Source Searching in Unknown Obstructed Environments through Source Estimation, Target Determination, and Path Planning

Yatai Ji[a], Yong Zhao[a], Bin Chen[a,b,*], Zhengqiu Zhu[a], Yu Liu[c], Hai Zhu[a], and Sihang Qiu[a,b]

[a] *National University of Defense Technology*

[b] *Hunan Institute of Advanced Technology*

[c] *South China University of Technology*

* *corresponding author, chenbin06@nudt.edu.cn*

Abstract

Autonomous mobile robots have been gradually employed to search unknown sources in indoor environments. However, current studies have not fully addressed the source searching problem in unknown obstructed environments with limited sensing abilities. To deal with these problems, we propose an active source searching framework, in which mobile robots can avoid obstacles actively and realize the balance between exploration and exploitation in unknown obstructed environments through an iterative process: source estimation, target determination, and path planning. First, we describe the source searching problem and introduce the environment and sensor models. Then, a novel source searching algorithm based on particle filter, MEGI-taxis, and A-star is proposed. Specifically, the particle filter is used to estimate the source term parameters. The MEGI-taxis algorithm is developed to obtain a globally optimal searching target, which leverages the Gaussian Mixture Model to extract the features of probability information. Based on the heuris-

tic rule, the A-star algorithm is employed to plan a collision-free path for the robot navigating to the target in unknown environments. When compared to state-of-the-art solutions in simulations, our method shows better performance in success rate, mean searching steps, and stability in the source searching process. Moreover, the effectiveness of the proposed framework is verified in the diffusion field generated by the computational fluid dynamics (CFD) model based on an indoor scene. The results reveal the important practicality of our proposed framework for source searching tasks in unknown obstructed environments.
Keywords: indoor source localization; unknown obstructed environments; source searching; source estimation; target determination; path planning;

---

1. Introduction

Source searching is a common problem faced by nature and human society. A typical example is the source term estimation of a hazardous gas leakage source in the indoor environment [1, 2, 3, 4]. In the problem, searchers need to collect chemical or other signals released by the source to determine the location of the source. Traditional source term estimation methods [5, 6, 7, 8] are limited by the deployment of fixed sensor networks. Nowadays, with the technological developments in sensors and robotics, mobile robots carried on sensors are chosen to complete the task for their high efficiency, low risk and accuracy of locating the source. This way establishes probabilistic estimation of the source location by sensing the concentration of leaked substances. Then, it continuously collects information to update the estimation of the source. Finally, mobile robots declare the source location and obtain the source term parameters.

The early source searching algorithms were based on bionics principles [9]. They studied animals' ways of searching for the odor source and carrying out path planning [10]. For instance, Muller *et al.* [11] proposed the spiral searching program, taking inspiration from the foraging of ants. The Lévy searching pattern was [12] discovered by studying the dataset of the movements of predatory fish in the high seas. While observing the trajectories of animals, researchers also studied the mechanisms behind their movements. For instance, motile bacteria are easily attracted by certain chemicals [13]. Learned from this phenomenon, Alder *et al.* designed a Chemotaxis strategy to guide a searcher to move in the direction of the concentration gradient [14]. Incorporated with fluid and chemical concentration measurements and estimation of the mass flux, Zarzhitsky *et al.* [15] developed a physics-based approach to the localization of chemical sources, which found the source by climbing up the mass flux gradient. The bionics principles show superiority in low computational complexity due to their simplicity in theory, but their performance is limited by the ubiquitous turbulence.

Other than the bio-inspired algorithms, researchers also proposed and developed various cognitive strategies [16, 17, 18, 19, 20, 21] based on information-theoretic principles to solve source searching problems. Through guiding searchers to move along the information entropy gradient, Infotaxis algorithm [16] realized a more accurate estimation of source terms within a shorter searching time, compared with bio-based algorithms. Ristic *et al.* [17] adopted the particle filter method to estimate the source term parameters and compared the influence of different reward functions on cognitive strategies. Based on that, Hutchinson *et al.* [18] devised a reward function based on maximum entropy sampling to locate the source with fewer steps, namely Entrotaxis. Later on, a study [19] that combines the entropy and the potential energy is proposed to realize the exploration-exploitation balance. With the development of Artificial Intelligence (AI), AI methods are applied to the source searching field [22, 23, 24, 25, 26]. Wang *et al.* [27] designed a fuzzy controller to localize odor sources via adaptive bio-inspired navigation. Deep reinforcement learning techniques are applied as a source searching approach for the first time in the literature [28]. Though these strategies greatly improved the performance of source searching in turbulent situations, they would face new challenges when considering more practical environments, for example, the indoor scenes with obstacles.

Facing possible obstacles in indoor environments, current studies have adopted various mechanisms to guide the searcher to avoid obstacles and further to reduce the possibility of being trapped. For instance, Jatmiko *et al.* [29] modified the particle swarm optimization algorithm to limit the possibility of being trapped in a local maximum. To search in a scene with simple obstacles, Liu *et al.* [30] designed a supervisory program to control a group of mobile robots. By integrating the Lévy searching pattern, the Entrotaxis-Jump algorithm [31] was proposed to guide the mobile sensors to search in a chemical cluster with complex obstacles. To simulate how gases disperse in any 3D environment (including obstacles), Monroy *et al.* [32, 33] present an open-source gas dispersion simulation framework, GADEN, which is widely used to evaluate and test gas source localization algorithms [34, 35]. Moreover, some studies also focused on the searching process in an unknown scene. For example, Ristic *et al.* [36] devised a strategy based on Rao-Blackwellised particle filter to drive the searcher. Kamarudin *et al.* [37] combined the simultaneous localization and mapping (SLAM) algorithm with Gas distribution mapping (GDM) to solve the problem. In addition, to solve the searching problem in a random obstructed environment, Zhao *et al.* [38] devised a passive escaping mechanism in the cognitive strategies to avoid obstacles. Although these attempts can solve the source searching problem in complex scenes with obstacles to some extent, they fail to provide an active and efficient solution for source searching in unknown obstructed environments.

Taking more practical factors into account when searching in unknown obstructed environments (i.e. indoor environments), the searchers often have to make effective and efficient motion decisions with limited sensing abilities and instantly available information. To solve the searching problem in this condition, we have to face several new challenges: a) existing source searching strategies based on the reward function often trap the searcher in the local part of the scene when the source searching environments are complex since they fail to provide globally optimal decisions at each step. Therefore, it is difficult to design efficient strategies for the searcher to choose the globally optimal action for the current state. b) obstacles in the searching scene would hinder the searcher's movement, especially when the searcher has less knowledge of the environment. Thus, it is difficult to design a strategy for the searcher to actively avoid the obstacles during the process of reaching its searching target; c) searching for a source in an unknown obstructed scene requires the searcher to collect more information than that in a simple scene, so it is difficult to balance the exploration and exploitation during the searching process, i.e., choose to collect more information to update the estimation of the source term or take actions according to the current estimation.

To overcome these challenges, we propose an active source searching framework for the searching problem in unknown obstructed environments, which realizes the active searching of a leakage gas source at high efficiency in unknown obstructed environments through source estimation, target determination, and path planning. To put the framework into practice, we propose the **A**ctive source searching algorithm based on **P**article filter, **M**EGI-taxis and **A**-star (the APMA algorithm). The performance of our proposed framework and algorithm is further verified through theoretic analysis and extensive simulations. The main contributions of this work are concluded as follows:

- This paper proposes an active source searching framework to solve the source searching problem in unknown obstructed environments. The framework actively avoids obstacles to search the source in unknown obstructed environments by integrating source estimation, target determining and path planning with limited sensing abilities.

- To address the first challenge, this paper adopts the Gaussian Mixture Model (GMM) to fit the distribution of samples in particle filter, and obtains the mean point of the Most Efficient Gaussian dIstribution (MEGI). We take the mean point as the searching target, which provides searchers with a globally optimal solution for the current situation.

- To address the second challenge, this paper introduces the occupancy grid map to represent the source searching scenarios and describes the environment and sensor models. Based on the models, the heuristic rule is employed with the A-star algorithm to plan a path in the partially known regions, which actively assists searchers to avoid the obstacles.

