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Mitigating Peak Sidelobe Levels in Pulse Compression Radar using Artificial Neural Networks

K. Raja Rajeswari, N. Roopa Vathi, B. Vijaya Lakshmi, P. V. K. Chaitanya

Abstract: ***In this paper, Artificial Neural Networks (ANNs) are being considered to obtain low sidelobe pattern for binary codes and thereby to improve the performance of pulse compression radar. Pulse compression is a popular technique used for improving range resolution in the radar systems. This paper proposes a new approach for Pulse Compression using various types of ANN networks like Multi-Layer Perception (MLP), Recursive Neural Networks (RNN), Radial Basis Function (RBF) and Recurrent Radial Basis Function (RRBF) and a special class of Feed-Forward Wavelet Neural Network (WNN) with one input layer, one output layer and one hidden layer are being considered. Networks of 13-bit Barker code and extended binary Barker codes of 35, 55 and 75 length codes were used for the implementation and thereby to improve the performance of pulse compression radar. WNN-based networks using Morlet and Sigmoid activation function in hidden and output layers respectively, a special class of Artificial Neural Network is considered in this paper. The performance metrics used are Peak Sidelobe Ratio (PSLR), Integrated Sidelobe Ratio (ISLR) and Signal-to-Sidelobe Ratio (SSR). Further the performance in terms of range and Doppler resolution is also presented in this paper. Better performance in terms of sidelobe reduction can be achieved with ANNs compared to Autocorrelation Function (ACF) called as matched filter. If the sidelobe values are high there is possibility of masking weaker return signals and there by detection becomes difficult. From this paper it can be established that RRBF gives better result than other ANN networks. Further, WNN gives the best performance even compared with RRBF in terms of sidelobe reduction in pulse compression radar.***

Keywords: ***ACF, ANNs, WNN, PSLR, ISLR, SSR, Pulse Compression, Barker code, MLP, RNN, RBF, RRBF, Range resolution, Doppler resolution, Matched Filter.***

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I. INTRODUCTION

Pulse Compression plays an important role in improving range resolution. Two important factors considered in radar waveform design are i) Range resolution ii) Range detection. Range resolution is the ability of the radar receiver 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 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 will be decreased then the maximum range detection gets slow. To overcome this limitation, pulse compression mechanism is utilized in radar systems. Pulse compression allows for training the average transmitted power of a reasonably long pulse, while acquiring the range resolution corresponding to short pulse. Low sidelobe distribution leads to peak sidelobe ratios in the range from -30 to -60 dB have recently attracted more interest for the researchers. There are several techniques available in the literature for sidelobe reduction in pulse compression radar e.g. Mismatched filter, transversal filter and genetic algorithm [1-6][21][22]. In some cases, radar transmitted waveform itself can be modified in a signal domain itself to reduce the sidelobes in ACF [7, 8][23].

Motivation behind the objective of this paper is to achieve for better pulse compression in terms of main lobe to peak side lobe ratio should be as high as possible. This can be obtained by reducing the side lobes to maximum extent possible so that unwanted clutter gets suppressed. In other words, high sidelobes mask the useful information and detection becomes difficult. Range resolution is the ability of the radar or sonar to distinguish between two or more targets at different ranges. Velocity resolution is the minimal radial velocity difference between two objects travelling at the same range. Aperiodic autocorrelation functions (ACFs) reveal numerous inherent properties of radar waveforms e.g., Range resolution and an anti-interference capability [4][24].

Matched filter is main part of the any radar receiver. It is a correlator that maximizes the output peak signal to noise ratio of the radar receiver which in turn maximizes the delectability of a target. In some cases, ACF (Autocorrelation Function) or matched filter output is used to suppress sidelobes; these are called as Post filtering techniques e.g., Woo filters[3, 5, 9].

These are also called as mismatched filters. In this paper sometimes ACF is referred for matched filter. However, the limitation of these techniques is that the application of the hardware of the filter increases computational burden. This integrated filter, Matched filters along with Woo filter is called as “Enhanced Matched Filter”.

In this paper matched filter has been replaced by ANNs (Artificial Neural Networks). Binary codes are also called as biphase codes. Binary Barker codes exist up to length 13. Larger length codes will be obtained by using Kronecker Product of two binary Barker codes. For example, 35lengths binary Barker can be obtained using Kronecker product of two binary Barker codes of length 7 and 5. But these are called as extended binary Barker codes. These codes will not follow the property of the Barker code as actual binary Barker codes will not exist beyond length 13 [10]. The property of Barker code is that the maximum sidelobe value of ACF is equal to ±1.

To mitigate the interference caused by range-Doppler sidelobes in pulsed radar systems, a new method has been proposed to construct Doppler resilient complementary waveforms from Golay codes [11]. In this paper extended binary Barker codes are considered up to length 75 to evaluate the performance of the codes in terms of reduced sidelobes to avoid the masking of the weaker signals and enhancing the likelihood of detection.

