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PSL and ISL Reduction for Px Code by Neural Network and Particle Swarm Optimization

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Abstract— New two approaches are proposed for pulse compression the first one is using N.N. with seven training functions (cgf, bfg, br, oss, lm, rp, scg); the second one is using NNPSO and that by training N.N. using Particle PSO. In this paper, networks have been implemented for three lengths of Px code (4, 5 and 7). For training these networks, the seven functions above and PSO are used. Simulation results show that NNPSO approach has significant improvement, while for N.N. approach, three training functions (oss, cgf and bfg) show a good improvement in: error convergence speed (very low training error about 10^{-25}), good noise rejection performance and good range resolution ability compared with other neural network approaches. The results of PSL and ISL were around (-30, -300) dB for Px code with lengths (4, 5 and 7).

Index Terms— N.N (Neural Network), PSO (Particle Swarm Optimization), BP (Back-Propagation), M.F (Matched Filter).

1 Introduction

The advantage of using narrow pulses in radar is improving range resolution. Due to maximum peak power limitations of the transmitter, pulse width is increased to improve detection capability. Pulse Compression techniques utilize signal processing to provide the advantages of extremely narrow pulse width [1]. Px code was introduced by Rapajic and Kennedy; it is a modified version of Frank code but having lowered integrated side-lobe .In this paper two different approaches are presented for code optimization. The first one is to use N.N. with seven different training functions, the iterations was between (2-45) epochs, which consider a fast training. The second approach is to use NNPSO, which present a better PSL and ISL. While in [1-8], where N.N is used or PSO alone, the optimization was around (5-30) dB. The two approaches implemented by using two multilayered Neural Networks one for real part and the other one is for imaginary part. In both these approaches, three lengths of Px code were used as the signal codes.

2- Theoretical Description

Detailed submission guidelines can be found on the author Pulse Compression correlates the received signal to a delayed copy of that which was transmitted [9]. This correlation is a cross correlation because the echo is different from the transmitted waveform [10]. Phase Coded waveforms are well adapted to digital pulse compression which might be binary phase , with two possible phases being 0 and 180, or Polyphase codes , their elements can be any number between 0 and 180[11]. Pulse compression waveform design is predicted on simultaneously achieving wide pulse width for detection and wide bandwidth for range resolution. The waveform's ACF determine its ability to resolve in range narrow autocorrelations, corresponding to wide bandwidths, are necessary for good range resolution [12]. To obtain Px code sequences, equation 1 must be used.

$$q(i,j) = \begin{cases} \frac{2\pi}{P}\left[\frac{(P+1)}{2} - j\right]\left[\frac{(P+1)}{2} - i\right], & P \text{ even} \\ \frac{2\pi}{P}\left[\frac{P}{2} - j\right]\left[\frac{P}{2} - i\right], & P \text{ odd} \end{cases} \qquad (1)$$

where: $1 \le i \le P$, $1 \le j \le P$ and P is the code length. Three lengths of Px code are used which is (4, 5 and 7). In this paper, we have carried out these sequences. For relative comparison, the amplitude of the ACF of 5 bit Px code is shown in Figure 1.