- To address the third challenge, this paper identifies the factors influencing searchers to balance exploration and exploitation, and conducts extensive experiments to determine a better combination of parameters to realize the exploration-exploitation balance.

- Based on the framework, this paper proposes the APMA algorithm. The algorithm is extensively tested both in simulated concentration field and realistic concentration field by comparing with existing methods [18, 38], which performs well in success rate and mean search steps.

The remainder of this paper is organized as follows. In Section 2, we describe the source searching problem and introduce the environment and sensor models. In Section 3, we propose an active source searching framework working in unknown obstructed environments, which includes source estimation, target determination and path planning. In Section 4, we propose the APMA algorithm to put the framework into practice. In Section 5, we present an illustrative run and conduct extensive simulations to explore the properties of the MEGI-taxis algorithm. Finally, we present the conclusion and future work in Section 6.

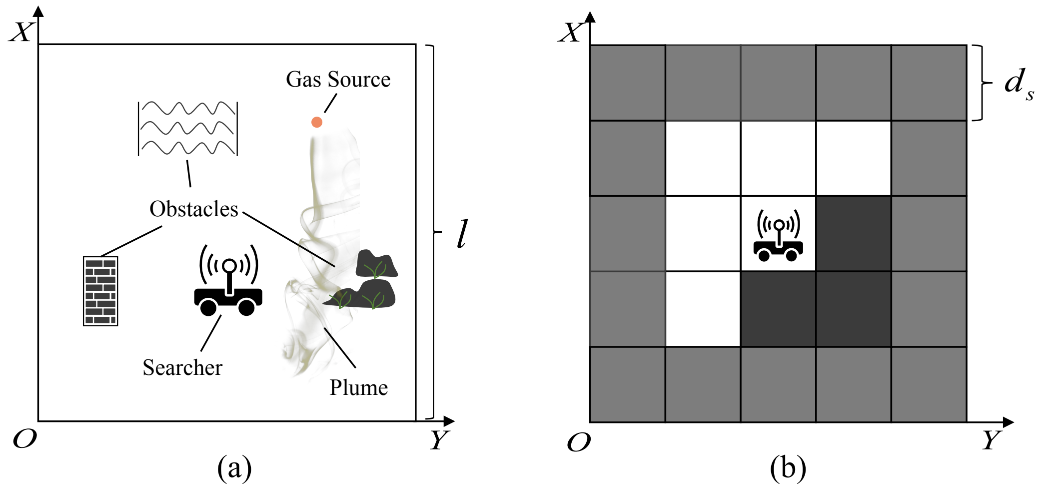


Figure 1: Environment representation. (a) An example of the source searching scenario; (b) occupancy grid map. In (b), white, black and gray grids represent free, occupied and unmapped grids respectively. Free grids represent the area where the searcher can move in. Occupied grids denote the area where obstacles exist. Unmapped grids mean the area unknown to the searcher.

2. Problem formulation

2.1. Source searching problem

The source searching problem addressed in this paper is to guide a mobile robot searcher to localize a gas source in an unknown environment with obstacles, as illustrated in Fig. 1 (a). A gas source S that constantly emits gas particles in the environment is considered. Denote by $r_s = \{x_s, y_s\}$ the source's location and Q its emitting rate. The searcher, a mobile robot with sensors located at $r = \{x, y\}$, shall move in the environment and collect measurements to estimate the source term parameters $\theta_s = \{r_s, Q\}$. Considering that the gas is affected by a mean current or wind with V of its speed and φ_V of its direction in the diffusion process, according to the steady-state convective diffusion equation [16, 18], the gas concentration at the location $r = \{x, y\}$ is formulated as:

$$c(r|\theta_s) = \frac{Q}{4\pi D|r - r_s|} e^{\frac{-(x-x_s)V\sin\varphi_V}{2D}} e^{\frac{-(y-y_s)V\cos\varphi_V}{2D}} e^{\frac{-|r-r_s|}{\lambda}} \tag{1}$$

where $\lambda = \sqrt{\frac{D\tau}{1+V^2\tau/4D}}$, D is the gas effective diffusion coefficient and τ is the gas molecular lifetime. Assuming that the gas effective diffusion coefficient D, gas molecular lifetime τ, wind speed V and direction φ_V are known, the quantity to be estimated for the gas source search process is the source term parameter $\theta_s = \{r_s, Q\}$.

The objective of the source searching task is to guide the searcher to move in the environment and constantly collects measurements along its travelled path (gas concentration data) to eventually find an accurate estimation of the source's parameter θ_s. In the following, we will describe the environment model and the robot's gas sensor model in detail.

2.2. Environment and sensor models

2.2.1. Environment representation

As illustrated in Fig. 1 (b), a two-dimensional environment with a set of static obstacles is considered. The environment is represented as an occupancy grid map that consists of $N_m \times N_n$ grids. Each grid has a length d_s and is either marked as free or occupied according to if there is an obstacle occupying it. Let N_{ob} be the total number of occupied grids of the map, then $P_{ob}=\frac{N_{ob}}{N_m \times N_n}$ is defined as the obstacle percentage of the environment. Intuitively, when P_{ob} is larger, it might be infeasible for the searcher to find a passable path to move along in the environment. Hence, in this paper, we set $P_{ob} < 0.4$ to ensure satisfactory connectivity of the environment [39].

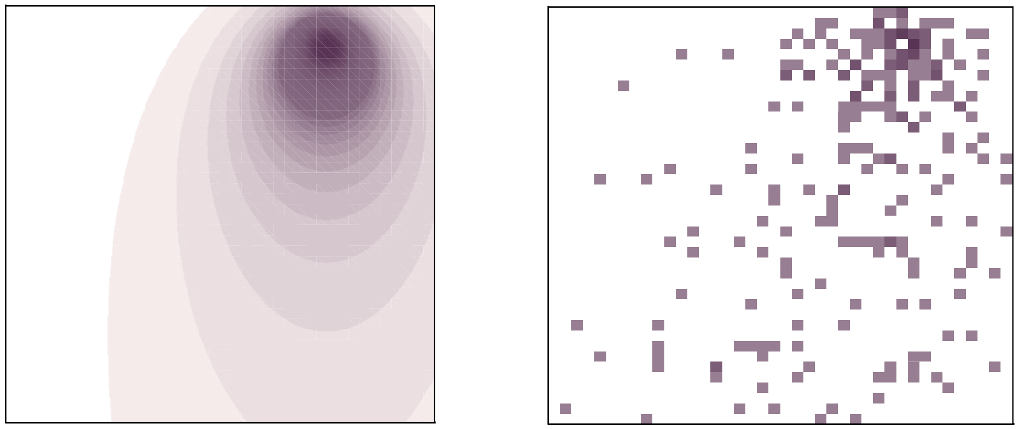
The occupancy map is initially unknown to the searcher. With the robot moving in the environment, it can sense the surrounding areas and thus explores the map. Hence, the map can be divided into two regions for the robot: the known (explored) and the unknown (unexplored). To simplify the problem, we assume that the robot can only move between two connected free grids and has a limited sensing range $R \geq d_s$. The states (free or occupied) of the grids within the robot's sensing range are known to the robot. This can be achieved by equipping the robot with onboard sensors such as a depth camera or 2D rangefinders [40, 41].

2.2.2. Gas sensor model

When the searcher moves along a path, its gas sensor will collect the gas concentration data at its current position. During the source searching process, the sensor needs to sense the signal within a limited time for the purpose of saving time [16]. Berg *et al.* [42] studied the chemoreception process of spherical sensor (radius a) under the condition of limited measurement time and concentration. Similar to that process, we convert the gas concentration data at location r, using the Smoluchowski formula [43], into the average number of contacts between the sensor and the gas molecules per unit time:

$$N_c(r|\theta_s) = 4\pi D \cdot a \cdot c(r|\theta_s) \tag{2}$$

In real environments, the gas diffusion is affected by turbulence, resulting in a disturbing concentration field. Thus, the sensor can only obtain sporadic and intermittent effective readings when sensing. In the cognitive search strategy, we use the Poisson process to simulate the effect of turbulence effect on the gas concentration field [18] as shown in Fig. 2 (b), and define $N_c(r|\theta_s)$ as the intensity of the Poisson process. Then, the probability that the sensor touches the gas molecules $d(r)$ times per unit time at position r is



(a)

(b)

Figure 2: Gas Sensor model. (a) Gas diffusion scenario based on the steady-state convective diffusion equation; (b) Detection value of sensors.

$$P_c(d(r)|\theta_s) = \frac{N_c(r|\theta_s)^{d(r)}}{d(r)!} e^{-N_c(r|\theta_s)} \tag{3}$$

The number of gas contacts at any location of the source search scene can be generated according to the random number generation method of Poisson distribution [16].

