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DESIGN OF BINARY PHASE SEQUENCES USING MODIFIED PARTICLE SWARM OPTIMIZATION FOR SPREAD SPECTRUM AND RADAR APPLICATIONS

Srinivasa Rao S.[1] and Siddiah P.[2]
[1]Department of Electrical and Computer Engineering, Mahatma Gandhi Institute of Technology, Hyderabad, Telangana, India
[2]Department of Electrical and Computer Engineering, Universal College of Engineering and Technology, Andhra Pradesh, India
E-Mail: sirasani33@gmail.com

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. 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. Binary phase sequences of lengths varying from 31 to 120 have been synthesized using MPSO and synthesized sequence sets achieved have better values of the above two properties compared with the literature. The synthesized binary phase sequences are promising for practical application to Netted Radar System and spread spectrum communication. The outcome of Doppler shift on synthesized sequences set is also investigated using ambiguity function.

Keywords: hamming scan algorithm, radio detection and ranging, genetic algorithm, auto-correlation function, cross-correlation function.

INTRODUCTION

The binary 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 binary phase signals 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 binary phase codes have the advantages of the presence of the lower sidelobes in the pulse compressed signal.

The major task in the design of the binary phase codes is to derive the codes with better auto and cross-correlation properties. The design of the binary 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 [3-7] to improve the correlation of the binary 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].

The primary intention of this paper is to design and develop a technique for binary 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 are considered in the proposed system design to develop a new optimization function. A new optimization function is developed to find the poly-phase code design, and it is solved using the proposed optimization algorithm. A new optimization algorithm called MPSO is developed by modifying the particle swarm optimization algorithm (PSO) with hamming scan algorithm. Unlike in Genetic Algorithms [9], in PSO, there are no mutation and cross-over operations which increase the speed and reduce complexity of the algorithm. As the sequences length increase, the genetic algorithm consumes

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more time. Here, the binding of the hamming scan with the particle swarm optimization algorithm improves the speed to find the optimal code sequence. The implementation is done using MATLAB, and the performance of the proposed system is compared with the existing algorithms using correlation and objective function. The paper mainly consists of three sections. The section one 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 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. In section three, 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.

POLY PHASE CODES

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

$$\{S_l(n) = e^{j\phi_l(n)},\ n = 1,2,3,\ldots,N\},\qquad l = 1,2,3,\ldots,L \tag{1}$$

where, $\emptyset_l(n)$ is the phase of n^{th} 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.

$$\emptyset_l(n) \in \left\{0, \frac{2\pi}{M}, 2\frac{2\pi}{M}, \ldots\ldots, (M-1)\frac{2\pi}{M}\right\} \tag{2}$$
$$= \{\Psi_1, \Psi_2, \Psi_3 \ldots\ldots\ldots, \Psi_M\}$$

For a binary phase sequence, the value of M is 2 and the values of $\{\Psi_1, \Psi_2\}$ are 0 and π 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.

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

where the phase sequence in row l $(1 < l < L)$, is the 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:

$$A(s_l, k) = \begin{cases} \frac{1}{N}\sum_{n=1}^{N-k} s_l(n)s_l^*(n+k) = 0, & 0 \le k < N \\ \frac{1}{N}\sum_{n=-k+1}^{N} s_l(n)s_l^*(n+k) = 0, & -N < k < 0 \end{cases} \tag{4}$$

and,

$$C(s_p, s_q, k) = \begin{cases} \frac{1}{N}\sum_{n=1}^{N-k} s_l(n)s_l^*(n+k) = 0, & 0 \le k < N \\ \frac{1}{N}\sum_{n=-k+1}^{N} s_l(n)s_l^*(n+k) = 0, & -N < k < 0 \end{cases} \tag{5}$$

$p \neq q,\ p, q = 1,2,\ldots.L$

where, $A(s_l, k)$ is the a periodic 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

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

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

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.

