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Simulation and Performance Analysis of Chaotic Sequences using Enhanced Cuckoo Search Optimization Method

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Abstract: ***The mostdesirable property required for pulse compression is that the output should have low peak sidelobes that prevent weaker targets from being masked off in the nearby strong targets. Pulse compression can be obtained with matched filter. Matched filter is an optimal linear filter used in radar signal processing and various communication fields to increase the signal to noise ratio. The output of matched filter consists of unavoidable sidelobes which causes false alarm for multiple target detection in many radar system design.For this purpose, mismatched filter is used after matched filter. Inthis paper a new method of design of mismatched filter is discussed which reduces these sidelobes in the compressed waveform. Here new version of cuckoo search algorithm is used along with differential evolution techniquefor complete design of proposed filter to compare the performance of chaotic sequence. The performance of pulse compression is measured in terms of peak sidelobe ratio. The simulation results showthatdevelopmentin the performance of chaotic sequence is obtained at the output of cascaded filter. And further improved performance is achieved with adaptive filters.***

Keywords: ***Pulse compression, Auto-correlation, Peak sidelobe ratio (PSLR), Matched filter (MF), Mismatched Filter (MMF), Cross-correlation, Enhanced Cuckoo search algorithm.***

I. INTRODUCTION

With the view of increase in applications of modern radars, navigation and ultrasonic systems there is a continuous requirement of better accuracy and high range resolution with limited peak power. These requirements have been met with pulse compression technique that is widely used in radar and navigation systems. This is mainly used to solve the problems of extending the range of radar by keeping the desired range resolution. Short pulses having high peak power helps to detect the targets at long distance. The detection capability is improved with the transmission of long coded pulse whereas narrow pulse retains itsresolution capability. When a matched filter at the receiver is fed with anecho signal from target along with additive noise that results in large value of signal power with respect to noise power [1],[2].

The peak sidelobe is defined as the highest sidelobe in the output pattern. A major drawback of pulse compression techniques is relatively weak sidelobe suppression which can overcome by using mismatched filter in the receiver. But in some cases removing sidelobes comes out with some important information**.** Lots of research work has been carried out to reduce theseunwanted sidelobes.

Binary sequence with large PSLR is suitable for many applications. Rohling and Plagge proposed a methodof eliminating range sidelobes in periodic binary sequences with the help of mismatched filtering. The peak sidelobe ratio and the integrated sidelobe ratio are two important parameters to measure radar performance.Since drawbacks appears with longer length binary sequences, the analysis is carried out with multi-level sequences. The theory of chaos is applicable in radar and various chaotic systems that depends on initial conditions [3], [4]. The application of chaos with different algorithms is also studied [5]- [7]. Therefore, in this paper the performance of chaotic sequences is tested with enhanced version of cuckoo search method.

The role of matched filter and mismatched filter makes it convenient to use in various areas of applications. The design of mismatched filter has been studied from years together by many scientists and engineers [8], [9]. It was studied that the optimization has to be done for the signal whose ACF contains lower peak sidelobes. The design of longer mismatched filter is proposed earlier [10]. The cross-correlated output of mismatched filter with input as binary and ternary chaotic code is discussed here which is not symmetric about zero delay. Generally, the performance of mismatched filter depends on filter elements or coefficients.

In this paper cascaded mismatched filter weights are designed where differential evolution is integrated with enhanced version ofcuckoo search method and its performance is studied. The generation of chaotic sequence using chaotic maps was discussed in [11], [12] and their performance with adaptive filters is compared [13].

II. METHODOLOGY

This paper begins with the generation of random population which are considered as elements of mismatched filter. The design of mismatched filter using differential evolution is studied. The differential evolution algorithm (DE) is a direct search optimization technique. The applications of this technique is quite easy, fast and gives robust performance. It can be used in linear and non-linear optimization problems due to its high reliability and consistent nature.

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The DE algorithm is achieved with perturbation of individuals, mutation and their crossover operation which is suggested by Price and Storn [14]. Here random population uses one difference vector for DE. The recombination of elements is controlled by the binomial decisionas in [15].The optimized weightsobtained in DE is again processed through new cuckoo search method for optimization.