3. An active source searching framework in unknown obstructed environments

The source searching algorithms [16, 17, 18] based on the cognitive search strategy perform well in simple environments without obstacles. However, in the unknown obstructed environments, the concept of using reward function to guide the movement of searchers may not be applicable. Since the reward function only provides the searcher with a locally optimal decision, searchers are easily trapped in areas with complex obstacles and eventually fail to complete the searching mission. In this section, we propose an active source searching framework to solve the source searching problem in unknown obstructed environments.

As the source location is unknown until it is found, the searcher needs to establish the estimation of source location based on sensing cues during the searching process. To avoid being trapped in locally optimal decisions, it is necessary to integrate the estimation information, which determines a global target instead of optimizing at every step. However, in the unknown obstructed environments, it is difficult for the searcher to plan the path navigating to the target in the partially known obstructed environments due to the obstruction of obstacles. Therefore, traditional path planning algorithms need to be devised to adapt to unknown obstructed environments. Based on the above requirements, the framework shown in Fig. 3 consists of three parts: source estimation, target determination and path planning.

Source estimation: the posterior probability density function (Bayesian method) is carried out to estimate the source term parameters. The searcher updates the source estimation according to the Bayes rules as sensory data are obtained. The method of estimation includes particle filter [17], Kalman filter [44], particle swarm optimization [2], etc.

Target determination: By integrating the probability information of the source term estimation, we will find the regions with the highest probability of existing the source. The center of the regions is determined as the target of the source searching process. The method of integrating the probability information includes DBSCAN [38], GMM, neural network, etc.

Path planning: Based on the occupancy grid map built in Section 2.2.1,

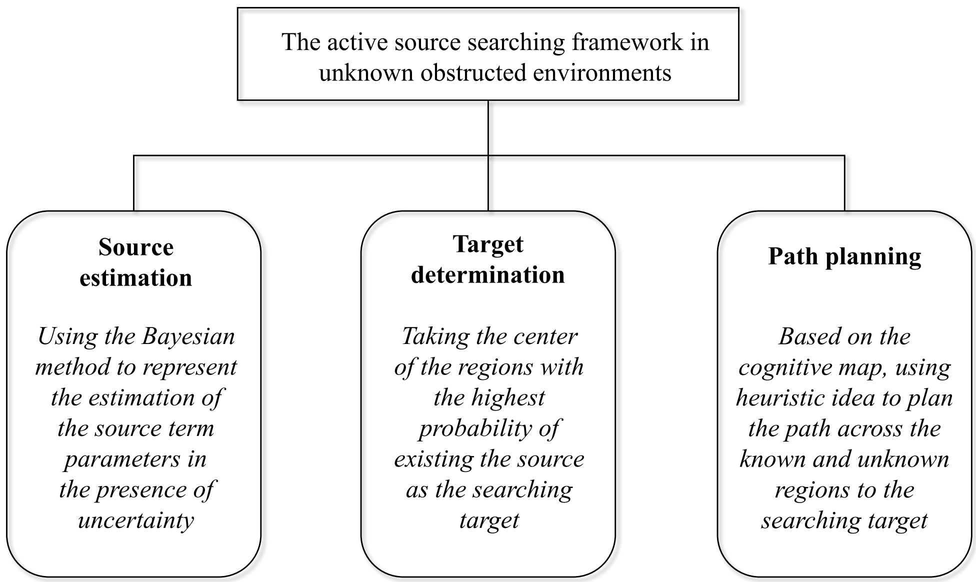


Figure 3: The active source searching framework in unknown obstructed environments.

a heuristic idea is introduced to address the problem of how to use a path planning algorithm to plan an optimal path navigating to the target in the partially known obstructed regions. The method of path planning includes Rapid-exploration Random Tree (RRT), A-star, etc.

The proposed framework provides a novel and feasible solution for source searching in unknown obstructed environments. To realize the framework, the APMA algorithm consisting of three parts is proposed. The method of particle filter is adopted to estimate the source term parameter. The target is determined by the MEGI-taxis algorithm. The A-star algorithm is employed to plan paths navigating to the target in the partially known obstructed environments. The detail of the APMA algorithm is described in Section 4.

4. The APMA algorithm

Based on the framework in Section 3, we design the flow of the Active source searching algorithm based on particle filter, MEGI-taxis and A-star, as shown in Fig. 4. Firstly, the searcher obtains sensory readings by sensing the surroundings. Then, the estimation of the particle filter is updated according to the sensing data, which generates new samples of the particle filter. We use the GMM to fit the samples and produce several Gaussian distributions. As the source is highly possible to exist in the region of the Most Efficient Gaussian dIstribution (MEGI), the searcher takes the mean point of the MEGI as the searching target. In addition, we use the A-star algorithm [45] to plan the path across the known and unknown regions based on the heuristic idea. Finally, the searcher moves along the planned path and checks if the source is determined. If the searching process is not terminated, the searcher will continue to search the source, as described in the above-mentioned process.

4.1. Source term estimation based on the particle filter

In the cognitive search strategy, the source search process is modeled as a Partially Observable Markov Decision Process (POMDP) [18]. Based on the information sensed at each step, the searcher updates the information state and selects the appropriate action to execute from a set of available actions. Then the searcher obtains new sensing information and keeps repeating this decision process until the source is determined.

In this section, we use the Bayesian method to estimate the source term parameters, and define the information state in the partially observable Markov decision process as a posterior probability density function. Then,

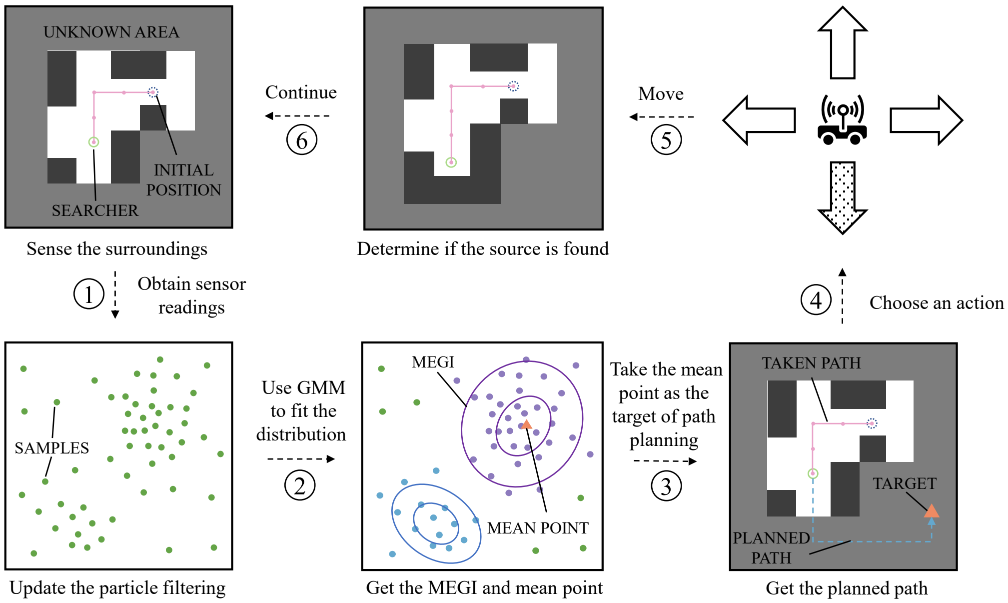


Figure 4: Flowchart of the APMA algorithm

we use the posterior probability density function to represent the estimation of the source term parameters. As the information perceived at each step updates our estimate of the source term parameters, the posterior probability density function at step k can be expressed as $P(\theta_k|N_a^k)$, where $N_a^k = \left\{N_c^1(r_1), N_c^2(r_2), \cdots, N_c^k(r_k)\right\}$ denotes all the information collected in the first k steps, and θ_k denotes the source term parameter estimated at k step. When the sensors collects new information, the posterior probability distribution can be updated using the Bayesian formula [18, 46]:

$$P(\theta_k|N_a^k) = \frac{P(\theta_{k-1}|N_a^{k-1})P(N_c^k(r_k)|\theta_k)}{P(N_c^k(r_k)|N_a^{k-1})} \tag{4}$$

where

$$P(N_c^k(r_k)|N_a^k) = \int P(\theta_{k-1}|N_a^{k-1})P(N_c^k(r_k)|\theta_k)d\theta_k \tag{5}$$

