Bio-Signal Identification using Simple Growing RBF-Network (OLACA)

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Abstract - An enhanced online adaptive centre allocation algorithms (or resource allocation network (RAN)) using simple/ stochastic back-propagation method with minimal weight update variant are developed for Direct-Link Radial Basis Function (DRBF) networks. These algorithms are developed primarily for applications with fast sampling rate which demands significant reduction in computation load per iteration. The new algorithms are evaluated on a chaotic nonlinear biological based time series signals such as electroencephalographic (EEG) and electrocardiography (ECG). The EEG and ECG signals not only shows non-stationary behaviour but also large oscillation or changes. When the sample time is in milliseconds, both neural network adaptation and weight update must take place within the short time frame thus any learning rule must be computationally simple. The second order techniques, such as Extended Kalman Filter (EKF), need large amount of memory $O(N^2)$ and computationally intensive. The main goal of this paper is to develop a simple back-propagation based (SBP) resource allocation network (RAN), or also known as sequential learning technique using Radial Basis Function by incorporating Gaussian kernel, in order to identify (model) EEG and ECG signals. Simulation results show the modeled data show good representation of the original signals with less prediction error.

I. INTRODUCTION

The Radial Basis Functions (RBF) has been introduced as the basis for neural network architecture. They able to identify the underlying function by combining a set of basis functions (normally Gaussian)

$$y_k = f(\boldsymbol{x}_k) = \sum_{i=1}^{m} h_i \phi_i(\boldsymbol{x}_k, \boldsymbol{c}_i, \mathbf{s}_i) + b \quad (1)$$

$$\phi(\boldsymbol{x}_k, \boldsymbol{c}_i, \mathbf{s}_i) = \exp\left(-\frac{\|\boldsymbol{x}_k - \boldsymbol{c}_i\|^2}{\mathbf{s}_i^2}\right) \quad (2)$$

Here h_i are the linear output layer weights, $\boldsymbol{c}_i$ and s_i are the centres and widths of the Gaussian basis functions and b is an optional bias weight. The RBF networks have a number of advantages with regard to training, locality of approximation and transparency in comparison other globalise network. In particular, RBF networks with localised basis functions learn information at one operating point of a nonlinear process without degrading information assimilated at other operating regimes [1][2].

Platt [3] first introduced Resource allocating networks (RAN) as a solution to these problems in which RBFs recursive training of parameters (using adaptive gradient decent) is combined with a procedure for recursively adding centres. Kadirkamanathan *et al.* [4] developed a second order

recursive method, known as RAN-EKF (extended Kalman filter) or sequential learning. Yingwei [5] extended the work on RAN-EKF by including a pruning strategy to obtain a compact RBF network and called it minimal RAN (MRAN). Recently the present authors [6]-[8] introduced minimal update sequential learning in which only the parameters of the *winner neuron* (defined as the neuron whose centre is nearest to the current input vector $\boldsymbol{x}_k$) are adapted. One similarity with all the recent methods, in exception to Platt's RAN method, is that the use of second order method to enhanced prediction capability. Such adaptive learning will be not being feasible when applied to micro-machine with real-time implementation where memory constraints have to be taken into account. When the control sample time is in milliseconds, during which time both neural network adaptation and control law update must take place thus any learning rule must be computationally simple.

This paper uses an adaptive algorithms using for a more general class of RBF network referred to as Direct-link RBF networks (DRBF) for identifying a biological signal. It is actually an extension of RBF adaptive learning proposed by Mcloone [9], known as Online Adaptive Centre Alocation (OLACA) Network, which is quite similar in structure to RAN method but applied on DRBF. DRBFs are simply conventional RBFs, as defined by equation (1), augmented by a linear input-output mapping, that is:

$$y_k = \sum_{i=1}^{m} h_i \phi(\boldsymbol{x}_k, \boldsymbol{c}_i, \mathbf{s}_i) + \boldsymbol{b}^T \bar{\boldsymbol{x}}_k \tag{3}$$

The bias term is included as weight b_0 in vector $\boldsymbol{b}$,

$$\boldsymbol{b} = \begin{bmatrix} b_0 & \cdots & b_{n_i} \end{bmatrix}^T \quad \text{and} \quad \bar{\boldsymbol{x}}_k = [1 \;\; \boldsymbol{x}_k^T]^T \tag{4}$$

Parameter n_i is the number of inputs fed to the network.