II. ARTIFICIAL NEURAL NETWORKS (ANNs)

ANN is motivated by the biological structure of the human brain. Generally neural network consists of a neuron, weight vector, bias, activation function etc. Each node, an artificial neuron, connects to another. Artificial Neural Networks (ANNs) are comprised of various layers, containing an input layer, one or more hidden layers and an output layer. Neural networks can be utilized in Radar Target Detection (RTD) due to their learning ability. Usually more complex ANN detector with multiple hidden layers would give better performance [12].

In this paper the inputs to the first layer are time–shifted version of the code under consideration as shown in `figure 1. Output gives relative value of the main lobe and sidelobes. In the recent literature, the better sidelobe reduction and improvement in range resolution ability and Doppler shift tolerance have been achieved using ANNs than merely with Autocorrelation Filter (ACF) [13]. If data is having large dimensions to give an optimum solution, 3 to 5 hidden layers can be used. Having fewer dimensions or features then neural networks with 1 to 2 hidden layers will work. The various neural network structures considered are MLP, RBF, RNN and RRBF [14]. In the case of RBF networks typically there will be three layers as input layer, hidden layer with a non-linear RBF activation function.

The Activation Functions used for various networks are:

MLP : Sigmoid, Linear
RNN : Sigmoid, Tanh
RBF : Parabolic
RRBF :Parabolic

Time shifting of 13-bit barker code:

[1 1 1 1 1 -1 -1 1 1 -1 1 -1 1]

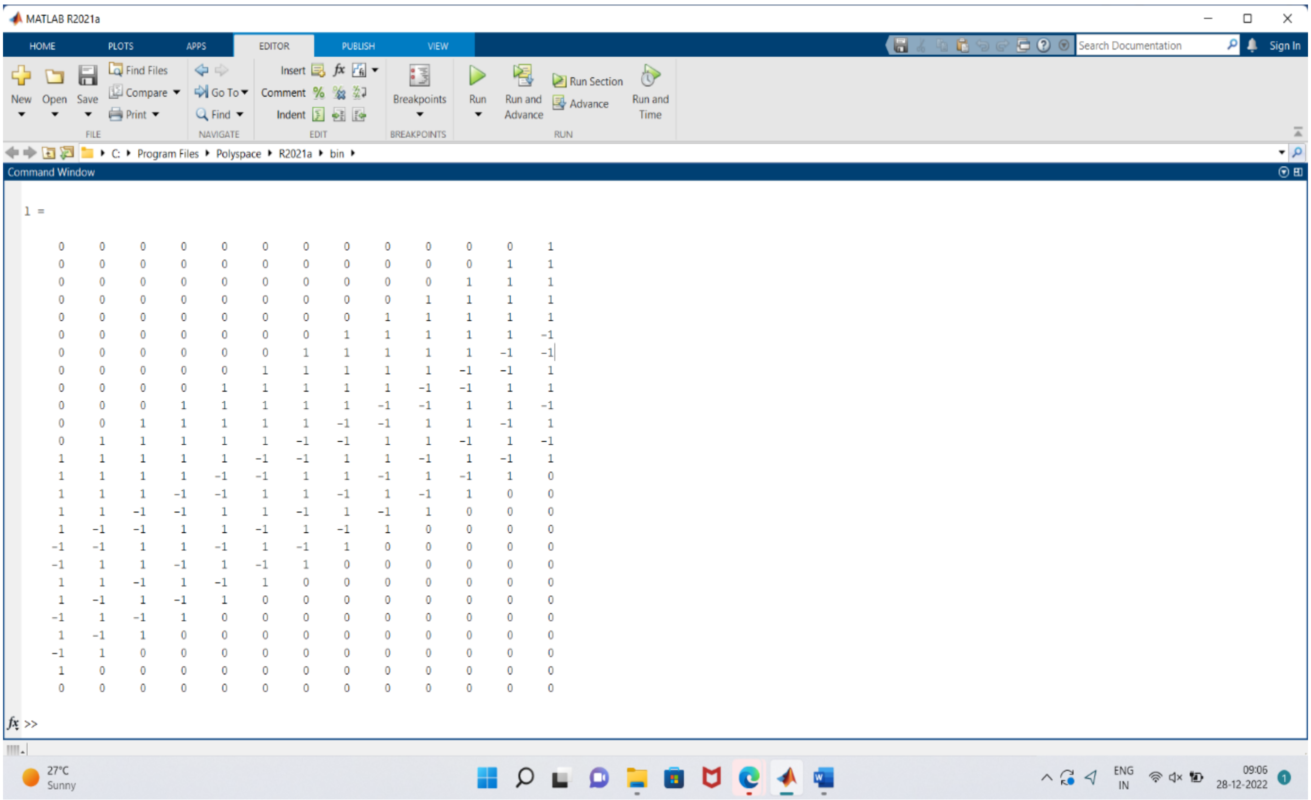

Fig. 1. Training Sequence to the Network

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A. Wavelet Fundamentals

Zhang and Benveniste [15][25] proposed Wavelet Neural Networks (WNN) as an alternative way for feed forward 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. [16] 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 modeling and prediction. Therefore, it can be a powerful tool in digital signal processing.

