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Polyphase Code Signal with minimum Autocorrelation and Correlation

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Abstract
This paper aims primarily to design a complete sequence set with low Auto-correlation Side-lobe and low Cross-correlation tops for MIMO Radar. A new set of polyphase sequences was introduced with good relational properties. This sequence is built using numerical development based on link structures. The structure of the structure is set in a well-formed polyphase sequence. Particle swarm optimization (PSO) method is used to increase consistency. The correlation results are compared to the normal data domain and are shown to be better.
Keyword: Auto-correlation side lobe peaks(ASPs),Cross-correlation side lobe peaks(CPs), Particle Swarm Optimization (PSO), Simulated Annealing Algorithm (SAA), Hill Climbing Algorithm (HCA), Taboo Search Algorithm (TSA),

1. Introduction

Nowadays, a lot of research is being done with a multi-output radar system that includes transmitting and receiving antennas to transmit and receive multiple waveforms simultaneously. In the installation of many outputs, producing pulse sequences of different horns without interference between them is a major task and at the same time providing sound tolerance and doppler strength in these codes is the most difficult task to meet, when researchers move from Hai. Deng is doing well all these days. These challenges have prompted the research to find practical solutions, using polyphase coding inputs for many outgoing radar applications. Recently, much of the development of polyphase codec research has been done using Artificial Intelligence intelligence techniques such as genetic algorithm, mimic annealing, which requires additional parameters in order to be fully utilized.

When using a single transmitter and receiver, signals are damaged due to multiple transmission, which in turn reduces the ability to connect and the system reliability. Also in 1990, the Multiple Output System (MIMO) system was introduced to provide spatial variability as well as local frequency and antenna structure, with which to improve efficiency and effectiveness as well as the full range of integration. appropriate use to improve spatial adjustment and to provide increased protection against disturbances. MIMO contains multiple antennas where each transmits and receives horns simultaneously emitting radiation and receiving an unusual waveform other than the other antennas. A field antenna with N transmitters and K receivers is mathematically displayed in the visible K * N area within the expanded optical opening size. Orthogonality of the transmitted waveform is required to allow for waveform separation at the receiving end [1,2].

MIMO is categorized as Mono-Static, Bi-Static and Multistatic models based on the space between the areas of its horns. Radar systems are widely used by monostatic, in which one says it performs the function of sending a transmitter and receiver based on a double-digit fashion. Both antennas are mounted together. Bistatic systems consist of a single transmitter and a highly differentiated receiving receiver. The Multistatic system consists of two or more transmitting antennas or receivers spaced longer than the horn sizes [3,4]. The following relationships are used to define radar 2 * 2 MIMO.A MIMO system with 2 × 2 model is shown in Fig.1.

$$R_1 = h_{11} T_1 + h_{21} T_2 \tag{1}$$

$$R_2 = h_{12} T_1 + h_{22} T_2 \tag{2}$$

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

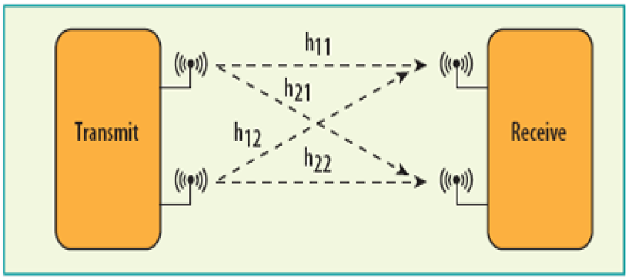

Figure 1: MIMO systems with 2 × 2 model

The single-output single-output system (SISO) consists of a single transmit and a single receiver. Although simple, it does not require further processing and variation. However, distraction and blurring reduce its effectiveness. The single-input system (SIMO) has single transmissions and multiple reception horns .Many receive the support of the horns to receive a powerful signal for a variety of purposes. These systems require a lot of processing on the receiver and are also referred to as acceptance variants. The Multiple-input single-output system (MISO) incorporates multiple transmission horns and a single reception. Recipient processing changes to the sender side and therefore requires complex recipient processing. It has a positive effect on the size, cost, and usage of the battery and is also referred to as transmission variability. The MIMO system uses a number of horns used on the transmitter and receiver. The different configurations of SISO, SIMO, MISO, MIMO horns are shown in Figure 1. MIMO is used to provide improvements in both channel strength and channel capacity that can be achieved in MISO and SIMO systems [5].
MIMO promotes spatial adjustment, provides the most advanced protection against distortion, provides horn separation, spatial repetition [6,7]. how to reduce the resulting signal dullness, thereby improving the performance of the error rate. In other words, a signal with multiple copies of it is transmitted for profit over multiple blurred independent tracks which ensures that all links will not sink to the same depth at the same time. Thus, the chances of getting reliable data from the recipient are very high. Variability provides the number of signal signals transmitted over time, frequency or space [8,9]. Time Differences The same data is repeatedly transmitted to the same channel at

