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SIDELOBE REDUCTION USING WAVELET NEURAL NETWORK FOR BINARY CODED PULSE COMPRESSION

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ABSTRACT

Pulse compression technique is a popular technique used for improving waveform in radar systems. Series of undesirable sidelobes usually accompany the technique that may mask small targets or create false targets. This paper proposed a new approach for pulse compression using Feed-forward Wavelet Neural Network (WNN) with one input layer, one output layer and one hidden layer that consists of three neurons. Networks of 13-bit Barker code and 69-bit Barker code were used for the implementation. WNN-based back-propagation (BP) learning algorithm was used in training the networks. These networks used Morlet and sigmoid activation functions in hidden and output layer respectively. The simulation results from the proposed method shows better performance in sidelobe reduction where more than 100 dB output peak sidelobe level (PSL) is achieved, compared to autocorrelation function (ACF). Furthermore, the results show that WNN approach has significant improvement in noise reduction performance and Doppler shift performance compared to Recurrent Neural Network (RNN) and Multi-Layer Perceptron (MLP).

Keywords: wavelet neural network (WNN), pulse compression, barker code.

INTRODUCTION

Pulse compression plays an important role in improving range resolution. Two important factors are considered in radar waveform design; range resolution and maximum range detection. Range resolution is the capability of the radar to separate closely spaced targets, which is related to the waveform pulse width, while maximum range detection is the ability of the radar to detect the farthest target and it is related to the transmitted energy. The narrower the pulse width the better is the range resolution. However, if the pulse width is reduced the amount of energy in the pulse is decreased and hence the maximum range detection gets low. To overcome this limitation, pulse compression mechanism is utilized in radar systems [1]. Pulse compression technique enables radar to get the resolution of short pulse and simultaneously to obtain high energy and that can be achieved by internal modulation of the long pulse [2]. However, this technique has a drawback which generating sidelobe level. If there is a multi-targets environment the sidelobe of one large target may appear or mask small target in another range [3]. The advantages and limitations of pulse compression are discussed in Skolnik [4]. Several techniques were proposed to overcome these limitations, such as mismatched filter [5-7], transversal filter [8], neural network [9-12], fuzzy neural network [13] and genetic algorithm [14].

The mismatched filter and transversal filter techniques can reduce sidelobe by using pules compression filter. However, the limitation of these techniques is that the application of hardware filter increases computational burden and limits real time possibilities. Padaki and George [12] developed both Feedforward Neural Network (FFNN) and Radial Basis Function (RBF). They compared the performance of networks target detection and demonstrated that the feedforward neural network offers better performance. In addition, the RBF is more complex than FFNN. The approach in [13] integrates neural fuzzy network to deal with pulse compression. This approach has advantages in noise reduction performance, range resolution ability, and Doppler tolerance. However, this approach has limitation of computational complexity. Baghel and Panda presented a hybrid model for suppressing sidelobes [15]. The model was designed by combining a matched filter (MF) and a Radial function (RF). The performance of the model is better compared to other techniques such as MLANN and RBFNN.

Zhang and Benveniste [16] proposed Wavelet Neural Networks (WNN) as an alternative way for feedforward neural networks that improved the limitations of neural networks and wavelet analysis while it has the advantages and best performance of both of these methods. Chen, *et al.* [17] implemented WNN in time series prediction and system modeling based on multiresolution learning and the experimental results revealed that WNN has a significant approximation capability and suitability in modelling and prediction. Therefore, it can be a powerful tool in digital signal processing.

We have conducted a study and discussed available methods applied in sidelobe reduction, to the best of our knowledge, there no method for sidelobe reduction using WNN. Thus, we presents our study on the

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application of WNN that has been implemented in different fields such as de-noising [18] and classification [19], in sidelobe reduction. The application of WNN in these areas has demonstrated a significant improvement over Multi-Layer Perceptron (MLP), Recurrent Neural Network (RNN), Radial Basis Function (RBF) and Recurrent Radial Basic function (RRBF) in terms of convergence. This paper presents a new approach for sidelobe reduction using WNN. The simulation results obtained from this approach were compared with those obtained by FFNN, RNN and Autocorrelation Function (ACF).

The structure of this paper is as follows. Section II discusses on Barker code wavelets and their learning algorithm. Section III discusses wavelet neural network and learning algorithm. Section IV illustrates the performance of WNN compared to other methods ACF, MLP, and RNN. The concluding remarks are provided in Section V.

