A Network Robot System for Multiple Odor Source Localization using Glowworm Swarm Optimization Algorithm

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Abstract

In this paper we address the problem of multiple odor source localization using mobile robot swarms modelled as network robot systems. These networked robots are used to locate multiple radiation/odor sources like oil spills, leaks in pressurized systems, hazardous plumes/aerosols resulting from nuclear/chemical spills, deep-sea hydrothermal vent plumes, fire-origins in forest fires, and hazardous chemical discharge in water bodies. The robots are assumed to be constrained by limited communication and sensor range and field of view. We present a swarm robotic communication and decision network that enables the robots to obtain information about the environment from their designated neighbors and compute movement decisions autonomously. We use a modified version of the glowworm swarm optimization (GSO) algorithm, which is specially designed for such applications. This algorithm uses an adaptive decision range that enables the agent swarm to partition into disjoint subgroups, simultaneously taxis towards, and rendezvous at multiple source locations of interest. Certain algorithmic aspects need modifications while implementing in a robotic network mainly because of the point-agent model of the basic GSO algorithm and the physical dimensions and dynamics of a real robot. We briefly describe the basic GSO algorithm and the modifications incorporated into the algorithm in order to make it suitable for a robotic implementation. We conduct embodied robot simulations by using a multi-robot-simulator called Player/Stage that provides realistic sensor and actuator models, in order to demonstrate the efficacy of the networked robot system in simultaneously detecting multiple odor sources. The study, based on embodied simulation experiments, also shows the robustness of the algorithm to implementational constraints.

Key words: Network robot systems, multiple odor source localization, glowworm swarm optimization

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1 Introduction

Network robot systems (NRS) have evolved out of a systematic synergism between several fields such as robotics, sensor systems, ubiquitous computing, and network communications. Owing to the recent technological advances in these fields, networked robotics is becoming increasingly pervasive with a wide range of applications including mobile robot networks for exploration of harsh environments [1], [2], sensor-robot networks for disaster response [3], environmental monitoring [4], [5], [6] and search/rescue tasks in urban settings [7], and human-robot networked teams for home automation [8] and collaborative observation of natural environments [9]. An NRS may be defined as a collection of mobile robots that interact among themselves or with fixed-sensors embedded in the environment or with humans, through wireless communication channels, in order to carry out a prescribed mission. Design of such mobile robotic networks invites major research challenges related to the areas of cooperative localization and navigation, distributed environment perception, cooperative map building, cooperative planning, human-robot interaction, and communications.

Localization of radiation/odor sources using networked mobile robot swarms has received some attention recently in the collective robotics community [1], [2], [10]−[19]. These applications involve the deployment of a group of mobile robots that use their sensory perception of odor-signatures at distances that are potentially far from a source and interaction with their neighbors as cues to guide their movements to taxis towards and eventually co-locate at the odor-emitting source. Examples of such odor-sources include oil spills [2], leaks in pressurized systems [10], hazardous plumes/aerosols resulting from nuclear/chemical spills [12], [14], deep-sea hydrothermal vent plumes [20], fire-origins in forest fires [21], hazardous chemical discharge in water bodies [22], etc.

Most prior work related to source localization was devoted to using either single or multiple robot systems for seeking, detecting, and tracking of a single emission source location [1], [2], [10]−[18]. However, very little attention has been given to simultaneous localization of multiple sources [19], [20]. This

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problem has practical relevance to situations where it is imperative to simultaneously identify and neutralize all the radiating sources using a swarm of robots before they can cause a great loss to the environment and people in the vicinity. The above problem presents several challenges such as multiplicity of sources, time-varying nature of the sources, dynamically changing environment, and perceptional noise. Thus the objective is to devise local control strategies that allow a swarm of networked mobile robots − equipped with only rudimentary sensing and communicating capabilities − to perform the task of multiple source localization while coping well with the challenges described above.

In this paper, we present a swarm robotic network that implements a modification to an algorithm called the glowworm swarm optimization (GSO) algorithm and demonstrate the GSO based network robotic system's special suitability for multiple source localization tasks. The basic GSO algorithm, which is originally developed for multimodal optimization problems, enables a homogeneous swarm of mobile agents to split into subgroups, exhibit simultaneous taxis towards, and rendezvous at multiple optima (not necessarily equal) of a multimodal function. The underlying principles of the GSO algorithm and numerical experiments to show the algorithm's efficacy in capturing multiple peaks of a wide range of multimodal functions are presented in [25]. We show the GSO algorithm's applicability to the problems of hazard sensing in ubiquitous environments in [26] and chasing of multiple mobile signal sources in [27]. We also examine the behavior of the glowworm algorithm in the presence of uncertainty due to perceptional noise in [29]. However, in all the above work, the algorithm's suitablity for multiple source localization tasks is tested using only non-embodied point simulations, where agents are considered as points and agent-collisions are ignored. While our work in [28] describes a real-robot-platform, consisting of four wheeled mobile robots, for multiple source localization tasks, the experiments shown are restricted to localization of only a single sound source. In this paper, we conduct embodied robot simulations [1], by using a multi-robot-simulator called Player/Stage [31] that provides realistic sensor and actuator models, in order to assess the GSO algorithm's suitability for multiple source localization tasks. The use of embodied simulations, instead of a swarm of physical robots, offers a quick and efficient way for feasibility testing and has the potential to save time and money in the development process of the real robotic system. They also serve as a tool to perform off-line optimization of task performance across various algorithmic parameters (e.g., group size) before validation with real robots [12]. There are mainly three issues that arise during a robotic implementation and are not taken into account in the algorithmic description of GSO:

(1) The linear and angular movements of agents in the algorithm are in-

[1] Simulations whose behavior is constrained by models of physical laws [30].

stantaneous in nature. However, embodied robots spend a finite time in performing linear and angular movements based on their prescribed speeds and turn rate capabilities.

(2) In the algorithm, agents are considered as points and agent collisions are ignored. These are tenable assumptions for numerical optimization problems. However, robots have a physical shape and foot print of finite size, and cannot have intersecting trajectories. Thus, robots must avoid collisions with other robots in addition to avoiding obstacles in the environment.

