Design of Eight-Phase Sequences using Modified Particle Swarm Optimization for Spread Spectrum and Radar Applications

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Abstract - For a multiple access communication system and radar system, it is desirable to have a set of sequences such that each sequence has a peaky autocorrelation and each pair of sequence has a negligible cross-correlation as possible. Peakyness of the auto-correlation of a sequence is measured in terms of its discrimination, which is to be maximized. The negligibility of a cross-correlation is judged based on the energy in the cross-correlation which is to be minimized. Obtaining such sequences is a combinatorial problem for which many global optimization algorithms like genetic algorithm, particle swarm optimization algorithm, simulated annealing algorithm were reported in the literature. In this paper a Modified Particle Swarm Optimization (MPSO) Algorithm is being designed to achieve these sequences. The MPSO Algorithm is a combination of the Hamming Scan Algorithm (HAS) and Particle Swarm Optimization (PSO) and has the fast convergence rate of Hamming Scan and Global minima convergence of Particle Swarm Optimization. Eight-phase sequences of lengths varying from 40 to 300 have been synthesized using MPSO and synthesized sequence sets achieved have better values of the above two properties compared with the literature.

Keywords - Hamming Scan algorithm (HSA), Radio Detection and Ranging (RADAR), Genetic Algorithm, Auto-Correlation Function (ACF), Cross-Correlation Function (CCF).

I. INTRODUCTION

The poly-phase signals with good correlation properties find application in the high-frequency applications such as RADAR and the communication. In, addition poly-phase signals have more complicated signal structure and therefore difficult to detect and analyze by enemy's electronic measures (ESMs). In a spread spectrum system each user uses a different code to modulate their signal. Choosing the codes used to modulate the signal is very important in the performance. The best performance will occur when there is good separation between the signal of a desired user and the signals of other users. The separation of the signals is made by correlating the received signal with the locally generated code of the desired user. If the signal matches the desired user's code then the correlation function will be high and the system can extract that signal. If the desired user's code has nothing in common with the signal the correlation should be as close to zero as possible (thus eliminating the signal); this is referred to as cross-

correlation. If the code is correlated with the signal at any time offset other than zero, the correlation should be as close to zero as possible. This is referred to as auto-correlation and is used to reject multi-path interference or self-clutter.

The poly-phase sequences also find applications in pulse compression techniques. The pulse compression improves the transmission power of the RADAR without compensating the range resolution. The pulse compression techniques have the combined advantages of using the long pulse and the short pulse for the location of the target. To achieve better range and resolution of the target object, the choice of the waveform used for the pulse compression is of prime importance [4]. The presence of the lower sidelobes in the pulse compression makes the signal processing easier. The poly-phase codes have the advantages of the presence of the lower sidelobes in the pulse compressed signal.

Some of the poly-phase codes examples are as follows: frequency derived codes, frank code, Lewis and Kretschmer code, etc. The poly-phase frank code finds application in the omnidirectional RADAR systems. The major task in the design of the poly-phase codes is to derive the codes with better auto and cross-correlation properties. The design of the poly-phase codes with the better correlation properties can be taken as the optimization problem [8]. Some of the algorithms such as genetic algorithm (GA) and the particle swarm optimization (PSO) have been used in the existing papers [3-8] to improve the correlation of the poly-phase codes. The existing models design the poly-phase codes by defining an individual fitness value with the use of the objective function. It searches the optimal solution from the legal area [2]. For the continuous poly-phase signals, the existing techniques estimate the subcode rate and the modulation period [5]. In the dynamic environments, the signal suffers from the Doppler shift. The existing models are inefficient for the poly-phase code design in the dynamic environments since the code gets degraded due to the Doppler shift [4].

In this paper, the poly-phase code design is done to overcome the difficulties faces by the existing models. The primary intention of this research is to design and develop a technique for poly-phase code design for the radar and communication systems. The poly-phase code for the radar system should possess the two properties such as auto-correlation and cross-correlation. These two properties will be considered in the proposed system design to develop a new optimization function. A new optimization function

will be developed to find the poly-phase code design, and it will be solved using the proposed optimization algorithm. A new optimization algorithm called MPSO will be developed by modifying the particle swarm optimization algorithm (PSO) with HSA. Here, the binding of the hamming scan with the particle swarm optimization algorithm improves the speed to find the optimal code sequence. The implementation will be done using MATLAB, and the performance of the proposed system will be compared with the existing algorithms using correlation and objective function.

The paper mainly consists of three sections.

