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CAT SWARM OPTIMIZATION: APPLICATIONS AND EXPERIMENTAL ILLUSTRATIONS TO DATA CLUSTERING

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Abstract: This paper presents a novel technique of Artificial Intelligence (swarm), specifically Cat Swarm Optimization (CSO). This is basically engendered by noticing the conduct of cats and improvement in the basic optimization algorithm. That is further distributed into two sub groups, i.e. locating & pursuing mode. These modes are the base for the cat swarm optimization. Experimental results using various benchmarks mathematical function show that cat swarm optimization (CSO) has improved performance than PSO and cat swarm optimization.

Key Words: *Function, Optimization, Swarm, Cats, Locating and Pursuing Mode, PSO, ACO, GA.*

I. INTRODUCTION

In Recent years various methods were projected, e.g. GA [1], ACO) [2], PSO [3], and SA [4] etc. A number of these optimisation procedures were established using brainpower of swarms. Improved CSO is projected during this paper is encouraged from CSO [5], According to the literatures, the coefficient issues[8] alongside the Particle Swarm optimization [PSO] and it have better and quick solution than the particle swarm optimization [PSO], and the experimental outcomes shows that Improved Cat Swarm optimisation (ICSO) offerings even far improved performance. Via perceptive the behaviour of individuals, we find out some plan for determination the optimization issues by learning the behaviour of ants ACO achieved, and PSO. Through reviewing the behaviour of cat, we tend to gift Cat Swarm optimisation (CSO) formula[7,8,9,10].

As per biological classification, in feline there are a unit concerning cardinal fully completely dissimilar species of individuals, for example snow leopard, living cat's, tiger, jaguar, lion, leopard, etc. and each and every one have their own or different living style& nature, most of the cats the square measure still several behaviours at the same time exist[11,12].

In spite of the searching ability isn't characteristic for kittens, it'll be qualified to accumulate. Except for the inside cats the wild kittens, searching talent confirms the existence of their rivalries; it shows the natural nature of powerfully interested by any moveable objects.

Each and every cat has the strong inquisitiveness, most of time, indolent. If you devote some time to lookout the presence of cats, you will simply realize

Most of time of cats they square measure alert on relaxing. The vigilance of cat's square measure terribly high, they forever keep alert albeit they're resting. Thus, you'll purely recognize that the cats sometimes appearance lethargic, but looking everywhere in surrounding [13, 14, 15, 16]. There on moment, they're

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aware the atmosphere. They seem to be lethargic, however truly cats are good and deliberate. Two outstanding properties are observed by behaviour of cats.

