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Invited Review Paper

Recent Progress and Trend of Robot Odor Source Localization

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Accurate and prompt localization of hazardous release sources ensures a timely emergency response to potential damages. Robot odor source localization is the study of locating the release source based on mobile robots in real-time, which has been experiencing rapid growth in recent years. This paper presents a review of this field, focusing on recent progress and development trends. Research works are grouped according to method principles, leading to four categories: reactive methods, heuristic searching methods, probabilistic inference methods, and learning methods. The odor-source direction and distance prediction via *in situ* sensing and developments of simulators are also listed separately for discussion. Several outlooks are highlighted at the end. Along with the developments of related fields and practical needs, we believe this field is bound to keep on flourishing in the future. © 2021 Institute of Electrical Engineers of Japan. Published by Wiley Periodicals LLC.

Keywords: odor source localization; robot; reactive methods; heuristic searching; probabilistic inference; learning methods

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1. Introduction

1.1. What is odor source localization? By and large, organisms live in one of two fluid environments: air or water [1]. In these environments, vital information is transmitted with fluids such as air or water flow in the form of odor or pheromone. Odor source localization (OSL), coined in Ref. [2] as an abstract of olfactory searching behaviors, means finding the release source of an odor or pheromone, which is an essential task for organisms [3]. Organisms rely on their olfactory searching ability to locate and evaluate food, shelter, mates, as well as to avoid predators and other dangers [4].

In the long evolutionary history, organisms have evolved their own methods of locating odor sources. For example, a mosquito finds hosts through tracking a sparse carbon dioxide (CO_2) plume [5], as shown by phases (a)–(g) in Fig. 1. The whole process could be divided into three subtasks [6]:

Plume finding: Before finding any target odor [before phase (a)], the mosquito searches the surrounding space randomly;

Plume traversal: Once encountering a CO_2 plume [phase (a)], the mosquito follows the plume [phases (b)–(d)];

Source declaration: After approaching a candidate source, the mosquito uses different kinds of information to identify the source, such as odor, heat, moisture, and vision cues [phases (e)–(g)].

There are similar needs for OSL in human society, such as hazardous gas leakage localization, air monitoring, etc. In recent years, with the rapid development of industry, the number of chemical plants has grown significantly, leading to higher risks

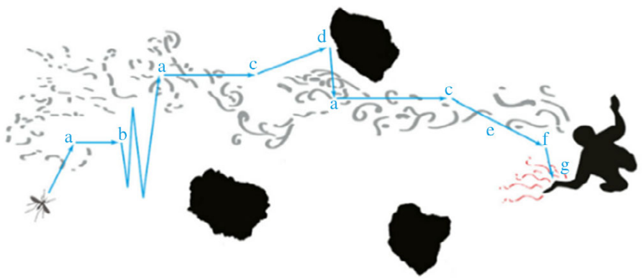

Fig. 1. The process of a mosquito locating its host [5]

of hazardous gas leakage. Increasing social concerns and strict regulations on air pollution and global warming have promoted the growing interest in air monitoring research. Besides, many other practical applications, such as searching survivors and locating unexploded mines and bombs, put forward more requirements for locating odor sources accurately and efficiently. Inspired by biological behaviors, since the 1990s, researchers began to integrate OSL algorithms with mobile robots, which is the topic of this review.

1.2. Why this review? There have been several surveys published on the robot OSL. Lilienthal *et al.* [7] and Kowadlo *et al.* [8] provided comprehensive reviews on the literature. However, since these surveys were published more than a decade ago, some new methods were not included. Up to then, most researches concentrated on analyzing and mimicking organisms' OSL behaviors, and these works were grouped according to the applicable environment conditions in Refs. [7,8]. Ishida *et al.* [9] reviewed three main tasks of chemical sensing and spent half of the pages predicting current trends and future directions of this field, which still have continuous enlightenments nowadays. Chen *et al.* [10]

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presented the latest survey on the robot OSL up to now, which adopts a new taxonomy method: using the algorithm principle as the top-level of the taxonomic rank. This taxonomic pattern could provide more direct inspirations for algorithm improvement and fusion, but it seems inevitable to introduce a little overlapping between different categories.

This paper presents a review of progress in the robot OSL, mainly focusing on the literature published recently. This survey follows the taxonomy based on the algorithm principle, but in a stricter manner. Machine learning based methods, which emerge as a new direction recently, are reviewed as a separate category. Besides, some aspects not discussed in previous surveys are highlighted, including prediction via *in situ* gas sensing and OSL simulators.

