Doppler Performance Evaluation of Different Frequency Coded Pulse Compression Sequences

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Abstract:

Phase coding and linear frequency modulation are commonly used in radar and sonar systems for pulse compression to achieve high range resolution. In this paper, the performance of the liner frequency modulated (LFM) pulse, normalized liner frequency modulated (NLFM) pulse and stepped frequency modulated (SFM) pulse are evaluated in the presence of Additive White Gaussian Noise (AWGN) using Adaptive Least Mean Square algorithm and particle swarm optimization. Doppler performance is evaluated using the metrics PSLR3 and ISRL3. The results show significant improvement with the proposed algorithms.

Key Words: Complementary sequences, Auto correlation, PSLR3, ISLR3, Adaptive LMS algorithm, Particle swarm optimization.

I. INTRODUCTION

Pulse compression techniques involve transmission of a long coded pulse and compression of the received echo using matched filter to obtain a narrow pulse [1, 2]. As a result, in an increased detection performance associated with a long–pulse radar system while still maintaining the fine range resolution of a short–pulse system. The matched filter maximizes the output signal to noise ratio (SNR) [1,2,10]. A measure of degree to which the pulse is compressed is given by the compression ratio defined as

$$CR = \frac{T}{\tau} = TB \qquad (1)$$

Where, T= transmitted pulse length, $\tau = 1/B$ = Compressed pulse length, and B is the bandwidth of the transmitted waveform. For range resolution radar, a coded waveform or a sequence can be taken as

$$X = x_0, x_1, x_2, \ldots, x_{N-1} \qquad (2)$$

with aperiodic autocorrelation

$$r(k) = \sum_{i=0}^{N-1-k} x_i x_{i+k} \qquad (3)$$

where $k = 0, 1, 2, \ldots, N-1$

For coded waveform to be good, the ambiguity function should have very large peak for zero shift with very small side lobes in Doppler as well as range domains [3,4,5,7].

Pulse compression radar waveforms offer several advantages over uncompressed waveforms. First, a significant increase in unambiguous range can be obtained within transmit power limitations. Second, range and Doppler resolution can be greatly improved. The idea of pulse compression is not new and formally came about from Woodward's work [l0] in 1953. His radar waveform analysis and mathematical framework allowed the realization that range resolution is a function of bandwidth rather than pulse width.

Pulse compression is performed by correlating the received sequence with a filter represented by a stored set of filter coefficients. The filter may be a matched filter (in time and amplitude) or mismatched, in time, amplitude, and phase, designed to realize improvements in pulse compression parameters beyond those of the matched filter performance. By implementing a mismatched filter to reduce correlation side lobes [11, 12, 13, 14], some of this SNR processing gain and/or target resolution is lost. The benefit of using a matched filter is that it maximizes the gain in signal-to-noise ratio (processing gain).

In realistic environments, targets of interest are often in motion and it is often the Doppler phase shift induced by this relative motion between the radar and a target that can enable the detection of a target when it is in the presence of stationary background clutter. However, large Doppler shifts over the length of a single pulse (i.e., the radar waveform), which are caused by high relative target velocities and/or the use of long waveforms, can be quite detrimental to radar detection performance due to severe mismatch between the expected and actual received waveforms (even when using Doppler-tolerant waveforms such as linear FM [2]. The result of this mismatch is reduced target SNR as well as an overall increase in range sidelobe levels. In fact, a very high time-bandwidth product coupled with extraordinarily high target velocity can cause relativistic effects [15,16,17] whereby the reflected radar waveform undergoes dilation in time thus exacerbating the mismatch, though such extreme effects are not considered here. It is well known that a bank of phase-shifted matched filters tuned to the expected target velocities can compensate for the SNR loss due to Doppler mismatch. However, this does nothing to address the inherent range sidelobes of the matched filter. For LS-based mismatched filters, the effects of large Doppler can be more severe since it is inherently more sensitive than matched filtering and because LS estimation is known to be non-robust to deviations from the assumed signal model [18].

Recently, an adaptive approach based upon a recursive implementation of minimum mean-square error (MMSE) estimation known as adaptive pulse compression (APC) has been developed [19,20,21] which is capable of almost complete range sidelobe mitigation thereby enabling estimation of the range profile illuminated by a radar to the level of the noise.

