A Brief Review of Cuckoo Search Algorithm (CSA) Research Progression from 2010 to 2013

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Abstract – Cuckoo Search Algorithm is a new swarm intelligence algorithm which based on breeding behavior of the Cuckoo bird. This paper gives a brief insight of the advancement of the Cuckoo Search Algorithm from 2010 to 2013.

The first half of this paper presents the publication trend of Cuckoo Search Algorithm. The remaining of this paper briefly explains the contribution of the individual publication related to Cuckoo Search Algorithm. It is believed that this paper will greatly benefit the reader who needs a bird-eyes view of the Cuckoo Search Algorithm's publications trend. Copyright © 2014 Praise Worthy Prize S.r.l. - All rights reserved.

Keywords: Cuckoo Search Algorithm, Publication Trend, Swarm Intelligence

I. Introduction

Nowadays, Swarm Intelligence (SI) algorithms have become famous due to its simplicity. In fact, there are numerous SI algorithms that have become visible and often being applied in real world problems. Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Genetic Algorithm (GA) and Differential Evolution (DE) are few examples of the well-established SI algorithms [1].

On the other hand, Cuckoo Search Algorithm (CSA) is considered to be one of the latest SI algorithms [1]. It is based on breeding and Levy-flight based foraging behavior of the Cuckoo birds. Based on the finding of the original author, CSA is considered a superior algorithm which surpasses PSO and GA [2].

The publication papers include journals and conference proceedings are accumulated from wellestablished online databases like IEEE Explore, Scopus, ScienceDirect, Elsevier and Scientific.Net. The keyword "Cuckoo Search Algorithm" is used to search the papers. After collecting papers from the online databases, the process of elimination is done to get rid of unwanted and unrelated papers. Lastly, it only left with 71 papers related to CSA.

In these 71 papers, there are 27 papers brief about the modifications or hybridizations of CSA and the rest are application of original CSA. The papers are collected from 2010 to 2013.

Note that the analysis of the publications of CSA is based on the framework in [3].

Only information that tells the development of CSA that also includes the number of publications, year of publications, journal and countries' institutions are acquired through collecting and analyzing 71 papers related to CSA.

II. Format of Manuscript

II.1. Publication by Year

Fig. 1 indicates the number of publication of CSA on yearly basis from year 2010 to 2013. It is clearly seen that the number of publication increases in exponential order throughout the 4 years duration.



Fig. 1. Number of publications by year

II.2. Publication by Type of Publication

From the 71 papers, there are 43 journals and 28 conference proceedings. Table I shows the contribution of journals towards CSA publications. These are the few scientific journals that contributed the most; International Journal of Bio-Inspired Computation (3 papers), Journal of Applied Mathematics (3 papers), and Advances in Intelligent Systems and Computing (4 papers).

II.3. Publication by Country

Besides analysis of publications by year and type of publications, countries of publications are also recorded and the most notable publications comes from India

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which contributed 22% from the total publications of CSA. This follows by China (22.5%), Malaysia (11.2%) and United Kingdom (8.4%). Countries that contribute around 1% of the total publications are from United States, Sweden, Romania, Germany, Algeria, Mexico and Jordan. Table II shows number of publications and the percentage of publications of each country which involved.

TABLE I	
JOURNALS/ PROCEED	INGS

No	No Journals/ Proceedings	
140		
1	Electrical Engineering/Electronics, Computer,	1
	Telecommunications and Information	
	Technology	
2	Communications and Information Technologies:	1
3	Advances in Intelligent Systems and Computing	4
4	AIP Conference Proceedings	1
5	Applied Mathematics and Information Sciences	2
6	Journal of Beijing Jiaotong University	1
7	American Journal of Applied Sciences	1
8	Computers and Industrial Engineering	1
9	Engineering with Computers	1
10	Computers and Operations Research	1
11	Energy Education Science and Technology	1
12	Expert Systems with Applications	1
13	IET Microwaves, Antennas and Propagation	1
14	Power Engineering, Energy and Electrical Drives	1
15	Indian Journal of Science and Technology	1
16	International Journal of Advanced Manufacturing	2
	Technology	
17	International Journal of Bio-Inspired	3
	Computation	
18	International Review on Computers and Software	1
19	Journal of Applied Mathematics	3
20	Journal of Experimental and Theoretical	1
	Artificial Intelligence	
21	Journal of Theoretical and Applied Information	1
	Technology	
22	Journal of Theoretical and Applied Information	2
	Technology	
23	Mechanism and Machine Theory	1
24	IEEE International Advance Computing	1
	Conference	
25	International Conference on Advances	1
26	Research Journal of Applied Sciences,	1
	Engineering and Technology	
27	Swarm and Evolutionary Computation	1
28	Structural Design of Tall and Special Buildings	2

