A KERNEL BASED SYSTEM FOR THE ESTIMATION OF NON-STATIONARY SIGNALS

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ABSTRACT

A new signal estimation technique is introduced for highly non-stationary signals. The system uses the wavelet transform to extract time-frequency components of the signal plus noise, followed by a radial basis function neural network that adaptively estimates the underlying signal. The method is applied to the visual evoked potential (EP) signal, which is a transient signal corrupted by the ongoing elctroencephalogram (EEG) noise, with a signal-to-noise ratio often less than -6 dB. The proposed system gives good time-varying estimates of the EP, while suppressing the on-going EEG.

1. INTRODUCTION

Traditionally the EP signal has been estimated by ensemble averaging. This approach assumes that the background EEG is random, and that the EP is time-locked to the stimulus presentation and similar in both latency and contour for every response. This estimate requires hundreds of responses and also can discard meaningful information [1], like latencies of peaks in a single response. Other methods were developed where *a priori* [2] and *a posteriori* [3] information about the EEG was used to characterize the statistics of the noise. The intense post processing makes these methods unsuitable for real-time implementation.

Other adaptive methods were applied (e.g.[4]), using the LMS algorithm. These led to better results but suffered from the high variability in the EEG noise, thus leading to a poor attenuation of the noise. The Fourier Transform was used to orthogonalize the data, but results continued to show loss of signal components in the early peaks.

According to deWeerd [5], the EP signal is a superposition of a number of short duration components, occurring at high frequency near the stimulus, and longer and at lower frequency occurring further from the stimulus. This analysis was done using a bandpass filter bank with constant relative frequency, and it further showed the time-frequency structure of the EP signal.

This suggests the use of a transform localized in time and frequency as a feature extraction tool. The wavelet transform meets this description, and is well suited for the analysis of transient signals with time-varying spectra like the EP [6]. The discrete wavelet transform (DWT) represents signals with temporally-ordered coefficients in a time-frequency plane. Trevo and Shensa [7] showed the advantages of using the DWT to represent event-related potentials for signal detection. Ghosh et al. [8] used the DWT efficiently as a feature extraction tool for noisy transient underwater acoustic signals.

The proposed system makes use of a neural network that will *learn* and *recognize* the time-frequency components of the EP while *suppressing* those of the EEG. The neural network used will be introduced in the next section.

2. METHODS

The wavelet transform of a signal $x(t)$ is:

$$W(a,b) = |a|^{-1/2} \int x(t)\, \psi(\frac{t-b}{a})\, dt \qquad (1)$$

where $\psi(t)$ is the mother wavelet, shifted by b and dilated by a, to generate the different wavelets. The mother wavelet can be chosen to generate an orthonormal set of basis function, like the Daubechies' discrete wavelets [6], where a and b are chosen as $a = 2^n$ and $b = n \cdot a$. Therefore the DWT, when chosen as above, can represent signals in a unique manner in a time-scale plane, and allows the exact reconstruction of the original signal. Also the wavelet coefficients, at any scale (frequency), are a series that measures energy within the bandwidth of that scale as a function of time, the EP signals are studied from their DWT representation.

On the other hand, artificial neural networks (ANN) have several properties that make them promising for the automatic signal estimation and classification [8]. They can serve as adaptive classifiers that learn from examples, thus, they do not require a good *a priori*

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mathematical model for the underlying signal characteristics. This is advantageous since a comprehensive characterization of EP signal is not available yet. The network discussed in this paper is a radial basis function (RBF) neural network. RBF's are a class of single hidden layer feedforward networks in which radially symmetric basis functions are used as the activation functions for the hidden layer units. If $x_p = (x_{p1}, x_{p2}, \cdots, x_{pN})^T$ is the input vector to the RBF network, then the output of the jth hidden node $R_j(x_p)$, and that of the ith output node $f_i(x_p)$, are given by

$$f_i(x_p) = \sum_j w_{ij} R_j(x_p) \tag{2}$$

$$R_j(x_p) = R\left(\frac{\|x_p - x_j\|}{\sigma_j}\right) \tag{3}$$

where $R(.)$ is a radially symmetric function such as a Gaussian, x_j is the location of the jth centroid, where each centroid is a kernel/hidden node, σ_j is a scalar denoting the "width" of its receptive field and w_{ij} is the weight connecting the jth kernel/hidden node to the ith output node. For the Gaussian RBF's the width σ_j is the standard deviation, so that we have

$$R_j(x_p) = e^{-1/2(\|x_p - x_j\|^2/\sigma^2)}$$

The system structure is illustrated by Figure 1.

