IMPROVED EVOKED POTENTIAL ESTIMATION USING NEURAL NETWORK

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ABSTRACT

Networked structures have shown good capabilities for filtering non gaussian processes. Based on this approach, in the present paper the Multi-Layer Perceptron (MLP) neural network model is used for adaptive non linear filtering. The resulting structures have the advantage that they are able to learn the representation by axamples, which is of great benefit when the nature of the process is unknown or is difficult to characterize.

The purpose of this paper is to analyse the possibility of using the MLP neural network for the processing of the Evoked Potentials (EP). In this case the process can be conceived as deterministic low amplitude signal (damped sine waves), corresponding to the brain response to stimuli, embedded in strongly coloured noise, the EEG background activity. Typical values of the signal-to-noise ratio are less than 0dB.

The network, used as a non-linear filter, is trained using iteratively as input signal one of a set of available EP ensembles and as target signal another ensemble of the same set. Experimental results, both on synthetic and real data, show that the proposed method provides good results with very few EP ensembles. Therefore it allows to noteworthy reduce the signal non-stationarity and the patient's annoyance.

INTRODUCTION

A variety of approaches to adaptive waveform estimation have been developed in various disciplines. The linear adaptive systems such as the Adaptive Linear Combiner (ALC) and the Kalman filter have actracted the interest of many researchers because of their favourable properties. However, their use is limited to applications for which linear descriptions are appropriate. This assumption can be too restrictive in many cases where the process cannot be considered linear.

The recent resurgence of research activity in neural networks has shown the actractive properties of these systems for nonlinear processing. Moreover, the neural network can be considered a promising metaphor for the structure suggested by Palmieri and Boncelet [1] for nonlinear adaptive filtering, where an intermediate mapping function is introduced after a delay line and before a linear combiner, in order to try to linearize the input signal. The neural network approach has the further advantage that it can learn the representation of the process also when the nature of the nonlinearity is difficult to characterize, or is unknown.

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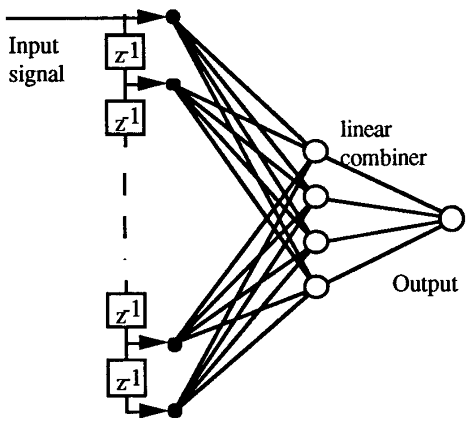

Fig.1 The MLP with a single linear output node.

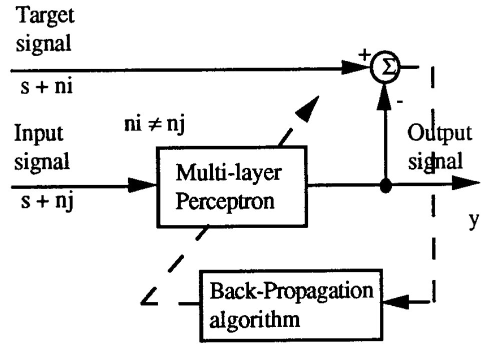

Fig.2 Scheme of the proposed adaptive architecture for EP processing.

In order to evaluate the performance of the proposed technique a set of synthetic EP signals were generated. These signals consist of one cycle of a sine wave followed by a half cycle of attenuated sine wave added to various uncorrelated noise realizations [7]. The noise samples were generated by filtering sequences of random numbers with uniform distribution through the following 11-point smoothing filter:

$$y_n = (-36x_{n-5} + 9x_{n-4} + 44x_{n-3} + 69x_{n-2} + 84x_{n-1} + 89x_n + 84x_{n+1} + 69x_{n+2}$$
$$+ 44x_{n+3} + 9x_{n+4} - 36x_{n+5}) / 429.$$

Each obtained ensemble consists of 96 samples (Fig. 3a, dashed line). The SNR, defined as the ratio Signal Power / Noise Variance, was assumed equal to -6 dB. The following parameters of the neural network were chosen for the experiment:

units in the input layer:	= 10;
units in the hidden layer:	= 6;
samples processed in the learning phase :	= 576,000;
learning rate constant :	= 0.01;
momentum constant :	= 0;

sigmoid : $f(x) = \text{Gain} * [2 / (1+\exp(-x * \text{Slope}) - 1]$. Gain = 2; Slope $= \frac{1}{2}$;

Fig. 3a shows the filtered signal (solid line) compared with the true synthetic EP (dotted line) and Fig. 3b shows the filtered signal, averaged on 12 ensembles, compared to the signal obtained by simply averaging the input signals on the same number of ensembles.