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different times [10]. Frequency Diversity data is repeatedly transmitted on the same channel to different frequency bands. Spatial Diversity is the number of horns separated by the distance λ / 2 for the use of diminished independent channels [11].

2. Optimization Techniques

The Development Approach determines the number of jobs or the minimum number of jobs in a viable area .Developed development strategies are essential in determining the appropriate solution for delayed and unrestricted and varied activities. Development of improvement strategies is divided into two types. They are Non Evolutionary Computation (NEC) and Evolutionary Computation (EC). Non Evolutionary Computation (NEC) is divided into Simulated Annealing Algorithm (SAA), Hill Climbing Algorithm (HCA), Taboo Search Algorithm (TSA), Evolutionary Computation (EC) divided into Evolutionary Algorithm as Genetic Algorithm, Differential Evolution and and Swarm intelligence. A breakdown of the development method is given below

The Simulated Annealing Algorithm (SAA) strategy is used for the purpose of heating and controlling the cooling environment of objects that help increase crystal size and reduce errors. The presence of heat causes random atomic movements in all high-energy conditions. Slow cooling provides a lower internal power setting than the original. The main advantages of this algorithm are high quality, robust and easy to achieve and large turnaround depends on the longevity of the development process [12,13,14,15]. Hill Climbing Algorithm (HCA) is a graph search algorithm. where an extension of the current method with a follower node and is found to be closer to the solution than to the end of the current method. The first adjacent node is selected for the simple ascent while at the ascent of the ascent all consecutive nodes are compared and the adjacent or adjacent areas of the solution are considered. Failure occurs when the nearest location is not available. This problem arises because of the size of the area in the search area. The current node records the status and value of the target function as this algorithm does not save the search tree.

It's too fast, for some problems. Then the disadvantage of this process is that the foothill trap occurs when the size of the area is found, Ridge trap occurs when several connected nodes have higher values than the surrounding nodes, Plateau trap occurs when all neighboring nodes have the same values. When there are many peaks, the climbs are trapped on all the peaks known as the local maxima. Taboo Search Algorithm (TSA), a global stochastic optimization system developed by Glover to perform large integration tasks. Movement and neighborly concepts are common to many heuristic and algorithmic processes. The TSA is a robust search engine based on a global optimization algorithm. Deficiency depends on the initial solution and the serial iterative search process [16,17,18,19,20].

Genetic Algorithm (GA), the search method determines mainly the closest solutions in the search area. It is a local search method and contains several evolutionary algorithms. The advantages of Genetic Algorithm is that it can find the right solutions in the shortest possible time .The random modification ensures to some extent that we see many different solutions. Coding is really easy compared to other algorithms that do the same job. This Algorithm is really complex and many parameters need to be set [21,25,26]. . A common difference that exists between GA and HAS is that GA may offer many random conversions. For example, consider two sets of consecutive clauses {1, -1}, in which 1 value is substituted -1 and eligibility is assessed. If the updated qualification value has improved compared to the original sequence, a new computer-generated qualification is accepted otherwise the actual sequence is retained. This process is repeated for all sequence elements.

Swarm intelligence is further divided into Ant Colony (ACO) and Particle Swarm Optimization (PSO). ACO promotes ant behavior and finds application in various performance problems. The concept of Particle swarm optimization (PSO) has emerged as a simple social simulation program. Particle Swarm Optimization (PSO) is a single SI algorithm and is only ten years old in the development domain. Particle swarm optimization (PSO) is a demographic-based development technique developed by [27], which promotes community behavior of bird populations or fish learning. PSO is a stochastic algorithm that shows several similarities to solve development problems. The PSO actually mimics the dietary lifestyle of the community. PSO has advantages such as ease of use, adjusting a few parameters than GA. PSO is successfully used in a variety of areas and is initiated using a random human solution that updates the speed and condition of finding the best solution [16,23].

