Optimization of Orthogonal Polyphase Coded Waveform for Mimo Radar using Mo-Micro Particle Swarm Optimization Algorithm

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Abstract: **A novel modified optimization technique kenned as the multi-objective micro particle swarm optimization (MO-MicPSO) which is proposed for polyphase coded signal design. The proposed MO-MicPSO requires a minuscule population size when compared with the standard particle swarm optimization that utilizes more immensely colossal population size. This incipient method is guided by an elite archive to culminate the multi-objective optimization. The orthogonal polyphase coded signal (OPCS) can fundamentally ameliorate the multiple input multiple output (MIMO) radar system performance, with which the radar system has high resolution and abundant signal channels. Simulation results on the polyphase coded signal design show that the MO-MicPSO can perform quite well for this high-dimensional multi-objective optimized quandary. When compared with particle swarm optimization or genetic algorithm, the proposed MO-MicPSO has more preponderant optimized efficiency and will consume less time.**

Using multiple antennas at both transmitter and receiver to ameliorate communication performance is referred to as multi-input multi-output (MIMO) system. In this paper an incipient approach utilizing evolutionary algorithm micro-MO particle swarm optimization (PSO) to design polyphase coded signal is proposed. These methods have desirable autocorrelation and cross correlation characteristics for orthogonal MIMO radars.

Keywords: Poly phase, MIMO radars, and evolutionary algorithms.

1. INTRODUCTION

A variety of waveforms have been used for radars till date. Several properties of radar waveforms are discussed in [2], [3], [4]. Radar waveforms are application specific. The performance of radar depends on the properties of the waveform chosen. An un-modulated or modulated continuous signal is used in continuous wave (CW) radar. Such a system can detect targets using Doppler offset, but range measurements become difficult. Since the radar transmits continuous waves, the need for secondary antenna for reception arises which is considered as another short coming of such a system. Pulsed radar transmits signals at regular time intervals. Unlike the CW radar, pulsed radars could give range measurements. But the selection of pulse width is a compromise between the required resolution of the system and the maximum detectable range. Various characteristics of a radar system such as the accuracy, resolution, range, range Doppler ambiguity etc. are decided by the radar waveforms. Thus the choice of radar waveform decides the performance of the system. For example, the shorter the pulse width of the pulsed radar, the more accurate resolution the system has. But at the same time, short pulse cannot support a good detection range. These issues were solved by the technique of Pulse Compression. Pulse compression shares the idea of transmitting a long pulse with some modulation embedded which spreads the energy over the bandwidth necessary for the required resolution. Pulse compressed waveforms have larger time bandwidth (BT) product compared to uncompressed pulses whose BT=1.The technique of pulse compression in waveforms is employed either in the form of Frequency coding or Phase coding. This gives rise to following waveforms. An LFM signal is a frequency modulated waveform whose carrier frequency varies linearly with time, over a specific period. This is one of the oldest and frequently used waveforms. It finds application in CW and pulsed radars. Since an LFM waveform is a constant amplitude waveform, it makes sure that the amplifier works efficiently. Also, this waveform spreads the energy widely in frequency domain.

Here, the carrier frequency of the waveform is varied according to any non-linear law over time. The variation can be symmetrical or asymmetrical over time. Some of the nonlinear frequency modulations can be summed up as quadratic.

A variation of the discrete FM uses N contiguous pulses with discrete frequency. This type of waveforms is known as Costas FM. This is similar to a frequency hopping system where the FM frequencies are chosen so that resulting waveform has a minimum sidelobe over the delay Doppler plane. Costas FM signals are generated using Welch construction or using some frequency hopping codes.

The pulse is divided into a number of subpulses of equal duration and the phase of each subpulse is varied according to a coded sequence. This can be broadly classified into binary and M phase coding. Following are various popular phase coded waveforms.

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1. In this technique, the phase of any subpulse takes any of the two values, either 0 or 180degrees, according to the sequence. Various types of binary codes with good autocorrelation properties are used in bi-phase coding. Some of the commonly used codes are Barker codes, Maximal length sequences.
Figure 1 demonstrates the binary phase coded waveform and the code sequence.

