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HIGH DIMENSIONAL CLUSTER DATA PARAMETERS OPTIMIZATION USING SOCIAL GROUP OPTIMIZATION (SGO)

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Abstract:- In the recent years, the optimization of high-dimensional data contributes vital role in Data engineering applications. In this paper, we addressed a novel population based optimization algorithm called Social Group Optimization (SGO) which is motivation of perception for social behavior of human toward solving a hard problem. In SGO algorithm consists mainly two stages such as improving stage and acquiring stage. In the first stage coordination of people positions based on objective function and in the acquiring stage allowing the people to find the best potential solution for the complex problem under concern. SGO has been simulated for high dimensional benchmark function optimizations and comparison study made among well familiar state – of – art techniques such as Particle Swarm Optimization (PSO) and Teaching– Learning-Based Optimization (TLBO). The outcome of Results clearly shows that SGO more effective and efficient and also its scope is used wide variety of applications.

Key words:- Clustering, High dimensional data, Fitness Function, TLBO, SGO.

I.INTRODUCTION

Even though there is a huge amount of work dealing with global optimization, there are still not many powerful techniques to be used for dense high-dimensional functions. One of the main reasons is the high-computational cost involved. Usually, the approaches are computationally expensive to solve the global optimization problem reliably. Very often, it requires many function evaluations and iterations and arithmetic operations within the optimization code itself. For practical optimization applications, the evaluation of f is often very expensive to compute and large number of function evaluations might not be very feasible. In recent past, there is growing demand in using evolutionary computationtechniques for solving global function optimization problems. Among them, Genetic Algorithm [14], Particle Swarm Optimization (PSO) [4, 8], Differential Evolution (DE) [15] and Artificial Bee Colony (ABC)[12, 13] etc. are widely used ones. These techniques and its several variants have been implemented for many benchmark global constrained and unconstrained function optimizations [2, 9]. However, it remains as a great challenge to solve high dimensional problems with reasonably less function evaluations because they suffer from the “curse of dimensionality” [6], which simply put, implies that their performance deteriorates as the dimensionality of the search space increases. One way to overcome this exponential increase in difficulty is to partition the search space into lower dimensional subspaces, as long as the optimization algorithm can guarantee that it will be able to search every possible region of the search space. Guoliang
[16] had suggested that the search spaces should be partitioned by splitting the solution vectors into smaller vectors and each of these smaller search spaces is then searched by a separate GA. Frans applied Potter’s technique to the PSO [16]. This method can guarantee particles' search whereas the complexity of the algorithm increases at the same time.
Recently, a new optimization techniques based on Teaching learning approach known as Teaching Learning based optimization (TLBO) [1, 3, 5] is reported to produce better results as regard to the convergence speed. In this paperit has been attempted to simulate SGO algorithm for various benchmark functions with different dimensions ranging from 10 to 500 to establish the effectiveness of SGO over very popular classical PSO and DE.

2.SOCIAL GROUP OPTIMIZATION

The SGO algorithm is inspired based on mimicking the behavior and knowledge transfer practice among human groups. The SGO approach consists of two phases, such as 'improving phase' and 'acquiring phase'. In 'improving phase,' the level of knowledge for each person in the grouped community is boosted with the influence of the best person in that group. The estimation of best person in the grouped community is based on who have the highest knowledge level and caliber to get the solution of the problem. Where as in the 'acquiring phase,' persons in a group enhances their knowledge with the mutual interaction with another person in the group and the select best person in the group at that time instant. The mathematical formalization of SGO as follows:

$$Xnew_{i,j} = c * Xold_{i,j} + R * (Gbest_j - Xold_{i,j}) \quad (2.1)$$

Consider the initial knowledge of population in a group denoted as X_i , where i = 1, 2, 3, . . . , N, with N as the total size of people in the group. Suppose the optimization task for D-dimensional search space, the knowledge term can be expressed as $X_i = (x_{i1}, x_{i2}, x_{i3}, \ldots x_{iD})$. For any problem, the fitness value can be defined as *fj*, with j = 1, 2, . . . , N. Thus, for the maximization problem, the fitness value can have represented as:

In order to update the position (knowledge) of every individual in the group, the improvingphase considers the following relation:

where X_{new} is the new knowledge, X_{old} is the old knowledge, G_{best} is the global best knowledge, R is a random numeral [0,1], and c represents the self-introspection parameter [0,1]. The value of c is chosen as 0.2 in [2, 3], while, in the current work, the value of c was defined as 0.5 based on the trial and error approach.