Section One: This section introduces to well organized particle swarm optimization algorithm for synthesizing good codes. It is a novel population based stochastic algorithm, which is efficient as it converges to global minima, but has slow convergence rate.

Section Two: This section deals with synthesizing codes having good auto-correlation and cross-correlation properties using hamming scan algorithm. It is a deterministic algorithm, which is efficient in convergence, but it is sub-optimal.

Section Three: In this section, we used the "Modified Particle Swarm Optimization Algorithm" to synthesize the good poly-phase codes. It is a combination of the Hamming Scan (deterministic) algorithm and Particle Swarm Optimization (stochastic) algorithm which overcomes the drawbacks, and retains the merits of these algorithms at the same time.

II. POLY PHASE CODES

Consider a set of poly-phase sequences of length N bits which can be represented by the given complex number sequence

$$\left\{ S_l(n) = e^{j\emptyset_l(n)},\ n=1,2,3,.....,N \right\},\quad l=1,2,3,.....,L \qquad (1)$$

where, $\emptyset_l(n)$ is the phase of nth bit of the sequence which lies between 0 to 2π and L is the set size. The phase of the poly-phase code signal has M number of phases. The phases of the poly-phase coded signal can only have the following admissible values.

$$\emptyset_l(n) \in \left\{ 0, \frac{2\pi}{M}, 2\frac{2\pi}{M}, ..., (M-1)\frac{2\pi}{M} \right\} \qquad (2)$$

$$= \left\{ \Psi_1, \Psi_2, \Psi_3 ...., \Psi_M \right\}$$

For example, if M=4, the values of $\{\Psi_1, \Psi_2, \Psi_3$ and $\Psi_4\}$ will be 0, $\pi/2$, π and $3\pi/2$ respectively. Consider a poly-phase code set S having code length N, set size L, and distinct phase number M, the phase values of S is given by the following L by N phase matrix.

$$S(L,N,M) = \begin{bmatrix} s_1(n) \\ s_2(n) \\ s_3(n) \\ . \\ . \\ s_l(n) \\ s_{L(n)} \end{bmatrix} = \begin{bmatrix} \emptyset_1(1) & \emptyset_1(2) & \emptyset_1(3) & ...\,...\,... & \emptyset_1(N) \\ \emptyset_2(1) & \emptyset_2(2) & \emptyset_2(3) & ...\,...\,... & \emptyset_2(N) \\ & & & \vdots & \\ \emptyset_L(1) & \emptyset_L(1) & \emptyset_L(1) & ...\,...\,... & \emptyset_L(N) \end{bmatrix} \qquad (3)$$

where the phase sequence in row l $(1<l<L)$, is the four-phase sequence of signal l. All the elements in the matrix can be selected from the given set of phases specified in equation (2). The auto-correlation and cross-correlation of orthogonal poly-phase codes have the following properties:

$$A(s_l,k) = \begin{cases} \dfrac{1}{N}\displaystyle\sum_{n=1}^{N-k} s_l(n)s_l^*(n+k) = 0, & 0 \le k < N \\[4mm] \dfrac{1}{N}\displaystyle\sum_{n=-k+1}^{N} s_l(n)s_l^*(n+k) = 0, & -N < k < 0 \end{cases} \qquad (4)$$

and,

$$C(s_p,s_q,k) = \begin{cases} \dfrac{1}{N}\displaystyle\sum_{n=1}^{N-k} s_l(n)s_l^*(n+k) = 0, & 0 \le k < N \\[4mm] \dfrac{1}{N}\displaystyle\sum_{n=-k+1}^{N} s_l(n)s_l^*(n+k) = 0, & -N < k < 0 \end{cases} \qquad (5)$$

$$p \ne q,\ \ p,\, q = 1,2,....L$$

where, $A(s_l, k)$ is the aperiodic autocorrelation function of the sequence s_l and $C(s_p, s_q, k)$ is the cross-correlation function of sequences s_p and s_q respectively. A more practical approach to design a poly-phase code set from the above equations (4) and (5) is to numerically search for the best poly-phase sequences by minimizing a cost function that measures the degree to which a specific result meets the design requirements. For the design of poly-phase code sets, used in radar applications, the cost function depends on the auto-correlation sidelobe peaks and cross-correlation peaks. Therefore, from equations (4) and (5) the cost function can be

$$E = \sum_{l=1}^{L} \left(\max_{k \ne 0} |A(s_l,k)| \right)^2 + \lambda \sum_{p=1}^{L-1} \sum_{q=p+1}^{L} \left(\max_{k} |C(s_p,s_q,k)| \right)^2 \qquad (6)$$

where λ is the weighting coefficient between auto-correlation and cross-correlation.