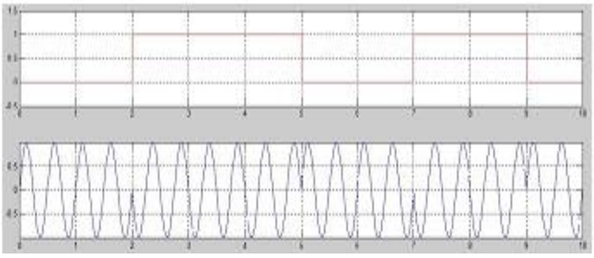

Fig. 1: Binary Phase coded waveform

2. In poly phase coding or M phase coding, the phase of the subpulse takes any of the M arbitrary values. Frank codes, polyphase Barker sequence, P codes, quadriphase-coded waveform are some of the commonly used sequences in Polyphase coding. The range side lobes for polyphase coded waveforms are lower than that of binary-coded waveform of same length, but the Doppler performance gets deteriorated.

2. LITERATURE SURVEY

Recent research in this field has been around the idea of transmission and reception of multiple signals, as in, Multiple Input Multiple Output (MIMO) radar as studied in [5]. MIMO radars differ from the phased array systems in the fact that each antenna transmits different waveforms while phased array uses weighted copies of a single waveform. Thus, MIMO radar comes with additional degrees of freedom as discussed in [6] and gives the experimental results promising enhanced performance [7]. MIMO radar comes in two configurations, with collocated antenna and widely distributed antenna. In MIMO radar with collocated antennas, transmit and receive antennas are placed close enough that they see the target alike.

Multi-Objective Optimization Utilizing NSGA-IINSGA (Non-Dominated Sorting in Genetic Algorithms) is a popular non-ascendance predicated genetic algorithm for multi-objective optimization. It is a very efficacious algorithm but has been generally reprehended for its computational intricacy, lack of elitism and for culling the optimal parameter value for sharing parameter share. A modified version, NSGA-II was developed, which has a more preponderant sorting algorithm, incorporates elitism and no sharing parameter needs to be culled a priori.

3. PROPOSED ALGORITHM

3.1 Orthogonal Polyphase Signal Design for MIMO

Consider that orthogonal polyphase code comprise L signals that each signal containing N subpulses represented by a complex number sequence, the signal set can be shown as follows:

$$S_1(t) = e^{j\varphi_l(n)}, n = 1,2,\dots.N, l = 1,2,..L \quad \dots\dots.(1)$$

Where $\varphi_l(n), (0 \leq \varphi_l(n) \leq 2\pi)$ is the phase of subpulse n of signal L in the signal set.
Assume a polyphase code set s with code length of N, set size of L, one can concisely represent the phase values of s with the following L×N phase matrix:

$$s(L,N)= \begin{matrix} \varphi_1(1) & \varphi_1(2)\dots. & \varphi_1(n) \\ \varphi_2(1) & \varphi_2(2)\dots.. & \varphi_2(n) \\ \varphi_L(1) & \varphi_L(2) \;\dots. & \varphi_L(n) \end{matrix} \quad \dots\dots.(2)$$

where the phase sequence in row l (1≤ l ≤ L) is the polyphase sequence of signal l, and all the elements in the matrix can only be chosen from the phase set in (2).From the autocorrelation and cross correlation characteristic of orthogonal polyphase codes, we get:

$$A(\varphi_l, k) = \frac{1}{N}\sum_{n=1}^{N-k} \exp j[\varphi_l(n) - \varphi_l(n+k)] = 0, 0 < K < N \; l = 1,2,\dots,L \dots\dots.(3)$$

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

$$C(\varphi_p, \varphi_q, k) = \frac{1}{N}\sum_{n=1}^{N-k} \exp^{j[\varphi_q(n) - \varphi_q(n+k)]} = 0, 0 < K < N \quad l = 1,2,\dots,L \dots\dots.(3)$$

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

where $A(\varphi_l, k)$ and $C(\varphi_p, \varphi_q, k)$ are the aperiodic autocorrelation function of polyphase sequence S_l and the cross correlation function of sequences S_p and S_q and k is the discrete time index. Therefore, designing an orthogonal polyphase code set is equivalent to the constructing a polyphase matrix in (2) with $A(\varphi_l, k)$ and $C(\varphi_p, \varphi_q, k)$ constraints in (3) and (4).For the design of orthogonal polyphase code sets used in MIMO radar systems, an optimization criterion is not only to minimize the autocorrelation sidelobe peak (ASP) and the cross correlation peaks (CP), but also minimize the total autocorrelation sidelobe energy and cross correlation energy in (3) and (4).

