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The improvement of glowworm swarm optimization for continuous optimization problems

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ABSTRACT

Glowworm swarm optimization (GSO) algorithm is the one of the newest nature inspired heuristics for optimization problems. In order to enhances accuracy and convergence rate of the GSO, two strategies about the movement phase of GSO are proposed. One is the greedy acceptance criteria for the glowworms update their position one-dimension by one-dimension. The other is the new movement formulas which are inspired by artificial bee colony algorithm (ABC) and particle swarm optimization (PSO). To compare and analyze the performance of our proposed improvement GSO, a number of experiments are carried out on a set of well-known benchmark global optimization problems. The effects of the parameters about the improvement algorithms are discussed by uniform design experiment. Numerical results reveal that the proposed algorithms can find better solutions when compared to classical GSO and other heuristic algorithms and are powerful search algorithms for various global optimization problems.

1. Introduction

The computational drawbacks of existing derivative-based numerical methods have forced the researchers all over the world to rely on meta-heuristic algorithms founded on simulations to solve engineering optimization problems. A common factor shared by the meta-heuristics is that they combine rules and randomness to imitate some natural phenomena. During the last decade, nature inspired intelligence has become increasingly popular through the development and utilization of intelligent paradigms in advanced information systems design. Cross-disciplinary team-based thinking attempts to cross-fertilize engineering and life science understanding into advanced inter-operable systems.

The term swarm is used for an aggregation of animals such as fish schools, birds, flocks and insect colonies such as ant, termites and bee colonies performing collective behavior. The individual agents of a swarm behave without supervision and each of these agents has a stochastic behavior due to her perception in the neighborhood. Local rules, without any relation to the global pattern, and interactions between self-organized agents lead to the emergence of collective intelligence called swarm intelligence. Swarms use their environment and resources effectively by collective intelligence. Self-organization is a key feature of a swarm system which results global level (macroscopic level) response by means of low level interactions (microscopic level). Recently researchers have been inspired by those models and they have provided novel problem-solving techniques based on swarm intelligence for solving difficult real world problems such as traffic routing, networking, games, industry, robotics, economics and generally designing artificial self organized distributed problem-solving devices. In 1990s, especially two approaches based on ant colony described by Dorigo (1992) and on fish schooling and bird flocking introduced by Kennedy and Eberhart (1995) have highly attracted the interest of researchers. Both approaches have been studied by many researchers and their new versions have been introduced and applied for solving several problems in different areas. Following this tradition, in 2005, Krishnanand and Ghose (2005) proposed glowworm swarm optimization algorithm, a derivative-free, meta-heuristic algorithm, mimicking the glow behavior of glowworms. The algorithm shares some common features with ant colony optimization (ACO) and with particle swarm optimization (PSO), but with several significant differences. The agents in GSO are thought of as glowworms that carry a luminescence quantity called luciferin along with them. The glowworms encode the fitness of their current locations, evaluated using the objective function, into a luciferin value that they broadcast to their neighbors. The glowworm identifies its neighbors and computes its movements by exploiting an adaptive neighborhood, which is bounded above by its sensor range. Each glowworm selects, using a probabilistic mechanism, a neighbor that has a luciferin value higher than its own and moves toward it. These movements based only on local information and selective neighbor interactions enable the swarm of glowworms to partition into disjoint subgroups that converge on multiple optima of a given multimodal function.

Since its inception, GSO has been used in various applications and several papers have appeared in the literature using the GSO

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algorithm. Krishnanand and Ghose (2006a, 2006b, 2009) implemented a large class of benchmark multimodal functions to tested against the capability of GSO in capturing multiple optima. Numerical simulation results showed the algorithm's efficacy in capturing multiple peaks of a wide range of multi-modal functions. Krishnanand and Ghose (2006c, 2008) researched theoretical foundations involving local convergence results for a simplified GSO model. Krishnanand, Amruth, Guruprasad, Bidargaddi, and Ghose (2006), Kaipa et al. (2006) applied the GSO algorithm to multiple source localization tasks that demonstrated through real-robot experiments. Where four wheeled mobile robots implemented the GSO algorithm to collaborate and achieve a sound source localization task. Krishnanand and Ghose (2007) described the application of the GSO algorithm to hazard sensing in ubiquitous environments. Bharat (2008) used GSO to estimate the eigen values obtained from a corresponding transcendental equation, which was used to research analytical solutions for flow of chemical contaminants through soils. The proposed solver quickly estimates the design parameters with a great precision on a real world inverse problem in environmental engineering. He and Zhu (2010) presented a multi-population glowworm swarm optimization algorithm, the simulation results showed the improved algorithm could enhance the accuracy of the solution and reduce the computing time.