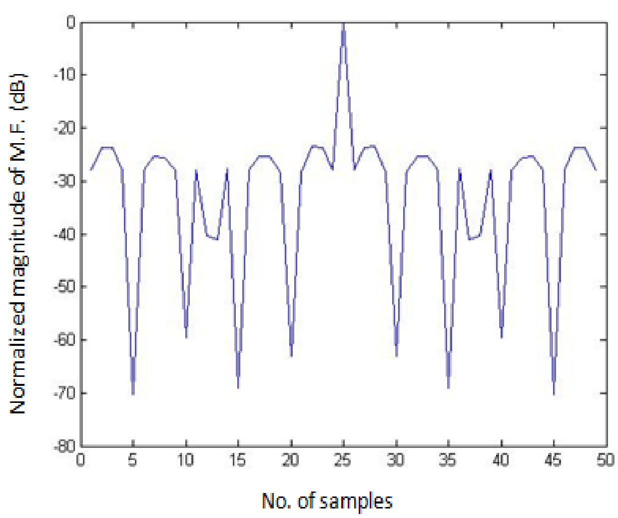

Figure (1) The Normalized cross-correlation of Px code 25-bit

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3- Optimization Process

In any Neural Network application, training of the network plays an important role [13]. In the pulse compression application under investigation, once the network is trained, it can distinguish between the transmitted signal and the other received signals, which could be external disturbances or time shifted versions of the transmitted signal. The transmitted signals used are three lengths of Px code. The network consists of three layers. The first layer is containing one input node. The second layer is the hidden layer, contain nonlinear units that are connected directly to the input node, the number of node in the hidden layer is 3 nodes due to equation 2 [14].

$$Nh \geq (2*Ni) + 1 \qquad (2)$$

Where Nh is the number of nodes in the hidden layer and Ni is the number of nodes in the input layer. The activation functions of the individual hidden units in the N.N are tan-sigmoid. The last layer is the output layer, which consists of one node. For updating the weights of N.N, several training methods were used, which are (cgf, bfg, br, oss, lm, rp, scg), also Particle Swarm Optimization (PSO) used to train N.N, where every particle represents all weights and biases for one N.N.

PSO is a population based stochastic optimization technique inspired by social behavior of fish schooling or bird flocking. PSO share many similarities with evolutionary computation techniques like Genetic Algorithms [15].

All particles are initialized with random N.N weights and biases. The particles evaluate their position relative to the iteration goal. In each iteration, every particle update its trajectory (by its velocity) toward its own previous best position (local best), and toward previous best position obtained by any member of its topological neighborhood (global best) [16]. If any particle's position is close enough to the goal function it is considered as having found the global best and the recurrence is ended.

The particles adjust it velocity and positions due to equations (3 and 4) respectively [15].

$$V_i(t+1) = \Phi V_i(t) + c_1 r_1 (Pbest_i(t) - X_i(t)) + c_2 r_2 (Gbest(t) - X_i(t)) \qquad (3)$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \qquad (4)$$

Where ϕ represents the inertia weight c1 and c2 represent positive constants, r1 and r2 represent two random numbers between 0 and 1, Xi represents the position of ith particle; Pbest is the local best, the Gbest is the global best Vi is the rate of position change (velocity) for particle i. Every iteration the weights and biases that produced from PSO are tested by calculate the error ,which represent the difference between the desired output and the current output, then measured the Gbest and Pbest to start the next iteration and its continues until the minimum error among all particles is reached. For the seven N.N training methods, the same procedure is used but without the particles part.

4- Simulation results and performance evaluation

Once the training is over, the N.N can be exposed to various sets of input sequences. This section illustrates the performance of the NNPSO which is then compared with the seven training functions and the output of M.F.

4.1 Convergence performance

The convergence speeds of the BP training methods and NNPSO are alternate between (2-80) epoch, (cgf, bfg and oss) show the best convergence speed.

4.2 Peak Side-lobe Level (PSL) and Integrated Side-lobe Level (ISL) reduction

Peak Side-lobe Level defined as a measure of the largest side-lobe power as compared with the main lobe power. Integrated Side-lobe Level defined as a measure of the energy distributed in the side-lobes as compared with the main lobe power. The results of the investigation are depicted in table 1.

Table 1. Conventional, NN, and NNPSO results for free noise case

L	4		5		7	
	PSL	ISL	PSL	ISL	PSL	ISL
M.F	20	10	17	9.2	18	7.1
Cgf	284	279	206	198	213	210
Rp	62	53	63	49	63	46
Scg	48	47	61	55	69	52
Lm	82	67	72	64	72	65
Br	81	69	86	71	79	62
Bfg	296	296	168	162	214	194
Oss	127	127	212	209	256	236
PSO	247	231	260	248	258	241

4.3 Noise performance

It is important to test the algorithm by adding noise to the pulse because the echo signal from the target, in real life, is corrupted by noise. In this study WGAN is added with two values (SNR=7 dB and SNR=5 dB). The performance of the original ACF, the seven N.N training method and NNPSO for the noisy case is shown in tables (2 , 3).