3.2 Evolutionary Algorithms for MIMO radar

Previously engineers have worked on heuristic methods to solve optimization problems. In this way they have tried to inspire from nature and from this point of view. Finally, they have succeeded to achieve to different evolutionary algorithms including PSO, MOPSO, BA and ABC. In this paper, to Optimization of Orthogonal Polyphase Coded Waveform for MIMO Radar Using MO-Micro Particle Swarm Optimization Algorithm is used.
The Particle Swarm Optimization (PSO) algorithm is a relatively recent heuristic based on the simulation of social behavior of birds within a flock. In the last few years, a variety of proposals for extending the PSO algorithm to handle multiple objectives have appeared in the specialized literature.

This paper proposes a new multi-objective particle swarm optimizer (MOPSO), called micro-MOPSO because of the very small population size that it adopts.

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3.3 Micro-MOPSO

Our proposed micro-MOPSO is based on the global version of the PSO algorithm. It uses two external archives: one (called auxiliary) for storing the nondominated solutions that the algorithm finds throughout the search and another (called final) for storing the final nondominated solutions obtained. Our proposed algorithm performs the nondominated sorting introduced in and uses a crowding distance for selecting leaders. As indicated before, our approach first selects the leader and then selects the neighborhood for creating the swarm. Our micro-MOPSO withal utilizes a reinitialization process for preserving diversity and a mutation operator is incorporated to amend the overall exploratory capabilities of this heuristic.

3.3.1Final archive

Since the micro-MOPSO uses a very small population size (only five particles), it needs an external archive for reporting the final solutions that it has found (this is called the final archive). Our algorithm uses this archive for selecting leaders. The upper bound of the final archive (FAB) is a parameter that needs to be set by the user. At each iteration, and after updating the particles' positions, the non-dominated solutions are obtained from the population of the micro-MOPSO. These solutions enter into the final archive and remain there only if no other solution dominates them during the entire evolutionary process. If a solution dominates another solution stored in the final archive, the stored solution is deleted. When the maximum capacity of the archive is reached, then the algorithm applies the crowding distance as the criterion to prune the contents of the archive.

3.3.2Auxiliary Archive

The micro-MOPSO uses another external archive called auxiliary archive, which is used for storing the solutions that the algorithm finds along the search process. Our algorithm uses it for selecting the neighbor in the swarm.

3.3.3 Algorithm 1:

Pseudo code of the Micro-MOPSO

Input: Number of particles, number of generations, number of reinitialization particles (p_r), number of reinitialization generations (gr), auxiliary archive bound (AAB), final archive bound (FAB), mutation rate.

Output: Nondominated solutions (final archive)

```
begin
Initialize the final archive (empty);
Initialize the auxiliary archive (empty);
for i = 1 to Number of particles do
Initialize position and velocity randomly;
end
Store the swarm into the auxiliary archive;
Get the set nondominated solutions;
Store the nondominated solutions into the final archive;
cont = 1;
repeat
until Maximum number of generations ;
Select the leader;
Select the neighborhood;
if cont == number of generations for reinitialization then
Reinitialization process;
cont = 1;
end
for i = 1 to Number of particles do
Update the velocity;
Compute the actual position;
if xi dominates to xpbi then
for d = 1 to Number of dimensions do
xpbid = xid; // Update the pbest;
end
end
end
Performs mutation;
Store the swarm into the auxiliary archive;
if auxiliary archive length > AAB then
Filter out the auxiliary archive;
End

Get the nondominated solutions;
Store the nondominated solutions into the final archive;
if final archive length > FAB then
Filter out the final archive;
end
cont =cont +1;
Report the nondominated solutions (final archive)
end
```

The upper bound of the auxiliary archive (AAB) is a parameter that needs to be set by the user. At each iteration and after updating the particles' positions, the swarm is stored into the auxiliary archive.

When the maximum limit imposed on the size of the archive is reached, the algorithm performs nondominated sorting for keeping the solutions located into the first five fronts or the best AAB solutions.

3.3.4 Leader Selection

Algorithm 2 shows the mechanism for selecting a leader. The leader is selected from a sub-set of the final archive members that have the best crowding distances (i.e. the best spread). The size of the subset of leaders is a percentage (defined by the user) of the total population size.

3.3.4 Algorithm 2:

Pseudo code of the leader selection mechanism adopted in our micro-MOPSO.

