Evoked potential signal estimation using Gaussian radial basis function network

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Abstract. Gaussian radial basis function neural networks are used to capture the functional mapping of the evoked potential (EP) signal buried in the additive electroencephalographic noise. The kernel parameters are obtained from the signal edges detected using direct spatial correlation at several adjacent scales of its undecimated non-orthogonal wavelet transform (WT). The segment of the data, where the WT is highly correlated across Scales, is considered a component region and its width is employed as the variance of the Gaussian kernel placed at the center of the region. The weights of the kernels are computed using gradient descent algorithm. Results obtained for both simulated and real brainstem auditory EPs show the superior performance of the technique. Because the technique incorporates signal knowledge into the network design, the number of hidden nodes reduces, and a more accurate estimation of signal components ensues.

1 Introduction

Evoked potentials (EP) are the responses of the brain to specific external sensory stimuli. EP's are used for the diagnosis of a variety of neurological disorders, and also in psychophysics research. The times of occurrence (latencies) and the amplitudes of individual components are the information of interest in EPs. These responses are buried in the ongoing electroencephalogram (EEG) with a signal-to-noise ratio (SNR) less than 0 dB. Hence, an ensemble of hundreds of responses to identical stimuli must be averaged to yield a reliable signal estimate. The focus of EP research has been on improving the ensemble average (EA) of fewer number of EP sweeps resulting in reduction in experimental time and improvement of the SNR of EA.

Most of the earlier research in EP estimation have used linear parametric models, both time [1] and frequency domain [2] ones. A relatively new approach uses neural network filters, which possess built-in nonlinear processing elements. Fung et al [3] used a Gaussian radial basis function network (GRBFN) as a model for the EP signal to account for the nonlinear nature of the signal. They assume that EP responses can be modelled by a finite number of Gaussian RBFs with their centers evenly distributed in time. Their weights are adaptively determined using LMS algorithm.

However, EP's are usually complex, and consist of both low and high frequency components of longer and shorter durations, respectively. Hence, an uniform parameter RBF network (U-RBFN), with its centers uniformly placed over the length of signal and with equal variances, cannot model the signal components efficiently. We propose a method, termed as W-RBFN, where the RBF parameters are deduced from the wavelet transform (WT) of the noisy signal to enable the network to learn the functional form of the underlying EP signal effectively. Once the number of hidden nodes and the kernel parameters are fixed, their weights are computed using gradient descent algorithm.

2 GRBFN for EP estimation

It is assumed that EP responses can be modelled by a finite number of Gaussian RBFs. The recorded j^{th} evoked response, $\mathbf{X}_j$, may be vectorially denoted as,

$$\mathbf{X}_j = \mathbf{S}_j + \mathbf{V}_j \tag{1}$$

where $\mathbf{S}_j = [s_j(1) \ \cdots \ s_j(M)]$ and $\mathbf{V}_j = [v_j(1) \ \cdots \ v_j(M)]$ denote the signal and noise content in the j^{th} sweep with the time index ranging from 1 to M. The signal and the noise are assumed to be stationary random processes with Gaussian distribution and uncorrelated to each other. We choose *Gaussian function* as the RBF to capture the underlying dynamics of $\mathbf{S}_j$ in (1) resulting in

$$\mathbf{Y}_j = y(\mathbf{X}_j) = \sum_{k=1}^{N} w_k exp \left(-\frac{\| \mathbf{X}_j - C_k \|^2}{{\sigma_k}^2} \right) \tag{2}$$

where C_k and σ_k are the Gaussian kernel parameters and N is the number of hidden nodes. The output of the GRBFN may be written as,

$$\mathbf{Y}_j = \sum_{k=1}^{N} w_k \mathbf{H}_{kj} \tag{3}$$

In the above equation, $\mathbf{H}^T = [\mathbf{H}_1 \ \mathbf{H}_2 \ \cdots \ \mathbf{H}_N]$ is the hidden layer output matrix, and $\mathbf{H}_k = [h_j(1) \ h_j(2) \cdots \ h_j(M)]$ represents the output of the k^{th} hidden node. The weights $\mathbf{W} = [w(1), \cdots, w(N)]$ can be determined using optimization methods such as gradient search algorithm by providing the input $\mathbf{X}_j$ and the corresponding desired output $\mathbf{Y}_j$ for few input-output measurements. A schematic of the GRBF network with N hidden nodes is shown in Fig. 1. The key problem is the placement of the centers C_k and determination of the radial dilation factors (usually called *widths*) to achieve best performance. This problem is often approached by clustering the data points and then using the cluster centers as the RBF centers C_k. In the proposed method, the number of hidden nodes and the Gaussian kernel parameters are obtained from the WT of the noisy signal.