(3) The GSO algorithm uses a leapfrogging behavior (described in Section 3), where agents move over one another, to perform local search. Since robots perform collision avoidance with other robots, an embodied implementation of the leapfrogging effect becomes a critical issue and is not straightforward.

The above issues are very important and need a careful consideration as they call for changes in the agent movement models and alter the working of the basic algorithm when it is implemented on a swarm of real robots. For instance, since physical robots cannot move over one another, a direct implementation of the leapfrogging behavior is not possible. However, the obstacle avoidance feature alters the algorithm's behavior, giving rise to a partial leapfrogging effect, which is described in Section 3. Therefore, the embodied robot simulation experiments that we conduct in this paper serve as an efficient means to model the algorithmic modifications required for robotic implementation, examine the altered algorithm's behavior, and study the robustness of the algorithm to implementational constraints.

The paper is organized as follows. Prior work on source localization is given in Section 2. An overview of the GSO algorithm and its special suitability for localizing multiple sources are described in Section 3. The GSO variant for robotic implementation is presented in Section 4. The results of embodied simulation experiments are discussed in Section 5. Concluding remarks and directions for future work are given in Section 6.

2 Related Work

Approaches to robotic odor source localization include gradient-based [15], model-based [24], biomimetic [16]− [18], occupancy grid-based [23], [20] strategies. Multi-robot networks have been proposed to evaluate the performance of adding cooperation as an additional layer to the above strategies [15], [18]. Recently, bio-inspired optimization algorithms [**?**] and swarm intelligence based algorithms [10]− [14] have also been applied to the source localization problem.

Sandini et al. [15] present a robotic plume tracing strategy where the robot computes temporally integrated differential gradients by using the instantaneous concentration measurements obtained from a pair of sensors and uses such gradient information to reach the point of highest concentration of a gas leak. The authors also propose a cooperative strategy where robots broadcast their sensed concentration within the environment such that each robot's movements is driven not only by the self-measure of concentration, but also by the indirect measure of concentration received from neighbors. Dhariwal et al. [16] present an approach where mobile robots emulate bacterial-taxis behavior in order to move towards and locate gradient-inducing sources. Grasso et al. [17] develop a biomimetic robot lobster that implements a biologically scaled chemotaxis algorithm by using two point concentration sampling in order to track a statistically characterized turbulent plume. Lytridis et al. [18] report the results of using cooperation among a group of mobile robots that implement a combination of chemotaxis and biased random walk (BRW) strategies to perform odor source localization tasks. The robots exchange information about their current position and the field strength at their current positions, thereby enabling a robot with the lower reading to modify its heading towards others which detect a stronger field by an amount proportional to the difference of the two field strengths. Jatmiko et al. [11] use a variation of particle swarm optimization algorithm on multiple simulated robots to perform odor source localization in natural environment where the odor distribution changes over time. An ad-hoc wireless network and global position system are assumed to be established among all the robots that enable each robot to collect the gas concentration values from all the members in the population and determine its *local-best* and *global-best* positions that are used as inputs to the PSO algorithm to update its velocity. Fronczek and Prasad [10] propose bio-inspired sensor swarms to detect leaks in pressurized systems where sensory perception of agents is based on the biological response of cockroaches to changes in ambient air-flow patterns, communication architecture is modeled around a bee colony localizing an odor source, and the self-repair abilities emulates human decision making. Hayes et al. [12] describe a spiral-surge algorithm in which a collection of autonomous mobile robots use spiral plume finding, surge, and spiral casting behaviors to find the source of an odor plume. The authors validate the algorithm on a group of real robots and show that an embodied simulator can faithfully reproduce these real robots experiments.

All the above algorithms are designed for seeking, detecting, and localization of a single odor source. However, very little attention has been given to simultaneous localization of multiple odor sources. Some researchers have used approaches based on occupancy grid maps to address the multiple source localization problem [19], [20]. Cui et al. [19] present a multiple source localization algorithm in which mobile agents use a grid map to represent the unknown environment, collect concentration values from all other agents through adhoc communication, and calculate a positive gradient direction using a biasing expansion swarm approach (BESA). According to this approach, each agent moves to one of the neighboring eight cells on which the net influence (called the biasing parameter) of other agents is maximum. Each agents influence is proportional to the concentration of the diffused source at its location and inversely proportional to the square of its distance to the cell. The cohesion property of this swarming approach maintains the connectivity of the ad-hoc network. Note that each agent uses global information to decide its movements. The authors validate their approach only in non-embodied simulations. Jakuba [20] presents a stochastic mapping framework for autonomous robotic localization of multiple hydrothermal vents on sea-floors. The proposed mapping framework is an adaptation of occupancy grid mapping where the binary state of map nodes is redefined to denote either the presence (occupancy) or absence of an active plume source. Even though, the authors in [19] and [20] consider multiple sources, these algorithms do not explicitly take into account the interference problems that are caused due to multiplicity of sources. However, the GSO algorithm, that was originally designed for multimodal optimization problems [25], is specially suited for multiple source localization tasks, which is described in the next section.

3 The GSO Algorithm

The glowworm swarm optimization (GSO) algorithm is an optimization technique that is originally developed for simultaneous capture of multiple optimums of multimodal functions. The underlying principles of the GSO algorithm and numerical experiments to show the algorithms efficacy in capturing multiple peaks of a wide range of multimodal functions are presented in [25]. Other earlier work on the GSO algorithm can be found in [26]-[29]. As this paper focusses on the implementation aspects of GSO based network robot system for multiple source localization tasks using a real-robot-simulator, we limit ourselves to a brief description of the GSO algorithm.

3.1 GSO algorithm description

In the GSO algorithm, the agents are initially deployed randomly, according to a uniform distribution, in the objective function space. Each agent carries a luminescence quantity called *luciferin* that encodes the information about the function profile at its current location. Agents are thought of as glowworms that emit a light whose intensity is proportional to the associated luciferin. A glowworm considers other glowworms that are located within its local-decision domain and those with a higher luciferin value than that of its own as neighbors. The decision domain is adaptive by nature and is bounded above by a circular sensor range. Each glowworm selects a neighbor using a probabilistic mechanism and moves towards it. That is, each glowworm is attracted by the brighter glow of other neighboring glowworms. These individual agent movements, that are based only on local information, enable the swarm of glowworms to split into subgroups, exhibit simultaneous taxis-behavior towards, and rendezvous at multiple optimums of a given multimodal function.