Wavelet analysis is a mathematical tool that is derived from Fourier analysis. Wavelet transform has been used to analyze signal processing due to its ability to analyze frequency in a specific period of time [16]. 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. [17].

Wavelet analysis is a waveform of limited duration that has an average value of zero. The procedure adopts a particular wavelet function called family wavelet, which satisfies equation 1. 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 functionΨ (mother wavelet) which satisfies the equations 1 and 2 respectively.

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

$$\int \psi(t)dt = 0 \qquad (2)$$

B. Wavelet Neural Network

Wavelet Neural Network is a new class of neural network family. It is suitable for approximating arbitrary non-linear function and for processing real time operation. The structure consists of input, output and hidden one hidden layer as illustrated in Fig. 2. However, there are no specific rules for calculating the number of hidden layers. In our case one hidden layer has been taken.

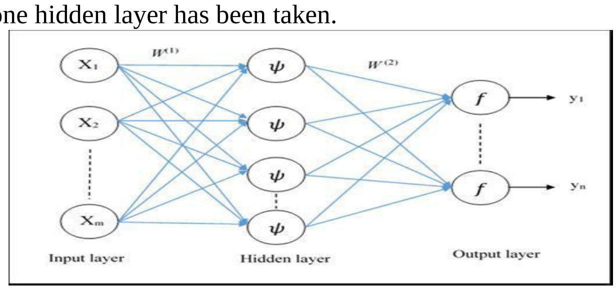

Fig. 2. The structure of Wavelet Neural Network

If data is less complex and is having fewer dimensions or features then neural networks with 1 to 2 hidden layers would work. If data is having large dimensions or features then to get an optimum solution, 3 to 5 hidden layers can be used. Several researchers suggested some rules to choose the number of hidden layers such as [18, 19].

WNN –based networks uses Morlet and sigmoid activation function in hidden and output layers respectively. The Morlet function can be represented as

$$\psi(t) = \cos(1.75t)\exp\left(\frac{-t^2}{2}\right) \qquad (3)$$

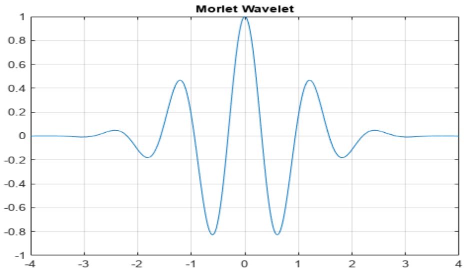

Fig. 3. Morlet Wavelet Function

III. METHODOLOGY

For the obtained output of ACF, the Performance Metrics PSLR and ISLR will be computed. Autocorrelation can be computed from the following equation 4. This is obtained by correlating the signal by itself. If it is between two different signals, known as Cross Correlation.

$$r[k] = \sum_{i=0}^{N-1-K} x_i x_{i+k}^{*} \qquad (4)$$

Where k=0,1,2,3, --------------, N-1

Second term is a complex conjugate of the first term in the case of complex codes such as Polyphase codes as each element of a complex code is having magnitude and phase. For binary and other type of codes * is ignored.

A. Peak Side Lobe Ratio (PSLR)

PSLR gives the value that how much the peak sidelobe is lower from the main lobe. It is mathematically expressed as follows [20].

$$PSLR(db) = 20\log_{10}\left(\frac{{}_{k\neq 0}|r(k)|_{\max}}{r(0)}\right) \qquad (5)$$

measured in dB.

B. Integrated Side Lobe Ratio (ISLR)

This gives the ratio of energy distributed in the sidelobes to the energy in the mainlobe can be represented as follows [20].

$$ISLR(db) = 10\log_{10}\left(\frac{2\sum_{k=1}^{N-1} r^2(k)}{r^2(0)}\right) \qquad (6)$$

measured in dB.

The numerator is multiplied by 2 as autocorrelation function is symmetric from either side of the mainlobe. For code length of N, total number of sidelobes will be 2N-1.

C. Signal to Sidelobe Ratio (SSR)

This is defined as the ratio of mainlobe value to peak sidelobe value. 20log (SSR) gives its value in dB.

