at the 8 subjects used in the validation of the neural network for two electrodes and frequency of stimulation of 8 Hz. Analysis for each subject, where the solid line represents the real values and the dotted line represents the values estimated by neural network.

of the first harmonics. These harmonics have been shown to exhibit higher coherence [15] when compared to results from other harmonics. On the other hand, the values of the detection rates become smaller as the number of channels used in the multiple coherence increases. A possible explanation is the decrease in magnitude of the coherence. This difference can be observed in Figures 5 and 6, where the values of the coherence are smaller for the first harmonics. This shows that, for very small values of coherence, the precision of the estimation reduces in the same way as what occurs in the case of multiple coherence between 4 and 6 electrodes [15].

It is believed that the same analysis performed here can be extended to other groups of patients (e.g. EEG of children exhibits different characteristics from those ones of the adults) and in other applications, as the identification of stages of sleep [4]. Another possible study would be the identification of Brain Electrical Silence in newborns (signals with threshold around two micro-Volts) [13].

Acknowledgments The authors gratefully acknowledge FAPEMIG, FAPERJ, FUNARBE, CNPq and CAPES for financial support.

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