Glowworm Swarm Optimization (GSO) Algorithm

deploy_agents_randomly;
$\forall\ i, \text{set}\ \ell_i(0) = \ell_0$
$\forall\ i, \text{set}\ r_d^i(0) = r_0$

{
for each glowworm i do:

$$\ell_i(t) \ \leftarrow\ (1-\rho)\ell_i(t) + \gamma J(x_i(t+1)); \tag{1}$$

for each glowworm i do:
{

$$N_i(t) = \{j : d_{ij}(t) < r_d^i(t); \ell_i(t) < \ell_j(t)\}; \tag{2}$$

for each glowworm $j \in N_i(t)$ do:

$$p_j(t) = \frac{\ell_j(t) - \ell_i(t)}{\sum_{k \in N_i(t)} \ell_k(t) - \ell_i(t)}; \tag{3}$$

$j = \mathit{select\_glowworm\_j}$; % (using $p_j(t)$)

$$x_i(t) \ \leftarrow\ x_i(t) + s\left(\frac{x_j(t) - x_i(t)}{\|x_j(t) - x_i(t)\|}\right); \tag{4}$$

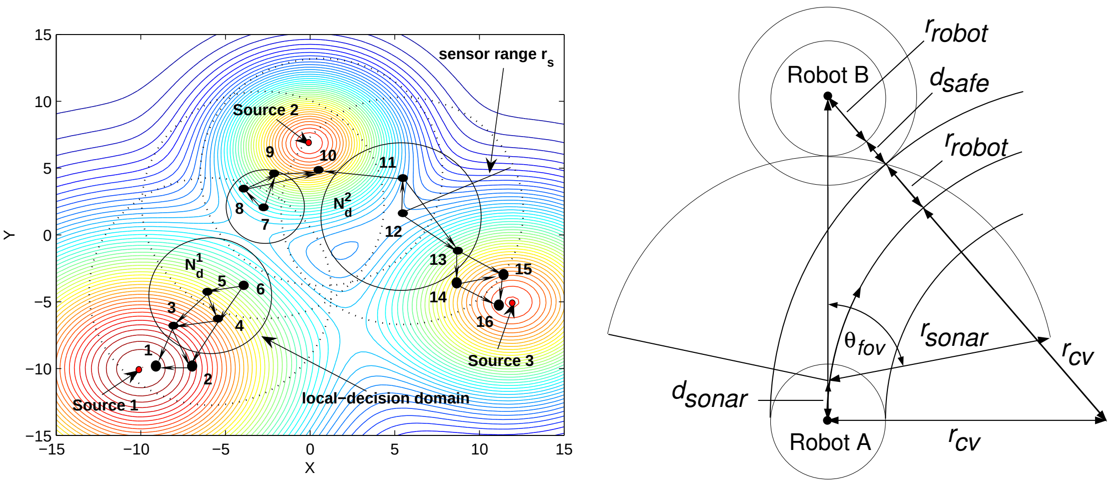
$$r_d^i(t) \ \leftarrow\ \min\{r_s, \max\{0, r_d^i(t) + \beta(n_t - |N_i(t)|)\}\}; \tag{5}$$

} $\quad t \ \leftarrow\ t+1$;
}

The various steps of the GSO algorithm are given in the inset box, where $j \in N_i(t), N_i(t) = \{j : d_{i,j}(t) < r_d^i(t); \ell_i(t) < \ell_j(t)\}$ is the neighborhood of glowworm i at time t, $d_{i,j}(t)$ represents the euclidian distance between glowworms i and j at time t, $\ell_i(t)$ represents the luciferin level associated with glowworm i at time t, $r_d^i(t)$ represents the variable local-decision range associated with glowworm i at time t, and r_s represents the radial range of the luciferin sensor, the glowworm i selects a glowworm $j \in N_i(t)$ with probability $p_j(t)$, ρ is the luciferin decay constant ($0 < \rho < 1$) and γ is the luciferin enhancement constant and $J(x_i(t))$ represents the value of the signal strength at agent i's location at time t.

3.2 Network architecture: Special suitability for multiple sources

The constraints of communication range r_s and adaptive decision-range r_d^i that are imposed on each glowworm lead to the emergence of two different networks − an undirected communication-network N_c and a directed decision-network N_d − of the same set of glowworms. From the algorithm's description, it is clear that agents in the GSO algorithm do not maintain fixed-neighbors during their movements, which means, existing links between neighbors may break and new links may establish between glowworm pairs. Therefore the networks N_c and N_d are dynamic in nature. We use an illustrative example (Figure 1(a)) in order to describe the network architecture of agents in a glowworm swarm and its special suitability for localizing multiple sources. A group of 15 glowworms is randomly deployed in a workspace that consists of three odor-sources placed at different locations. Note from Figure 1(a) that the graph N_c is connected. If the glowworms use a constant local-decision domain whose range is equal to the maximum sensing range r_s, all the glowworms converge to the global peak. This observation is also supported by simulations in **??**. However, note that the graph N_d is partitioned into two disjoint weakly connected components N_d^1 and N_d^2, which can be explained in the following way. When the glowworms use an adaptive decision-domain whose range is updated according to (5), the glowworms adjust their decision-domain ranges until they acquire a pre-specified number of neighbors ($n_t = 2$ in the example used for illustration purpose). This property enables each glowworm to select its neighbors in such a manner that its movements get biased towards the nearest peak. The above individual agent behavior leads to a collective behavior of agents that constitutes the automatic splitting of the whole group into disjoint subgroups where each subgroup of agents gets allocated to a nearby peak (that is a peak to which the agent-distance, averaged over the subgroup, is minimum among those distances to all the peaks in the environment). In Figure 1(a), glowworms $5, 6, 8, 9, 10$ are within the sensing-range of glowworm 7. However, glowworm 7 considers only glowworms 8 and 9 as neighbors. Therefore its movements get biased towards source 2, while it avoids moving towards glowworm 5, even though glowworm 5 has a higher luciferin value than that of itself. Accordingly, the subgroups of glowworms $\{1, 2, 3, 4, 5, 6\}$, $\{7, 8, 9, 10\}$, and $\{13, 14, 15, 16\}$ taxis towards source 1, source 2, and source 3, respectively. Note that glowworms 11 and 12 may move towards either source 2 or source



