

Design of DFC Waveforms for MIMO Radar using Accelerated Particle Swarm Optimization Algorithm

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Abstract-In this paper the Discrete Frequency Coded Waveforms (DFCWs) with good correlation properties are numerically designed utilizing Accelerated Particle Swarm Optimization Algorithm for MIMO Radar. To achieve this object the cost function was intended based on Peak Side lobe level Ratio (PSLR) and Integrated Side lobe Level Ratio (ISLR). The simulation results show that the DFCWs signal utilized in MIMO radar are designed effectively using the proposed algorithm.

Key-Words: -- Multiple Input and Multiple Output (MIMO) Radar, Peak Side lobe level Ratio (PSLR), Integrated Side lobe Level Ratio (ISLR), Discrete Frequency Coded Waveform (DFCW), Accelerated Particle Swarm Optimization Algorithm (ACC_PSO).

I. INTRODUCTION

In present scenario Multiple Input and Multiple Output (MIMO) Radar frameworks can possibly significantly enhance the execution over single radio wire framework [1]. The MIMO radar utilizes various transmitting waveforms and the signals got at numerous getting radio wires are mutually prepared, and this kind of radars uses the generally isolated transmitters and recipients such that the objective is seen from a wide range of viewpoints all the while, bringing about spatial differences, which can enhance radar detection execution [2-4]. MIMO radar can expand the quantity of accessible level of flexibility. This level of flexibility can be used to enhance determination, arrangement execution and clutter mitigation. The distributed MIMO radar has greatest level of opportunity instead of monostatic radar. The resolution performance upgrade is one of the critical properties for MIMO radar. The range resolution can be altogether enhanced by utilizing short pulses. This outcome in the abatement in received signal to noise ratio (SNR). Various Pulse compression techniques were developed to increase

signal to noise ratio. To avoid the detection confusion and self-interference the orthogonal waveforms utilized by the MIMO radar systems must be designed carefully. The aperiodic autocorrelation functions of sequences should have low peak sidelobe level for high range and multiple target resolution. For the implementing MIMO radio detection and ranging systems, the orthogonal code sets should be designed with low Crosscorrelation Peaks (CP) and Autocorrelation Sidelobe Peaks (ASP) is crucial. The correlation properties of orthogonal waveforms judge the performance criteria. MIMO Radar systems are coded with binary codes, polyphase codes, Costas codes and Discrete Frequency Codes etc. But the Costas and DFC signal have larger main lobe-to-peak side lobe ratio and high resolution capability over binary and polyphase signal of the same code length.

Therefore DFC sequences are increasingly becoming a favorable alternative for radar systems to achieve high range resolution and improve detection capability [3]. The optimization of DFC sequence sets with good autocorrelation properties can be viewed as nonlinear multivariable optimization problem, which is usually difficult to tackle. Deng [3] in 2004 and Liu [4] in 2008 have published some results on DFC sequences with desired properties of correlation for radar by using Simulated Annealing (SA) algorithm. But convergence rate of the SA algorithm is very slow and also there is a probability to miss the global minimum. In this paper the Discrete Frequency Coded Waveforms (DFCWs) with good correlation properties are numerically designed using Accelerated Particle Swarm Optimization algorithm for MIMO radar. In this proposed scheme we employ a modified accelerated particle swarm optimization algorithm in which particles of considered swarm able to communicate with

update velocity and employ best positions as well as accelerations that are mutual to each other that fine tune their velocity, acceleration and position among all the particles. Also simulation results are compared.

A. Pulse Compression

Pulse compression allows the radar to simultaneously achieve the energy of a long pulse and at the same time resolution of particle short pulse by employing long pulse in the intermodulation technique.

The following are several benefits of using pulse compression methods in the area of radar.

1. Peak Power Reduction.
2. Relevant high voltages reduction in RADAR Transmitter.
3. Protection against decoding by radar detectors.
4. To achieve Maximum range resolution.

Types of compression Techniques: The pulse compression is measure of the degree to which the pulse is compressed. It is particularly defined as the ratio of the uncompressed pulse width to the compressed pulse width. There are many types of modulations used for pulse compression and they are broadly classified as shown Fig.1 below.