Any information about the source can be used to generate a prior knowledge to represent the prior probability $P(N_c^k(r_k)|N_a^{k-1})$. If no prior information is available, then a uniform distribution is used to represent the initial prior probability distribution. Meanwhile, the prior distributions are replaced by the posterior probability distribution in subsequent iterations.

The cognitive search strategy uses a particle filter approach to achieve Bayesian estimation of the source term parameters [18]. Since Eq.5 is difficult to calculate by functional expressions, $P(\theta_k|N_a^k)$ can be approximated by a set of N weighted random samples (particles) $\{(\theta_k^i, w_k^i)\}_{1\leq i\leq N}$ as:

$$P(\theta_k|N_a^k) \approx \sum_{i=1}^{N} w_k^i \delta(\theta - \theta_k^i) \tag{6}$$

where θ_k^i denotes the point estimate of the i_{th} sample at k step for the source term parameter, w_k^i denotes the normalized weight of the i_{th} sample at k step satisfying $\sum\limits_{i=1}^{N} w_k^i = 1$. δ is the Dirac delta function.

We then update the sample weights by sequential importance sampling [47] according to:

$$\tilde{w}_k^i{=}w_k^i P(N_c^k(r_k)|\theta_k^i) \tag{7}$$

The new approximate Bayesian estimate is obtained after standardization:

$$w_k^i = \frac{w_k^i}{\sum_{i=1}^{N} \tilde{w}_k^i} \tag{8}$$

To avoid samples degeneracy, we use a resampling step to increase particle diversity [47]. The resampling step occurs under the conditions that $\sum_{N_c=0}^{\max} P(N_c|N_a^k) > \eta$, where η denotes the resampling threshold.

4.2. Target determination based on the MEGI-taxis algorithm

We proposed a source searching algorithm (MEGI-taxis) based on the Gaussian Mixture Model (GMM). The algorithm uses the GMM to fit the particle filter estimation of the source location to obtain multiple Gaussian distributions of the particles. The distribution of samples in the particle filter process represents a probabilistic estimate of the source location. The source has a high probability to exist in the area of dense samples distribution. Therefore, we assume that it has the highest probability for source location to exist in the area where the largest proportion of sub-Gaussian distributions (MEGI) are located. In this paper, we prefer to explore the MEGI area instead of moving guided by a reward function.

The posterior probability distribution of the source term parameters can be fitted by the Gaussian mixture model as:

$$P(\theta_k|N_a^k) = \sum_{i=1}^{K} \pi_i G\left(\theta|\mu_i, \Sigma_i\right) \tag{9}$$

where $G\left(\theta|\mu_i, \Sigma_i\right)$ denotes the Gaussian distribution with mean μ_i and covariance Σ_i. The coefficients of the Gaussian distribution π_i satisfy $\sum_{i=1}^{K} \pi_i = 1$. The above equation can be solved by the EM algorithm [48].

Since the Gaussian distribution with the largest π_i occupies the largest number of samples, and the Gaussian distribution is defined as the Most Efficient Gaussian dIstribution (MEGI), the source in the region where MEGI is located has the highest probability of existence, so the mean point of this Gaussian distribution, μ_i, can be used as the target point for source searching. The target point of the whole source searching scene

4.3. Path planning based on A-star algorithm

The MEGI-taxis algorithm provides searchers with the global optimal searching target, but it is still challenging to plan an optimal path through known and unknown regions to the target. To solve the problem, this paper introduces the path planning algorithm to the active source searching framework based on a heuristic idea and proves the optimality of the algorithm. Firstly, we divide the path planning process into two parts, the path planning of the known regions and the path planning of the unknown regions. Then we make the following definitions.

Definition Denote the searcher's current position as the start point s and the center of the MEGI area (the mean point of the Gaussian distribution) as the endpoint e. Define the boundary nodes between the known region and the unknown region as n. The valuation function $h(n)$ expresses the distance from node n to the target node e, and $g(n)$ expresses the distance from the searcher's current position s to the boundary node n. Then the total cost for the searcher to move to the target node is:

$$F(n) = g(n) + h(n) \tag{10}$$

The optimal cost under the optimal path i:

$$F^*(n) = g^*(n) + h^*(n) \tag{11}$$

Theorem Assume the unknown region as a blank region in the path planning process. Then we can find a node n that makes the path through known and unknown regions to the target is the globally optimal solution.

Proof For the known region, $g^*(n)$ can be obtained directly by existing path planning algorithms, while for the unknown region, we define

$$h(n) = |X_e - X_n| + |Y_e - X_n| \tag{12}$$

which is the Manhattan distance from the boundary node n to the target node e. As there are obstacles in the unknown region, it is obvious that

$$h(n) \leq h^*(n) \tag{13}$$

If the Eq.13 holds, according to the heuristic rule, we can prove that planning a path through known and unknown regions to the target is admissible, i.e., the searcher can find a optimal path from the initial node to the target node in a finite number of steps.

When we assume the unknown regions as a blank region in the search process, the requirements of Eq.13 are satisfied. Therefore, we can use the existing path planning algorithm like A-star [45] to plan the optimal path through known and unknown regions to the target based on the theorem.

5. Experiments

In this section, this paper demonstrates the performance and generality of the APMA algorithm through several numerical simulations. In section

5.1, we use an illustrative run to describe the detail of the typical source searching process. Then, to show the superiority of the APMA algorithm, we compare the results of existing source searching strategies with that of our method in Section 5.2. Furthermore, in Section 5.3, we analyze the impact of several important parameters on the sensitivity and stability of the APMA algorithm. Finally, the Computational Fluid Dynamics (CFD) software, FLUENT, is employed in Section 5.4 to generate the gas diffusion field that can be considered as close to the ground truth. The confirmatory experiments are conducted in that field to further verified the effectiveness of the proposed algorithm.

5.1. An illustrative run

An illustrative run of the APMA algorithm is shown in Fig. 5. The associated simulation parameters are set as follows: l=20, d_s=1, P_{ob}=0.35, Q=2, D=1, V=2, φ_V=0, N=2000, $r_s = \{7.76, 13.30\}$, $r = \{3.5, 1.5\}$. The source searching process is terminated when the Euclidean distance between the searcher and the source $dis < 1$ or the variance of the samples in the particle filter var < 1. The former situation means that the searcher has successfully found the source location, while the latter situation denotes the convergence of the estimation of the source location. If the estimate location that converged by the source term estimation is the source location, the source searching is successful. Otherwise, the source searching fails. In addition, if the searcher cannot find the source within the specified number of search steps ($step$ = 500), the source searching process also will be terminated denoting the failure of the searching mission.