Input: Final archive FA, final archive maximum limit (FAB), population percentage for selecting leader (PPS).

Output: Leader

```
begin
for i = 1 to Final archive length do Compute the crowding distance CDi;
end
Sort the final archive members (according to CD);
Get a percentage of particles (pps) from the population based on their
CD values;
Choose a particle in a random way; Make this particle the leader;
end
```

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The use of the crowding distance for selecting leaders allows the micro-MOPSO to select nondominated solutions that are located in less crowded. The process finds the particles of the first nondominated front for all the archive members. If the front length is lower than the maximum limit, the front is kept into the archive. Then, in order to find the individuals in the next front, the solutions of the first front are temporarily disregarded and the above procedure is repeated until five fronts are found. Case a).

When the front is kept into the archive and it exceeds the allowable limit, a crowding distance is computed (just for the front) in order to filter out solutions, and the following fronts are deleted. Case b) the micro-MOPSO keeps into the auxiliary archive at most five fronts.

4. SIMULATION RESULTS

In this paper Optimization of Orthogonal Polyphase Coded Waveform for MIMO Radar Using Mo-Micro Particle Swarm Optimization Algorithm is carried out. In the present work, Mo-Micro Particle Swarm Optimization Algorithm is used to optimize the order polyphase (Four Phase) Coded sequence to achieve good auto correlation properties.

Based on the proposed algorithm the polyphase (four phase) Coded sequences are set with lengths varying from 40 to 500 and L=3, L=4. The Maximum autocorrelation sidelobe peak (ASP) and Maximum cross correlation peak (CP) values obtained using proposed (Algorithm is compared with literature values. The results shows an improvement in Autocorrelation Sidelobe Peak (ASP)s and Cross Correlation Peak (CP)s. It infers that sequences generated by MO-Micro Particle Swarm Optimization Algorithm have good correlation properties..

Correlation properties of Four phase synthesized sequence sets with L=3, and Sequence length N= 40 to 128.

Length of the sequence	Max(ASP)	Max(ASP) Literature	Max(CP)	Max(CP) Literature
40	0.0790	0.1601	0.2045	0.2062
48	0.0751	0.1473	0.1957	0.1976
51	0.0808	0.1427	0.1804	0.1808
60	0.0745	0.1374	0.1800	0.1802
65	0.0769	0.1314	0.1657	0.1774
70	0.0769	0.1317	0.1593	0.1629
75	0.0777	0.1147	0.1500	0.1520
80	0.0760	0.1179	0.1575	0.1581
85	0.0705	0.1085	0.1473	0.1535
100	0.0670	0.1077	0.1423	0.1456
110	0.0692	0.1037	0.1286	0.1376
120	0.0671	0.1003	0.1176	0.1193
128	0.0662	0.0891	0.1048	0.1085

Table.1 Correlation properties of Four phase synthesized sequence sets with L=3, and Sequence length N= 40 to 128.

Correlation properties of Four phase synthesized sequence sets with L=3, and Sequence length N= 150 to 500.

Length of the sequence	Max(ASP)	Max(ASP) Literature	Max(CP)	Max(CP) Literature
150	0.0614	0.0971	0.1222	0.1217
155	0.0645	0.0821	0.1054	0.1074
170	0.0625	0.0836	0.1048	0.1059
175	0.0588	0.0857	0.1045	0.1051
200	0.0583	0.0808	0.0978	0.0997
220	0.0578	0.0765	0.0939	0.0957
250	0.0536	0.0721	0.0846	0.0848
275	0.0529	0.0720	0.0835	0.0837
300	0.0521	0.0641	0.0811	0.0825
350	0.0480	0.0594	0.0753	0.0760
400	0.0469	0.0562	0.0682	0.0691
450	0.0449	0.0560	0.0639	0.0668
500	0.0429	0.0528	0.0643	0.0646

Table.2 Correlation properties of Four phase synthesized sequence sets with L=3, and Sequence length N= 150 to 500.

