Indonesian Journal of Electrical Engineering and Computer Science
Vol. 3, No. 2, August 2016, pp. 475 ~ 480
DOI: 10.11591/ijeecs.v3.i2.pp475-480

An Improved Chaos Electromagnetism Mechanism Algorithm for Path Optimization Problem

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Abstract

As we all know, traditional electromagnetism mechanism (EM) algorithm has the disadvantage with low solution precision, lack of mining ability and easily falling into precocity. This paper proposes a new chaos electromagnetism mechanism algorithm combining chaotic mapping with limited storage Quasi-Newton Method (EM-CMLSQN). Its main idea is that it adopts limit quasi-Newton operator to replace the local optimization operator in EM algorithm for local searching in the late of algorithm. In the process of algorithm, the chaos mapping is introduced into optimization processes, and it generates new individuals to jump out of local to maintain the population diversity according to characteristics of chaos mapping random traversal. Finally, the experiments show that the new algorithm can effectively jump out of local optimal solution through comparing three continuous space test functions. The new algorithm has obvious advantages in terms of convergence speed compared to traditional EM algorithm, in addition, it is more accuracy than particle swarm optimization (PSO) algorithm. We compare the new chaos electromagnetism mechanism algorithm with ant colony optimization (ACO) algorithm, PSO algorithm, the results represent that new scheme can obtain the optimal path in the path optimization process, which shows that the new method has better applicability in the discrete domain problem.

Key words: *electromagnetism mechanism, limited storage quasi-newton method, limit quasi-newton operator, chaos mapping, particle swarm optimization, discrete artificial bee colony algorithm*

1. Introduction.

Electromagnetism Mechanism (EM) algorithm [1, 2] is a kind of random search methods based on principle of attraction and repulsion between different charged particles in Coulomb law and electromagnetic field. This algorithm firstly establishes the relationship of fitness function value and individual's value affected by electric field, then it is as the population movement trend according to the principle of "excellent solutions attract poor, poor solutions reject the excellent" and puts forward a global stochastic optimization heuristic algorithm [3]. The global stochastic optimization heuristic algorithm has been used in many aspects, such as fault location in distribution networks and pipeline assemble. Nevertheless, the EM algorithm has the shortcoming of premature convergence, low local search accuracy in late and slow convergence rate, which resembles other global intelligent algorithms. To solve these problems, this paper proposes an improved local optimization strategy using high precision local optimization operator and limited storage Quasi-Newton operator [4]. It seeks optimization value for solution domain near optimal individual and adopts chaos mapping [5] to increase the diversity of population. As a mature intelligent algorithm, Particle Swarm Optimization (PSO) algorithm [6, 7] has a very good effect on searching the optimization value in continuous domain. There is an improved PSO algorithm named particle swarm optimization with Time-Varying Accelerator Coefficients (TVAC) [8, 9], which has a better ability of searching optimization. Therefore, we compare TVAC with our new method (EM-CMLSQN), and the simulation results show that EM-CMLSQN has a better convergence rate and performance of jumping out of local solution than PSO and TVAC method. We also apply EMCMLSQN algorithm into path planning problem, and the results represent that EM-CMLSQN algorithm can search the optimal path more precisely and can be better applied into solving discrete domain problems than genetic algorithm and PSO algorithm [10, 11].

Received March 2, 2016; Revised June 25, 2016; Accepted July 10, 2016

2. Electromagnetism Mechanism.

The basic EM algorithm is composed of initialization, local search, resultant force calculation, particle displacement and judgment terminated.

a) Initialization. Initialization process of EM algorithm is a random process of initialization. In the solution domain, it randomly generates several solutions as the original generation. The charge value of particle $x_{i,j}$ is:

$$q_{k,i} = e^{-n\frac{f(x_{k,i})-f(X_{k,best})}{\sum_{i=1}^{m}(f(x_{k,best}))}} \quad (1)$$