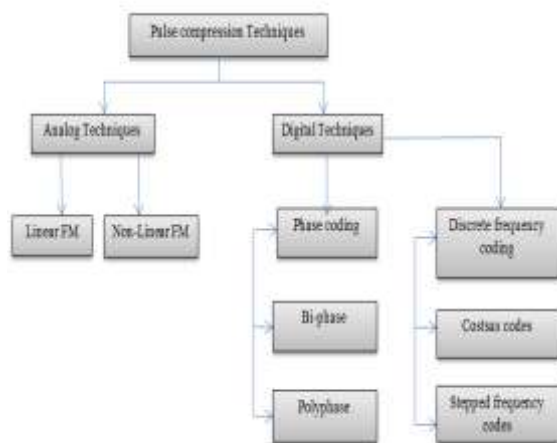


Fig.1 Types of modulations

Orthogonal Waveforms: As analysis point of view for MIMO system to employ for radar application that consists with multiple transmitting antennas denoted as T_X . Here we considered X_i in which $(1, 2, \dots, T_X)$ that denotes the positions of transmitting antennas that is located at particular angle θ_i that is viewed exactly from origin. Now in this situation every element transmits N coding

frequencies on every subpulse of waveform. So therefore receiver R_x particularly receives and that processes signal among all transmitters and thus return signals from the clutter and target so in turn each element having pulse repetition frequency of f_r .

Polyphase waveforms: Consider the orthogonal polyphase code set consists of T_X orthogonal waveforms, each represented by a sequence of N samples with M phases. The t^{th} waveform of T_X orthogonal waveform set is as follows

$$S_t(t) = e^{\frac{j2\pi\phi_t(n)}{M}}, n=1,2,\dots,N \quad (1)$$

The polyphase code set S, with code length of N, code set size of T_X , and distinct phase number M, one can concisely represent the phase values of S with the following $T_X \times N$ phase matrix.

$$S(T_x, N, M) = \phi_1(1)\phi_1(2) \dots \phi_1(N)$$

$$\phi_2(1)\phi_2(2) \dots \phi_2(N)$$

$$\phi_{T_x}(1)\phi_{T_x}(2) \dots \phi_{T_x}(N) \quad (2)$$

From the autocorrelation and cross correlation properties of orthogonal polyphase codes, we get

$$A(\phi_1, m, k) = \frac{1}{N \sum_{l(n=1)}^{l(N-k)}} \exp [j[\phi_1, m(n) - \phi_1 m(n+k)]] = 0, 0 < k < Nm = 1,2, \dots, T_x]$$

$$\frac{1}{N} \sum_{n=-k+1}^N \exp j[\phi_m(n) - \phi_m(n+k)] = 0, -N < K < 0 \quad (3)$$

$$C(\phi_p, \phi_q, k) = \frac{1}{N} \sum_{n=1}^{N-k} \exp^{j[\phi_q(n) - \phi_q(n+k)]} = 0,$$

$$0 < k < N \quad P \neq 1,2, \dots, T_x \quad (4)$$

$$\frac{1}{N} \sum_{n=-k+1}^N \exp j[\phi_q(n) - \phi_q(n+k)] = 0, -N < K < 0$$

Where $A(\Phi_m, k)$ and $C(\Phi_p, \Phi_q, k)$ are the aperiodic autocorrelation function of polyphase sequence S_m and the cross correlation function of sequences S_p and S_q , and k is the discrete time index. Therefore, designing an orthogonal polyphase code set is equivalent to the constructing a polyphase matrix in (2) with the $A[\Phi_m, k]$ and $C(\Phi_p, \Phi_q, k)$ in (3) and (4)[7].

