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Research on Multirobot Chemical Source Positioning Based on Glowworm Swarm Optimization

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The leakage of harmful chemical sources will cause great harm to the environment and human beings; therefore, it is of great social significance to use intelligent mobile robots to achieve accurate and rapid positioning and control of chemical sources. Based on the basic Glowworm Swarm Optimization (GSO), this paper proposes a self-searching mechanism and variable step size optimized GSO for solving the problems of low accuracy and slow convergence speed. This paper studies chemical source positioning problem of multi-robots under no-ventilation environment, and establishes an improved multi-source superposition Gaussian smoke-plume model and a robot model for the simulation experiments. The results show that the accuracy and speed of the positioning of chemical sources by the optimized GSO have been significantly improved.

1. Introduction

With the development of many fields such as computer technology and artificial intelligence, the performance of the smart mobile robots (Gueaieb, 2008) has been continuously improved, and its application range has also been extended to a wider range. They can be applied not only in agriculture, medical care, and service industries, but also have more important applications in harmful and dangerous situations (Kowadlo, 2008) such as urban security and space exploration fields (Ishida, 1994). Intelligent robots integrate advanced technologies of many fields such as information and communication technology (Morioka, 2004), automation control, microelectronics, they can replace humans in harsh and dangerous environments. The chemical industry is a pillar industry of the national economy, but the characteristics of highly flammable, explosive and toxic of the chemical production process make the chemical accidents of huge harms. Therefore, for harmful chemical sources, such as the toxic gases and liquids, their positioning and controlling is an important application scenario for the intelligent robots.
At present, studies of chemical source positioning (Li, 2006) are mostly on single robot finding single chemical source, but as the complexity of the environment increases, the characteristics of low chemical source positioning efficiency and small search range of single robot can no longer satisfy the difficult and wide-ranged searching tasks, therefore, before chemical sources cause greater harm to the environment, rapid positioning and timely control are the research focus of chemical source positioning, and studies of multi-robot chemical source positioning have important practical significance. Basing on GSO, this paper studies multi-robot chemical sources positioning and establishes a simulation environment of chemical sources positioning to perform simulation experiments to verify the effectiveness of the method.

2. Chemical source positioning and related methods

2.1 Chemical source positioning

With the development of science and technology such as sensors (Liao, 2011) and bionics (Lu, 2004), robots can also “smell” like animals to obtain information (Lytridis, 2001). Chemical source positioning refers to the process of locating the source of gas emitted from a chemical odor source using an intelligent mobile robot. Chemical odor propagates through both processes of convection and diffusion. Usually in a closed environment, the spread of odor is dominated by convection; while in a ventilated environment, the spread of

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odor is dominated by diffusion. The following figure (1) is the process of chemical source positioning of mobile robots, and it is divided into smoke plume finding, smoke plume tracing, and identification of chemical sources.

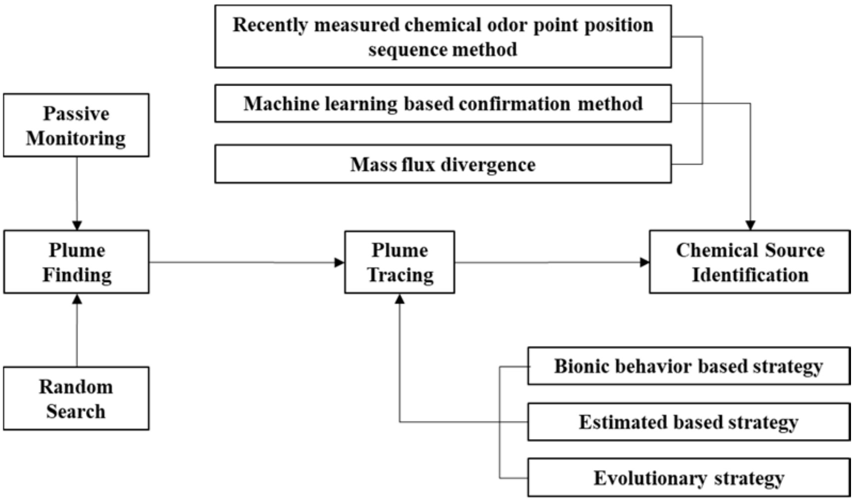


Figure 1: Process of chemical source positioning

2.2 Multirobot chemical source positioning

2.2.1 Multirobot chemical source positioning strategy

With the development of science and technology, the working environment of robots has become more and more complex and the tasks have become more and more difficult. A single robot's small search area and low efficiency can no longer meet the demands, therefore, cooperation between multiple robots is required to complete the task with high efficiency. Multiple robots are applied to the process of chemical source detection and positioning through certain algorithms, which can increase the search area and simultaneously detect chemical odors in multiple areas. The following figure (2) is a strategy used by multi-robot chemical source positioning.