TABLE II

No.	Country	Number of Publications	Percentage
1	India	22	30.9
2	China	16	22.5
3	Malaysia	8	11.2
4	U.K	6	8.4
5	Iran	4	5.6
6	Thailand	4	5.6
7	Serbia	2	2.8
8	Turkey	2	2.8
9	USA	1	1.4
10	Sweden	1	1.4
11	Romania	1	1.4
12	Germany	1	1.4
13	Algeria	1	1.4
14	Mexico	1	1.4
15	Jordan	1	1.4



Fig. 2. Country of Publications

II.4. Publication by Type of Contribution

Most of the CSA publications can be divided into three main area of contributions: CSA modification, hybridization of CSA, and the application of the CSA.

Based on our findings, there are 14 papers related to CSA modification which majority shows improvement from the original CSA, 13 papers related to the hybridization of CSA with other optimization algorithms, and 66 papers including those of the CSA modification papers and CSA hybridization papers are related to the applications of CSA.

Modifications of CSA

The improvement of CSA has been growing from 2010. There are various enhancement done on CSA performance and Table III states the modification of CSA.

Hybridizations of CSA

There are many combinations or hybridization of CSA with other algorithms are also been introduced. These combinations have bought great advancement in term of performance: better fitness value or faster convergence rate, which outperforms CSA itself, PSO, GA, ACO and etc. The following Table IV shows the result of the combination of CSA.

Applications of CSA

The interests in exploiting CSA capabilities lead to the increase of application of CSA in various areas. The main areas are Computer Science, Mathematics, Energy, Engineering, etc. Table V shows the areas and applications of CSA.

III. Conclusion

In this paper, the development of CSA has been reviewed from 2010 to 2013. CSA is still considered as a new algorithm, but its growth is remarkable during these four year.