B. Modified DFCW_LFM

DFCW is still is the most popular pulse compression method. The main idea is to curve the (fb) frequency band ‘B’ linearly through the pulse duration T. B is the total frequency deviation and the time (BW) bandwidth product of the signal is ‘BT’. The spectral efficiency of the LFM improves as the time-bandwidth(BT) product rises, because the spectral density approaches a rectangular shape. The DFCW_LFM waveform is used in this paper and is defined as [5-6].

$$S_p(t) = \begin{cases} \sum_{n=0}^{N-1} e^{j2\pi f_n^p(t-nT)} \cdot e^{j\pi kt^3} & 0 \leq t \leq T(5) \\ 0 & elsewhere \end{cases}$$

Where, p= 1, 2,... L, T is the subpulse time duration. N is the number of subpulse that are continuous with the coefficient sequence { } N n , n , n , n 1 2 3 with unique permutation of sequence{0,1,2,3,..... N -1}. $f_n^p = n \cdot \Delta f$ is the coding frequency of subpulses n of waveform p in the waveform. Δf is the frequency step k is the frequency slope, $k = B/T$

The process of optimization involves the selection of the order of the sequence that gives nearly ideal noise like autocorrelation properties. The auto correlation function is given as

$$A(s, \tau) = \frac{1}{N} \int_t s(t) s^*(t - \tau) dt = \begin{cases} 1 & \tau = 0 \\ 0 & otherwise \end{cases} \quad (6)$$

Where $A(s, \tau)$ is the aperiodic auto correlation function of the signal s(t). Therefore, to design DFC sequences for detection purposes, the optimized sequence must satisfy the conditions given in above equation. The performance analysis is expressed in terms of Peak Side Lobe Ratio and integrated Sidelobe Level Ratio. The PSLR is a ratio of the peak sidelobe amplitude to the main lobe peak amplitude and is expressed in decibels. The autocorrelation and Cross correlation PSLR are defined as [7].

$$PSLR_A = 20 \log_{10} \left\{ \frac{\max_n \epsilon \text{ sidelobe} |A(S_l, n)|}{\max_n \epsilon \text{ mainlobe} |A(S_l, n)|} \right\}$$

$$PSLR_C = 20 \log_{10} \left\{ \frac{\max_a \epsilon \text{ sidelobe} |C(S_p, S_q, n)|}{\max_a \epsilon \text{ mainlobe} |C(S_p, S_q, n)|} \right\}$$

where $q \neq p(7)$

The ISLR is a ratio of the integrated energy of all side lobes which spread across the whole time domain to the integrated energy of the main lobe in the pulse compression function.

$$ISLR_s = 20 \log_{10} \left\{ \frac{\sum \text{only sidelobe} |A(S_p, n)| \sum |C(S_p, S_q, n)|}{\sum \text{only mainlobe} |A(S_p, n)|} \right\}$$

where $q \neq p$ (8)

The cost function can be written as $CF = \sum_{l=1}^L (\min(PSLR_{Al}) + \min(PSLR_{cl})) + \lambda \cdot \sum_{l=1}^L ISLR_{sl}$ (9) where λ is the relative weigh assigned to the ISLR and PSLR.

II. GLOBAL OPTIMIZATION TECHNIQUES

Earlier pulse compression sequence (binary ternary, quandary and Costas have been designed using algebraic methods. Recently, polyphase sequences have been synthesized as alternative to binary and ternary sequences. But it seems to be very difficult to algebraically design sequences of large length with low cross correlation properties. This demands to solve a signal design problems for the pulse compression radars using exhaustive search methods, which employ global optimization techniques like

1. Simulated Annealing Algorithm,
2. Genetic Algorithm,
3. Particle Swarm Optimization
4. Neural Networks
5. Artificial Immune Systems
6. Fuzzy Optimization etc.

A. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a population predicated stochastic optimization technique developed in 1995 by Dr. Kennedy and Dr. Eberhart, that job is to shares so many similarities with the modern evolutionary computational techniques such as Simulated Annealing, Genetic Algorithms. The system is initially set with a population of arbitrary/random solutions and searches for optima by generations updating. However, unlike Genetic Algorithm, Particle Swarm Optimization Algorithm has no evolution operators such as mutation, crossover etc. In Particle Swarm Optimization (PSO), the possible solutions (particles) fly through the problem space by following the existing optimum particles. Each particle keeps path of its coordinates in the problem

space which are linked with the fitness (best solution) it has achieved thus far. (The best value is additionally stored.) This value is called Pbest. And the "Best" value that is traced by the Particle Swarm Optimizer is the best value that obtained until by any particle in the neighbors of the particle. This position/location is called Lbest. When a particle sequences all the population as its topographical neighbors, the best value is a Global Best and is so-called as gbest.