From these tables, it is clear that the performance of NNPSO is much better than any other method. The normalized amplitude of the ACF of Px code length (5) for the output of the M.F and the output of N.N with noise case (SNR=5 dB) are shown in Figure (2).

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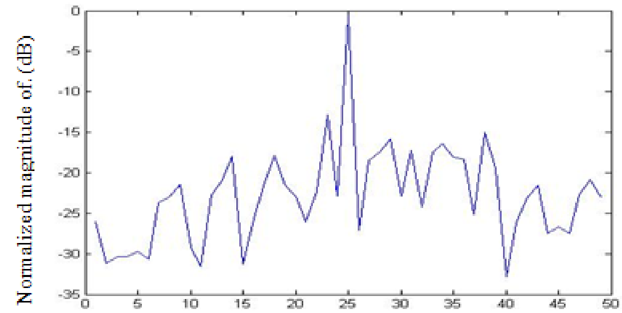
Table 2. peak and integrated side-lobed of Px code for length (4, 5 and 7) with noise (SNR= 5 dB)

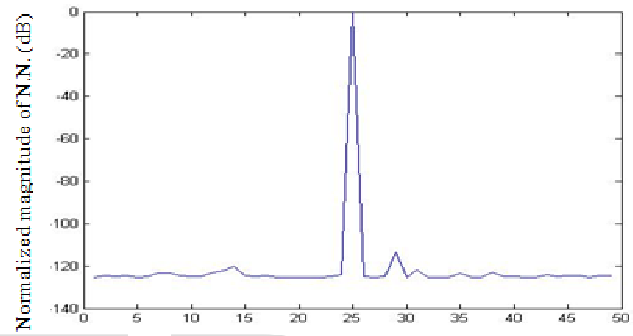
L	4		5		7	
	PSL	ISL	PSL	ISL	PSL	ISL
M.F	10	3.6	12	3.5	12	3.8
Cgf	176	166	144	138	138	133
Rp	48	44	52	44	58	45
Scg	67	56	60	50	54	49
Lm	76	70	65	60	71	62
Br	80	67	77	62	78	59
Bfg	210	208	113	101	127	111
Oss	128	120	210	201	120	114
PSO	143	135	164	157	132	127

Table 3. peak and integrated side-lobed of Px code for length (4, 5 and 7) with noise (SNR= 7 dB)

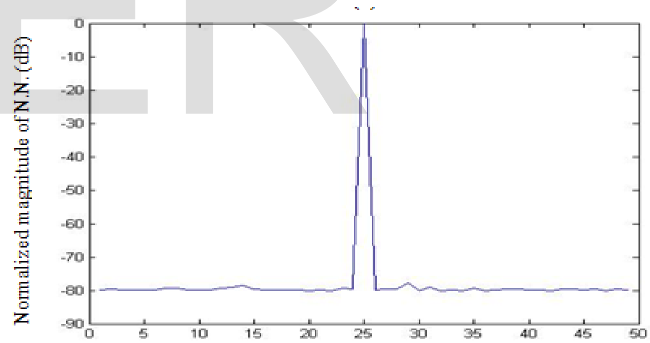
L	4		5		7	
	PSL	ISL	PSL	ISL	PSL	ISL
M.F	12	3.8	12	4.6	14	4.7
Cgf	166	165	203	203	130	117
Rp	44	41	51	43	57	44
Scg	58	53	56	52	63	51
Lm	72	68	72	61	73	62
Br	79	66	81	64	69	58
Bfg	218	271	159	146	119	118
Oss	188	182	190	189	141	123
PSO	215	206	224	224	219	218