(a) (b)

Fig. 1. *a) Network architecture resulting from the constraints of communication range r_s and adaptive decision-range r_d^i that are imposed on the agents in the GSO algorithm. b) The obstacle avoidance model used by the robots in embodied simulations of the GSO algorithm.*

3. The local-search and convergence of each subgroup to a source location is achieved by the *leapfrogging* effect inherent in the GSO algorithm, which is explained below. *The leapfrogging effect:* Consider a subgroup of glowworms that advances towards a source. Among the subgroup members, the glowworm j that is initially located closest to the source has the highest luciferin value and hence according to the GSO algorithm, it remains stationary. Consequently, all other glowworms within the subgroup converge to the glowworm j. As a result, all the agents get co-located away from the peak-location, except when the glowworm g_l is co-located at the source. This problem is automatically resolved in the following way. During the movement phase, each glowworm moves a distance of finite step-size s towards a neighbor. Hence, when a glowworm i approaches closer to the glowworm j such that the inter-agent distance becomes less than s, i leapfrogs over the position of j and becomes a leader to j. In the next iteration, i remains stationary and j overtakes the position of i thus regaining its leadership. This process of interchanging of roles between i and j repeats giving rise to a local-search behavior of the glowworm pair. A group of glowworms use the same principle to perform local-search and eventually converge to the source location. This phenomenon was also observed in simulations in [25].

Algorithmic aspects such as usage of a point-agent model with instantaneous linear/angular agent-movements, allowing of collisions between agents, and enabling the agents to move over one another (as also mentioned in Section 1) are expected to create problems during implementation on real robots. These aspects that may change the algorithm's behavior will be discussed next.

4 GSO Variant for Robotic Implementation

A robotic implementation of the GSO algorithm would require a collection of mobile robots where each robot has the following capabilities:

(1) Sensing and broadcasting of profile-value (luciferin level) at its location.
(2) Detection of number of neighbors and their localization with respect to its own position.
(3) Receiving profile-values (luciferin levels) from all neighbors.
(4) Selecting a neighbor using a probability distribution (based on the relative luciferin levels of its neighbors) and making a step-movement towards it.
(5) Obstacle avoidance behavior in order to avoid collisions with obstacles and other robots in the environment.
(6) Leapfrogging behavior for performing local search.

As we use a real-robot simulation platform and assume perfect sensing and broadcast in our initial experiments, the first three robot capabilities are rather straightforward to implement and do not need a discussion. Implementation details of obstacle avoidance and leapfrogging behaviors are given below:

4.1 Obstacle avoidance model

The footprint of the robot is considered to be an octagon with a circumcircle radius r_{robot}. A pair of sonar based proximity-detection sensors with a range r_{sonar} and field of view θ_{fov} are mounted in the frontal region of the robot at a distance d_{sonar} from the robot-center. A simple obstacle avoidance rule is used where the robot decides to turn right (left) if the left (right) sensor detects the other robot. The robot performs the collision-avoidance maneuver by moving along an arc, whose radius of curvature is r_{cv}, and never reaching closer than a safe-distance d_{safe} to the other robot/obstacle. This situation is shown in Figure 1(b). Using simple geometry, the radius of curvature r_{cv} can be calculated as below:

$$r_{cv} = \frac{(d_{sonar} + r_{sonar} + r_{robot})^2 - (2r_{robot} + d_{safe})^2}{2(r_{robot} + d_{safe})} \tag{6}$$

4.2 Leapfrogging behavior

The leapfrogging effect of the GSO algorithm requires a glowworm to move over another glowworm whenever two glowworms are within a step distance

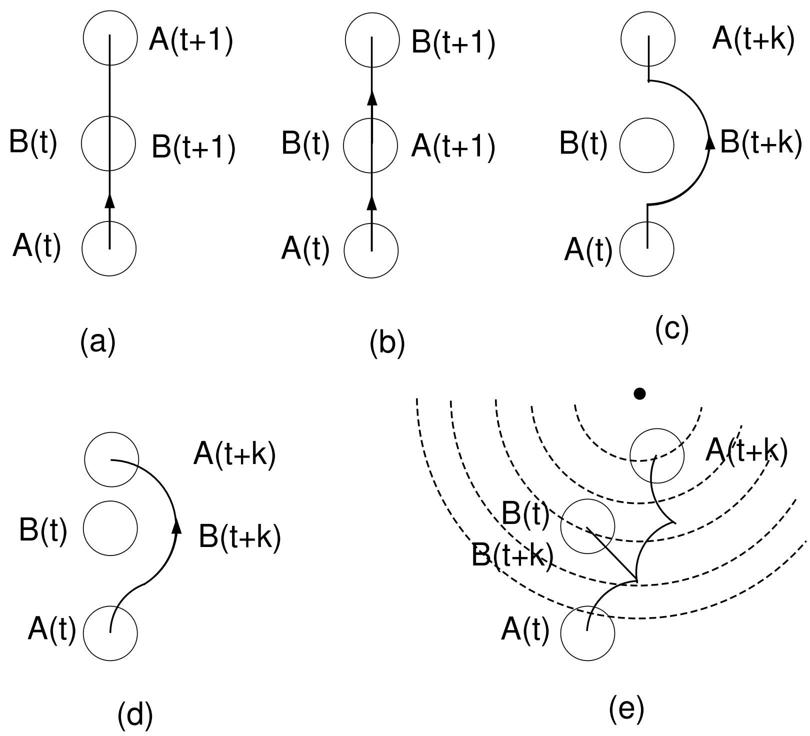


Fig. 2. *a) Leapfrogging behavior according to the GSO algorithm. b), c), and d) Three methods of robotic implementation of explicit leapfrogging behavior. e) Implicit leapfrogging behavior due to obstacle avoidance.*

