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Polyphase Code Signal with Low Correlation

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ABSTRACT

Now a days, most of the research is carried on multiple input multiple output radar system which comprise multiple transmitting and receiving antennas to transmit and receive multiple wave forms simultaneously. In multiple input multiple output, generating pulse sequences for different antennas without interference among them is a major challenging task and at the same time imparting more noise tolerance and doppler resilience to these codes is even harder task to be met, for which researchers starting from Hai Deng are thriving for all these days. These challenges motivated us for the research to find meaningful solutions, using polyphase codes for multiple input multiple output radar applications. Recently, most optimization researches of polyphase codes are carried using Artificial Intelligence techniques like genetic algorithm, simulated annealing, which require more parameters for optimization.

I. INTRODUCTION

When a single transmitting and receiving antenna is used, signals are degraded due to multipath propagation, which in turn lowers the link capability and reliability of the system. And in 1990, Multiple Input Multiple Output (MIMO) system was introduced to provide spatial diversity and spatial multiplexing and antenna beam formation, by which link performance and efficacy and total coverage range can be improved.Multiple Input Multiple Output (MIMO) systems finds an appropriate use to enhance the spatial resolution and to offer a substantially increased immunity against interference. MIMO comprises multiple antennas in which each transmit and receive antennas simultaneously radiates and receives an arbitrary waveform independent of the other antennas. Field antenna with transmitters N and receivers K are mathematically expressed in a K*N virtual field within increased virtual aperture size. Orthogonality of the transmitted waveform is required to allow waveform separation at the receiving end [1,2].

The MIMO are classified as Mono-Static, Bi-Static and Multistatic models based on the spacing between the locations of their antennas. Most commonly used radar systems are monostatic, in which a single antenna performs the task of transmitter and receiver based on time multiplexed fashion. Both the antennas are co-located. Bistatic systems comprise one transmitter and receiver antenna that is separated significantly. Multistatic system consists of two or more transmitter or receiver antennas partitioned by long distances than that of antenna sizes [3,4].The following relations are used to define a 2*2 MIMO radar. A MIMO system with 2 × 2 model is shown in Fig.1.

$$R_1 = H_{11}T_1 + H_{21}T_2 \quad (1)$$

$$R_2 = H_{12}T_1 + H_{22}T_2 \quad (2)$$

Where, H_{ij} is Channel Information

R_1 is signals received at antennas 1

R_2 is signals received at antennas 2

T_1& T_2 are data stream

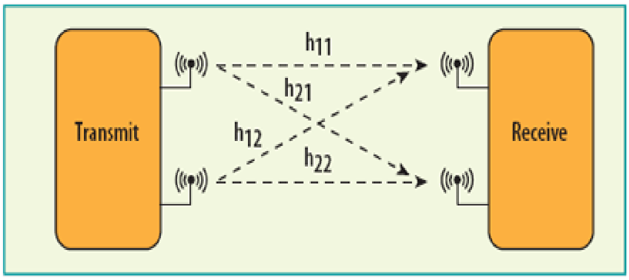

Figure 1: MIMO systems with 2 × 2 model

Single-input single-output (SISO) system consists single transmit and single receive antenna. Although it is simple, it does not require additional processing and diversity. However, interference and fading limit its performance. Single-input multiple-output (SIMO) system has single transmit and multiple receive antennas .The multiple receive antennas support to get a stronger signal through diversity. These systems require most of the processing at the receiver and also termed as receive diversity. Multiple-input single-output (MISO) system comprises of multiple transmit antennas and single receive antenna. The receiver processing is shifting to transmitter side so it requires less complex receiver processing. It has positive impact on size, cost, and battery consumption and also termed as transmit diversity. MIMO system employs the number of antennas used at the transmitter as well as the receiver. Different antenna arrangements of SISO, SIMO, MISO, MIMO is shown in figure 1. MIMO is used to provide improvements in both channel robustness as well as channel capacity which is unable to achieve from MISO and SIMO systems [5].

MIMO improving spatial resolution, providing a considerably enhanced immunity to interference, provide antenna diversity, spatial multiplexing [6, 7].The basic idea behind antenna diversity is to transmit the same information over many independent fading paths and then combine these paths in such a way to reduce the fading of the resultant signal, thereby improving the error rate performance. In other words, the signal with its multiple copies are transmitted to achieve the benefit from multiple independent fading paths which assure that all the links will not go in deep fade simultaneously. Thus, the possibility of obtaining reliable data from receiver increases significantly. Diversity offers a number of replicas of a transmitted signal over time, frequency or space [8,9]. Time Diversity is same data is repeatedly transmitted to the same channel at different times [10]. Frequency Diversity is the same data is repeatedly transmitted to the same channel at different frequency bands. Spatial Diversity is a number of antennas are separated by approximately $\lambda/2$ distance to implement independent fading channels [11].