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IV. SIMULATION RESULTS

TABLE-1: SSR Comparison in dB for Different Lengths

Algorithm	Different Lengths			
	13-Bit	***35-Bit***	***55-Bit***	***75-Bit***
Matched Filter	22.27	13.97	13.97	13.97
MLP	45.13	44.41	44.23	43.78
RNN	47.91	47.72	47.53	47.12
RBF	53.51	53.21	53.07	52.98
RRBF	54.53	54.33	54.12	54.08
WNN	82.21	162.71	199.98	248.16

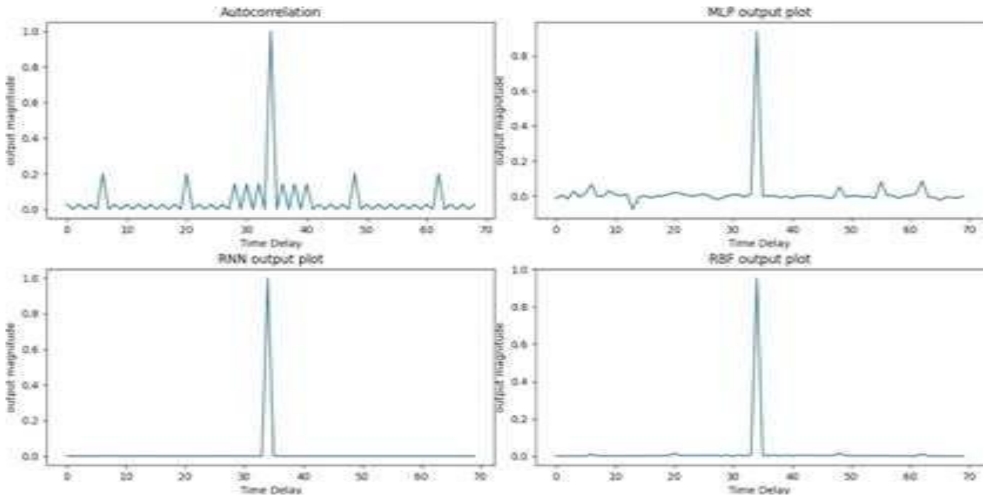

Fig. 4. Autocorrelation Plot for 35-bit Binary Code using MLP, RNN and RBF

Table-2. PSLR & ISL Rcomparisonin dB for Different Lengths

Algorithm	Different Lengths							
	13-Bit		***35-Bit***		***55-Bit***		***75-Bit***	
	PSLR	***ISLR***	***PSLR***	***ISLR***	***PSLR***	***ISLR***	***PSLR***	***ISLR***
Matched Filter	-22.70	-8.47	-13.97	-12.18	-13.97	-21.90	-13.97	-29.10
MLP	-28.32	-15.04	-32.03	-20.00	-49.06	-34.29	-58.15	-40.55
RNN	-28.46	-15.93	-40.08	-27.74	-49.97	-36.36	-59.12	-44.23
RBF	-28.56	-16.77	-44.90	-34.05	-51.09	-39.06	-60.88	-48.92
RRBF	-40.89	-29.27	-67.94	-51.94	-69.75	-55.00	-66.93	-55.42
WNN	-49.73	-36.67	-98.77	-69.25	-172.32	-73.25	-213.56	-76.85

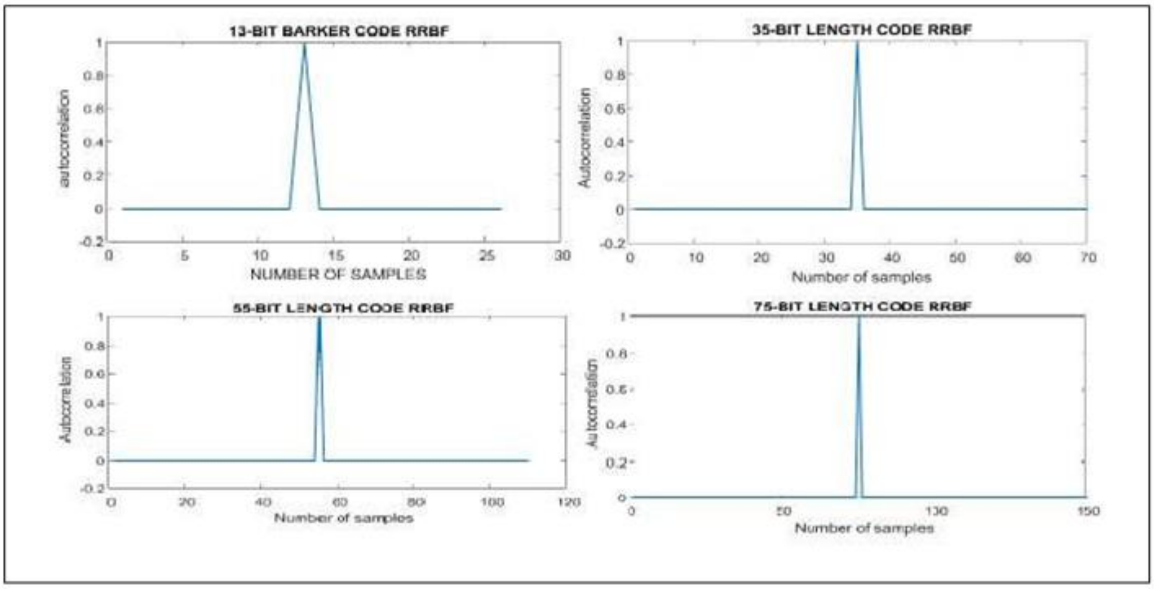

Fig. 5. Autocorrelation Plot using RRBF for the Lengths 13, 35, 55 and 75bit Binary Codes