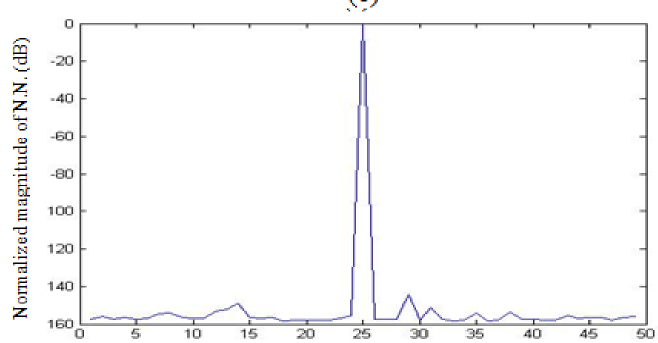
No. of samples
(a)



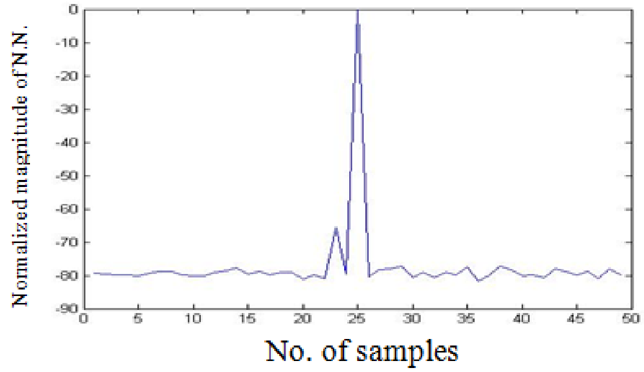
No. of samples
(b)



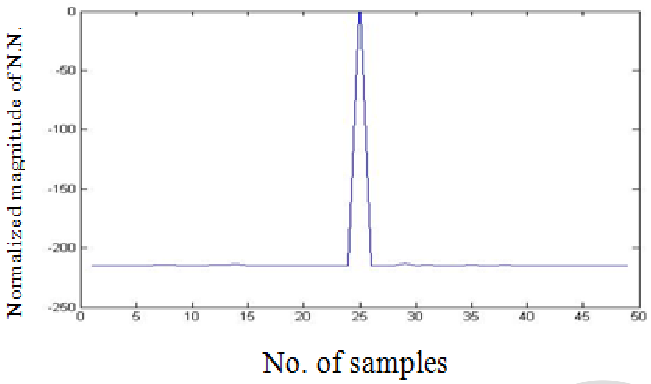
No. of samples
(c)



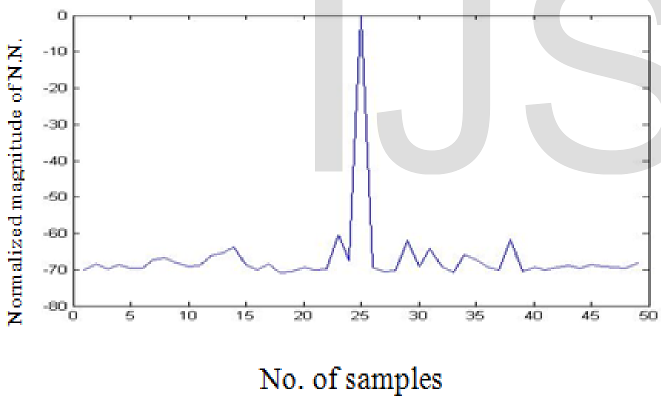
No. of samples
(d)



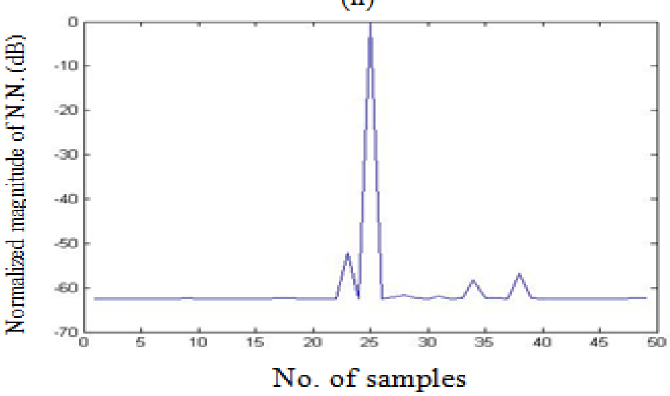
(e)



