A Survey of Applications of Glowworm Swarm Optimization Algorithm

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ABSTRACT
This paper presents a survey of applications of Glowworm swarm optimization (GSO) algorithms designed in the various fields. Glowworm Swarm Optimization (GSO) is a recent nature-inspired optimization algorithm that simulates the behavior of the lighting worms. GSO algorithm is suitable for a concurrent search of several solutions, having dissimilar or equal objective function values. A number of references are provided that describe applications of GSO algorithms in different domains, such as clustering and various optimization problems.

Keywords:
Swarm intelligence, Glowworm swarm optimization algorithm, clustering, optimization problems

1. INTRODUCTION

Swarm intelligence (SI) is a type of artificial intelligence, based on the collective behavior of decentralized, self-organized systems. It focuses on the study of the collective behavior that is made up of a population of simple agents interacting locally with one another and with their environment. Natural examples of SI include ant colonies, bird flocking, animal herding, bacterial growth, and fish schooling. Glowworm swarm optimization (GSO), introduced by Krishnanand and Ghose in 2005 [4] is mainly used for simultaneous computation of multiple optima of multimodal functions.

This paper describes the application of GSO in the various arenas ranging from clustering of bench mark data sets both real and artificial data sets, clustering satellite images, detection of multiple sources of a general nutrient profile that is distributed spatially on a two dimensional workspace using multiple four wheeled-mobile robots, a sensor deployment scheme which can maximize the coverage of sensors with limited movement after an initial random deployment, optimizing dispatching system of public transit vehicles, solving nonlinear equations, to solve the problem of oil chromatographic on-line data distortion caused by outside environment and equipment error by optimizing SVM parameters, to solve the problem of rectangle layout optimization with equilibrium constraint, to solve the multi-constrained (QoS) multicast routing problem (MQMR) problem, and to accomplish localization for multiple odor sources. This paper is systematized as follows: Section II describes the functioning of glowworm swarm optimization. In Section III, the applications of GSO in the various arenas have been discussed followed by conclusions in Section IV.

2. GLOWWORM SWARM OPTIMIZATION ALGORITHM

In GSO [3,4,8,14], a swarm of glowworms are randomly distributed in the search space of object functions. The agents in the glowworm algorithm carry a luminescence quantity called luciferin along with them. Each glowworm is attracted by the brighter glow of other neighboring glowworms. A glowworm identifies another glowworm as a neighbor, when it is located within its current local-decision domain. The glowworms' luciferin intensity is related to the fitness of their current locations. The higher the intensity of luciferin, the better is the location of glowworm in the search space. In each iteration, all the glowworms position will change, and then the luciferin value also follows updates. Each iteration consists of a luciferin-update phase followed by a movement-phase based on a transition rule.

a) *Luciferin-update phase:* At time *t*, the location of the glowworm *i* is xi(t), and its corresponding value of the objective function at glowworm i's location at time t is J(xi(t)). The luciferin level associated with glowworm *i* at time is given by eq (1)

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

where ρ is the luciferin decay constant($0<\rho<1$), γ is the luciferin enhancement constant.

b) *Movement-phase:* Find the neighbors j for each glowworm *i* : $N_i(t)$ using eq.(2)

$$j \in N_i \; iff \; Distance_{ij} < rd_i\,(t) and \; l_j(t) > l_i(t)$$

(2) Each Glowworm *i* moves towards a neighbor *j* with a certain probability computed by equation (3)

$$p_{ij}(t) = \frac{l_j(t)-l_i(t)}{\sum_{k\epsilon N_i(t)} l_k(t)-l_i(t)} \tag{3}$$

The glowworm *i* position is updated using eq (4)

$$x_i(t+1) = x_i(t) + st * \left(\frac{x_j(t)-x_i(t)}{\|x_j(t)-x_i(t)\|}\right) \tag{4}$$

where st is the step size.

c) Local-decision range update rule: The neighborhood range is updated using eq (5).

