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AN ADAPTIVE RBF NEURAL NETWORK MODEL FOR EVOKED POTENTIAL ESTIMATION

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Abstract **- A method for evoked potential estimation based on an adaptive radial basis function neural network (RBFNN) model is presented in this paper. During training, the number of hidden nodes (number of RBFs) and model parameters are adjusted to fit the target signal which is obtained by averaging. In order to reduce computational complexity and the influence of noise in estimating single-trial evoked potential (EP), the number of hidden nodes is also minimized in training. After training, both peak latency and amplitude, being distinctive features of an EP, are characterized by the center and height of the corresponding RBF respectively. In EP estimation, an adaptive algorithm is employed to track the peaks from trial to trial by adapting the center and height of RBFs directly. The adaptive RBFNN is tested on a computer simulated data set and clinical EP recording. Our proposed algorithm is suitable for tracking EP waveform variations.**

Index Terms **- RBF neural network, evoked potential estimation, adaptive signal processing.**

I. INTRODUCTION

EP is a gross electrical potential generated in the brain from sensory stimulation, and EP is often heavily contaminated by noise mainly from the background activity of the brain (e.g. ongoing EEG). For many years, ensemble averaging (EA) has been the tool to obtain EP. However EA ignores the fact that the components of EP are time-varying [1] and the averaged signal tends to smear any variation from trial to trial. Many approaches have been proposed to detect the underlying signal in a single-trial EP. Among them, adaptive filtering is commonly employed [2] to tackle the time-varying characteristic of EP and noise removal. In this paper, we propose an adaptive model for EP estimation which combines the basic idea of adaptive processing with modeling the components of EP. The RBFNN have been known to be suitable for many non-linear model approximations provided that there are enough basis functions [3]. Based on the LMS approach, the model estimates EP signal from a single-trial. Any change of EP component is directly reflected in the model parameters, thus, a fast response could be achieved.

II. THE METHOD

The RBFNN model consists of N RBFs arranged in a hidden layer and a linear output node [4]. Its output at time instant k is expressed as

$$y(k) = \sum_{i=1}^{N} w_i e^{-\left(\frac{k-\mu_i}{\sigma_i}\right)^2} = \sum_{i=1}^{N} w_i \varphi_i \qquad (1)$$

In the i^{th} node, w_i, μ_i and σ_i represent the height, center and width of the RBF. Initial setup of the model is accomplished with information from peak latency and amplitude in the target signal, $d(k)$, which is obtained by averaging EPs. Such information is used to define the center and height of the characteristic RBFs. Auxiliary RBFs is added uniformly between characteristic RBFs to increase details of approximation. The RBFNN is then trained to model the target signal by minimizing the MSE, ξ, between the target and model output.

$$\xi = \frac{1}{M}\sum_{k=1}^{M}(e(k))^2 = \frac{1}{M}\sum_{k=1}^{M}(d(k)-y(k))^2 = \mathrm{E}_k\left[(d(k)-y(k))^2\right] \qquad (2)$$

where M is the number of data samples in target signal. Define $\mathbf{P}$ as a vector of free parameters

$$\mathbf{P} = \left[w_1\, \mu_1\, \sigma_1 \ldots w_i\, \mu_i\, \sigma_i \ldots w_N\, \mu_N\, \sigma_N\right] \qquad (3)$$

At each iteration, a steepest-descent type of training is specified by

$$\Delta\mathbf{P} = -\lambda\frac{\partial\xi}{\partial\mathbf{P}} = 2\lambda\, \mathrm{E}_k\left[e(k)\mathbf{Q}\right] \qquad (4)$$

$$\mathbf{Q} = \left[\ldots\varphi_i \quad \varphi_i\frac{2w_i(k-\mu_i)}{\sigma_i^2} \quad \varphi_i\frac{2w_i(k-\mu_i)^2}{\sigma_i^3}\ldots\right] \qquad (5)$$

where λ is an empirical parameter determining the rate of convergence. During training, the number of RBFs is optimized (network optimization) to avoid over-fitting and reduce adaptation error induced by noise which will be proved in the section below. When training is converged such that $\Delta\xi/\xi < \varepsilon$, the network will be further optimized according to the following procedures [5]:

(i) Remove RBFs which have negligible contribution to the output, if $\frac{|w_i|}{\max(|w_i|)} < \eta$.