II. OPTIMIZATION TECHNIQUES

An Optimization technique finds the maximum or minimum functions in feasible region .The improvised strategies in the optimization methods are valuable in determining the suitable ideal solution for constrained or unconstrained of continuous and discrete functions. The enhancement of optimization techniques are characterize into two kinds. They are Non Evolutionary Computation (NEC) and Evolutionary Computation (EC). Non Evolutionary Computation (NEC) categorized into Simulated Annealing Algorithm (SAA), Hill Climbing Algorithm (HCA), Taboo Search Algorithm (TSA), Evolutionary Computation (EC) categorized into Evolutionary Algorithm such as Genetic Algorithm, Differential Evolution and Swarm intelligence. The classification of the Optimization technique is given below.

Simulated Annealing Algorithm (SAA) technique is used for the purpose of heating and controlling the cooling nature of material which helps to increase the crystal size and minimizes the defects. The presence of heat results in the motion of atoms randomly across high energy states. Slow cooling gives the lower internal energy configurations than the initial one. The main advantages of this algorithm are high quality performance, robust and easy of realization and the biggest drawback relies on the long time duration of optimization process [12, 13, 14, 15]. Climbing Algorithm (HCA) is a graph search algorithm in which an extension of current path with a successor node is performed and is found to be nearer to the solution than the current path end. The first nearest node is chosen in simple hill climbing whereas in steepest ascent hill

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climbing all successors nodes are compared and the nodes that are nearer or closer to the solution are considered. Failure occurs when closer node are not found. This problem arises due to the local maxima in the search space. The current node records the state and the value of objective function since this algorithm does not maintain a search tree.

It is very fast, for certain problems. Then the disadvantages of this algorithm are foothill trap occurs when local maxima found, Ridge trap occurs when several adjoining nodes have higher values than surrounding nodes, Plateau trap occurs when all neighboring nodes have the same values. If there are multiple peaks, hill climbing gets stuck at all peaks known as local maxima. Taboo Search Algorithm (TSA), a stochastic global optimization method developed by Glover for performing a large combinational optimization tasks. The move and neighborhood concepts are common to most of the heuristic and algorithmic procedures. TSA is a strong local search ability of the global iterative optimization algorithm. The deficiency depends on the initial solution and serial iterative search process [16,17,18,19,20].

Genetic Algorithm (GA), a search technique mainly determines the approximate solutions in search space. It is a local search technique and consists of several evolutionary algorithms. Advantages of Genetic Algorithm are it can find fit solutions in a very less time .The random mutation guarantees to some extent that we see a wide range of solutions. Coding them is really easy compared to other algorithms which does the same job. This Algorithm is really hard and many parameters need to set [21,22].One of the traditional greedy optimization algorithms is the Hamming Scan Algorithm (HSA) that searches the neighborhood points in every directions to reduce the functional cost and offer faster convergence rate. The common difference that exists between GA and HAS is that GA possibly offer random multiple mutations of sequence elements. For example, consider two phase sequence sets {1, -1}, in which the value 1 is replaced with –1 and the fitness is evaluated. If the evaluated fitness value has improved when compared to the original sequence, then the newly computed fitness is accepted otherwise the original sequence is retained. This procedure is repeatedly performed for all the sequence elements.

Swarm intelligence further classified into Ant Colony (ACO) and Particle Swarm Optimization (PSO). ACO inspires the ant behavior and finds application in discrete optimization problems. Particle swarm optimization (PSO) concept is emerged as a simplified social simulation system. Particle Swarm Optimization (PSO) is one kind of the SI algorithm and is only a few decade old in the optimization domain. Particle swarm optimization (PSO) is a stochastic population based optimization technique developed by [23], inspired by social behavior of bird flocking or fish schooling. PSO being a stochastic algorithm exhibits several similarities to solve optimization problems. PSO essentially imitates the food foraging behaviour of social life. PSO possess advantages like easy implementation, adjusting few parameters than GA. PSO is successfully implemented in various areas and is initialized using a random population solution that updates the velocity and position to find the optimum solution [16,23].

