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An Enhanced Searching Electromagnetism-like Mechanism Algorithm for Global Optimization Problem

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Abstract

A global optimal algorithm derived from electromagnetism-like mechanism (EM), called as enhanced searching electromagnetism-like (ESEM) algorithm, was developed in this paper. The original EM is a meta-heuristic algorithm utilizing an attraction-repulsion mechanism (called as force F) to move sample points towards optimality in global optimization problems. Compared to the original algorithm, the best historical visited positions of each point were added into the search process in the improved algorithm. In ESEM, the search direction and step length of points were determined together by its best previously visited position, best point in current swarm and total force F. Preliminary experiments showed that additional best historical positions can help to improve the convergence property. More importantly, the improved searching mechanism can effectively solve the problem of stagnation of the original algorithm caused by too small values of force F.

Keywords*: electromagnetism-like; stochastic search method; global optimization*

1. Introduction

The problem that is addressed in this paper considers finding a global optimal solution of a nonlinear optimization problem as following form:

$$\begin{aligned} &\min \quad f(x) \\ &\text{subject} \quad x \in \Omega \end{aligned} \tag{1}$$

Where f: $R^n \rightarrow R$ is a nonlinear continuous functions and the closed set Ω is defined by $\Omega=\{x \in R^n : l \leq x \leq u\}$, where l and u are, respectively, the lower and upper bounds of x. Here we assume that the objective function f is non-convex and existing many local minima in the feasible region. This class of global optimization problems is very important and frequently encountered in engineering applications. In the last decades, many algorithms have been proposed to solve problem (1). Probably the most extensively used in practice are stochastic-type algorithms [1-3]. In this paper, we are interested in the electromagnetism-like (EM) algorithm proposed in [4,5]. This is a population-based algorithm that simulates the electromagnetism theory of physics by considering each point in the population as an electrical charge. The method uses an attraction-repulsion mechanism to move points towards the optimum.

Many revised versions have been developed to improve the original EM. The modifications in [6] are concerned with the charges associated with each point in the population, and a new formula for calculating charge of point is proposed. A local search

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based on the original pattern search method of Hooke and Jeeves and a shrinking strategy that aims to reduce the population size are proposed in [7]. A new modified EM algorithm is proposed in [8] using a linear combination of the total force exerted on a point, computed at the current iteration, with that of the previous iteration to define the force vector to move that point in the population. In [9], a hybrid IEM algorithm combining the advantages of the EM algorithm and the genetic algorithm is proposed for recurrent fuzzy neural controller design. Another hybrid approaches combining an electromagnetism-like method with a strong local search method, known as Solis and Wets and modified DFP, are proposed in [10,11]. A hybrid technique incorporating concepts of PSO and EM is proposed in [12], which creates individuals in a new generation not only by features of PSO, but also by attraction-repulsion mechanism of EM.

In this paper, a modified attraction-repulsion mechanism of EM is presented. In the proposed algorithm, the best previously visited position of each point is added into the search process, and search direction and step length for point from one generation to next are synthetically determined by following factors: current point's best previously visited position, the best particle in current swarm and total force F. Introduction of the best historical positions can help to improve the property of convergence. More importantly, this improved search mechanism can help solve the problem of stagnate of the original algorithm caused by too small values of the total force F, especially during the latter stage of iteration.

The rest of this paper is organized as follows. In Section 2, a review of the original EM and motivation of this paper are introduced. The general scheme of the proposed algorithm is demonstrated in Section 3. In Section 4, computational results on a set of test problems are presented. Some conclusions are given in Section 5.

2. A Brief Review of EM

2.1. The Principle of EM

EM algorithm is a stochastic search method for global optimization. Similar to GA, population-based algorithm starts with randomly sampling points from the feasible region. According to the objective function values of these sample points, the regions of attraction are determined. Then a mechanism, similar to the attraction-repulsion mechanism of the electromagnetism theory, is invoked for further exploitation of these candidate regions. In EM, the charge of each point relates to the objective function value. This charge also determines the magnitude of attraction or repulsion of the point over the sample population – the better the objective function value, the higher the magnitude of attraction. The direction for each point to move in subsequent iterations can be determined by evaluating a combination force exerted on the point via other points. Like the electromagnetic forces, this force is calculated by adding the forces from each of the other points calculated separately. Then this attraction-repulsion mechanism encourages the points to converge to the optimal regions rapidly.

