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Performance Analysis Of Modified Social Emotional Optimization Algorithm

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Abstract

Swarm intelligence (SI), an artificial intelligence (AI) discipline, is concerned with the design of intelligent artificial computation systems. These computation systems are designed to solve the complex computational problems. These computation systems are based on nature-inspired computation mechanisms. The most successful artificial computation systems are evolutionary algorithms (EAS). The best evolutionary algorithms (EAS) are, the genetic algorithm (GA)[1], the particle swarm optimization(PSO)[2][3] and the ant colony algorithm(ACO) [10]. Particle Swarm Optimization, a stochastic optimization technique developed by Kennedy and Eberhart in 1995, is based on swarm behaviour of bird flocking or fish schooling. Although GA, PSO and ACO 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. This paper focuses on the performance analysis of Modified Social Emotional Optimization Algorithm in comparison with most successful methods 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.

Keywords: *Social Emotional Optimization, Particle Swarm Optimization and Swarm intelligence.*

1. Introduction

To solve complex computational problems, artificial computation systems are designed that is based on nature-inspired intelligent multi-agent systems. These artificial computation systems take inspiration from the collective behaviour of social insects such as ants, termites, bees and wasps, as well as from other animal societies such as flocks of birds or schools of fish. Each member of a colony of social insects is a non-sophisticated individual, but able to achieve complex tasks in cooperation. In PSO, each particle is considered as a potential solution to a problem in a D-dimensional space. Each particle flies around the search sphere at a variant velocity according to his experience and swarm experience 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 guide to the global best. 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, having better fitness, cause algorithm to converge at global best position. These algorithms have advantages in solving complex problems. The application of PSO is widely used in pattern recognition and the neural network training. But PSO simulates group behaviours animal foraging, 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 is organized as follows:
Section 2 describes the Standard Particle Swarm Optimization algorithm. Section 3 describes Modified Social Emotional Optimization algorithm. Section 4 presents the performance analysis comparison of modified SEOA with standard SEOA and standard PSO and Section 5 concludes the paper with future work.

2. Particle Swarm Optimization

Particle swarm optimization (PSO), originally proposed by Kennedy and Eberhart, intimates the social behaviour of herds, schools, and flocks. In PSO, each particle represents a solution to a problem and its movement to the optimal point is driven by cognition and social interactions between particles [2, 3]. All particles have fitness values which are evaluated by fitness function to be optimized. The particles fly through the problem space with velocities which direct the flying of the particles. In basic PSO, a particle moves following two guides. One is its own history best (pbest), the other is local best (lbest) in a local neighbourhood or global best (gbest) in the whole swarm [2, 3].

2.1 Standard PSO Algorithm:

In standard PSO algorithm [2,3], each particle, representing a potential solution for a numerical problem. Two equations are used to describe the movement of each particle in the solution space. For the ith particle, the position and velocity is updated as follows:

$$v_{id} = w * v_{id} + c_1 * r_1 * (p_{id} - x_{id}) + c_2 * r_2 * (p_{gd} - x_{id}) \ldots (1)$$
$$x_{id} = x_{id} + v_{id}$$

Where w is the inertia weight. The function of inertia weight is to balance global exploration and local exploration. c_1 and c_2 are two positive constants known as learning factors which control the influence of pbest and gbest on the search process. Two random functions $rand_1$ and $rand_2$ are limited in the range [0,1]. Equation (1) calculates a new velocity for each particle. This new velocity depends upon the previous velocity. In Standard PSO, it is easy to get trap into premature convergence. Equation (1) shows that particles only interchange social information with the best particle in the neighbourhood but ignore the information from the others. However, in social life, an individual makes a decision depending on other individuals' decisions.

