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Comparative Analysis of Modified Social Emotional Optimization Algorithm & Particle Swarm Optimization Techniques

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Abstract: ***This paper presents a comparative analysis of Modified Social Emotional Optimization Algorithm and Particle Swarm Optimization techniques. Social Emotional Optimization Algorithm is a population based stochastic optimization technique in which the impact of human beings' emotional factors on decision-making practices is emphasized where as Swarm intelligence (SI) techniques like Genetic algorithm, Ant Colony Optimization and Particle Swarm Optimization are based on swarm behaviour. Although GA [1], PSO [2][3] and ACO[9] algorithms have lot of advantages but they simply simulate group behaviours and animal foraging. Social Emotional Optimization Algorithm (SEOA)[5] is a new swarm intelligent technique, that simulates human social behaviour. In SEOA, each individual represents one virtual person who communicates through cooperation and competition in the society. This paper focuses on the comparative analysis of Modified Social Emotional Optimization Algorithm in comparison with most successful method of optimization techniques inspired by Swarm Intelligence (SI) : Particle Swarm Optimization (PSO) and a novel swarm intelligent population-based optimization algorithm Social Emotional Optimization (SEOA). An elaborate comparative analysis is carried out to endow these algorithms, aiming to investigate whether the Modified Social Emotional Optimization Algorithm improves performance which can be implemented in many areas.***

Index Terms: Social Emotional Optimization, Particle Swarm Optimization and Swarm intelligence.

I. INTRODUCTION

Among all evolutionary computational techniques, PSO is easy to implement. A very few parameters are required to be adjusted. Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995. Particle Swarm Optimization is inspired by social behaviour of bird flocking or fish schooling. The members of colonies of social insects are non-sophisticated individuals but they are able to achieve complex tasks in cooperation. In PSO, each particle is considered as a potential solution to the problem, flying around the search sphere adjusting his velocity dynamically. The velocity formulae has three components, the first is the inertia which makes the particle move to next position, the second is the cognition component, which represents individual learning and the third is the social cognition component, which represents individual learning from other particles that guide to the global best. PSO has been successfully applied in many areas: function optimization, artificial neural network training, fuzzy system control and other areas In order to improve the premature convergence which can occur in standard PSO, a significant modification is made to the dynamics of particles in PSO to decide a position. Particles with better fitness values, cause algorithm to converge at global best position. These algorithms have advantages in solving complex problems. But they simply simulate group behaviours, with no attention of influence of emotions to individual thinking or decision-making ability ideas. Social Emotional Optimization Algorithm (SEOA) gives attention to individual thinking. Social Emotional Optimization Algorithm is an algorithm that simulates human social behaviours, in which individual decision-making ability is having importance and reserved, considering the impact of human beings' emotional factors on decision-making practices. Social Emotional Optimization Algorithm has been applied in solving Nonlinear Equations, LJ Clusters and Ag clusters, power optimization in power systems, nonlinear constrained optimization problems. The only shortcoming associated with Social Emotional Optimization Algorithm (SEOA) is that it can easily get trapped into local optima when handling multi-modal problems. To avoid this shortcoming, a modification is introduced to improve the performance of SEOA. Social Emotional Optimization Algorithm (SEOA) can be analyzed for future enhancements such that new research could be focused to produce better solution by implementing the effectiveness and reducing the limitations of SEOA.

The paper has been organized in five sections. Section 2 describes the various benchmark functions. Section 3 describes the Standard Social Emotional Optimization algorithm. Section 4 presents the comparison of performance of modified SEOA with other optimization techniques over various benchmark functions and Section 5 concludes the paper.

II. BENCHMARK FUNCTIONS

Stochastic Algorithms experience difficulty in optimizing complex multimodal optimization problems with multiple minima, therefore well-known standard benchmark functions which have many local minima are focused. To evaluate and compare the performances of the standard Particle Swarm Optimization, Social Emotional Optimization Algorithm and the modified Social Emotional Optimization Algorithm, two famous benchmark functions are chosen. The benchmark functions are numbered with their names.

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Sr. No.	Benchmark Functions
F1	Griewank
F2	Schwefel 2.26

F1: The Griewank function F3 is a multimodal with multiple minima. It has a product term, introducing interdependency between the variables.