In general, mathematical modelling is used in several areas where optimization plays vital role[16]. Basically,the optimization is broadly divided into two types. One is deterministic method of optimization which provides only theoretical way of finding local minimum of the objective function. It requires some theoretical assumptions and analytical properties for problem formulation. Second one is stochastic method which is faster in locating global minima[17]. Evolutionary algorithms are the members of stochastic group which is a combination of several natural phenomena.

Some of the methods depends on the behaviour of animal like Ant Colony optimization (ACO) algorithm which is proposed by Dorigo et al. [18], Ant bee colony by Karaboga & Basturk, 2007 [19], bat algorithm by Yang, 2010 [20], bat flower pollinator by Salgotra & Singh, 2016 [21], and Particle Swarm optimization (PSO) algorithm by Kennedy and Eberhart [22].In EA, global optimum value is obtained by properly selecting a parameter value which is quite expensive and also limit their use in real world application. Therefore, it is required to search for many local optima along with the global optima as in multimodal optimization [23].Hence the quality of acceptable performance with a local minimum is achieved with moderate cost.

Recently a nature inspired meta-heuristic optimization algorithm known as Cuckoo Search (CS) algorithm that is used to solve various complex problems in optimization suggested by Yang and Deb in 2009 [24].This is finding popularity not only in engineering optimization problems, but also it finds in areas such as business management, stock market and finding optimal path in travelling. Here the candidate solutions are updated continuously by applying small changes which enhances the searching capabilities[25]. The wide application of CS in recent years is due to its simple structure, adaptability and is most efficient as comparedto other optimization techniques. Exploration of population and exploitation are the two important factors in the search process that decides the performance of optimization. These two properties are satisfied by cuckoo search method which helps in enhancing the searching capability. Cuckoos are very fascinating birds. They have the characteristics of not only making interesting sound but also have the tendency of aggressive reproduction strategy.

Brood parasitism says that some cuckoos put down their eggs gently in the nests of others. As long as the eggs are not identified by host birds they will get the chance to grow up in new nest and can get more feed from the host birds. Hereeach cuckoo egg correspondsto a new candidate solution. Alsocuckoo eggs hatch earlier than host eggs and propels the host eggs out of the nest. But if the host bird recognizes the eggs which are not its own then it may throw the eggs or vacate the nest.

In this algorithm the search process is divided into two partswhich are called as local phase and global phase. New nests are generated in global phase and a fraction of worst nests are removed in local phase. That means global phase indicates the exploration while local phase refers to exploitation. It is enhanced by Lévy flight to generate step size that improves the search space effectively. Therefore, new candidate solutions are generated with Lévy distribution as in (1) and (2) in global and local phases that replaces worse solutions in the population or nest.

$$x_i^{t+1} = x_i^t + \alpha \otimes Lèvy(\lambda)(x_{best} - x_i^t) \qquad (1)$$

Equation (1) shows global random phase. While the local random walk isdefined in (2)

$$x_i^{t+1} = x_i^t + \alpha \otimes H(p_a - \epsilon) \otimes (x_j^t - x_k^t) \qquad (2)$$

Where x_i^t represents the previous solution and x_{best} is the current best solution. Similarly x_j^t and x_k^t are random solutions from the population. α is the step size that depends on the problem. 'H' stands for heavy-side function, 'ϵ' is the random number and 'p_a' represents switching probability. This is the basic background of CS algorithm. The evolution process of CS is defined by three different operators: (i) the distribution function such as Lévy flight, Cauchy distribution, (ii) generation of new solutions by replacing some nests and (iii) elitist selection strategy. The first step is to generate new solution with the help of distribution function. The next step is the selection of a uniform random number in the range [0,1]. If this random number is less than the switching probability $p_a \in [0,1]$ that particular solution or sequence is selected and used for further computation. The third step is to choose high quality eggs or solutions x_i^{t+1} whose fitness value is better than x_i^t .

$$x_i^{t+1} = \begin{cases} x_i^{t+1}, & iff(x_i^{t+1}) < f(x_i^t) \\ x_i^t, & otherwise \end{cases}$$

In this way the best solutions are derived which will exist in the next generation.