Take the following Figure 1 for example. There are three particles and their own objective values are 15, 10 and 5, respectively. Because particle 1 is worse than particle 3 while particle 2 is better than particle 3, particle 1 represents a repulsion force which is the F_{13} and particle 2 encourages particle 3 that moves to the neighborhood region of particle 2. Consequently, particle 3 moves along with the total force F. More details about EM can be available in [4].

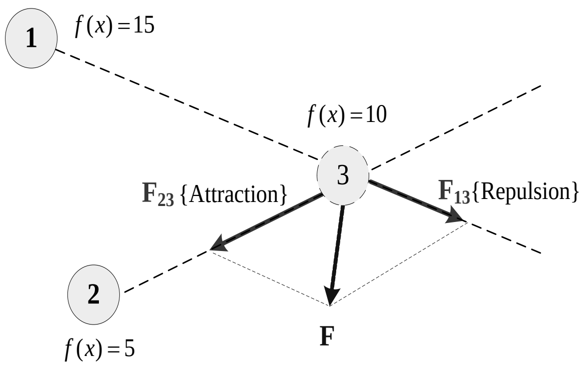


Figure 1. An Example of Attract-Repulse Effect

2.2. Motivation

In original EM, all particles except current best particle will be updated and previous positions will not be reserved. Although it has been proved that EM can converge to the vicinity of global optimum with probability one [5], it does not guarantee that the newly generated particles are all better than the previous per iteration. This means that a lot of useful historical information conducive to find the optimal solution may lose during the search process. To solve this problem, the best previously visited positions of all particles will be recorded and applied in the revised method.

There is another issue we need to consider about EM. As discussed above, the EM utilizes an attraction-repulsion mechanism to move particles towards the optimality. The moving direction and step of particles are determined by evaluating a combination force F exerted on the point via other points. Obviously, if force F is too weak, the movement of particle will fall into stagnation. It isn't conductive to the exploration of the optimality. Unfortunately, this situation is more likely to occur in the search process of EM, especially during the later stage. The problem of stagnation can be illustrated by using Figure 2 below.

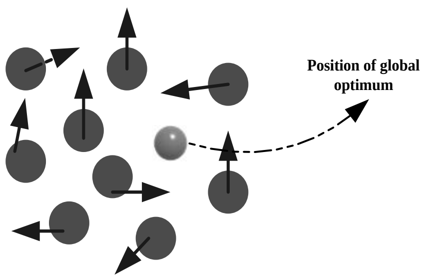


Figure 2. An Illustration of Stagnation Problem

As shown in Figure 2, most particles are concentrated around the position of global optimum. According to the work mechanism of EM, the situation showed in Figure 2 often occurs during the latter stage of iteration [4]. Because positions of all particles are close to each other, the objective function values of the corresponding particles in Figure 2 are also close. In this situation, it is most likely to happen that the combination forces F exerted on the points are close to 0. Consequently the particles will stagnate according to the search mechanism of EM. In order to avoid this problem, we will add an independent force exerted on the point from the current best point. More detailed discussions are available in 3.4.

3. The Revised Algorithm

Similarly to the original EM, the revised algorithm also consists of four steps: initialization, local search, calculation of charge and total force vector and movement of point.

3.1. Initialization

The procedure initialization is used to sample m points, $\left\{x^1,\cdots,x^m\right\}$, randomly from the feasible domain of the variables, where $x^i=\left[x_1^i,\cdots,x_n^i\right],\left(i=1,\cdots,m\right)$,where n represents the dimension of problem. The procedure uniform sampling can be determined by following:

$$x_k^i=l_k+rand\cdot(u_k-l_k) \qquad k=1,\cdots,n \tag{2}$$

The procedure ends with m points identified, and the point that has the best function value is stored in $\boldsymbol{x}^{\text{best}}$.