An important source of PSO search power depends on the interaction between the member and the response in order to achieve the goal. Based on PSO terms each particle represents a swarm member. The word wick comes from the unusual movement of particles in the problem area. All the particles in the search field represent a possible solution. With D-dimensional search space, location and ith particle speed

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

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

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

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

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.

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.

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

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1} \tag{7}$$

Where v_{id}^{t+1} v_{id}^{t} , p_{id}^{t} and p_{gd}^{t} There, and the previous and current speeds, the vector area, the best personal position and the world's leading particle size i to dimension d during 't'. C1 and c2 are learning elements .When c1 = c2 = 0, particles are considered a plane at first speed until they reach the final value. if c1> 0 and c2 = 0 show independent particles, if c1 = 0 and c2> 0, one point attracts a subset, i.e. gBest. w is the Inertia weight a large number of w supports global search and a small number facilitates local search .so the Inertia weight decreases by line from 0.9 to 0.4. r1 and r2 are distributed equally by a random number between (0,1) .The number of particles considered depends on its use. 10 to 50 particles can be considered as a simple application and 100 to 200 particles with complex problems.

3. Results

Comparison of ASPs with CPs of Differential Length of Sequences.At autocorrelation side lobe peaks (ASPs) and intermediate peak concentrations (CPs) are obtained by setting the Category (M = 4), Set size (L = 3) and 0.9 as fixed and changing the sequence length (N = 40 to 500) and the inertia weight (w = 0.9 to 0.4) respectively.

Table 1. Maximum ASPs & 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
450	0.025	0.027
475	0.025	0.026
500	0.024	0.025
Average	ASPs=0.039	CPs=0.048

From Table 1 it is revealed that the autocorrelation side lobe peaks (ASPs) and PSO peaks of the PSO tend to decrease as the sequence length (N) increases and the ASP and CPs ratio is found to be 0.039 and and 0.048 respectively. Since targeted identification is given priority rather than distortion between nearby transmitting signals, more weight and anxiety are given to the automatic integration function. namely = 0.9.

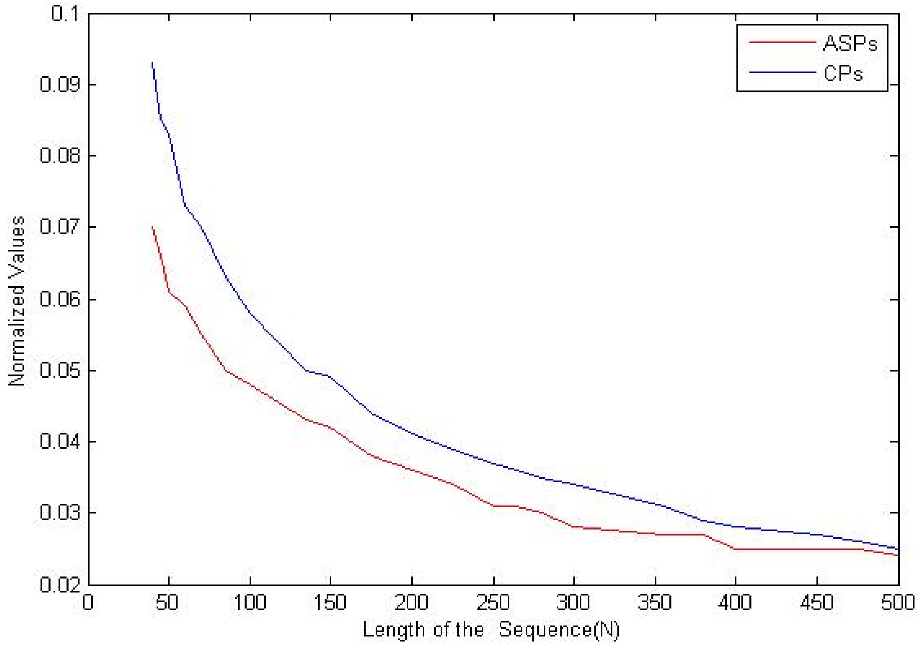

Fig. 1. Comparison of maximum ASPs & CPs values of polyphase sequences at $\lambda = 0.9$.