A. Proposed variants

The necessity of switching over to enhanced version of cuckoo search method from Lévy flight method is discussed here. The detailed analysis of modifications in search process and their implementation are presented. The Lévy flight behaviour of CS helps to increase the search space. So it is better than simple random walk. The probability switch determines the global explorative and the local exploitative random search. Hencethe above method is more efficient for achieving the convergence. But as days going on the complexity in optimization problems increases. Hence it is required to design a new algorithmthat is based on particular problem.

This paper deals with two new concepts which are based on division ofgenerations and population. These two concepts are clearly explained with the help of proposed method. Using this method, abetter position of cuckoo is obtained with some modificationsin local and global search phase. The modification is included for second half of the generation in which enhanced global search is followed by two divisions in local phase. But for the first half of the generation, Cauchy operator is used to obtain new solution in global search and original CS concept is used for local search.

B. Division of generations:

The explorative tendency of CS makes the algorithm in ignoring local minimaand the exploitative tendency decides its convergence properties.

The division of population and generation has been implemented to keep the balance between theexploitation and exploration. To achieve this balance, a standard equation is used for one half of the generation to obtain best explorative tendency and the remaining half should have more intensive exploitation.

C. Division of Population

In division of population, the population is split into smaller groups and each group is computed with separate search equation that will add up the balance. The extensive global walkalways followsintensive local walkTwo different search equations are adapted for each half of the population to complete the search process.

III. ENHANCED VERSION OF CUCKOO SEARCH METHOD

In the enhanced version of CS, the first half of the generation uses Cauchy distributed random number 'δ' in global search to obtain the new solutions.

The probability density function is definedin (3)

$$f(\delta) = \frac{1}{\pi}\left(\frac{g}{g^2+\delta^2}\right) \quad (3)$$

where the scale parameter 'g' is considered as 1. Similarly, the Cauchy distribution functioncan be written in (4)

$$y = 0.5 + \frac{1}{\pi} arctan\left(\frac{\delta}{g}\right) \quad (4)$$

Where $y \in [0,1]$. From the above equation the Cauchy random number 'δ' is as in (5)

$$\delta = tan\big(\pi(y - 0.5)\big) \quad (5)$$

whose range is between 0 and 1. The Cauchy distribution helps in escaping local minima by examining the search space. In one half of generations,the new solution in global search is obtained by using (6)

$$x_i^{t+1} = x_i^t + \alpha \otimes Cauchy(\delta)\big(x_i^t - x_j^t\big) \quad (6)$$

Which is similar to(1) of original CS algorithm, but instead of Lévy distribution, Cauchy distribution is used in (6) due to its flatter tail and larger step size.

In second half of iterations, the improvement in global search phase is obtained by using (10) where the average of the three solutions is considered which are defined below in (7), (8) & (9)

$$x_1 = x_i - S_1(V_1 * x_{best} - x_i^t) \quad (7)$$

$$x_2 = x_i - S_2(V_2 * x_{best} - x_i^t) \quad (8)$$

$$x_3 = x_i - S_3(V_3 * x_{best} - x_i^t) \quad (9)$$

and $x_{new} = \frac{x_1+x_2+x_3}{3}$ (10)

Where S_1, S_2 and S_3 are obtained by using (11) for different random values.

$$S = 2rd_1 - r \text{ and } V = 2d_2 \quad (11)$$

$d_1$and d_2 are uniformly distributed random number that helps in obtainingnew location in the search spacewhich improves the explorative tendency. 'r' is the linearly decreasing random number between 0 to 2. This concept has been taken from Grey Wolf Optimization where the new solutions are achieved by adjusting the parameters of best search agent. Therefore, the new solution will become (12).

$$x_i^{t+1} = x_{new}^t + \alpha \otimes Cauchy(\delta)(x_{best}^t - x_{new}^t) \quad (12)$$

The performance of original CS can be improved with some enhanced search in local phase. Here the population is divided into two halves. The first half is computed with (2) of standard CS to obtain new solution.However, the second half of the populationuses(13).

$$x_i^t = x_i^t + D.\big((x_k^t - x_l^t) + (x_m^t - x_n^t)\big) \quad (13)$$

The parameter D is in the range 0 to 1. The new solution is updated withthe four random solutions x_k^t, x_l^t,x_m^t and x_n^t. Finally,the Cauchy global search and dual division local search maintains balance between the exploration and the exploitation.