As shown in Fig. 5, orange round and triangle indicate the source lo-

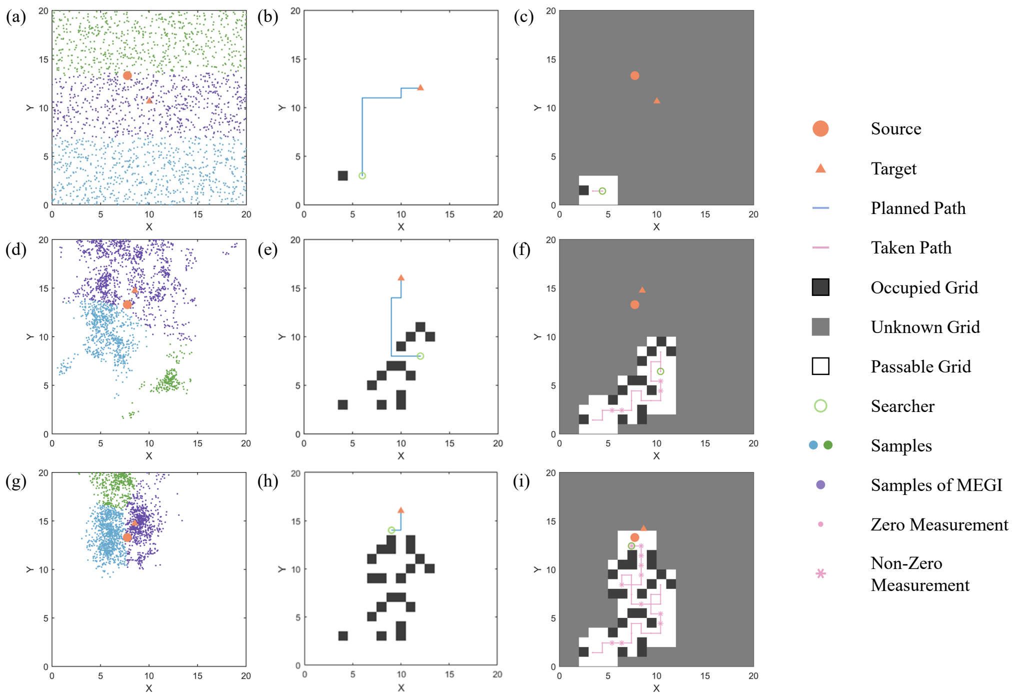


Figure 5: An illustrative run of the source searching process at step: (a), (b), (c) indicates $k = 2$; (d), (e), (f) indicates $k = 21$; (g), (h), (i) indicates $k = 36$. In addition, (a), (d), (g) show that how the samples of particle filter is clustered by the GMM and how the target is determined; (b), (e), (h) show that how the path from the searcher to the target is planned in the unknown obstructed environments; (c), (f), (i) show the whole source searching process.

cation and the mean point of the MEGI (target) respectively. Blue lines represent the path planned the by A-star algorithm and pink lines represent the path taken by the searcher. Green circles denote the position of the searcher. Blue, green and purple dots denote samples of the particle filter, where purple samples belong to MEGI. Pink dots and pink asterisks mean the zero measurement and non-zero measurement. The grids have three different colors in the source searching scene: black grids are regions that have obstacles, gray grids are unknown regions, white grids are regions that the searcher can pass.

In Fig. 5, at step $k = 2$, the initial state of the source searching process, the samples in the particle filter are uniformly distributed in the source searching scene. The APMA algorithm guides the searcher to move toward the center of the MEGI to obtain more information about the source items estimation. At step $k = 21$, as the number of source searching steps increases, the known regions sensed by the searcher is also expanded. The samples in the particle filter gradually gather near the source location, showing that the distance between the target and the source location is decreasing. Finally, at step $k = 36$, the searcher successfully finds the source location and the source searching task is successful.

5.2. Comparisons to baselines

In this section, we compare the APMA algorithm proposed in this paper with three baselines through extensive simulation experiments. We selected the Entrotaxis algorithm [18], a classical algorithm based on cognitive strategy, and the IWFA and EWFA algorithm [38] which are demonstrated as performing well in obstructed scenes. Simulation parameters follow the settings in section 5.1 except for independent variables. The experimental scenes have five different types $P_0 = 0.15 : 0.05 : 0.35$ of obstructed scenes, each type of which sets 100 randomly generated maps. The source location and the initial position of the searcher are generated randomly in each map. To avoid the interference of irrelevant variables, the same set of random scenes is used in each control group.

The performance of the source searching algorithms is evaluated with two metrics common, the Success Rate (SR) and the Mean Search Steps (MSS)

Table 1: PERFORMANCE COMPARISON OF DIFFERENT SOURCE SEARCHING ALGORITHMS (ENTROTAXIS, IWFA, EWFA AND APMA) ACROSS THE FIVE DIFFERENT TYPES OF SCENES ($P_0 = 0.15 : 0.05 : 0.35$) IN EACH 100 DIFFERENT MAPS.

		Entrotaxis	IWFA	EWFA	APMA
SR					
	$P_0 = 0.35$	44%	91%	71%	**100**%
	$P_0 = 0.30$	62%	91%	81%	**98**%
	$P_0 = 0.25$	67%	96%	89%	**99**%
	$P_0 = 0.20$	90%	**99**%	98%	**99**%
	$P_0 = 0.15$	92%	**99**%	98%	**99**%
MSS					
	$P_0 = 0.35$	90.32±98.85	81.41±61.05	86.83±94.21	**68.17±50.52**
	$P_0 = 0.30$	85.74±94.79	70.90±47.99	76.38±82.60	**63.94±42.14**
	$P_0 = 0.25$	75.66±86.97	64.61±52.14	75.20±83.06	**60.71±41.04**
	$P_0 = 0.20$	71.78±63.31	64.96±58.75	62.26±52.17	**61.20±48.04**
	$P_0 = 0.15$	52.51±52.80	60.41±49.40	**48.85±42.09**	52.22±36.32

conventionally. As shown in Table 1, the APMA algorithm proposed in this paper shows well performance in two metrics, and the superiority is more obvious with an increase of P_0. The SR of the APMA algorithm is close to 100%, which is better than baselines, especially when $P_0 = 0.35$. The maximum improvement in MSS of APMA is 16.26% when $P_0 = 0.35$. However, the MSS of the APMA algorithm is higher than that of the EWFA algorithm in simple obstructed scenes like $P_0 = 0.15$. This reason is that the APMA algorithm proposed in this paper is designed for source searching in unknown obstructed scenes, which results in that simple obstructed scenes cannot reflect its superiority. In addition, the variance of both metrics of the APMA algorithm is significantly reduced compared to the other algorithms. More precisely, the APMA algorithm reduces the uncertainty and error of source searching in unknown obstructed environments. In conclusion, compared with baselines, the APMA algorithm not only has advantages in the searching efficiency, but can also complete the source searching task more stably.

5.3. Impact of parameters in the APMA algorithm

Three important parameters might affect the performance of the APMA algorithm: sensing range R, the number of Gaussian distributions K and resampling threshold η. R is the main parameter influences the known regions to the searcher. K mainly impacts the result of the GMM estimation, which determines the location of the target point. η is the parameter that balances the exploration and exploitation of the source searching process. In this section, we will examine the result of the simulation experiments when these parameters are varied.

5.3.1. Sensing range R

The sensing range of different source searching robots is various. For instance, the ground-based robot generally can only sense the surrounding obstacles with a limited sensing range while the UAV-based searcher can acquire a panoramic view with a large sensing range. The increase of the sensing range enables the searcher to update the occupancy grid map more quickly. Consequently, a better search path may be found that lets the searcher find the source with fewer steps. To investigate the impact of different sensing range on the search performance, we set three values of sensing range like 1, 2, 3, which correspond to the situations that the searcher can obtain the information of obstacles in 8, 24, 48 surrounding grids in each step, respectively. The experiments are conducted with the three values of sensing range in five types of obstructed scenarios with $P_0 = 0.15 : 0.05 : 0.35$, resulting in 15 groups of experiments. The results are shown in Table 2.

Table 2: PERFORMANCE COMPARISON OF DIFFERENT R IN APMA ($R = 2 : 1 : 4$) ACROSS THE FIVE DIFFERENT TYPES OF SCENES ($P_0 = 0.15 : 0.05 : 0.35$) IN EACH 100 DIFFERENT MAPS FOR TEN TIMES.