Figure 1 shows the values of ASP values and standard CPs relative to the sequence length (N) .It is predicted that initially, the average values of ASPs and CPs values are 0.070 and 0.093 in N = 40. As the N value increases, the standard values decrease and reach a minimum value of 0.024 and 0.025 respectively at N = 500. It is also noted that CPs show higher values compared to N-growth ASPs

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 & 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
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 Table 2 above, it is shown that the values of ASP and CPs decrease with the increase in N value and the average number of ASPs and CPs is 0.047 and 0.041 respectively. In contrast to the table above 1, here a lot of weight is given to the integration factor (= 1.2) because the initial value is given to the distortion between the closely transmitted signals compared to the intended identifier.

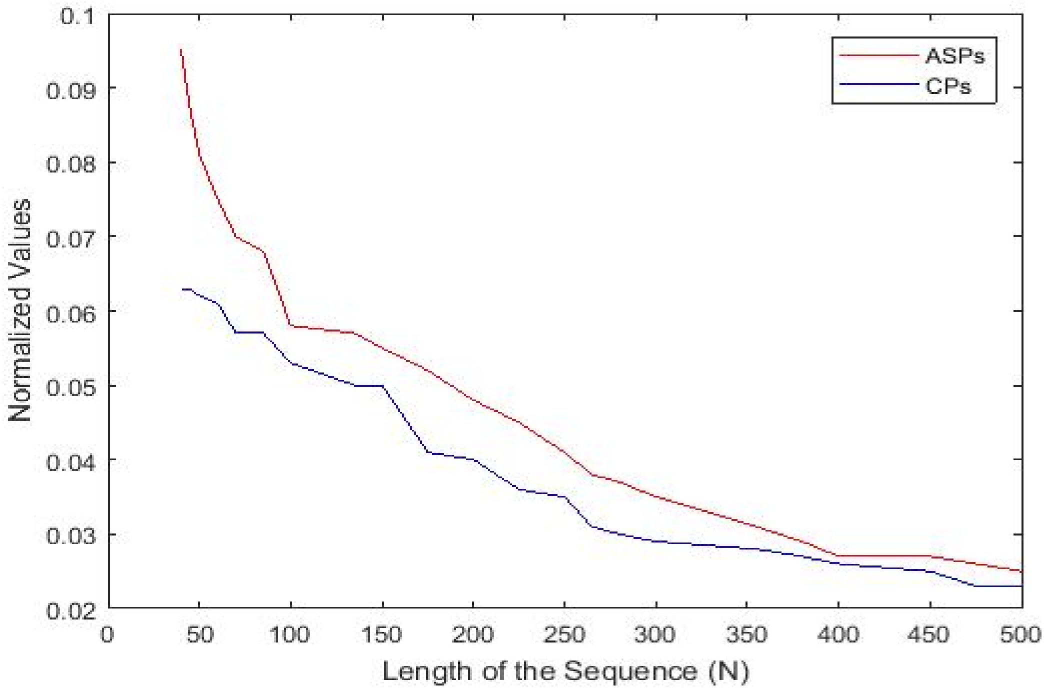

Fig. 2. Comparison of maximum ASPs & CPs values of polyphase sequences at $\lambda = 1.2$.

Figure 2 shows the variance in the standard values depending on the sequence length and the weight of the Inertia .Here, it is known that the average values of ASPs and CPs decrease with increasing sequence lengths (N = 40 to 500). The maximum number of ASPs and CPs is known as 0.095 and

0.063 at N = 40. Although a small number is predicted as 0.025 and 0.024 respectively. In addition to this, it was noted that at = 1.2, ASPs give a higher value than the number of CPs.

Table 3. Maximum ASPs values of polyphase codes for (M=4,L=3 , N= 40 to 500 , λ =0.9 and Fixed and Variable values of Inertia weight) using PSO.

N	Max(ASPs) Fixed values of w	Max(ASPs) Variable value of w
40	0.066	0.059
80	0.057	0.051
120	0.050	0.046
160	0.044	0.040
200	0.039	0.034
240	0.036	0.030
280	0.034	0.029
320	0.033	0.026
360	0.029	0.021
400	0.028	0.014
440	0.027	0.011
500	0.025	0.001
Average	ASPs=0.039	ASPs=0.030

In the fixed and variable values of w and N = 40 to 500, the highest ASP values are found to be 0.066 and 0.059, while the low values are known as 0.025 and 0.001 respectively of N = 500. This further checks that ASPs provide higher values of fixed values than the variable w values and the average number of ASPs known as 0.039 and 0.030.

