Theoretical Computer Science 641 (2016) 75–84

Contents lists available at ScienceDirect

Theoretical Computer Science

www.elsevier.com/locate/tcs

An improved electromagnetism-like algorithm for numerical optimization

Jian-Ding Tan [a,*], Mahidzal Dahari [a], Siaw-Paw Koh [b], Ying-Ying Koay [b], Issa-Ahmed Abed [c]

[a] Department of Mechanical Engineering, University of Malaya, 50603, Kuala Lumpur, Malaysia
[b] College of Engineering, Universiti Tenaga Nasional, 43000 Kajang, Selangor, Malaysia
[c] Engineering Technical College Basrah, Southern Technical University, Iraq

ARTICLE INFO

Article history:
Received 24 October 2015
Received in revised form 28 December 2015
Accepted 31 May 2016
Available online 3 June 2016
Communicated by G. Dowek

Keywords:
Electromagnetism-like Mechanism algorithm
Global optimization
Meta-heuristic
Split-Probe-Compare

ABSTRACT

This paper presents a new Electromagnetism-like Mechanism (EM) algorithm with Split, Probe and Compare feature (SPC-EM). The proposed algorithm replaces the local search segment of a standard EM with a new search scheme named Split, Probe, and Compare (SPC). A nonlinear equation is designed to systematically and dynamically adjust the length of the probes based on the outcome of the Compare segment in each iteration. Extensive computational simulations and comparisons on 10 different benchmark problems from the literature were carried out. Results show that the new modified mechanism outperformed all other algorithms involved in the benchmarking. We thus conclude that the proposed SPC-EM works well with the designed probe-length tuning equation in solving numerical optimization problems.

1. Introduction

In the early 1960s, computer scientists attempted to implement evolution concepts in solving engineering optimization problems. From it, genetic algorithms (GA) was born [1]. Since then, optimization algorithms have evolved from local optima search to algorithms with better exploration of global optima points. Over the past few decades, researchers around the world have been coming up with many meta-heuristic search techniques to solve complex global optimization problems and ways to improve them. Many of which are nature-inspired, for example particle swarm optimization (PSO) [2], differential evolution (DE) [3], and more recently, the Electromagnetism-like Mechanism algorithm.

Electromagnetism-like Mechanism algorithm (EM) is a relatively new meta-heuristic search algorithm [4] first introduced by Birbil and Fang [5]. This algorithm is inspired by the attraction and repulsion mechanism of charges in the electromagnetism theory to solve unconstrained nonlinear optimization problems in a continuous domain. Due to its capability to yield well diversified results and solve complicated global optimization problems [6,7], EM has been widely used as an optimization means in numerous fields such as single machine scheduling problems [7], green energy harvesting [8], maximum betweenness problems [9], machines path-planning [10], inverse kinematic problems for robot manipulator [11] and many more.

* Corresponding author. Tel.: +60 016 5576 736.
E-mail addresses: jdtan2003@yahoo.com, jdtan@um.edu.my (J.-D. Tan).

http://dx.doi.org/10.1016/j.tcs.2016.05.045
0304-3975/

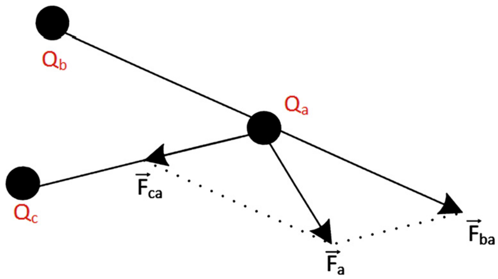

Fig. 2.1. Total force exerted on Q_a by Q_b and Q_c.

The search mechanism of EM can generally be divided into its exploration and exploitation segments. The exploration segment of EM conducts a much global search by moving the particles in accordance with the superposition theorem. The exploitation segment involves a local search procedure which gathers the information around the neighborhood of a particular solution. Several modifications have been suggested in the literature of some other EM related researches by adapting other search methods into the local or global search sections of EM. Sels and Vanhoucke introduced a fusion of EM and tabu search procedure for single machine scheduling problems [12], Yurtkuran proposed a hybrid of EM and Random-Key Procedure to solve capacitated vehicle routing problems [13], and the successful infusion of EM and Simulated Annealing (SA) by Jamili et al. in solving periodic job shop scheduling problems [14], just to name a few. Most of the proposed infusions have proven to be able to provide competitive results in their respective fields of applications.

Even though EM has shown good achievements in solving various types of complex optimization problems, there is still room for improvement especially in terms of accuracy. Generally speaking, the performance of a global optimization algorithm can be influenced by many factors. Among others is the search step. The size of the search step employed in an optimization algorithm can show huge impact in the accuracy and general convergence performance of the algorithm itself [15]. Yet, this issue has received relatively little attention in the EM literature. In fact, in a standard EM, the particle search is based on random step size and the iterations are terminated immediately upon achieving one comparatively better objective value. The method is clearly not acceptable as it may show impact on the balance between the speed and accuracy of the convergence. This motivated us to come up with a modified EM with better exploitation strategy. In this research, a Split, Probe and Compare mechanism (SPC) is implemented in the local search segment of the EM. A nonlinear equation is designed to systematically and dynamically regulate the length of the probe based on certain pre-determined rules and conditions. A better convergence performance is achieved by using this SPC strategy, especially in terms of its accuracy.

The contribution of this paper is twofold and can be summarized along the line as follows. Firstly, an analytical study on the effect of the local search step length in the EM is carried out. This is done by modifying the EM into two sets of algorithms with two different extremes of search step size each. The purpose is to investigate the gravity of it to the overall convergence performance especially in terms of accuracy. Secondly, a new EM with SPC feature (SPC-EM) is proposed. The performance of the proposed algorithm is evaluated and benchmarked through a set of 10 benchmark problems from the literature.

The outline of this paper can be divided into 5 major sections. In Section 2, the general procedure of a standard EM is summarized. Section 3 offers an analysis of the proposed modification on the algorithm in details. The computational experiment results of the proposed algorithm are benchmarked, compared and discussed in Section 4. Some samples of the convergence process are also shown in the form of graphs. In Section 5, an overall conclusion is drawn.

2. EM Procedure

Electromagnetism-like Mechanism (EM) is a stochastic optimization method proposed by Birbil and Fang [5] in 2003. Guided by the electromagnetism theory, EM imitates the attraction–repulsion mechanism of charges in order to reach a global optimal solution using bounded variables. In the algorithm, all solutions are considered as charged particles in the search space and the charge of each particle relates to the objective function value. Particles with better objective yields will apply attracting forces while particles with worse objective values will apply repulsion forces onto other particles [16]. The better the objective function value, the higher the magnitude of attraction or repulsion between the particles will be. The particles are then moved based on superposition theorem. Fig. 2.1 shows an example of the total force, F_a applied on Q_a by the repulsive force from Q_b and attractive force from Q_c.

The overall flow of a standard EM is as shown in Table 1. There are five critical operations in EM, namely the initialization, the local search, the charge calculation, the force calculation, and the movement of particles. Like most optimization algorithm, it begins with initialization.

Initialization: In the initialization stage of EM, the feasible ranges of all the tuning parameters (upper bound, u_k and lower bound, l_k) are defined. Then, m sample of initial particles are randomly picked, each contains an N-tuple of real values $(v_1, v_2, \ldots, v_N)$. Each random value in the N-dimensional hyper-solid is assumed to be uniformly distributed within the defined feasible range $(l_i < v_i < u_i)$ [17]. After calculating the objective value of each particle, the point with best function value is marked as the best particle.