III. PSO ALGORITHM

Optimization is the search for set of values which maximizes or minimizes value of a function.

The PSO algorithm is population-based stochastic algorithm in which a set of prospective solutions evolves to approach a suitable solution for a problem. Being an optimization method, the aim is finding the global optimum of a fitness function defined in a given search space. The concept of PSO algorithm was first introduced by Dr. Kennedy and Dr. Eberhart in 1995 and its basic thought was originally inspired by simulation of the social behavior of animals such as fish schooling, bird flocking and so on [1]. It is based on the natural process of group communication to share individual knowledge when a group of insects or birds look for food or migrate and so forth in a searching space, although all insects or birds do not know where the best position is. But from the nature of the social behavior, if any member can find out a desirable path to go, the remaining members will follow quickly.
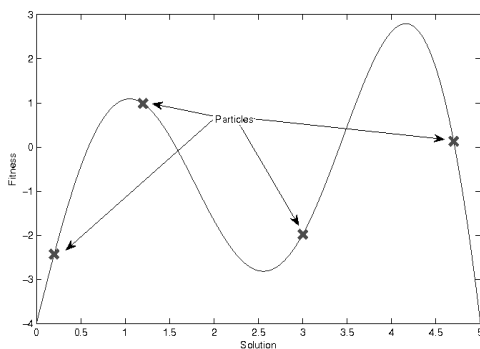

Figure 1: Working of PSO.

The PSO algorithm works by considering several candidate solutions randomly in the search space. Each candidate solution is called a particle. The particles fly through the search space to find the maximum or minimum of the objective function. In each iteration of the algorithm, each candidate solution is evaluated by the objective function being optimized, determining the fitness of that solution.

For a D-dimensional search space the position and velocity of ith particle can be represented by vectors $X_i = (x_{i1}, x_{i2}, ... , x_{id})$ and $V_i = (v_{i1}, v_{i2}, ...,v_{id})$ respectively. In PSO each particle maintains a memory of the best known position explored so far by it called personal best (**pbest**$_i$) and the best one among the all particles known as global best (**gbest**). So the position and velocity of the particle is updated in each iteration using following expressions

$$v_{id}[t+1] = w\ v_{id}[t]\ +\ c_1 r_1\ (\ pbest_{id} -\ x_{id}[t]\ )$$
$$+\ c_2 r_2\ (\ gbest_d - x_{id}[t]\ ) \qquad (7)$$

$$x_{id}[t+1] = x_{id}[t]\ +\ v_{id}[t+1] \qquad (8)$$

where $v_{id}[t]$ and $v_{id}[t+1]$ are the previous and the current velocities of the ith particle. Here $x_{id}[t]$ represents the position of the ith particle. $0 \leq w < 1$ is an inertia weight which determines how much the previous velocity is

retained (chosen $w = 0.99$). This signifies that the previous velocity is almost preserved, but not completely, to avoid escaping from the optimum value. c_1 and c_2 are the accelerating constants assigned a random value picked between 0 and 1 from an uniform distribution, and finally r_1 and r_2 are uniformly distributed random numbers ranging between [0, 1].

The basic steps of PSO algorithm can be summarized as follows:

Step1: Generate initial particles by randomly generating the position and velocity for each particle.

Step 2: Evaluate each particle's cost (E).

Step 3: For each particle, if the cost (E) is less than its previous best fitness then update personal best (pbest).

Step 4: For each particle, if the cost (E) is less than the best of all particles then update global best (gbest).

Step5: Generate a new particle according to the equations 7 and 8.