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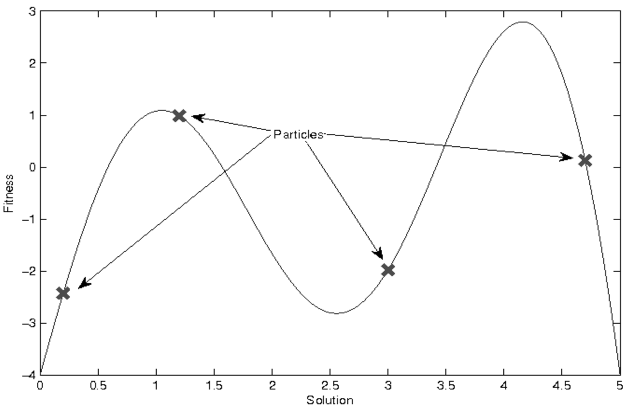

Figure-1. Working of PSO.

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 i^{th} 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.

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

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

where $v_{id}[\ t\ ]$ and $v_{id}[\ t+1]$ are the previous and the current velocities of the i^{th} particle. Here $x_{id}[t]$ represents the position of the i^{th} particle. $0 \le w < 1$ 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).
Step 5: Generate a new particle according to the equations 7 and 8.
Step 6: If the stop criterion is satisfied, then stop, else go to Step 2.

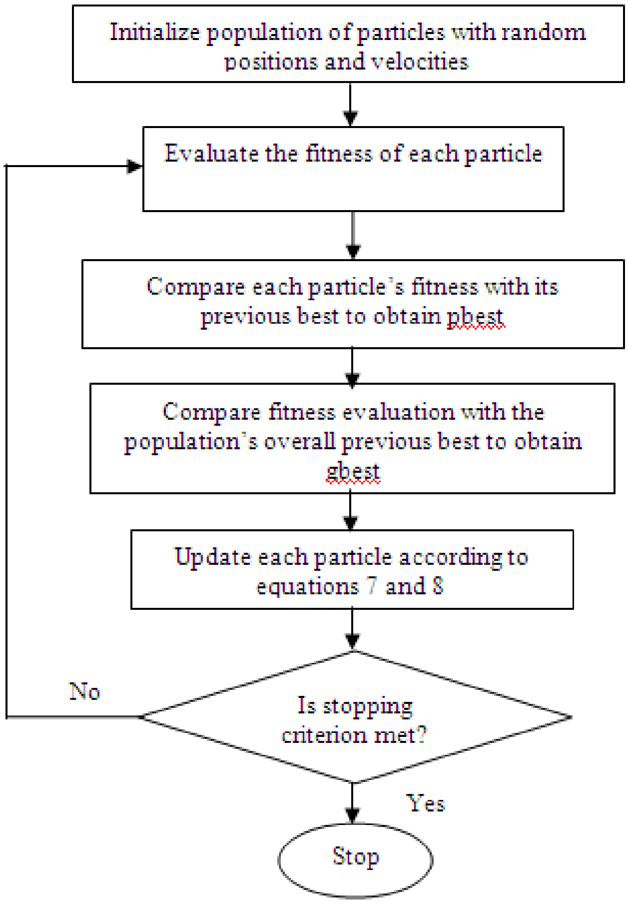

Figure-2. Flow chart of PSO.

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 [10].

