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Radar Pulse Compression Using LM Neural Network

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***Abstract* - High range resolution and short duration pulses obtain range accuracy in radar system. If radar is working 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. Also, a reduction in pulse width reduces the maximum range of radar. Pulse compression in radar achieves the energy of a long pulse and the resolution of a short pulse simultaneously, without the requirement of a high energy short duration pulse. Thus increased detection capability of a long pulse radar system is achieved while retaining the range resolution capability of a narrow pulse system. In this paper we have described various techniques for radar pulse compression.**

Keywords - Radar pulse, 13-bit Barker code, 35-bit barker code, Phase shift code, Neural Network.

I. INTRODUCTION

Radar systems are composed of many different subsystems, which themselves are composed of many different components. There is a great diversity in the design of radar systems based on purpose, but the fundamental operation and main set of subsystems is the same. The radar antenna acts as the interface between the radar system and free space through which radio waves are transmitted and received. The purpose of the radar antenna is to transducer free space propagation to guided wave propagation during reception and the opposite during transmission. During transmission, the radiated energy is concentrated into a shaped beam which points in the desired direction in space. During reception, the antenna collects the energy contained in the echo signal and delivers it to the receiver.

Pulse compression plays significant role in signal processing field[1],used in radar system for reduction of peak power of radar pulse increase length without affecting the range resolution associated with pulse.If two pulses having same energy with different pulse width and peak power.For the large range detection ability of long pulse is phase or frequency modulation for incresed bandwidth.The use of neural networks brought to a multiple propagation in the processes of interest, viz.discrimination and merit factor. The search for the best sequences is a new signal designproblem, once decide to use neural network processing at the receiver.The interest of a pulse compression system is dependent upon the type ofwaveform provided and the procedure of generation and processing. The primaryfactors affecting the selection of a particular waveform are usually the radarrequirements of range coverage, doppler coverage, range and doppler sidelobelevels, waveform flexibility, interference rejection, and signal-to-noise ratio(SNR). The methods of implementation are divided into two general classes, activeand passive, depending upon whether active or passive techniques are usedfor generation and processing,Edward C. Farnett,George H. Stevens[3].Kwan and Lee [4] used an MLP network for pulse radar detection to suppress the unwanted signal.Digital pulse compression techniques are routinely used for both the generation and the matched filtering of radar waveforms. The digital pulse radar uses a predefined phase-versus-time profile to control the signal. This predefined profile may be stored in memory or be digitally generated by using appropriate constants.Khairnar et. al [5] developed a Radial Basis Function Neural network whichconverges faster with higher Sidelobe Suppression Ratio in adverse situations ofnoise and better robustness in Doppler shift tolerance thanMulti Layer Perceptron and other traditional algorithms like ACF algorithm[15].

II. LITERATURE SURVEY

Basic Neural Network Architecture

McCullochand Pitts' Neuron Model
Among numerous neural network models that have been proposed over the years, all share acommon building block known as a neuron and a networked interconnection structure. The mostwidely used neuron model is based on McCulloch and Pitts' work and is illustrated inequation(1) each neuron consists of two parts: the net function and the activation functionThenet function determines how the network inputs are combined inside the neuron.

General ANN $y = [\sum_{i=1}^{N} w_i x_i + b]$ (1)

In a neural network, multiple neurons are interconnected to form a network to imitate decentralized computing. The configuration of the interconnections can be described efficiently with adirected graph. A directed graph consists of nodes (in the case of a neural network, neurons, as wellas external inputs) and directed arcs (in the case of a neural network, synaptic links).

Multilayer perceptron (MLP) neural networks with sufficiently many nonlinear units in a singlehidden layer have been established as universal function approximators[7]. MLPs have severalsignificant advantages over conventional approximations.MLP testing error is difficult to predict from training data. The leave-one-out crossvalidation technique can be used, but it is very time consuming.Determining the optimal amount of training for an MLP is difficult. A common solutionto this problem involves stopping the training when the validation error starts toincrease [8].Essentially,if one considers that an MLP is a universal approximator, then it may approximate an RBFnetwork and vice versa that for normalizedinputs, MLPs can be considered to be RBF networks with irregular basis functions.

The radial basis function network can be viewed as a feedforward neural network with a single hidden layer whichcomputes the distance between input pattern and the center[6]. It consists of three layers, an input layer, a hidden layerand an output layer. The input layer connects the network tothe environment. The second layer is the only hidden layerwhich transfer the input space nonlinearly using radial basisfunction. The hidden space is greater than the input spacein most of the applications.The response of the networkprovided by the output layer which is linear in nature.An RBF network generally consists of two weight layers the hidden layer and the output layer.They can be described by the following equation:

$$y = w_0 + \sum_{i=1}^{n_h} w_i \, f(\, \|x - c_i\|) \qquad (2)$$

where f are the radial basis functions,$w_i$are the output layer weights, w_0 is the output offset, **x**arethe inputs to the network, $c_i$are the centers associated with the basis functions,$n_h$is the number ofbasis functions in the network, and ‖ · ‖ denotes the Euclidean norm.Given the vector

$$\mathbf{x} = [x_1, x \ldots \ldots \ldots x_n]' \qquad (3)$$

on *n*, the Euclidean norm on this space measures the size of the vector in a general sense and defined as

$$\|x\| = (\sum_{i=1}^{n} x_i^2)^{\frac{1}{2}} \qquad (4)$$

radial basis function networks are able to model data in a local sense.

