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***Abstract*—Matched filtering of biphase coded radar signals create unwanted sidelobes which may mask some of the desired information. This paper presents a new approach for pulse compression using recurrent neural network (RNN). The 13-bit and 35-bit barker codes are used as input signal codes to RNN. The pulse radar detection system is simulated using RNN. The results of the simulation are compared with the results obtained from the simulation of pulse radar detection using Multilayer Perceptron (MLP) network. The number of input layer neurons is same as the length of the signal code and three hidden neurons are taken in the present systems. The Simulation results show that RNN yields better signal-to-sidelobe ratio (SSR) and doppler shift performance than neural network (NN) and some traditional algorithms like auto correlation function (ACF) algorithm. It is also observed that RNN based system converges faster as compared to the MLP based system. Hence the proposed RNN provides an efficient means for pulse radar detection.**

***Keywords*—RNN, pulse compression, ACF, SSR, biphase code.**

I. Introduction

In radar, high range resolution and range accuracy is obtained by short duration pulses. If the radar is operating with sufficiently narrow pulse widths, then it has the ability to perform limited target classification. But to detect targets over long ranges by using short pulses, a high peak power is required to obtain large pulse energy [1]. Also, a reduction in pulse width reduces the maximum range of radar. Pulse compression in radar achieve the energy of a long pulse and the resolution of a short pulse simultaneously, without the requirement of a high energy short duration pulse. In pulse compression technique a long coded pulse is transmitted and the received echo is processed to obtain a relatively narrow pulse. Thus increased detection capability of a long pulse radar system is achieved while retaining the range resolution capability of a narrow pulse system. The range resolution is determined by bandwidth of the signal. Wide bandwidth is necessary for good range resolution. The signal bandwidth is obtained by modulating phase or frequency of the signal, while maintaining constant pulse amplitude. Mostly biphase pulse compression is used in radar system where the phase of the transmitted signal is 0 degree or 180 degree relative to a local reference corresponds to '+1' or '-1' in the binary code respectively. There are two different approaches for pulse compression. The first one is to use a matched filter where codes with small side lobes in their ACF are used. In second approach, two kinds of inverse filters, namely, recursive time variant and non recursive time invariant causal filters are used.

The importance of the detection filter design is to reduce the output range sidelobe level to an acceptable level. Zrnic $et.al$ [2] proposed a self-clutter suppression filter design using the modified recursive least square (RLS) algorithm which gives better performance compared to iterative RLS and ACF algorithms. To suppress the sidelobes of Barker code of length 13, an adaptive finite impulse response(FIR) filter is placed next to a matched filter pulse [3] and the filter is implemented through least mean square (LMS) and recursive least square (RLS) algorithms. The SSR and doppler performance of this type of filters are very poor. A multilayered neural network approach which yields better SSR than basic autocorrelation approach is reported in [4]. There is a scope of further improvement in performance in terms of SSR, error convergence speed, and doppler shift. In this paper, a new approach using RNN is proposed for effective pulse compression so that improved detection is possible. In section II, the proposed RNN network is described. Simulation results in different conditions are presented in section III. Some concluding remarks based on simulation results are discussed in section IV.

II. Problem Formulation and Training Using RNN

The input signal codes used are 13-bit and 35-bit barker codes, which are phase modulated waveforms. The 35-bit code is obtained by Kronecker tensor product of 5-bit and 7-bit barker codes. These input codes are time shifted and given as training samples for the network to be trained. The target or desired signal code is '1', when training set at the network is input code, and for the other sets it is '0'.

The recurrent neural network is a network with feedback connections. These networks are computationally more effi-

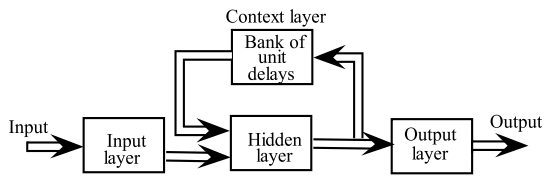


Fig. 1. Elman's network

cient than traditional feed forward networks. Toha and Tokhi [8] have used Elman RNN for modeling the twin rotor multi input multi output system. RNN is used for Arabic speech recognition instead of traditional hidden Markov models as described in [7].

The simple recurrent network used here is Elman's network as shown in Fig. 1. This two-layer network has recurrent connections from the hidden neurons to a layer of context units consisting of bank of unit delays [8]. These context units store the outputs of hidden neurons for one time step and feed them back to the input layer.