This new form Direct Link Radial Basis Function architecture with fast weight update designed well for application in which the sampling frequency is high such as for bio-signal application. The author of the paper showed that using fixed sized MLP it is possible to identify chaotic ECG signal with reasonable level of accuracy[10]. In this paper a new RBF growing structure is used to identify electroencephalographic (EEG) and electrocardiography (ECG) signals which have small sample intervals (normally in milliseconds).

The remainder of the paper is organised as follows. Section 2 describes sequential learning for RANs. Section 3 introduces DRBFs and enhanced OLACA method (e-OLACA). Simulation results evaluating the enhanced OLACA scheme on biosignal modelling (in both cases EEG and ECG) are presented in section 4 and finally section 5 concludes the paper.

II SEQUENTIAL LEARNING ALGORITHM

Sequential learning algorithms or OLACA, to be consistent this method is referred in this paper as sequential learning, differ from classical RBF training rules in that they combine centre allocation with the weight update simultaneously. The sequential learning algorithm is being described as follows.

$$y_k = \sum_{i=1}^{m} h_i \exp\left(-\frac{\left\| \boldsymbol{x}_k - \boldsymbol{c}_i \right\|^2}{\mathbf{s}_i^2} \right) \tag{5}$$

Let $(\boldsymbol{x}_k, y_k)$ be a new data point, in the sample space to be fitted by the RBF network in. The sequential learning growth criteria for the network are based on OLACA method proposed by McLoone [9] slighty differ to conventional sequential learning methods.

$$d_{nc} = \min_i \left\| \boldsymbol{x}_k - \boldsymbol{c}_i \right\| > 2\alpha\sigma_{nc}, \quad i = 1, 2, \ldots m \tag{6}$$

$$\sum_{j=k-(M-1)}^{k} \frac{|e_j|}{M} > \bar{\varepsilon}_{min}, \quad e_j = d_j - y_j \tag{7}$$

where d_{nc} is the distance between the input vector $\boldsymbol{x}_k$ and the centre of the nearest hidden neuron, Φ_{nc}, while σ_{nc} is the width of the nearest neuron. The desired output corresponding to input $\boldsymbol{x}_j$ is given by d_j while the scalar α (determines the Gaussian locality range) is usually 1.0. An average moving-window instantaneous error is used as a novel criterion instead of the instantaneous error e_{k} due to its sensitivity to noise in the input data [11].

If the either (or both) criteria in (6) and (7) are not satisfied then all the network parameters are adapted to fit the new point using a recursive Gauss-Newton method, also known as the extended Kalman filter (EKF) algorithm by Kadirkamanathan and Niranjan, [4]. This can be described as follows:

$$\boldsymbol{w}_k = [\boldsymbol{c}_1^T, \sigma_1, h_1, \ldots, \boldsymbol{c}_m^T, \sigma_m, h_m]^T_{N_w x 1} \tag{8}$$

$$\boldsymbol{w}_{k+1} = \boldsymbol{w}_k + P_k \psi_k e_k \; e_k = d_k - y_k \tag{9}$$

$$\psi_k = \frac{\partial}{\partial \boldsymbol{w}_k} y(\boldsymbol{x}_k, \boldsymbol{w}_k) \tag{10}$$

$$P_k = P_{k-1} - \frac{P_{k-1}\psi_k \psi_k^T P_{k-1}}{1 + \psi_k^T P_k \psi_k} \tag{11}$$

On the other hand if the growth criteria in (6) and (7) are satisfied then a new Gaussian basis function hidden neuron is assigned as follows:

$$\boldsymbol{c}_{m+1} = \boldsymbol{x}_k, \; h_{m+1} = |e_k| \tag{12}$$

$$\sigma_{m+1} = \beta \frac{d_{nc}}{2} \tag{13}$$

$$P_k = \begin{bmatrix} P_{k-1} & 0 \\ 0 & I_{n_w x n_w} \end{bmatrix} \tag{14}$$