BARKER CODE AND WAVELETS

A. Barker code

Barker code is the most popular and widely used binary phase code. It is a sequence of N values of 1 and -1, C = [c(0) , c(1) , . . . , c(N-1)] such that

$$\left|\sum_{j=1}^{(N-1)-1} c(j).c(j+k)\right| \leq 1 \quad forall\ 1 \leq k \leq N \qquad (1)$$

Each segment phase represents 0º or 180º conformity with the element sequence in the phase code. It is commonplace to distinguish a sub-pulse that has 0 phase (amplitude of +1 volt) as either "1" or "+". Alternatively, a sub-pulse with phase equals to π (amplitude of -1 volt) is distinguished by either "-1" or "-" [8]. If these phases are selected randomly, the result of the waveform will be a noise-modulated one and if the phases are chosen in accordance with a criterion, the generated binary coded signal will have the best sequences [20].

B. Wavelet fundamentals

Wavelet analysis is a mathematical a tool that is derived from Fourier analysis. Wavelet transform has been used to analyze signal processing due to its ability to analyze frequency domain in specific period of time [17]. Besides, it is regarded as powerful tool used in various areas of research such as image processing, signal de-noising and in different biomedical applications, etc. [21].

Wavelet Analysis (WA) is a waveform of limited duration that has an average value of zero. The procedure adopts a particular wavelet function called family wavelet, which satisfy equation (4). A wavelet family is a set of orthogonal basis functions generated by dilation and translation of a compactly supported scaling function φ (or father wavelet), and a wavelet function ψ (or mother wavelet) which satisfy equations (2) and (3) respectively [21].

$$\int \varphi(t)\, dt = 1 \qquad (2)$$

$$\int \psi(t) dt = 0 \qquad (3)$$

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a_j}}\, \psi\left(\frac{t-b}{a}\right) \qquad (4)$$

WAVELET NEURAL NETWORK

Wavelet neural network (WNN) is a new class of neural network family. It is hybrid of wavelet with neural network. It is suitable for approximating arbitrary non-liner functions and for processing real time operation. The structure of WNN consists of input, output and one hidden layer as illustrated in Finger-1. This WNN has m, p, n nodes in the input layer, hidden layer and output layer respectively.

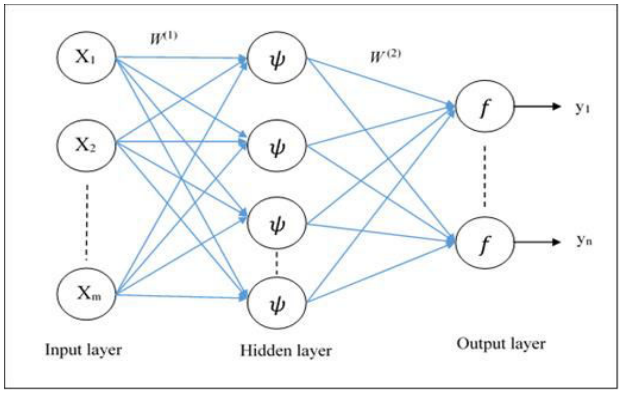

Figure-1. The structure of Wavelet Neural Network.

The parameters of WNN are as follows:
The weight between input and hidden layer
$w^{(1)} = \left(w_{jk}^{(1)}\right)_{p\times m}$
The weight between hidden and output layer
$w^{(2)} = \left(w_{ij}^{(2)}\right)_{n\times p}$
Dilation vector of the hidden layer neuron:
$a_j = \left(a_1, a_1, \dots a_p\right)$
Translation vector of the hidden layer neuron:
$b_j = \left(b_1, b_1, \dots, b_p\right)$

This research used one node for input and one node for output. However, there are no specific rules for calculating the number neurons in hidden layer. Several researchers suggested some rules to choose the number of hidden layer such as [22, 23]. The rules suggested in [19, 20] may sometimes lead to generating too many neurons depending on the area of application. On the other hand,

using too many neurons in hidden layer could lead to some problems. First, increasing neurons in hidden layer results in increasing in the time of training date and the processing of data gets more complex. Secondly, overfitting which occurs when the neural network have so much information processing capacity that makes the neural network weak to detect the signals. The proposed number of the hidden layer is three neurons and the activation function of the WNN for the hidden layer and the output layer are Morlet and sigmoid function respectively. Equation (5) and figure-2 below illustrate the Morlet function.

$$\psi(t) = \cos(1.75t)exp\left(-\frac{t^2}{2}\right) \tag{5}$$

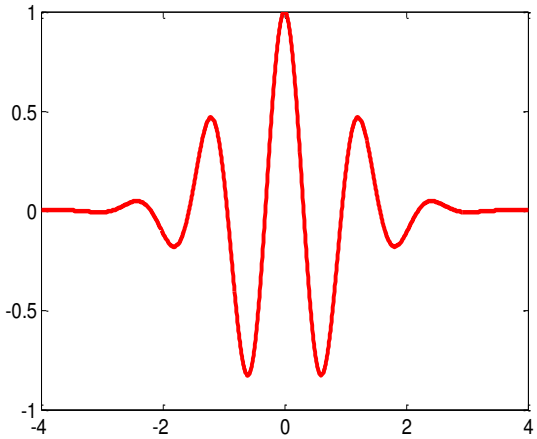

Figure-2. Morlet Wavelet function.

