EEG NOISE CANCELLATION BASED ON NEURAL NETWORK

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Abstract: Electroencephalogram (EEG) recordings often experience interference by different kinds of noise, including white and muscle, severely limiting its utility. Artificial neural networks (ANNs) are effective and powerful tools for removing interference from EEGs, but the quality of the separation is highly dependent on the type and degree of contamination. Several methods have been developed, but ANNs appear to be the most effective for reducing muscle contamination, especially when the contamination is greater in amplitude than the brain signal. We propose an ANN as a filter for EEG recordings, developing a novel framework for investigating and comparing the relative performance of an ANN incorporating real EEG recordings from the Clinical Neurophysiology Service at the Virgen de la Luz Hospital in Cuenca (Spain). This method was based on a growing ANN that optimised the number of nodes in the hidden layer and the coefficient matrices, which were optimised by the simultaneous perturbation method. The ANN improved the results obtained with the conventional EEG filtering techniques: wavelet, singular value decomposition, principal component analysis, adaptive filtering and independent components analysis. The system was evaluated within a wide range of EEG signals in which noise was added. The present study introduces a method of reducing all EEG interference signals with low EEG distortion and high noise reduction.

1 INTRODUCTION

Noise reduction is a matter of considerable importance in biomedical signal processing applications, especially electroencephalogram (EEG) analysis (Sörnmo, 2005); (Bronzino, 2000); (Rangayyan, 2002).

Noncortical biological artifacts are the principal source of contamination in EEG recordings and are generated primarily by movements, cardiac pulse, and muscle activity, particularly that of the face (especially the jaw) and neck. EEG experimental design is generally constrained by the desire to minimise the effect of these artifacts.

Several methods have been suggested for muscle noise reduction. Signal processing techniques used for noise elimination include bandpass filtering, fast Fourier transform, autocorrelation, autoregressive modelling, adaptive filtering, Kalman filtering, Bayesian filtering, singular value decomposition (SVD) (Paul 2000); (Shao, 2009); (Zhang, 2006); (Sameni, 2008) one of the common approaches is the adaptive filtering (AF) architecture which has been used for the noise cancellation of ECG (Olmos, 2002) and wavelet (Castellanos, 2006). Recently, principal component analysis (PCA) (Lagerlund, 2004) and independent component analysis (ICA) (Crespo-Garcia, 2008) have become popular for analysing biomedical data. One of the main advantages of these approaches relates to their applicability to multisensory observations of mixed signals. However, PCA is unable to separate some artifact signals from brain signals when they have similar amplitudes. In addition, both PCA and SVD perform well only if the noise level is low enough and a signal subspace and noise subspace are orthogonal to each other. For practical applications, the orthogonality requirement is usually not valid. On the other hand, ICA cannot guarantee that some individual independent components (ICs) contain only noise and not information about useful sources, especially in biomedical applications. Thus, the problem of detection and filtering the "useful" part of each IC is still open, and additional tools are needed to solve it.

In the present study, we created an artificial neural network (ANN) that can act as a filter for EEG recordings. The network was trained using the

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simultaneous perturbation (SP) method. The ANN was chosen mainly because of its adaptability to the nonlinear and time-varying features of the noise. This system was evaluated within a wide range of EEG signals in which white noise and muscle noise were added from the Clinical Neurophysiology Service at Virgen de la Luz Hospital. Thus, this algorithm could serve as an effective framework for filtering noise in EEG recordings. We expect that the distortion of this signal will be reduced compared to conventional methodologies. The results demonstrate that this method can maintain the original shape of the EEG signal in very low SNR conditions in which the brain signal is mixed with the noise.

2 MATERIALS

The signals considered in the present study originated from patients at the referred hospital. All signals were recorded using Viasys Healthcare – NicoletOne equipment, which had been implemented within a concrete period of time. Sleep studies were also included.

All signals obtained from the hospital were randomly classified into three groups, and each of them used a different phase in the filtering process with ANN. Forty signals were chosen to integrate the first group, which was used for network training. The second group was used to validate and compare proper ANN function, and the third group was used to compare ANN with the other systems.

The first and second groups were comprised of 80 signals that lasted 25-50 minutes. Also, 10 sleep testing of approximately eight hours, have been included in these groups. These signals were filtered through ICA (Crespo-Garcia, 2008) to remove any current noise.