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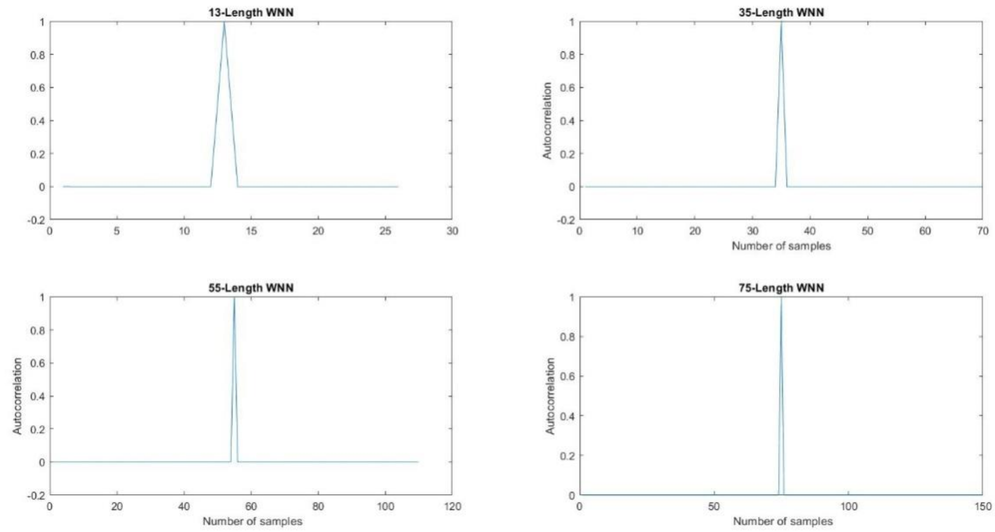

Fig. 6. Autocorrelation Plot using WNN for the Lengths 13, 35, 55 and 75bit Binary Codes

A. Range Resolution Ability

The two waveforms are overlapped by delaying second one by some delays and are applied as input to the network and SSRs calculated.

The SSR values for the delays 1, 2 and 3 are shown in Tables 3. The delays 1, 2 and 3 are represented as 1-DA, 2-DA and 3-DA respectively. DA represents Delay Apart.

Table-3.SSR Comparison in dB for Range Resolution Ability of Two Targets with 2 Delay Apart (2DA) for Different Lengths

Algorithm	Different Lengths			
	13-Bit	***35-Bit***	***55-Bit***	***75-Bit***
Matched Filter	16.90	17.23	18.85	19.21
MLP	45.09	46.62	47.76	48.91
RNN	47.89	48.97	49.11	50.12
RBF	48.83	49.52	50.23	51.33
RRBF	49.21	50.56	51.87	52.98
WNN	66.76	69.92	71.22	73.56

Table-4. SSR Comparison in dB for Range Resolution Ability of Two Targets with Different Delay Apart (DA) for 35-bit Length Binary Barker Code

Algorithm	1-DA	2-DA	3-DA
Matched Filter	15.23	17.23	23.12
MLP	44.52	46.62	45.96
RNN	45.96	48.97	48.62
RBF	47.82	49.52	49.76
RRBF	48.55	50.56	50.92
WNN	65.55	67.74	69.93