The wavelet training uses back-propagation algorithm (BP), which is popularly used (regardless of its limitation) in most commonly used training algorithm. BP is a simple algorithm and computational less expensive [21]. The concept of this algorithm consists of two passes. First path, called forward pass, in which the output is calculated and then the error can be calculated as well by subtracting the desired signal from the output result. Let assume the input vector is$X = (x_1, x_2, \dots, x_m)$. The following equations demonstrate the forward pass as shown below.

$$\psi_{a_j,b_j}\left(\sum_{k=1}^{m} w_{jk}^{(1)} x_k\right) = \psi_{a_j,b_j}\left(net_j^{(1)}\right) = \frac{1}{\sqrt{a_j}}\,\psi\left(\frac{net_j^{(1)} - b_j}{a_j}\right) \tag{6}$$

in which

$$net_j^{(1)} = \sum_{k=1}^{m} w_{jk}^{(1)} x_k \tag{7}$$

The output of the ith node of output layer is:

$$y_i = f\left(\sum_{j=1}^{p} w_{ij}^{(2)} \psi_{a_j,b_j}(net_j^{(1)})\right) = f(net_j^{(2)}) \tag{8}$$

Where

$$net_j^{(2)} = \sum_{j=1}^{p} w_{ij}^{(2)} \psi_{a_j,b_j}(net_j^{(1)}) \tag{9}$$

where (y) is the output vector for the wavelet neural network as illustrated in equation (8). Assuming the number of training is Q. For each sample q, the desired output vector is$D_q = (d_{q1}, d_{q2}, \dots, d_{qn})$, with these Q training samples, after calculating the output, the Mean Square Error (MSE) needs to be calculated. Therefore, the value of MSE must be very small value, which is the difference between the target and the network output equation as shown in the equation below.

$$E = \frac{1}{2}\sum_{q=1}^{Q}\sum_{i=1}^{n}\left(d_{qi} - y_{qi}\right)^2 \tag{10}$$

The second path is known as the backward pass is used to obtain the amount of change of the parameters by finding the derivative of error with respect to weight, translation and dilation; equations bellow illustrates the derivation of error.

$$\frac{\partial E}{\partial w_{ij}^{(2)}} = -\sum_{q=1}^{Q}\left(d_{qi} - y_{qi}\right).y_{qi}.\left(1 - y_{qi}\right).\psi_{a_j,b_j}\left(net_{qj}^{(1)}\right) \tag{11}$$

$$\frac{\partial E}{\partial w_{jk}^{(1)}} = -a_j^{-1}\sum_{q=1}^{Q}\left[\psi'_{a_j,b_j}\left(net_j^{(1)}\right).x_{qk}.\sum_{i=1}^{n}\left(d_{qi} - y_{qi}\right).y_{qi}.\left(1 - y_{qi}\right)w_{ij}^{(2)}\right] \tag{12}$$

$$\frac{\partial E}{\partial a_j} = -a_j^{-1}\sum_{q=1}^{Q}\left\{\left[\frac{a_j^{-1}}{2}\psi_{a_j,b_j}\left(net_{qj}^{(1)}\right) + \frac{net_{qj}^{(1)} - b_j}{a_j^2}\psi'_{a_j,b_j}\left(net_{qj}^{(1)}\right)\right].\sum_{i=1}^{n}\left(d_{qi} - y_{qi}\right).y_{qi}.\left(1 - y_{qi}\right)w_{ij}^{(2)}\right\} \tag{13}$$

$$\frac{\partial E}{\partial b_j} = -a_j^{-1}\sum_{q=1}^{Q}\left[\psi'_{a_j,b_j}\left(net_j^{(1)}\right).\sum_{i=1}^{n}\left(d_{qi} - y_{qi}\right).y_{qi}.\left(1 - y_{qi}\right)w_{ij}^{(2)}\right] \tag{14}$$

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where

$$\psi'_{a_j,b_j}\left(net_{qj}^{(1)}\right) = \frac{1}{\sqrt{a_j}}\psi'\left(\frac{net_j^{(1)} - b_j}{a_j}\right)$$