Where $q_{k,i}$ is the charge value of *i−th* particle at *k−th* iteration process, *n* is the total number of particles. *f(·)* is evaluation function. $x_{k,i}$ is the *i−th* particle at *k−th* iteration process. $x_{i,best}$ is one particle with the best evaluation function value at *k−th* iteration process.

b) Local search. Local search strategy in EM algorithm adopts linear search. Its expression is as follows:

$$Y_i = \begin{cases} X_i + \alpha（U - X_i） & \alpha > 0.5 \\ X_i - \alpha（X_i - U） & \alpha \leq 0.5 \end{cases} \quad (2)$$

Where x_i is i − *th* particle. Y_i is the searched particle in neighborhood of X_i. α is a random number from 0 to 1. *L* is lower bound of feasible region. *U* is upper bound of feasible region.

c) Resultant force calculation. According to the principle of superposition, resultant force F_i of each particle can be defined as the following formula:

$$F_i = \begin{cases} \sum_{j\neq i}^{m} \frac{q_i q_j (X_j - X_i)}{\|X_j - X_i\|^2}, & f(X_j) \geq f(X_i) \\ \sum_{j\neq i}^{m} \frac{q_i q_j (X_{j\_} X_i)}{\|X_j - X_i\|^2}, & f(X_j) \geq f(X_i) \end{cases} \quad (3)$$

It can be seen from (3) that particles with better function value would attract the particles with poorer function value, and particles with poorer objective function value will reject particles with better function value. If f(（X_j） < f(X_i)), then they have attraction, on the contrary, they have repulsive force. The direction of the resultant force between any two particles points to particles with better objective function value, which ensures that the algorithm is finally able to find the optimal solution.

d) Particle displacement. Moving formula of X_i is defined as:

$$Z_i = X_i + \lambda \frac{F_i}{\|F_i\|} \quad (4)$$

Where λ is random step length ranging [0,1]. Z_i is a new particle after moving. Then f(Z_i) and f(X_i) can be recalculated and algorithm starts to carry out greedy selection.

e) Judgment terminated. As with the rest of the intelligent algorithms, it sets the terminating condition, if it meets the condition, then stop. Otherwise continue to execute iteration.

3. Chaos Electromagnetism Mechanism Algorithm Based on CLMSQN.
3.1. The Confined Quasi-Newton Local Operator

With the calculation method in formula (3)(4), when individual i is close to optimal individual X_{best}, the $|X_i - X_j| \to 0$, then $|F_i| \to \infty$. The i will sustain a bigger resultant force. There is a great error with particle moving direction. And it cannot make searching near optimal solution. So this paper adopts ECMLSQN algorithm to search local solution. ECMLSQN algorithm is a effective optimization method using derivative operator with the advantages of fast convergence speed, strong local search ability. Assuming $S_k = S_{k+1} - X_k$, Y_k = 5f(X_{k+1})−5f(X_k). So we can get the Hessen matrix formula as (5).

$$\begin{aligned} H_{k+1} &= V_k^T H_k V_k + \rho_k s_k s_k^T \\ &= V_k^T [V_{k-1}^T H_{k-1} V_{k-1} + \rho_{k-1} s_{k-1} s_{k-1}^T] V_k + \rho_k s_k s_k^T \\ &= \ldots\ldots = [V_k^T \ldots V_{k-\hat{m}+1}] H_{k-\hat{m}+1} [V_{k-\hat{m}+1} \ldots V_k] \\ &= \rho_{k-\hat{m}+1} [V_{k-1}^T \ldots V_{k-\hat{m}+2}] s_{k-\hat{m}+1} s_{k-\hat{m}+1}^T [V_{k-\hat{m}+2} \ldots V_{k-1}] + \ldots + \rho_k s_k s_k^T \end{aligned} \quad (5)$$