Step6: If the stop criterion is satisfied, then stop, else go to Step 2.
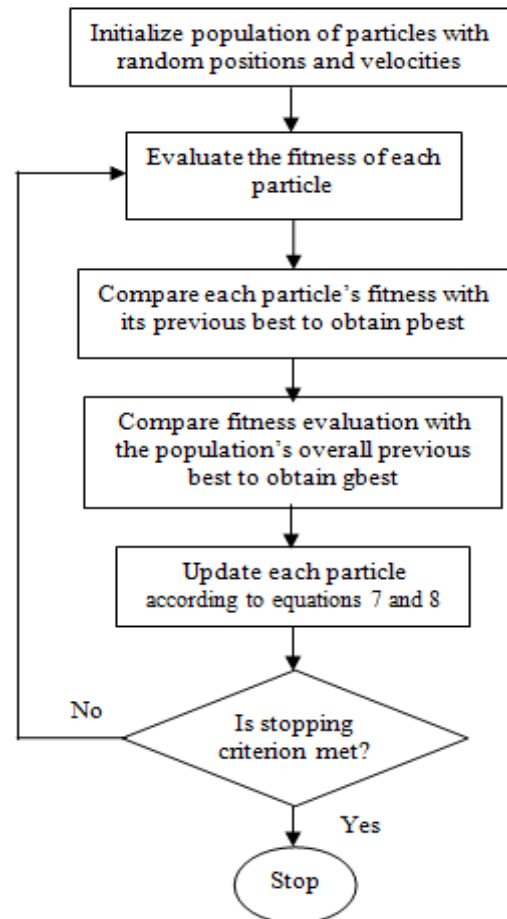

Figure 2: Flow Chart of PSO

IV. HAMMING SCAN ALGORITHM

HSA is a traditional optimization algorithm, which searches in the vicinity of the point in all directions one by one to reduce the fitness function and has fast convergence rate. In HSA, each element of the sequence is mutated with all other

possible in the sequence. For example, in the case of binary sequence mutation of element implies +1 is changed to -1 or -1 is changed to +1. If the cost is reduced after mutation, then the new element is accepted, else the original element is retained. This recursive process is applied to all elements in the sequence. Thus, HSA performs search among all the neighbors of the sequence and selects the one whose objective function value is minimum.
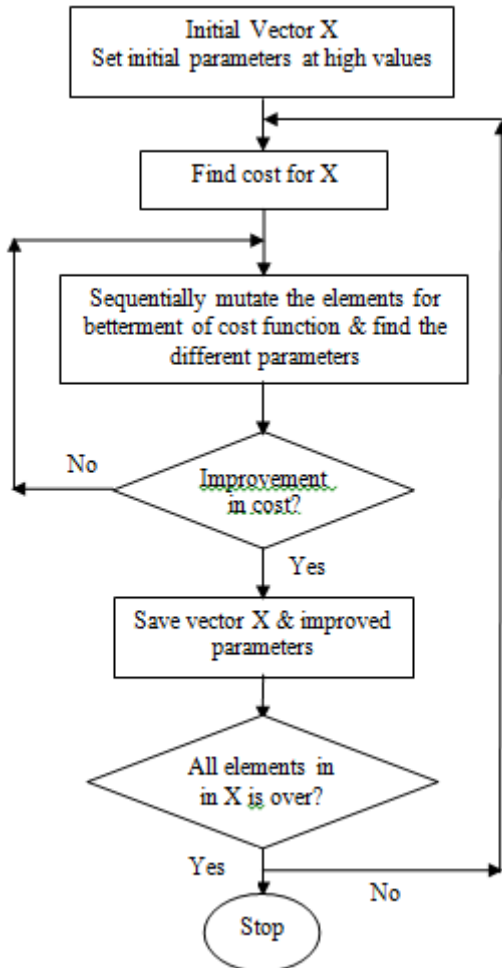

Figure 3: Flow Chart of HAS

V. MPSO ALGORITHM

The demerit of Hamming Scan Algorithm is that even though it has fast convergence rate it gets struck in the local minimum point as it has no way to distinguish between local minimum point and global minimum point. The HAS searches only in the vicinity of point in all directions so it finds only the local minima. The drawback of Particle Swarm Optimization is that even though it finds global minima it has slow convergence rate. To effectively utilize the convergence rate of Hamming Scan and global minima convergence of Particle Swarm Optimization, we present a new algorithm called Modified Particle Swarm Optimization (MPSO) which is combination of these two algorithms which traps all local minima including the global minima during the simulation. The new algorithm is better

than Particle Swarm Optimization and Hamming Scan algorithms. The working of MPSO algorithm can be summarized as follows:

Let S be the number of particles in the swarm, each having a position $\mathbf{x}_i$. Let **pbest**$_i$ be the best known position of particle i and let **gbest** be the best known position of the entire swarm. The MPSO Algorithm is then:

- ➢ For each particle $i = 1, ..., S$ do:

  - Initialize the particle's position with a uniformly distributed random vector: $\mathbf{x}_i$
  - Initialize the particle's best known position to its initial position: **pbest**$_i \leftarrow \mathbf{x}_i$
  - Initialize the particle's velocity: $\mathbf{v}_i$