F2: The Schwefel function F4 is also a multimodal function. The most important property of Schwefel function is that it traps all other algorithms in local optima.

III. MODIFIED SOCIAL EMOTIONAL OPTIMIZATION ALGORITHM

Social emotional optimization algorithm (SEOA)[5] is a new swarm intelligent technique that simulates human social behaviours. The word SOCIAL relates to human society. People, in the society work hard to increase their society status. To achieve high status, people try their best to achieve the best status. Inspired by this phenomenon, Zhihua Cui et al in [5] proposed a new methodology, Social Emotional Optimization Algorithm (SEOA) that is inspired by human society. In SEOA, each individual represents a virtual person. In each iteration, the individual selects the behaviour according to the corresponding emotion index. Here emotion index is divided into three parts: Low, Medium and High. According to this emotion index, a behaviour is selected and then a status value based on selected behaviour will be fedback from the society to confirm whether the selected behaviour is right or not. If this choice increases the social status value, the emotion index of the individual will increase, otherwise, emotion index decreases to decrease the social status value. In order to simulate the behaviour of human, three kinds of manners are designed [5] and the next behaviour is changed according to the following three cases:

Case1: If emotion index $_j(t+1) < TH_1$

This is the case when emotion index is too low and the individual tries to simulate other persons' experiences.

Then $x_j(t+1) = x_j(t) \oplus manner_a$

$$manner_a = k2 \cdot rand_2 \cdot (\overrightarrow{status}(t) - \vec{x}_j(t)) \quad (1)$$

Where *status*(*t*) represents the social status value obtained from other individuals having fitness values from the lowest to the highest in the society in each iteration. $rand_1$, $rand_2$ and $rand_3$ are three random functions in the range [0,1]. The values of two thresholds limits TH_1 and TH_2 are restricted in the range of [0,1] to differentiate the three behaviour manners.

Case 2: If $TH_1 <$ emotion index $_j(t+1) < TH_2$

This is the case when emotion index is in medium range and the individual tries to simulate his own experiences and other individuals' experiences in the society.

Then $x_j(t+1)=x_j(t) \oplus manner_b$

$$manner_b = k3 \cdot rand_3 \cdot (\vec{x}_{j\,best}(t) - \vec{x}_j(t)) + k2 \cdot rand_2 \cdot (\overrightarrow{status}(t) - \vec{x}_j(t)) - k1 \cdot rand_1 \cdot \sum_{s=1}^{W}(\vec{x}s(t) - \vec{x}j(t)) \quad (2)$$

Where $\vec{x}_{j\,best}(t)$ denotes the best social status value obtained by individual *j* previously and w is the number of individuals having worst fitness values in the given population.

Case 3: if emotion index $_j(t+1) > TH_2$

This is the case when emotion index is in high range and the individual learns mostly from his own experiences.

$x_j(t+1)=x_j(t) \oplus manner_c$

$$manner_c = k3 \cdot rand_3 \cdot (\vec{x}_{j\,best}(t) - \vec{x}_j(t)) - k1 \cdot rand_1 \cdot \sum_{s=1}^{W}(\vec{x}s(t) - \vec{x}j(t)) \quad (3)$$

In the standard version of SEOA, only one individual with highest social status advices others to help them in decision making. Although he has the highest social status, his advice may be right in some cases and may be wrong in some other cases. To avoid this shortcoming, a modification is introduced to improve the performance of SEOA[5]. In the decision making process, people use two kinds of information: the first one is individual's own information, while second one is other individuals' information. While making decision, people use their own information as well as other individuals' information. Based on this phenomenon, a modification is introduced in SEOA, in which a new position is estimated considering from worst to best current positions of other individuals in the society in each iteration. This means while making a decision, an individual will learn from current society status of all other individuals instead of making a decision based on a single highest status value of any individual. Modified SEOA is more effective when compared with other swarm intelligent algorithms, especially for high-dimensional cases. Modified SEOA has a superior performance in terms of accuracy.

IV. RESULTS

To test the performance of proposed modified Social Emotional Optimization Algorithm, two other algorithms are used to compare, they are the standard Particle Swarm Optimization (SPSO) and the standard Social Emotional Optimization Algorithm (SEOA). This paper selects Greiwank and Schwefel 2.26 Benchmark functions for comparison of SPSO, SEOA and Modified SEOA.