The Particle Swarm Optimization conception consists of, at each time span, changing the velocity of each particle towards Lbest locations and personnel best so called as Pbest. Acceleration is subjective by a random term, with separate arbitrary/random numbers which are generated for acceleration towards the personnel best and Lbest locations. Since several years, PSO (Particle Swarm Optimization) has been successfully applied in many application and research areas. It is proven that PSO gets enhanced results in a faster, cheaper way compared with other optimization methods. Another reason that that is particle swarm optimization is attractive as it has very few parameters to modify. Single technique, with slight changes, works well in an ample range of applications. Particle swarm optimization has been utilized for methods that can be utilized across a wide variety of applications, as well as for specific applications utilized on a specific requirement. Compared to Genetic Algorithm, the advantages of PSO are that is easy to implement and there are only few parameters to adjust. PSO has been successfully implemented in many areas: function optimization, fuzzy system control, artificial neural network training and various areas where GA can be implemented.

B. PSO Technique

As specified in section above, Particle Swarm Optimization simulates the behaviors of birds flocking. Suppose the following circumstances: a crowd of birds are randomly flying in search of food in an area. Let assume that there is only single piece of food in the searching area. All the birds in the crowd do not know where the piece of food is. But they know in each iteration, how far the food is. So now what is the best approach to find the food? The best one is to fly along the bird which is nearer to the food. Particle Swarm Optimization learned from the circumstance and utilized in solving the optimization problems. In this

optimization technique, each one solution is a "bird" in the searching area/search space. And we call as "Particle". All the particles in the space have fitness values which are compared by the fitness function to be optimized and also have the velocities which will direct flew of the particles. The particles flew through the problem space by succeeding the present optimum particles.

Particle Swarm Optimization technique is initialized with a crowd of arbitrary/random particles (solutions to the problems) and then searches for optima by generation updating. For every iteration, by following two "best" values each particle is updated. The first one is the best solution (fitness value) it has been achieved. (This fitness value is also stored). And this value is so-called as Pbest. The other "best" value that is traced by the (PSO) Optimizer is the best value, achieved so far by any (solutions) particle in the population (problem Space). This best value is known as Global Best and so-called as gbest. When a particle sequences the population as its topographical neighbors, the best value is a local best and is generally called as lbest. Now after obtaining the two best values, the particle immediately updates its position and velocities by considering equations (10) and (11).

$$v[i] = v[i] + c1 * rand() * (Pbest[i] - present[i]) + c2 * rand() * (gbest[i] - present[i]) \quad (10)$$

$$Present[i] = Present[i] + v[i] \quad (11)$$

Where

p: particle's position

v: path direction

c1: weight of local information

c2: weight of global information

pbest: best position of the particle

gbest: best position of the swarm

rand: random variable

III. ACCELERATED PARTICLE SWARM OPTIMIZATION

In this paper, we utilize ACC_PSO to outline discrete frequency-coding waveform to acquire great relationship properties. To accomplish this protest the cost capacity was composed in Peak Side lobe level Ratio and Integrated Side lobe Level Ratio. This calculation employs a optimization engine to acquire an ideal answer for this issue furthermore balances out to the arrangement in impressively lesser computational endeavors. In this algorithm the Particles of a

swarm convey great positions to one another and also progressively modify their own position, speed and quickening got from the best position of all particles.