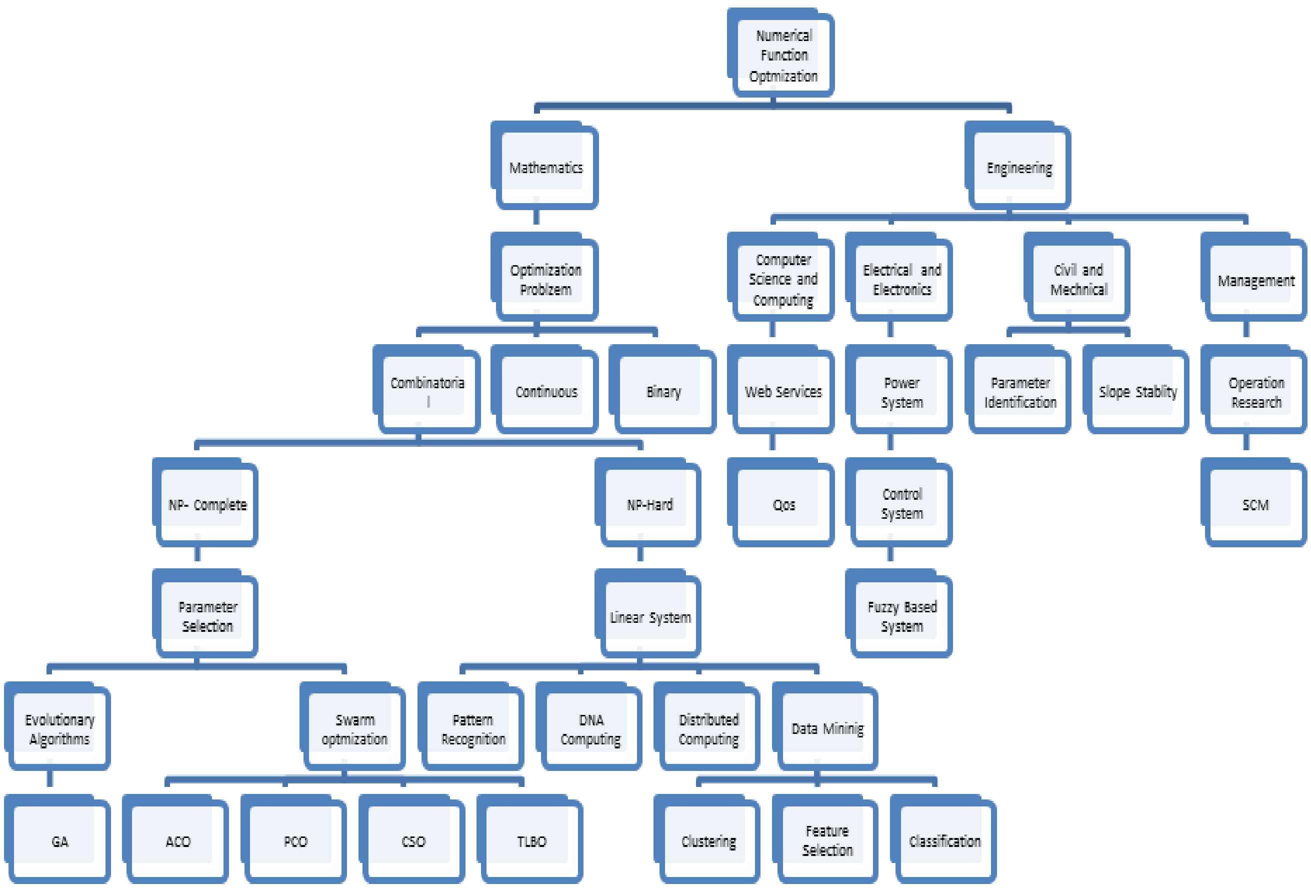

Figure 1. Classification for NFOM

II. THE CLUSTERING PROBLEM

Clustering is the process of recognizing natural groupings or clusters in multidimensional data based on some similarity measures [6]. Distance measurement is generally used for evaluating similarities between patterns. In particular the problem is stated as follows: given N objects, allocate each object to one of K clusters and minimize the sum of squared Euclidean distances between each object and the center of the cluster belonging to every such allocated object. The clustering process, separating the objects into the groups (classes), is realized by unsupervised or supervised learning. In unsupervised clustering which can also be named automatic clustering, the training data does not need to specify the number of classes. However, in supervised clustering the training data does have to specify what to be learned; the number of classes. The data set that we tackled contains the information of classes. Therefore, the optimization goal is to find the centers of the clusters by minimizing the objective function, the sum of distances of the patterns to their centers[18,19].

Table -1 Nature Inspired Optimization Techniques with years and Author Detail[19 ,20,21,22,23,24,25]

Year	Author	Algorithm
1960	John Holland	Genetic algorithm
1992	Marco Dorigo	Ant colony optimization
1995	J. Kennedy and R. Ederhart	PSO
	Memetic algorithm	Dawkin's
2002	Kevin M. Passino	Bacterial foraging optimization Algorithm (BFOA)
2003	Muzaffar Eusuff and Kevin Lansey	Shuffled Frog Leaping Algorithm (SFLA)
2005	Dervis Karaboga	Artificial Bee Colony Algorithm (ABC)
2007	Xin-She Yang	Firefly Algorithm (FFA)
2008	Dan Simon	Biogeography Based Optimization (BBO)
2009	Xin-She Yang and Suash Deb	Cuckoo Search Algorithm (CSA)
2010	Yang	Bat Algorithm (BA)
2012	Xin-She Yang	Flower Pollination Algorithm (FPA)