The inputs to the hidden layers are combination of the present inputs and the outputs of the hidden layer which are stored from previous time step in context layer. Hence the outputs of the Elman network are functions of present state, previous state (that is stored in context units) and present inputs. For the simulations, the number of input neurons is equal to length of the sequences, and 3 hidden neurons and only one output neuron are chosen. Let each layer has its own index variable, k for output nodes, j (and h for recurrent connections) for hidden nodes and i for input nodes. The input vector is propagated through a weight layer $\mathbf{V}$ and combined with the previous state activation through an additional recurrent weight layer, $\mathbf{U}$. The output of jth hidden node is given by,

$$n_j(t) = \phi\left(a_j(t)\right) \tag{1}$$

where

$$a_j(t) = \sum_i x_i\left(t\right) v_{ji} + \sum_h n_h\left(t-1\right) u_{jh} + b_j \tag{2}$$

and a_j is output of jth hidden node before activation. x_i is the input value at ith node. b_j is the bias for jth hidden node, and ϕ is the activation function. The logistic function is used as activation function for both hidden and output neurons and is represented by,

$$\phi\left(y\right) = \frac{1}{1+e^{-y}} \tag{3}$$

The output of the Elman's network is determined by a set of output weights,$\mathbf{W}$, and is computed as,

$$est_k(t) = \phi(a_k(t)) \tag{4}$$

$$a_k(t) = \sum_j n_j(t) w_{kj} + b_k \tag{5}$$

where est_k is the final estimated output of kth output node. The cost function for nth iteration is given by,

$$\xi(n) = \frac{1}{2}\sum_q^N (d_{qk} - est_{qk})^2 \tag{6}$$

where N is the total number of training samples and q represents pattern given to the network at each iteration.

The learning algorithm used in training the weights is backpropagation [6]. In this algorithm, the correction to the synaptic weight is proportional to the negative gradient of the cost function with respect to that synaptic weight and is given as,

$$\Delta\mathbf{W} = -\eta\frac{\partial\xi}{\partial\mathbf{W}} \tag{7}$$

where η is the learning rate parameter of the backpropagation algorithm.

The local gradient for output neurons is obtained to be,

$$\delta_{qk} = -\frac{\partial\xi}{\partial est_{qk}}\frac{\partial est_{qk}}{\partial a_{qk}} = (d_{qk} - est_{qk})\phi'(est_{qk}) \tag{8}$$

and for hidden neurons,

$$\begin{aligned}\delta_{qj} &= -\left(\textstyle\sum_k \frac{\partial\xi}{\partial est_{qk}}\frac{\partial est_{qk}}{\partial a_{qk}}\frac{\partial a_{qk}}{\partial n_{qj}}\right)\frac{\partial n_{qj}}{\partial a_{qj}} \\ &= \textstyle\sum_k \delta_{qk} w_{kj}\phi'(n_{qj})\end{aligned} \tag{9}$$

The correction to output weights is given by,

$$\Delta w_{kj} = \eta\sum_q^N \delta_{qk} n_{qj} \tag{10}$$

and for hidden layer weights,

$$\Delta v_{ji} = \eta\sum_q^N \delta_{qj} x_{qi} \tag{11}$$

The correction to recurrent weights is given by,

$$\Delta u_{kj} = \eta\sum_q^N \delta_{qj}(t) n_{qh}(t-1) \tag{12}$$

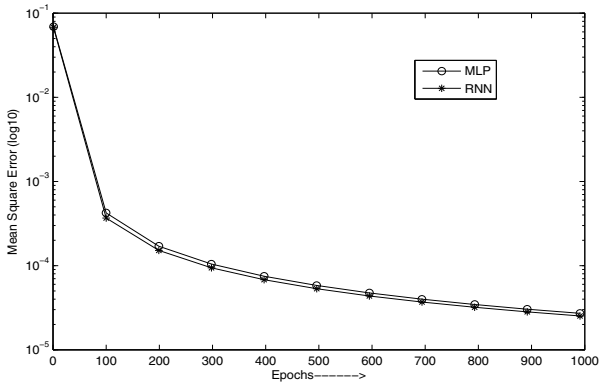
Hence all weights are updated based on the corresponding weight correction equations.

III. Simulation Results and Performance Evaluations

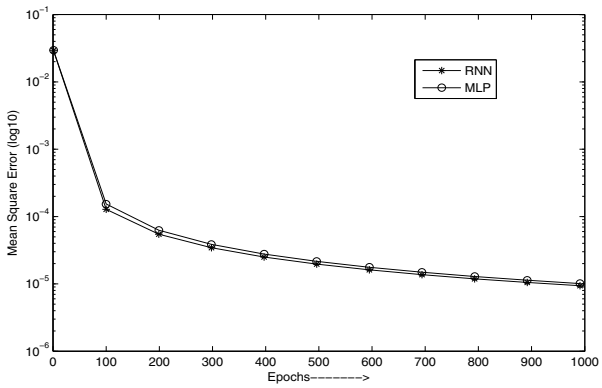
The time shifted version of the barker codes are applied to both the RNN and MLP. The training is performed for 1000 epochs. The weights of all the layers are initialized to random values between ± 0.1 and the value of η is taken as 0.99. After the training is completed, the network is employed for pulse detection.