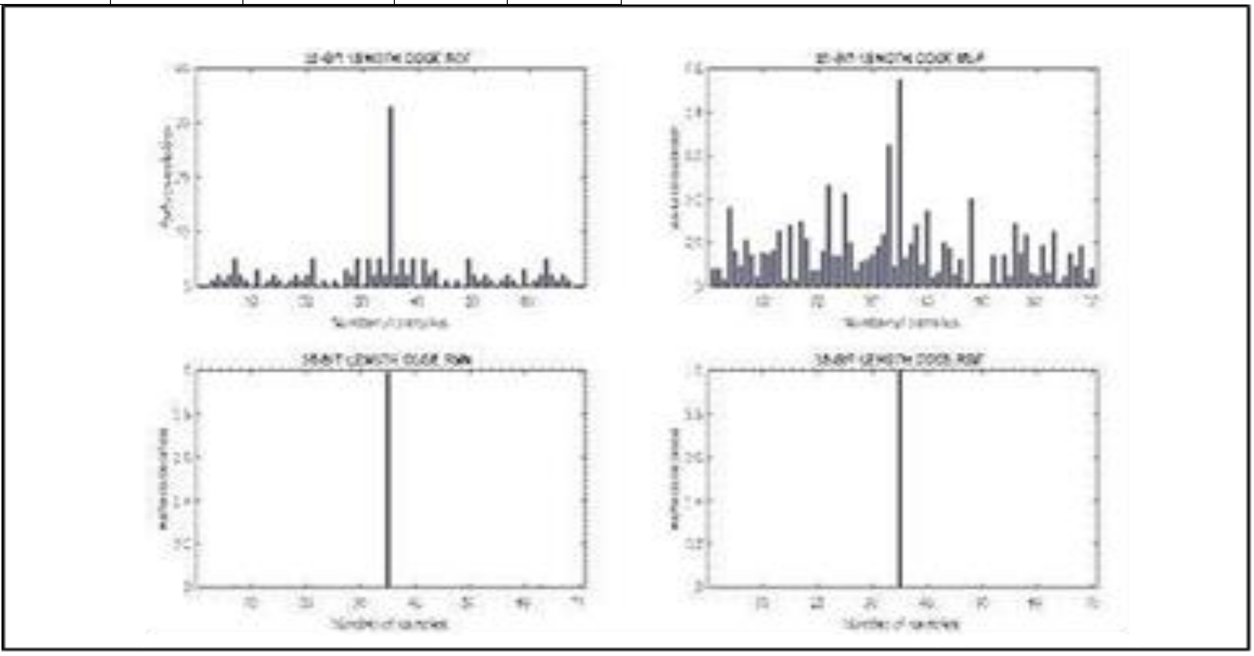

Fig. 7. SSR Comparison in dB for Range Resolution Ability for 2-DA for 35-bit length (a) Matched Filter (b) MLP (c) RNN (d) RBF

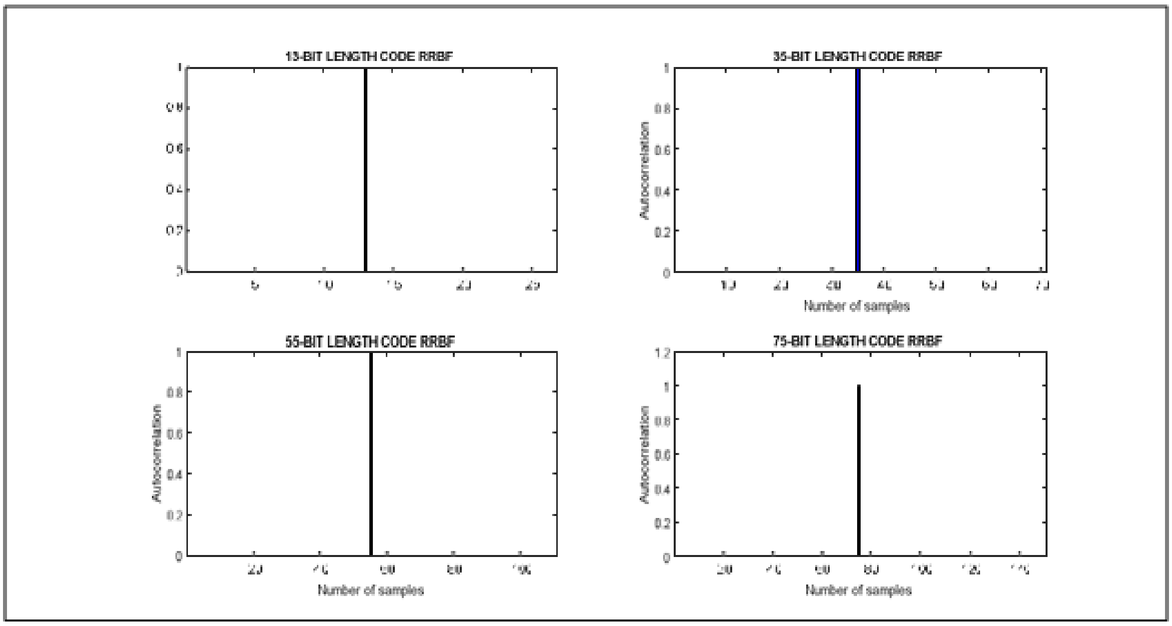

Fig. 8. SSR Comparison in dB of Range Resolution Ability for 2-DA for Different Lengths using RRBF Network