TABLE III				
Author	Technique	Modification/Problem	Result	Ref.
Zhou, Y., Zheng, H., Luo, Q., Wu, J.	Improved CSA (ICSA)	Modification: Three strategies are introduced: walking one strategies, swap and inversion strategies and greedy strategies	ICS is more efficient and accurate than modified PSO towards graph coloring	[2]
Zheng, H., Luo, Q., Zhou, Y.	Cuckoo Search Algorithm and Simplex Method (SMCS)	Problem: Solving planar graph coloring problem Modification: Combination of excellence global finding capability of CS and excellence local finding capability and fast convergence of SM Problem: Improving converged speed and solution precision of cuckoo search algorithm	problem Calculation accuracy and convergence speed and performance of SMCS is better than CS	[4]
Zhang, Y., Wang, L., Wu, Q.	Modified Adaptive Cuckoo Search	Modification: MACS includes grouping, incentive, adaptive and information-sharing characteristic. Problem: Improving the strategies of formal descriptions	MACS outperforms basic CS algorithm in test problem	[5]
Zheng, H., Zhou, Y., He, S., Ouyang, X.	Discrete Cuckoo Search Algorithm	Modification: Discrete Binary Cuckoo Search (DBCS) is designed to meet the need of qualitative distinction between variables. Problem: Solving knassack problem	DBCS perform better due to it has a better convergence speed and accuracy	[6]
Zhao, P., Li, H.	Opposition-Based Cuckoo Search Algorithm (OCS)	Modification: Combine the opposition-based learning into CS algorithm and the OCS algorithm for the benefit of best solution. Problem: Improving the searching of solution space in solving optimization problems	OCS shows its superiority in exploitation	[7]
Ouyang, X., Zhou, Y., Luo, Q., Chen, H.	Novel Discrete Cuckoo Search Algorithm	Modification: Discrete Cuckoo Search Algorithm generate a city number of every call. Problem: Solving spherical Traveling Salesman Problem which includes all points locate on the surface of the sphere		[8]
Yang, XS., Deb, S.	Multi- objective Cuckoo Search Algorithm (MOCS)	Modification: Cuckoo Search combines with mutation, crossover, Levy flight and selective elitism Problem: Solving multi objective optimization problems	Performance of the overall search moves of MOCS is more subtle compare to PSO	[9]
Abdul Rani, K.N., Hoon, W.F., Abd Malek, M.F., Mohd Affendi, N.A., Mohamed, L., Saudin, N., Ali, A., Neoh, S.C.	Modified Cuckoo search (MCS) algorithm	Modification: The MCS algorithm uses fitness to lead the Lévy flights in the process of finding the feasible nest (solution) in the N-dimensional space. Problem: Solving the synthesis of symmetric linear array geometry with minimum side lobe level (SLL) and nulls control	Performance of MCS algorithm excel Evolutionary Algorithm and originally Cuckoo Search Algorithm	[10]
Chaowanawatee, K., Heednacram, A.	Improved Cuckoo Search (ICS) algorithm	Modification: Gaussian distribution involves in producing a cuckoo egg Problem: Solving training network problem in the classical method	CSA via Gaussian distribution perform better in time taken and prediction error.	[11]
Saelim, A., Rasmequan, S., Kulkasem, P., Chinnasarn, K., Rodtook, A.	Modified Cuckoo search (MCS) algorithm	Modification: Cuckoo Search is altered in two ways; in finding new nest, random replacement replace Lévy fight algorithm and a context sensitive parameter replace a constant parameter Problem: Improving searching path for migration planning	MCS perform better than ACO and originally CSA	[12]
Tuba, M., Subotic, M., Stanarevic, N.	Modified Cuckoo search (MCS) algorithm	Modification: From the sorted section determines the step size, instead of permuted fitness matrix Problem: Solving unconstrained optimization problems	Performance of MCS is better compare to originally CSA	[13]
Layeb, A.	Novel Quantum Cuckoo Search	Modification: Cuckoo search Algorithm corporate with some of quantum computing principles Problem: Solving Knapsack problems	Ability of the novel quantum cuckoo search shows a good quality in obtaining solutions	[14]
Wang, L., Yang, S., Zhao, W.	Improved Cuckoo Search (ICS) Algorithm	Modification: CSA is improved by focusing on dynamic detection probability, step length and levy flight method Problem: Solving structure damage characteristics of bridge erecting machines	Improvement in convergence speed and global optimization capability and the accuracy in prediction	[15]
Walton, S., Hassan, O., Morgan, K.,Brown, M.R.	Modified Cuckoo Search (MCS) Algorithm	Modification: Modify best solution by adding addition information exchange between the top eggs Problem: Modify cuckoo search to improve its robustness	Performance of MCS is better compare CSA	[16]

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Author	Technique/ Hybridization	Problem	Result	Ref.
	evolutionary and cuckoo search algorithm which includes population of organization and organization of dynamic individuals			
Li, XT., Yin,	Technique:	Improving the	The performance of this algorithm is better compare	[29]
МН.	CSA and Orthogonal strategy	estimation of parameter of	to PSO and GE in getting a quality solution	
	Hybridization:	Lorenz system		
	Combination of the stochastic exploration (CS) and	and Chen system		
	the exploitation capability (orthogonal learning			
	strategy)			