R		2	3	4
SR				
	$P_0 = 0.35$	98.8%	**99.3**%	99.2%
	$P_0 = 0.30$	99.4%	99.4%	**99.5**%
	$P_0 = 0.25$	99.4%	99.2%	**99.6**%
	$P_0 = 0.20$	**99.4**%	99.0%	99.1%
	$P_0 = 0.15$	**99.9**%	99.5%	99.8%
MSS				
	Po = 0.35	68.66±51.52	66.72±49.33	**65.59±44.65**
	Po = 0.30	65.37±47.04	**62.77±45.36**	62.87±48.58
	Po = 0.25	62.59±45.82	62.61±48.51	**61.64±45.82**
	Po = 0.20	**63.90±45.97**	64.03±46.29	64.83±49.91
	Po = 0.15	57.22±41.25	57.67±43.99	**55.81±41.64**

As shown in Table 2, the performance of the proposed algorithm shows stability with different sensing ranges. In terms of the MSS, the searcher with a wide sensing range has a slight advantage in general. An increase in the sensing range allows the searcher to obtain more information of the obstructed environments, enabling it to detect obstacles in advance and plan a better path to approach the target, therefore, the MSS is reduced to some extent.

However, the SR does not exhibit any obvious trends. After repeated observation and analysis of the failed searching process, we find that the failure often occurs when the source is located near the edge of the entail scene. In that circumstances, the searcher may be too far from the source to gather enough information to make the estimation converge. In the worst case, samples of particle filter cluster in several areas of the scene causing the searcher to wander in those areas constantly while the source does not exist in any of those areas. These problems can be solved by increasing the sensing range.

The results in Table 2 demonstrate the robustness of the APMA algorithm to the sensing range. In other words, our algorithm can guide various types of searchers with different sensing ranges. The searcher with the sensing range $R = 1$ can also obtain good searching performance.

5.3.2. The number of Gaussian distributions K

The APMA algorithm proposed in this paper uses a Gaussian Mixture Model to fit the samples of particle filtering to obtain the mean point of the MEGI, which is also the target in path planning. There are two important parameters in the Gaussian mixture model that determine the fitting results: the number of Gaussian distributions K and the covariance of samples Σ. The covariance of samples can be calculated based on the data of samples, while the K needs to be determined artificially. Therefore, the effect of the variation of the K on the performance of the proposed algorithm is investigated in this section.

The experimental results are shown in Table 3. When $K = 2$, the MSS for different types of maps is above 70, which is significantly different from the experimental results when K takes other values. When $K = 3, 4, 5$, the algorithm achieves a similar level of performance. In the Gaussian mixture model, increasing the number of Gaussian distributions will increase the

Table 3: PERFORMANCE COMPARISON OF DIFFERENT K IN APMA ($K = 2 : 1 : 5$) ACROSS THE FIVE DIFFERENT TYPES OF SCENES ($P_0 = 0.15 : 0.05 : 0.35$) IN EACH 100 DIFFERENT MAPS FOR TEN TIMES.

K		2	3	4	5
SR					
	$P_0 = 0.35$	98.5%	98.8%	99.2%	**99.3**%
	$P_0 = 0.30$	99.2%	99.4%	**99.6**%	99.3%
	$P_0 = 0.25$	98.9%	99.4%	99.4%	**99.7**%
	$P_0 = 0.20$	98.2%	99.4%	99.5%	**99.6**%
	$P_0 = 0.15$	99.0%	**99.9**%	99.4%	99.7%
MSS					
	$P_0 = 0.35$	77.05±64.23	68.66±51.52	**67.42±46.93**	69.32±52.09
	$P_0 = 0.30$	74.70±60.96	65.37±47.04	66.16±47.53	**64.91±45.80**
	$P_0 = 0.25$	77.72±66.05	62.59±45.82	64.49±44.86	**62.22±44.54**
	$P_0 = 0.20$	82.00±67.05	**63.90±45.97**	65.61±45.87	65.12±44.31
	$P_0 = 0.15$	74.10±68.63	57.22±41.25	**56.64±40.10**	57.10±40.81

complexity of the calculation. From the experimental results in this section, when the value of K is taken above 3, increasing the value of K does not significantly improve the success rate and reduce the MSS. Therefore, under the condition of guaranteeing the source finding effect, the number of Gaussian distributions is determined as $K = 3$ to reduce the computational complexity.

5.3.3. Resampling threshold η

In the searching process, the target point extracted from the estimation may be far from the real source location since the searcher has not collected enough information. In this situation, the inaccurate estimation may not be adjusted if the searcher continues to move to the target with bias. Thus, the searcher needs to perform exploration to obtain more information to adjust the inaccurate estimation. When the target point is close to the real source location, the searcher needs to execute the planned path to arrive at the target, which is called exploitation. Therefore, how to balance exploration and exploitation during the searching process is a problem that needs to be solved.

In the resampling process of particle filter, the change of the resampling threshold coefficient η will cause the information required for the change of particle distribution to change. That is, the size of the resampling threshold coefficient η determines the number of exploration steps required to update the current estimate. A smaller η tends to favor the searcher to develop the current estimate of the source location with fewer explorations, and a larger η tends to favor the searcher to explore more to be more accurate the next time it is developed. In this section, we conduct numerical experiments by varying the size of this parameter, and the results are presented in Table 4.

Table 4: PERFORMANCE COMPARISON OF DIFFERENT η IN APMA ACROSS THE FIVE DIFFERENT TYPES OF SCENES ($P_0 = 0.15 : 0.05 : 0.35$) IN EACH 100 DIFFERENT MAPS FOR TEN TIMES.

η		**0.4**	**0.6**	**0.8**	**0.9**	**0.95**	**1**
SR							
	Po = 0.35	55.5%	60.0%	88.9%	98.8%	98.8%	**99.8**%
	Po = 0.30	58.0%	61.8%	87.8%	99.1%	**99.4**%	99.1%
	Po = 0.25	50.2%	55.8%	86.2%	99.0%	99.4%	**99.8**%
	Po = 0.20	48.6%	53.2%	87.3%	99.3%	99.4%	**99.6**%
	Po = 0.15	49.1%	57.6%	89.3%	99.3%	**99.9**%	99.5%
MSS							
	Po = 0.35	119.89±107.87	89.06±86.55	84.36±88.32	72.42±58.12	**68.66±51.52**	80.93±68.46
	Po = 0.30	119.34±110.51	98.68±86.58	97.98±88.36	69.02±56.11	**65.37±47.04**	80.88±71.12
	Po = 0.25	118.42±102.15	92.87±85.49	91.39±95.50	66.48±56.12	**62.59±45.82**	78.88 ±68.78
	Po = 0.20	115.16±108.42	95.49±87.54	90.64±80.87	68.43±64.27	**63.90±45.97**	74.92±63.50
	Po = 0.15	122.59±111.95	87.70±92.30	89.88±85.87	64.87±59.97	**57.22±41.25**	65.28±61.13

The experimental results show that the SR is low when the value of η is small, and more MSS are required to complete the source searching task.

As the value of η increases, the APMA algorithm becomes more and more effective. When $\eta = 0.95$, the performance of the algorithm reaches its peak. Raising the value of η after that will instead cause the searcher to consume more MSS while searching. The analysis results show that when η is small, the searcher tends to exploit, and less exploration leads to its inability to correctly estimate the location of the source, which eventually leads to the failure of the source searching task. When the value of η is larger, the searcher tends to explore. More exploration will improve the accuracy of source location estimation and increase the success rate of source search, but the reduction of exploitation will instead increase the number of source search steps. Therefore, the source search framework in this paper needs to balance the searcher's tendency to explore and exploit to find the optimal strategy parameters. The result shows that the source search performs best when $\eta = 0.95$, which is η reflection of the balance between exploration and exploitation.

5.4. Validation experiment with CFD

In the previous experiments, we compared the effectiveness of the APMA algorithm with baselines in unknown obstructed scenes and explored the performance of the algorithm of different parameters. The concentration fields in these experiments are generated by the convective diffusion equation model in Section 2.1.2. This model is commonly used for theoretical exploration and is widely used in the field of source searching. However, it cannot reflect the effect of obstacles in the scene on gas diffusion. In this section, we will use the Computational Fluid Dynamics (CFD) model to generate a realistic concentration field to test the applicability of the algorithm. Similar to previous works [49, 50, 51], we use the GAMBIT to generate and mesh an indoor scene shown in Fig. 6 (a) and get the predicted concentration data from the FLUENT which will replace the data from the convective diffusion equation model for the experiment.