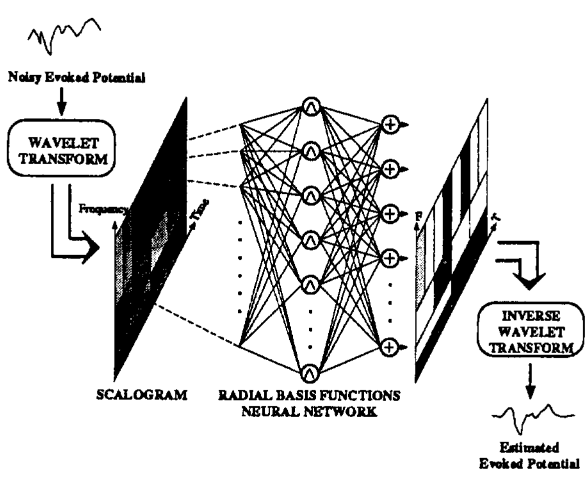

Figure 1: Overall diagram of the proposed system showing the signal flowgraph.

The signal is wavelet transformed, leading to a time-frequency representation vector itself fed to the radial basis neural network. The network should be first trained to recognize the transformed EP and attenuate EEG noise. The training is accomplished using as training pairs: (EP + EEG, EP)'s and (EEG, 0)'s.

3. SIMULATION DATA

The data used to test the proposed system included human 100 EEG and simulated EP's which are generated using a raised cosine model for the components. The amplitudes and latencies of these individual components have the following values and statistics [3]:

Peak	Latency(ms)	Latency St.Dev. (ms)	Amplitude (μV)
1	73.31	8.76	5.17
2	113.79	10.97	-12.42
3	166.40	5.72	-3.19
4	199.58	11.72	11.16

Table 1: Lower Checkerboard Latency Corrected Average Results at Electrode Cz. (subject 5)

To generate contaminated EP, human EEG noise was added to each of the simulated EP's, following the additive noise model of the data. Figures 2 and 3 show samples of the data used, along with the results of the simulations.

4. SIMULATIONS

The set of simulations reported in this paper were obtained using a 64-point data vector for each processed signal, 4-tap Daubechies' wavelets for the feature extraction and for the signal reconstruction. The neural network used has 64 neurons in the hidden layer, with a standard deviation $\sigma = 1.0$ selected after testing over a range of values for σ. The condition number of the weight matrix is equal to 1, meaning that the operation of the neural network is stable.

The performance of the neural network also depends on the type of data it is trained on. Especially, the capacity of the system to cancel EEG components when they are the only ones present in the input, depends on the training on EEG examples. A study of the proportion of the EP plus EEG samples to EEG only samples in the training set was conducted, and the number 12 of EEG examples revealed to yield the optimum results in terms of the performance criterea defined below.

Figure 2 shows that proposed system gives a *clean* estimate of the EP with an efficient cancellation of the EEG noise. Also when only EEG noise is inputed to the system reduces the output to zero, Figure 3. Figure 4 shows th bias introduced by the estimator when only EP signals are processed.

The following quantities are introduced to quantify the performance of this estimator:
The normalized minimum mean square error measures

the error between the system output and the optimum filter solution or desired output:

$$NMMSE = \frac{E[(x_k - y_k)^2]}{E(x_k^2)}, \qquad (4)$$

The signal bias factor is a measure of the signal distortion the system creates. It is the mean-square difference between the system output when the input is the desired output and the desired output.

The BF is normalized by the desired signal power and is given by

$$BF = \frac{E[(s_k - y_k)^2]}{E(s_k^2)}, \qquad (5)$$

The noise reduction factor is a measure of the system's ability to attenuate the noise. It is the output power when noise only is input to the system.

$$NRF = 10 \cdot log_{10} \left[\frac{E(y_{0,k}^2)}{E(n_k^2)} \right], \qquad (6)$$

where x is the system input (EEG +EP), y-system output for x or s as input, s-signal only input, n-noise only input, and y_0-system output when n is the input.

It was found that the proposed system performs better than ensemble averaging and the other mentioned methods, the NMSE has an average of 12.7 %, the NRF average is -12 dB, and the bias factor is found to around 0.06 %. These results were found with data having a Signal-to-Noise Ratio of -5.61 dB. Also the shifting of the peaks in the response has considerably decreased but still existent. This can be contributed to the fact that wavelet transform actually provides a measure of the average energy in each time-frequency bin, rather than a precise measure of the frequency response at that particular time sample.