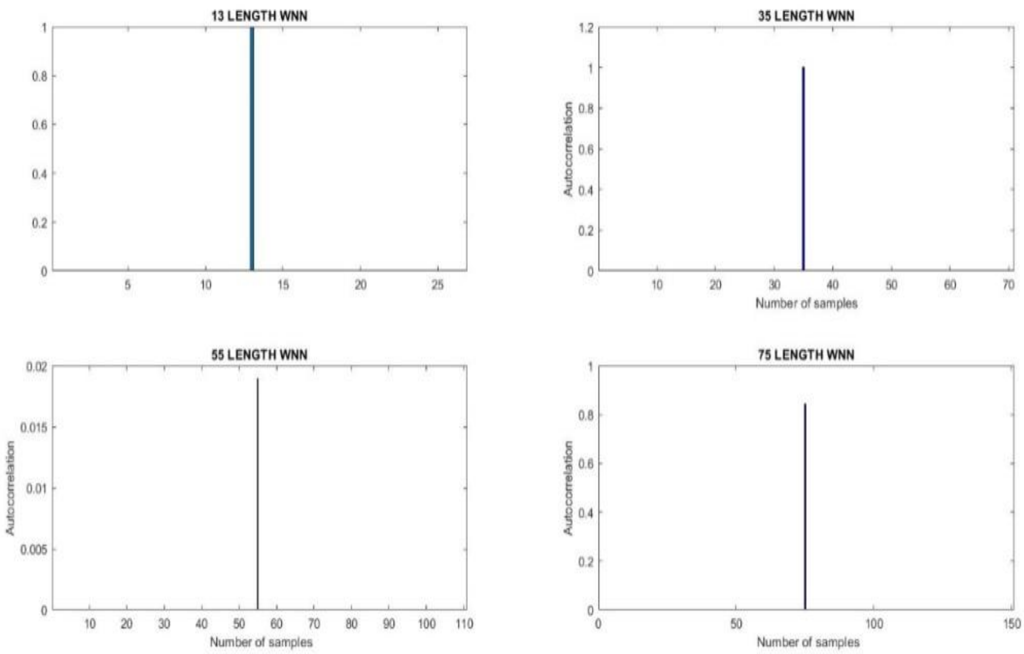

Fig. 9. SSR Comparison in dB of Range Resolution Ability for 2-DA for Different Lengths using WNN Network

B. Doppler Tolerance:

The Doppler sensitivity is caused by shifting the performance of individual elements of the phase code. In the extreme case the code word is no longer matched with the replica, if the last element is shifted by 180 degrees. For example, in the case of 13-bit binary Barker code, the code is changed from (1 1 1 1 1 -1 -1 1 1 -1 1 -1 1) to (-1 1 1 1 1 -1 -1 1 1 -1 1 -1 1) and is fed to the networks. In a similar way for other lengths 35, 55, 75 are followed.

TABLE-5. Doppler Shift Performance in dB

Algorithm	Different Lengths			
	13-Bit	***35-Bit***	***55-Bit***	***75-Bit***
Matched Filter	12.74	13.97	16.62	18.63
MLP	16.38	44.34	45.31	46.62
RNN	27.68	47.71	47.96	48.82
RBF	31.63	48.72	49.91	50.32
RRBF	32.06	49.56	51.23	52.62
WNN	48.26	65.56	69.24	71.55

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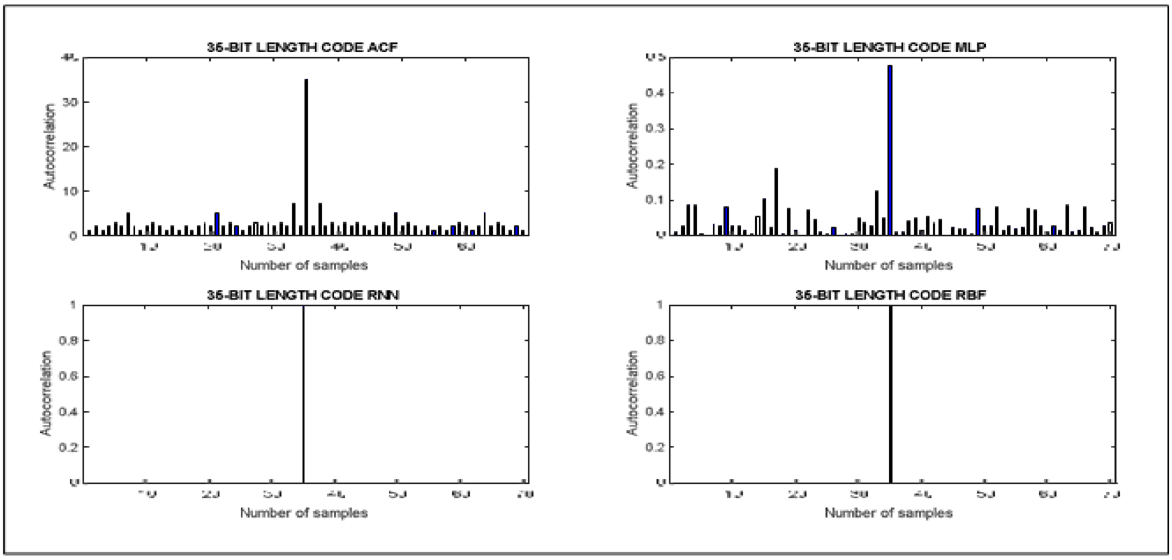

Fig. 10. Compressed Waveforms for Doppler Tolerance for 35- bit Binary Code (a)Matched Filter (b) MLP(c) RNN(d)RBF