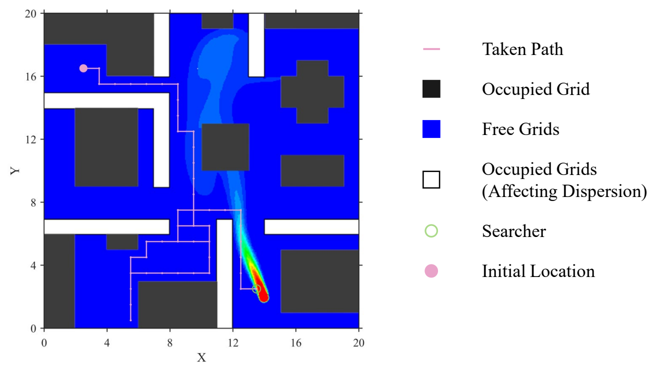


Figure 6: Validation experiment with CFD in an indoor scene. (a) An indoor scene; (b) the searching trajectory upon the diffusion field.

The diffusion field generated by FLUENT is shown in Fig. 6 (b). The wall in the indoor scene denoted by white grids can affect the diffusion of gas. The obstacles represented by black grids are assumed to have no effect on the diffusion but can block the movement of the searcher. The grids are marked as occupied grids when there are obstacles or part of obstacles in them. A steady wind blows from the window on the below boundary and the windows on the rest three boundaries are set pressure outlets. The source constantly releases hydrogen-sulfide (H_2S) into the environment. The higher concentration of H_2S is shown as brighter, and the red represents the highest concentration, whose location coincides with the source.

The simulation experiment based on the CFD model is conducted 100

Table 5: PERFORMANCE COMPARISON OF DIFFERENT SEARCHING METHODS IN DIFFUSION ENVIRONMENTS GENERATED BY FLUENT.

	Entrotaxis	IWFA	EWFA	APMA
SR	43%	99%	86%	**100%**
MSS	180.07±72.57	96.43±51.24	146.27±87.24	**79.75±54.35**

times. In each run, the searcher is launched at the same position. We compare our method with the Entrotaxis, IWFA and EWFA algorithm in this experiment. The results are provided in Table 5. The AMPA algorithm still maintains a high success rate in the more practical environments generated by FLUENT, and it shows a considerable superiority in both SR and MST. Finally, the results demonstrate the effectiveness of the proposed source searching framework in unknown obstructed environments.

6. Conclusions and future work

The active source searching framework is proposed to provide a generic solution for the source searching problem in unknown obstructed environments (e.g. indoor environments) with limited sensing abilities. We employed the occupancy grid map to represent the source searching scenarios and introduce the environment and sensor models to describe the statement of the source searching problem. Based on the models, the framework integrates source estimation, target determination and path planning. Source estimation translates sensing information into the probability information of the source location. Target determination provides a searching target by extracting the features of the probability information. Path planning introduces the heuristic idea with a path planning algorithm to plan the path navigating to the target in the partially known obstructed regions. To put the framework into practice, the APMA algorithm is presented based on Particle filter, MEGI-taxis and A-star. In extensive experiments, our proposed APMA algorithm outperforms the baseline algorithms both in the success rate and mean searching steps. To further explore the characteristics of the APMA algorithm, sensing range, number of sub-distributions and resampling threshold are varied to examine their influence on the performance of the APMA algorithm. Finally, we also validated the performance of the APMA algorithm in a more realistic scenario generated by the CFD model.

This work can further be extended in many aspects. Firstly, the MSS of the APMA algorithm in the scene of $P_0 = 0.15$ is higher than that of the baselines. In simple scenes, few obstacles block the searcher's movement, indicating that we need other mechanisms to accelerate the decision and path planning process in this condition. Meanwhile, the planned path is shorter in simple scenes, resulting in less information collected on the way to the target. To improve the algorithm, we could adjust the exploration-exploitation balance according to the complexity of the scene. In addition, multiple sub-distributions are obtained by the Gaussian Mixture Model (GMM) after fitting the samples of the particle filter. The mean point of the MEGI is determined as the searching target. However, the estimation information of other sub-distributions is wasted. In future work, we could improve the APMA algorithm by making use of the estimation information of all sub-distributions. Also, the GMM could be introduced to solve the multiple sources searching problem in indoor environments. Moreover, we will deploy the proposed framework and algorithms on real robots and verify their effectiveness with real-world experiments.

Acknowledge

This work is supported in part by the National Natural Science Foundation of China under Grant 62173337, 72071207, 21808181; and in part by the National Social Science Foundation of China under Grant 17CGL047.

References

[1] Y. Chen, H. Cai, Z. Chen, Q. Feng, Using multi-robot active olfaction method to locate time-varying contaminant source in indoor environment, Building and Environment 118 (2017) 101–112.

[2] Q. Feng, C. Zhang, J. Lu, H. Cai, Z. Chen, Y. Yang, F. Li, X. Li, Source localization in dynamic indoor environments with natural ventilation: An experimental study of a particle swarm optimization-based multi-robot olfaction method, Building and Environment 161 (2019) 106228.

[3] Y. Zhang, Y. Li, R. Wang, M. S. Hossain, H. Lu, Multi-aspect aware session-based recommendation for intelligent transportation services, IEEE Transactions on Intelligent Transportation Systems 22 (7) (2020) 4696–4705.

[4] T. Wiedemann, A. J. Lilienthal, D. Shutin, Analysis of model mismatch effects for a model-based gas source localization strategy incorporating advection knowledge, Sensors 19 (3) (2019) 520.

[5] S. K. Singh, M. Sharan, J.-P. Issartel, Inverse modelling methods for identifying unknown releases in emergency scenarios: an overview, International Journal of Environment and Pollution 57 (1-2) (2015) 68–91.

[6] M. Redwood, Source term estimation and event reconstruction: a survey, Contract Report for ADMLC 51790 (2011).

[7] K. S. Rao, Source estimation methods for atmospheric dispersion, Atmospheric environment 41 (33) (2007) 6964–6973.

[8] S. Qiu, B. Chen, R. Wang, Z. Zhu, Y. Wang, X. Qiu, Atmospheric dispersion prediction and source estimation of hazardous gas using artificial neural network, particle swarm optimization and expectation maximization, Atmospheric Environment 178 (2018) 158–163.

[9] J. A. Farrell, S. Pang, W. Li, R. M. Arrieta, Biologically inspired chemical plume tracing on an autonomous underwater vehicle, in: 2004 IEEE International Conference on Systems, Man and Cybernetics (IEEE Cat. No. 04CH37583), Vol. 7, IEEE, 2004, pp. 5991–5996.

[10] H. Ishida, K.-i. Suetsugu, T. Nakamoto, T. Moriizumi, Study of autonomous mobile sensing system for localization of odor source using gas sensors and anemometric sensors, Sensors and Actuators A: Physical 45 (2) (1994) 153–157.

[11] M. Müller, R. Wehner, The hidden spiral: systematic search and path integration in desert ants, cataglyphis fortis, Journal of Comparative Physiology A 175 (5) (1994) 525–530.

[12] N. E. Humphries, N. Queiroz, J. R. Dyer, N. G. Pade, M. K. Musyl, K. M. Schaefer, D. W. Fuller, J. M. Brunnschweiler, T. K. Doyle, J. D. Houghton, et al., Environmental context explains lévy and brownian movement patterns of marine predators, Nature 465 (7301) (2010) 1066–1069.

[13] H. C. Berg, Chemotaxis in bacteria, Annual review of biophysics and bioengineering 4 (1) (1975) 119–136.

[14] J. Adler, Chemotaxis in bacteria, Annual review of biochemistry 44 (1) (1975) 341–356.

[15] D. Zarzhitsky, D. F. Spears, Swarm approach to chemical source localization, in: 2005 IEEE international conference on systems, man and cybernetics, Vol. 2, IEEE, 2005, pp. 1435–1440.