3.2. Local Search

In the original EM, the local search procedure is used to gather local information and improve the current solutions. Application of the local search procedure might produce better results. Notice that the performance of the algorithm improves but at the cost of the number of function evaluations required by the Local procedures. Therefore, the combined local search algorithm should be as simple as possible in the improved EM.

3.3. Calculating of Charge and Force Vector

In the original EM, the charges of the points are calculated according to their objective function values, and the charge of each point is not constant and changes from iteration to iteration. The charge of each point i, denoted by q^{i}, determines point *i*'s power of attraction or repulsion. This charge is evaluated as following:

$$q^i=\exp\left(-n\frac{f(x^i)-f(x^{best})}{\sum_{k=1}^{m}(f(x^k)-f(x^{best}))}\right),\forall i \tag{3}$$

In this way, the points that have better objective values possess higher charges. From formula (3), the total force $\mathbf{F}^{\text{i}}$ exerted on point *i* is computed by the formula (4).

$$\mathbf{F}^i=\begin{cases}\sum_{j\neq i}^{m}x^j-x^i\dfrac{q^iq^j}{\left\|x^j-x^i\right\|^2} & if \quad f(x^j)<f(x^i)\\ \sum_{j\neq i}^{m}x^i-x^j\dfrac{q^iq^j}{\left\|x^j-x^i\right\|^2} & elseif \quad f(x^j)\geq f(x^i)\end{cases},\forall i \tag{4}$$

According to formula (4), the direction of force between two points is decided after comparing their objective function values. The point that has a better objective function value attracts the other one. Contrarily, the point with worse objective function value repels the other.

3.4. Moving Points

After evaluating the total force vector Fi, the point i is moved by a step given by following formula:

$$x_{ij}^t=x_{ij}^{t-1}+\omega_1(p_{ij}^{t-1}-x_{ij}^{t-1})+\omega_2(g_j^{t-1}-x_{ij}^{t-1})+F_{ij}^t \tag{5}$$

Where, p_{ij} is the j-dimensional component of the best historical position of point *i*. g_j is the *j*-dimensional component of the best point of the current the swarm. ω_1 and ω_2 are weighting factors, such that:

$$\omega_1 + \omega_2 = 1$$

The value of above weighting factors are randomly generated from [0 1]. Note that the new positions should be checked (and modified if necessary) to ensure the allowed feasible movement toward the upper bound, or the lower bound, that:

$$x_{ij}^{t+1} = \begin{cases} \text{upper bound } u_j & if\ x_{ij}^{t+1} > u_j \\ \text{lower bound } l_j & if\ x_{ij}^{t+1} < l_j \end{cases} \tag{6}$$

Finally, after updating all points, the termination criteria will be checked to determine to stop calculation or modify (if necessary) the pi and g, and repeat the search process. The general scheme of the proposed algorithm can be given in Figure 3.

m: number of sample points
x_i: the coordinate of point *i*
g、p_i: coordinate of the best point in the swarm and best historical position of point *i*.

1. Initialization{}
   - 1.1 Sample *m* points randomly from the feasible domain according to (2), and calculate the corresponding objective function value $f(x_i)$.
   - 1.2 Set p_i equal to be x_i obtained by step 1.1 (Since there no previously visited position in the first iteration).
   - 1.3 Find the best point *g* in the swarm.
2. Check the stop criteria, if the stop criterion is not satisfied, go to Step 3.
3. Calculation of charge and total force F{}
   - 3.1 Calculate the charge by formula (3).
   - 3.2 Calculate the force **F** by formula (4).
4. Movement of points{}
   - 4.1 Update the positions of points by formula (5).
   - 4.2 Check and modify the new positions by formula (6).
   - 4.3 Recalculate the objective function value, and update p_i an *g*, go to Step 2

Figure 3. The General Scheme of the Proposed Algorithm

The formula (5) plays a very important role in the process of searching optimal solution. According to formula (5), search direction and step length are synthetically determined by the best previously visited position of point i, the best point in current swarm and total force F. Let us consider again the question shown in Figure 2. According to formula (5), all particles in Figure 2 except the current best still can move encouraged by its best previous position and the best position of the current swarm even if the total force F is equal to 0. Obviously, the new search mechanism can help solve the stagnate problem of the original algorithm caused by too small values of the total force F. Moreover, introduction of the best historical positions can help improve the property of convergence.