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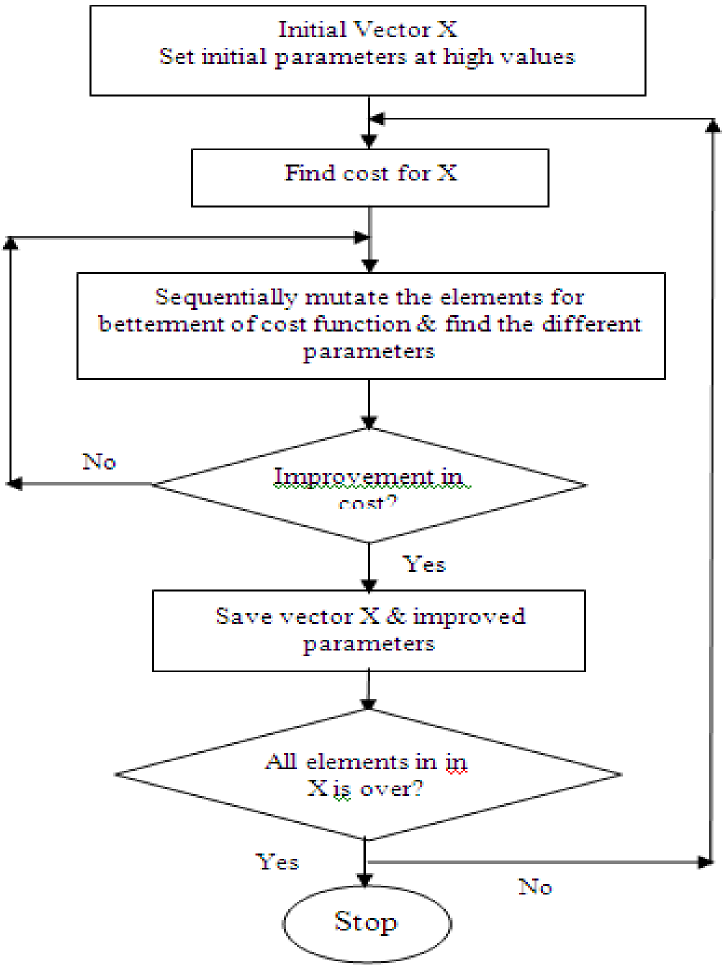

Figure-3. Flow chart of HAS.

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

- ✓ Endif

- End for

- Now gbest holds the best found solution.

Figure-4. Pseudo code for MPSO.

RESULTS AND DISCUSSIONS

A set of binary-phase sequences (L=2 and M=2) 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, the auto-correlation sidelobe peak (ASP) and cross-correlation (CCP) values are normalizes with respect to sequence length (N). Table-1 shows the comparison between synthesized results of the proposed algorithm and literature values [14]. It can be observed that our synthesized results are better than available in literature. As an example when the length of the sequences N is 31, the maximum of the cross-correlation peak of our result is 0.259 while literature value is 0.226 which indicates our result is better than literature value, whereas auto-correlation properties are same i.e., 0.13. Similarly other length sequences 37, 41, 53, 63, 67, 79, 84, 91, 100, 109, 120, 50 and 36 have lower values of maximum auto-correlation sidelobe peak than the literature values. When the length of the sequence is 50 and number of sequences (L), in a set are 6 there is a considerable reduction in both maximum of auto-correlation sidelobe peak and maximum of cross-correlation peak as shown in Table-1. The maximum peak sidelobe of our result is 0.16 while literature value is 0.20, which is reduced from 0.20 to 0.16 and maximum peak cross-correlation value in literature is 0.30 while our result is 0.24 which is reduced from 0.30 to 0.24. Figures 7(a)-(b) shows the normalized auto-correlation of sequence 1 and sequence 2 respectively with N = 63 and L = 2. It may be observed that the autocorrelation functions are like impulse, which indicate that resolution capability of the signal is good and generate very less self-clutters. Figure-7(c) shows the normalized cross-correlation between sequences 1 and 2 and it indicates that designed sequences are orthogonal as correlation between signals is very low.

Table-1. Comparison of correlation properties of sequences set synthesized using proposed algorithm and correlation value reported in literature with various values of L and N

Sequence length (N)	Number of sequences in a set (L)	Maximum ASP		Maximum CCP	
		Literature values	Our results	Literature values	Our results
31	2	0.13	0.13	0.259	0.226
37	2	0.163	0.136	0.244	0.244
41	2	0.171	0.147	0.196	0.196
53	2	0.151	0.133	0.17	0.17
63	2	0.127	0.112	0.175	0.175
67	2	0.12	0.12	0.165	0.165
84	2	0.12	0.108	0.167	0.143
91	2	0.121	0.11	0.132	0.132
100	2	0.11	0.09	0.14	0.14
109	2	0.101	0.101	0.138	0.138
120	2	0.109	0.084	0.117	0.125
64	3	0.157	0.125	0.188	0.188
50	6	0.2	0.16	0.3	0.24
36	8	0.25	0.195	0.306	0.306