A. Convergence Performance

The mean square error curves of recurrent neural network and MLP for 13-bit and 35-bit barker codes are shown in Fig. 2. It is observed from the figure that, the RNN provides better convergence speed than that of MLP.



(a)



(b)

Fig. 2. Mean Square Error Curve of RNN and MLP for (a)13-bit and (b)35-bit barker code

B. SSR Performance

Signal-to-sidelobe ratio (SSR) is the ratio of peak signal amplitude to maximum sidelobe amplitude. The SSR in this case is calculated using RNN based approach and is compared with those obtained by MLP and ACF algorithms. The results are tabulated in Table I, which shows that RNN gives improved SSR than other algorithms.

TABLE I
SSR COMPARISON IN dB

Algorithms	13-Bit Barker Code	35-Bit Barker Code
ACF	22.27	13.97
MLP	45.13	44.41
RNN	47.19	47.72

C. Noise Performance

The additive white Gaussian noise is added to input signal code then the output is degraded and SSR is decreased gradually. The noise performance at different SNRs using 13-bit and 35-bit barker codes for RNN and MLP are listed in Table II and Table III. The results show that RNN achieves higher SSR as compared to all other approaches.

TABLE II
SSR COMPARISON IN dB FOR DIFFERENT SNRS FOR 13-BIT BARKER CODE

Algorithms	SNR=1dB	5dB	10dB	15dB	20dB	25dB
ACF	2.98	8.39	13.08	16.38	18.61	20.08
MLP	27	41.67	43.97	45.05	45.08	45.10
RNN	31.78	44.30	46.01	46.88	47.34	47.59

TABLE III
SSR COMPARISON IN dB FOR DIFFERENT SNRS FOR 35-BIT BARKER CODE

Algorithms	SNR=1dB	5dB	10dB	15dB	20dB	25dB
ACF	9.26	10.86	12.09	12.87	13.34	13.61
MLP	12.34	31.62	40.84	42.84	43.87	44.11
RNN	24.85	41.14	45.35	46.73	47.24	47.45

D. Range Resolution Ability

Range resolution is the ability of radar to resolve two or more targets at different ranges. The two waveforms are overlapped by delaying the second one by some delays and are applied as input to the network and SSR is calculated. The performance of RNN is observed to be better than others and is depicted in Table IV, varying the delays from 2 to 5. Fig. 3 shows the compressed waveforms of the added pulse trains with five delay apart having same magnitude for 13-bit barker code. By varying the magnitude of one input or changing the input magnitude ratio (IMR), which is the ratio of magnitude of the first pulse train to the delayed one, the SSR values are calculated and listed in Table V.

TABLE IV
SSR COMPARISON IN dB FOR RANGE RESOLUTION ABILITY OF TWO TARGETS HAVING SAME IMR BUT DIFFERENT DELAYS FOR 13-BIT BARKER CODE

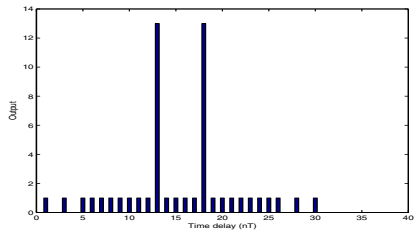
Algorithms	2-DA	3-DA	4-DA	5-DA
ACF	16.90	22.3	16.90	22.3
MLP	45.09	45.1	45.1	45.08
RNN	47.89	47.88	47.89	47.87

TABLE V
SSR COMPARISON IN dB FOR RANGE RESOLUTION ABILITY OF TWO TARGETS HAVING DIFFERENT IMRS AND DIFFERENT DELAYS FOR 13-BIT BARKER CODE.