$$rd_i(t) = min\,\{rs, max[0, rd_i(t-1) + \beta(nt - |N_i(t-1)|)]\} \tag{5}$$

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

Some of the differences between PSO and GSO are as follows [14]: PSO algorithm uses a memory element in the velocity update mechanism of the particles whereas, GSO do not retain any information in the memory. The directions of particle movements in PSO are adjusted according to its own and global best previous positions. The GSO agents movement directions are aligned along the line-of-sight between neighbors. In PSO, the dynamic neighborhood is achieved by evaluating the first k nearest neighbors. In GSO, the requirement of k neighbors is used only as an implicit parameter to control the range of the variable decision domain and the maximum range is hard limited by finite sensor range. PSO is limited to numerical optimization model and GSO allows effective detection of multiple peaks/sources in addition to numerical optimization tasks.

Some of differences between ACO and GSO are as follows [14] : ACO techniques are used and found to be effective in a discrete setting whereas GSO can be applied to continuous domain. Each glowworm in the GSO technique uses the luciferin information available only in its current local neighborhood to select a neighbor with higher luciferin value, whereas each agent of ACO, at the nest selects a region based on a probability distribution which is a function of the pheromone levels associated with all the N regions. While the selected region's center is shifted to a new point in a random direction in the ACO, each glowworm deterministically moves a step distance towards the selected neighbor.

3. APPLICATIONS OF GSO

Ibrahim et al. [1] has presented GSO algorithm, for formulating the clustering problem as a multimodal optimization problem to extract the optimal centroids based on glowworms' movement. Clustering is a common data mining technique used to analyze homogeneous data instance groups based on their specifications which can be used in many applications, for instance, pattern recognition, document categorization, and bioinformatics applications. The proposed GSO algorithm for clustering can discover the numbers of clusters without needing to provide the number in advance. Experimental results of GSO based clustering on several real datasets namely iris, Ecoli, glass, Balance, seed and two artificial data sets namely: mouse and vary density has proved to be efficient compared to well-known clustering methods that have been used in the literature such as K-Means clustering, average linkage agglomerative Hierarchical Clustering (HC), Furthest First (FF), and Learning Vector Quantization (LVQ).

A new k-means image clustering algorithm based on GSO (ICGSO) has been submitted by Yongquan etal.[2] for clustering several benchmark images namely Lena, Mandrill and Peppers. Image classification is an image processing method of distinguishing between dissimilar categories of objects according to the different features contained in their image information. It is pattern recognition's application in the field of image processing. K-means works through several iterations, and updates every cluster center gradually until getting the best clustering results. However, there are two downsides for this algorithm. It depends on the initial condition, which may cause the algorithm to converge to suboptimal solutions and it falls into local optimum easily. To overcome this K-means image clustering algorithm based on glowworm swarm optimization (ICGSO) is proposed by combining GSO with K-means algorithm. Experimentation results have exposed that ICGSO algorithm performed very well when compared to the both K-means algorithm and fuzzy k-means clustering algorithm.

Krishnanand et al. have recommended Glowworm swarm based algorithm to find solutions for optimization problems with multiple optima continuous functions. The algorithm developed has been anticipated to be applied to a class of problems related to collective robotics. In particular, the Glowworm metaphor based optimization algorithm has been used to detect multiple source locations of a nutrient profile, that is distributed spatially on a two dimensional workspace, using a collection of mobile robots. This problem is representative of a wide variety of applications. For instance, during a nuclear spill, or a hazardous chemical spill in an industrial plant, it is imperative to detect the multiple sources of the spills and contain all the spills in a quick and proficient manner before they can cause a great loss to the environment and people in the vicinity. Other applications include search and rescue in a building on fire or putting off forest fires (where robots have to depend on temperature gradients to reach all the different fire locations). Another application is localization and decommissioning of hostile sensors or transmitters, scattered over a landscape, by sensing signals radiating from them. The GSO algorithm is projected for detection of multiple sources of a general nutrient profile that is distributed spatially on a two dimensional workspace using multiple robots using a set of four wheeled-mobile robots called Kinbots as GSO agents [3,8].