[16] M. Vergassola, E. Villermaux, B. I. Shraiman, 'infotaxis' as a strategy for searching without gradients, Nature 445 (7126) (2007) 406–409.

[17] B. Ristic, A. Skvortsov, A. Gunatilaka, A study of cognitive strategies for an autonomous search, Information Fusion 28 (2016) 1–9.

[18] M. Hutchinson, H. Oh, W.-H. Chen, Entrotaxis as a strategy for autonomous search and source reconstruction in turbulent conditions, Information Fusion 42 (2018) 179–189.

[19] C. Song, Y. He, X. Lei, Autonomous searching for a diffusive source based on minimizing the combination of entropy and potential energy, Sensors 19 (11) (2019) 2465.

[20] X.-x. Chen, J. Huang, Odor source localization algorithms on mobile robots: A review and future outlook, Robotics and Autonomous Systems 112 (2019) 123–136.

[21] Z. Zhu, B. Chen, W. Liu, Y. Zhao, Z. Liu, Z. Zhao, A cost-quality beneficial cell selection approach for sparse mobile crowdsensing with diverse sensing costs, IEEE Internet of Things Journal 8 (5) (2020) 3831–3850.

[22] X. Chen, C. Fu, J. Huang, A deep q-network for robotic odor/gas source localization: Modeling, measurement and comparative study, Measurement 183 (2021) 109725.

[23] L. Wang, S. Pang, J. Li, Learn to trace odors: Autonomous odor source localization via deep learning methods, in: 2021 20th IEEE International Conference on Machine Learning and Applications (ICMLA), IEEE, 2021, pp. 1429–1436.

[24] N. Gunawardena, K. K. Leang, E. Pardyjak, Particle swarm optimization for source localization in realistic complex urban environments, Atmospheric Environment 262 (2021) 118636.

[25] T. Wiedemann, C. Vlaicu, J. Josifovski, A. Viseras, Robotic information gathering with reinforcement learning assisted by domain knowledge: an application to gas source localization, IEEE Access 9 (2021) 13159–13172.

[26] R.-G. Li, H.-N. Wu, Multi-robot plume source localization based on

swarm evolution mechanisms, in: Proceedings of the 2021 International Conference on Control and Intelligent Robotics, 2021, pp. 692–698.

[27] L. Wang, S. Pang, Robotic odor source localization via adaptive bio-inspired navigation using fuzzy inference methods, Robotics and Autonomous Systems 147 (2022) 103914.

[28] Y. Zhao, B. Chen, X. Wang, Z. Zhu, Y. Wang, G. Cheng, R. Wang, R. Wang, M. He, Y. Liu, A deep reinforcement learning based searching method for source localization, Information Sciences 588 (2022) 67–81.

[29] W. Jatmiko, A. Nugraha, B. Kusumoputro, K. Sekiyama, T. Fukuda, Modified niche pso with flow of wind for multiple odor source localization problems in dynamic environments, in: SCIS & ISIS SCIS & ISIS 2008, Japan Society for Fuzzy Theory and Intelligent Informatics, 2008, pp. 1749–1754.

[30] Z. Liu, T.-F. Lu, Multiple robots plume-tracing in open space obstructed environments, in: 2009 IEEE International Conference on Robotics and Biomimetics (ROBIO), IEEE, 2009, pp. 2433–2439.

[31] Y. Zhao, B. Chen, Z. Zhu, F. Chen, Y. Wang, D. Ma, Entrotaxis-jump as a hybrid search algorithm for seeking an unknown emission source in a large-scale area with road network constraint, Expert Systems with Applications 157 (2020) 113484.

[32] J. Monroy, V. Hernandez-Bennetts, H. Fan, A. Lilienthal, J. Gonzalez-Jimenez, Gaden: A 3d gas dispersion simulator for mobile robot olfaction in realistic environments, Sensors 17 (7) (2017) 1479.

[33] P. Ojeda, J. Monroy, J. Gonzalez-Jimenez, A simulation framework for the integration of artificial olfaction into multi-sensor mobile robots, Sensors 21 (6) (2021) 2041.

[34] P. Ojeda, J. Monroy, J. Gonzalez-Jimenez, An evaluation of gas source localization algorithms for mobile robots, in: Proceedings of the 3rd International Conference on Applications of Intelligent Systems, 2020, pp. 1–6.

[35] P. Ojeda, J. Monroy, J. Gonzalez-Jimenez, Information-driven gas source localization exploiting gas and wind local measurements for autonomous mobile robots, IEEE Robotics and Automation Letters 6 (2) (2021) 1320–1326.

[36] B. Ristic, A. Skvortsov, A. Walker, Autonomous information driven search for a diffusive source in an unknown structured environment, in: 2014 IEEE Workshop on Statistical Signal Processing (SSP), IEEE, 2014, pp. 296–299.

[37] K. Kamarudin, A. Y. Md Shakaff, V. H. Bennetts, S. M. Mamduh, A. Zakaria, R. Visvanathan, A. S. Ali Yeon, L. M. Kamarudin, Integrating slam and gas distribution mapping (slam-gdm) for real-time gas source localization, Advanced Robotics 32 (17) (2018) 903–917.

[38] Y. Zhao, B. Chen, Z. Zhu, F. Chen, Y. Wang, Y. Ji, Searching the diffusive source in an unknown obstructed environment by cognitive strategies with forbidden areas, Building and Environment 186 (2020) 107349.

[39] D. Ben-Avraham, S. Havlin, Diffusion and reactions in fractals and disordered systems, Cambridge university press, 2000.

[40] S. Liu, M. Watterson, K. Mohta, K. Sun, S. Bhattacharya, C. J. Taylor, V. Kumar, Planning dynamically feasible trajectories for quadrotors using safe flight corridors in 3-d complex environments, IEEE Robotics and Automation Letters 2 (3) (2017) 1688–1695.

[41] A. Bircher, M. Kamel, K. Alexis, H. Oleynikova, R. Siegwart, Receding horizon" next-best-view" planner for 3d exploration, in: 2016 IEEE international conference on robotics and automation (ICRA), IEEE, 2016, pp. 1462–1468.

[42] H. C. Berg, E. M. Purcell, Physics of chemoreception, Biophysical journal 20 (2) (1977) 193–219.

[43] M. v. Smoluchowski, Versuch einer mathematischen theorie der koagulationskinetik kolloider lösungen, Zeitschrift für physikalische Chemie 92 (1) (1918) 129–168.

[44] R. Zhao, S. Liu, J. Liu, N. Jiang, Q. Chen, Generalizability evaluation of k-ε models calibrated by using ensemble kalman filtering for urban airflow and airborne contaminant dispersion, Building and Environment (2022) 108823.

[45] N. J. Nilsson, Principles of artificial intelligence, Springer Science & Business Media, 1982.

[46] M. S. Arulampalam, S. Maskell, N. Gordon, T. Clapp, A tutorial on particle filters for online nonlinear/non-gaussian bayesian tracking, IEEE Transactions on signal processing 50 (2) (2002) 174–188.

[47] B. Ristic, S. Arulampalam, N. Gordon, Beyond the Kalman filter: Particle filters for tracking applications, Artech house, 2003.

[48] H. Xiao, R. Cui, D. Xu, A sampling-based bayesian approach for cooperative multiagent online search with resource constraints, IEEE Transactions on Cybernetics 48 (6) (2017) 1773–1785.

[49] F. Xue, X. Li, R. Ooka, H. Kikumoto, W. Zhang, Turbulent schmidt number for source term estimation using bayesian inference, Building and Environment 125 (2017) 414–422.

[50] G. C. Efthimiou, I. V. Kovalets, C. D. Argyropoulos, A. Venetsanos, S. Andronopoulos, K. E. Kakosimos, Evaluation of an inverse modelling methodology for the prediction of a stationary point pollutant source in complex urban environments, Building and Environment 143 (2018) 107–119.

[51] M. Awadalla, T.-F. Lu, Z. F. Tian, B. Dally, Z. Liu, 3d framework combining cfd and matlab techniques for plume source localization research, Building and Environment 70 (2013) 10–19.