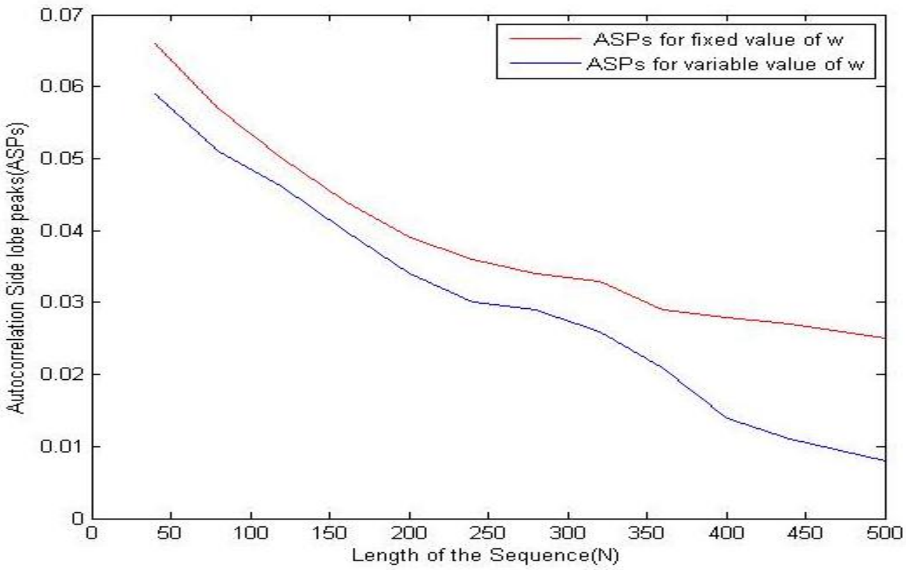

Fig. 3. Comparison of maximum ASPs value with fixed and variable values of inertia weight (w).

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Table 4. Maximum CPs values of polyphase codes for (M=4,L=3 , N= 40 to 500 , λ =0.9 and Fixed and Variable values of Inertia weight) using PSO.

N	Max(CPs) Fixed values of w	Max(CPs) Variable value of w
40	0.092	0.092
80	0.067	0.067
120	0.056	0.054
160	0.048	0.047
200	0.042	0.046
240	0.038	0.039
280	0.036	0.035
320	0.032	0.033
360	0.031	0.030
400	0.029	0.030
440	0.027	0.029
500	0.026	0.026
Average	CPs=0.043	CPs=0.044

In the case of CPs, the fixed and variable values of w, the maximum and minimum values are found to be 0.092 and 0.026 at N = 40 to 500 respectively. This re-evaluates that the CP provides higher fixed values compared to different w values and the average number of CPs known as 0.043 and 0.044. Variation in CPs values occurs based on sequence lengths and w values.

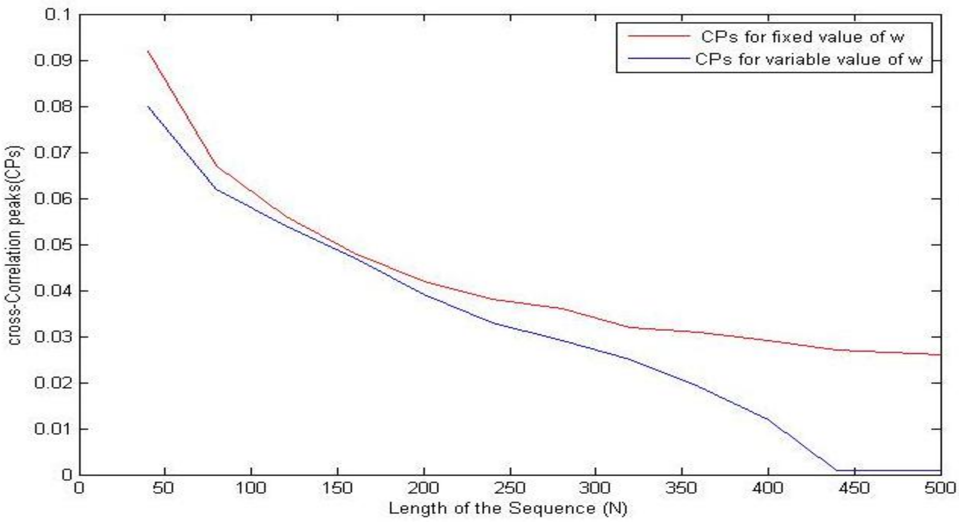

Fig. 4. Comparison of maximum CPs values with fixed and variable value of inertia weight (W).