Wen-Hwa et al have anticipated a sensor deployment scheme based on glowworm swarm optimization, which can maximize the coverage of sensors with limited movement after an initial random deployment. Wireless sensor networks (WSNs) are becoming a rapidly developing area both in research and application. A WSN consists of a large number of sensor nodes scattered in the region of interest to acquire some physical data. The sensor nodes have the capabilities of sensing, processing, and communicating. They operate in an unattended environment, with limited computational and sensing capabilities. Because the WSNs have dynamic topology and need to accommodate a large number of sensors, the algorithms and protocols designed should be distributed and localized in order to better accommodate their scalable architecture. Therefore a sensor deployment approach based on glowworm swarm optimization to enhance the coverage after an initial random placement of the sensors can be used. Each sensor node is considered as individual glowworm emitting a luciferin and the intensity of the luciferin depends on the distance between the sensor node and its neighboring sensors. A sensor node is attracted towards its neighbors having lower intensity of luciferin and decides to move towards one of them. In this way, the coverage of the sensing field is maximized as the sensor nodes tend to move towards the region having lower sensor density. The approach has the advantage that it does not need centralized control and hence, it is easily scalable for large sensor networks. The algorithm achieves higher coverage rate with limited sensor movements compared to the virtual force algorithm (VFA) deployment scheme [5].

Yongquan et al proposed GSO with random disturbance factor, namely R-GSO and applied for solving the dispatching system of public transit vehicles. The intelligent schedule of vehicles operation is one of the problems which need to be solved in the dispatching system of public transit vehicles. Investigations results have shown that R-GSO has obtained the good result in the convergence rate and the computational accuracy aspect when compared to Artificial fish-swarm algorithm (ASFA), Particle swarm optimization (PSO) and GSO [6].

Yongquan zhao et al recommended a Leader Glowworm swarm Optimization (LGSO) for solving nonlinear equation systems. Systems of nonlinear equations arise in many domains of practical importance such as engineering, mechanics, medicine, chemistry, and robotics. Solving such a system involves finding all the solutions of the polynomial equations contained in the mentioned system. Although there are several existing approaches for solving systems of nonlinear equations, there are still limitations of the existing techniques, and, still, more research is to be done. In LGSO approach, before each generation of the algorithm, the best glowworm's position is set as the leader in the current generation. After each generation, all glowworms are moved to the location of the leader, so that the glowworm swarm has high ability of searching global optimization, and improving the algorithm's ability in high dimensional space optimization. Experiments show that the new algorithm has strong global search ability and fast convergence rate, accuracy has greatly improved, when compared to Artificial fish-swarm algorithm (ASFA), Particle swarm optimization (PSO) and GSO and can be effectively used in high-dimensional problems of nonlinear equations [7].

Min li et al. suggested a method to use the oil chromatographic off-line data to reconcile the oil chromatographic on-line data using GSO optimized SVM. GSO has been used to optimize the SVM parameters, including error penalty factor, insensitive parameter and kernel parameter. The oil chromatographic on-line monitoring of the transformer can promptly grasp the operating status of the transformer, detect and track potential fault, and provide guarantee for reliable operation of the transformer. However, due to the influences of ambient temperature, humidity and equipment error, oil chromatographic on-line data may be distorted, and data reconciliation is required prior to status evaluation and fault diagnosis. The experimental results show that the GSO optimized can obtain smaller fitting error, achieve more stable and accurate result, and more suitable for field reconciliation of oil chromatographic on-line data when compared to performance of Neural Network trained using back propagation method [9].