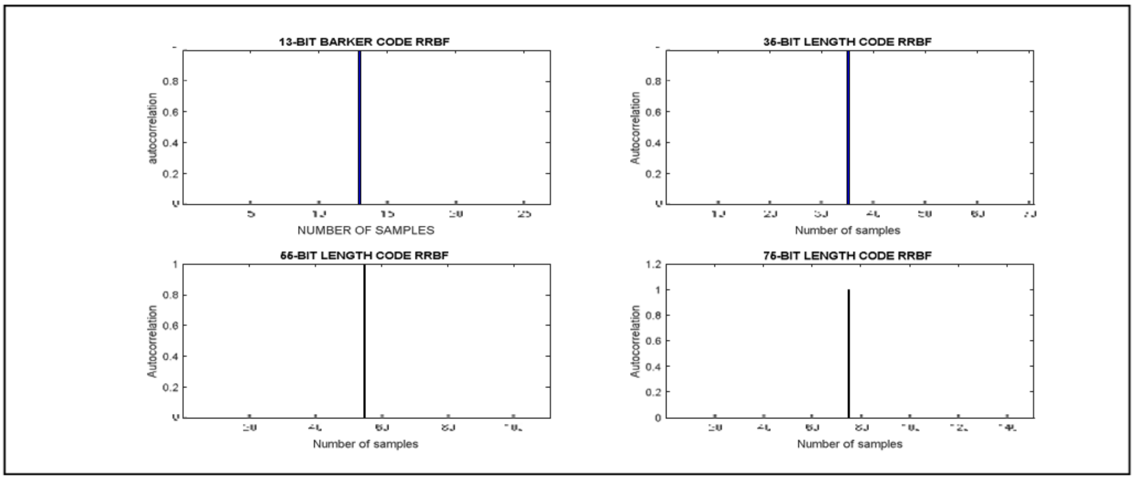

Fig. 11. Compressed waveforms for Doppler tolerance for 13, 35, 55 and 75 length binary codes with RRBF

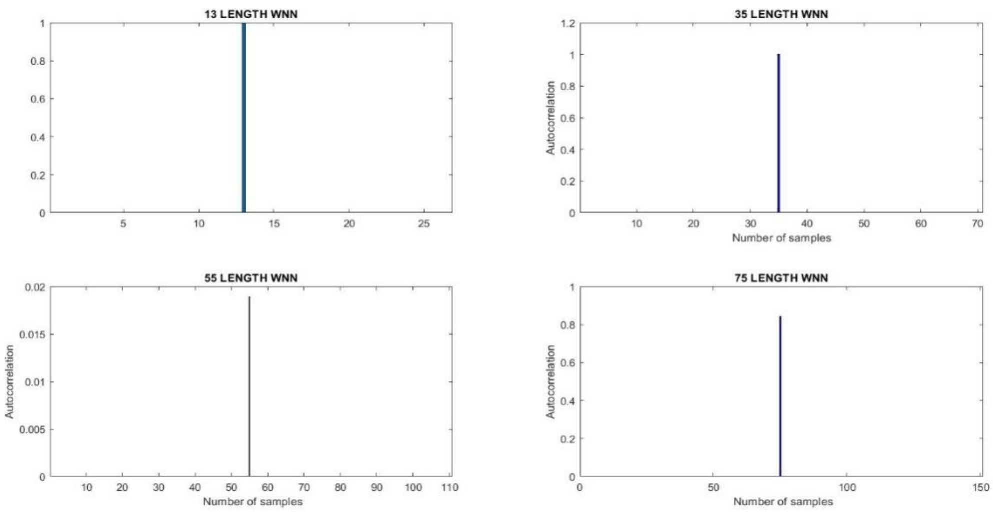

Fig. 12. Compressed Waveforms for Doppler Tolerance for 13, 35, 55 and 75 Length Binary Codes With WNN

V. CONCLUSION

RRBF network is giving almost negligible sidelobe pattern for all lengths compared to other neural networks like MLP, RNN and RBF. In fact, MLP is giving very poor result as evident from figures 4, 7, 10. In these investigations, the neural networks have been applied for achieving improved pulse compression applicable to pulsed radar.

The simulation results clearly demands that the WNN and RRBF yields improved performance than other networks like Matched Filter, MLP, RNN and RBF. And also, the RRBF pulse detection system converges faster than MLP, RNN and RBF based systems.

In fact, WNN network is giving improved sidelobe reduction compared to RRBF. From the Table 1, it can be concluded that the SSR improvement for WNN over RRBF is 27.68 dB for 13 length, 108.38 dB for 35 length, 145.86 dB for 55 length, 194.08 dB for 75 length. This shows that the tremendous improvement in sidelobe reduction has been observed using WNN network over RRBF. In a similar way PSLR improvement is evident from Table 2.

Overall, WNN and RRBF networks are exhibiting challenging results for sidelobe reduction, Range resolution performance and Doppler tolerance performance. Finally it can be concluded that WNN network is performing extremely well. This work can be extended to any of the larger length data within the limitations of computational complexity.

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Ethical Approval and Consent to Participate	No, the article does not require ethical approval and consent to participate with evidence.
Availability of Data and Material/ Data Access Statement	Not relevant.
Authors Contributions	All authors have equal participation in this article.

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