To quantify the performance of the network, the mean of the MSEs over each available ensemble was calculated after the learning phase (Fig. 4). Moreover the after training output ensembles were averaged and the corresponding MSE was compared with those obtained by the averaging technique (Fig. 5). The proposed method provides good results with very few EP ensembles and without the necessity of a-priori knowledge of the signal characteristics.

The purpose of this paper is to analyse the possibility of using the MLP neural network [2] for the processing of the electrical responses of the brain to stimuli or Evoked Potentials (EP).

EP can be conceived as deterministic low amplitude signals embedded in coloured noise, the EEG background activity, which has temporal and spectral characteristics similar to the EP waveforms.This fact increases the difficulty of detecting and estimating the parameters of the EP themselves. Typical values of the signal-to-noise ratio are less than 0dB.

This characteristic of the process requires to repeatedly stimulate the subjects and to improve the low SNR by averaging a large number of trials in order to extract the response of interest. The average is a special kind of filter, the so-called "comb" filter which improves the signal to noise ratio between EP and EEG background activity by the factor $\sqrt{M}$, where M is the number of averaged trials (ensembles). A crucial assumption implicit with averaging is:

1) EEG background activity, as a stochastic signal, and EP are uncorrelated and additive. This means for the single ensemble s(t) with noise EEG n(t) and EP x(t) that:

$$s(t) = n(t) + x(t),$$

$$E[\, n(t_1)\, x(t_2) \,] = E[\, n(t_1) \,]\, E[\, x(t_2) \,] = 0, \text{ because } E[\, n(t) \,] = 0.$$

2) The EP is stationary in phase, form, latency and amplitude.

The validity of hypothesis 2) is rarely verified when M increases. Since normally many averages are required and the troubles for the patient have to be minimized, many powerful signal processing techniques have been employed [3,4] in order to rapidly improve the SNR reducing the number of trials. Alternative approaches, based on minimization of the Mean-Square-Error (MSE) between the signal and the output of a filter, have recently been developed. In particular, the use of Wiener filtering [5] and optimal filters derived taking into account the nonstationarity of signal and noise [6] have been proposed. Both these methods require extensive complex calculations of covariance or correlation matrices, which presupposes knowledge of signal characteristics (such as power spectra) of a large number of tests.

In this paper a nonlinear adaptive processing technique using a MLP is proposed for processing the brain EEG evoked potentials. Experiments are performed on both synthetic and real signals.

THE MLP FILTER

The proposed MLP architecture is characterized by linear input nodes, sigmoidal hidden nodes and a single linear output node (Fig. 1). The linear output layer operates as a linear combiner and allows to circumvent dynamic range limitations. This structure can be viewed also as the cascade of a nonlinear mapping and a linear combiner.

The learning of the MLP is obtained by the Back-Propagation Algorithm (BPA) [2]. The proposed adaptive processing scheme is shown in Fig. 2. The processing is carried out in the following way. The input signal is one of a set of stimulated responses of a subject and the target signal is another response of the same set. The network is trained by iteratively presenting the EP ensembles of the available set. Each ensemble consists of N samples which are successively fed into the network through a sliding window wide as the number of input nodes. No average is required before the processing. After the training phase the output signal is a filtered version of the available EP ensemble. Averaging very few output ensembles improves dramatically the quality of the EP estimation.