An important source of search capability of PSO relies on the interaction between the member and the reactions to attain the goal. Based on PSO terminology each particle represents the swarm member. The word swarm comes from the irregular movement of the particle in the problem space. Every particle in the search space represents a potential solution. For a D-dimensional search space, the position and velocity of the i^{th} particle is

$$X_i = (x_{i1}, x_{i2}, \ldots x_{id}) \qquad (3)$$

$$V_i = (v_{i1}, v_{i2}, \ldots v_{id}) \qquad (4)$$

For a D-dimensional search space, the particle maintain its previous best position

$$P_i = (p_{i1}, p_{i2}, \ldots p_{id}) \qquad (5)$$

During search process, personal best (pBest) resembles the current position and self position of the particle. Global best (gBest) explores the information and the search space to determine the best particle.

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Random particles are initialized in PSO and searches for optima by updating velocity and position. The values of values pBest and gBest are updated in each iterations .The velocity and position is updated using the following equations.

$$v_{id}^{t+1} = wv_{id}^{t} + c_1 r_1 (p_{id}^{t} - x_{id}^{t}) + c_2 r_2 (p_{id}^{t} - x_{id}^{t}) \quad (6)$$

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1} \quad (7)$$

Where v_{id}^{t+1} v_{id}^{t} , p_{id}^{t} and p_{gd}^{t} is the velocity, position vector, personal best position and global best position of particle i in dimension d at time t. C_1 and C_2 are Learning factors.If C_1= C_2 =0, particle are considered to be flying with initial velocity until they reach the final value. if C_1> 0 and C_2=0 denotes an independent particles , if C_1=0 and C_2>0 , single point attracts the swarm, i.e gBest. w is the Inertia weight the large value of w facilitates a global search and small value facilitates a local search .so Inertia weight linearly decrease from 0.9 to 0.4. r_1 and r_2 are uniformly distributed with a random number between (0,1).The number of particles considered is dependent on application. 10 to 50 particles can be considered for simple application and 100 to 200 particles for complex problems.

III. RESULTS

Comparison of ASPs and CPs Values for Different Length of the Sequence.The average autocorrelation side lobe peaks (ASPs) and average cross-correlation peaks (CPs) are obtained by setting the Phase (M=4), Set size (L=3) and $\lambda = 0.9$ as constant and varying the length of the sequence (N=40 to 500) and inertia weight (w=0.9 to 0.4) respectively.

Table 1: Maximum ASPs and CPs values of polyphase codes for

(M=4 ,L=3,N= 40 to 500, $\lambda = 0.9$ and w=0.9 to 0.4) .

N	Max(ASPs) (PSO)	Max(CPs) (PSO)
40	0.070	0.093
45	0.066	0.085
50	0.061	0.083
60	0.061	0.073
70	0.055	0.070
85	0.050	0.063
100	0.048	0.058
135	0.043	0.050
150	0.042	0.049
175	0.038	0.044
200	0.036	0.041
225	0.034	0.039
250	0.031	0.037
265	0.031	0.036
280	0.030	0.035
300	0.028	0.034
355	0.027	0.031
380	0.027	0.029
400	0.025	0.028

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450	0.025	0.027
475	0.025	0.026
500	0.024	0.025
Average	ASPs=0.039	CPs=0.048

From the table 1 it is revealed that the maximum autocorrelation side lobe peaks (ASPs) and maximum cross-correlation peaks (CPs) for PSO tends to decrease as the length of the sequence (N) increases and the average ASPs and CPs is found to be 0.039 and 0.048 respectively. As the target identification is given prior importance than that of interference between the adjacent transmitted signals, more weightage and concern is given to the auto correlation function. i.e. λ =0.9.

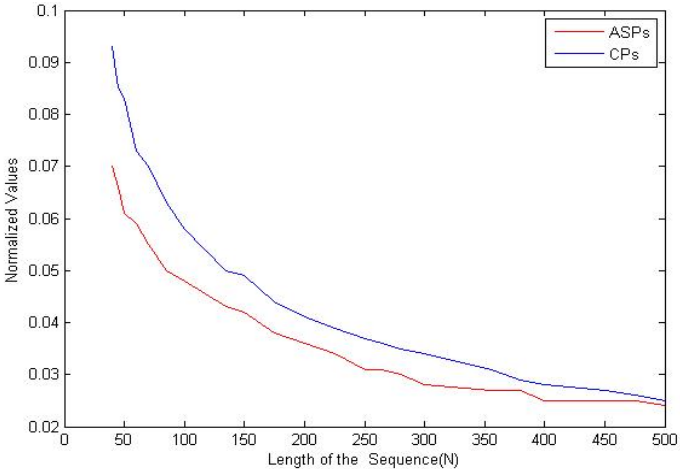

Figure 2: Comparison of maximum ASPs and CPs values of polyphase sequences at $\lambda = 0.9$.