TABLE V CSA APPLICATIONS				
Area	Applications	Authors	Year	Ref
Computer Science	Solve structural optimization problems	Gandomi, A.H., Yang, XS., Alavi, A.H.	2013	[1]
	Solving planar graph coloring problem	Zhou, Y., Zheng, H., Luo, Q., Wu, J.	2013	[2]
	A novel hybrid Cuckoo Search algorithm based on simplex operator	Zheng, H., Luo, Q., Zhou, Y.	2012	[4]
	Formal description for global optimization	Zhang, Y., Wang, L., Wu, Q.	2012	[5]
	Solving knapsack problems	Zheng, H., Zhou, Y., He, S., Ouyang, X.	2012	[6]
	Opposition-	Zhao, P., Li, H.	2012	[7]
	based cuckoo search algorithm for optimization problems		0010	503
	Spherical traveling salesman problem	Ouyang, X., Zhou, Y., Luo, Q., Chen, H.	2013	[8]
	Design optimization	Yang, XS., Deb, S.	2013	[9]
	Migration planning	Saeiim, A., Rasmequan, S., Kuikasem, P., Chinnasarn, K., Rodtook, A.	2013	[12]
	Unconstrained optimization problems	Tuba, M., Subotic, M., Stanarevic, N.	2012	[13]
	Reliability-	Kanagaraj G., Ponnambalam S.G., Jawahar N	2013	[17]
	Redundancy Allocation Problems		0010	[10]
	Job scheduling	Babukarthik R.G., Raju R., Dhavachelvan P.	2013	[18]
	Multi-objective scheduling problem	Chandrasekaran, K., Simon, S.P.	2012	[20]
	Automated test data generation	Srivastava, P.K., Knandelwal, K., Knandelwal, S.,	2012	[21]
	A mouth Country Country and and invitation allocations have an	Kumar, S., Kanganatha, S.S.	2012	[24]
	gauss distribution	Zneng, H., Znou, Y.	2012	[24]
	A new Cuckoo Search Based Levenberg-	Nawi, N.M., Khan, A., Rehman, M.Z.	2013	[26]
	Marquardt (CSLM) algorithm			
	Correction method for short-term load forecasting	Kavousi-Fard, A., Kavousi-Fard, F.	2013	[27]
	Channel estimation of MIMO-OFDM	Vidya K., Shankar kumar K.R.	2013	[31]
	Edge magnitude based multilevel thresholding	Panda R., Agrawal S., Bhuyan S.	2013	[32]
	Tsallis entropy based optimal multilevel thresholding	Agrawal S., Panda R., Bhuyan S., Panigrahi B.K.	2013	[33]
	Particle filter for Non-linear state estimation	Walia G.S., Kapoor R.	2013	[34]
	Clustering	Senthilnath J., Das V., Omkar S.N., Mani V.	2013	[35]
	Supplier selection: Reliability based total cost of ownership	Kanagaraj, G., Ponnambalam, S.G., Jawahar, N.	2012	[39]
	Bloom filter optimization	Natarajan, A., Subramanian, S.	2012	[40]
	A novel strategy of biomimicry	Goel, S., Sharma, A., Bedi, P.	2011	[41]
	Energy efficient cluster formation in wireless sensor networks	Dhivya, M., Sundarambal, M., Vincent, J.O.	2011	[42]
	Path optimization for software testing	Srivastava, P.R., Chis, M., Deb, S., Yang, XS.	2011	[43]
	Design optimization for reliable embedded system	Kumar, A., Chakarverty, S.	2011	[44]
	Data clustering	Manikandan P., Selvarajan S.	2013	[45]
	Inverse problems and topology optimization	Yang, XS., Deb, S.	2013	[46]
	Business optimization applications	Yang, XS., Deb, S., Karamanoglu, M., He, X.	2012	[47]
	optimization	Yang, XS.	2012	[49]
	Solving the problem of optimum synthesis of a six-bar double dwell linkage	Bulatovi, R.R., Dordevi, S.R., Dordevi, V.S.	2013	[53]
	Optimizing the semantic web service composition process	Chifu, V.R., Pop, C.B., Salomie, I., Suia, D.S., Niculici, A.N.	2011	[54]
	Multimodal function optimization	Jamil, M., Zepernick, HJ.	2013	[55]
	Training spiking neural models	Vazquez, R.A.	2011	[57]
Engineering	Weighted sum optimization for linear antenna array	Abdul Rani, K.N., Hoon, W.F., Abd Malek, M.F.,	2012	[10]
	synthesis	Mohd Affendi, N.A., Mohamed, L., Saudin, N., Ali, A., Neoh, S.C.		
	Structural damage identification of bridge erecting machine	Wang, L., Yang, S., Zhao, W.	2013	[15]
	Energy conscious clustering of Wireless Sensor Network	Karthikeyan, M., Venkatalakshmi, K.	2012	[19]
	Solving runway dependent aircraft landing problem	Zheng, H., Zhou, Y., Guo, P.	2013	[22]
	UCAV path planning	Wang, G., Guo, L., Duan, H., Liu, L., Wang, H.,	2012	[23]
	Back-	Nawi, N.M., Khan, A., Rehman, M.Z.	2013	[25]