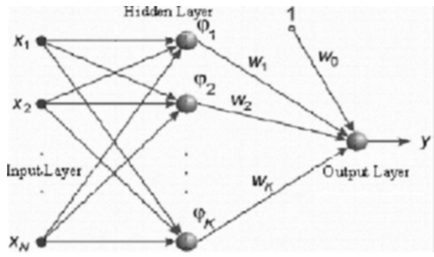

Fig. 2.1 - Structure of the RBFN [11].

For each input datavector, one or more basis functions provide an output. In the extreme case, one basis function is usedfor every input data vector, and the centers themselves are identical to the data vectors.

III. DIGITAL PULSE COMPRESSION

Pulse compression correlates the received signal to adelayed copy of that which was transmitted. This correlationis a cross-correlation because the echo is differentfrom the transmitted waveform. Phase-coded waveformsare well adapted to digital pulse compression.Therefore pulse compression techniques areused to obtain pulse radar detection. In practice two differentapproaches are used to obtain pulse compression. Thefirst one is to use a matched filter; here codes with smallsidelobes in their autocorrelation function (ACF) are used[10][11]. An interesting approach to real time

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correlation ofpulse coded radar waveforms has been implemented usingSAW convolver devices [12]. The method achieves correlationof 255-bit PSK sequence in 8 ns, which is muchfaster than any of the digital techniques discussed in thispaper. Digital waveformsare usually bi-phase modulated sinusoids. Bi-phase modulation isused because it yields the widest bandwidth for a givencode sequence. Pulse compression waveform design ispredicted on simultaneously achieving wide pulse widthfor detection and wide bandwidth for range resolution. Thespectrum of a waveform is a critical parameter. The waveform's determines its ability to resolve in range.Narrow autocorrelations, corresponding to wide bandwidths,are necessary for good range resolution.

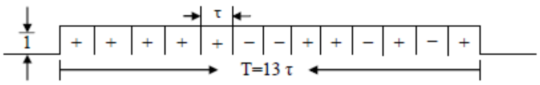

Fig. 3.1 - 13bit barker code

Optimalbinary amplitude sequence is the one having a peak (largest) sidelobe magnitude that is the smallest possiblefor a given sequence length[9][13]. The optimal codes havingpeak sidelobe levels of one are called Barker codes. Some ofthe sequences used are 13-element Barker code (as shown in figure 3.1) and 35-elementBarker code.

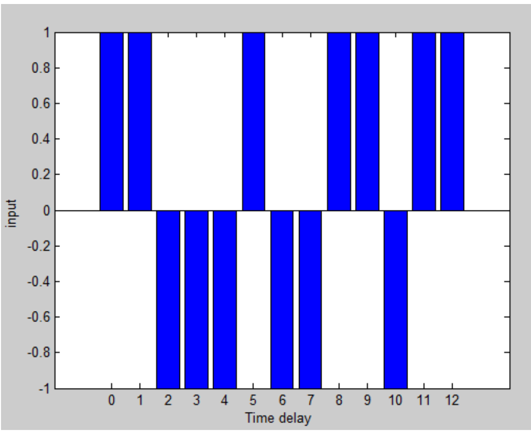

Fig. 3.2 - Repesentation of input barker code.

Digital pulse compression techniques are routinely used for both the generation and the matched filtering of radar waveforms. The digital generator uses a predefined phase-versus-time profile to control the signal. This predefined profile may be stored in memory or be digitally generated by using appropriate constants[14]. The matched filter may be implemented by using a digital correlator for any waveform or else a "stretch" approach for a linear-FM waveform.

The filter input x(t) consists of a pulse signal g(t) corrupted by additive channel noise w(t), as shown by

$$x(t) = g(t) + w(t), 0 \leq t \leq T \qquad (5)$$

where T is an arbitrary observation interval. The pulse signal g(t) may represent a binary symbol I or 0 in a digital communication system. The w(t) is the sample function of a white noise process of zero mean and power spectral density No/2. The source of uncertainty lies in the noise w(t).

IV. Problem specification

Usually the pulse compressions achieved by matched filters in traditional pulse compression mechanisms have a lower signal-to-sidelobe ratio, which can degrade the performance of detection system. Matched filtering of biphase coded radar signals create unwanted sidelobes which may mask some of the desired information . Here our approach is an effort to propose a neural network based method, which has significant improvement in noise performance and range resolution ability.

V. Proposed Method

The Levenberg-Marquardt (LM) method is based on an iterative technique that locatesthe minimum of a multivariate function which is expressed as the sum of squaresof non-linear real-valued functions.LM can be thought of as a combination of steepest descent and theGauss-Newton method. When the current solution is far from the correct one,the algorithm behaves like a steepest descent method: slow, but guaranteed to1converge. When the current solution is close to the correct solution, it becomes aGauss-Newton method.