Accelerated particle Swarm Optimization is an accelerated version of Particle Swarm Optimization Algorithm. It adopts the same concept of PSO to locate the optimum value. Process begins with a randomly initialized population moving in randomly chosen directions. In PSO the particles would update their position and velocity for the next move after locating the pbest and gbest in each iteration. ACC_PSO updates acceleration in addition to position and velocity thus speeding up the process of search exploration. Finally, over the searching process all swarm particles will fly towards better and better positions until the swarm moves closer to its optimum value. Thus, in Accelerated Particle Swarm Optimization there are three important parameters to be considered for optimization which includes velocity, position and acceleration unlike in PSO there were only two parameters. This makes ACC_Particle Swarm Optimization faster than Particle swarm optimization though the difference can be noticeable when the dimension of the problem becomes more unlike when it's dealt with lower order dimension.

The movement of a swarming particle consists of two major components: a stochastic component and a deterministic component. Each particle is attracted towards the position of its own best location x_i^* in history and the current global best g^* , while at the same time particle has a tendency to move randomly. During iterations there is a current best for all n_p particles at any time t . The standard particle swarm optimization uses both the individual best x_i^* and the current global best g^* to update the particle position. The purpose of using the individual best is to increase the diversity in the search space. Notwithstanding, this assorted qualities can be accomplished by utilizing some arbitrariness. Therefore, there is no convincing purpose behind utilizing the individual best, unless the optimization problem interest is multimodal and highly nonlinear. A streamlined form which could accelerate the speed up the convergence of the algorithm is to custom the global best only.

Thus, in the Accelerated PSO, the velocity vector at iteration t is generated by a simpler formula

$$v_i^{t+1} = v_i^t + \alpha \xi_n + \beta (g^* - x_i^t) \quad (12)$$

Where ξ_n is a random vector in the interval of $\{0,1\}$. The update equation for position vector is simply

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (13)$$

The rate of convergence of algorithm can further be increased by updating the location of particle in a single step as follows

$$x_i^{t+1} = (1 - \beta)x_i^t + \beta \cdot g^* + \alpha \xi_n \quad (14)$$

The typical values for ACC_PSO are α from 0.1 to 0.4 and β from 0.1 to 0.7, though $\alpha = 0.2$ and $\beta = 0.5$ can be taken as the initial values for most unimodel objective functions. It is worth pointing out that the parameters α and β should in general be related to the scales of the independent variables and the search domain.

In Accelerated PSO, every individual from the population is known as a particle and the population is known as a swarm. Beginning with an arbitrarily instated population and moving in haphazardly picked directions, every particle experiences the searching space and recollects the best past positions, speed and accelerations of itself and its neighbors. Particles of a swarm convey great speed, position and acceleration to one another and in addition overwhelmingly suit their own particular speed, position and acceleration got from the best position of all particles. The following step starts when the sum total of what particles have been moved. At long last, all particles tend to fly towards better and better positions over the testing process until the swarm move to near an ideal of the optimum of the fitness function as depicted in fig.2

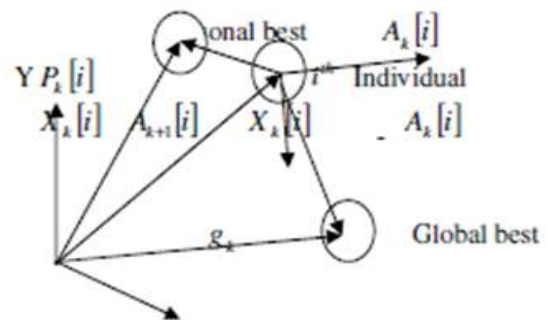


Fig.2 Behavior of an individual in 2-dimensional search

ACC_PSO has been utilized as a vigorous method to solve optimization problems in a ample variety of applications. In ACC_PSO for the optimization we have considered three parameters velocity, position and acceleration for each particle, where as in PSO only two parameters velocity and position are considered for each swarm particle. Here in this algorithm the swarms are the random sequence and random positions are generated. From these positions, the acceleration and velocity are generated [5].