Algorithms	2-DA 2-IMR	3-DA 3-IMR	4-DA 4-IMR	5-DA 5-IMR
ACF	13.97	12.74	10.63	8.29
MLP	44.97	44.44	36.18	11
RNN	45.45	47.57	42.15	22.16

E. Doppler Tolerance

The Doppler sensitivity is caused by shifting the phase of individual elements of the phase code. In the extreme case, the code word is no longer matched with the replica, if the



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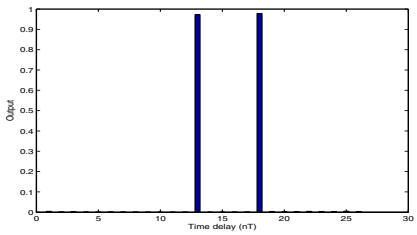

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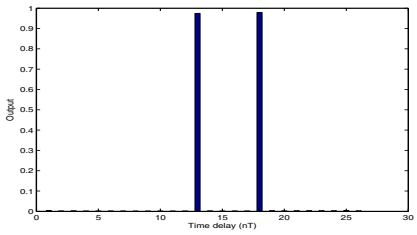
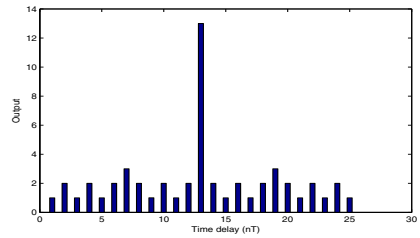
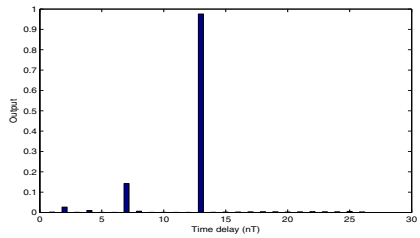


(c)

Fig. 3. Compressed waveforms for 13-bit barker code having same IMR and 5 DA (a)ACF (b)MLP (c)RNN



(a)



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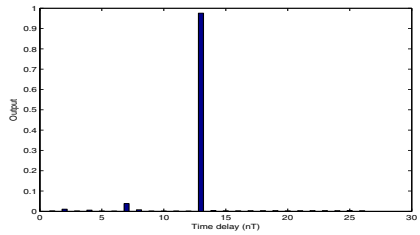

(c)

Fig. 4. Compressed waveforms for Doppler tolerance for 13-bit barker code (a)ACF (b)MLP (c)RNN

TABLE VI
DOPPLER SHIFT PERFORMANCE IN dB

Algorithms	13-Bit Barker Code	35-Bit Barker Code
ACF	12.74	13.97
MLP	16.38	44.34
RNN	27.68	47.71

last element is shifted by 180 degree. For 13-bit 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. The SSR is then calculated for both 13-bit and 35-bit barker codes and tabulated in Table VI. The compressed waveforms under doppler shift conditions for ACF, MLP and RNN are shown in Fig. 4. The results show that RNN gives better SSR as compared to other networks.

IV. CONCLUSION

In this investigation, Elman's recurrent neural network is applied for achieving improved pulse compression. The simulation results clearly demonstrate that the RNN yields improved performance than other networks like the MLP and ACF. The RNN based pulse detection system converges faster than the MLP based system. From the simulations it is also observed that RNN gives significant improvement in noise performance and range resolution ability. Finally under doppler shift conditions, the RNN gives much better SSR of 27.68dB as compared to the MLP which is only 16.38dB for 13-bit barker code.

REFERENCES

[1] Merrill I. Skolnik, *Introduction to radar systems*, McGraw Hill Inc.,2002.

[2] B. Zrnic, A. Zejak, A. Petrovic, and I. Simic, "Range sidelobe suppression for pulse compression radars utilizing modified RLS algorithm," *Proc. IEEE Int. Symp. Spread Spectrum Techniques and Applications*, Vol. 3, pp. 1008-1011, Sep 1998.

[3] J.S. Fu, and Xin Wu, "Sidelobe suppression using adaptive filtering techniques", *in Proc. CIE International Conference on Radar*, pp.788-791, Oct. 2001.

[4] H. K. Kwan and C. K. Lee, "A neural network approach to pulse radar detection", *IEEE Trans. Aerosp. Electron. Syst.*, vol. 29, pp. 9-21, Jan.1993.

[5] S. Haykin, *Neural networks, A comprehensive foundation*, McMillan College publishing Company, New York, 1994.

[6] Mikael Boden, " A guide to recurrent neural networks and backpropagation", Nov 2001, Online Available at: www.itee.uq.edu.au∼mikael papers/rn_dallas.pdf .

[7] M.M. Choubassi, H.E. Khoury, C.E. Alagha, J.A. Skaf, and M.A. Al-Alaoui, "Arabic speech recognition using recurrent neural networks",*in Proc. 3rd IEEE International Symposium*, pp. 543-547, Dec. 2003.

[8] S.F. Toha, M. O. Tokhi, "MLP and Elman recurrent neural network modelling for the TRMS", *7th IEEE International conference on Cybernetic Intelligent System.*, pp. 1-6, sept.2008