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Area	Applications	Authors	Year	Ref
	propagation neural network			
	Optimization of scaling factors in electrocardiogram	Dey N., Samanta S., Yang XS., Das A., Chaudhuri	2013	[30]
	signal watermarking	S.S.		
	Expedition of groundwater exploration	Gupta D., Das B., Panchal V.K.	2013	[36]
	Scheduling optimization of flexible manufacturing	Burnwal S., Deb S.	2013	[37]
	system		2012	5203
	An efficient algorithm for gray level image enhancement	Agrawal, S., Panda, R.	2012	[38]
	Symmetric linear antenna array geometry synthesis	Rani, K.N.A., Malek, F.	2011	[50]
	Flood forecasting	Chaowanawatee, K., Heednacram, A.	2012	[52]
	The selection of optimal machining parameters in milling operations	Yıldız, A.K.	2013	[56]
	Real-world simulation-based manufacturing optimization	Syberfeldt, A., Lidberg, S.	2012	[58]
	Design optimization of truss structures	Gandomi, A.H., Talatahari, S., Yang, XS., Deb, S.	2013	[59]
	Optimization of antenna arrays	Khodier, M.	2013	[60]
	Optimum design of steel frames	Kaveh, A., Bakhshpoori, T.	2013	[61]
	Side lobe suppression in a symmetric linear antenna array	Abdul Rani, K.N., Abd Malek, M.F., Siew-Chin, N.	2012	[62]
	A new approach for DG allocation in distribution network with time variable loads	Moravej, Z., Akhlaghi, A.	2012	[63]
Mathematics	RBF neural network	Chaowanawatee K Heednacram A	2013	[11]
	Knapsack problems	Laveb. A.	2011	[14]
	A new gradient free optimization algorithm	Walton, S., Hassan, O., Morgan, K., Brown, M.R.	2011	[16]
	A cooperative co-evolutionary cuckoo search algorithm	Zheng, H., Zhou, Y.	2013	[28]
	for optimization problem			L - J
	Engineering optimization	Yang, XS., Deb, S.	2010	[64]
	Determining optimal link capacity expansions in road	Baskan, O.	2013	[65]
	networks			
	Parameter estimation of photovoltaic models	Ma, J., Ting, T.O., Man, K.L., Zhang, N., Guan, S U., Wong, P.W.H.	2013	[66]
Energy	Optimal DG allocation in a smart distribution grid	Buaklee, W., Hongesombut, K.	2013	[51]
65	A soft computing MPPT for PV system	Ahmed, J., Salam, Z.	2013	[67]
	Parameters optimization of support vector machine	Ye, Z., Li, Q., Wang, C., Liu, W., Chen, H.	2013	[68]
	Allocation and sizing of DG	Tan, W.S., Hassan, M.Y., Majid, M.S., Rahman,	2012	[69]
		H.A.		
Physics and	Parameter estimation for chaotic systems	Li, XT., Yin, MH.	2012	[29]
Astronomy	Numerical function optimization	Ong, P., Zainuddin, Z.	2013	[70]
Multi-	Medical image retrieval system	Jaganathan, Y., Vennila, I.	2013	[3]
disciplinary	A new approach for solving the unit commitment problem	Gharegozi, A., Jahani, R.	2013	[71]

It can be clearly seen that CSA can solve real-world problems by the number of publications in various applications in the area of Computer Science, Mathematics, Energy, and Engineering. In fact the performance of CSA still can be improved through modification and hybridization. There are many enhancements introduced in the structure of CSA, and the result are promising.

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