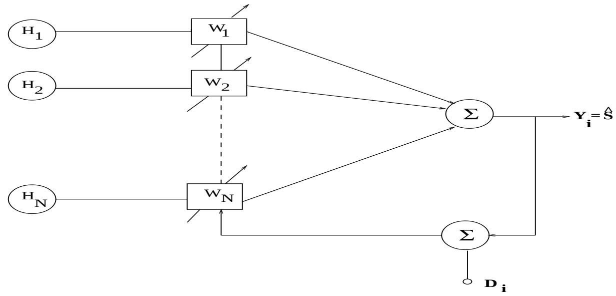


Fig. 1. Schematic of the GRBF network

3 Network parameters from the Wavelet Transform

The discrete wavelet transform $W(m,n)$ of a 1-D function $f(x)$ is defined as the projection of the function onto the wavelet set $\psi_{m,n}(x)$.

$$W(m,n) = \int_{-\infty}^{+\infty} \psi_{m,n}(x) f(x) dx \tag{4}$$

Since the set of $\psi_{m,n}(x)$ spans the space containing $f(x)$, the reconstruction of $f(x)$ from $W(m,n)$ is possible as,

$$\hat{f}(x) = \sum_m \sum_n \psi'_{m,n}(x) W(m,n) \tag{5}$$

where $\psi'_{m,n}$ is the normalized dual basis of $\psi_{m,n}(x)$. In our case, $\psi' \approx \psi$.

The WT gives a scale-space decomposition of signals into different resolution scales, with m indexing the scale and n indexing position in the original signal space. In wavelet domain, features are well localized in space and sharp transitions in signals are preserved faithfully as the WT modulus maxima, and the evolution of the latter across the scales characterizes the local regulariy of the signal. Hence, we use the correlation between adjacent scales to identify the signal transition regions.

The idea of using the strength of scale space correlation of the subband decompositions of a signal to distinguish significant edges from noise was introduced by Witkin [4]. A similar concept was used by Xu et al. [5] to filter noise from images. Direct spatial correlation $Corr_l(m,n)$ of WT is defined as

$$Corr_l(m,n) = \prod_{i=0}^{l-1} W(m+i,n), \qquad n = 1, \cdots, N \tag{6}$$

where N is the length of the signal and $m = 1, \cdots, M$ is the scale. For a signal, significant features are strongly correlated across scales in the wavelet domain, whereas noise is poorly correlated [4]. We use this fact in detecting the signal related coefficients in each scale m at any position $n = 1, \cdots, N$ for which

$$|Corr_2(m,n)| > |W(m,n)| \tag{7}$$

A binary mask vector of length N is created, in which only those elements meeting the above condition across all the scales except the finest one, are set to 1. The smallest scale is not considered because noise dominates it in low SNR signals, resulting in too many edges being extracted [7]. The mask indicates the important signal regions and their widths. The technique to detect edges in the wavelet domain is well explained in [5] and [6]. We used the number of edges detected in the scale-space domain as the required number of GRBF kernels; their centers are determined as the mid point of the estimated signal regions. The spacing between adjacent edges determines the variances of the kernels.

The individual sweeps of brainstem auditory evoked potentials (BSAEP) have a low SNR of -10 dB or less. Since the technique is based on edges detected in the wavelet domain from the input signal, we start with the EA of the first 100 sweeps. This improves the SNR to a reasonable degree and facilitates good results. This avoids detection of noise edges, which may dominate at very low SNR. Subsequently, we use the current EA as the desired signal in the GRBF network weight adaptation so that the model parameters converge fast.

4 Results

4.1 Results for simulated data

The proposed technique has been tested both on simulated and actual EP data. Results thus obtained are compared with those of the U-RBFN estimator. EEG is simulated as a 4-th order autoregressive (AR) process [3], with a spectral shape comparable to that of true EEG. In order to meet the assumption of uncorrelatedness, each trial of the simulated EEG is obtained from the steady-state response of an independently initialized AR process. The SNR of the simulated sweeps is 0 dB.