Fig. 2. shows the plots of normalized ASPs and CPs values with respect to the length of the sequence (N).It is predicted that initially, the normalized values of ASPs and CPs values is maximum 0.070 and 0.093 for N=40. As the value of N increases, the normalized values decrease and reaches a minimum value of 0.024 and 0.025 respectively for N=500. It is also noted that CPs exhibits higher values when compared to ASPs for increasing N

The maximum values of ASPs and CPs is further predicted by keeping the constant values M=4, L=3, $\lambda = 1.2$ and varying the N= 40 to 500 and w=0.9 to 0.4 respectively and the obtained results are tabulated.

Table 2: Maximum ASPs and CPs values of polyphase codes for (M=4, L=3, N= 40 to 500, $\lambda = 1.2$ and w=0.9 to 0.4) .

N	Max(ASPs) (PSO)	Max(CPs) (PSO)
40	0.095	0.063
45	0.087	0.063
50	0.081	0.062
60	0.075	0.061
70	0.070	0.057
85	0.063	0.057
100	0.058	0.053
135	0.051	0.050
150	0.048	0.050
175	0.045	0.041
200	0.040	0.040
225	0.037	0.036

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250	0.036	0.035
265	0.035	0.031
280	0.034	0.030
300	0.031	0.029
355	0.029	0.028
380	0.029	0.027
400	0.027	0.026
450	0.027	0.025
475	0.026	0.023
500	0.025	0.023
Average	ASPs=0.047	CPs=0.041

From the above table 2, it is showed that the ASPs and CPs values decreases with increase in the value of N and the average value of ASPs and CPs is said to be 0.047 and 0.041 respectively. In alternative to the above table 1, here more weightage is given to the autocorrelation factor (λ =1.2) because the prior importance is provided to the interference between adjacent transmitted signals when compared to target identification.

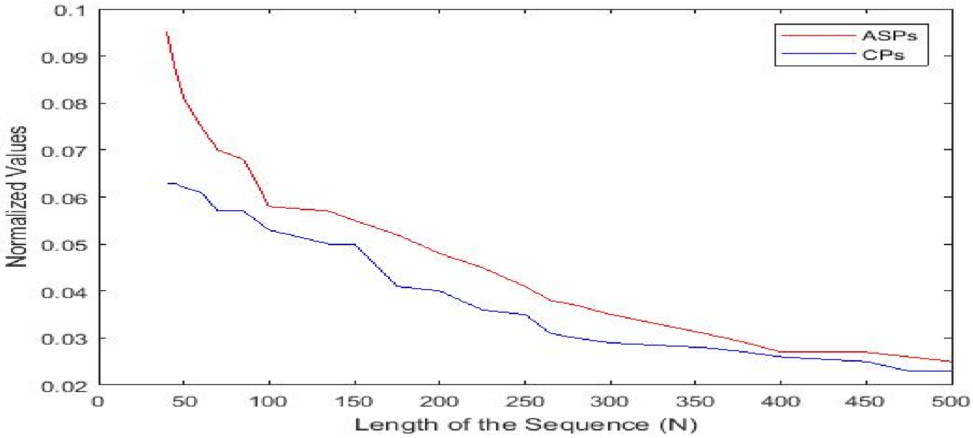

Figure 3: Comparison of maximum ASPs and CPs values of polyphase sequences at $\lambda = 1.2$.

Fig. 3 depicts the variation of normalized values depending on length of the sequence and Inertia weight .Here, it is known that the normalized values of ASPs and CPs decreases with increase in the sequence length (N=40 to 500). The maximum value of ASPs and CPs is known to be 0.095 and 0.063 for N=40. Whereas the minimum value is predicted as 0.025 and 0.024 respectively. In addition to this, it noted that for λ =1.2, the ASPs offer high value than CPs value.

IV. CONCLUSION

An efficient global optimization technique using particle swarm optimization algorithm is developed to design the optimal polyphase sequences with low autocorrelation peaks (ASPs) and low cross-correlation peaks (CPs) . The particle swarm optimization algorithm produces a decrement of 13.73 % in the average ASPs and 11.81 % decrement in CPs when compared with the standard literature values.

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