4. Computational Experiments

In this section, different types of benchmark functions are used to certify the effectiveness and the efficiency of the proposed algorithm. Moreover, we also compare our algorithm with the original EM. To avoid attributing the optimization results to the choice of a particular initial population and to conduct fair comparisons, we demonstrate our results for test functions in terms of the average number of function evaluations over 25 runs. The average and best objective function values are both reported. All the computations are conducted on an Intel(R) i5-4210M CPU 2.60GHz Pc. The algorithm is coded in Matlab R2012b.

4.1. Tests of the Basic Convergence Properties

This case including 15 general test functions focuses on the basic convergence properties of the proposed method [4, 13]. Hence, the local search procedure is totally excluded in test, and we shall compare our results with the original EM without Local procedure. In order to facilitate the comparisons, as shown in Table 1, all input parameters are the same with the Birbil and Fang's tests, and the detail parameters are available in [4].

Table 1. Parameters for General Test Functions

Function name	n	m	MAXITER	LSITER	δ
Complex	2	10	50	10	5.0e-3
Davis	2	20	50	30	5.0e-3
Epistacity(4)	4	30	50	10	1.0e-3
Epistacity(5)	5	40	100	20	1.0e-3
Grienwank	2	30	100	20	1.0e-3
Himmelblau	2	10	50	5	1.0e-3
Kearfott	4	10	50	5	1.0e-3
Levy(10)	10	20	75	5	1.0e-3
Rastrigin	2	20	50	10	5.0e-3
Sine Envelope	2	20	75	10	5.0e-3
Stenger	2	10	75	10	1.0e-3
Step	5	10	50	5	1.0e-3
Spiky	2	30	75	10	1.0e-3
Trid(5)	5	10	125	50	1.0e-3
Trid(20)	20	40	500	150	1.0e-3

The results in Table 2 show that the average and best solution values of the improved method are both better than that of the original EM method, except for function Levy. Especially for function Davis, as reported by Birbil and Fang, since function Davis is highly irregular in the neighborhood of the optimum, the average and best solution values for function Davis only can reach 0.4088 and 0.1322 respectively, although applying LOCAL search procedure to all points. However, our results show that even if we do not use any Local procedure in the proposed method, the results are still better than that EM with extra local search procedure.

However, function Levy of ten dimensions appears to be an exception. Our result is slightly worse than that of the original EM method. This is mainly because this type of algorithm is not good at solving higher dimensional problems. Hence, the effects of performance improvement are not obvious and the accuracy of the average function values is not good enough.

Overall, we observe that the performance of the improved method is better than the original EM for solving the general test functions, especially for those highly irregular functions.

Table 2. Results of Two Methods Without LOCAL Search Procedure

Function name	The revised method			The original EM	
	Known optimum	Avg f(x)	Best f(x)	Avg f(x)	Best f(x)
Complex	0.0	0.0073	0.0000	0.0175	0.0158
Davis	0.0	0.2226	0.1314	1.6157	1.5641
Epistacity(4)	0.0	0.0114	0.0000	0.0379	0.0149
Epistacity(5)	0.0	0.0110	0.0000	0.0355	0.0207
Grienwank	0.0	0.0306	0.0000	0.0896	0.0032
Himmelblau	0.0	0.0200	0.0009	0.0934	0.0759
Kearfott	0.0	0.0002	0.0000	0.0008	0.0000
Levy(10)	0.0	0.2084	0.0608	0.1429	0.0303
Rastrigin	-2.0	-1.9683	-1.9878	-1.9566	-1.9871
Sine Envelope	0.0	0.0012	0.0007	0.0744	0.0400
Stenger	0.0	0.0018	0.0005	0.0020	0.0019
Step	0.0	0.0000	0.0000	0.0000	0.0000
Spiky	-38.85	-38.7271	-38.7328	−38.6378	−38.7251
Trid(5)	-30.00	-29.9529	-29.9796	-28.2997	-29.0324
Trid(20)	-1520.0	-125.2031	-1013.6326	-33.2567	-177.6124