Fig. 2 illustrates an instantaneous average of 100 BSAEP sweeps and the signal estimated using the proposed technique. Significant regions, detected in

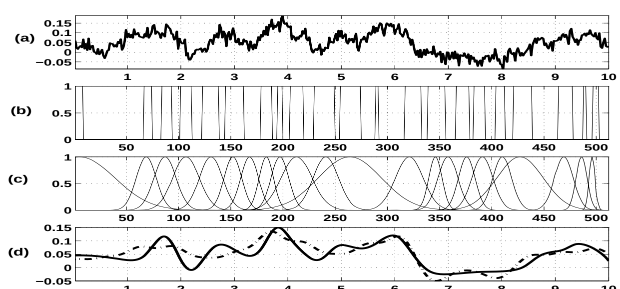
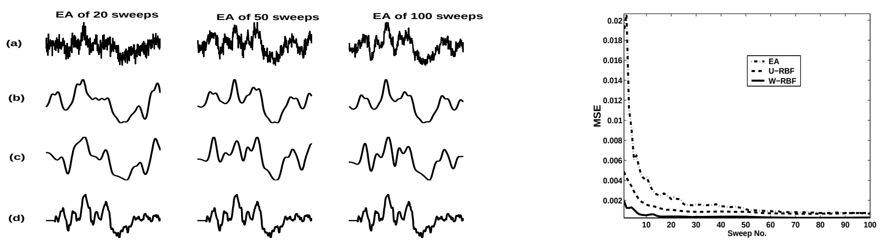


Fig. 2. Signal estimation using GRBF network (a)Simulated BSAEP signal, EA of 100 sweeps. (b) Binary mask vector in wavelet domain (c) Gaussian kernels (d) Estimated signals (x-axis: time in msec. y-axis: amplitude —:WRBFN - - -:URBFN)

the wavelet domain using the inter-scale correlation, are shown as a binary vector in Fig. 2(b). The number of significant regions detected is 22 and hence those many hidden nodes are used in the GRBF network. The corresponding Gaussian kernels used in time domain are shown in Fig.(c). It can be seen from Fig. 2 that the component latencies are well preserved in the W-RBFN method, whereas the U-RBFN method fails to estimate some of the components. A comparison of the component latencies estimated using both the methods is presented in Table 1, along with the true values. Fig. 3(1) presents both the signals, estimated using WRBFN and URBFN, from different instantaneous averages. The comparison,



(1) (2)

Fig. 3. (1) BSAEP signals estimated from different instantaneous averages. Row(a) Noisy BSAEP instantaneous EA signals (b) signals estimated using U-RBFN (c) signals estimated using W-RBFN (d)Original signal (2) MSE comparison for simulated data.(-.-.) EA (- -) U-GRBF (—)W-GRBF

in terms of MSE, as shown in Fig. 3(2), shows almost equal performance by both methods as it reflects only the mean error over the entire length of the signal. The plots show that GRBF entails a good approximation of the underlying signal from noisy observations, for any length of the ensemble. Further, wavelet preprocessing results in an accurate approximation of the component peaks of the underlying signal with fewer number of hidden nodes.

Latencies of BSAEP components, as detected by various techniques

Component peaks and their latencies in msec	I	II	III	IV	V
True	1.7	2.8	3.9	5.0	5.9
W-RBF	1.65	2.75	3.81	4.98	5.95
U-RBF	1.92	-	3.7	-	6.12

4.2 Results for Human data

The proposed technique has been tried on clinically recorded BSAEP's. BSAEP occurs within 12 msec of presentation of auditory clicks of 0.1 ms duration at 60 dB above auditory threshold, at the rate of 20 Hz. The subject keeps his eyes closed throughout the session to minimise ocular artifacts. Post stimulus data,

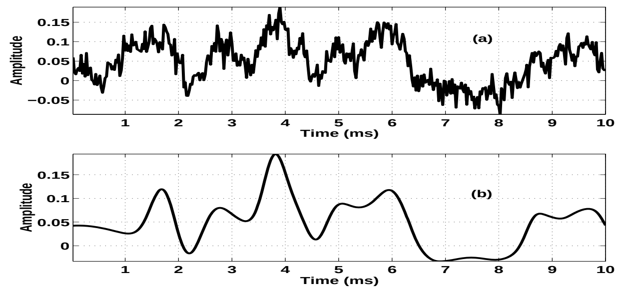


Fig. 4. Results using real BSAEP data (a) EA of 100 sweeps (b) Estimated signal

sampled at 40 kHz, is collected in each sweep. Clinically, BSAEP is estimated from more than 1000 sweeps. Fig. 4(a) presents the EA of 100 sweeps of a BSAEP and the signal estimated using our method is shown in Fig. 4(b). It can be seen that the latencies and amplitudes of the components can be easily measured from the estimated signal, which is not possible using the EA shown in Fig. 4(a).

5 Conclusion

The powerful capability of RBF networks is used to model the non-stationary characteristics of EP's. Results show that a network, whose parameters are derived from the signal itself, performs better than a network with fixed parameters. Results obtained from simulated and real EP data demonstrate the estimator's ability to suppress the noise even at low SNR. The advantages of using signal dependent kernel parameters for the GRBFNN are in terms of model accuracy, and fewer nodes in hidden layer, and thus, in the speed of convergence of the network too. The proposed technique entails enhanced signal components.

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