Table 5. Maximum ASPs & CPs values of Polyphase sequence for (M=4,L=3, N= 40 to 16384, λ =0.9, w = 0.4 to 0.9) using PSO.

N	Max(ASPs)	Max(CPs)
2	0.500	0.569
4	0.166	0.288
8	0.157	0.220
16	0.119	0.150
32	0.076	0.101
64	0.061	0.074
128	0.044	0.049
256	0.037	0.036
512	0.025	0.026
1024	0.017	0.018
2048	0.0126	0.013
4096	0.0092	0.009
8192	0.064	0.006
16384	0.0045	0.004
AVG ASPs & CPs Values	0.092	0.111

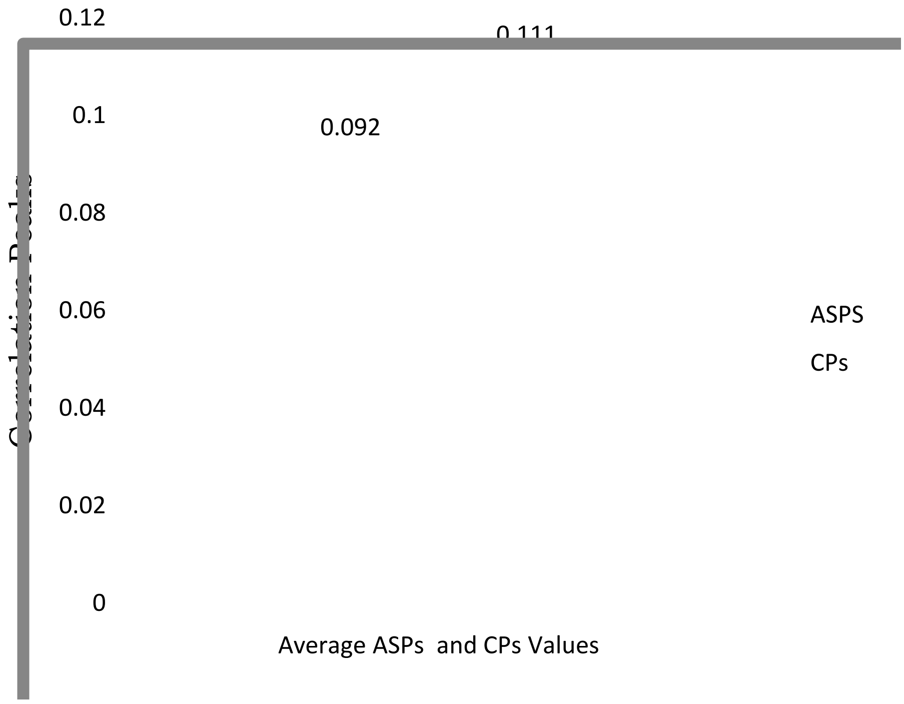

Fig. 5. Comparison of Average ASPs & CPs values of Polyphase sequence for N= 2 to 16384 at λ =0.9.

In this analysis the category value is set as M = 4, set the size as L = 3, and 0.9. The values of the ASPs and CPs are measured by varying the width of the N from 2 to 16384. Higher values of ASPs and CPs are recognized and average values are 0.092 and 0.111. Figure 5 shows the high values of the interaction between ASPs and CPs.

Table 6. Maximum ASPs & CPs values of Polyphase sequence for (M=4,L=3, N= 40 to 16384, λ =1.2, w = 0.4 to 0.9) using PSO.