Since the performance of classical GSO over numerical benchmark functions with high dimensions suffers from stagnation or false convergence. In the paper, we proposed new strategies for changing the position of the glowworms. In the movement phase of classical GSO, each glowworm selects probabilistically a neighbor that glow brighter and moves a step that a fix size step multiplied by the distance between the neighbors. This procedure is quite similar to the prey process of honey bees or birds. So, the new strategies are inspired by artificial bee colony algorithm (ABC) and particle swarm optimization (PSO). Moreover, as we know, the performance of population based meta-heurist greatly depends on the control parameters, but the various parameters of the classical GSO algorithm are fixed. The parameters of GSO through uniform design experiment are discussed.

The remaining of this paper is organized as follows. Review of GSO is summarized in Section 2. Section 3 describes the proposed methods, improvement GSO, shortly IGSO. Section 4 describes the benchmark problems and uniform design (UD) experiments. The parameters of the algorithm are discussed by UD experiments and the testing of the proposed methods through benchmark problems are carried out and the simulation results are compared with those obtained via other algorithms that have been reported to have good performance. Finally, the conclusion is drawn based on the comparison analysis reported and presented in Section 5.

2. Glowworm swarm optimization

GSO algorithm is developed by Krishnanand and Ghose (2005), which is improved from ACO approach to continuous optimization. It based on the glowworm metaphor and applied to manipulating collective robotics. In GSO, each artificial glowworm, agent, carries a light on two dimensional works space and has its own vision, called local-decision range. The luciferin level is associated with the objective value of the agent's position. The brighter agent means that it flies to a better position (has a better objective value). The agent is only attracted by a neighbor whose luciferin intensity is higher than its own within the local decision range and then flies towards the neighbor. The local-decision range depends on the number of neighbors. While the neighbor-density is low, the range is enlarged in order to find more neighbors, otherwise the range is reduced. The agent always changes its moving direction according to which neighbor is selected. The higher luciferin level the neighbor has, the more attraction which gains. Finally, most agents will get together at the multiple locations. Briefly, the GSO involves in three main phases: luciferin update phase, movement phase, and decision range update.

The luciferin update depends on the function value at the glowworm position. Although all glowworms start with the same luciferin value at the initial iteration, these values change according to the function values at their current positions. The luciferin value is proportional to the measured value of the sensed profile (temperature, radiation level) at that location. Each glowworm adds its previous luciferin level. At the same time, the luciferin level of glowworm is subtracted the previous luminescence value to simulate the decay in luminescence. The luciferin update rule is given by:

$$l_i(t+1) = (1-\rho)l_i(t) + \gamma J_i(t+1) \tag{1}$$

where $l_i(t)$, represents the luciferin level associated with glowworm i at time t, ρ is the luciferin decay constant $0 < \rho < 1$, γ is the luciferin enhancement constant, and J_i represents the value of objective function at agent i's location at time t.

During the movement phase, each glowworm uses a probabilistic mechanism to decide a movement of a neighbor that has a luciferin value more than its own. Glowworms are attracted by neighbors that glow brighter. For each glowworm i, the probability of moving toward a neighbor j is given by:

$$p_{ij} = \frac{l_j(t) - l_i(t)}{\sum_{k \in N_i(t)} l_k(t) - l_i(t)} \tag{2}$$

where $j \in N_i(t), N_i(t) = \{j : d_{i,j}(t) < r_d^i(t); l_i(t) < l_j(t)\}$ is the set of neighborhood of glowworm i at time t. $d_{i,j}(t)$ represents the Euclidean distance between glowworms i and j at time t, and $r_d^i(t)$ represents the variable neighborhood range associated with glowworms i at time t. Let glowworm i select a glowworm $j \in N_i(t)$ with $p_{ij}(t)$ given by (2). Then, movements of glowworms can be stated as:

$$x_i(t+1) = x_i(t) + s\left(\frac{x_j(t) - x_i(t)}{\|x_j(t) - x_i(t)\|}\right) \tag{3}$$

where s is the step-size. $\|\|$ represents the Euclidean norm operator.

Neighborhood range update rule: We associate with each agent i a neighborhood whose radial range r_d^i is dynamic in nature $0 < r_d^i < r_s.r_s$ represents the radial range of the luciferin sensor. The fact that a fixed neighborhood range is not used needs some justification. When the glowworms depend only on local information to decide their movements, it is expected that the number of peaks captured would be a function of the radial sensor range. In fact, if the sensor range of each agent covers the entire search space, the entire agents move to the global optimum and the local optima are ignored. Since we assume that a priori information about the objective function (e.g., number of peaks and inter-peak distances) is not available, it is difficult to fix the neighborhood range at a value that works well for different function landscapes. For instance, a chosen neighborhood range r_d would work relatively better on objective functions where the minimum inter-peak distance is more than r_d rather than on those where it is less than r_d. Therefore, GSO uses an adaptive neighborhood range in order to detect the presence of multiple peaks in a multimodal function landscape. A substantial enhancement in performance is noticed by using the rule given below:

$$r_d^i(t+1) = \min\{rs, \max\{0, r_d^i(t) + \beta(nt - |Ni(t)|)\}\} \tag{4}$$

where β is a constant parameter and nt is a parameter used to control the number of neighbors.

The computational procedure of the basic GSO algorithm can be summarized as follows Fig. 1.