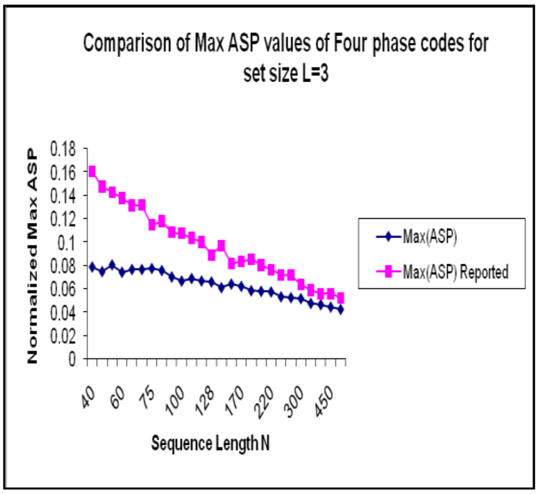

Fig.2 Max (ASP) values of four phase sequence set L=3 designed using MO- Micro PSO compared with literature values

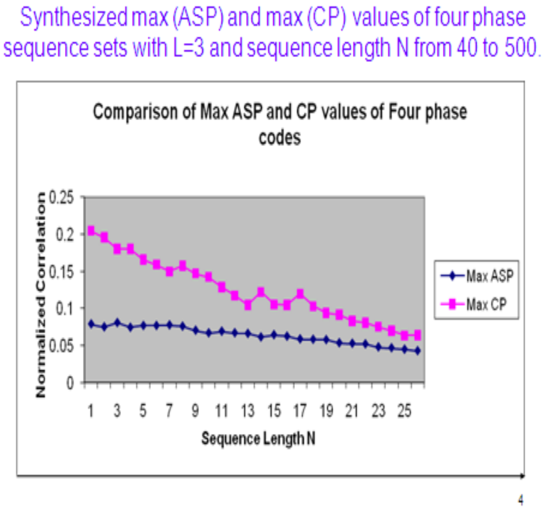

Fig.3 Synthesized max (ASP) and max (CP) values of four phase sequence sets with L=3 and sequence length N from 40 to 500.

Table 1 compares the obtained values of ASPs and CPs with literature values. Correlation properties of Four phase synthesized sequence sets with L=3, and Sequence length N= 40 to 128 are tabularized. And Table 2 compares the obtained values of ASPs and CPs with literature values. Correlation properties of Four phase synthesized sequence sets with L=3, and Sequence length N= 150 to 500.

Figure 2 and 3 illustrates the Max (ASP) values of four phase sequence set L=3 designed using MO- Micro PSO compared with literature values and Synthesized max (ASP) and max (CP) values of four phase sequence sets with L=3 and sequence length N from 40 to 500.

5. CONCLUSION

Correlation properties of Four phase synthesized sequence sets with L=3 for Sequence length N= 40 to 500 is obtained and compared with the literature values. From the design result, I conclude that the results obtained have great improvement in correlation properties of all the sequence lengths.

In order to carry out the implementation of micro-MOPSO algorithm for the optimization of polyphase (four phase) sequences a MATLAB code is developed.

REFERENCES

[1] M. Malekzadeh, A. Khosravi, S. Alighale and H. Azami, “Optimization of Orthogonal Poly phase Coding Waveform based on Evolutionary Algorithms for MIMO Radar”, Lecture notes in Computer Science (Springer Verlag), vol. 7389, pp. 95-102 (2012).
[2] C. C. Cook and M. Bernfeld, Radar Signals: An Introduction to Theory and Application.Artech House, 1993.
[3] N. Levanon and E. Mozeson, Radar Signals. Wiley, 2004.
[4] D. K. Barton and S. A. Leonov, Radar Technology Encyclopedia. Artech House, 1998.
[5] E. Fishler, A. Haimovich, R. Blum, D. Chizhik, L. Cimini, and R. Valenzuela, “Mimo radar: An idea whose time has come,” in Proc. IEEE Radar Conf., pp. 71–78, 2004.
[6] D. W. Bliss and K. W. Forsythe, “Multiple-input multiple-output (mimo) radar and n imaging: degrees of freedom and resolution,” in Program Comprehension, 2009. ICPC’09. IEEE 17th International Conference, pp. 100–109, 2009.
[7] F. C. Robey, S. Coutts, D. Weikle, J. C. McHarg, and K. Cuomo, “Mimo radar theory and experimental results,” in Proc. of 37th ASILOMAR 2004 Conf. on Signals, Systems and Computers, pp. 300–304, 2004.
[8] B. Liu, Z. He and Q. He, “Optimization of orthogonal discrete frequency-coding waveform based on modified genetic algorithm for MIMO Radar”, International Conference on Communications, Circuits and Systems, pp. 966-970 (2007).