s of each other. This is illustrated in Figure 3(a) where glowworm A moves over glowworm B to reach the position $A(t+1)$. However, this is not directly realizable with physical mobile robots. We describe three methods to achieve an explicit robotic implementation of the leapfrogging behavior. The first method (Figure 3(b)) involves interchange of agent-roles, through communication, where robot B moves to the desired position of robot A and robot A replaces robot B's position. The illustration in Figure 3(c) shows another method where the robot A takes a detour about robot B's position and reaches its desired position. As this method is difficult to implement, we propose a modification where the detour is achieved using a blend of two circular paths as shown in Figure 3(d). We also observe that the obstacle avoidance behavior automatically gives rise to an implicit leapfrogging effect, which is described using the illustration in Figure 3(e). Robot A alternatively performs collision avoidance with and seeks to move towards robot B until it crosses the equi-contour line on which robot B is situated. Thereafter, since robot A becomes a leader to robot B, robot performs similar movements with respect to robot A, thus leading to an implicit leapfrogging behavior of the glowworm-pair.

r_{robot}	d_{sonar}	r_{sonar}	r_{cv}	d_{safe}	V_{linear}
$8cm$	$4cm$	$75cm.$	$15cm.$	$58.6cm.$	$0.4m/sec$

Table 1
Robot parameters

r_s	ρ	γ	ϵ	β	n_t
8	0.4	0.6	3	0.08	2

Table 2
Values of algorithmic constants used in the simulations

	1	2	3
a_i	3	2.5	2.5
b_i	0.01	0.04	0.02
x_i	-10	0	12
y_i	-10	7	-5

Table 3
Values of a_i, b_i, x_i, and y_i used to generate the function profile $J(x, y)$

5 Embodied Simulation Experiments

We use Player/Stage real-robotic experiments to test the GSO algorithm's applicability to multiple source localization tasks. The various robot parameters used in the simulations are shown in Table 1. The values of the algorithmic constants used in the simulations are shown in Figure 2. We use the following function to model the multiple source (Figure 7) that are spread in the environment:

$$J(x, y) = \sum_{i=1}^{Q} a_i \exp(-b_i((x - x_i)^2 + (y - y_i)^2)) \tag{7}$$

where, Q represents the number of odor sources and (x_i, y_i) represents the location of each peak. A set of three peaks ($Q = 3$) is considered for the purpose. The values of $\{a_i, bi, x_i, y_i, i = 1, \ldots, 3\}$ are shown in Table 3.

We consider a workspace of size 30×30 sq. m $((-15, 15) \times (-15, -15))$ and deploy a set of 20 glowworms in a square region $(-4, 4) \times (-9, -1)$ of size 8×8 sq. m. The center of the workspace is chosen as the center of the circle circumscribing the triangle formed by the three source locations in order to avoid bias of robot movements towards any single source. Figure 4 and 5 show the various stages of an experiment where the swarm of 20 robots split into three subgroups, simultaneously taxis towards, and co-locate at the three source locations. It can be observed that the initial group of robots split into

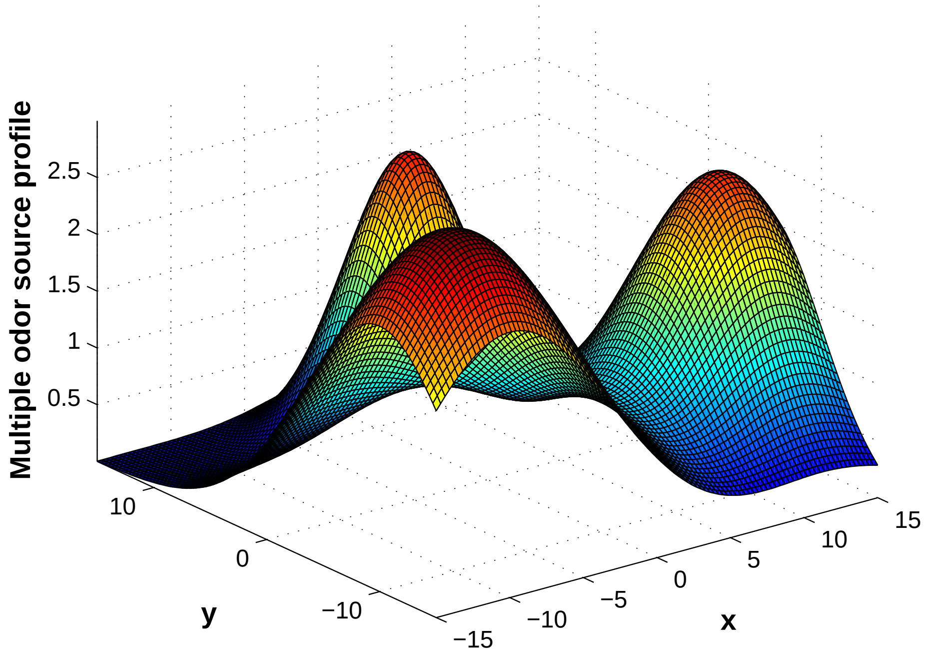


Fig. 3. *Model of the multiple odor-source profile used for the embodied simulations*

networked subgroups within the first 5 seconds. These subgroups now taxis towards the source locations in the remaining time. The implicit leapfrogging effect due to obstacle avoidance behavior is clearly apparent in these simulations. Note that the robots do not actually converge to the source locations in an exact sense, but hover around the source due to the collision avoidance. This is acceptable in a realistic scenario.

We then repeat the same experiment over a set of 30 trials and record performance measures such as the distance travelled by each robot, number of sources captured, and number of robots converging to each source. We consider the same initial deployment of robots for the first set of 15 trials and different random initial deployments for the next set of 15 trials.

Figure 6(a) shows the plot of distance travelled by each robot for the first 15 trials, along with the average behavior. An average of 5, 6, and 9 robots converge to the sources $(-10,-10)$, $(0,7)$, and $(12,-5)$, respectively, over the 15 trials of same initial placements.

In the second set of 15 experimental trials where different initial placements were used, the number of robots converging to each source and the number of sources captured were recorded, which are shown in Table 4.

