A Wavelet Based Neural Network for DGPS Corrections Prediction

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Abstract: - Neural Networks (NNs) are capable of learning high complex, nonlinear input-output mappings. This characteristic of NNs enables them to be used in nonlinear system modeling and prediction applications. On the other hand, the wavelet decomposition provides a powerful tool for functional approximation. In this paper, a kind of Wavelet Neural Networks (WNNs) is proposed for Differential GPS (DGPS) corrections prediction. The performance of proposed WNN is compared with Multilayer Perceptron (MLP) in the application of prediction. The propos ed algorithms in DGPS system is implemented by a low cost commercial Coarse/Acquisition (C/A) code GPS module. The experimental results demonstrate which WNN has great approximation ability and suitability in prediction than MLP. So, position components RMS errors are less than 0.4 meter after of WNNs prediction.

Key-Words: Neural Network, Wavelet, Multilayer Perceptron, DGPS, Corrections Prediction

1 Introduction

Precise Global Positioning System (GPS) kinematic positioning in the real time mode is now increasingly used for many surveying and navigation applications on land, at sea and in the air. In GPS, error can be defined as any deviation in position from the true position. Some errors are natural phenomena while others are intentional. These errors can combine and become significant. Errors include: satellite/receiver clocks, satellite orbits, prediction of atmospheric delays, multipath, Selective Availability (SA), and GPS receivers' internal circuitry [1].

In order to recover the accuracy of GPS, differential techniques must be applied. The principle of Differential GPS (DGPS) is to install a GPS receiver at a known point, to compute the difference in observed pseudo range from the computed range for each measurement cycle (epoch) and transmit these time-lagged pseudo range corrections over a fast and reliable data link to the mobile receiver. At the mobile the range corrections are applied to the observed pseudo ranges from the satellites and the corrected–observed pseudo ranges are then compute d into position. In practice the observed pseudo ranges are entered into a model to correct for the refraction of the signal caused by its path through the ionosphere prior to computing corrections; ionospheric data are sent as part of the GPS satellite message for this purpose. Differential techniques rely upon positive correlation of pseudo range errors over an area local to the reference station [2].

There are the types of problems that can be experienced with four main GPS components which are; The GPS itself, The User or Mobile Platform, Reference Station(s) and Monitoring Facilities and The Differential Transmission Method. It must also be recognized that some of these components are inherent to the overall system and a failure at one location can cause throughout the network. Because of above mentioned problems, DGPS corrections prediction has important rule in accurate and real time positioning of GPS [3].

Multilayer Perceptrons (MLPs) trained using Back Propagation (BP) algorithm and Radial Basis Function (RBF) networks have been used successfully to predict nonlinear and chaotic data. Wavelet techniques have generated tremendous interest among the signal processing community in recent years. Wavelet decomposition involves representing arbitrary functions in terms of simpler basis functions at different scales and positions. In other words, the wavelet decomposition represents the signal as the sum of contributions of components at different scales. By its very definition, the wavelet decomposition is hierarchical in nature [4].

Wavelet Neural Networks (WNNs) represent a fruitful synthesis of ideas from NNs and wavelet analysis. Recently the utility of wavelet in nonlinear system modeling and approximation was demonstrated in [5].

This paper is organized as follows. Section II provides a brief introduction to WNNs. Section III describes proposed WNN architecture. A brief introduction to MLP is provided in section IV. Experiments are reported in section V and finally conclusions follow in section VI.

2 Wavelet Neural Network

In these neural networks, the wavelet function replaces the role of sigmoid function in the hidden unit. The wavelet parameters and wavelet shape are adaptively computed to minimize an energy function for finding the optimal representation of the signal [6,7]. Fig.1 presents a kind of three layers WNN structure with both "wavlon nonlinearity" and "sigmoid neuron nonlinearity".