1.3. The main contents According to the different principles of the algorithm, the existing OSL research work can be divided into the following four categories:

Reactive methods refer to the OSL methods linking actions of the robot directly to the current sensory input, including early gradient-based algorithms and bio-inspired algorithms.

Heuristic searching methods regard the robot OSL task as an optimization problem, trying to find the best solution (i.e., the odor source location) from all the feasible solutions (i.e., the searching area) through heuristic means.

Probabilistic inference methods treat the odor-source location or the plume distribution as parameters of the dispersion model, and infer these parameters based on the measurements.

Learning methods, or more precisely the machine learning methods, mean learning the odor source information from the measured data, or learning OSL strategies directly from interactions with the environment. This direction still needs further study, but for the sake of taxonomic completeness, we list it separately.

This paper is organized as follows. Section 2 addresses some odor-source prediction methods based on *in situ* sensing. Section 3 gives a brief discussion on the robot OSL simulators. Sections 4–7 present reviews of the robot OSL literature according to the taxonomy. Section 8 provides some outlooks for future research. The contents and structure of this review are summarized in Fig. 2.

2. Prediction Via *In Situ* Gas Sensing

The most frequently used sensors in the robot OSL researches are the *in situ* sensors (e.g., metal oxide semiconductor, MOS), which could only provide concentration information in a small area around the sensors [11]. Obtaining some important OSL-related information (such as odor concentration gradient) requires a bunch of spatially distributed measurements, like samplings at different locations.

During the research on the robot OSL, a variety of sensor setups and signal processing algorithms have been proposed to provide more powerful sensing abilities. Some of them could predict the odor-source information, such as the direction and distance of the source, via *in situ* gas sensing (robot movement is not required).

2.1. Odor-source direction prediction The odor-source direction prediction via *in situ* sensing has another more popular term: the odor compass, a device could predict the direction from which odor patches come. The research on the odor compass can be traced back to the 1990s, focusing on the structure design of the sensing module in the early stage. Ishida and Nakamoto *et al.* [12,13] proposed two biologically inspired implementations of two-dimension (2D) and three-dimension (3D) odor compasses. The proposed odor compasses use plates to separate gas sensors (like the septum in biological noses) and use a fan to draw the air towards the sensors (like the sniffing effect

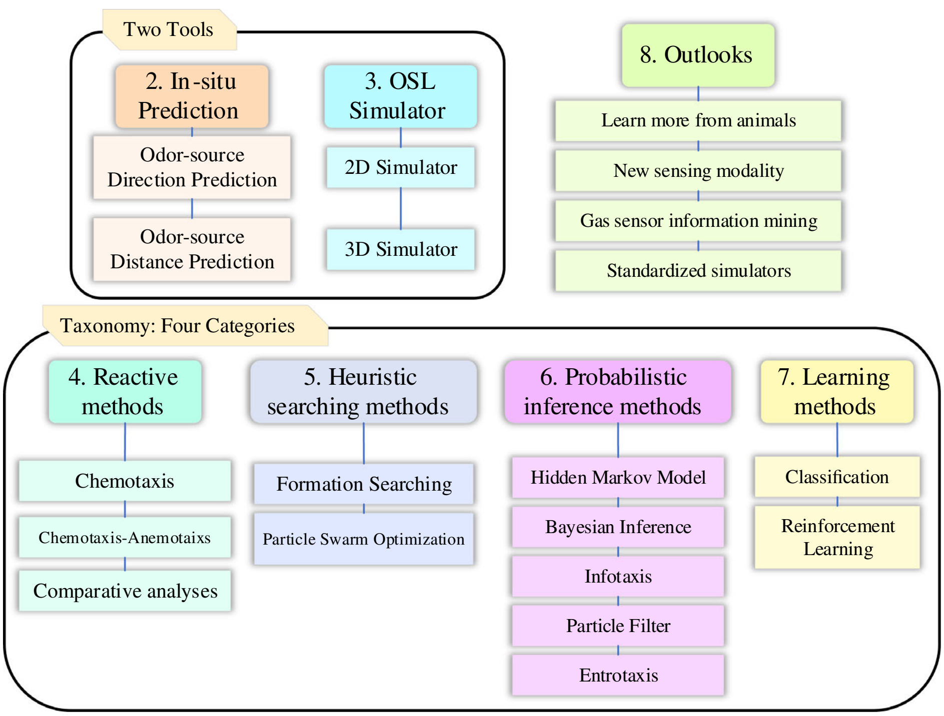
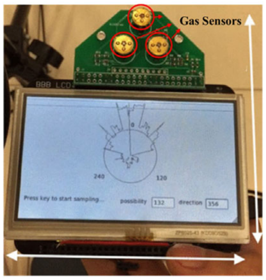
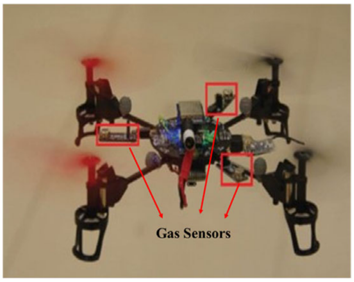