(ii) Combine two adjacent RBFs if $y(\mu_i + \mu_{i+1}/2) > \max(w_i, w_{i+1})$. The combined RBF has its weight, center and width equal to $w_i + w_{i+1}$, $\mu_i + \mu_{i+1}/2$ and $\sigma_i + \sigma_{i+1}/2$ respectively. Fig. 1 shows an undesirable situation when a peak is modeled by two RBFs. This procedure is important to make sure that each peak in the target signal is modeled by only one RBF with its center located at the peak.

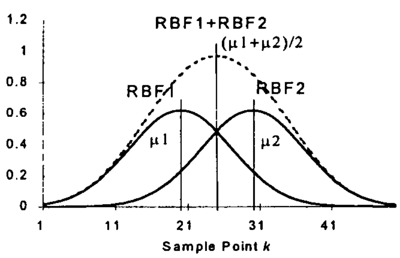

Fig. 1. A virtual peak with its center at (μ1+μ2)/2 is formed by two adjacent RBFs.

Training will be stopped when ξ is smaller than a predefined error threshold and the number of RBFs is stabilized. However if training could not reduce the error below the threshold, a new RBF will be added with its weight, center and width set to $e(k_{max})$, k_{max} and average of σ_i respectively where $e(k_{max}) = \max(e(k))$. The above training process is resumed.

After the model is properly trained, EP estimation is achieved by replacing the target signal with single-trial EP, $d(k)=s(k)+n(k)$ where $s(k)$ is the deterministic underlying EP buried in noise $n(k)$. The model parameters are adapted according to equation (4), so that

$$\Delta \mathbf{P} = 2\lambda\, \mathrm{E_k}\left[((s(k) - y(k))\mathbf{Q}\right] + 2\lambda\, \mathrm{E_k}\left[n(k)\mathbf{Q}\right] = \Delta \mathbf{P_s} + \Delta \mathbf{P_n} \tag{6}$$

We can see that the parameters are adjusted to estimate $s(k)$ while the adaptive process is disturbed by the noise component, $n(k)$. The sum of squared parameter misadjustment due to noise is

$$Mis = \Delta \mathbf{P_n} \cdot \Delta \mathbf{P_n}^T = 4\lambda^2\, \mathrm{E_k}\left[n(k)\mathbf{Q}\right] \cdot \mathrm{E_k}\left[n(k)\mathbf{Q}\right]^T \tag{7}$$

Obviously, decreasing the rate of convergence could reduce the misadjustment considerably in the expense of some tracking speed of the algorithm. Influence of noise component could be further reduced by considering the misadjustment induced in parameter w_i,

$$Mis_{w_i} = 4\lambda^2\left(\mathrm{E_k}\left[n(k)\varphi_i\right]\right)^2 \tag{8}$$

Inside the bracket is the expected value of noise bounded within an envelope φ_i. Since the noise could be assumed to have zero-mean, it is desirable to have a wide RBF in order to reduce the misadjustment. Therefore, the number of RBFs in the network, N, should be minimized. Considering other free parameters like μ_i and σ_i, similar conclusion could be obtained using the above argument.

III. Experimental Results

The RBFNN has been trained to model brainstem auditory evoked potential (BAEP) and visual evoked potential (VEP). Using VEP as the target, the network optimization process is displayed in Fig. 2. At the beginning, there are 13 hidden nodes assigned to the network. When training converges at 28th and 45th iteration, excess nodes are removed. We can see that the network reorganize itself to fit the target with less number of RBFs. Fig. 3 shows the trained RBFNN with 11 and 7 hidden nodes for BAEP and VEP respectively. Note that the peaks in the target signal are modeled by RBFs.

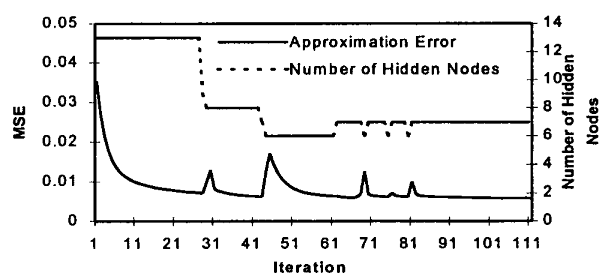

Fig. 2. The number of hidden nodes is being optimized during training with VEP as the target.

The trained RBFNN is applied to estimate single-trial VEP and the results of 10 consecutive estimates are shown in Fig. 4. Inspecting the peaks in each trail, obviously their latencies are varying slowly across trials. The performance of RBFNN in tracking changes in the peaks is further examined by computer simulated signals. The VEP, $s(k)$, obtained by averaging 100 ensembles is used as the underlying signal. The background is white noise and the SNR is -5dB which is similar to the SNR of single-trial VEP. The variation of $s(k)$ along time axis from trial to trial could be simulated as $s(k+D)$ with its variation velocity (ΔD per trial) set at ±0.2, ±0.266, ±0.4 and ±0.8 successively. A sudden change of peak latency is also simulated. The results shown in Fig. 5, are compared with adaptive filter (AF) using $s(k)$ as the reference signal.