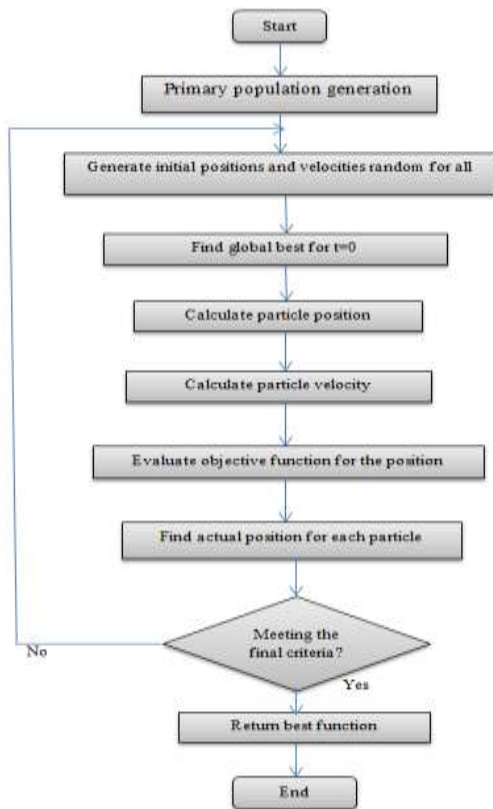


Fig.3 Flow diagram of ACC_PSO

The succeeding steps are shadowed to optimize the sequence.

1. Produce the individuals $x_0[i], i \in [0, 2, \dots, N - 1]$ of initial generation ($k=0$) arbitrarily.
2. Now for every particle, calculate the position, velocity and acceleration and update $P_x[i], V[i]_x, A_x[i]$ for all individuals.
3. Calculate the level for each and every particle dependent on the weight of each particle. The new vector created is considered as swarm particle.
4. Calculate the best acceleration for each particle and the best acceleration for all particles and called as local best and global beat in the iterations.
5. Update the new acceleration and add it to the swarm particle and get the new particle.

$$x_{k+1}[i] = x_k[i] + A_k[i], \forall i$$

$$A_k[i] = K \cdot \{A_{k-1}[i] + c_1 \cdot \Delta(g - x_k[i]) + c_2 \cdot \omega(p_k[i] - x_k[i])\}, \forall i$$

Where, c_1, c_2 and $K \in \mathbb{R}^{1, 2}$, are weighting coefficients.

$$\Delta = \text{diag}[\alpha_1, \alpha_2, \dots, \alpha_d]$$

$$\omega = \text{diag}[\beta_1, \beta_2, \dots, \beta_d] \text{ where } \alpha_i \in [0, 1],$$

$$\beta_i \in [0, 1]$$

Where i is a pseudorandom numbers.

6. After updating all the particles convert the level vector to the weight of each particle and compute Cost Function mentioned in equation (9). If the fitness function is satisfied the process ends otherwise the whole process is repeated from the step 3.

IV. DESIGN RESULTS

Using the ACC_PSO algorithm in section 4, DFC wave form are designed and the PSLR values of DFC sequence with Binary and Polyphase sequences are compared and shown in table.1. From the table it is observed that the peak side lobe levels of discrete frequency coded sequences are less when compared to the Binary, Poly-Phase coded sequences.

Table.1 Comparing binary, polyphase and DFC PSLR for certain sequences

Sequence length N	PSLR in dB of		
	Binary	PolyPhase	Optimized DFC
100	-23.10	-31.62	-36.32
169	-25.47	-33.00	-37.43
256	-26.58	-34.13	-38.62
400	-27.96	-34.24	-40.00
500	-28.87	-36.24	-41.57
600	-29.54	-36.35	-41.98
700	-30.05	-36.35	-42.24
800	-29.76	-36.88	-42.50

Figs. 4 – 6 show the Autocorrelation Functions (ACF) in dB of the Optimized/synthesized sequences of length N=169,500 and 800.