Therefore, the processes of ECMLSQN algorithm are as follows:

a) Choosing initial node X_0 ∈ Rn and setting positive integral m.
b) Assuming H_0 = I, k = 0. Calculating gradient g_k = 5f(X_k) of objective function f(x) at X_k .
c) Determining the search direction d_k let $d_k = H_k g_k$.
d) Starting from the X_k, it searches solutions along the direction of the d_k to calculate λ_k: $f(x_k + \lambda_k d_k) = \min \min_{\lambda \geq 0} \{ f(x_k + \lambda_k d_k) \}$.
e) Let $x_{k+1} = x_k + \lambda_k d_k$. If ||f(x_{k+1})||≤ε, Then stop iteration and get optimal solution, otherwise return step6.
f) Selecting $\hat{m}$ = min{k + 1,m}, according to (5), it updates H_0 for $\hat{m}$ times and gets H_k .

3.2. Chaos Operator

Considering chaotic movement has a good diversity so using chaotic operator for local search can improve the performance of the algorithm, its detailed process is as follows. Let Up and Low be upper and lower bounds of feasible region respectively. $x_{best} = (X_1, X_2, \cdots, X_3)$ is current optimal position. So it executes mapping process as shown in formula (6).

$$\alpha = \frac{x_{best} - Low}{U_p - Low} \quad (6)$$

Obviously, after mapping the interval is [0,1], so this paper can use Logistic mapping to generate chaos variables as shown in (7).

$$\alpha' = \mu\alpha\,(1-\alpha) \quad (7)$$

Where µ is controls parameter, when *µ = 4*, system is in a state of complete chaos, which is conducive to jump out of local optimum. Finally, we inverse chaotic variables mapping to the solution domain through (8). Then it experiences repetitive process until that the function value is unchange.

$$x'_{best} = Low + \alpha'(U_p - Low) \quad (8)$$

3.3 EM-CMLSQN Algorithm Process

The detailed processes are as follows:

Step1. Initialization.

Step2. Local search. It conducts local search and greedy selection around the initial solution according to(2).

Step3. Determine whether make confined quasi-Newton method and local optimization. Setting threshold value ε, when $|x_i - x_j| < ε$, it randomly selects k confined quasi-Newton local operator to search local optimal solution and jump to step5. Otherwise it does go to step4.

Step4. Computing resultant force. According to (3) (4), it calculates resultant force of particles and the fitness function value of particle movement.

Step5. Particle movement. Algorithm calculates the fitness value of individual in step4 and compares to best individuals in last generation. If $f(X_0') > f(X_i)$, it makes greedy selection, otherwise it enters into chaotic mapping process. Firstly, we set chaotic search iterative threshold *Ibet*; Secondly, the existing particle is mapped to the chaotic space according to formula(6); Thirdly, for variables after mapping, we adopt formula (7) to generate new chaotic variables; Fourth, we use formula (8) to reflect the shooting method, projection solution domain and get new particles. If the fitness of new particles is greater than the that in original particles, then it makes greedy choice, otherwise remain unchanged.

Step6. Judgment termination. It determines that whether the number of iterations satisfies the initial threshold value. If it does not satisfies the condition, then it returns to step2. Otherwise it outputs results.

4. Experiments and Analysis.

In this paper, we adopt three continuous domain test functions: Sphere (f_1), Griewank (f_2) and Rosenbrock (f_3) to make experiments under MATLAB R2010a platform (Processor: 2.13GHz, Memory: 4GB). In order to show the superiority of the improved algorithm, we make 100 experiments with the above three functions for EM algorithm and EM-CMLSQN algorithm. Iteration number of (f_1), (f_2) and (f_3) is 1000, 6000 and 4000 respectively. Number of dimensions is 30 and population number is 50. Compared to the traditional algorithm, the new algorithm obtains the outcomes as Figure1-3. It can be clearly seen from Figure 1 that EM algorithm and EM-CMLSQN algorithm can effectively make optimization for Sphere test function, but the latter adopts confined quasi-Newton local optimization operator after reaching set threshold which can accelerate convergence and gets higher precision than the EM algorithm.