This paper deals with comparison of the Doppler performance for different frequency coded signals by using the adaptive techniques.

II. ADAPTIVE LMS

Adaptive filters [6] are digital filters that have their filter coefficients changed by an algorithm. Here Least Mean Squared (LMS) [6] algorithm is used for processing the signal.

The computational procedure for the LMS algorithm is summarized below:

1. Initially, set each weight $w_k(i)$, i=0,1,…,N-1, to an arbitrary fixed value, such as 0.

For each subsequent sampling instant, k=1,2,…, carry out steps (2) to (4) below:

2. Compute filter output

$$\hat{n}_k = \sum_{i=0}^{N-1} w_k(i) x_{k-i}$$

3. Compute the error estimate

$$e_k = y_k - \hat{n}_k$$

4. Update the next filter weights

$$w_{k+1}(i) = w_k(i) + 2\mu e_k x_{k-i}$$

The simplicity of the LMS algorithm and ease of implementation, evident from the above, make it the algorithm of first choice in many real-time systems. The LMS algorithm requires approximately 2N+1 multiplications and 2N+1 additions for each new set of input output samples.

III. PARTICLE SWARM OPTIMIZATION (PSO)

Kennedy and Eberhant [8] proposed an approach called "Particle Swarm Optimization" which was inspired on the choreography of bird flock. It is a population based search algorithm that exploits a population of individuals to probe promising regions of the search space. In the context, the population is called a swarm, and individuals are called particles. Each particle moves with an adaptable velocity with in the search space and retains in its memory the best position it ever encountered.

Considering a D-dimensional search space, an i^{th} particle is associated with the position attribute $X_i = [x_{i,1}, x_{i,2}, \ldots\ldots x_{i,D}]$ and velocity attribute $V_i = [v_{i,1}, v_{i,2}, \ldots\ldots v_{i,D}]$. The best position encountered by the i^{th} particle is denoted as $P_i = [p_{i,1}, p_{i,2}, \ldots\ldots p_{i,D}]$. Assume **g** to be index of the particle that attained the best position found by all particles in the swarm. The swarm is manipulated in the same form resembling the following equations

$$v[i+1] = v[i] + c1 * rand * (pbest[i] - present[i]) + c2 * rand * (gbest[i] - present[i]) \quad (4)$$

$$present[i+1] = present[i] + v[i+1] \quad (5)$$

Where i=1,2, … … Np is the particles index, d=1,2, … …,D is the dimension index and t=1,2, .. indicates the iteration number. The variable C_1 and C_2 are positive constants, which are referred to as cognitive and social parameters, respectively and rand is a function which generates a random number that is uniformly distributed within the interval {0,1}. The variable w is a parameter called inertia weight, which plays the role of balancing the global and local searches. It is positive linear function of iteration, given as

$$w = w_{last} - \frac{(w_{last} - w_{start}) * iteration}{\max imum \quad iteration} \quad (6)$$

IV. PERFORMANCE EVALUATION AND SIMULATION STUDIES

The resolution properties of signal in range and Doppler are represented by Ambiguity function (AF) [1,2]. This is given by [10]

$$|\chi(\tau, f_d)| = \left| \int_{-\infty}^{\infty} u(t) u^*(t+\tau) e^{j2\Pi f_d t} dt \right| \quad (7)$$

In other words, χ(0,0) to be very large and χ (k≠0,l≠0) to be ideally zero is required. In this Doppler domain, the goodness of a sequence is judged by the Peak Side Lobe Level Ratio3 (PSLR3) [10] and Integrated Side

Lobe Level Ratio3 (ISLR3)[10] which are given by the equations (10) and (11).

$$PSLR3(dB) = 20\log\left[\frac{\left|Max\left[Max(\text{SidelobePeak})\right]\right|^2}{\left|r(0)^2\right|}\right] \tag{8}$$

$$ISLR\ 3 = 10\ \log\left[\frac{2\sum_{n+1}^{\tau}\sum_{m+1}^{f}\left|\chi(\tau_m, f_n)\right|^2}{\sum_{-n}^{+n}\sum_{-m}^{+m}\left|\chi(\tau_m, f_n)\right|^2}\right] \tag{9}$$

V. RESULTS

By using the above-mentioned algorithms the values of PSLR3 and ISLR3 are obtained at various noise levels.

