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Social Emotional Optimization Algorithm for Nonlinear Constrained Optimization Problems

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Abstract. Nonlinear programming problem is one important branch in operational research, and has been successfully applied to various real-life problems. In this paper, a new approach called Social emotional optimization algorithm (SEOA) is used to solve this problem which is a new swarm intelligent technique by simulating the human behavior guided by emotion. Simulation results show that the social emotional optimization algorithm proposed in this paper is effective and efficiency for the nonlinear constrained programming problems.

1 Introduction

Many realistic problems cannot be adequately represented as a linear program owing to the nature of the nonlinearity of the objective function or the nonlinearity of any constraints. Therefore, nonlinear constrained optimization problem becomes a hot issue. It is an important type of problems which are widely used in the area of engineering, scientific, and operational applications. Up to date, many methods have been proposed to solve them especially for swarm intelligence optimization algorithms.

Recently, swarm intelligence algorithms have become a hot topic for nature-inspired computation family. This type of algorithms based on the swarm intelligence is a simulated evolutionary method that simulating the behaviors of social insects searching for food and building for nest, and including ant colony optimization[1][2], particle swarm optimization[3][4] and artificial fish-swarm algorithm[5].

SEOA is a novel swarm intelligent population-based optimization algorithm by simulating the human social behaviors. In SEOA methodology, each individual represents one person, while all points in the problem space constructs the social status society. In this virtual world, all individuals aim to seek the higher social status. Therefore, they will communicated through cooperation and competition to increase personal status, while the one with highest score will win and output

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as the final solution. In this paper, SEOA is used to solve nonlinear constrained optimization algorithms.

The rest of this paper is organized as follows: The detailed description of nonlinear constrained problem is given in section 2, while in section 3,the details of social emotional optimization algorithm is presented. Finally, simulation results are presented.

2 Nonlinear Constrained Optimization Problems

The typical nonlinear constrained optimization problems can be defined as:

$$\begin{cases} min\ f(x) \\ s.t. \quad g_i(x) \geq 0, i = 1, 2, ...m \end{cases} \tag{1}$$

where the objective function,$f(x)$:$IR^n \rightarrow IR$, and the constraint functions, $g_i(x)$:$IR^n \rightarrow IR$, maximization problems can be solved by multiplying the objective by -1.

The key question when dealing with this problems is how to deal with the constrains. One general constrain-handling technique is translate the constrained problem into an unconstrained one by adding a penalty function to the objective function. In other words, objective function can be re-formatted to:

$$F(x, r) = f(x) + r \sum_{i=1}^{m} \frac{1}{g_i(x)} \tag{2}$$

where r is a small positive number. In this paper, r sets to 0.00000000001.

3 Social Emotional Optimization Algorithm

In human society, all people do their work hardly to increase their society status. To obtain this object, people will try their bests to find the path so that higher rewards can be obtained from society. Inspired by this phenomenon, Cui et al.[6-8] proposed a new methodology, social emotional optimization algorithm (SEOA) in which each individual aims to increase the society status.

In SEOA methodology, each individual represents a virtual person, in each iteration, he will choice the behavior according to the corresponding emotion index. After the behavior is done, a status value will be feedback from the society to confirm whether this behavior is right or not. If this choice is right, the emotion index of himself will increase, otherwise,emotion index will decrease.

In the first step, all individuals' emotion indexes are set to 1, with this value, all individuals' emotion indexes is the largest value, therefore, they will think their behavior in this iteration is right, and choice the next behavior as follows:

$$\overrightarrow{x_j}(1) = \overrightarrow{x_j}(0) \oplus Manner_1 \tag{3}$$

while $\overrightarrow{x_j}(0)$ represents the degree of $j's$ individual in the initialization period, the corresponding fitness value is denoted as the society status value. Symbol $\oplus$

meas the operation, in this paper, we only take it as addition operation +. Since the belief index of j is 1, the next behavior motion $Manner_1$ is determined by:

$$Manner_1 = -k_1 \cdot rand_1 \cdot \sum_{s=1}^{L}(\overrightarrow{x_s}(0) - \overrightarrow{x_j}(0)) \tag{4}$$

while k_1 is a parameter used to control the size, $rand_1$ is one random number with uniform distribution. total L individuals are selected whose status values are the worst to provide a reminder for individual j to avoid the wrong behaviors.