The time-frequency adaptive estimator addresses the dimensionality of the mapping problem between the noisy evoked potentials and the true response. The estimator exploits the time-frequency distribution of the signal, transforming it into a signal space which is more localized and sparse reducing the dimensionality of the problem and producing a better estimate.

5. REFERENCES

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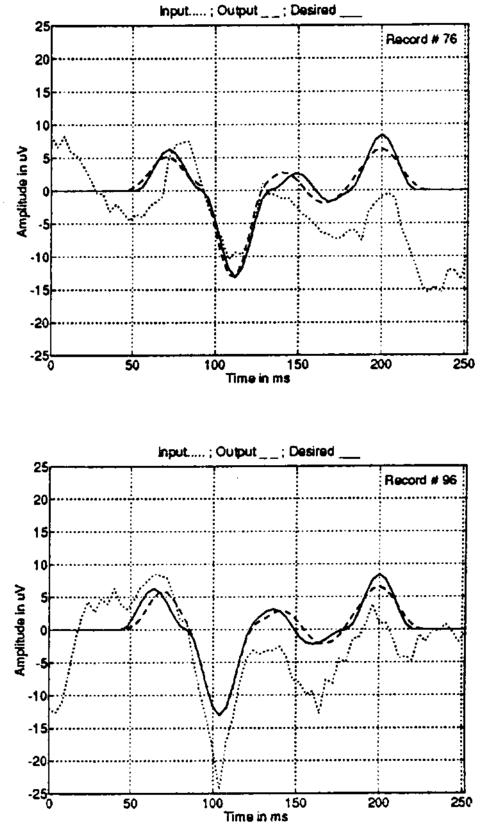

Figure 2: Samples of processing simulated EP signals corrupted with EEG noise.

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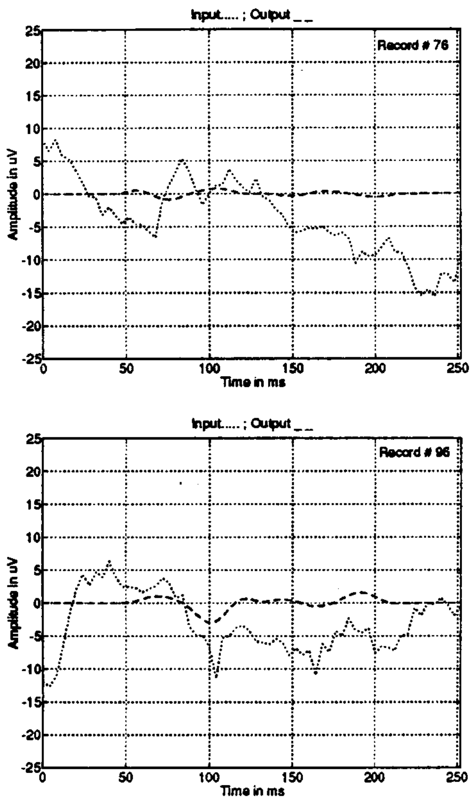

Figure 3: Sample of processing EEG noise only.

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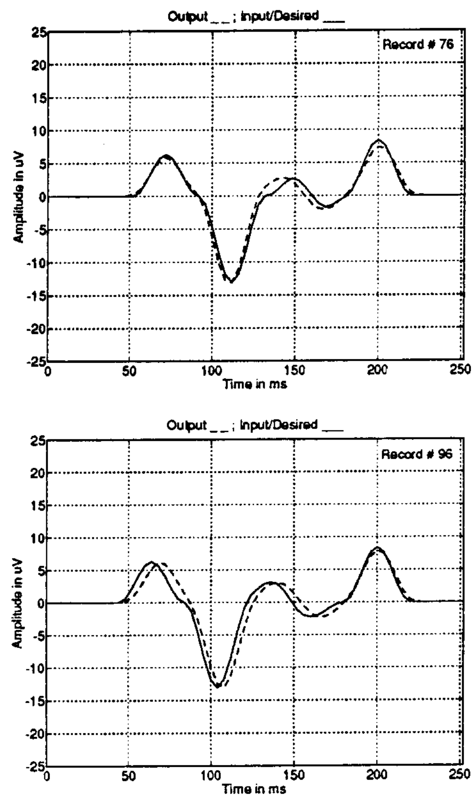

Figure 4: Sample of processing simulated EP signals only (no EEG noise).