N	Max(ASPs)	Max(CPs)
2	0.500	0.569
4	0.250	0.315
8	0.107	0.217
16	0.085	0.153
32	0.060	0.105
64	0.053	0.073
128	0.040	0.051
256	0.036	0.037
512	0.025	0.026

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1024	0.018	0.018
2048	0.012	0.013
4096	0.009	0.009
8192	0.0064	0.006
16384	0.0045	0.004
AVG ASPs & CPs Values	0.086	0.114

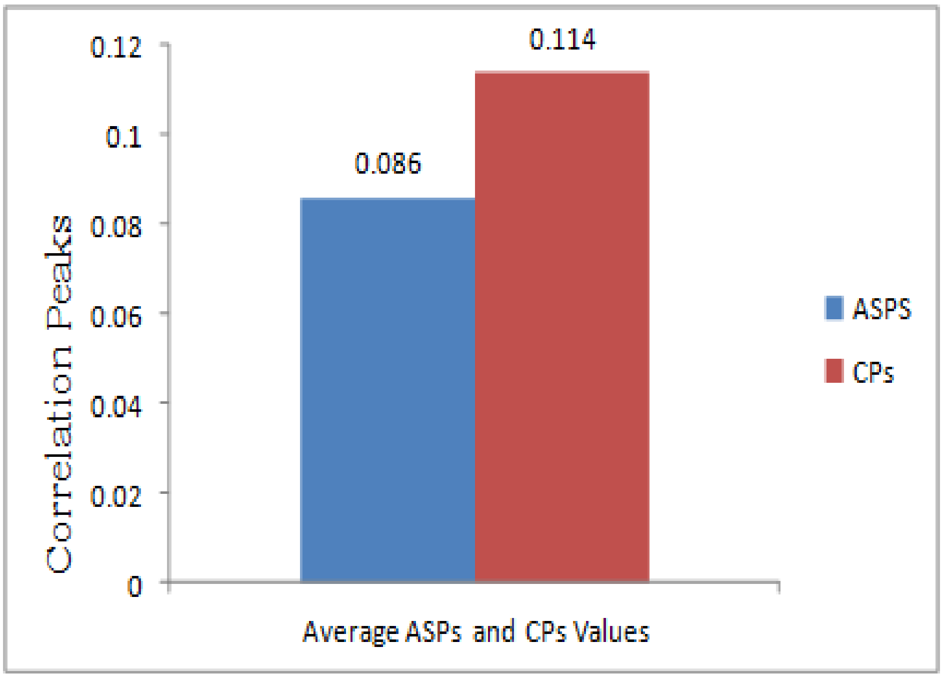

Fig. 6. Comparison of Average ASPs & CPs values of Polyphase sequence for N= 2 to 16384 at λ =1.2.

Higher ASP and CP values are noted and average values of ASPs and CPs are 0.086 and 0.114. Figure 6 shows the high values of the correlation between ASPs and CPs with respect to variance in sequence lengths.

4. Conclusion

An effective international method of development using a particle swarm optimization algorithm is developed to design complete polyphase sequences with low autocorrelation peaks (ASPs) and low integration peaks (CPs). The particle swarm optimization algorithm produces a 13.73% decrease in intermediate ASPs and a 11.81% decrease in CPs compared to standard textbooks.

Reference

[1]. Hongbo Sun, Frederic Brigui, and Marc Lesturgie, “Analysis and Comparison of MIMO Radar Waveforms,” International Radar Conference, 2014, pp. 1 – 6.

[2]. Caicai Gao, Kah Chan Teh, and Aifei Liu, “Piecewise Nonlinear Frequency Modulation Waveform for MIMO Radar,” IEEE Journal of Selected Topics in Signal Processing, Vol.11, No.2, 2017, pp. 379 – 390.

[3]. B. Friedlander, “On the relationship between MIMO and SIMO radars,” IEEE Transaction on Signal Processing, Vol.57, No.1, 2009, pp.394–398.

[4]. V.Tarokh, H.Jafarkhani, and A.R.Calder bank, "Space-time block coding for wireless communications: performance results," IEEE Journal on selected areas in communications, Vol.17, 1999, pp.451-460.

[5]. Dr.J.Pandu and Dr. N.Murali Krishna , “Precise and Robust Iris Segmentation in Specular Noisy Iris Images for Iris Biometrics,” International Journal of Future Generation Communication and Networking ,Vol.14,No.1, pp.84-98, Feb,2021.

[6]. Dr.J.Pandu and Dr. N.Murali Krishna , “Dector Signal Design for MIMO Radar ,” International Journal of Future Generation Communication and Networking ,Vol.13,No.4, pp.4461-4472, Dec,2020.

[7]. Dr.J.Pandu and Dr. N.Murali Krishna , “Optimal Polyphase Coded Signal Design,” International Journal of Recent Technology and Engineering (IJRTE),Vol.8,No.4, pp.9372-9376, November,2019.