3. Modified Social Emotional Optimization Algorithm

Social emotional optimization algorithm (SEOA)[5], a new swarm intelligent technique, is developed by Zhihua Cui. Social Emotional Optimization Algorithm (SEOA) simulates human social behaviours. The word SOCIAL relates to human society where all people work hard to increase their society status. To achieve high status in the society, people work very hard and try their best to achieve the best status in the society. Inspired by this phenomenon, 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 (virtual person) 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 the selected behaviour is chosen. To confirm whether the selected behaviour is right or not, the status value is feedback from the society. If this choice increases the social status value, the emotion index of the individual will increase, otherwise, emotion index decreases to low 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 corresponding value of emotion index. The entire range of emotion index is divided into 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 $x_j(t+1) = x_j(t) \oplus manner_a$

$$manner_a = k2 \,.\, rand_2 .\, (\overrightarrow{status}(t) - \vec{x}_j(t))\text{-------}\mathbf{(1)}$$

Where *status*(t) represents the social status value obtained from other individuals having fitness values from lowest to 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.

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

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

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 $_j(t+1) > TH_2$

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

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

In the standard version of SEOA, only one individual with highest social status advices others to help them in decision making. His advice may be right in some cases. His advice may be wrong in some other cases even if he has the highest social status. To avoid this shortcoming, a modification is introduced in the algorithm to improve the performance of Social Emotional Optimization Algorithm [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. When people make decision, they use their own information as well as information from other individuals. Based on this phenomenon, a modification is introduced in Social Emotional Optimization Algorithm, 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 other individuals instead of making a decision based on a single highest status value of any individual. This 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.

4. Results

The modified SEOA provides more chances to enter the global optima. Rosenbrock Function is a classic complicate optimizing function ,whose global best position is inside a smooth, long and narrow parabolic-shaped valley owing to supply less information for optimizing function, which makes it impossible to judge the searching direction and find the global best position. So Rosenbrock Function is used to evaluate the efficiency. This paper selects Rosenbrock benchmark function which is a famous multi-modal function with only a few local optimums for comparison of SPSO, SEOA and Modified SEOA. To test the performance of the proposed modified social emotional optimization algorithm, two other algorithms the standard particle swarm optimization (SPSO) and the social emotional optimization algorithm (SEOA) are used to compare. The coefficients of SPSO, SEOA and modified SEOA are set as follows: In SPSO, the inertia weight ω is set to 1.0, two positive constants which are the accelerator coefficients $c1$ and $c2$ are both set to 2.0. Two thresholds $TH1$ and TH2 are set to 0.49 and 0.60 respectively for SEOA and modified SEOA. Three accelerator coefficients $k1$, $k2$ and $k3$ all are set to 2.0. The population size is fixed to100. The dimensions chosen for performance analysis 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.

Table 1 to 3 illustrate the results of modified SEOA in comparison with SPSO and SEOA. Mean and standard deviations are listed in Table 1 to 3.

Table 1: Rosenbrock Function for Modified SEOA with Dimension 30.

Algorithm	Dim.	Mean	Std.Variance
SPSO	30	5.6170e+001	4.3585e+001
SEOA	30	4.7660e+001	2.8463e+001
Modified SEOA	30	2.8944e+000	2.3677e-003

Table 2: Rosenbrock Function for Modified SEOA with Dimension 50.

Algorithm	Dim.	Mean	Std.Variance
SPSO	50	1.1034e+001	3.7489e+001
SEOA	50	8.7322e+001	7.4671e+001
Modified SEOA	50	4.8669e+000	2.8663e-003

Table 3: Rosenbrock Function for Modified SEOA with Dimension 100.

Algorithm	Dim.	Mean	Std.Variance
SPSO	100	4.1604e+002	1.0585e+002
SEOA	100	1.3473e+002	5.4088e+001
Modified SEOA	100	9.9085e+000	3.7874e-003

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.

5. Conclusion and Future Work

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. To compare the performance of Modified SEOA Rosenbrock benchmark function is 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. Performance of Modified SEOA is almost constant throughout the entire dimension range. 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. A future research is required for the application of Modified SEOA to the other problems.

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