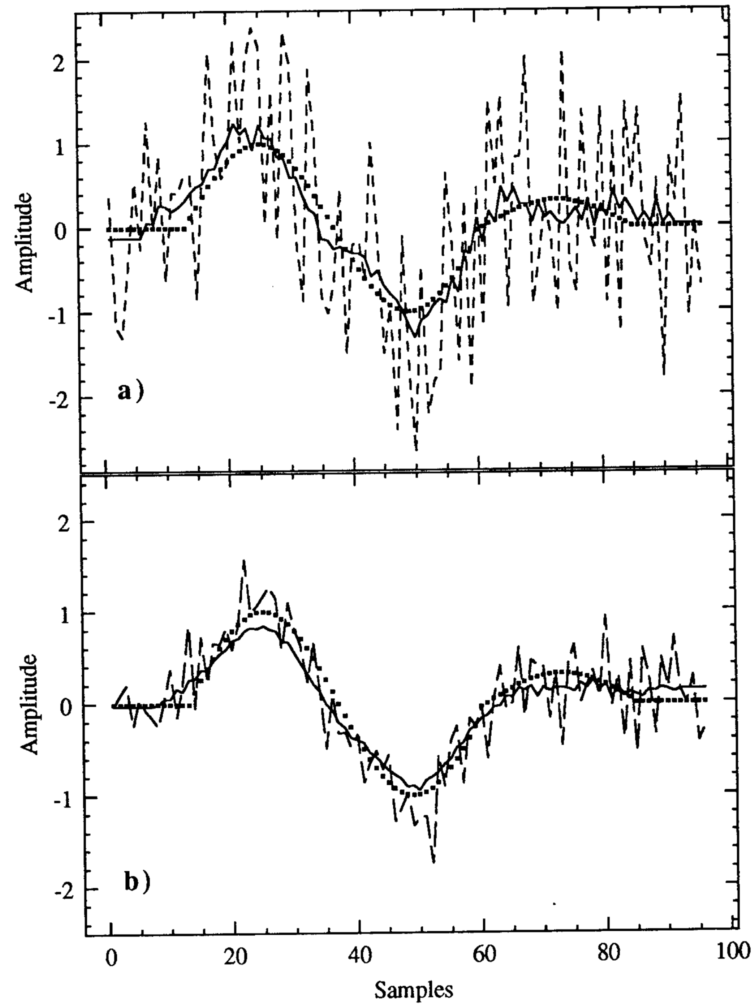

Fig.3
a) An ensemble of the measured EP (dashed line) compared to the filtered EP (solid line) and the true synthetic EP (dotted line);
b) the averaged filtered signal (solid line) compared to the signal obtained by the simple average method (dashed line) and true synthetic EP (dotted line).

In Fig. 6. a comparison between the proposed NN filter and an adaptive linear combiner with no hidden units is reported.

Another experiment on real evoked potentials was made using a neural network equal to that used with the synthetic data. A set of four evoked potentials of 96 samples (sampling frequency = 64 Hz) was used. The evoked potentials were obtained by a "simple reaction time" (SRT)-experiment, where the probands have to push a button as fast as possible at every appearance of a 2.54 cm^2 quadratic flash. The stimuli onset are presented in a room with reduced luminosity for 54 ms in the center of the proband's visual field. They appear at regular intervals of 4 seconds.

The results are reported in Fig. 7, where the effectiveness of the filtering procedure on each single EP is proved by filtering the EP's through respectively a 10-6-1 NN and a 10-10-10-6-1 NN.

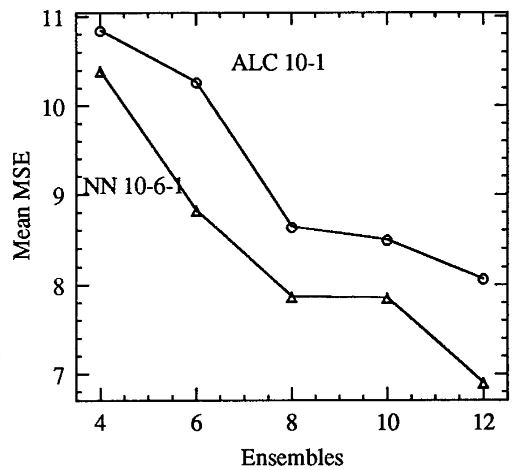

Fig. 4 Mean MSE obtained averaging over various ensembles.

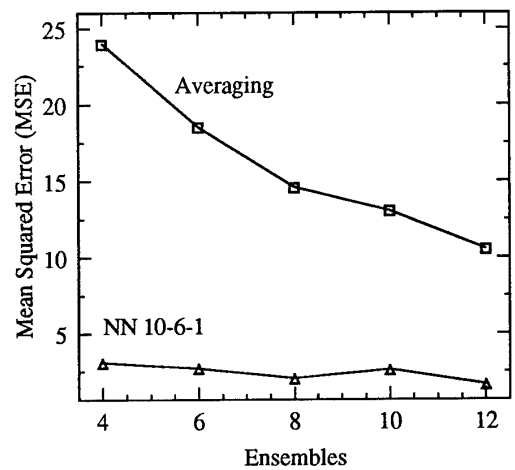

Fig. 5 MSE obtained after averaging over various ensembles.