In the t generation, if individual j do not obtain one better society status value than all previous values, the $j's$ emotional index is decreased as follows:

$$BI_j(t+1) = BI_j(t) - \Delta \tag{5}$$

while Δ is a predefined value. In this paper, this parameter is set to 0.05, this value is coming from experimental tests. If individual j is rewarded a new status value which is the best one among all iterations, then

$$BI_j(t+1) = 1.0 \tag{6}$$

Remark: If $BI_j(t+1) < 0.0$ is occur according to Eq.(3), then $BI_j(t+1) = 0.0$.

In order to simulate the behavior of human, we define a behavior set which contains three kinds of manners $\{Manner_2, Manner_3, Manner_4\}$. Since the emotion affects the behavior behavior, the next behavior will be changed according to the following three rules:

If $BI_j(t+1) < TH_1$

$$\overrightarrow{x_j}(t+1) = \overrightarrow{x_j}(t) + Manner_2 \tag{7}$$

If $TH_1 \leq BI_j(t+1) < TH_2$

$$\overrightarrow{x_j}(t+1) = \overrightarrow{x_j}(t) + Manner_3 \tag{8}$$

Otherwise

$$\overrightarrow{x_j}(t+1) = \overrightarrow{x_j}(t) + Manner_4 \tag{9}$$

Two parameters TH_1 and TH_2 are two thresholds aiming to restrict the different behavior manner. For Case 1, because the belief index is too small, individual j prefers to simulate others' successful experiences. Therefore, the update equation is

$$Manner_2 = k_2 \cdot rand_2 \cdot (\overrightarrow{Status}_{best}(t) - \overrightarrow{x_j}(t)) \tag{10}$$

while $\overrightarrow{Status}_{best}(t)$ represents the best society status degree obtained from all people previously. In other words, it is

$$\overrightarrow{Status}_{best}(t) = \arg\min_{s}\{f(\overrightarrow{x_s}(h)|1 \leq h \leq t)\} \tag{11}$$

With the similar method, $Manner_3$ is defined

$$\begin{aligned} Manner_3 = & k_3 \cdot rand_3 \cdot (\overrightarrow{x_j}_{best}(t) - \overrightarrow{x_j}(t)) \\ & + k_2 \cdot rand_2 \cdot (\overrightarrow{Status}_{best}(t) - \overrightarrow{x_j}(t)) \\ & - k_1 \cdot rand_1 \cdot \sum_{s=1}^{L} (\overrightarrow{x_s}(0) - \overrightarrow{x_j}(0)) \end{aligned} \tag{12}$$

while $\overrightarrow{x_j}_{best}(t)$ denotes the best status value obtained by individual j previously, and is defined by

$$\overrightarrow{x_j}_{best}(t) = \arg\min\{f(\overrightarrow{x_j}(h)|1 \leq h \leq t)\} \tag{13}$$

For $Manner_4$, we have

$$\begin{aligned} Manner_4 = & k_3 \cdot rand_3 \cdot (\overrightarrow{x_j}_{best}(t) - \overrightarrow{x_j}(t)) \\ & - k_1 \cdot rand_1 \cdot \sum_{s=1}^{L} (\overrightarrow{x_s}(0) - \overrightarrow{x_j}(0)) \end{aligned} \tag{14}$$

Because the phase "social cognitive optimization algorithm(SCOA)" has been used by Xie et al.[9] in 2002, we change this algorithm into social emotional optimization algorithm(SEOA) in order to avoid confusing, although they are two different algorithms.