The scalar β is a user defined parameter (usually set to 1.0) which determines the degree of overlap between neurons and the vector dimension n_w is equal to the number of new parameters arising from the inclusion of the new Gaussian basis function. This form of sequential learning is known as RAN-EKF [4]. In Platt's RAN [3] algorithm the weight vector update in (8) reduces to

$$\boldsymbol{w}_k = \boldsymbol{w}_{k-1} + \lambda_k \psi_k e_k \tag{15}$$

where λ_k is the learning rate which can be a constant or time varying. Meanwhile the new parameter assignments for the ew basis function are simplified to (12-13) without the need for the second order weight covariance matrix P_k in (13)

YingWei et.al [5] have showed by implementation by including pruning strategy have create a more parsimonious network with additional computational cost. Since the sampling time is very high for the case of bio-signals (both EEG and ECG) and the computational requirement is high for determining windowed mean average output of the hidden neuron (Gaussian basis function) thus pruning strategy is not being implemented in this paper.

SEQUENTIAL LEARNING ON DRBF

The gradient vector of the extended DRBF network can be equivalently decomposed into four portions:

$$\mathbf{y}_k = \left[\psi_{k(C)}^T \; \psi_{k(W)}^T \; \psi_{k(H)}^T \; \psi_{k(\boldsymbol{b})}^T \right]^T \tag{15}$$

where each portions can represent the gradient of centres, ***c***, width, ***s***, ,height, ***h*** and the direct parameters, ***b***, of the DRBF (shown in Fig. 1) network. There make it a potential for parallel implementation as the weight vector update, using simple back-propagation algorithms, in order to maintain its simplicity, is decomposed into four (4*)* sub-algorithms:

$$\boldsymbol{c}_k = \boldsymbol{c}_{k-1} + \psi_{k(\boldsymbol{C})} e_k \quad \mathbf{s}_k = \mathbf{s}_{k-1} + \psi_{k(\sigma)} e_k$$

$$\boldsymbol{h}_k = \boldsymbol{h}_{k-1} + \psi_{k(\boldsymbol{h})} e_k \tag{16}$$

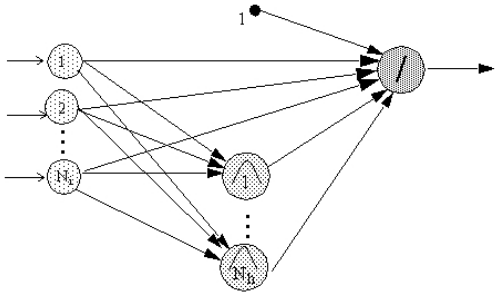

Figure 1. Structure of DRBF

Finally the direct link weights can also be simultaneously updated using

$$\boldsymbol{b}_k = \boldsymbol{b}_{k-1} + \psi_{k(\boldsymbol{b})} e_k \tag{17}$$

This new form of OLACA method is as stochastic back-propagation on Direct-Link Radial Basis Function using sequential learning method or in short (DRBF-SBP).

III. SIMULATION AND RESULTS

The robust DRBF is being tested on two commonly known biological based signals or bio-signals which are the electroencephalographic (EEG) and electrocardiography

(ECG). The identification for both benchmark problems uses nonlinear autoregressive technique with model order of

$$y_k = f([y_{k-1}, y_{k-2}, y_{k-3,}] \quad (18)$$

for ECG and the following NAR model order is being used for EEG

$$y_k = f([y_{k-1}, y_{k-2}, y_{k-3,} y_{k-4}, y_{k-5,}] \quad (19)$$

Table 1 summarizes the user defined parameters initially set before the experience.

Table 1.
Initial Parameter Setting

Parameters	EEG	ECG
σ	2	2
β	1	1
λ	0.0001	0.001
e_{min}	5 (20%)	0.5 (20%)

A. Analyzing EEG Signals

The online centre allocation technique method is being tested on an EEG signal electrode (Pz). The names and positions of the electrodes are shown here in Figure 1.