IV. PROBLEM IDENTIFICATION

The computation for the coefficients of mismatched filter using different optimization techniques has been reported earlier [26], [27]. In this paper mismatched filter elements are designed as per differential evolution and then same procedure is adapted to optimize the mismatched filter coefficients using cuckoo search algorithm to obtain optimized coefficients. The sidelobe levels are reduced in the output of mismatched filter. Here random chaotic sequences are given as input to matched filter which results in aperiodic autocorrelation function in phase coded pulse compression. The ternary chaotic sequences of length $'N'$ represented by +1,0,-1 are taken as input given by

$$S = \{s_0, s_1, s, \ldots\ldots s_{N-1}\}$$

whose autocorrelation without doppler shift for positive delays is represented in (14)

$$RR(k) = \sum_{j=0}^{N-1-k} s_j s_{j+k}\, for'k'rangefrom\ 0\ to - 1 \quad (14)$$

The coefficients or weights of mismatched filter are real with filter length considered as $'M'$ but greater than $'N'$, $M \geq N$. The output of mismatched filter is defined in (15)

$$CC_k = \sum_{j=0}^{M-1} y_j s_{j-k} for - (N-1) \leq k \leq (M-1) \quad (15)$$

where Y is the filter elements $Y = \{y_0, y_1 \ldots y_{M-1}\}$ and x_i existing between 0 to N-1. Depending on whether N is even or odd, M will be even or odd respectively. The value of 'x' will become zero for $i < 0\ and i > N - 1$. The objective function of mismatched filter is defined in (16)

$$PSLR = 20 * log\frac{abs(sidelobemaximum)}{\text{abs}(\max(CC_K))} \quad (16)$$

where $F = \max(H_K)$ is the main lobe peak that is to be maximized. Each solution or individual is considered as impulse response coefficients of mismatched filter. The initial random population is chosen as per differential evolution algorithm. The mismatched filter length is taken as three times longer than that of the input sequence.

V. SIMULATION RESULTS

This paper deals with thedetailed analysis of proposed method which is clearly shown in Fig. (1). The performance of chaotic sequence is measured in terms of peak sidelobe ratio. The sequence is undergone mismatched filter 1 whose elements are designed by using differential evolution method followed by mismatched filter 2 that is designed with new cuckoo search algorithm.

The simulation is being carried out using Matlab and the performance of mismatched filters are discussed for barker code, binary and ternary chaotic code for different lengths. The optimized results of DE mismatched filter and cascaded MMF are tabulated in I and II.

It is evident that the proposed method achieved better results than the MMF which is implemented only with DE. The parameter 'α' is taken as 0.01 and the probability switch 'P_a' as 0.5 for simulation. The output is obtained by cross-correlating the chaotic sequence and the coefficients of mismatched filter which is taken as random population initially. The cascaded mismatched filter output for chaotic sequence of length 20 is shown in Fig. (2). Further improvement of PSLR is obtained with adaptive filter that is connected after cascaded MMF.

The coefficients of the adaptive filter are updated with least mean square and binary step size least mean square algorithm.