The update of WNN parameters W_{ij} , W_{jk} , a_j and b_j as follows:

$$w_{ij}^{(2)}(t+1) = w_{ij}^{(2)}(t) - \eta\frac{\partial E}{\partial w_{ij}^{(2)}} + \alpha\left[w_{ij}^{(2)}(t) - w_{ij}^{(2)}(t-1)\right] \quad (15)$$

$$w_{jk}^{(1)}(t+1) = w_{jk}^{(1)}(t) - \eta\frac{\partial E}{\partial w_{jk}^{(1)}} + \alpha\left[w_{jk}^{(1)}(t) - w_{jk}^{(1)}(t-1)\right] \quad (16)$$

$$a_j(t+1) = a_j(t) - \eta\frac{\partial E}{\partial a_j} + \alpha\left[a_j(t) - a_j(t-1)\right] \quad (17)$$

$$b_j(t+1) = b_j(t) - \eta\frac{\partial E}{\partial b_j} + \alpha\left[b_j(t) - b_j(t-1)\right] \quad (18)$$

More details regarding the framework adapted in this study have been simplified in a flowchart as shown in Appendix A.

SIMULATION RESULTS

This section discusses the performance of the different network for radar pulse compression. The finding of MLP and RNN are discussed for comparison purpose. The MLP and RNN networks are trained with the time shifted sequences of the 13-bit and 69-bit Barker code.

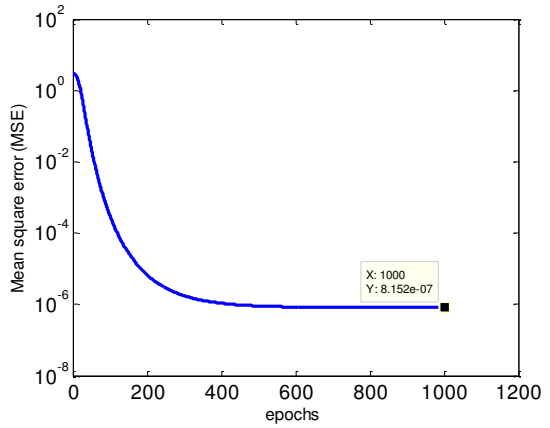
The design of the MLP and RNN consists of three layers namely: input, hidden and output layers. The proposed activation function is log-sigmoid for both hidden and output layer. The number of neurons in the input layer, hidden layer and output layer are chosen as one, three and one neurons respectively. The length of the desired output (target) has the same length with the input sequence. The modelling of the desired output of the pulse compression filter has contained all zero vectors except one point, which is located in the middle and has the same length as in Baker code. For more illustration, the example of 13-bit Baker code of the desired output is d=[(12 zero), 13, (12 zero)]. The matrix of the weight and bias are randomly initialized. The learning rate (η) and momentum (α) that is chosen in this paper are 0.2 and 0.99 respectively. After training, the networks can be used for pulse radar detection using different input sequence. The network performance has been studied as follows:

A. Convergence performance

By comparing the result of MSE for MLP and RNN with WNN. It is observed that for 13 and 69-bit Barker code, the MSE values of WNN are less than the MLP and RNN as shown in Table-1. This means that the WNN network performance is better than the performance of the other methods. Note that the number of iteration used for all the methods is between 8 to 1000 Epochs.

Table-1. Training values performance.

Motheod	Performance (MSE)	
	13-Bit Barker code	69-Bit Barker code
MLP	1.1121e-04	2.029e-04
RNN	3.3797e-05	2.681e-04
WNN	8.152e-07	3.841e-04



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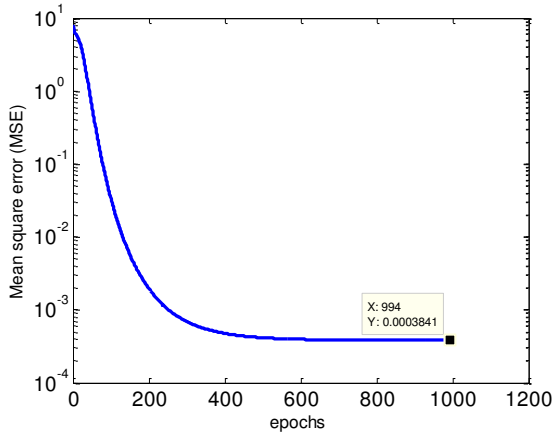

(b)

Figure-3. Training of WNN (a) 13-bit (b) 69-bit Barker code.