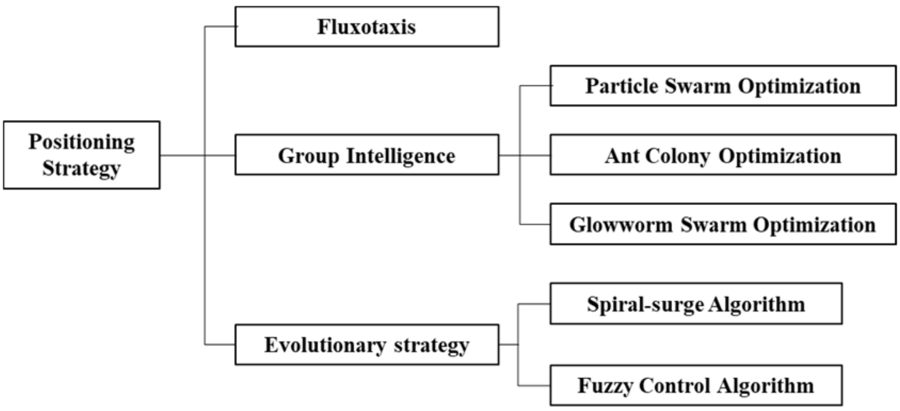


Figure 2: Multirobot positioning strategy

2.2.2 GSO

Glowworm Swarm Optimization (GSO) is an algorithm based on swarm intelligence (Krishnanand, 2009). It is a stochastic optimization algorithm that simulates the glow characteristics of glowworms. It has features such as simple logic and less parameters, which has a wide range of application prospects in the fields of signal positioning. Because the glowworms are different in sex, size, and growth cycle, during the courtship process, the brightness of the fluorescein glow on their tail is different as well, finding the space location of the brightest glowworm can achieve the goal of finding the best individual, namely the positioning of the chemical source, the following figure (3) is the flow chart of the standard GSO.

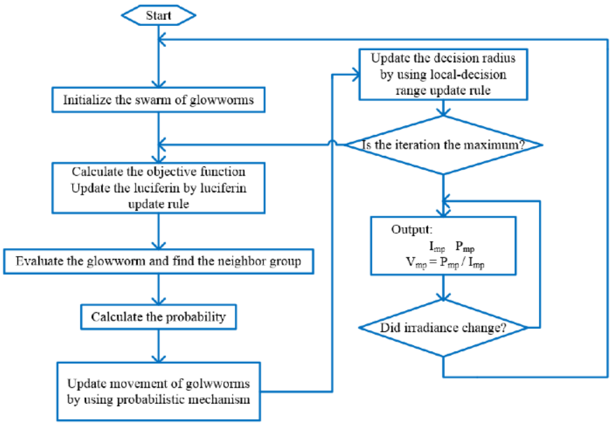


Figure 3: Standard GSO implementation flow chart

3. Simulation environment construction of chemical source positioning

3.1 Environment of chemical source positioning

At present, in the research of multi-robot chemical source positioning, there are three methods of environment construction: real environment, simulation environment and wind tunnel environment. Compared with the other two methods, the simulation environment is applied to the initial stage of problem research because of its low cost and flexible environment setting, and it can validate the effectiveness of the algorithm quickly and efficiently. Therefore, this paper uses the simulation environment smoke plume model to study the positioning of chemical sources by multi-robots.

3.2 Construction method of simulation environment model

The smoke plume model can be divided into two categories: static and dynamic. The Gaussian smoke plume model is a commonly used static model, while the Farrell smoke plume model and CFD continuous smoke plume model are commonly used dynamic models. This paper uses the Gaussian smoke plume model in the subsequent GSO, so we will briefly introduce this model.