Table -2 Benchmark function set that is used in experiments

S.No	Function	Characteristics	Range	Di	Min.
F1	Stepint	Unimodal Separable	[-5.12, 5.12]	5	0
F2	Step	Unimodal Separable	[-100, 100]	30	0
F3	Sphere	Unimodal Separable	[-100, 100]	30	0
F4	SumSquares	Unimodal Separable	[-10, 10]	30	0
F5	Quartic	Unimodal Separable	[-1.28, 1.28]	30	0
F6	Beale	Unimodal Non-Separable	[-4.5, 4.5]	5	0
F7	Easom	Unimodal Non-Separable	[-100, 100]	2	-1
F8	Matyas	Unimodal Non-Separable	[-10, 10]	2	0
F9	Colville	Unimodal Non-Separable	[-10, 10]	4	0
F10	Trid6	Unimodal Non-Separable	[-D2,D2]	6	-50
F11	Trid10	Unimodal Non-Separable	[-D2,D2]	10	-210
F12	Zakharov	Unimodal Non-Separable	[-5,10]	10	0
F13	Powell	Unimodal Non-Separable	[-4,5]	24	0
F14	Schwefel 2.22	Unimodal Non-Separable	[-10, 10]	30	0
F15	Schwefel 1.2	Unimodal Non-Separable	[-10, 10]	30	0
F16	Rosenbrock	Unimodal Non-Separable	[-30, 30]	30	0
F17	Dixon-Price	Unimodal Non-Separable	[-10, 10]	30	0
F18	Foxholes	Multimodal Separable	[-65.536, 65.536]	2	0.998
F19	Branin	Multimodal Separable	[-5,10]x[0,15]	2	0.398

F20	Bohachevsky1	Multimodal Separable	[-100, 100]	2	0
F21	Booth	Multimodal Separable	[-10, 10]	2	0
F22	Rastrigin	Multimodal Separable	[-5.12, 5.12]	30	0
F23	Schwefel	Multimodal Separable	[-500, 500]	30	-12569.5
F24	Michalewicz2	Multimodal Separable	[0, π]	2	-1.8013
F25	Michalewicz5	Multimodal Separable	[0, π]	5	-4.6877
F26	Michalewicz10	Multimodal Separable	[0, π]	10	-9.6602
F27	Schaffer	Multimodal Non-Separable	[-100, 100]	2	0
F28	Six Hump Camel Back	Multimodal Non-Separable	[-5, 5]	2	-1.03163
F29	Bohachevsky2	Multimodal Non-Separable	[-100, 100]	2	0
F30	Bohachevsky3	Multimodal Non-Separable	[-100, 100]	2	0
F31	Shubert	Multimodal Non-Separable	[-10, 10]	2	-186.73
F32	GoldStein-Price	Multimodal Non-Separable	[-2, 2]	2	3
F33	Kowalik	Multimodal Non-Separable	[-5, 5]	4	0.00031
F34	Shekel5	Multimodal Non-Separable	[0, 10]	4	-10.15
F35	Shekel7	Multimodal Non-Separable	[0, 10]	4	-10.4
F36	Shekel10	Multimodal Non-Separable	[0, 10]	4	-10.53
F37	Perm	Multimodal Non-Separable	[D, D]	4	0
F38	PowerSum	Multimodal Non-Separable	[0, D]	4	0
F39	Hartman3	Multimodal Non-Separable	[0, 1]	3	-3.86
F40	Hartman6	Multimodal Non-Separable	[0, 1]	6	-3.32
F41	Griewank	Multimodal Non-Separable	[-600, 600]	30	0

Table -3 List of Various Parameters used for Comparsion between various optimization Techniques

Methodology	Inspiration
Technique	Dimension
Developer	Known Application area
Efficencioncy	variants
Constrained/unconstrained	Linear /Non Linear