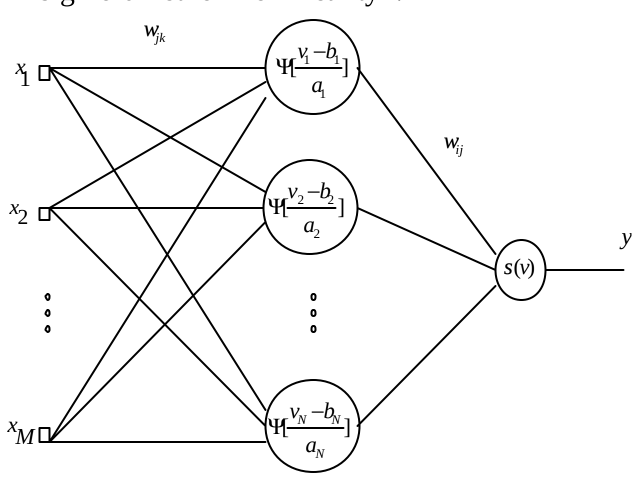

Fig.1. A three layers WNN

This network consists of three layers: an input layer, a hidden layer, and an output layer. The input layer has M nodes. The output layer also has only one neuron whose output is the signal represented by the weighted sum of several wavelets. The hidden layer is composed of a finite number of wavelets representing the signal.

2.1 Forward Calculations for WNN

Consider a network consisting of a total of N neurons in hidden layer with M external input connections (Fig.1). Let $X(n)$ denotes the $M-by-1$ external input vector applied to the network, $y(n)$ denotes the output of the network, $w_{jk}(n)$ presents the weight between the hidden unit j and input unit k, $w_{ij}(n)$ denotes the connection weight between the output unit i and hidden unit j, $a_j(n)$ and $b_j(n)$ present dilation and translation coefficients of wavlon in hidden layer at discrete time n, respectively.

The net internal activity of neuron j at time n, is given by:

$$v_j(n) = \sum_{k=0}^{k=M} w_{jk}(n).x_k(n) \tag{1}$$

Where, $v_j(n)$ is the sum of inputs to the $j\,th$ hidden neuron, $x_k(n)$ is the $k\,th$ input at time n. The output of the $j\,th$ neuron is computed by passing $v_j(n)$ through the wavelets $y_{a,b\,j}(.)$, obtaining:

$$y_{a,b}[v_j(n)] = y\left[\frac{v_j(n)-b_j(n)}{a_j(n)}\right] \tag{2}$$

The sum of inputs to the output neuron is obtained by:

$$v(n) = \sum_{j=0}^{j=N} w_{ij}(n).y_{a,b}[v_j(n)] \tag{3}$$

The output of the network is computed by passing $v(n)$ through the nonlinear function $s(.)$, obtaining:

$$y(n) = s[v(n)] \tag{4}$$

2.2 Learning Algorithm for WNN

The instantaneous sum of squared error at time n as:

$$E(n) = \frac{1}{2} e^2(n) = \frac{1}{2}[y(n) - d(n)]^2 \qquad (5)$$

Where, $d(n)$ denote the desired response of output at time n.

To minimize of above cost function, the method of steepest descent is used. The weight between the hidden unit j and input unit k can be adjusted according to:

$$\Delta w_{jk}(n+1) = -h.\frac{\partial E(n)}{\partial w_{jk}(n)} + m.\Delta w_{jk}(n)$$

$$= h.e(n).s'[v(n)].w_{ij}(n).y'_{a,b}[v_j(n)] \qquad (6)$$

$$.\frac{x_k(n)}{a_j(n)} + m.\Delta w_{jk}(n)$$

Where, h is a learning rate. The connection weight between the output unit i and hidden unit j is updated as follow:

$$\Delta w_{ij}(n+1) = -h.\frac{\partial E(n)}{\partial w_{ij}(n)} + m.\Delta w_{ij}(n) \qquad (7)$$

$$= h.e(n).s'[v(n)].y_{a,b}[v_j(n)] + m.\Delta w_{ij}(n)$$

The translation coefficient of the jth wavlon in hidden layer can be adjusted according to:

$$\Delta b_j(n+1) = -h.\frac{\partial E(n)}{\partial b_j(n)} + m.\Delta b_j(n)$$

$$= -h.e(n).s'[v(n)].w_{ij}(n).y'_{a,b}[v_j(n)] \qquad (8)$$

$$.\frac{1}{a_j(n)} + m.\Delta b_j(n)$$

The dilation coefficient of the jth wavlon in hidden layer is updated as follow:

$$\Delta a_j(n+1) = -h.\frac{\partial E(n)}{\partial a_j(n)} + m.\Delta a_j(n)$$

$$= -h.e(n).s'[v(n)].w_{ij}(n).y'_{a,b}[v_j(n)] \qquad (9)$$

$$.\frac{v_j(n) - b_j(n)}{a_j(n)^2} + m.\Delta a_j(n)$$

3 WNN Predictor

Work in WNNs has concentrated on forecasting future developments of DGPS corrections from values of x up to the current time. Formally this can be stated as: find a function $f : \Re^N \longrightarrow \Re$ such as to obtain an estimate of x at time $t+d$, from the M time steps back from time t, so that [8]:

$$x(t+d) = f(x(t), x(t-1), \cdots, x(t-M+1)) \quad ; \; for \; d, M \in Z_+ \qquad (10)$$

Normally d will be one, so that f will be forecasting the next value x. The proposed WNN in this research is shown in Fig.2. The choice of the order for f is also important. In this paper, the order was based on the experimental results.

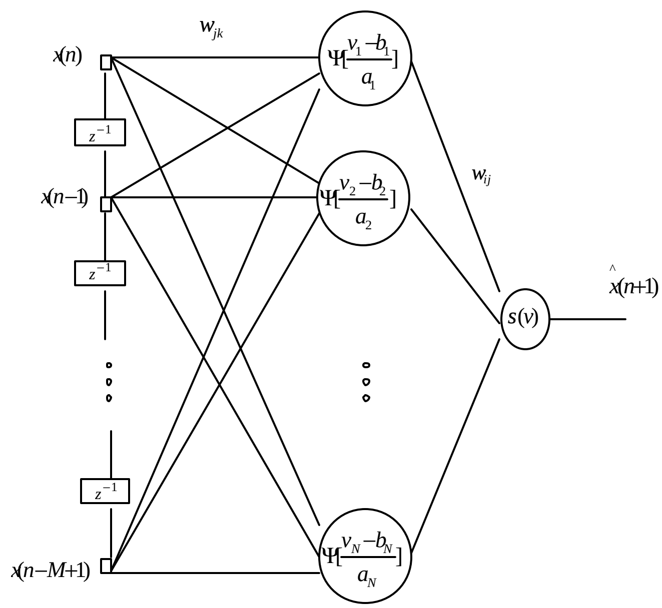

Fig.2. A proposed WNN for DGPS correction prediction

The wavelet function which we have considered here is the so called "Gauusian-derivative" function as:

$$y(x) = -x.e^{-\frac{1}{2}.x^2} \qquad (11)$$

As the general approximation theorem described in [4] applies. The usual sigmoid function of used in this research is as follow:

$$s(x) = \frac{1}{1+e^{-x}} \qquad (12)$$

4 Prediction Using MLP NNs

MLPs have been applied successfully to solve some difficult and diverse problems by training them in a supervised manner with a highly popular algorithm known as the error BP algorithm. Fig.3 shows a MLP NN with p node in input layer, q neurons in hidden layers, and one neurons in output layer. For the prediction problem, $y(n) = x(n+1)$.

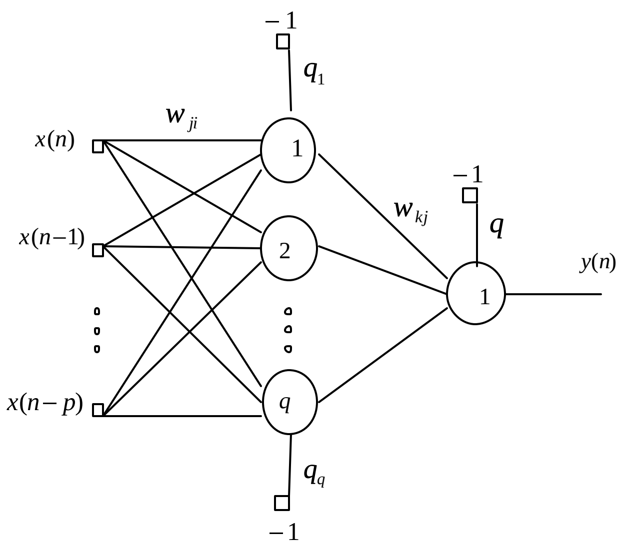

Fig.3. MLP Architecture

The training equations are provided in the following [1].