In the final set of experiments, we assess task performance by monitoring

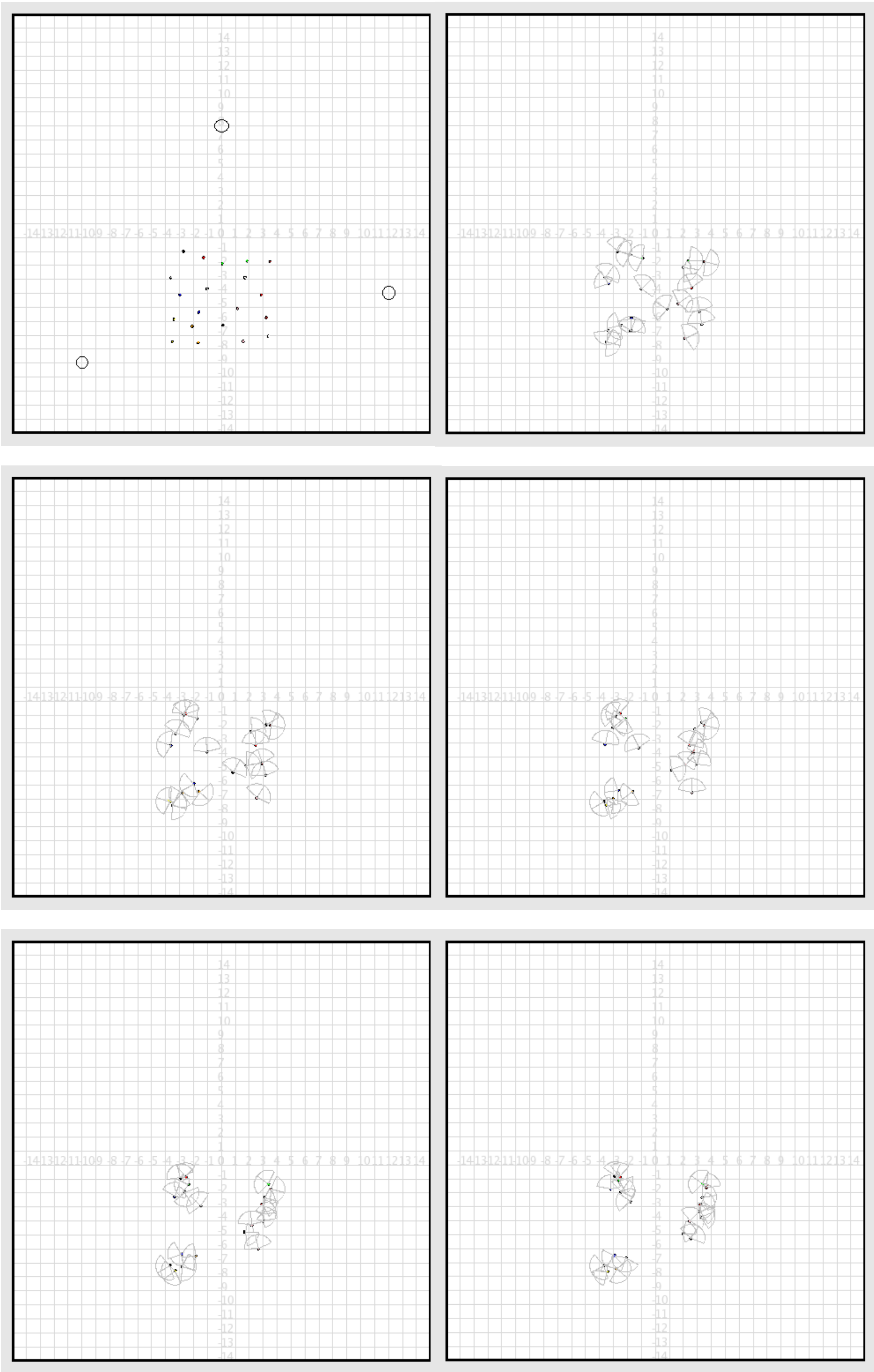


Fig. 4. *A swarm of* 20 *glowworms deployed in the region* $(-4,4) \times (-9,-1)$ *split into three subgroups, taxis towards, and localize three sources. The snapshots, from left, are shown at 0, 3, 3.5, 4, 4.5, and 5 seconda of simulation time.*