III. EXPERIMENT RESULT

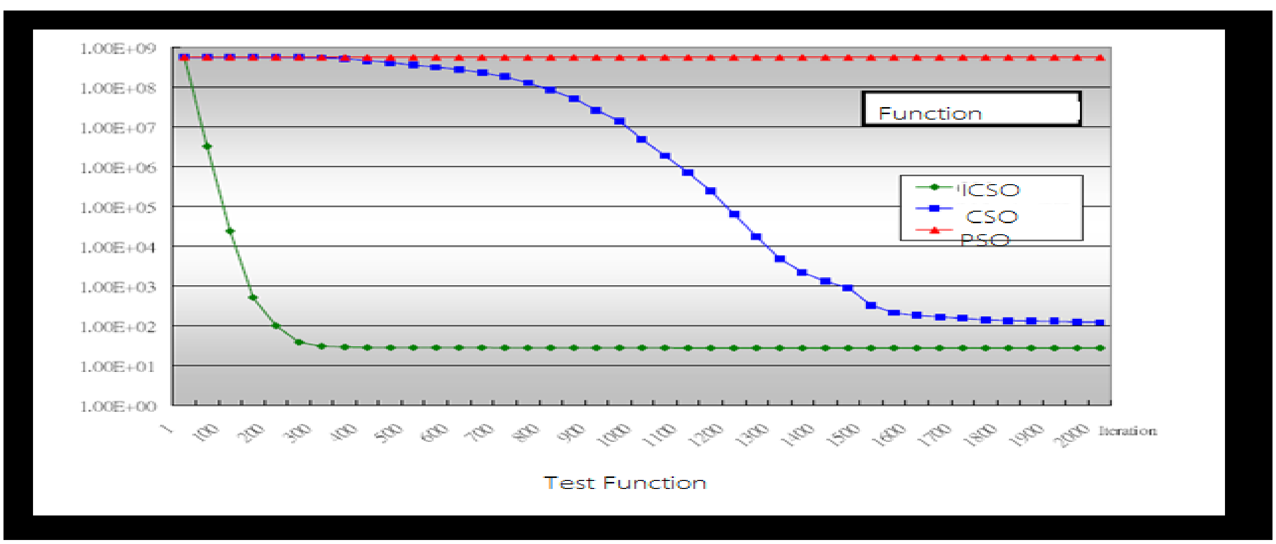

Table -4 Comparsion of Performance of various Datasets

DataSet	Classes	Attributes	Instances in each Classes	Total Instances
ART 1	3	2	(100,100,100)	200
ART 2	2	2	(100,100,100)	300
ART 3	3	3	(100,100,100)	200
Wine	2	12	(58,70,50)	170
CMC	2	6	(150,30,50)	345
Vowel	2	9	(150,444)	683

Clustering Algorithms using ART1 Dataset

Dataset	Parameters	K-means	GA	PSO	ACO	CSS	MCSS
ART 1	Best	157.12	154.46	154.06	154.37	153.91	153.18
	Average	161.12	158.87	158.24	158.52	158.29	158.02
	Worst	166.08	164.08	161.83	162.52	161.32	159.26
	Std	0.34	0.281	0	0	0	0
	F-Measure	99.14	99.78	100	100	100	100

IV.CONCLUSION

Below table shows the simulation results of the datasets, PSO, CSO, and ICSO algorithms. It’s shown that the MCSS algorithmic program provides higher ends up in comparison to alternative algorithms. It’s conjointly noted that enhancements within the CSO algorithmic program (ICSO algorithms) not solely improves the results with set1 and cancer datasets however conjointly enhances the results with all alternative datasets mistreatment all of the parameter

Parameter	PSO	CSO	ICSO
Max. Iter.	100	100	100
SRD	-	(0, 1)	(0, 1)
SMP	-	5	5
SPC	-	(0, 1)	(0, 1)
w	1	-	-
c_1	2	2	2
Vel. $_{Max.}$	0.9	0.9	0.9
W_{max}	-	-	0.5
W_{min}	-	-	-0.5

REFERENCES

[1] MacQueen J. On convergence of k-means and partitions with minimum average variance. Annals of Mathematical Statistics. 1965, 36(3), 1084-1088.

[2] Selim S. Z., Ismail M. A., K-means-type algorithms: a generalized convergence theorem and characterization of local optimality. IEEE Transactions on Pattern Analysis and Machine Intelligence. 1984, 6(1), 81-87.

[3] Jain A. K. Data clustering: 50 years beyond K-means. Pattern Recognition Letters. *2010*, 31(8), 651-666.