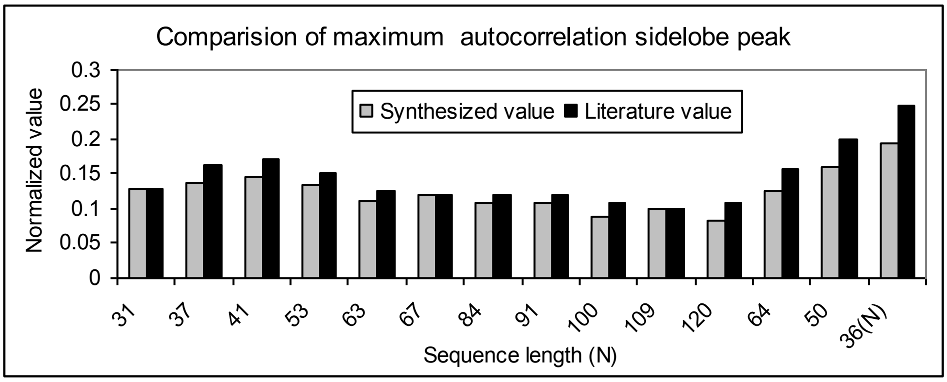

Figure-5. Comparison between synthesized maximum autocorrelation sidelobe peak values and literature values with different value of sequence lengths (N) and number of sequences in the set (L).

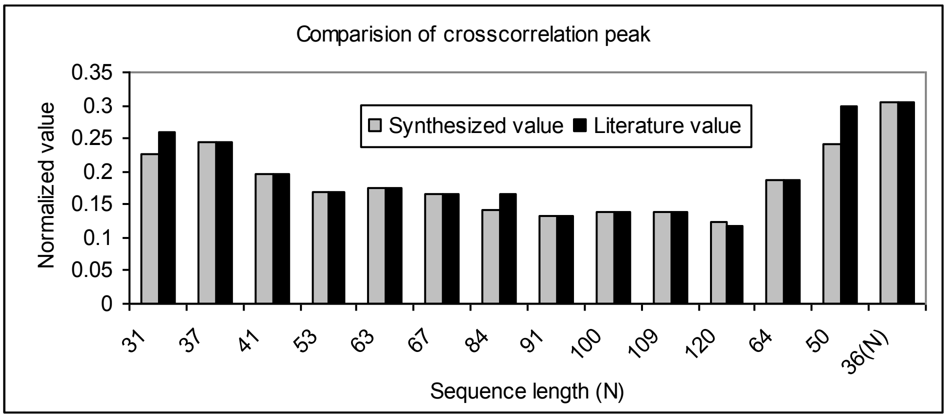

Figure-6. Comparison between synthesized maximum cross-correlation peak values and literature values with different value of sequence lengths (N) and number of sequences in the set (L).