4 Simulation Results

A typical nonlinear programming problem is used to test the performance of the SCOA.It is a high dimension nonlinear constrained problem which is derived from [10][11].

$$\begin{cases} max f(x) = \frac{\left|\sum_{i=1}^{n} (\cos x_i)^4 - 2\prod_{i=1}^{n} (\cos x_i)^2\right|}{\sqrt{\sum_{i=1}^{n} i x_i^2}} \\ s.t. \\ \prod_{i=1}^{n} x_i - 0.75 \geq 0 \\ 7.5n - \prod_{i=1}^{n} x_i \geq 0 \\ 0 \leq x_i \leq 10, i = 1, ...n \end{cases} \tag{15}$$

In order to achieve the The minimum,we can multiply the objective by -1.

Table 1. Results for G4

Dim	Median	Std	Best	Worst
30	-7.3504e-001	1.0095e+000	-6.0237e+000	-4.2590e-001
50	-6.0381e-001	2.1289e-001	-1.3339e+000	-3.6399e-001
100	-7.5899e-001	4.6181e-001	-2.9174e+000	-3.6143e-001
150	-8.0688e-001	5.3088e-001	-2.2063e+000	-4.9713e-001
200	-5.8417e-001	4.0397e-002	-6.4290e-001	-4.9830e-001
250	-6.0457e-001	7.5309e-002	-7.1342e-001	-4.9262e-001
300	-7.3245e-001	3.7443e-001	-1.7219e+000	-5.2621e-001