Let f be functional relation which maps a parameter vector ¡ $\in \mathbb{R}^m$to an estimated measure vector $\bar{x} = f(P), \bar{x} \in \mathbb{R}^n$. Initial Parameter estimate P_0 and a measured vector x are provided and it is desired to find the vector P^{+}that best satisfies the functional relation$f$,means minimizes the squared distance$\epsilon^T\epsilon$ with $\epsilon = x - \bar{x}$ .The basis of LM method is a linear approximation to f in the neighbourhood of P.For a small $||\delta_P||$,a which leads to the approximation

$f(P+\delta_P) \approx f(P) + J\delta_P$,

Where $J$is the jacobian matrix$\frac{\partial f(P)}{\partial P}$.So LM is iterative :initiated at the starting point P_0,the method producesa series of vectors $P_1, P_2, P_3 \ldots \ldots$, that converges towards a local minimize $P^+$for f.Hence at each step,it is required to find the $\delta_P$that minimizes the quantity $\|x - f(P+\delta_P)\| \approx \|x - f(P-\delta_P)\| = \|\epsilon - J\delta_P\|$.The Levenberg-Marquardt (LM) algorithm is an iterative technique thatlocates the minimum of a function that is expressed as the sum of squaresof nonlinear functions.

VI. SIMULATION RESULTS

On the 13 element barker code,the output as shown in figure 6.1,with time delay,the proposed model the parameters for trainning are MSE (mean square root error),performance and validation.Table 6.1 and Table 6.2 show the comparison on the methods for described as radial basis function curve,gradient descent method and proposed Levenberg-Marquardt NN method.

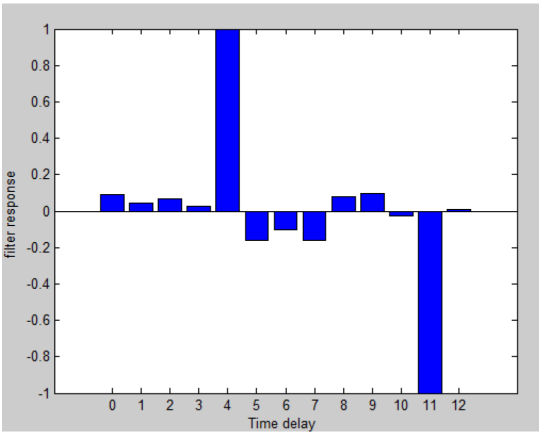

Fig. 6.1 - Compression using Neural Network with Levenberg-Marquardt function

S.No.	Structure	MSE on scale of 10 Dataset
1	RBFCurve	0.698
2	DM-NN	0.699
3	LM-Curve-NN	0.812

Table 6.1 - MSE performance

S.No.	Structure	percentage
1	RBFCurve	91.7
2	DM-NN	96.4
3	LM-Curve-NN	97.9

Table 6.2 - Regression Performance

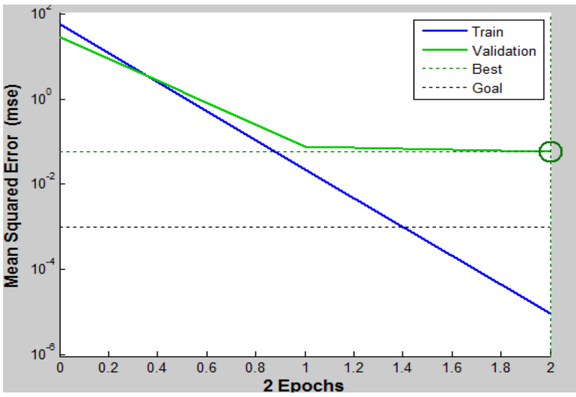

Fig. 6.2 - Performance graph for MSE vs Epochs

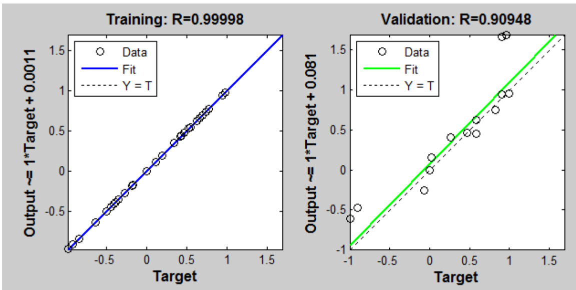

Fig. 6.3 - Regressive performance graph for MSE vs Epochs

S.No	Structure	SSR in dB
1	RBFCurve	64.49
2	DM-NN	68.78
3	LM-Curve-NN	73.2

Table 6.3 - Comparison of SSR in dB for 13 Element Barker code.

VII. CONCLUSION

In this paper, here are presented novel techniques for pulse radar detection and compression. The concepts of pulse compression, phase coded pulse compression and 13 element barker codes are studied. The major aspects for any pulse compression technique are signal to sidelobe ratio performance, regression performance and MSE performance.Here proposed the Leverage-Marquardt neural network for pulse radar detection with compression which gave better results compared to other techniques. There is a scope of futher improvement in all the aspects for most of the applications.

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