During the acquiring phase, the agents will find the global solution based on knowledge updating process by randomly select one person from the group (Xr) based on i 6= r. Once the fitness value becomes f(Xi) < f(Xr), then the following knowledge procedure is executed:

$$Xnew_{i,j} = Xold_{i,j} + R_a * (X_{i,j} - X_{r,j}) + R_b * (Gbest_j - X_{i,j}) \quad (2.2)$$

where Ra and Rb are random numbers having the range [0,1] and Xr,j is the knowledge (position) value of the chosen individual. From the above, it can be observed that the implementation of the SGO algorithm is simple compared to other algorithms existing in the image processing domain

3.EXPERIMENTAL SETUP

The experiments were conducted in the environment of windows 10 platform, i3 processor and 4 GB main memory desktop. Experiments are implemented in MATLAB 9.2. In this paper, we consider for the simulation purpose two classes of optimal functions are chosen that are Unimodal and Multimodal. Apart from tis classes we took six bench mark functions such as Sphere, sum square, quadratic, Ackley, Scwefel 1.2 and Griewank.

All simulations of this work, the values of the common parameters used in each algorithm such as population size and total evaluation number were chosen to be the same. Population size is 50 and the maximum number fitness function evaluation is fixed as 100,000 for all functions. The other specific parameters of algorithms are given below:

PSO Settings: Cognitive and Social components, c_1,c_2 are constants that can be used to change the weighting between personal and population experience, respectively. In this experiment cognitive and social components are both set to 2 [15]. Inertia weight, which determines how the previous velocity of the particle influences the velocity in the next iteration, is 0.5[16].

TLBO Settings: In TLBO, F is a real constant which affects the differential variation between two solutions and set to F = 0.5*(1+ rand (0, 1)) where rand (0, 1) is a uniformly distributed random number within the range [0, 1]. In simulation the value of crossover rate, which controls the change of the diversity of the population, is chosen to be

R = (Rmax – Rmin) * (MAXIT–iter) / MAXIT where Rmax=1 and Rmin=0.5

are the maximum and minimum values of scale factor R, iter is the current iteration number and MAXIT is the maximum number of allowable iterations as recommended in [1, 2, 10].

In this work it has been simulated each function with different dimensions for each algorithm. The range of dimensions is chosen from 10 to 500. The simulated results are presented in Table 1 to Table 2. The fitness values and the number of function evaluations for six functions are shown in Table.1 and Table 2. The results are shown after 30 independent runs. The mean and standard deviations are calculated for obtaining global minimum values and for the number of function evaluations in each algorithm with different dimensions.

4.RESULT ANALYSIS

In the experimentation all functions are run for 10^5 function evaluations (FFs) and the simulation is terminated when it reached their maximum number of evaluations or when it reached the global minima value for each test function.

The results show that if the dimension is increases, then it is very difficult for both PSO and TLBO to locate the globalbest position and the algorithm traps into local point, but it is not the case for SGO. In other words, increasing dimensions will not effect for searching global best position in SGO. From the Table 2 it can be verified that the number of FEs are considerably less for Sphere and Sum Square functions in SGO compared to other two algorithms. Griwank, Ackley, quadratic, Schwefel 1.2 functions are finding optimal global values in SGO with less FEs compared to TLBO and PSO particularly in increasing dimensions shown in Table 1. In general, all the functions experimented in this work, SGO outperforms other two approaches. Fig. 4.1 to Fig. 4.6 presents the fitness curve of all tested functions against all algorithms.

Table 1. Performance comparisons of PSO, TLBO and SGO on different standard bench optimization functions