[4] Murthy C. A., Chowdhury N. In search of optimal clusters using genetic algorithms. Pattern Recognition Letters, 1996, 17(8), 825-832.

[5] Tseng L. Y., Yang S. B. A genetic approach to the automatic clustering problem. Pattern Recognition, 2001, 34(2), 415-424.

[6] Van der Merwe D. W., Engelbrecht A. P., Data clustering using particle swarm optimization," *Proceedings of the 2003 Congress on Evolutionary Computation (CEC'03)*, Canberra, Australia, 2003, 215-220.

[7] Shelokar P. S., Jayaraman V. K., and. Kulkarni B. D. An ant colony approach for clustering. Analytica Chimica Acta, 2004, 509(2), 187-195.

[8] Satapathy S.C.and Naik A. Data clustering based on teaching-learning-based optimization in Swarm, Evolutionary, and Mimetic Computing, Heidelberg: Springer, 2011, 148-156.

[9] Kumar Y. and Sahoo G., A charged system search approach for data clustering. Progress in artificial intelligence 2014, 2(2), 153-166.

[10] Kumar Y. and Sahoo G. A chaotic charged system search approach for data clustering.2014, 38(3), 249-261.

[11] Karaboga D.and Ozturk C. A novel clustering approach artificial Bee Colony (ABC) algorithm, applied soft computing. 2011, 11(1), 652-657.

[12] Al-Sultan K. S. A Tabu search approach to the clustering problem, Pattern Recognition.1995 28(9), 1443-1451.

[13] Krishna K. and Murty M. N.Genetic. K-means algorithm. IEEE Transactions on Systems, Man, and cybernetics, part B: Cybernetics, 1999, 29(3), 433-439.

[14] Niknam T. and Amiri B. An efficient hybrid approach based on PSO, ACO and k-means for cluster analysis, applied soft computing, 2010, 10(1), 183-197.

[15] Chu S. C, Tsai P.W. and Pan J. S. Cat swarm optimization in PRICAI Trends in Artificial intelligence. Heidelberg: Springer, 2006, 854-858.

[16] Santosa B. and Ningrum M. K. Cat swarm optimization for clustering. *Proceedings of IEEE International Conference of Soft Computing and Pattern Recognition (SOCPAR'09)*, Malacca, Malaysia, 2009, 54-59.

[17] Panda G, Pradhan P. M, and Majhi B. IIR system identification using cat swarm optimization, expert systems with applications, 2011,38(10),12671-12683.

[18] Pradhan P. M. and Panda G. Solving multi objective problems using cat swarm optimization, expert systems with applications, 2012, 39(3), 2956-2964.

[19] Kumar Y. and Sahoo G. A hybridize approach for data clustering based on cat swarm optimization, international journal of information and communication Technology, 2014,15(4) 65-69.

[20] Tsai P. W., Pan J. S., Chen S. M., and. Liao B. Y. Enhanced parallel cat swarm optimization based on the Taguchi method, expert systems with applications, 2012, 39(7), 6309-6319.

[21] Hu X. Elbehart R. C, and Shi Y. Swarm intelligence for permutation optimization: a case study on n-queens problem. *Proceedings of the 2003 IEEE Swarm Intelligence Symposium (SIS'03)*, Indianapolis, IN, 2003, 243-246.

[22] Yao X., Liu Y., Lin G., Evolutionary programming made faster, IEEE Transactions on Evolutionary Computation, 1999, 3(2), 82-102.

[23] Chu S. C. Tsai P. W., Computational intelligence based on behaviors of cats. International Journal of Innovative Computing, Information and Control, 2007, 3(1), 163-173.

[24] Wang H., Liu Y., Li C., and Zeng S., A hybrid particle swarm algorithm with Cauchy mutation," *Proceedings of IEEE Swarm Intelligence Symposium (SIS2007)*, Honolulu, HI, 2007, 356-360.

[25] Rahnamayan S., Tizhoosh H. R., and Salama M. M., "Opposition-based differential evolution algorithms," *Proceedings of IEEE Congress on Evolutionary Computation (CEC2006)*, Vancouver, Canada, 2006, 2010- 2017.