Generally, RBFNN and AF could track slow peak changes. However the delay between true latency and estimated latency becomes more noticeable as the rate of latency change increases. Such delay is due to the adaptation time constant which is related to the convergence rate. A larger convergence rate has a shorter time constant but the misadjustment will be more significant [6]. The effect of time-constant in the response to impulse change is shown in Fig. 5(b). Theoretically, the estimation error will vanish after infinite number of iterations. Apart from the delay, AF suffers from reduced performance when the correlation between underlying signal, $s(k+D)$, and reference signal, $s(k)$, drops as the displacement, D, getting larger. RBFNN has the advantage of powerful modeling ability that enables close estimation of EP changes.

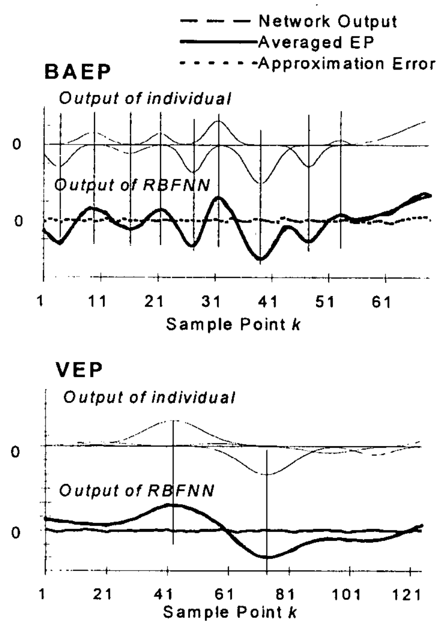

Fig. 3. The averaged AEP and VEP clearly shows their peak components. The number of RBFs used are 11 and 7 for AEP and VEP respectively. The parameters required in training are λ=0.01, η=0.05, ε=0.01 and error threshold=0.005.

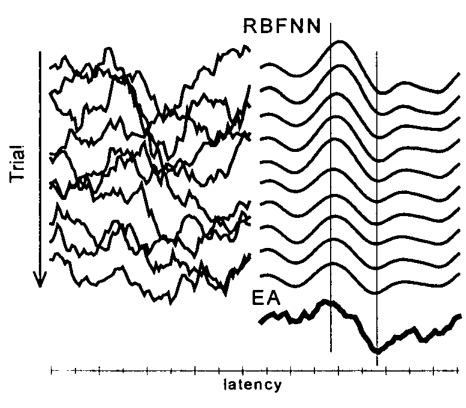

Fig. 4. The waveforms shown in the left column are 10 consecutive single-trail VEP signals. The results of estimation using RBFNN (λ=0.001) are shown in the right column while the bottom waveform is obtained by EA these 10 raw ensembles.

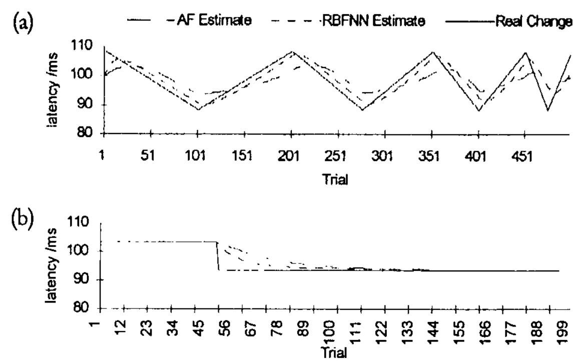

Fig. 5. The performance of RBFNN and AF in tracking of change in P100 latency. Convergence of RBFNN and AF are 0.001 and 0.05 respectively. Background is white noise and the SNR is -5dB.

IV. Conclusion

This paper introduces an alternative approach of EP estimation based on an adaptive RBFNN model and a network optimization algorithm. The peaks which being the main components of an EP, are modeled by RBFs in the network. Some relevant theoretical properties of the RBFNN were reviewed in the context of algorithm design. Simulation results confirm the successful operation of our approach. The results also show that the performance of adaptive RBFNN is superior to the AF, this may be accounted for by the powerful modeling characteristic of RBFNN, permitting accurate estimation of single-trial EP. Using adaptive RBFNN, trial-to-trial variation could be observed and such information is potentially useful for analysis by clinician.

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