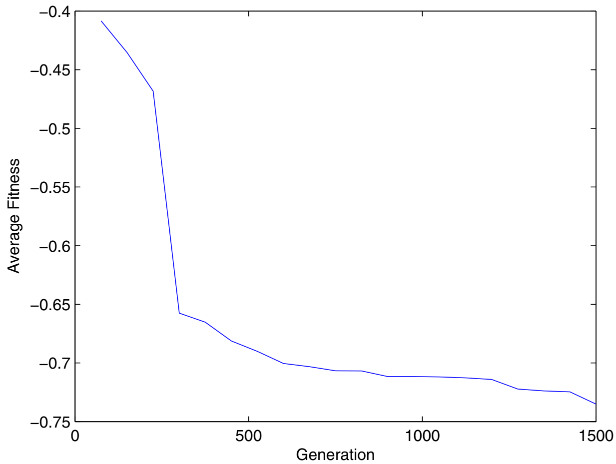

Fig. 1. $n = 30$

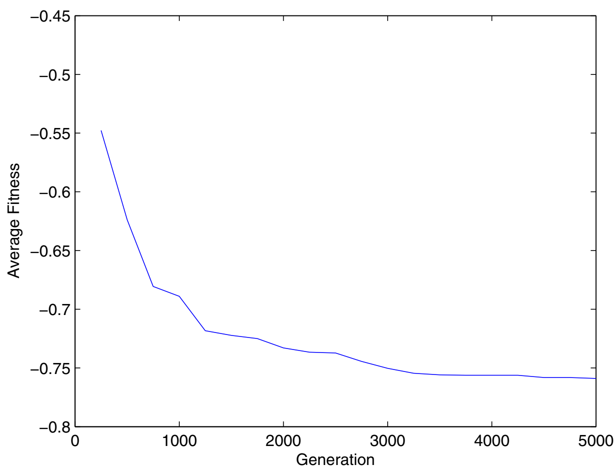

Fig. 2. $n = 100$

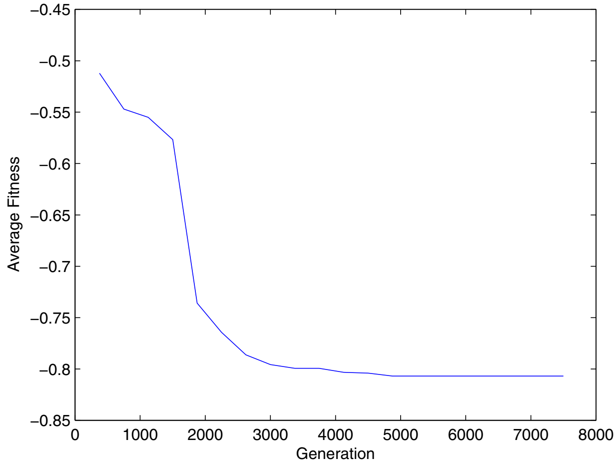

Fig. 3. $n = 150$

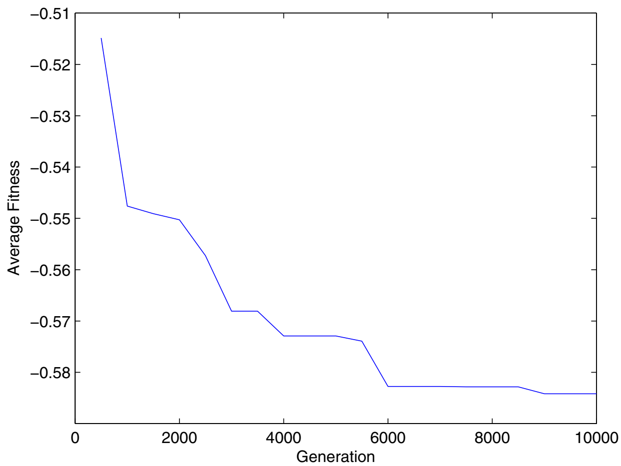

Fig. 4. $n = 200$

The number of population is 20, largest iteration is the $50 \times dimensions$. The simulation results are shown in Table I and Figure 1-2. The example demonstrates the efficiency, reliability and high speed of the proposed algorithm.

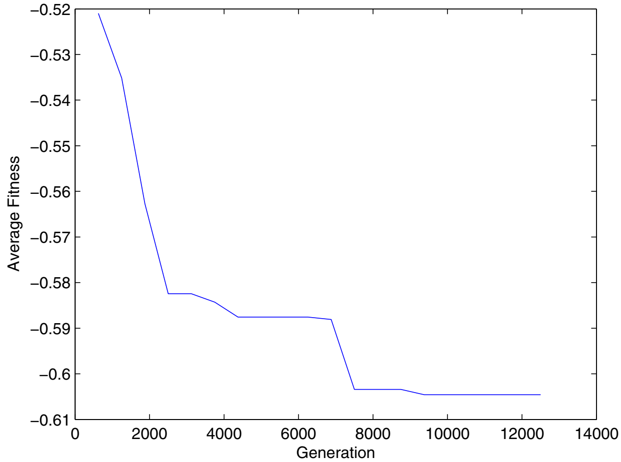

Fig. 5. $n = 250$

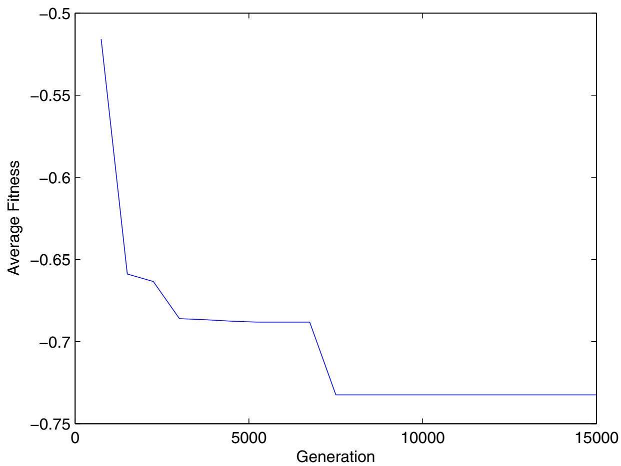

Fig. 6. $n = 300$

5 Conclusion

This paper presents a new swarm intelligent algorithm, social emotional optimization algorithm(SEOA) to solve the nonlinear constrained optimization problems. Simulation results show that SEOA is effective for this problem.

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