B. Performance of peak sidelobe level (PSL)

Peak sidelobe level is considered as an important aspect for performance analysis within the context of a radar system [3]. For an N-bit code, the sidelobe level is defined as

$$PSL = 10\log_{10}\max\left(\frac{X_i^2}{X_0^2}\right) \text{ dB} \quad (19)$$

where X_0: amplitude of the peak of the compressed pulse (mainlobe), X_i: all the output range sidelobes. The

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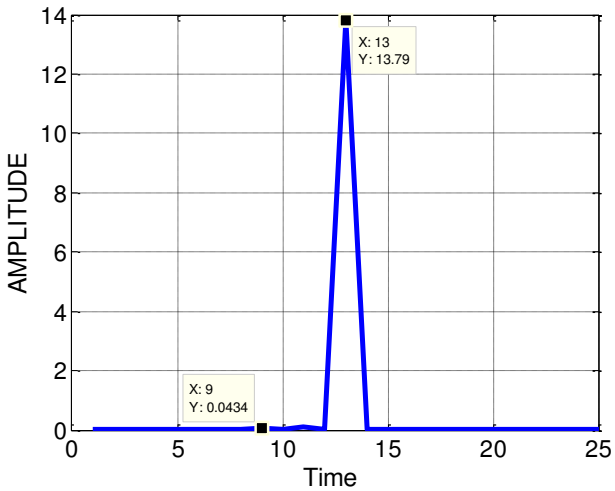
compressed output values of 13-bit and 69-bit Barker code are shown in Table-2. The output of 13-bit Barker code for ACF, MLP, RNN and WNN methods are shown in Figure-4 illustrates.

Table-2. PSL Obtained By Different Method.

Method	13-Bit Barker code (PSL in dB)	69-Bit Barker code (PSL in dB)
ACF	22.278	24.735
WNN	82.75	211.93
RNN	51.21	78.21
MLP	44.43	72.42



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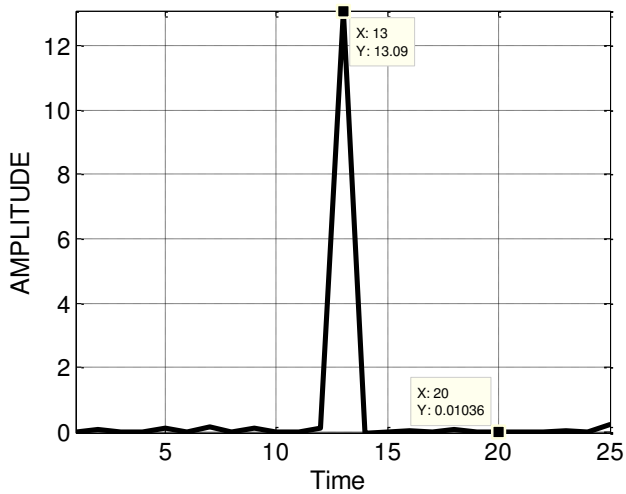

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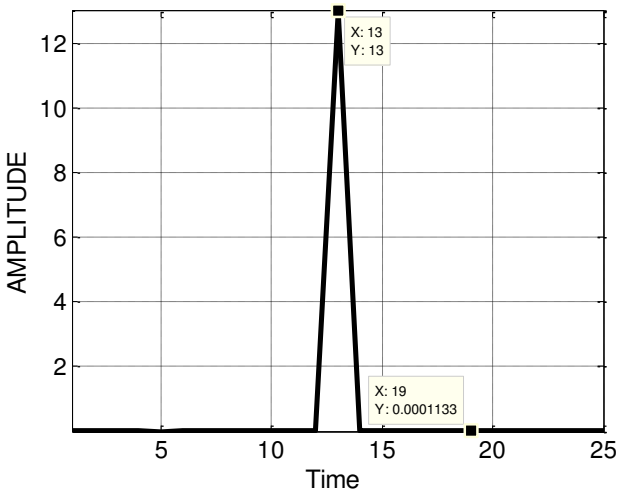


(c)

Figure-4. Output of 13-bit Barker code (a) RNN (b) MLP (c) WNN.

C. Noise performance

The target echo is influenced by noise. Thus, the testing of algorithm with noise signal should be conducted. We added white Gaussian noise for the simulation. Tables-3and 4 shows the comparison of PSL performance of different methods at various SNR between (0 dB to 20 dB).

Table-3. Comparison of PSL at different SNR for 13-bit barker code.

Method	PSL (dB)			
	SNR= 1 dB	SNR= 5 dB	SNR= 10 dB	SNR= 20 dB
ACF	11.94	13.79	17.46	19.98
WNN	39.28	51.60	61.10	79.60
RNN	19.27	24.13	31.65	50.70
MLP	15.61	18.57	27.29	43.98

Table-4. Comparison of PSL at different SNR for 69-bit barker code.