As shown in Figure 2, performance of EM-CMLSQN is better than the EM algorithm during the process of Griewank function(It is a multimodal function), on account for the fact that the confined quasi-Newton operator is adopted to improve the local search, and then it uses the chaotic mapping to avoid precocity, which reflects a good performance. In Figure 3, EM algorithm has difficulty in searching optimal solution, nevertheless, to a certain extent, this paper's method uses tentative mind based on the principle of chaos disorder leading the group in the direction of high quality solutions to search for Rosenbrock function. So the performance of EM-CMLSQN algorithm is better.

In order to verify the fast convergence ability of the new algorithm, we define that if the difference between optimal individual and the known extreme value is less than a certain value, then test function is convergent. The setting value of Sphere, Griewank and Rosenbrock function is $1.0e^{-15}$, 0.01 and 0.1 respectively. We select the most optimal solution for statistical comparison between EM-CMLSQN algorithm and EM, PSO, TVAC algorithm, and get the results shown in table 1. From table1 we can know that iteration time of EM-CMLSQN is the minimum in test function 1, 2. Also it has the fastest convergence speed. The rest of the algorithms have difficulty in reaching convergence state. But the confined quasi-Newton operator is introduced into new algorithm, which can effectively conduct local optimization and chaotic mapping is used to guide the optimization direction. Therefore, the scheme has fast convergence speed and less number of iterations.

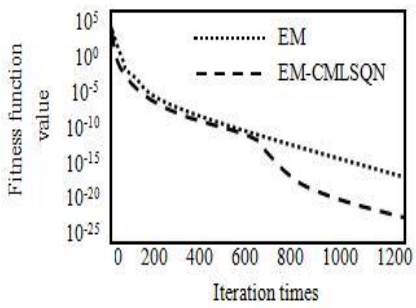

Figure 1. The Comparison Curve Of Iterative Convergence in Sphere functi on

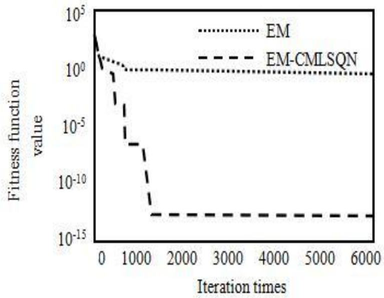

Figure 2. The Comparison Curve of Iterative Convergence in Griewank Function

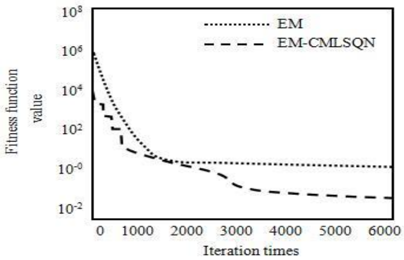

Figure 3. The Comparison Curve of Iterative Convergence in Rosenbrock Function.

Table 1. Comparison of Convergent Iterations

Algorithm	f_1	f_2	f_3
EM-CMLSQN	853	986	1520
EM	902	1685	4000
PSO	2380	3578	4000
TVAC	1709	2978	4000

5. Conclusions

In this paper, we simply describes the basic principle of EM and analyze its merits and demerits. To solve the problem of low local optimization ability in the late algorithm and easily falling into local optimum, we introduce the confined quasi-Newton local optimization operator to improve the local search algorithm performance. In the iteration process, the chaos operator is introduced to maintain the diversity of population, which effectively avoids the premature phenomenon of the algorithm and gets higher solution precision. Finally, the simulation results show that EM-CMLSQN in continuous domain optimization can jump out of local optimal solution and have a higher precision, faster convergence speed. When it is applied into the path planning problem, the new scheme can avoid the phenomenon of ”back and forth”, get the best path through optimizing capacity and high-precision search capability. In the future, we will study more improved electromagnetism mechanism algorithms to perfect optimization problems.

Acknowledgment

The authors also gratefully acknowledge the helpful comments and suggestions of the reviewers, which have improved the presentation.

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