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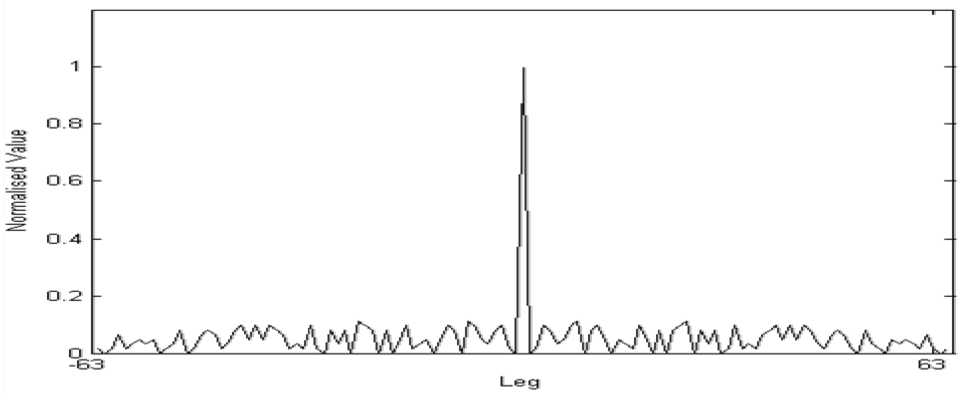
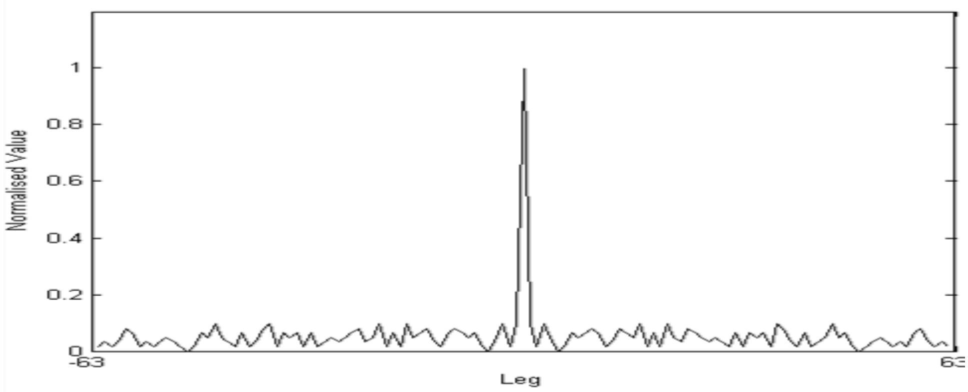
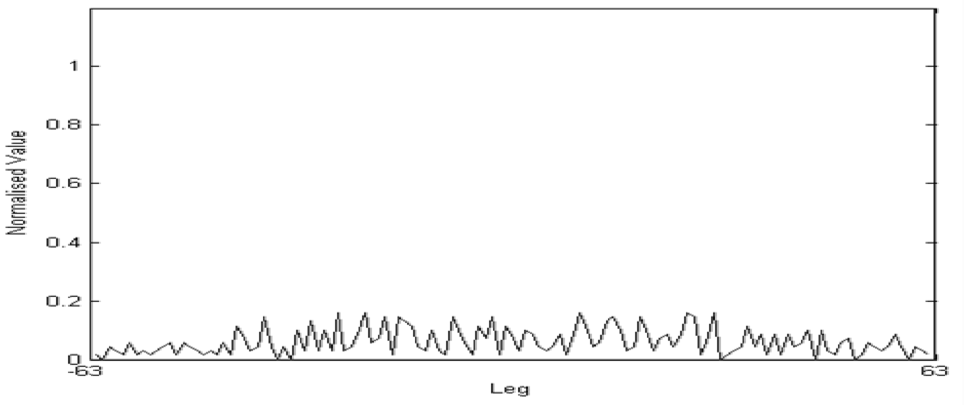


(a)



(b)



(c)

Figure-7. Correlation properties of synthesized sequences with L =2, M=2 and N=63 (a) Auto-correlation of sequence 1. (b) Auto-correlation of sequence 2. (c) Cross-correlation of sequences 1 and 2.

AMBIGUITY FUNCTION

Rather than auto-correlation and cross correlation functions, the radar signal design is actually based on ambiguity function. The ability of radar to distinguish targets as a function of delay and Doppler is indicated by the ambiguity function. The ambiguity function value for an ideal transmitted signal is zero for all non-zero delay and Doppler. This indicates that the responses from dissimilar targets are perfectly uncorrelated. It is also known that if the ambiguity function is sharply peaked about the origin, then simultaneous range and velocity resolution is good.

The ambiguity function can be defined as [12]

$$|\chi(\tau,\nu)| = \left| \int_{-\infty}^{+\infty} u(t)u^{*}(t-\tau)\exp(j2\pi\nu t)\,dt \right| \quad \ldots.. \quad (9)$$

where, u(t) is the transmitted signal. The ambiguity diagrams for the designed binary sequence set (sequences 1and 2) having length 100 are shown in figures 8(b) and (d). Synthesized sequences have thumbtack ambiguity diagrams which indicates that simultaneous