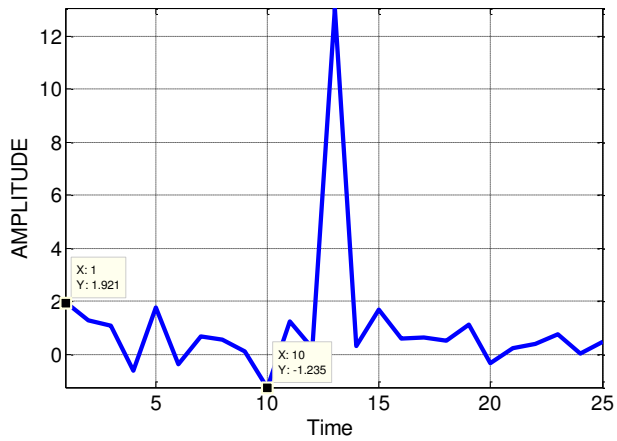
Method	PSL (dB)			
	SNR= 1 dB	SNR= 5 dB	SNR= 10 dB	SNR= 20 dB
ACF	14.94	16.85	19.46	22.48
WNN	60.28	78.60	142.10	202.60
RNN	26.27	32.62	53.65	70.40
MLP	20.61	27.29	48.29	65.98

The PSL values of WNN method that obtained in Tables-3and 4 above are the highest value compared to the other methods such as MLP and RNN. Therefore, the

performance of WNN method is better than other used methods. Figure-5 shows the output of noise for 5 dB and the output of each method for 13-bit Barker code.

D. Doppler shift performance

Doppler shift occurs when the target is moving. Therefore, the center of frequency of the echo signal will be changed according to the new position of the target. To obtain the maximum Doppler, the first bit of the Barker code will bechanged from -1 to 1 or vice-versa depending on the length code [15]. Figure-6 shows the signal after Doppler shift.



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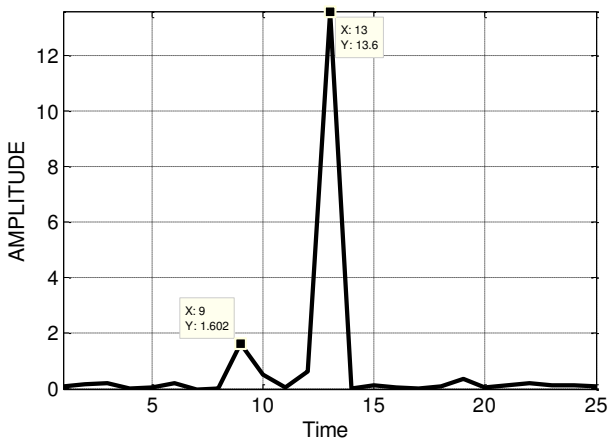

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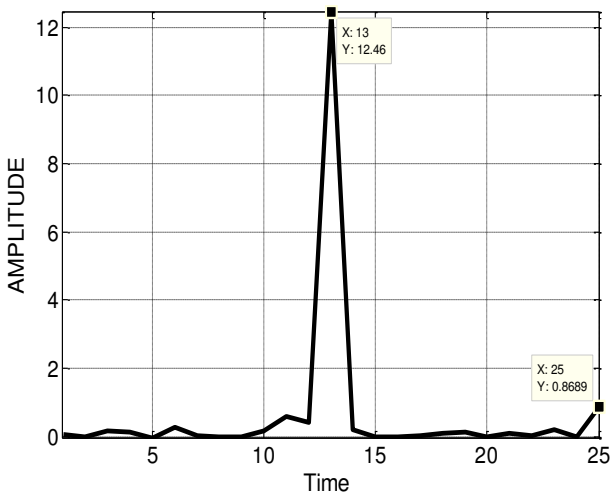

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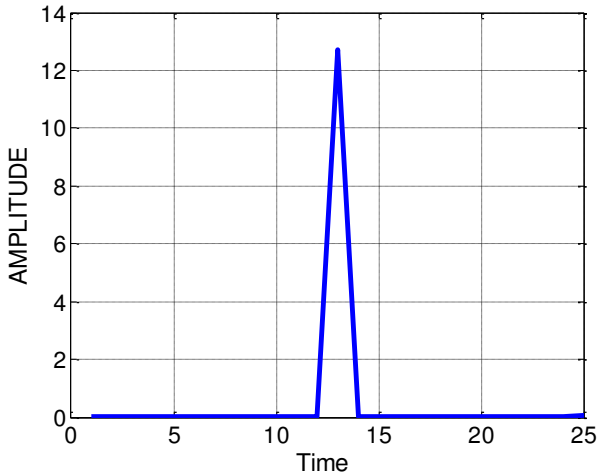