Once this process was completed, white and muscle noise were sequentially added to the EEG signal as defined by equation. 1, where d(*k*) is the EEG signal after ICA filtering, A is the amplitude of the added noise, and n(*k*) is the noise signal. Amplitude A was modified in order to obtain an SNR margin between -10dB and 30dB. The main aim was to estimate the clean signal d(*k*) from the noisy signal p(*k*). These recordings are synthetic signals (EEG records to which different noises were added).

$$p(k) = d(k) + An(k) \quad (1)$$

The third group of signals was made up of 50 signals; 40 signals that lasted 30-60 minutes and 10 sleep testing of 8 hours, and neither noise nor variation was added or modified in them (real signals). These signals were also used to compare the above mentioned methods to ANN.

3 METHOD

The Adaline network uses supervised learning and involves a sum of products using the input and weight vectors. An adaptive operation means that there is a mechanism by which w_i, v_i can be adjusted, usually iteratively, to achieve correct values. Regarding Adaline, the properties of the perturbation vectors are assumed to be as described by Maeda and De Figueiredo (Maeda, 1997).

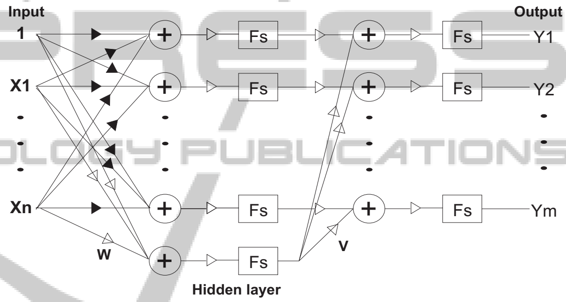

Figure 1: Proposed Neuronal Network with one neuron in the hidden layer. The black coefficients are constants.

For every input, the network output differs from the expected target value d_n by ($d_n - p_n$), where p_n is the current output and n is the number of signals.

This network structure was initially made up of three layers: an input layer, one hidden layer made up of 40 neurons, and an output layer. Once this network was trained, its work was re-evaluated and, if necessary, more neurons added to the hidden layer (Figure 1). This procedure was repeated until expected results are obtained. At all these stages, the ANN was adapted using the SP method in order to obtain the best results. The process of training and initialization was modified and implemented as described by Maeda (Maeda, 1995, 1997). The detailed strict convergence conditions of SP were described by Spall (Spall ,1992).

3.1 Learning Algorithm using Simultaneous Perturbation

Simultaneous perturbation technique for training neural networks has been introduced by Spall (Spall, 1992). Other authors (Maeda, 1995) have also reported results of similar methods. To adapt the weights of the system is necessary to consider the gradient of the error function, this is:

$$\nabla \cong \frac{\partial J(w)}{\partial w} \tag{2}$$

Defining the error function like:

$$J(w) = \frac{1}{2}(y-d)^2 \tag{3}$$

where;

$$\varepsilon = (y-d) \tag{4}$$

Using the equation (4) it is possible to measure the error between the present exit and the wished exit. On the other hand, the approach of differences is a procedure known to obtain the derived from a function, so this approach to reduce the complexity can be used (Haykin, 1994). c is a perturbation added to the i component (Maeda, 1997).

The neural network exit, Y, is a function of the vector of weights:

$$\frac{\partial J(w)}{\partial w^i} \approx \frac{f(Y(w^i)) - f(Y(w))}{c} \tag{5}$$

Nevertheless the above idea which is very simple, needs more operations. It is due to evaluate $J(w^i)$ for all the network weights to obtain the amount modified for all the weights.

$$\Delta w_t^i = \frac{Y(W_t + C_t, V_t + D_t) - Y(W_t, V_t)}{c_t^i} \tag{6}$$

The weights of the neural network are adapted using the following rule: $w_{t+1} = w_t - \Delta\alpha w_t$.

The best results have been obtained when 15 neurons were added to the hidden layer. When more than 15 neurons are added, there is no improvement of both the computational load and the noise reduction.

4 RESULTS

Noise reduction is important for obtaining a clear and useful signal. Some signals, such as EEG, are non-stationary, and the noise statistical property is complicated because of the complexity of the signal. Different techniques have been proposed to reject muscle noise in EEG signals; these conventional filtering techniques can contain ripples that do not correspond to the original EEG. ANN improves all results obtained by wavelet, SVD, PCA, AF and ICA, significantly reducing the interference, Figure 2. The methods are referred in introduction section.