<u>Summary of the Learning Algorithm for Fig.3</u>

Variables and Parameters:

x_i = The $i-th$ element of the input pattern

w_{ji} = The synaptic weight connecting the output of input neuron i to the input of hidden neuron j

q_j = The threshold applied to hidden neuron j

v_j = The net internal activity level of hidden neuron j

j_j = The activation function of hidden neuron j

o_j = The output of hidden neuron j

w_j = The synaptic weight connecting the output of hidden neuron j to the output of output neuron

q = The threshold applied to output neuron

v = The net internal activity level of output neuron

j = The activation function of output neuron

o = The output of output neuron

Δw_{ji} = The adjusted value of the weight w_{ji}

Δw_j = The adjusted value of the weight w_j

Δq_j = The adjusted value of the threshold q_j

Δq = The adjusted value of the threshold q

h = The learning-rate parameter

Step1: Weights Vector Initialization

Set all of the synaptic weights and threshold of the networks to small random numbers that are uniformly distributed.

Step2: Forward Computation

$$v_j(n) = \sum_{i=1}^{i=p} w_{ji}(n).x_i(n) - q_j(n) \tag{13}$$

$$o_j(n) = j_j[v_j(n)] \tag{14}$$

$$v(n) = \sum_{j=1}^{j=q} w_j(n).o_j(n) - q(n) \tag{15}$$

$$o(n) = j[v(n)] \tag{16}$$

Step3: Backward Computation

$$\Delta w_{ji}(n+1) = h.j_j^{'}[v_j(n)].(d(n)-o(n)) .j^{'}[v(n)].w_j(n).x_i(n) + \Delta w_{ji}(n) \tag{17}$$

$$\Delta w_j(n+1) = h.(d(n)-o(n)).j^{'}[v(n)] .o_j(n) + \Delta w_j(n) \tag{18}$$

$$\Delta q_j(n+1) = -h.j_j^{'}[v_j(n)].(d(n)-o(n)) .j^{'}[v(n)].w_j(n) + \Delta q_j(n) \tag{19}$$

$$\Delta q(n+1) = -h.(d(n)-o(n)).j^{'}[v(n)] + \Delta q(n) \tag{20}$$

Step4: Iteration
Increment time n by one unit and go back to step2.

5 Experiments

Performance of the proposed WNN was evaluated by data sets that were collected on the building of Computer Control and Fuzzy Logic Research Lab in the Iran University of Science and Technology. Fig.4 shows $Dx, Dy\ and\ Dz$ predictions for 100 test data by using proposed WNNs (After SA was turned off).

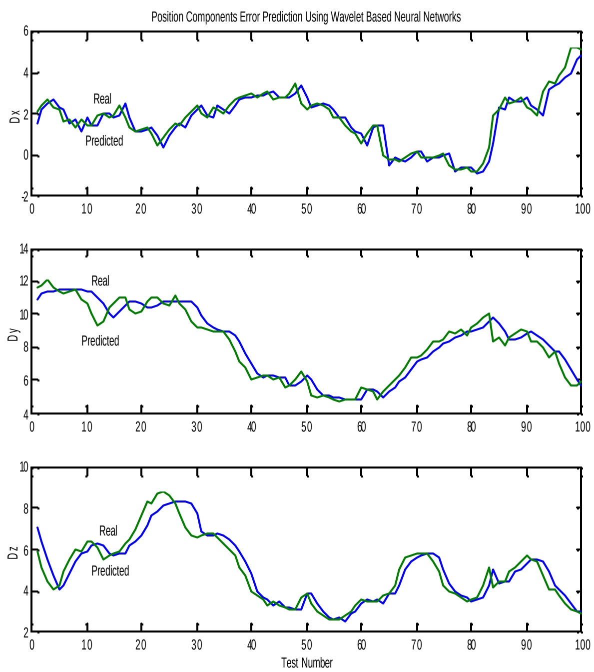

Fig.4. $Dx, Dy\ and\ Dz$ predictions by using proposed WNN $(M = 3, N = 3)$

5.1. Experimental System

Fig. 5 shows the implemented system. This system consists of GPS engine, microprocessor unit, DGPS transmitter, power supply, interface circuit, LCD display, and keyboard.