Yu Zeng et al combined heuristic strategy with GSO for the problem of rectangle layout optimization with equilibrium constraint. Layout optimization of satellite module concerns the best way to place a number of objects (such as instruments, equipments etc) with different shapes, sizes and quality. Placement of objects cannot exceed the satellite round bottom and squeeze each other. With the direct use of heuristic algorithms to search, not only the search time is longer, the accuracy is also low standard. With the background of satellite module layout heuristic strategy can be combined with the glowworm swarm optimization for the problem of rectangle layout optimization with equilibrium constraint. A heuristic strategy has been used to divide the circular container into four sub-regions, which are layout synchronously. When the rectangle layout area has been decided, the bottom left fill strategy is used to layout the rectangle. On the basis of the heuristic strategy, glowworm swarm optimization algorithm is applied to search for the optimal placing order, and finally the optimal layout is obtained. Simulation's numerical results have shown that proposed approach is more effective than the existing algorithms like Particle swarm optimization and Ant Colony optimization algorithm with least maximum, minimum and average enveloping circle radius, least computational time and maximum space utilization [10].

Deng-xu et al. applied glowworm swarm optimization to solve the multi-constrained (QoS) multicast routing problem (MQMR) problem using an improved encoding method. With the rapid development of Internet, more and more business request the quality of service of the network (QoS) is required. This is why multi-constrained QoS multicast routing is proposed. In the past, there are many ways to solve the unconstrained QoS multicast routing problem by several researchers, such as dijkstra algorithm, Steiner tree, etc. However, these traditional methods are helpless to solve the multi-constrained QoS multicast routing problem. Recently, the heuristic algorithms and swarm intelligence algorithms are applied to solve the multi-constrained QoS multicast routing problem and obtain the good performance, such as simulated annealing, genetic algorithms, ant colony algorithm, particle swarm optimization, etc. The simulation results substantiate that GSO outperforms ACO and GA performance for MQMR problem [11].

ZhangYuli et al. projected a multi-robot cooperation strategy for odor sources localization based on a modified GSO algorithm (M-GSO). The applications for employing autonomous robots to perform plume tracing and odor source localization are wide ranging, for instance, searching for explosives and demining operations (by tracing volatile chemicals dispersed from the ordnance), judging toxic or harmful gas leakage location, checking for contraband (e.g., heroin), searching for survivors and casualties following a disaster, and antiterrorist attacks. A multi-robot cooperation strategy based on a modified glowworm swarm optimization (M-GSO) strategy has been proposed to achieve localization for multiple odor sources. This mechanism can ensure robots to start searching for the next odor source after the discovery of an odor source and ensure that other robots would not re-locate this odor source. Simulation results confirms that the proposed M-GSO can effectively enable the robot system to search and find all the odor sources existed in the indoor environment quickly and accurately [12].

J. Senthilnath et al used Glowworm Swarm Optimization (GSO) clustering algorithm for hierarchical splitting and merging of automatic multi-spectral satellite image classification (land cover mapping problem). To make best use of land and its natural resource, there is a need to have good real information of the land and its features. Accurate knowledge on land-use is very vital for planning and efficient operation. The satellite image is one of the sources which can capture the temporal nature of this knowledge for land utilization. Land cover mapping information can be used to audit land usage, in the context of city planning and land-usage. For a given satellite image, if there is a lack of ground truth information then unsupervised technique can be applied for automatically classifying a satellite image into distinct land cover regions. This paper exemplifies the use of Glowworm Swarm Optimization (GSO) clustering algorithm for hierarchical splitting and merging of automatic multi-spectral satellite image classification (land cover mapping problem). Multi-spectral image such as Landsat 7 thematic mapper image acquired from southern region of India are used as inputs to the hierarchical classifier model. The hierarchical technique adopts GSO and Mean Shift Clustering (MSC) for splitting the data set by satisfying Bayesian Information Criterion (BIC) and k-means algorithm is used to merge the data set. The outcomes of the paper corroborate that the, hierarchical classifier model GSO performance is superior than the MSC unsupervised technique [13].

4. CONCLUSIONS

This paper describes the functioning of GSO and attempts to present an up-to-date survey on GSO in the several field like clustering, optimization problem, multicast routing problem (MQMR) problem and multi-robot based problems. The literature survey corroborates that the outcomes of GSO are superior when compared to that of earlier reported evolutionary algorithms specifically, PSO, ACO and GA.

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