[8]. J.Pandu and Dr. C.D.Naidu, “Optimal Sequence for MIMO Radar,” International Journal of Engineering Research and Development, Vol .13, No.13, pp. 24-32, December, 2017.

[9]. J.Pandu, Dr.C.D.Naidu and Dr. N.Balaji, “Six Phase Optimal Sequence Design for MIMO Radar ”, Global Journal of Researches in Engineering, Vol .17 ,No.3, pp 55-61 , June, 2017.

[10]. J.Pandu, Dr.C.D.Naidu and Dr. N.Balaji, “Eight Phase Optimal Sequence Design for MIMO Radar Using PSO”, International Journal of Advances in Engineering Research, Vol .13 ,No.5, pp 64-74 , May, 2017.

[11]. Dr. R. Murali Prasad, and Mr.J.Pandu “ FPGA Implementation of Electronic Warfare Threat Simulator” International Journal of Research in Technology and Management (IJRTM),Vol.2,No.5,July,2016.

[12]. Dr. R. Murali Prasd , and Mr.J.Pandu “FPGA Implementation of High Speed Radar Signal Processing” Global Journal of Researches in Engineering,Vol.16,No.1,2016.

[13]. J.Pandu, Dr. N.Balaji, and Dr.C.D.Naidu “FPGA based Solution for the Identification of RADAR Pulse Sequences for Defense Applications ”, Global Journal of Researches in Engineering, Vol .14 ,No.2, pp 17-24 , February, 2014.

[14]. A.Paulraj, R.Nabar, and D.Gore, “Introduction to space-time wireless communications,” Cambridge university press, 2003.

[15]. J.Ventura-Traveset, G.Caire, E.Biglieri, and G.Taricco, "Impact of diversity reception on fading channels with coded modulation-part-I: Coherent detection ," IEEE Transactions on Communications, Vol.45, 1997, pp.563-572.

[16]. V.Tarokh, N.Seshadri, and A.R.Calderbank, "Space-time codes for high data rate wireless communication: Performance criterion and code construction ," IEEE Transactions on Information theory, Vol.44, No.2, 1998, pp.744-765.

[17]. A.De Maio, M.Lops, and L.Venturino, “Diversity-integration trade-offsin MIMO detection,” IEEE Transaction on Signal Processing, Vol.56, No.10, 2008, pp. 5051–5061.

[18]. V.Cerny, “A thermodynamically approach to the travelling salesman problem: An efficient simulation algorithm ,” Journal of Optimization Theory and Applications, Vol.45, No.1, 1985, pp. 41-51.

[19]. M.Pincus, “A Monte Carlo method for the approximate solution of certain types of constrained optimization problems”, Operations Research, Vol.18, No.6, 1970, pp.1225-1228.

[20]. G.Plateau, and M.Elkihel, “A hybrid algorithm for the 0-1 knapsack problem”, Methods of Operation Research, Vol.49, 1985, pp.277–293.

[21]. Jing Zhang, “Comparative Study of Several Intelligent Algorithms for Knapsack Problem,” Procedia Environmental Sciences, Vol.11, 2011, pp. 163 – 168.

[22]. F.Glover, “Future paths for integer programming and links to artificial intelligence,” Computers and Operations Research, Vol.13,No.5, 1986,pp. 533 -549.

[23]. K.A.De Jong, “Genetic algorithms are not function optimizers, “Foundations of Genetic Algorithms, Vol.2, 1992, pp.5 –17.

[24]. S.Forrest, “Genetic algorithms: Principles of natural selection applied to computation,” Vol.61, No.5, 1993, pp. 872-878.

[25]. J.Kennedy and R.Eberhart, “Particle Swarm Optimization,” Proceedings of the IEEE International Conference on Neural Networks, 1995, pp.1942-1948.

[26]. Jing Zhang, “Comparative Study of Several Intelligent Algorithms for Knapsack Problem,” Procedia Environmental Sciences, Vol.11, 2011, pp. 163 – 168.

[27]. M.Dorigo, V.Maniezzo, and A.Colomi, “The ant system Optimization by a colony of cooperation agents,” IEEE Transactions on Systems, Man, and Cybernetics Part B, Vol.26, No.1, pp. 29-41.

ISSN: 2233-7857 IJFGCN