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Efficient Pulse Compression using Convolutional Neural Network

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ABSTRACT

Polyphase modulated pulses are commonly used as radar pulses for target detection. It has been shown in literature that high range resolution can be achieved by using these pulses. The output of the conventional matched filter for these pulses shows unwanted sidelobes. Sometimes these high sidelobes interpreted as wrong targets or sometimes mask the small targets. In the recent past, many neural network based methods have been proposed to achieve effective pulse compression performance for real coded transmitted waveforms. But the polyphase coded signals being complex valued, both the structure of the pulse compressor as well as the learning algorithm associated with it need to be complex in nature. Accordingly in this paper, a new method using a complex valued convolutional neural network (CVCNN) is proposed for efficient pulse compression for polyphase coded pulses. A polyphase modulated Lewis-Kretschmer P3 code is used for evaluation the comparison performance. Improved performance in terms of peak signal-to-sidelobe ratio (PSR) is demonstrated by new approach compared to matched filter (MF) method and multilayer feedforward neural network (MLP).

Keywords— Complex domain backpropagation, Matched filter, Multilayer feedforward neural network, Pulse compression

I.INTRODUCTION

To achieve high range resolution and long distant target detection pulse compression radar has been used for many years [1]. The main purpose of pulse compression techniques is to suppress range sidelobes which helps to improve the detection ability of the radar system. Conventional matched filtering technique has been used for pulse compression. The output of the matched filter is nothing but the correlated output of transmitted pulses and received pulses. Because of high sidelobes, the performance of the MF in terms of PSR is not satisfactory.

To suppress the undesired high sidelobes many mismatched filtering techniques have been proposed in the literature [2-3]. The performance in terms of PSR has been further improved by using the neural network based method [4]. In 1993, Kwan and Lee have reported a backpropagation (BP) based feedforward multilayer artificial neural network for achieving efficient pulse compression [5]. A radial basis function network (RBFN) based pulse compressor has been suggested in [6]. A hybrid model of radial function and matched filter (MF-RF) has been proposed in [7]. Unlike the other RBFN, there is no training required for this hybrid model. The computational complexity of this model is very low compared to other neural network based pulse compressor. Recently a complex valued neural network (FCC) has been proposed for polyphased coded waveforms [8].

The complex valued convolutional neural networks are widely used in many applications [9] but it has not been suggested for pulse compression task in radar signal processing. In this paper, a complex valued convolutional neural network (CVCNN) [10] based pulse compressor model has been proposed for effective radar pulse compression for polyphase coded pulses. In section II, the proposed CVCNN is described as a pulse compressor. Section III shows the simulation results of the proposed model along with the MF and MLNN for different targets conditions. Finally Section IV outlines the conclusion of the paper.

II.CVCNN BASED PULSE COMPRESSION MODEL

The convolutional neural network (CNN) is categories as deep learning model. To handle complex valued raw inputs, a modified version of CNN, named CVCNN, has been used for many applications. It is reported in literature that CNNs can achieve superior performance in compare to other existing neural networks. Each layer of CNN contains neurons and they are organized as a 3D array, two spatial and one division to channel. The channel is written as

$$o * K^{(k)} + b^{(k)}$$

where represents convolution layer input, $\{K^{(k)}, b$ represents convolutions' kernel and bias terms, respectively, which are the weights of the layer and represents convolution operation.

For the complex valued pulse compressor model, we have used the generalization form of complex valued CNN proposed by Shanshua [10].The activation function of the CVCNN is rectified linear unit (ReLU) and it is written as

$$ReLU(z) = \begin{cases} z & \arg(z) \in \left[0, \frac{\pi}{2}\right] \\ 0 & otherwise \end{cases}$$

In the pooling layer, patches are originated by splitting the input into two and a value is assigned to each patches of this layer according to the type of the pooling layer. Like in max pooling, the maximum value is assigned to the each patch. The operator *softmax* for pooling layer is defined as

$$softmax_{\alpha}(\{z_i\}_{i=1}^{n}) = \begin{cases} \arg\max_{z_i} \Re(z_i) & \alpha \to \infty \\ \frac{1}{n}\sum_i z_i & \alpha \to 0 \\ \arg\min_{z_i} \Re(z_i) & \alpha \to -\infty \end{cases}$$

Since the output of the pulse compressor should be real valued so the projection layer of the CVCNN labeled as real valued. The output of this last layer of CVNN is a normalized vector. To train this network we have used complex valued back propagation algorithm [11]. It is a gradient descent based algorithm. Random values have been assigned as initial weighs and each iteration these weights are updated to achieve minimum cost function.