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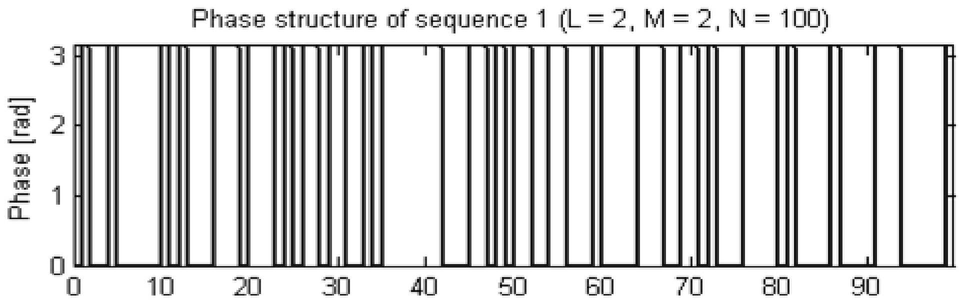
range and velocity resolution capability of the sequences are good.

Unlike the Frank codes or the poly-phase sequences described in [19-21], which are derived from linear frequency modulation (LFM) signals, the numerically designed binary sequences have thumbtack ambiguity diagram, and thus, the matched filtering results are very sensitive to the Doppler frequency in the radar echoes due to target movement. It can be seen that the output signal amplitude is not significantly reduced if the Doppler frequency is less than 0.5/T, i.e.,

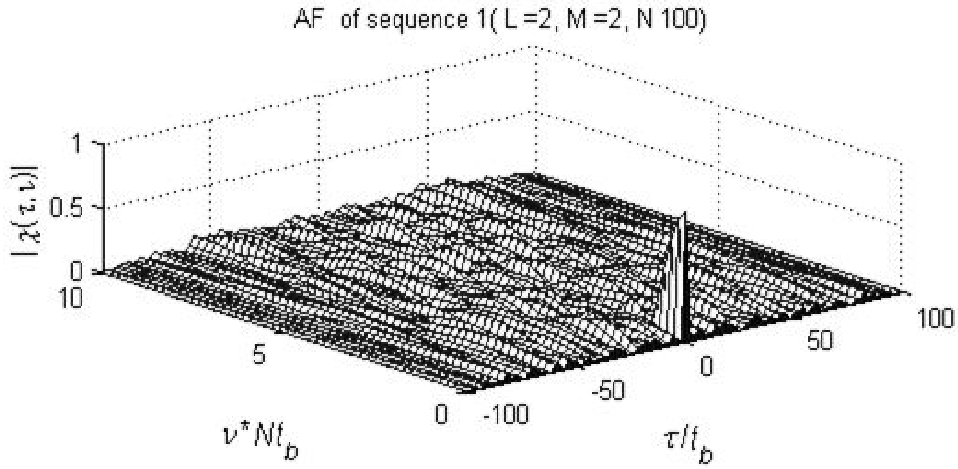
$$|\nu|T < 0.5 \tag{10}$$

where, T is the signal time duration equal to Nt_b, where t_b is the duration of sub pulse. Therefore, if (10) is satisfied, the Doppler effect on the processing result is negligible; otherwise, the correction processing must be conducted. A simple way to minimize the Doppler effect is to select the signal time duration such that (10) is satisfied for all expected target speeds. Another approach to overcome the Doppler effect is to use a bank of Doppler-matched filters for every signal. Each of the Doppler-matched filters is designed to match a different Doppler-shifted version of the signal. Target detection is based on the maximum output from the Doppler-matched filter bank. The Doppler shift frequencies and the number of the matched filters are chosen such that the signal loss is limited to a tolerable level (such as 3 dB) for all possible target speeds.

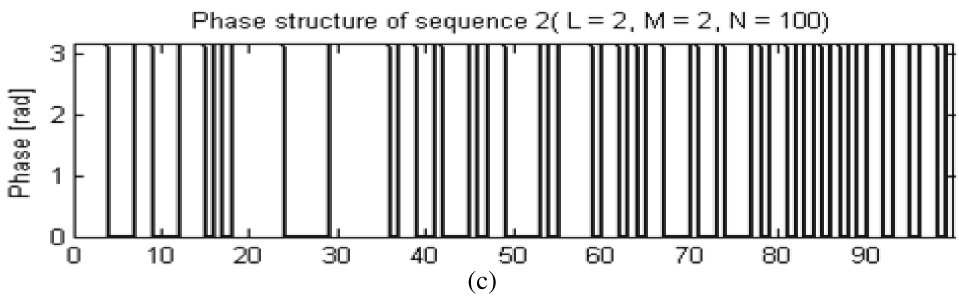
The effect of Doppler on cross ambiguity diagram for the binary sequences 1 and 2 is shown in Figure-8(e). The cross ambiguity function energy of the designed sequence set is uniformly distributed on surface of ambiguity diagram which indicates cross ambiguity diagram is very less sensitive to Doppler frequency shift.