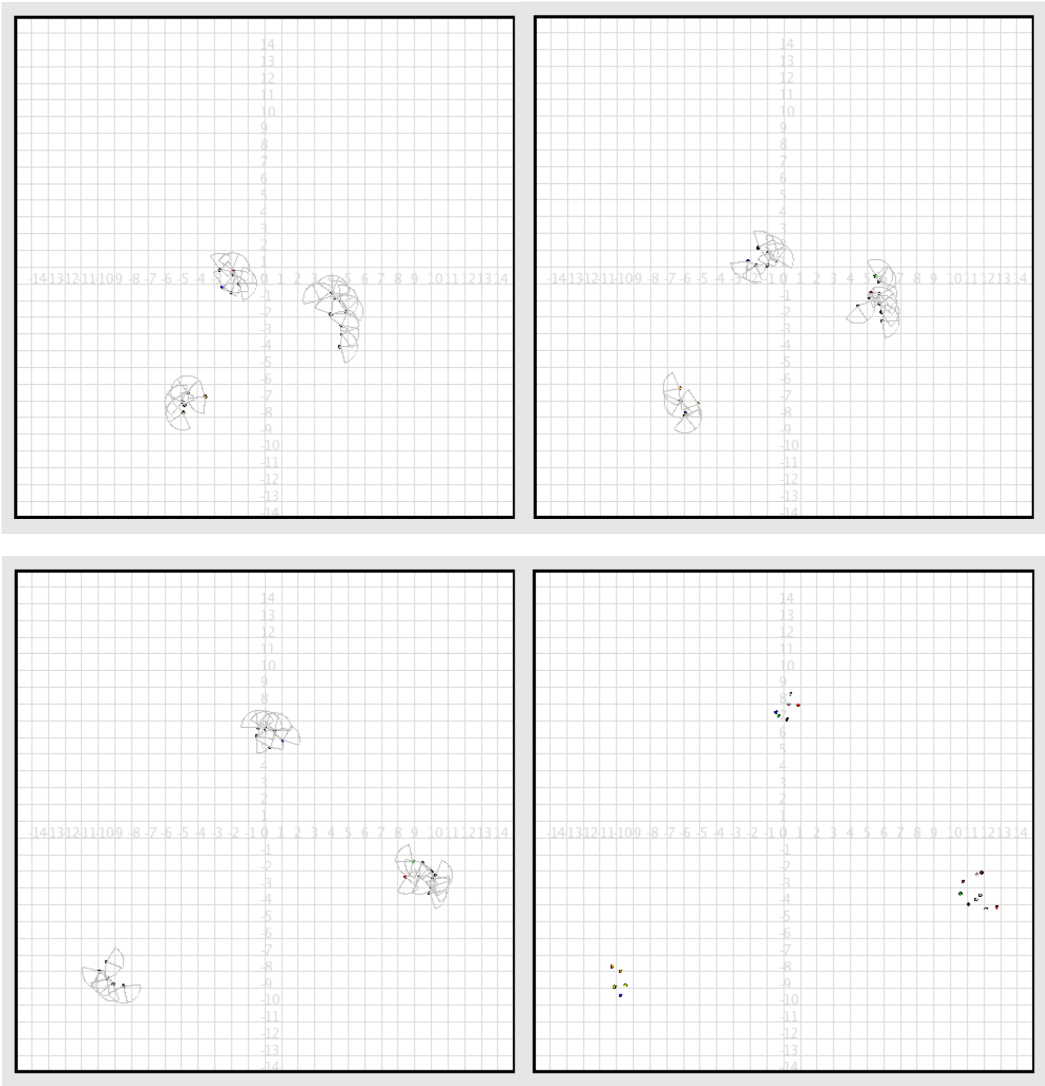


Fig. 5. *Results from Figure 4 (contd.) where the snapshots, starting from left, are shown at 10, 15, 30, and 50 seconds of simulation time.*

average number of sources captured as a function of the robot group size (Figure 6(b)).

These results validate the effectiveness of the GSO based networked robot system's ability to simultaneously locate multiple odor sources.

6 Concluding remarks

We present a network robot system that employs glowworm swarm optimization algorithm to address the problem of simultaneous multiple odor source localization. We briefly describe the basic GSO algorithm and the modifi-

Source 1	4	6	5	8	0	8	5	6	4	4	5	8	4	3	5
Source 2	14	0	15	0	12	0	15	5	8	3	7	0	16	7	3
Source 3	0	14	0	12	8	12	0	9	8	13	8	12	0	10	10
Sources captured	2	2	2	2	2	2	2	3	3	3	3	2	2	3	3

Table 4

The first three rows show the number of robots converging each source and the last row shows the number of sources captured over 15 *trials of different initial placements*

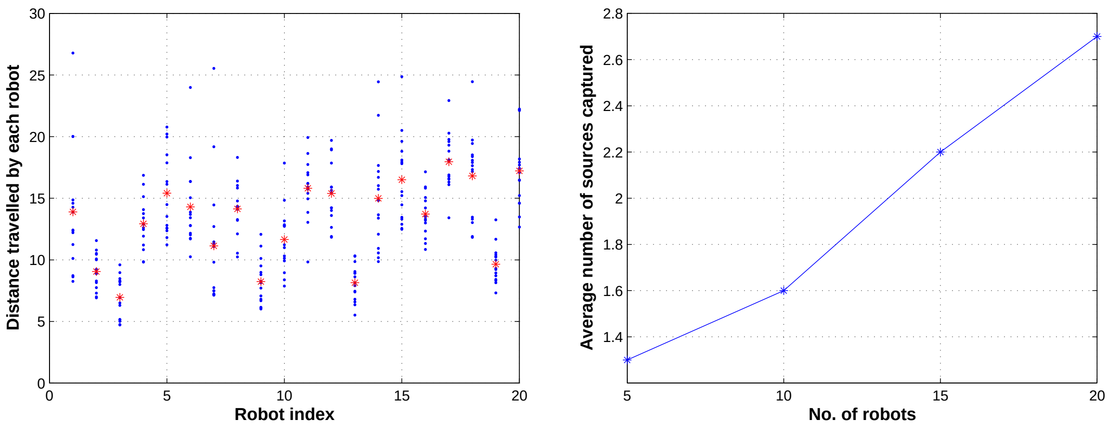


Fig. 6. *a) Distance travelled by each robot over* 15 *trials where the same initial placement is used. b) Performance across group size: Average number of sources captures in a set of* 10 *experimental trials*

cations incorporated into the algorithm in order to make it suitable for a network robotic implementation. We conduct embodied robot simulations by using a multi-robot-simulator called Player/Stage that provides realistic sensor and actuator models, in order to assess the GSO algorithm's suitability for multiple source localization tasks. The study based on embodied simulation experiments shows the robustness of the algorithm to implementational constraints.

References

[1] D.J. Bruemmer, D.D. Dudenhoeffer, M.D. McKay, and M.O. Anderson, A robotic swarm for spill finding and perimeter formation, in: Spectrum 2002 – International Conference on Nuclear and Hazardous Waste Management, Reno, NV, August 2002.

[2] J. Clark and R. Fierro, Cooperative hybrid control of robotic sensors for perimeter detection and tracking, in: Proceedings of American Control Conference, Portland, OR, June 2005, pp. 3500-3505.

[3] V. Kumar, D. Rus, and S. Singh, Robot and sensor networks for first responders, IEEE Pervasive Computing, Vol. 3, Issue 4, October 2004, pp. 24 - 33.

[4] P. Corke, R. Peterson, and D. Rus, Networked robots: Flying robot navigation using a sensor net, Robotics Research: Springer Tracts in Advanced Robotics, Springer-Verlag, 2005, pp. 234243.

[5] B. Mazzolai and V. Mattoli, From sensor networks to autonomous networked and cooperating platforms for environmental monitoring, ICRA 2007 Workshop: Robotic Olfaction - Towards Real Applications, Roma, Italy, April 2007.