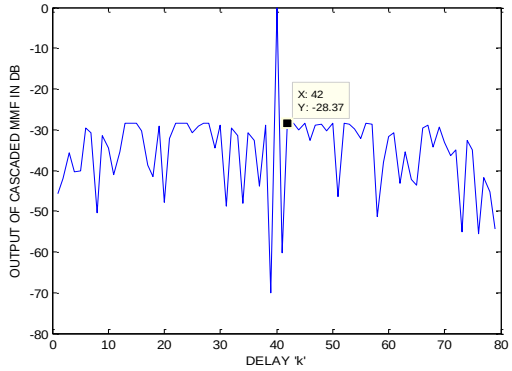

Fig.2 Mismatched filter response of ternary sequence

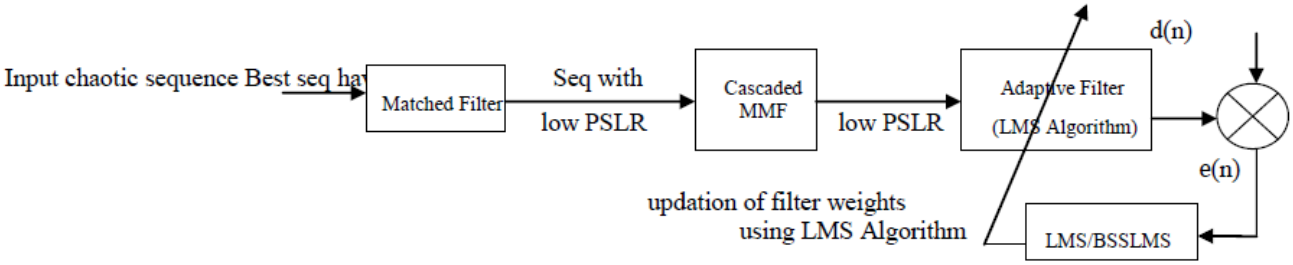

Fig. 1 Block diagram representation of proposed method

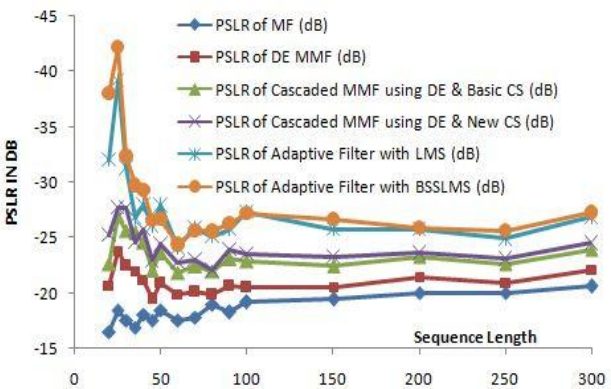

Fig.3 Performance of Binary code

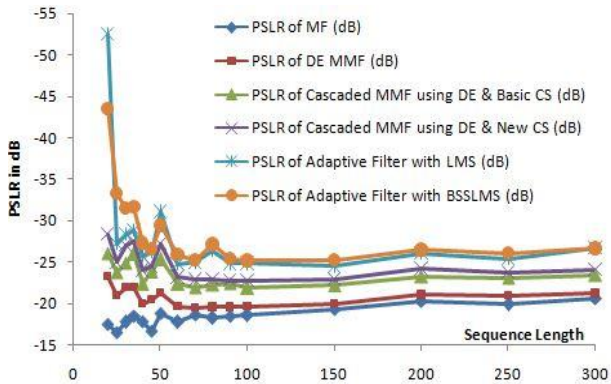

Fig.4 Performance of Ternary code

Table. I PSLR comparison of Binary Sequence using cascaded MMF along with adaptive filter

Sequence Length	PSLR of MF (dB)	MF ASP	PSLR of DE MMF (dB)	PSLR of Cascaded MMF using DE & Basic CS (dB)	PSLR of Cascaded MMF using DE & New CS (dB)	PSLR of Adaptive Filter with LMS (dB)	PSLR of Adaptive Filter with BSSLMS (dB)
20	-16.4782	0.15	-20.6710	-22.6344	-25.2326	-32.0434	-38.0054
25	-18.4164	0.12	-23.8117	-26.9161	-27.7399	-39.2191	-42.2132
30	-17.5012	0.1333	-22.4618	-25.6010	-27.6253	-31.3052	-32.3310
35	-16.9020	0.1429	-21.9650	-25.4385	-24.5308	-26.7982	-29.7076
40	-18.0618	0.1250	-21.2167	-24.5438	-25.7902	-28.0029	-29.3102
45	-17.5012	0.1333	-19.4290	-22.0227	-22.9612	-26.0669	-26.5547
50	-18.4164	0.1200	-20.8651	-23.6070	-24.3869	-27.8803	-26.6319
60	-17.5012	0.1333	-19.9053	-21.8712	-22.7521	-24.0994	-24.3901