Hardware system was designed and implemented based on a minimum system by using an 80C196KB microcontroller, one of the MCS-96 families. Digital board consists of microcontroller and other peripheral chips.

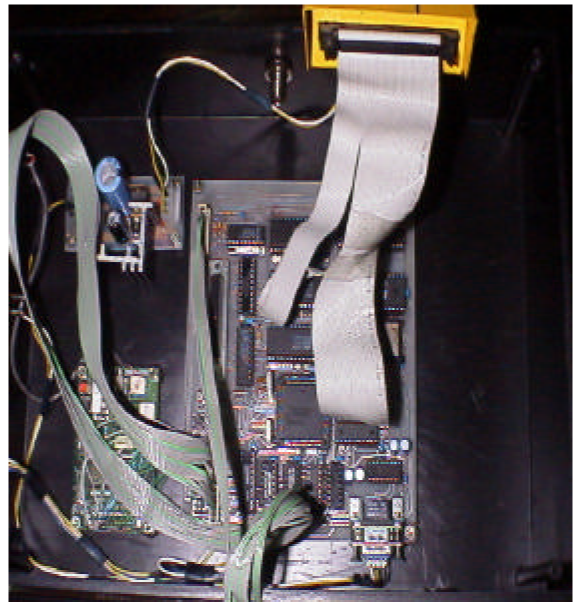

Fig. 5. Hardware Structure

In this research, a low cost GPS engine manufactured by Rockwell Company was used. The Rockwell "Microtraker Low Power (MLP)" receiver is a single board, five parallel-channels, L1-only Coarse Acquisition (C/A) code capability.

In order to communicate with the system, a keyboard and an indicator are needed. A simple 3 by 4 matrix keyboard was used as data entry device and command keys. Also, a 1 by 16 character LCD panel was used to display the measured position components and system status. In addition to, an optional UHF radio transiver (Transmitter/Receiver) with built-in modem was used. This radio is able to receiver or transfer DGPS corrections from or to differential reference station. A personal computer can easily connect to this system via its serial port.

5.2. Experimental Results

In order to evaluate the accuracy of the prediction, we used Root Mean Square (RMS) as below:

$$RMS = \sqrt{\frac{1}{M} \sum_{i=1}^{i=M} (d_i - y_i)^2} \qquad (21)$$

Where, M is test numbers, d_i denote the desired response of output, and y_i present the NN output at test i. Table1 to table 2 show prediction errors (the difference between the predicted and real values) statistical significance characteristics for 1000 test data using MLPs and WNNs, respectively.

Table 1: Prediction Errors Statistical Significance Characteristics Using MLP NNs

Parameters	X Component	Y Component	Z Component
Max	1.501729	1.774520	1.557686
Min	-1.688715	-1.656962	-1.530222
RMS	**0.424910**	**0.469731**	**0.424653**
Average	-0.003121	0.016066	0.009980
Variance	0.000181	0.000221	0.000181
Standard Deviation	0.013444	0.014862	0.013435

Table 2: Prediction Errors Statistical Significance Characteristics Using WNN NNs

Parameters	X Component	Y Component	Z Component
Max	1.655079	1.762146	1.591784
Min	-1.715484	-1.654277	-1.412574
RMS	**0.364747**	**0.435188**	**0.371481**
Average	-0.001879	0.017380	0.007539
Variance	0.000135	0.000172	0.000131
Standard Deviation	0.011621	0.013122	0.011428

As shown in table1 and table2, the WNNs have greater accuracy for DGPS corrections prediction.

6 Conclusions

In this paper has presented MLP and WNN architecture and its training algorithm for prediction of DGPS corrections. The proposed NNs were implemented on a low cost GPS receiver data. The results were highly effective predictions for accurate positioning. So, prediction RMS errors were less than 0.4 meter after of WNNs prediction. The experimental results demonstrate which WNN has great approximation ability and suitability in prediction than MLP.

Additional advantage of the investigated DGPS with NNs prediction is their low cost because of using only commercial C/A code GPS modules for reference and user.

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