The output of the affine layer is given by

$$Z_{n+1} = W_n Z_n + \widehat{w}_n . \mathbf{1}^T$$

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here Z_n,and Z represent the input, weights and output of the layer. The weight matrix $W_n = A_n +$ and the vector $\hat{w}_n = \hat{a}_n +$. The derivatives of the loss with respect to the input is given by

$$\delta_n = W_n^H \delta_{n+1}$$

here (represents the Hermitian operator and the backpropagation's output is

$$\frac{\partial l}{\partial A_n} + i\,\frac{\partial l}{\partial B_n} = \delta_{n+1}\, Z_n^H$$

$$\frac{\partial l}{\partial \hat{a}_n} + i\,\frac{\partial l}{\partial \hat{b}_n} = \delta_{n+1}\,.\mathbf{1}$$

where $l($ represents the loss function, which needs to be minimized. The output, at index (, of the activation function layer is given by

$$\delta_n(i,j) = \delta_{n+1}(i,j) f'\left(Z_n(i,j)\right)^{*}$$

The convergence of this learning algorithm is proven in [10].

III.SIMULATION RESULTS AND PERFORMANCE EVALUATIONS

A polyphase Lewis-Kretschmer P3 code of length (N) 30 is used for the simulation purpose [12]. The input patterns used for training of the MLP-CDBP and CVCNN models are the time-shifted sequences of the given code. For training purpose, the desired output is taken as '1', when complete code is presented at the input and for the others it is '0'. A 30−3−1 MLP is trained with the CDBP algorithms for the given code. The performance of MF, MLP-CDBP and CVCNN are compared in terms of PSR.

3.1 Noise Performance

Comparison of PSRs of MF, MLP-CDBP and CVCNN for Lewis-Kretschmer P3 code under 3dB noise condition has been made in Table 1. As illustrated in Fig. 1, the CVCNN model offers superior performance for the Lewis-Kretschmer P3 code measured in different SNR conditions.

TABLE I. **COMPARISON OF PSR UNDER DIFFERENT NOISY CONDITIONS**

Method	PSR (dB)			
	0 dB	***3 dB***	***5 dB***	***10 dB***
MF	11.29	14.13	15.79	19.33
MLP-CDBP	11.27	22.51	29.41	38.23
CVCNN	43.44	96.27	110.89	131.41

3.2 Range Resolution Performance

The compare the range resolution performance of different models, two n-delay apart overlapping Lewis-Kretschmer P3 code waveforms are used. The simulated results are shown in Table 2 which clearly indicates better performance of CVCNN model over other technique. A comparison of PSRs obtained for Lewis-Kretschmer P3 code for range resolution of two targets is shown in Fig. 2.

TABLE II. COMPARISON OF PSR FOR RANGE RESOLUTION OF TWO TARGETS

Method	PSR (dB)			
	2-DA	*3-DA*	*4-DA*	*5-DA*
MF	15.90	17.89	16.47	19.89
MLP-CDBP	37.37	36.53	37.68	39.10
CVCNN	141.39	139.35	137.48	141.74

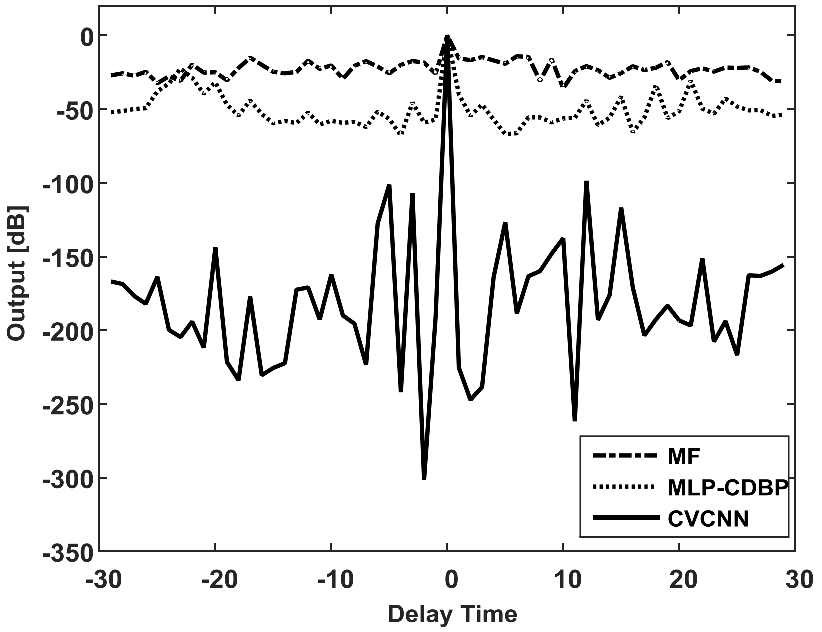

Fig. 1.Model response in dB for Lewis-Kretschmer P3 code obtained under 3dB noisy condition using (a)MF (b) MLP-CDBP (c) CVCNN