70	-17.8171	0.1286	-20.0811	-22.4277	-23.0139	-25.8099	-25.6433
80	-18.9769	0.1125	-19.8070	-21.9654	-22.0461	-25.0719	-25.5642
90	-18.2570	0.1222	-20.5831	-23.0612	-23.8999	-25.7750	-26.2920
100	-19.1721	0.1100	-20.5048	-22.9169	-23.5636	-27.3133	-27.1581
150	-19.4394	0.1067	-20.5520	-22.4128	-23.3062	-25.7065	-26.6462
200	-20	0.1000	-21.4678	-23.2856	-23.6161	-25.7473	-25.9144
250	-20	0.1000	-20.9450	-22.5748	-23.0781	-24.8840	-25.5893
300	-20.5993	0.0933	-22.1334	-23.9571	-24.4945	-26.8629	-27.2385

Table. II PSLR comparison of Binary Sequence using cascaded MMF along with adaptive filter

Sequence Length	**PSLR of MF (dB)**	**MF ASP**	**PSLR of DE MMF (dB)**	**PSLR of Cascaded MMF using DE & Basic CS (dB)**	**PSLR of Cascaded MMF using DE & New CS (dB)**	**PSLR of Adaptive Filter with LMS (dB)**	**PSLR of Adaptive Filter with BSSLMS (dB)**
20	-17.5012	0.1333	-23.2601	-25.9866	-28.3662	-52.4615	-43.5033
25	-16.4782	0.1500	-20.9613	-23.7410	-24.9498	-27.1811	-33.2651
30	-17.6921	0.1304	-21.9220	-24.8412	-27.0602	-28.3593	-31.4696
35	-18.4164	0.1200	-21.9297	-25.9506	-27.4511	-28.7865	-31.6038
40	-17.7860	0.1290	-19.9577	-22.3354	-23.9838	-25.6898	-27.2516
45	-16.6502	0.1471	-20.4160	-23.8290	-24.4505	-26.1543	-26.5626
50	-18.8402	0.1143	-21.2207	-25.2694	-27.1736	-31.0194	-29.3834
60	-17.6921	0.1304	-19.6591	-22.3488	-23.1368	-24.7326	-25.8957
70	-18.5884	0.1176	-19.4310	-21.9170	-22.8083	-24.9556	-25.2526
80	-18.2155	0.1228	-19.5246	-22.2077	-22.8863	-26.3259	-27.1024
90	-18.4597	0.1194	-19.5052	-22.4003	-22.7833	-24.8042	-25.3924
100	-18.5314	0.1184	-19.6528	-21.8209	-22.7707	-24.7692	-25.0977
150	-19.2442	0.1091	-19.9653	-22.1384	-22.9513	-24.4375	-25.1544
200	-20.2848	0.0968	-21.0265	-23.2507	-24.1258	-26.0649	-26.4356
250	-19.8618	0.1016	-20.8839	-23.0938	-23.7159	-25.3729	-26.0707
300	-20.5993	0.0933	-21.1811	-23.3418	-24.0003	-26.7309	-26.6204

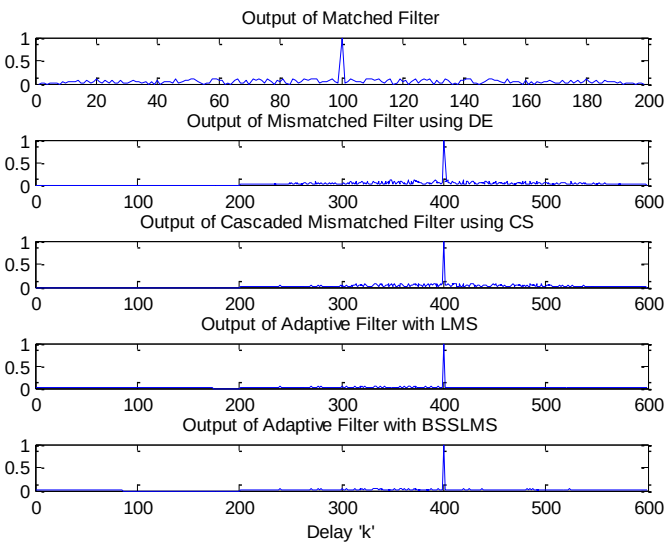

Fig. 5 Comparison of output for sequence length of 100 in each stage of block diagram