The coefficients of the standard Particle Swarm Optimization Algorithm are set as follows:

The inertia weight is set to 1.0, two learning or accelerator coefficients c1 and c2 are set to 2.0.

The coefficients of the standard Social Emotional Optimization Algorithm (SEOA) and the modified SEOA are set as follows:

Thresholds limits TH1 and TH2 are set to 0.49 and 0.6. All accelerator coefficients are set to 2.0. Population size is 100. Dimensions chosen for comparison are 30, 50 and 100. In each experiment, the simulation runs 30 times when dimensionality is 30, 50 and runs 20 times when dimensionality is 100. Each time the largest generation is 50 times the dimension.

Tables 1 to 6 illustrate the results of modified SEOA compared with SPSO and SEOA. Mean and standard deviations are listed in Table 1 to 3 for Griewangk function.

Table 1: Griewank function for Modified SEOA with Dimension 30.

Algorithm	Dim.	Mean	Std.Variance
SPSO	30	9.7240e-003	1.1187e-002
SEOA	30	5.6404e-002	4.1063e-002
Modified SEOA	30	2.9654e-004	4.0208e-005

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Table 2: Griewank function for Modified SEOA with Dimension 50.

Algorithm	Dim.	Mean	Std.Variance
SPSO	50	3.6945e-003	6.3651e-003
SEOA	50	5.4037e-003	4.0585e-003
Modified SEOA	50	3.7755e-004	4.2696e-005

Table 3: Griewank function for Modified SEOA with Dimension 100.

Algorithm	Dim.	Mean	Std.Variance
SPSO	100	2.1204e-003	4.3056e-003
SEOA	100	4.2727e-003	8.1775e-003
Modified SEOA	100	5.2935e-004	3.3354e-005

Mean and standard deviations are listed in TABLE 4 to 6 for Schwefel 2.26 function.

Table 4: Schwefel 2.26 function for Modified SEOA with Dimension 30.

Algorithm	Dim.	Mean	Std.Variance
SPSO	30	-6.2762e+003	1.1354e+003
SEOA	30	-1.0787e+004	3.4680e+002
Modified SEOA	30	-2.2121e-002	3.7710e-003

Table 5: Schwefel 2.26 function for Modified SEOA with Dimension 50.

Algorithm	Dim.	Mean	Std.Variance
SPSO	50	-1.0091e+004	1.3208e+003
SEOA	50	-1.7271e+004	6.8002e+002
Modified SEOA	50	-2.7611e-002	4.7066e-003

Table 6: Schwefel 2.26 function for Modified SEOA with Dimension 100.

Algorithm	Dim.	Mean	Std.Variance
SPSO	100	-1.8147e+004	2.2012e+003
SEOA	100	-3.1842e+004	1.0984e+003
Modified SEOA	100	-1.2163e-003	1.7403e-004

As seen from the simulation results presented in above tables, modified SEOA has the best performance among SPSO, SEOA and Modified SEOA in all dimensions. From Tables 1 to 6, it is clear to see that modified SEOA has generated best results. Modified SEOA is superior to SPSO and standard SEOA.

V. CONCLUSION AND FUTURE WORK

In this paper, a modification is proposed in the standard Social Emotional Optimization Algorithm through considering from worst to best current positions of other individuals in the society, which can provide useful information for search. Though Social Emotional Optimization Algorithm has much improved simulation results as compared to Particle Swarm Optimization, Modified SEOA performs better than standard Social Emotional Optimization Algorithm. To compare the performance of Modified SEOA, Griewank and Schwefel 2.26 benchmark fuctions are chosen and compared with other swarm intelligent algorithms like Standard PSO and SEOA. Modified SEOA is better as compared to SPSO and SEOA as its performance is slowly changed with the increased dimension. Modified SEOA can be applied in a number of areas like image processing for image segmentation, in neural networks for pattern classification and pattern matching and in the field of wireless communication. Modified SEOA can be analyzed for future enhancement such that new research could be focused to produce better solution by improving the effectiveness and reducing the limitations.

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