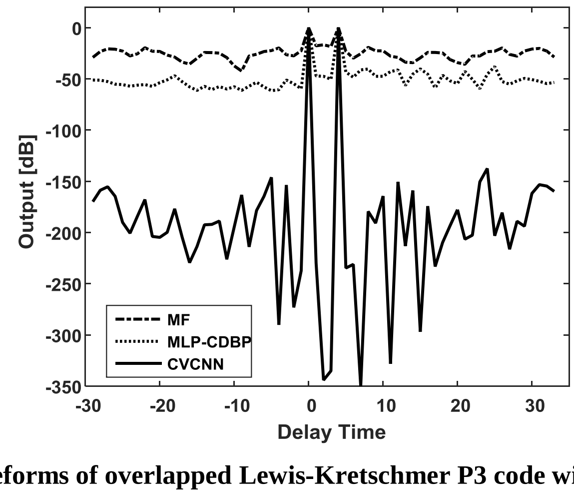

Fig. 2.Compressed waveforms of overlapped Lewis-Kretschmer P3 code with 4-delay apart obtained using (a) MF (b) MLP-CDBP (c) CVCNN

3.3 Doppler shift Performance

Due to the relative motion between the radar and target, with respect to transmit pulses phase of the received signal is changed. This phenomenon is called Doppler shift. Under Doppler shift condition, the simulated results are shown in Table 3. From this table, we conclude that under Doppler shift condition the CVCNN performance is better in comparison to MF and MLP-CDP methods. It is observed from Fig. 3 that CVCNN method exhibits best robustness to Doppler shift conditions compared to that of other methods.

TABLE III. COMPARISON OF PSR UNDER DOPPLER SHIFT CONDITION

Method	PSR (dB)
MF	15.47
MLP-CDBP	44.95
CVCNN	108.19

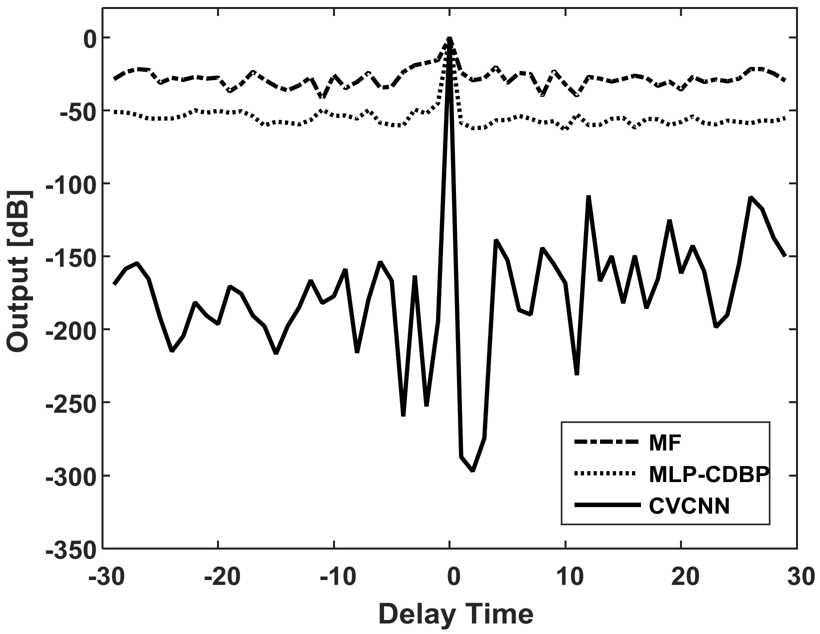

Fig. 3.PSR performance for Doppler shifted Lewis-Kretschmer P3 sequence using (a) MF (b) MLP-CDBP (c) CVCNN

IV.CONCLUSIONS

A new approach to design an efficient pulse compressor using CVCNN is proposed in this paper. The performance of MF, MLP-CDBP and our proposed model CVCNN based pulse compressors for Lewis-Kretschmer P3 code are compared and studied. The simulation results indicate that the new pulse compressor model is efficient and provides better PSR than the MF and MLP-CDBP based pulse compression method. The improvement in performance was better observed in terms of PSR under no noise and noisy conditions, range resolution, and Doppler shift.

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