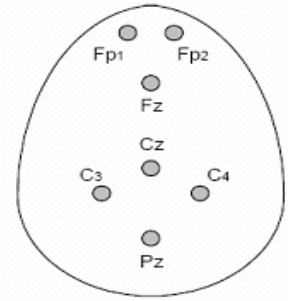

Figure 2. Seven (7) electrodes position for acquiring EEG

Table 2 shows the performance of various sequential learning techniques discussed in the paper. From the table it can be concluded the enhanced OLACA performed better compared to the other two approaches (RAN and RAN-EKF).

Table 2.
Performance Analysis for EEG Signals

Algorithms	NMSE	Std. Dev
RBF-SBP (RAN)	0.3815	0.1354
DRBF –SBP (OLACA)	0.3146	0.1053
RBF-EKF	0.4761	0.2291

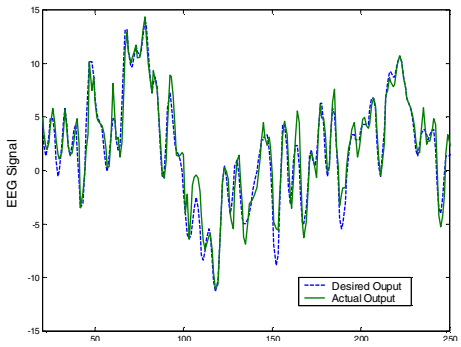

Figure 3. Tracking of EEG signals from brain activity

Fig. 3 depicts the model prediction capability of Direct Link RBF using stochastic or simple back-propagation technique for fast changing EEG signal.

B. Analyzing ECG Signals

The normal ECG signal time series is being illustrated in Figure 2 which consists of well defined P→QRS→T→U sequences for healthy periodic signal. Sample time interval for ECG is about 0.008 second or eight (8) milliseconds.

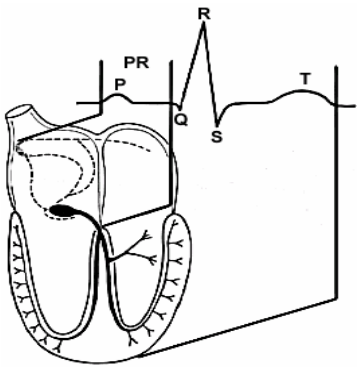

Figure 4. Tracing of ECG signals from cardiac activity

From these results it can be concluded that the DRBF decomposed sequential learning approach perform well both in terms of rate of convergence. In addition, the algorithms use less memory, require less computation time per iteration and produce more parsimonious in comparison to second order technique (RAN- EKF). Table 2 and Table 3 show the mean and standard deviation of training curves of both EEG and ECG respectively on a batch validation set.

Table 3.
Performance Analysis for ECG Signals

Algorithms	NMSE	Std. Dev
RBF-SBP (RAN)	0.4482	0.3765
DRBF –SBP (OLACA)	0.3152	0.6789
RBF-EKF	0.5086	1.2959

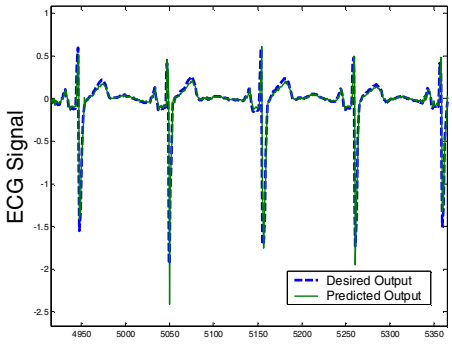

Figure 5. Tracking of ECG signals from cardiac activity

IV. CONCLUSIONS AND FUTURE WORK

An online neural network learning techniques for bio-signal identification being discussed for various simple structured growing Gaussian kernel RBF network. This paper also tries to introduce the growing RBF constructive form Direct Link Radial Basis Function network with simple back-propagation weight update technique (DRBF-SBP). Traditional approach of identifying bio-signal instantaneously, such as EEG and ECG, only can be implemented using linear filters due to their fast update properties.

Future work will look application of bio-signal which similar to what being discussed in this paper using technique of minimal dimensional update, which has been recently proposed by the present author [12].

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