Fig. 2. The contents in this review



(a)



(b)

Fig. 3. Odor compasses of triangular sensor layout: (a) The portable odor compass [14] (b) The flying odor compass [15]

of silkworm wings). The odor compasses estimate odor-source direction through seeking balanced outputs among the sensors by rotating the sensor module in the 2D or 3D space. Some signal processing methods [12,13] were proposed to increase the measuring speed based on a sensor response model.

Another focus of the odor compass research lies in the signal processing algorithms involved. Wei *et al.* [14] proposed a portable odor compass to predict the odor-patch direction under a windy environment based on the principle of time difference of signal arrival. Three gas sensors are placed in a compact regular triangle as shown in Fig. 3(a), and the response features are extracted with a scale-space algorithm and a feature-point matching algorithm. Luo *et al.* [15] improved the triangular odor compass in Ref. [14] for the rotorcraft platform [as shown in Fig. 3(b)] by proposing a new odor source orientation inference method. The continuous wavelet transform is applied to extract different frequency components from the responses and identify the arriving and departing events of the odor patches, then the odor flow direction could be calculated by time differences of these events.

2.2. Odor-source distance prediction

Apart from the odor-source direction, the odor-source distance is also valuable information. Some odor-source distance prediction methods have been put forward based on the transient features.

Previous studies [16] based on photo-ionization detectors indicate that the intermittent nature of a gas plume contains information about odor-source distance. Schmuker *et al.* [17] conducted a research demonstrating that the off-the-shelf MOS sensors are also able to provide odor-source distance correlated features, represented by a feature called ‘bout’. Bouts are the portions where the amplitude of the filtered signal is consistently rising. Through experiments based on an open-source wind tunnel dataset [18], it is shown that the number of bouts is a strong predictor for the source distance.

Burgués *et al.* [19] applied the bout feature to a gas distribution mapping research based on a small quadrotor, illustrating that the map based on the bout number is credible with respect to the true source location and wind direction. They also proposed a non-recursive bout extraction method [20], which is inherently stable and allowing easy algorithmic implementation and optimization.

Since the parameters of the bout extraction algorithm are regressed based on a specific dataset, the absolute odor-source distance prediction effect in other environments needs further verification. Nonetheless, the bout feature has been proved to be valid in predicting the relative odor-source distance.

3. OSL Simulator

Simulation is a conventional validation measure in robotics research. In recent years, OSL researchers are waking up to the importance of simulations. A series of simulators have been proposed for the robot OSL, based on frequently used robotic simulation platforms, such as ROS [21] (Robot Operating System), Webot [22], V-REP [23], Matlab [24], Player/Stage [25], and so on. Generally, an OSL simulator involves simulations of the scene, the wind field, the gas dispersion, gas sensors, and the robot itself.

3.1. 2D simulator

Farrell *et al.* [26] proposed a filament-based gas dispersion model, employing a simplified turbulence model to generate a time-varying plume distribution. This model regards odor patches as flowing filaments, which are transported by advection flow, and diffused and distorted by small eddies. Based on this gas dispersion model, they built a 2D OSL simulator with C++, which was then validated through comparing the simulated results with a wind tunnel dataset [27] under the same settings.

The simplified turbulence model in Ref. [26] is more suitable for simple scenes. Pashami *et al.* [28] improved the filament-based model by replacing the simplified turbulence model with a computational fluid dynamics (CFD) model, i.e. resorting to a CFD software (OpenFOAM) for wind field generation. The CFD software could provide wind field simulations for more complex scenes, but only in an offline manner due to the high computation complexity.

3.2. 3D simulator

Along with the development of algorithms, the focus of OSL simulators has been shifting from 2D to 3D. Sutton *et al.* [29] extended the 2D filament-based gas dispersion model to the 3D environment, and built an OSL simulator named CPT_M3D, which supports multiple robots and multiple sources.

Cabrita *et al.* [25] proposed a 3D OSL simulator using Player/Stage, which supports three kinds of plume simulation: analytical theoretical models (e.g., Gaussian dispersion model), offline data generated by CFD, and offline data acquired in a real environment.