    - For each particle $i = 1, ..., S$ do:
      - ✓ For each dimension $d = 1, ..., n$ do:
      - ✓ Find fitness: $f(\mathbf{x}_i)$
      - ✓ Initialize **gbest** $\leftarrow \mathbf{x}_i$ having max value of $f(\mathbf{x}_i)$
    - End for

- ➢ End for

- ➢ Until a termination criterion is met repeat:

  - For each particle $i = 1, ..., S$ do:

    - ✓ For each dimension $d = 1, ..., n$ do:
    - ✓ Update the particle's velocity and position according to equations 7 and 8
    - ✓ Find fitness: $f(\mathbf{x}_i)$
    - ✓ If $(f(\mathbf{x}_i) < f(\mathbf{p}_i))$ do:

      - ❖ Update the particle's best known position: $\mathbf{p}_i \leftarrow \mathbf{x}_i$
      - ❖ If $(f(\mathbf{p}_i) < f(\mathbf{gbest}))$ update the swarm's best known position: **gbest** $\leftarrow \mathbf{p}_i$
      - ❖ Sequentially perturb **gbest** using Hamming Scan
      - ❖ Find fitness: $f(\mathbf{gbest})$
      - ❖ Accept new **gbest** if there is improvement in fitness

    - ✓ End if

  - End for

- ➢ Now **gbest** holds the best found solution.

Figure 4: Pseudo Code for MPSO

VI. RESULTS AND DISCUSSIONS

A set of eight-phase sequences (L=3 and M=8) of length (N) varying from 40 to 300 were designed using proposed algorithm. The algorithm has been implemented using MATLAB 2015b software and tested on 2.5GHz Intel Core-i5 processor. The cost function for optimization is based on equation (6), and the value of λ is selected as 1. In this paper all the auto-correlation sidelobe peak (ASP) and cross-correlation (CCP) values are normalizes with respect to sequence length (N). The results obtained using proposed algorithm is presented and have better correlation properties than four-phase sequences available in literature [9]. The auto-correlation sidelobe peak and cross-correlation peak values of designed eight-phase sequence set are shown in

Tables 1 and 2 and the cross-correlation values obtained using proposed algorithm is far better than reported in literature [8-9]. The auto-correlation functions for the designed eight-phase sequence 1, 2, and 3 of length 128 are shown in Figures 5-7, respectively. The cross-correlation functions between sequences 1 and 2, sequences 2 and 3, and sequences 1and 3 for length 128 are shown in Figures 8-10. The average ASP and CCP values of designed sequence set for length varying from 40 t0 300 are shown in Figure 11. The normalized ASP and CCP values for N=40 is about 0.11 and 0.18 and for N=128 is 0.071 and 0.11 respectively.

Table 1: Auto-Correlation Sidelobe Peaks (Diagonal Terms) and Cross-Correlation Peaks (Off-Diagonal Terms) for Synthesized Codes with N=40, L=3 and M=8.

Sequences	1	2	3
1	0.1116	0.1829	0.1729
2	0.1829	0.1085	0.1837
3	0.1729	0.1837	0.1036

Table 2: Auto-Correlation Sidelobe Peaks (Diagonal Terms) and Cross-Correlation Peaks (Off-Diagonal Terms) for Synthesized Codes with N=128, L=3 and M=8

Sequences	1	2	3
1	0.0672	0.1094	0.1109
2	0.1094	0.0712	0.1115
3	0.1109	0.115	0.0750