Dimension of Function	Algorithms		Sphere	SumSquares	Quartic	Ackley	Schwefel 1.2	Griewank
Dim=10	PSO	Mean	2.2501e-237	2.04254e-183	0.0078	1.9233	1.3068e-124	100,000
		Std	3.8790e-065	1.02995e-184	0.0035	1.1285	2.7840e-132	0
	TLBO	Mean	1.0193e-094	4.20131e-72	0.0024	4.2319e-15	7.0701e-075	75585
		Std	8.8120e-095	1.50734e-72	0.0015	4.7217e-30	1.2262e-076	443.8004
	SGO	Mean	0	0	2.0195e-04	4.2409e-15	7.1545e-242	1.2633e+04
		Std	0	0	4.4103e-05	3.0617e-30	0	2.5549e+02
Dim=20	PSO	Mean	2.9510e-061	8.5320e-53	0.1624	4.1928	5.1571e-37	100,000
		Std	2.5190e-061	1.0168e-54	0.0089	2.2236	6.2894e-41	0
	TLBO	Mean	5.8951e-33	3.6406e-26	0.0151	2.5432e-13	3.3602e-025	86302
		Std	2.398e-34	1.7954e-26	0.0050	1.1177e-13	1.2985e-025	1.7816e+03
	SGO	Mean	0	0	2.5832e-04	4.3809e-15	6.2954e-242	9158
		Std	0	0	2.7889e-05	3.9817e-30	0	483.9493
Dim=30	PSO	Mean	8.3488e-021	1.6822e-14	0.6876	11.5325	3.2218e-13	100,000
		Std	3.0982e-021	1.0017e-14	0.0159	2.4765	8.7718e-15	0
	TLBO	Mean	6.6642e-016	3.8075e-12	0.0468	2.0331e-07	2.1987e-010	100,000
		Std	3.9046e-016	1.2023e-12	0.0138	7.5523e-8	6.5789e-011	0
	SGO	Mean	0	8.5671e+04	4.0267e-04	4.2405e-15	4.5467e-242	9248
		Std	0	466.8023	1.3156e-05	4.1617e-30	0	9.2955e+03
Dim=50	PSO	Mean	1.1986e-004	0.0058	3.5824	14.3316	109.7614	100,000
		Std	1.0179e-004	0.0043	0.5138	0.4213	100.5811	0
	TLBO	Mean	2.54155e-04	4.2433e-04	0.3142	2.7713e-02	20.0194	100,000
		Std	2.50131e-04	2.2978e-04	0.1732	1.1144e-02	5.22143	0
	SGO	Mean	0	0	1.7951e-04	4.4309e-15	8.7632e-241	8976
		Std	0	0	2.1128e-05	4.0302e-30	0	316.5626
Dim=100	PSO	Mean	1.1891e+04	3.6387e+03	58.174	15.8876	4.5923e+09	100,000
		Std	1.0696e+04	2.8212e+03	5.1411	1.1722	1.7021e+09	0
	TLBO	Mean	525.1128	12.2701	6.3488	0.0039	1.2512e+08	100,000
		Std	55.2829	0.7945	1.1746	0.0012	1.2159e+06	0
	SGO	Mean	0	0	2.1471e-04	4.4409e-15	5.3293e-244	9282
		Std	0	0	4.2842e-05	4.0022e-30	0	167.8812
Dim=150	PSO	Mean	6.2340e+04	7.1165e+04	218.1459	18.0105	1.7995e+011	100,000

		Std	2.2833e+04	4.1191e+04	30.1842	0.5182	1.6921e+011	0
	TLBO	Mean	1.2321e+04	134.2467	103.3588	3.5087	3.4338e+010	100,000
		Std	2.3322e+03	0.9464	6.4572	0.1188	1.3010e+09	0
	SGO	Mean	0	0	3.9184e-04	4.4522e-15	1.2719e-242	8915
		Std	0	0	1.8129e-05	4.0117e-30	0	173.9021
Dim=200	PSO	Mean	8.7767e+04	1.4879e+05	565.1726	18.1729	1.3216e+012	100,000
		Std	5.5923e+04	2.1178e+04	54.1612	0.0729	1.2078e+012	0
	TLBO	Mean	4.5189e+04	622.0177	429.7708	12.3357	5.1429e+011	100,000
		Std	1.5961e+04	0.9446	10.2209	0.1418	5.1112e+09	0
	SGO	Mean	0	0	2.1428e-04	4.4408e-15	5.4459e-242	8820
		Std	0	0	8.2207e-05	4.0121e-30	0	0
Dim=300	PSO	Mean	2.7364e+05	3.2245e+05	3.5439e+03	18.4357	2.5234e+013	100,000
		Std	1.8196e+05	2.6214e+04	1.4652e+03	0.0812	2.2344e+013	0
	TLBO	Mean	1.4832e+05	2.1310e+03	2.3104e+03	14.2215	1.4572e+013	100,000
		Std	6.3121e+04	1.0048e+02	1.0016e+02	0.2921	1.3249e+011	0
	SGO	Mean	0	0	2.1802e-04	4.4778e-15	2.8600e-241	8815
		Std	0	0	5.4412e-05	4.0136e-30	0	210.1912
Dim=400	PSO	Mean	4.6214e+05	7.1123e+05	6.0900e+03	18.5911	1.5514e+014	100,000
		Std	2.8201e+05	3.2129e+05	2.4416e+03	0.0801	1.0022e+014	0
	TLBO	Mean	3.2518e+05	3.5815e+03	6.3211e+03	17.2618	1.2883e+014	100,000
		Std	1.9201e+05	2.0017e+02	2.1829e+02	0.2924	1.2453e+013	0
	SGO	Mean	0	0	2.1091e-04	4.4789e-15	3.8864e-242	8811
		Std	0	0	2.7481e-05	4.0151e-30	0	114.1919
Dim=500	PSO	Mean	5.2103e+05	9.6918e+05	8.4835e+03	19.0144	6.7042e+014	100,000
		Std	3.7889e+05	3.3319e+05	1.1829e+03	0.8034	2.5421e+014	0
	TLBO	Mean	4.5829e+05	4.9811e+03	1.4512e+04	18.0042	5.4456e+014	100,000
		Std	1.2245e+05	1.0021e+03	141.1529	0.3017	2.3193e+013	0
	SGO	Mean	0	0	3.2573e-04	4.4819e-15	8.4432e-240	8785
		Std	0	0	8.2556e-05	4.0177e-30	0	119.1612