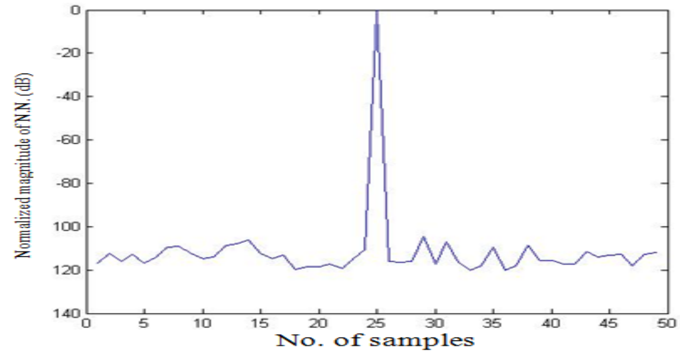
(f)



(h)



(g)



(i)

Figure(2) The Normalized crosscorrelation of Px code 25-bit of: (a) matched filter (b) N.N, bfg (c) N.N, br (d) N.N, cgf (e) N.N, lm (f) N.N, oss (g) N.N, rp (h) N.N, scg (i) NNPSO

4.4 Ambiguity function

The ambiguity function (AF) perform filter matched time response to a given limited energy signal when the signal is received with a Doppler shift ν and a delay τ related to the nominal values (zeros) expected by the filter [17].

$$|x(\tau,\nu)| = \left|\int_{-\infty}^{\infty} u(t)\check{u}(t+\tau)\exp(j2\pi\nu t)\,dt\right| \quad (5)$$

where u is the signal complex envelope. The ambiguity function represents the main tool for studying and analyzing radar signals. The performance in the range resolution is much better than in the Doppler resolution. In this paper the ambiguity function had been studied for the three Px lengths and the seven N.N training function. Figure (3) gives an example for the normalized autocorrelation function of Px code, length 5, when using (br) to train the N.N.

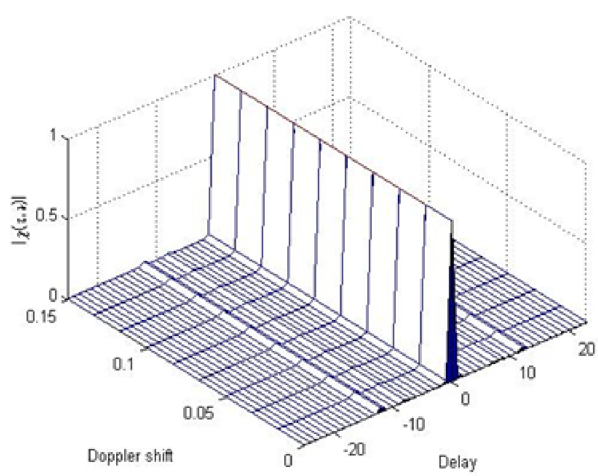


Figure (3) the normalized autocorrelation function of Px code when using (br) as training function

3- Conclusions

From the tables and figures above, it is clear that when used (cgf, bfg and oss) as Neural training method gave a best reduction than the other Neural training method in this work, they made PSL suppression, while the other methods gave a good PSL reduction. For the ISL, the seven methods, in some cases, gave smooth ISL while in other cases gave ISL with little ripple. While in case of PSO, it gave a PSL suppression even within noise case, and it made a little ripple with high noise case (SNR=5dB). Concerning the serial processing in one node for samples with respect to parallel processing of several nodes with on sample, the first approach gives more accurate results in ISL and PSL reduction.

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