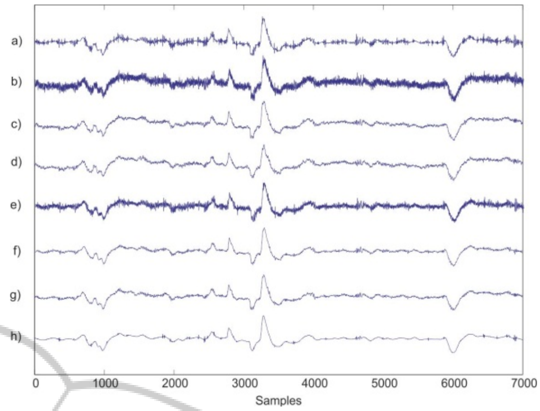

Figure 2: Comparison of the muscle noise removal by ANN and traditional techniques for F7-T3 derivation.

a) Original recording without processing. b) Input signal of 8 dB muscle noise used to compare the different methods. c) Filtering results for muscle noise with the wavelet method. d) SVD method. e) PCA method. f) AF method. g) ICA method and h) ANN

$$SIR = 20\log\left(\sqrt{\frac{E\{\|x_{in} - x\|^2}{E\{\|x_{out} - x\|^2}}\right) \tag{7}$$

Table 1: Obtained results of the cross correlation and SIR for muscle noise, average values.

Methods	Synthetic (CC)	Real(CC)	SIR
Wavelet	0.85 ± 0.03	0.82 ± 0.03	12.9 ± 1.2
SVD	0.88 ± 0.02	0.86 ± 0.03	13.5 ± 2.13
PCA	0.82 ± 0.04	0.80 ± 0.03	12.5 ± 1.3
AF	0.89 ± 0.03	0.86 ± 0.04	14.0 ± 2.27
ICA	0.91 ± 0.02	0.88 ± 0.03	15.2 ± 1.5
ANN	0.96 ± 0.02	0.95 ± 0.02	19.1 ± 1.1

Table 1 shows the cross-correlation average values and standard deviation in synthetic signals and real signals. Nevertheless table 1 shows the SIR average values calculated for synthetic recordings. Equation 7, shows SIR expression where x_{in} shows the input to the system, x_{out} the exit and x the original registry without noise. As can be seen from table 1, with ANN the values are higher than the values obtained with the other systems, both synthetic signals and real signals.

Figure 3 shows the time-frequency analysis of EEG signal with muscle noise. As can be seen the ANN system reduces fluctuations due to muscle noise and gets a more uniform signal.

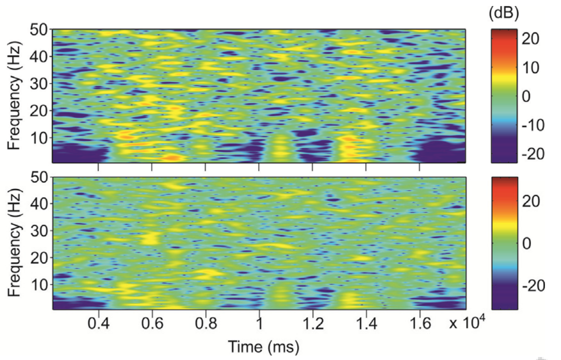

Figure 3: The time-frequency analysis for a noisy signal is shown in the upper figure and for ANN output is shown in the lower figure.

5 CONCLUSIONS

The present study demonstrates how ANN can be used to reduce muscle noise in EEG data. Throughout all stages, the ANN method was adapted using the SP method, which was improved to achieve our target. Our ANN method was shown to be an effective enhancement tool. The techniques proposed here can be applied in multichannel EEG. In all of the practical cases studied, different kinds of noise components appear in the recordings. For this reason, the removal of noise facilitates the clinical analysis for medical professional use.

As a way of conclusion, suffice is to say that the ANN - based approach obtains both more signal reduction and low distortion of the signal results in comparison with traditional filtering techniques. The results of this study show the maintenance of clinical information. The technique which has been proposing through this paper, finds its application by means of denoising biological signals (EEG, ECG, etc).

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