4.2. Further Test Set

Our initial experiments show that the improved method has a better convergence property. This implies our method can help solve more complicated functions. To further test the potential of the proposed method, in this section we continue conduct experiments on testing some standard functions given by Dixon and Szegö. These functions are highly irregular in the neighborhoods of the global optimum, or the global optimum is far from the highly attractive local optimal solutions. The performance of the original EM on these functions has been extensively studied by Birbil and Fang[4]. We use their results in comparing our method with the original EM.

Table 3. Parameters for Further test set

Function name	Known optimum	n	m	MAXITER
Shekel[S5]	-10.1532	4	40	150
Shekel[S7]	-10.4029	4	40	150
Shekel[S10]	-10.5364	4	40	150
Hartman[H3]	-3.8628	3	30	75
Hartman[H6]	-3.3224	6	30	75
GldsteinPrice	3.0000	2	20	50
Branin	0.3979	2	20	50
Six Hump Camel	-1.0316	2	20	50
Shubert	-186.7309	2	20	50

As said above, for the comparison, as shown in Table3, input parameters of the tests are all the same for both methods and the stopping criterion is used as the following equation:

$$\begin{cases} \dfrac{f(x^{best}) - f_{global}}{f_{global}} \le 10^{-\varepsilon} & \text{if } \mathrm{f_{global}} \neq 0 \\ f(x^{best}) \le 10^{-\varepsilon} & \text{if } \mathrm{f_{global}} = 0 \end{cases}$$

Similarly, 25 replications were run for each test function. Table 4 shows the performance comparison of our method with the original EM. The results show that both methods can find the global optimum for all test functions as reported in their best solution values, except for function Shekel [S10] in EM. However, as reported by Birbil and Fang, two of the 25 runs for function Shekel [S5] do not converge to the global optimum. Fortunately, the proposed method does not exhibit any difficulty to converge to the global optimum in all tests. Moreover, the average solution values of the test functions achieved by the proposed method are better than that of the original EM. Overall, we can find that the improved method performs better than the original on these test functions.

Table 4. Results of Two Methods for Dixon and Szegö Functions

Function name	Known optimum	The improved EM		The original EM	
		Avg f(x)	Best f(x)	Avg f(x)	Best f(x)
Shekel[S5]	-10.1532	-10.1520	-10.1532	-9.7320	-10.1532
Shekel[S7]	-10.4029	-10.4025	-10.4029	-10.4024	-10.4029
Shekel[S10]	-10.5364	-10.5350	-10.5364	-10.5019	-10.5019
Hartman[H3]	-3.8628	-3.8626	-3.8628	-3.8625	-3.8628
Hartman[H6]	-3.3224	-3.3028	-3.3224	-3.3072	-3.3224
Glodstein Price	3.0000	3.0001	3.0000	3.0001	3.0000
Branin	0.3979	0.3980	0.3979	0.3980	0.3979
Six Hump Camel	-1.0316	-1.0316	-1.0316	-1.0316	-1.0316
Shubert	-186.7309	-186.7300	-186.7309	-186.7227	-186.7309

4.3. Graphic Illustration of the Performance

In order to more clearly illustrate the performance of the improved algorithm, the Beale and Sphere test functions are used to demonstrate some typical run results of the proposed algorithm. Figure 4 and 5 respectively show that the iterative trajectories of the current optimal solution of Beale function of two methods. The right graphs in Figure 4 and 5 show the partially enlarged parts of dashed box. The stopping criterion is set to be 10^{-6} in the test. The results show that both methods can find an approximate optimal solution. However, the original EM fails to find the desired precision of solution. The improved method can gradually approach the desired solution by contraries.