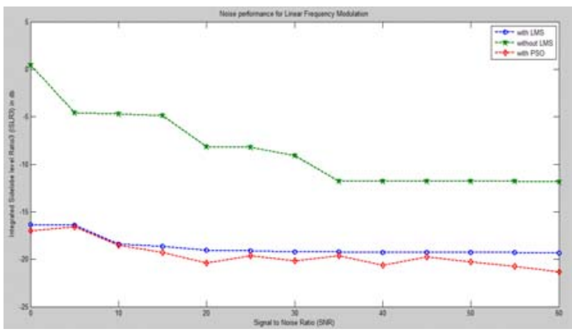

Fig.1 ISLR3 of Linear Frequency Modulation Using LMS and PSO

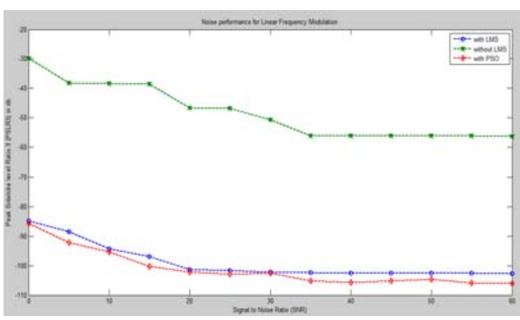

Fig.2 PSLR3 of Linear Frequency Modulation Using LMS and PSO

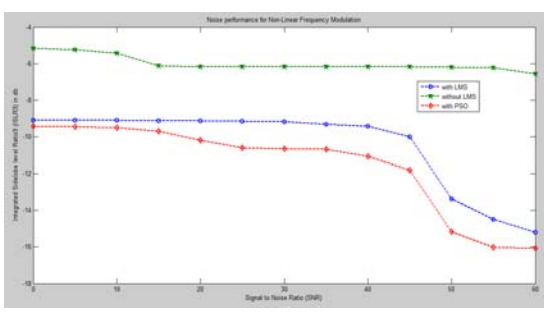

Fig.3 ISLR3 of Non-Linear Frequency Modulation Using LMS and PSO

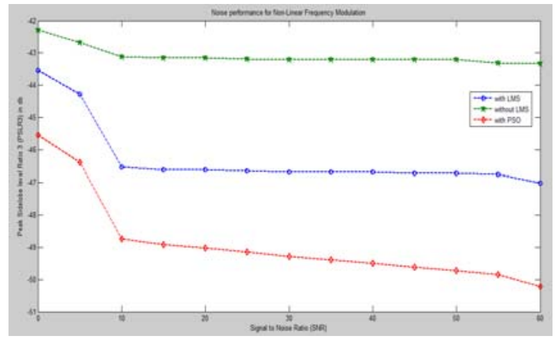

Fig.4. PSLR3 of Non-Linear Frequency Modulation Using LMS and PSO

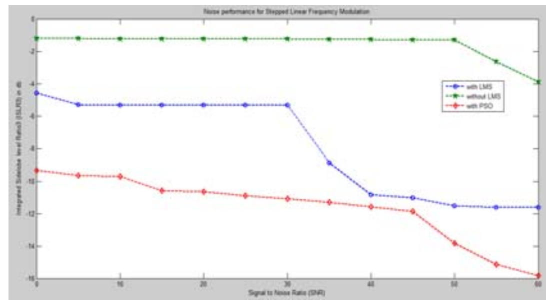

Fig.5 ISLR3 of Stepped Frequency Modulation Using LMS and PSO

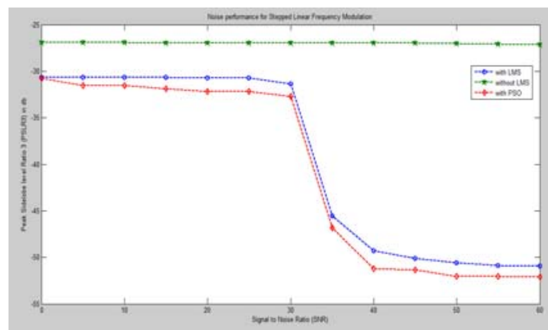

Fig.6 PSLR3 of Stepped Frequency Modulation Using LMS and PSO

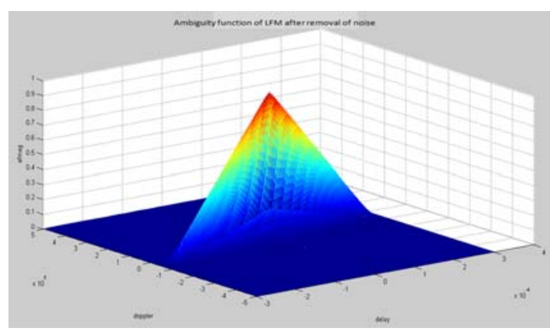

Fig.7. Ambiguity function of LFM after removal noise using LMS

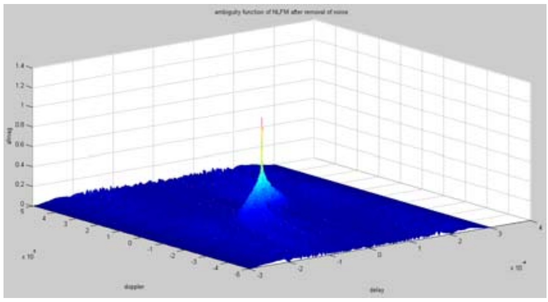

Fig.8. Ambiguity function of NLFM after removal noise using LMS

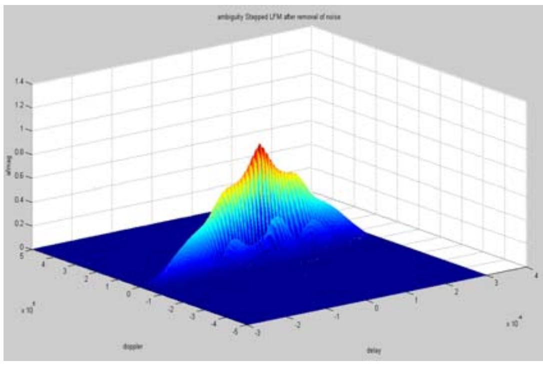

Fig.9 Ambiguity function of Stepped LFM after removal noise using LMS

Fig.1 to Fig.6 shows the PSLR3 and ISLR3 for LFM, NLFM and Stepped LFM in the presence of Additive White Gaussian Noise (AWGN) using LMS algorithm, PSO.

Fig.1 to Fig.2 shows PSLR3 and ISLR3 for linear frequency modulation using LMS algorithm and PSO. The integrated side lobe level ratio3 (ISLR3) and peak side lobe level ratio3 (PSLR3) for PSO is superior compared to LMS algorithm by 3.5dB.

Fig.3 to Fig.4 shows PSLR3 and ISLR3 for non linear frequency modulation (NLFM) using LMS algorithm and PSO. The integrated side lobe level ratio3 (ISLR3) and peak side lobe level Ratio3 (PSLR3) for PSO is superior compared to LMS algorithm by 4dB.

Fig.5 to Fig.6 shows PSLR3 and ISLR3 for stepped frequency modulation (SFM) using LMS algorithm and PSO. The integrated side lobe level ratio3 (ISLR3) and peak side lobe level Ratio3 (PSLR3) for PSO is superior compared to LMS algorithm by 5dB.

Fig.7 to Fig.9 shows the ambiguity diagrams after removal of noise using LMS algorithm for LFM, NLFM and Stepped LFM respectively.

In all cases, the extensive simulation studies indicate that the stochastic based particle swarm optimization is outperforming the gradient based LMS algorithm.

VI. CONCLUSION

From the above results we can conclude that the Particle Swarm Optimization technique which is soft evolutionary computing technique yields better performance when compared to Least Mean Square Algorithm for getting best performance of Doppler in Pulse Compression. Other optimization Techniques such as Genetic Algorithm, Honey bee, Differential Evolution, etc. techniques can be used for yielding better performance.

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