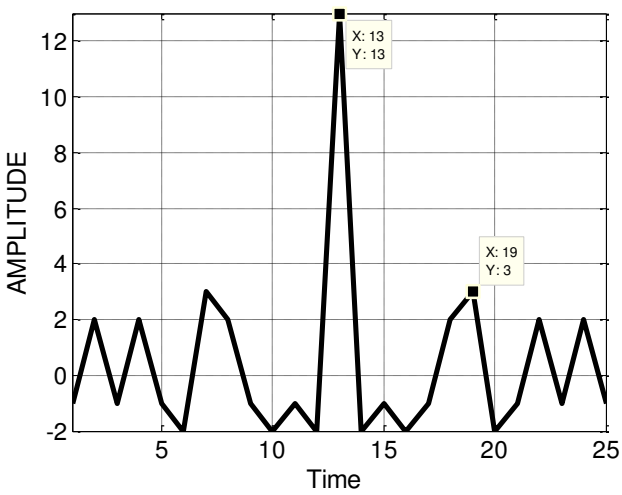
(d)

Figure-5. Output of networks after noise 5 dB for 13-bit Barker code (a) ACF after noise (b) RNN (c) MLP (d) WNN.

Table-5. Doppler shift.

Method	13-Bit Barker code (PSR in dB)	69-Bit Barker code (PSR in dB)
ACF	12.7364	21.2140
WNN	49.93	203.36
RNN	23.45	70.92
MLP	19.23	66.34

Table-5 shows the output of ACF, WNN, RNN and MLP. From the data provided in the table, it is revealed that the performance of WNN is better than any other methods. Figure-6 illustrates the Doppler shift of 13-bit and 69-bit Barker code signals, and shows the output signal of each method.



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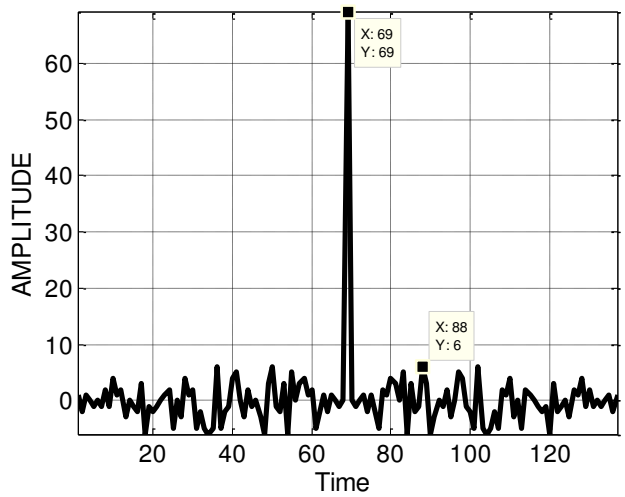

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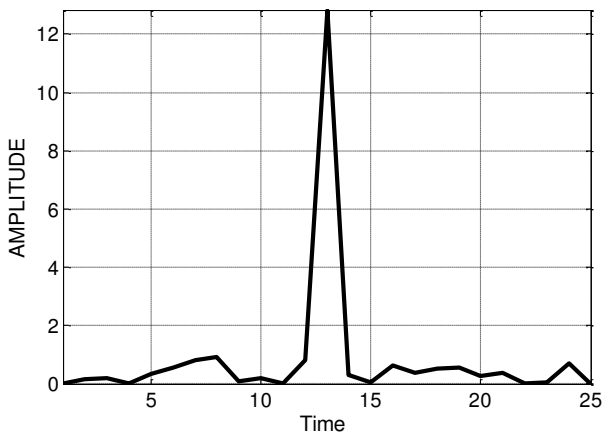

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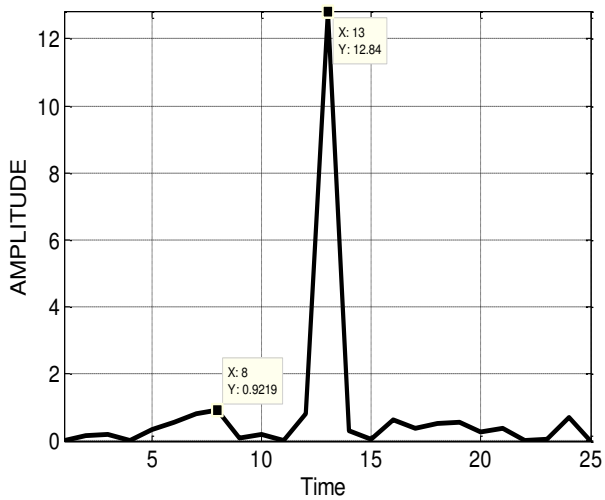