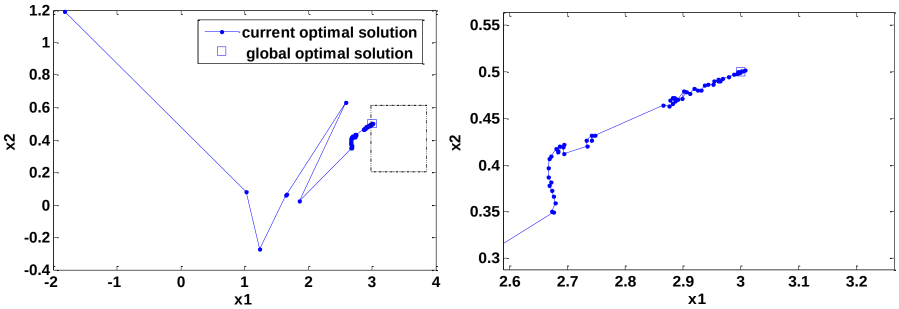


Figure 4．Iterative Trajectories of Current Optimal Solution of Proposed Method

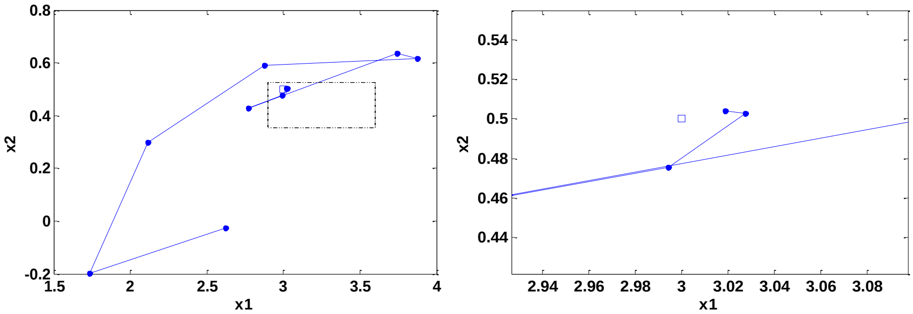
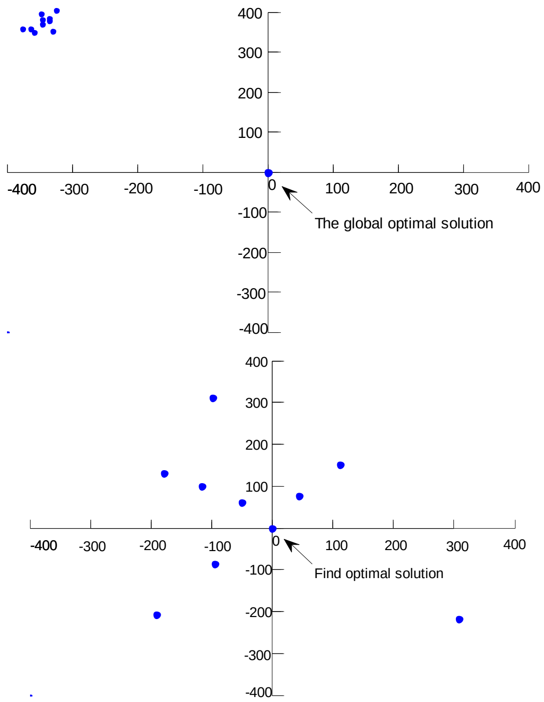


Figure 5. Iterative Trajectories of Current Optimal Solution of Original EM

Next, we use the Sphere function with wide-bounds [−400,400] in each dimension to demonstrate the performance of the proposed algorithm. As shown in Figure 6 (a), one worst case is considered in the test. That's the initial positions of the particles concentrate and far away from the global optimal solution. Generally, this situation is not conducive to search for the optimal solution. However, from Figure 6(b) the improved method can still rapidly find the global optimal solution in wide search domains. This indicates that the improved method has strong capabilities of exploration for the unknown variable space.