Figure 7: Auto-Correlation Function of Sequence 3

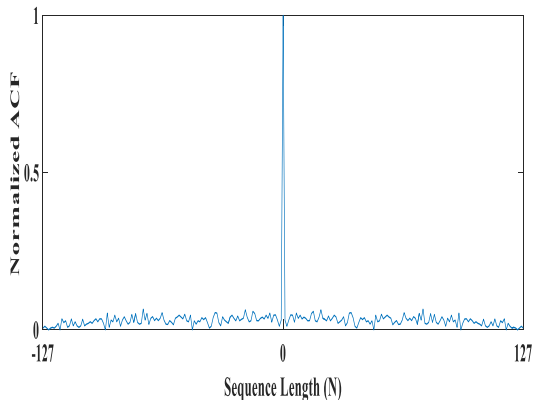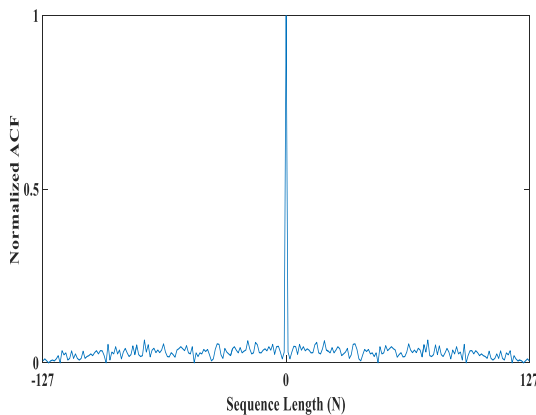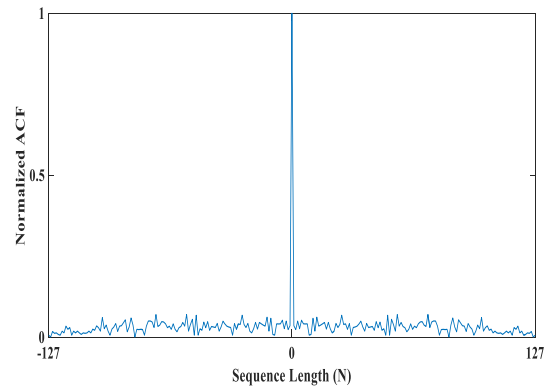Figure 8: Cross-Correlation Function of Sequences 1 and 2.

Figure 5: Auto-Correlation Function of Sequence 1.

Fig 9: Cross-Correlation Function of Sequences 2 and 3.

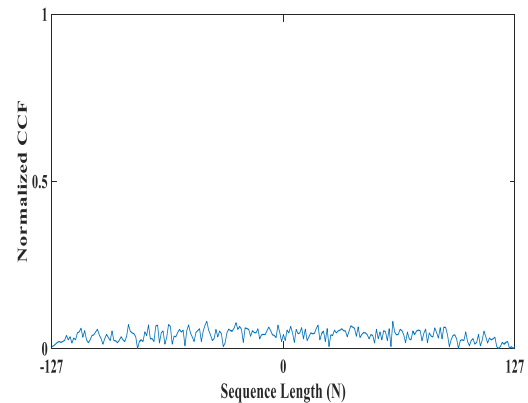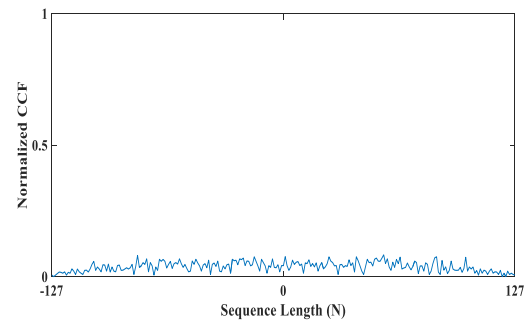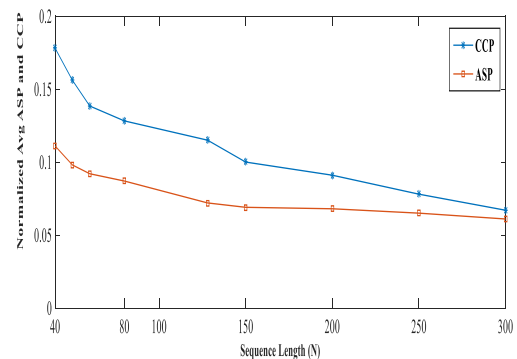Figure 6: Auto-Correlation Function of Sequence 2

Figure 10: Average ASP and CCP for Designed Sequence Set with Length Varying from 40 to 300.

VII. CONCLUSION

The objective of this paper is mainly to demonstrate the significance of the MPSO algorithm in the generation of Eight-phase sequences with good correlation values. These sequences are widely used in radar and spread spectrum communications for improving system performance. The new algorithm includes PSO and HAS and provides a powerful tool for the design of eight-phase sequence sets with good correlation properties. From the obtained results it is observed that for large sequence lengths, both average auto-correlation sidelobe peak and cross-correlation sidelobe peak approximately decrease at a rate of $1/\sqrt{N}$ with code length N. This property confirms to that of other poly-phase sequences designed using algebraic methods. The results obtained indicate that the proposed algorithm (MPSO) outperforms the existing algorithms like Genetic Algorithm. Unlike in Genetic Algorithms, in PSO, there is no selection operation which increases the speed and reduces complexity of the algorithm. As the sequences length increase, the genetic algorithm consumes more time. Hence global optimization techniques such as PSO algorithm are used for the generation of sequences with good correlation properties.

VIII. ACKNOWLEDGEMENT

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