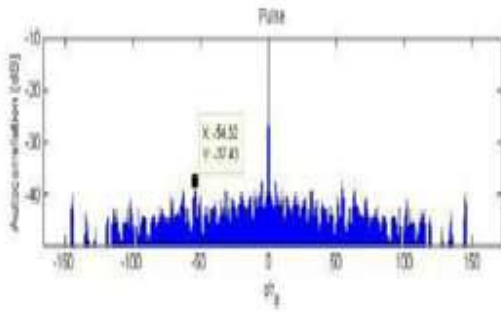


Fig 4: Autocorrelation plot for N=169 length

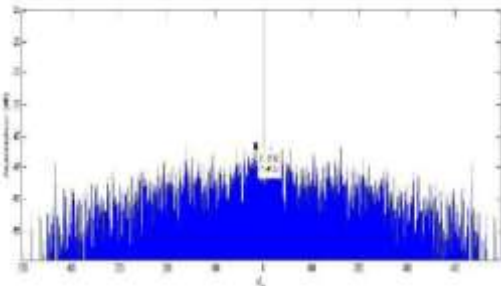


Fig.5: Autocorrelation plot for N=500 length

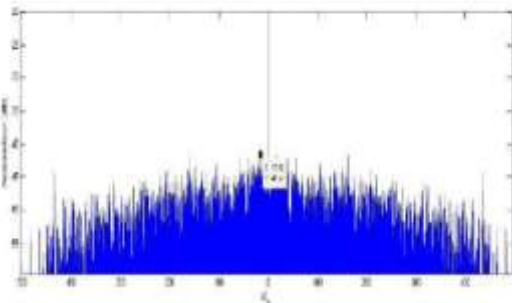


Fig 6: Autocorrelation plot for N=800 length

Figs.7-9 show the Ambiguity Functions of the optimized/synthesized sequences

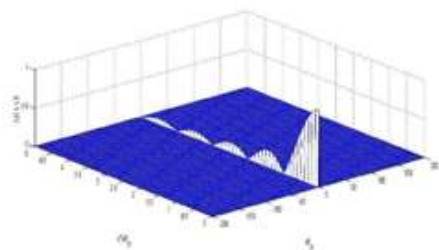


Fig 7: Ambiguity plot for N=169 length

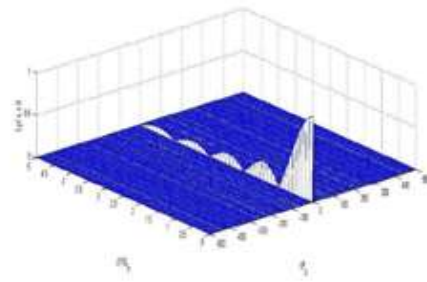


Fig 8: Ambiguity plot for N=500 length

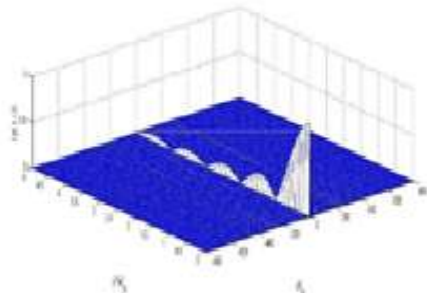


Fig 9: Ambiguity plot for N=800 length

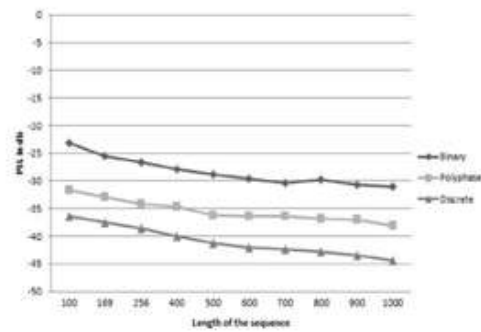


Fig 10 Comparison of PSLR values for DFC, Binary and Poly-phase Sequences

V. CONCLUSION

Design of Discrete Frequency Coding Waveforms with good correlation properties using Accelerated Particle Swarm Optimization algorithm, have been presented in this paper. In order to carry out the implementation of ACC-PSO algorithm for the design of discrete frequency sequences a MATLAB code is developed. The results obtained are compared with the literature values of sequences of the same lengths, and it is observed that there is substantial improvement in PSLR of all the sequence lengths. With the above observations, conclude that the DFC codes can be designed with lower time side lobes. And the performance of the proposed algorithm is demonstrated with the design results obtained.

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