(a) (b)

Figure 6. The Original and Final Locations of the Particles

5. Conclusions

This paper proposes a new heuristic algorithm derived from electromagnetism-like mechanism for solving global optimization problems with box constraints. Compared to the original EM, the search mechanism of the proposed method uses the best historical visited positions of each point. Moreover, the next search direction and step length of points are determined together by its best previously visited position, the best point in current swarm and the total force. The preliminary experiments show that our method can improves the convergence property, especially during the latter searching process.

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References

[1] Y.-R. Li and C.-N. Zhang, "A Hybrid Intelligent Optimization Algorithm of Fast Convergence", International journal of Hybrid Information Technology, vol.8, no.1, **(2015)**, pp.295-304.
[2] W. B. Powell and J. Ma, "A Review of Stochastic Algorithms with Continuous Value Function Approximation and some New Approximate Policy Iteration Algorithms for Multidimensional Continuous Applications", Journal of Control Theory and Applications, vol.9, no.3, **(2011)**,pp.336-352.
[3] Xu Sun, Fulin Wang and Shifa Wen, "An Improved Evolutionary Strategy of Genetic Algorithm and a New Method on Generation of Initial Population When Using Genetic Algorithms for Solving Constrained Optimization Problems", International journal of Hybrid Information Technology, vol.7, no.4, **(2014)**, pp.331-344.
[4] S. I. Birbil and S. C. Fang，"An Electromagnetism-like Mechanism for Global Optimization", Journal of Global Optimization, vol.23, no.3, **(2003)**, pp.263-282.
[5] S. I. Birbil, S. C. Fang and R L. Sheu, "On the Convergence of a Population-based Global Optimization Algorithm", Journal of global optimization, vol.30, no.2, **(2004)**, pp.301-318.
[6] A. M. A.C. Rocha and Edite M. G. P. Fernandes, "On Charge Effects to the Electromagnetism-like Algorithm", International Conference 20th EURO Mini Conference, Neringa, LITHUANIA, **(2008),** May 20-23.
[7] A. M. A.C. Rocha and Edite M.G.P.Fernandes, "Numerical Experiments with a Population Shrinking Strategy within a Electromagnetism-like Algorithm", International journal of mathematics and computers in simulation, vol.1, no.3, **(2007)**, pp.238-243.
[8] Ana Maria A.C.Rocha and Edite M.G.P.Fernandes, "Modified Movement Force Vector in a Electromagnetism-like Mechanism for Global Optimization", Optimization Methods and Software, vol.24, no.2, **(2009)**, pp.253-270.
[9] C.-H. Lee, F.-K. Chang and Y.C. Lee, "An Improved Electromagnetism-like Algorithm for Recurrent Neural Fuzzy Controller Design", International Journal of Fuzzy Systems, vol.12,no.4, **(2010)**,pp.280-290.
[10] M. Gol Alikhani, N. Javadian and R. Tavakkoli-Moghaddam, "A Novel Hybrid Approach Combining Electromagnetism-like Method with Solis and Wets Local Search for Continuous Optimization Problems", Journal of Global Optimization, vol.44, no.2, **(2009)**,pp.227-234.
[11] Y. Feng, Y. Wang and S.Wei, "Inverse Kinematic Solution for Robot Manipulator based on Electromagnetism-like and Modified DFP Algorithms", ACTA AUTOMATICA SINICA ,vol.37, no.1, **(2011)**,pp.74-82.
[12] Y. Tian, D. Liu, X. Ma and C. Zhang, "A hybrid PSO with EM for Global Optimization", International Journal of Modelling Identification&control, vol. 8, no.4, **(2009)**,pp.327-334.
[13] M. Demirhan, L. Özdamar, L. Helvacoglu and S. Evktilkerbirbil, "FRACTOP: A Geometric Partitioning Metaheuristic for Global Optimization", Journal of global optimization, vol.14, no.4, **(1999)**, pp.415–436.

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