Table 2. Performance comparisons of PSO, TLBO and SGO on different standard benchoptimization functions

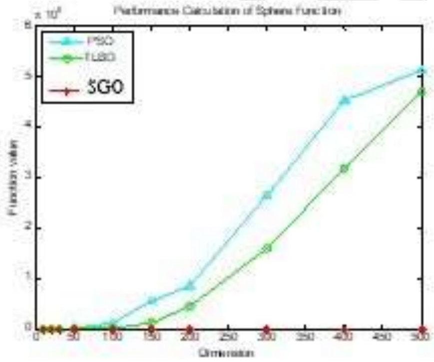

Fig. 1 Performance of Sphere function

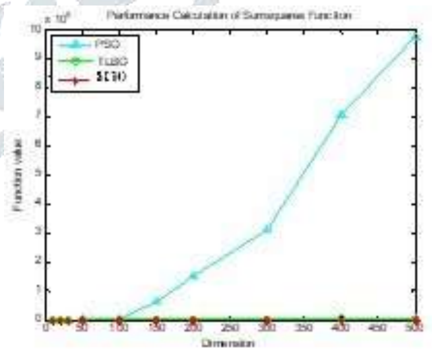

Fig. 2 Performance of Sum Square function

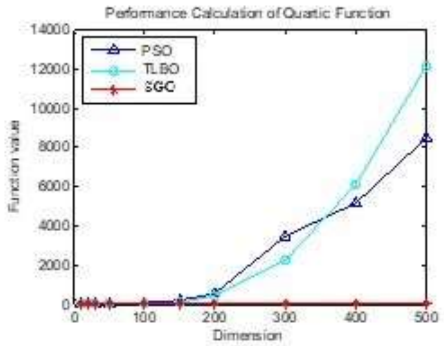

Fig. 3 Performance of Quartic function

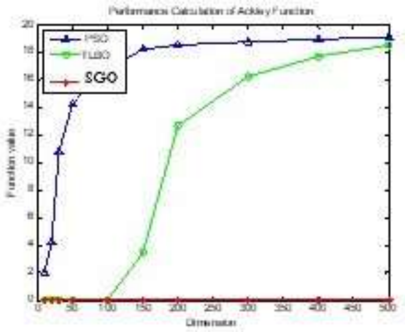

Fig.4 Performance of Acklay function

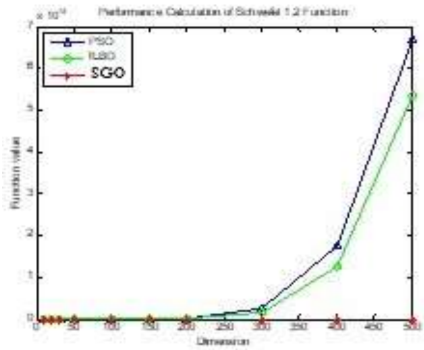

Fig. 5 Performance of Schwefel 1.2 function

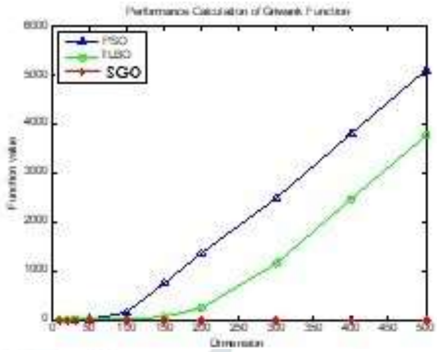

Fig. 6 Performance calculation of Griwank function

Table 4.3. Comparison Fitness function values of PSO, TLBO and SGO

Dimension /Function	Algorithms		Sphere	SumSquares	Quartic	Ackley	Schwefe l1.2	Griewank
Dim=10	PSO	Mean	100,000	100,000	100,000	100,000	100,000	100,000
		Std	0	0	0	0	0	0
	TLBO	Mean	100,000	100,000	100,000	100,000	100,000	75466
		Std	0	0	0	0	0	453.6814
	SGO	Mean	64675	6.5217e+04	100,000	100,000	100,000	1.2455e+04
		Std	431.4427	8.5898e+03	0	0	0	2.5731e+03
Dim=20	PSO	Mean	100,000	100,000	100,000	100,000	100,000	100,000
		Std	0	0	0	0	0	0
	TLBO	Mean	100,000	100,000	100,000	100,000	100,000	87386
		Std	0	0	0	0	0	1.7815e+03
	SGO	Mean	64966	65466	100,000	100,000	100,000	9114
		Std	708.3524	736.5163	0	0	0	463.7463
Dim=30	PSO	Mean	100,000	100,000	100,000	100,000	100,000	100,000
		Std	0	0	0	0	0	0
	TLBO	Mean	100,000	100,000	100,000	100,000	100,000	100,000
		Std	0	0	0	0	0	0
	SGO	Mean	65179	8.2271e+04	100,000	100,000	100,000	9003
		Std	392.4805	457.8023	0	0	0	9.1846e+03
Dim=50	PSO	Mean	100,000	100,000	100,000	100,000	100,000	100,000
		Std	0	0	0	0	0	0
	TLBO	Mean	100,000	100,000	100,000	100,000	100,000	100,000

		Std	0	0	0	0	0	0
	SGO	Mean	64435	6.2209e+04	100,000	100,000	100,000	8754
		Std	448.3805	271.9371	0	0	0	306.4626
Dim=100	PSO	Mean	100,000	100,000	100,000	100,000	100,000	100,000
		Std	0	0	0	0	0	0
	TLBO	Mean	100,000	100,000	100,000	100,000	100,000	100,000
		Std	0	0	0	0	0	0
	SGO	Mean	66076	1.2512e+03	100,000	100,000	100,000	9234
		Std	263.1428	7.6653	0	0	0	135.7317
Dim=150	PSO	Mean	100,000	100,000	100,000	100,000	100,000	100,000