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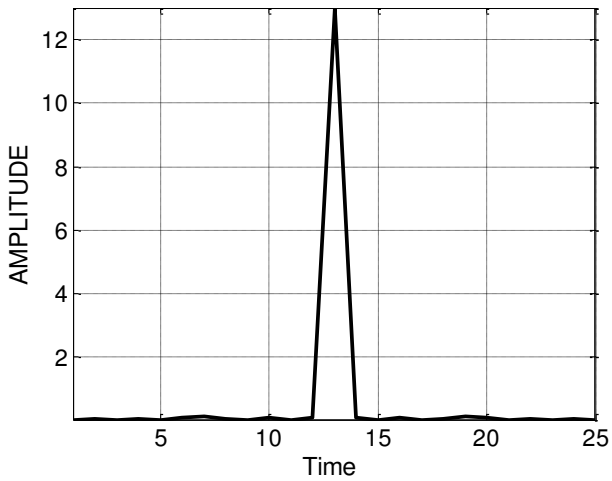


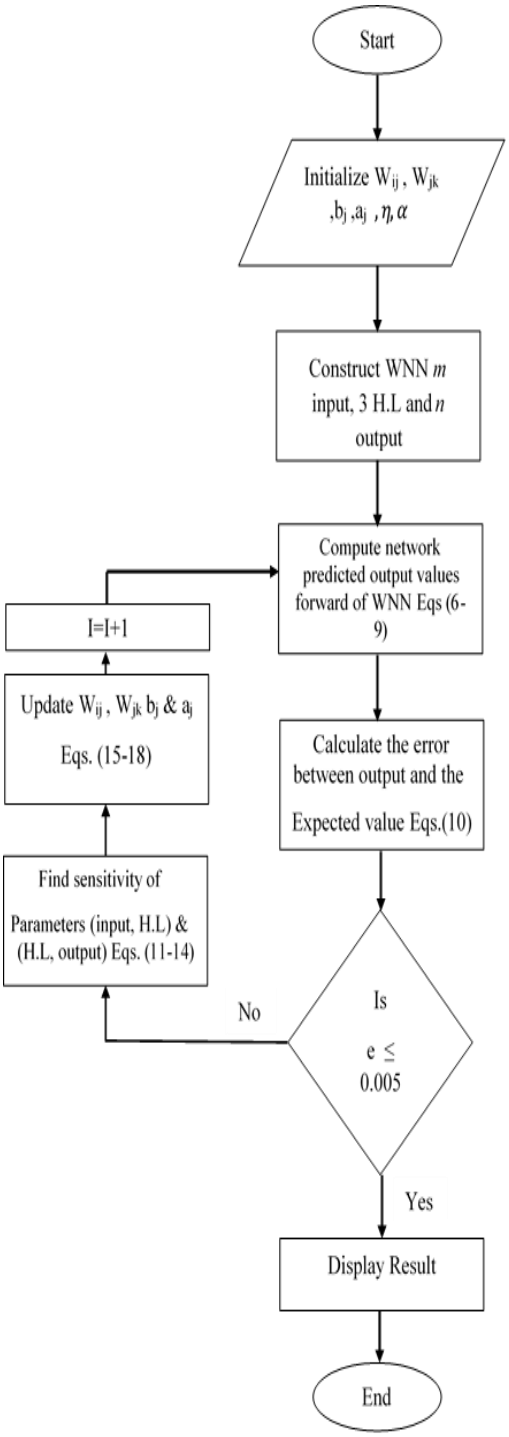
(f)

Figure-6. Doppler shift (a) ACF 13-bit (b) ACF 69-bit (c) MLP (c) RNN (f) WNN.

CONCLUSIONS

This work contributes to the growing foundation of using NN for sidelobe reduction in radar systems. We presented a new technique for sidelobe reduction of compressed binary phase coded waveforms using WNN. We used Feed-forward Wavelet Neural Network with one input layer, one output layer and one hidden layer that consists of three neurons for pulse compression. The networks of 13-bit Barker code and 69-bit Barker code that used Morlet and Sigmoid activation functions in hidden and output layer respectively were used, which were trained using WNN-based back-propagation (BP) learning algorithm. The output results obtained from the evaluation is satisfactory compared to MLP and RNN. Our technique shows a significant improvement in PSL over the results obtained in previous methods [11, 15, 24]. We believed that it would be a powerful technique for

classification and de-noising due to the presence of mother function.



Framework of apply WNN algorithm.

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