(a)



(b)



(c)

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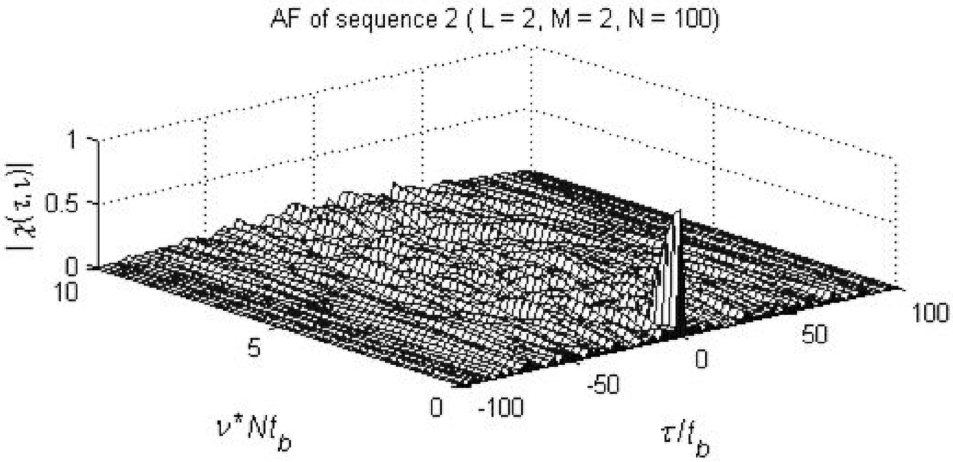
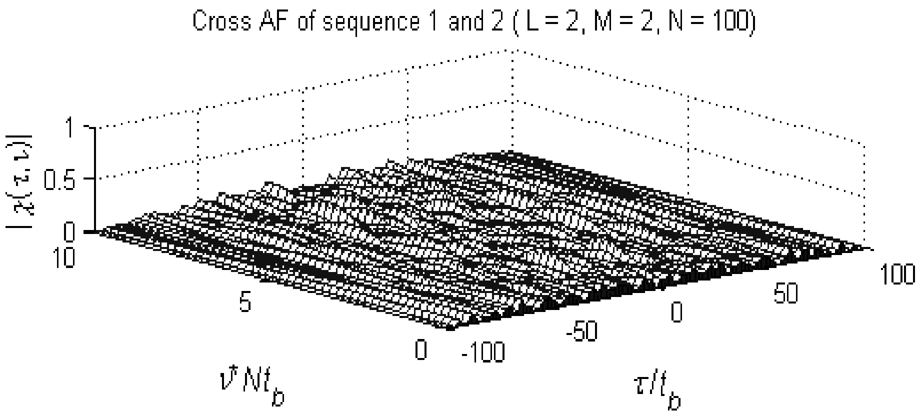


(d)



(e)

Figure-8. Normalized ambiguity function and cross ambiguity function for sequences set with L =2, M =2 and N =100 (a) Phase structure of sequence 1 (b) Ambiguity function of sequence 1 (c) Phase structure of sequence 2 (d) Ambiguity function of sequence 1 (e) Cross ambiguity function of sequence 1 and 2.

CONCLUSIONS

The objective of this paper is mainly to demonstrate the significance of the MPSO algorithm in the generation of binary 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 binary 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 effect of Doppler shift on designed sequences is also investigated using ambiguity and cross ambiguity functions. The proposed algorithm (MPSO) is better than existing algorithms like Genetic Algorithm. Unlike Genetic Algorithms, in PSO, there is no cross-over operation which increases the speed and reduces complexity of the algorithm. As the sequences length increase, the genetic algorithm consumes more time.

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