[6] H.V.D Parunak, S.A. Brueckner, and J. Odell, Swarming pattern detection in sensor and robot networks, in: Proceedings of 10th International Conference on Robotics and Remote Systems for Hazardous Environments, Gainsville, Florida.

[7] J. Reich and E. Sklar, Toward automatic reconfiguration of robot-sensor networks for urban search and rescue, in: First International Workshop on Agent Technology for Disaster Management (ATDM): Fifth International Joint Conference on Autonomous Agents and Multiagent Systems, Hakodate, Japan, May 2006.

[8] S. Jia and K. Takase, Network distributed monitoring system based on robot technology middleware, International Journal of Advanced Robotic Systems, Vol. 4, No. 1 (2007) 69 - 72.

[9] D. Song and K. Goldberg, Networked robotic cameras for collaborative observation of natural environments, in: Proceedings of the 12^{th} International Symposium of Robotics Research, San Francisco, CA, October 2005.

[10] J.W. Fronczek and N.R. Prasad, Bio-inspired sensor swarms to detect leaks in pressurized systems, in: Proceedings of IEEE International Conference on Systems, Man and Cybernetics, October 2005, pp. 1967-1972.

[11] W. Jatmiko, Y. Ikemoto, T. Matsuno and T. Fukuda, Distributed odor source localization in dynamic environment, in: Proceedings of IEEE Conference on sensors, October 2005, pp. 254-257.

[12] A.T. Hayes, A. Martinoli, and R.M. Goodman, Swarm robotic odor localization: Off-line optimization and validation with real robots, Robotica (2003), 21: 427-441.

[13] W. Naeem, R. Sutton, and J. Chudley, Chemical plume tracing and odour source localisation by autonomous vehicles, The Journal of Navigation 60 (2007) 173190.

[14] D. Zarzhitsky and D.F. Spears, and W.M. Spears, Swarms for chemical plume tracing, in: Proceedings of IEEE Swarm Intelligence Symposium, Pasadena, California, June 2005, pp. 249-256.

[15] G. Sandini and G. Lucarini and M. Varoli, Gradient Driven Self-organizing Systems, in: Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Sysrems Yokohama, Japan, July 1993, pp. 429-432.

[16] A. Dhariwal, G.S. Sukhatme, and A.A.G. Requicha, Bacterium-inspired robots for environmental monitoring, in: Proceedings of IEEE International Conference on Robotics and Automation, New Orleans, LA, April 2004, pp. 1436-1443.

[17] F.W. Grasso, T.R. Consi, D.C. Mountain, and J. Atema. Biomimetic robot lobster performs chemo-orientation in turbulence using a pair of spatially separated sensors: Progress and challenges, Robotics and Autonomous Systems 30 (2000) 115131.

[18] C. Lytridis, G.S. Virk, and E.E. Kadar, Co-operative smell-based navigation for mobile robots, Climbing and Walking Robots, in: Proceedings of the 7th International Conference CLAWAR 2004, Springer-Verlag, 2004, pp. 1107-1117.

[19] X. Cui, C. T. Hardin, R. K. Ragade, and A. S . Elmaghraby, A swarm approach for emission sources localization, in: Proceedings of the 16th International Conference on Tools with Artificial Intelligence (ICTAI 2004), Boca Raton, Florida, November 2004, pp. 424-430.

[20] M.V. Jakuba, Stochastic mapping for chemical plume source localization with application to autonomous hydrothermal vent discovery, PhD Thesis, Massachusetts Institute of Technology and Woods Hole Oceanographic Institution, 2007.

[21] H. Ishida, T. Nakamoto, and T. Morizumi, Gas/odor plume tracing robots, Sensor Update, Vol. 6 Issue 1, 1999, pp. 397418.

[22] J. Farrell, W. Li, S. Pang, and R. Arrieta, Chemical plume tracing experimental results with a REMUS AUV, Oceans 2003 Marine Technology and Ocean Science Conference, San Diego, CA, 2003, pp. 962968.

[23] A. Lilienthal and T. Duckett, Building gas concentration gridmaps with a mobile robot, Robotics and Autonomous Systems 48 (2004) 316.

[24] J.A. Farrell, S. Pang, and W. Li, Plume mapping via hidden markov methods, IEEE Transactions on System, Man, and Cybernetics, 33 (2003) 850 863.

[25] K.N. Krishnanand and D. Ghose, Glowworm swarm based optimization algorithm for multimodal functions with collective robotics applications, Multiagent and Grid Systems (Special Issue on Recent Progress in Distributed Intelligence), Issue 3, Vol. 2, 209-222.

[26] K.N. Krishnanand and D. Ghose, Glowworm swarm optimization algorithm for hazard sensing in ubiquitous environments using heterogeneous agent swarms, Soft Computing Applications in Industry, Spriner-verlag publications (to appear).

[27] K.N. Krishnanand and D. Ghose, Chasing multiple mobile signal sources: A glowworm swarm optimization approach, in: 3^{rd} International Conference on Artificial Intelligence, Pune, 2007 (to appear)

[28] K.N. Krishnanand, P. Amruth, M.H. Guruprasad, Sharschchandra V. Bidargaddi, and D. Ghose, Glowworm-inspired robot swarm for simultaneous

taxis towards multiple radiation sources, in: Proceedings of IEEE International Conference on Robotics and Automation, Orlando, Florida, May 2006, pp. 958-963.

[29] K.N. Krishnanand, P. Amruth, M.H. Guruprasad, S.V. Bidargaddi, and D. Ghose. Rendezvous of glowworm-inspired robot swarms at multiple source locations: A sound source based real-robot implementation, Lecture Notes in Computer Science, ISBN. 978-3-540-38482-3, August 2006, pp. 259 269.

[30] M.J. Mataric, Learning in behavior-based multi-robot systems: policies, models, and other agents. Journal of Cognitive Systems Research 2 (2001) 81-93.

[31] R.T. Vaughan and B.P. Gerkey, Really reusable robot code and the Player/Stage project, Software Engineering for Experimental Robotics: Springer Tracts in Advanced Robotics, Springer-Verlag, 2007, pp. 267-289.