Table. III Improvement in PSLR of Ternary Sequence with Number of Iterations

Sequence Length	PSLR of MF (dB)	MF ASP	No. of Iterations	PSLR of DE MMF (dB)	PSLR of Cascaded MMF using DE & Basic CS (dB)	PSLR of Cascaded MMF using DE & New CS (dB)	PSLR of Adaptive Filter with LMS (dB)	PSLR of Adaptive Filter with BSSLMS (dB)
20	-17.5012	0.1333	**50**	-18.9502	-23.0076	-23.6411	-32.3949	-38.3997
20	-17.5012	0.1333	**100**	-21.2409	-24.8603	-26.2322	-44.6002	-39.1501
20	-17.5012	0.1333	**200**	-23.2601	-25.9866	-28.3662	-52.4615	-43.5033
20	-17.5012	0.1333	**300**	-24.5978	-27.3246	-29.7682	-63.1376	-47.2109
20	-17.5012	0.1333	**400**	-25.3689	-28.4107	-29.1387	-57.9792	-46.8573
20	-17.5012	0.1333	**500**	-26.3723	-28.1916	-29.2455	-60.7179	-46.1775

Fig.3 and Fig.4 represents the comparison of PSLR for different length of sequence at the output of each stage of the block diagram. As the number of iterations increased the value of PSLR is also increased which is shown in III. The output for sequence length 100 from each filter is shown in Fig.5

VI. CONCLUSION

In this work, the performance of chaotic sequence is optimized by using enhanced version cuckoo for the design of mismatched filter along with DE. The length of the mismatched filter should increase proportionally with input sequence. Due to this, implementation of the filter will be difficult for practical applications for larger length codes.The PSLR of barker code with cascaded filter is increased to -41.8877 dB whose value with matched filter is -22.2789. Better improvement in performance of sequencesis observed for lower length than compared to larger length. The values in I and II will change every time when the matlab program is being executed. This is because of random population that is taken as the coefficients of MMF. DE finds wide application due to its interesting characteristics such as better convergence, robustness and versatility. With this advantages of DE when it is integrated with new cuckoo search for designing of mismatched filter results in significant improvement in the performanceof sequence compared to Lévy flight standard cuckoo search.These values will increase with increase in number of iterations.