		Std	0	0	0	0	0	0
	TLBO	Mean	100,000	100,000	100,000	100,000	100,000	100,000
		Std	0	0	0	0	0	0
	SGO	Mean	66765	66243	100,000	100,000	100,000	8858
		Std	374.2970	189.6022	0	0	0	173.9021
Dim=200	PSO	Mean	100,000	100,000	100,000	100,000	100,000	100,000
		Std	0	0	0	0	0	0
	TLBO	Mean	100,000	100,000	100,000	100,000	100,000	100,000
		Std	0	0	0	0	0	0
	SGO	Mean	67855	66845	100,000	100,000	100,000	9342
		Std	439.1244	432.5822	0	0	0	0
Dim=300	PSO	Mean	100,000	100,000	100,000	100,000	100,000	100,000
		Std	0	0	0	0	0	0
	TLBO	Mean	100,000	100,000	100,000	100,000	100,000	100,000
		Std	0	0	0	0	0	0
	SGO	Mean	67883	66786	100,000	100,000	100,000	8985
		Std	306.0239	313.4063	0	0	0	201.2612
Dim=400	PSO	Mean	100,000	100,000	100,000	100,000	100,000	100,000
		Std	0	0	0	0	0	0
	TLBO	Mean	100,000	100,000	100,000	100,000	100,000	100,000
		Std	0	0	0	0	0	0
	SGO	Mean	67158	66965	100,000	100,000	100,000	8875
		Std	596.7228	302.0576	0	0	0	112.1919
Dim=500	PSO	Mean	100,000	100,000	100,000	100,000	100,000	100,000
		Std	0	0	0	0	0	0
	TLBO	Mean	100,000	100,000	100,000	100,000	100,000	100,000
		Std	0	0	0	0	0	0
	SGO	Mean	67758	6.4826e+04	100,000	100,000	100,000	8855
		Std	359.6867	429.2236	0	0	0	111.5812

V.CONCLUSION

In this paper Social Group Optimization (SGO) is implemented for solving high dimensional real parameter optimization benchmark functions. The experimental results are compared with other two familiar optimization approaches as Particle Swarm Optimization (PSO) and Teaching-Learning based Optimization (TLBO). From the simulation results, it is clearly noted that SGO is a very powerful optimization technique in handling high dimension functions. We consider Six benchmark functions belonging unimodal and multimodal category are simulated with different dimensions ranging up to 500. For all bench mark functions, PSO could able to locate global minimum function values with less number of function evaluations (FEs) compared to TLBO and PSO. This has clearly demonstrated the capability of SGO as candidateto solve very high dimension industrial application problems.

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