The earliest Gaussian smoke plume model is built for single chemical source, but it can be applied to locate multiple chemical sources after improvement. Assume that the model consists of 10 superposed Gaussian smoke plume models in a plane of 1000 x 1000 units, as shown in (4), which can be expressed by the following equation:

$$f(x, y) = \sum_{i=1}^{10} I_i \exp\left(-\frac{(x-x_i)^2 + (y-y_i)^2}{2\sigma_i^2}\right) \text{ (i = 1,2, …, 10)} \quad (1)$$

Where I_i, σ_i represents the chemical source intensity and the mean squared error, respectively.

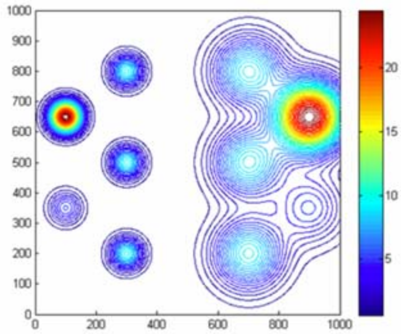


Figure 4: Benchmark with 10 Gaussian source smoke plume models

The following table (1) shows the parameters of the position and intensity of 10 different chemical sources. As shown in Figure (4), in some regions, the chemical sources are superposed, in some regions, the chemical sources do not have any odor, so it is relatively difficult to locate these chemical sources.

Table 1: Parameters of 10 Gaussian source smoke plume models

Chemical Source i	x_i	y_i	I_i	σ_i
1	100	340	5	30
2	100	660	20	30
3	300	200	15	30
4	300	490	15	30
5	300	800	15	30
6	700	220	15	70
7	700	480	15	70
8	700	800	15	70
9	900	350	5	70
10	900	660	20	70

3.3 Robot model

This paper uses a two-wheeled, but independently driven, circular simulation mobile robot that can be represented by the following vector:

$$\mathrm{R} = [\mathrm{x}, \mathrm{y}, \theta, \varphi_r, \varphi_l] \tag{2}$$

According to the kinematic model, the orientation and position of the robot can be expressed as:

$$x_{t+1} = x_t + Vcos\theta\Delta t \tag{3}$$

$$y_{t+1} = y_t + Vsin\theta\Delta t \tag{4}$$

$$\theta_{t+1} = \theta_t + \omega\Delta t \tag{5}$$

Where, x and y represent the center position of the mobile robot, θ represents the direction angle of the movement direction, Δt represents the step size, φ_r and φ_l represent the rotation angles of the right and left wheels, respectively.

Three kinds of sensors are required for robots to locate the chemical sources: wind speed sensor, odor sensor, and ultrasonic sensor. Their roles are shown in the following table 2.

Table 2: Sensor type and their functions

Type	Function
Wind Speed Sensor	Detection of wind speed and direction
Odor Sensor	Detecting the concentration of odor plume
Ultrasonic sensor	Detecting obstacles around

The wind speed and odor concentration at the location of the robot can be measured directly. At the same time, for the robot to avoid obstacles, we can install five ultrasonic sensors to cover the 180° forward direction, as shown in the figure 5 below.

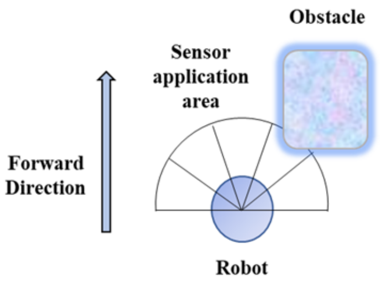


Figure 5: Configuration of the ultrasonic sensors of the robot

4. GSO-based multi-robot chemical source positioning

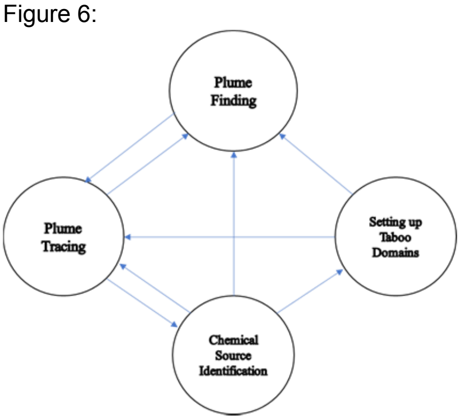
4.1 Defects of basic GSO

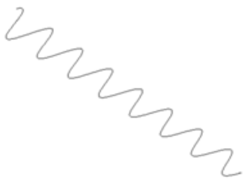
The chemical source positioning problem of multiple robots can be regarded as the problem of finding the optimal solution for a multimodal function, and the GSO is the algorithm for solving the optimization problem of