REFERENCES

1. M I Skonik, “Introduction to Radar Systems,”Tata McGraw Hill Book Co.,New York, 3rd Ed., 2001.
2. E Mozeson, N Levanon, Radar Signals, Hoboken, NJ:John Wiley & Sons, Inc.2004.
3. A Ashtari, G Thomas, B C Flores, “Radar signal design using chaotic signals,”In Proceedings of International Waveform Design and Diversity Conference. Pisa (Italy), June 2007, p. 353-357.
4. S Saremi, S Mirjalili and A Lewis, “Biogeography-based optimisation with chaos,”NeuralComputing&Applications, vol.25, no. 5, 2014, pp. 1077–1097.
5. Z Y Guo, B Chen, M. Ye, and B. Cao, “Self-adaptive chaos differential evolution,” in Advances in Natural Computation:Second International Conference, ICNC 2006, China,September 24-28, 2006. Proceedings, Part I, L. Jiao, L. Wang, X.-B. Gao, J. Liu, and F. Wu, Eds., vol. 4221 of Lecture Notes in Computer Science, Springer, Berlin, Germany, 2006, pp. 972–975.
6. R Ebrahimzadeh and M Jampour, “Chaotic genetic algorithm based on Lorenz chaotic system for optimization problems,” International Journal of Intelligent Systems and Applications, vol. 5, no. 5, 2013, pp. 19–24.
7. A H Gandomi, X S Yang, S Talatahari and A H Alavi, “Firefly algorithm with chaos,” Communications in Nonlinear Science and Numerical Simulation, vol. 18, no. 1, pp. 89–98, 2013.
8. B Kiranmai and P Rajesh Kumar, “Performance evaluation of compound barker codes using cascaded mismatched filter technique,” International Journal of computer applications, vol.121-no.19, July 2015, pp.31-34.
9. H Rohling, and W Plagge, “Mismatched-Filter Design for Periodic Binary Phased Signals,” IEEE Transactions on Aerospace Electron. Systems, vol. AES-25, No.6, November 1989, pp. 890-897.
10. N Levanon, “Cross Correlation of long binary signals with long mismatched filters,”IEE proc.-Radar and Sonar navigation, July 2005.
11. Xin Wu, Weixian Liu, Lei Zhao, Jeffrey.S. Fu, “Chaotic Phase Code for Radar Pulse Compression,” IEEE Radar Conf. 2001, pp. 27-28.
12. J B Seventline, D Elizabeth Rani and K Raja Rajeswari, “Ternary Chaotic Pulse CompressionSequences,” Journal of Radio Engineering, Vol.19, No:3, September 2010,pp.415-420.
13. K Renu and P Rajesh Kumar, “Performance of Ternary Sequences using Adaptive Filter,” ICMEET-2017, Proceedings of Springer conference LNEE series 471, 8-9 September 2017, pp.63-74.
14. R Storn and K Price, “Differential evolution-a simple and efficient adaptive scheme for global optimisation over continuous spaces,” Tech. Rep. TR-95-012, ICSI, Berkeley, California, USA, 1995.
15. J B Seventline, G V K Sharma, KSridevi, D Elizabeth Rani and K Raja Rajeswari, “Development and Performance Evaluation of Mismatched Filter using Differential Evolution,” International Journal of Computer Applications, Vol. 46-No.8, May 2012,pp. 56-60.
16. P M Pardalos, H E Romeijn, and H Tuy, “Recent developments and trends in global optimization,” Journal of Computational and Applied Mathematics, vol. 124, no. 1-2, 2000, pp. 209– 228.
17. A Georgieva and I Jordanov, “Global optimization based on novel heuristics, low-discrepancy sequences and genetic algorithms,” European Journal of Operational Research, vol. 196, no.2, 2009pp. 413–422.
18. M Dorigo, V Maniezzo, and A Colorni, “Positive feedback as a search strategy,” Tech. Rep. 91-016, Politecnico di Milano, Milano, Italy, 1991.
19. D Karaboga andB Basturk, “Artificial bee colony (ABC) optimization algorithm for solving constrained optimization problems,” In International fuzzy systtems association world congress, 2007, pp. 789–798.
20. X S Yang,“A new metaheuristic bat-inspired algorithm in Nature inspired cooperative strategies for optimization,” (NICSO 2010),Springer, 2010, pp. 65–74.
21. R Salgotra, U Singh, “A novel bat flower pollination algorithm for synthesis of linear antenna arrays,”Neural Computing and Applications, doi: 10. 10 07/s0 0521- 016- 2833- 3, 2016, pp-1-14.
22. JKennedy and R Eberhart, “Particle swarm optimization,” In Proceedings of the IEEE International Conference on Neural Networks, vol. 4, December 1995, pp. 1942–1948
23. F Yahyaie and S Filizadeh, “A surrogate-model based multimodal optimization algorithm,” Engineering Optimization, vol. 43, no. 7,2011 pp. 779–799.
24. X S Yang and S Deb, “Cuckoo search via Lévy flights,” in Proceedings of the World Congress on Nature & Biologically Inspired Computing (NABIC ’09),” Coimbatore, India, December 2009, pp. 210–214.

25. I Pavlyukevich, "Lévyflights, non-local search and simulated annealing," *Journal of Computational Physics*, vol. 226, no. 2, pp. 1830–1844, 2007.
26. S Das, A Abraham and A Konar, "Particle Swarm Optimization and Differential Evolution Algorithms: Technical Analysis, Applications and Hybridization Perspectives," Studies in Computational Intelligence (SCI) 116, 2008, pp.1-38.
27. P Srihari and K Raja Rajeswari, "Development and performance evaluation of PSO based adaptive mismatch filter for radar pulse compression," Proceedings of 9th international radar symposium India-2013, 10-14 December 2013, pp.1-4.

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