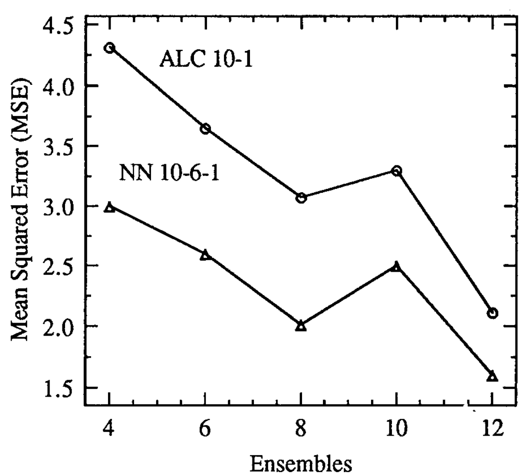

Fig. 6 Comparison between the proposed NN filter and the adaptive linear combiner (MSE computed as in Fig. 5).

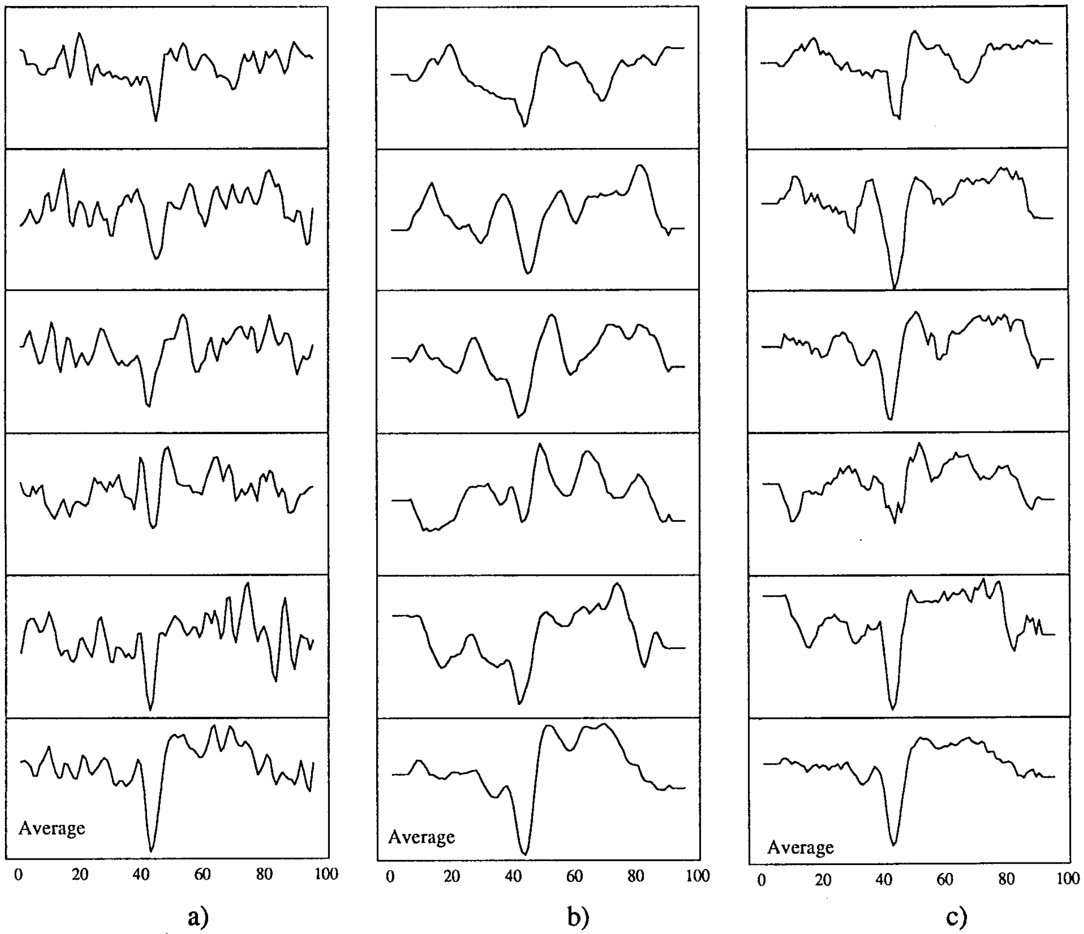

Fig. 7
a) Five EPs and the corresponding average (in the lowest box);
b) the same EPs filtered by a 10-6-1 NN;
c) the same EPs filtered by a 10-10-10-6-1 NN.

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