the multimodal function. The basic GSO has defects in the following aspects:
(1) The computational complexity is high;
(2) The accuracy of the multimodal function is not high and the convergence speed is slow;
(3) When a glowworm has no neighbor, it will stand still, thus reducing the probability of finding peaks;
(4) More parameters need to be set during calculation.
Therefore, in order to find the optimal solution for the multimodal function of multi-robot chemical source positioning problem, optimization and improvement are proposed based on the basic GSO.

4.2 Optimization of GSO

The multi-robot chemical source positioning strategy of GSO is divided into following four parts, as shown in Figure 6:





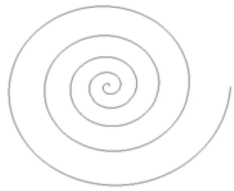


Figure 6: Schematic illustration of chemical source positioning

Figure 7: Logarithmic spiral search and wave-shape search

(1) Smoke plume finding - global search (based on self- searching mechanism)
To improve the stand-still situation of glowworms in the GSO algorithm, in the initial stage of the search, self-searching mechanism is used to perform the searching, namely the glowworms use spiral-shape or wave-shape search to expand the search range until the threshold value of the objective function of the glowworm at a certain position is larger than the threshold value of the adjacent position.
(2) Smoke plume tracing - local search (GSO algorithm based on variable step size)
In order to improve the slow convergence of the GSO algorithm, we introduce a variable step size search method. At the beginning of the search, due to the relative position of the glowworms at the edge, there is less useful information. You can use a larger step size to expand the search and improve the search efficiency. In the middle and later stages of the search, using small steps to perform a local search to find the optimal solution. The change of step size s with the number of iterations is as follows:

$$\mathrm{S(t)} = \frac{(s_0 - s_{min})(T_{max} - t)}{T_{max}} + s_{min} \tag{6}$$

(3) Chemical source identification
When the glowworms are looking for suspected peaks, certain conditions must be met to identify the chemical source.
(4) Setting up taboo domain
The taboo domain is set so that the robot can be released to find other chemical sources within a certain radius after a certain point is determined as a chemical source, and other robots do not reposition the chemical source. This ensures the efficiency and the results won't be a mess.

4.3 Simulation experiments and simulation results

The model used in this paper is the Gaussian smoke plume model in a closed environment described in the previous section. In the simulation experiment, by comparing the GSO algorithm and the optimized MGSO algorithm, we can know the robot's chemical source positioning situation under different distribution conditions. The simulation experiment uses the MATLAB software, and the condition for terminating the experiment is that, the multi-robots have located all chemical sources or the iteration number reached 400.

4.3.1 Simulation results of uniformly distributed multi-robots

The search results of the two algorithms are shown in Table (3). The results show that the search performance of the optimized GSO algorithm is much better than that of the basic GSO algorithm, not only in the search speed, but also in accuracy.

Table 3: Comparison on algorithm performance with uniform initial distribution 50

Algorithm	s	Number of positioning chemical sources	Number of iterations
GSO	S=10	6	-
	S=10	10	90
MGSO	S=15	10	88
	S=20	10	112

4.3.2 Simulation results of linear distribution of multi-robots

The simulation results show that the chemical source located by the GSO algorithm is zero, and the optimized GSO locates all the chemical sources. This is because the multi-robots are linearly distributed in an odorless region, robots in the GSO algorithm remains still, while the optimized algorithm can change the step size to detect the presence and location of chemical sources. Therefore, the chemical source positioning function of the optimized GSO algorithm has been enhanced.

5. Conclusion

Basing on GSO, this paper studies the positioning of chemical sources by multi-robots, the specific research results are as follows:

(1) For the positioning problem of chemical sources in a no-ventilation indoor environment, an improved multi-source superposition Gaussian smoke plume model and a robot model were established for the simulation experiments.

(2) Based on the problem of low accuracy and slow convergence speed of basic GSO, a self-searching mechanism and a variable step size optimization GSO were proposed and simulated. The results showed that the accuracy and speed of the optimized GSO for positioning the chemical sources had improved significantly.

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