Focusing on the indoor environment, Awadalla *et al.* [24] put forward a 3D OSL simulator, combining CFD with Matlab. The CFD software (ANSYS/Fluent) was used to generate both the offline wind field and the gas concentration field. The offline CFD data were imported into Matlab for the OSL algorithm simulation.

Monroy *et al.* [21] developed another 3D OSL simulator based on the ROS platform, named GADEN. GADEN combines CFD model with a 3D filament-based model. This simulator supports 3D scene customization and multiple-source simulation, and provides good expansibility thanks to the abundant third-party ROS packages.

3.3. Expectation for simulators

Simulation is playing a more and more crucial role in the robot OSL research. Even though there are already some simulators at present, different teams tend to build and develop their own simulator due to distinct research focuses. However, a standardized and widely shared simulator is more valuable for algorithm comparison, and more beneficial for the community development. We think a practical OSL simulator should be easy to deploy, extend, and customize. Employing a widely used robotic simulation platform (like ROS) as a basis will make it easier to utilize the achievements of other robotic research fields. Taking some details into consideration, such as the aerodynamic olfactory effect [30] (the wind field induced by robot movements) and interactions between gas dispersion and obstacles, will ensure a more realistic simulation. Incorporating open-source wind tunnel datasets as offline data, and providing basic implementations of common OSL algorithms as benchmarks may also be helpful for new users. Last but not least, open source will be beneficial for both users and developers, through which a well-designed template is promising to grow into a powerful tool.

4. Reactive Methods

According to the definition from the book, Behavior-based Robotics [31], a reactive robotic system tightly couples perception to action without the use of intervening abstract representations or time history. Reactive OSL methods [32] act as a multiphase search with a state machine, based on predefined movement sequences triggered by odor perceptions, with no or little history information used. The theoretical counterpart of reactive OSL methods is the cognitive OSL methods [32], which produce adaptive behaviors as current perceptions are weighted by past clues and actions, i.e. learning and memory are involved. Reactive OSL methods are the earliest outcomes in this area, represented by a series of pure chemotaxis and chemotaxis-anemotaxis algorithms [9].

4.1. Reactive chemotaxis methods Pure chemotaxis methods, also termed as gradient-based methods [10], means moving the robot along the gradient of chemical concentration, which is calculated by measurements at different positions or from separated sensors. These methods repeat the progress of stepping forward and then turning, thus moving the robot towards the side of higher concentration along different types of paths [33], such as the hex-path algorithm, and the planarian worm algorithm.

The principle of gradient-based OSL methods resembles the gradient ascent in convex optimization, which takes steps proportional to the positive gradient to approach a local maximum (the odor source) of a function (the concentration distribution). From this perspective, gradient-based OSL methods possess similar parameters to the gradient ascent, such as the robot turning angle versus the gradient direction, the robot forward step size after turning versus the ascent step size, and measurements considered in one gradient calculation versus the batch size in the stochastic gradient descent. Just like the gradient ascent method is suitable for optimization of the convex function on convex sets, the gradient-based OSL methods are applicable for diffusion-dominated environments, where the concentration distribution decreases continuously from the source, like underground environments [33].

Yang *et al.* [34] evaluated three gradient-based algorithms in indoor environments with no strong airflows, including the *E. coli* algorithm, the hex-path algorithm, and a spiral-based algorithm. All the three algorithms outperformed the random walk algorithm in terms of success rates and step numbers, showing that gradient-based algorithms are practical in weak windy indoor environments.

While in the air or underwater environments where turbulence dominates, the instantaneous concentration shows a turbulent (not a 'convex function') and intermittent structure (not a 'convex set'). Prolonging measuring duration at one position may reduce this influence by averaging effect, but also lead to unfeasible efficiency.

4.2. Reactive chemotaxis-anemotaxis methods Inspired by the olfactory behaviors of animals such as silkmoths, lobsters, and dung beetles which use fluid information to search odor sources, chemotaxis-anemotaxis methods incorporate wind or water cues during searching. These methods focus on a more macroscopic structure of the odor distribution: the odor plume, which is formed as the wind disperses odor molecules from their source [35].

Organisms have evolved outstanding plume tracing ability with two common features: upwind search to approach the source, and local search after losing plume [9]. In a windy environment, a detected odor cue means possible odor sources in the upwind direction, so the organisms perform an upwind surge responding to a valid odor measurement, which is termed as odor-gated anemotaxis in the air or rheotaxis underwater [36]. Due to the intermittent and meandering structure of odor plumes, losing plume happens frequently during the upwind surge. In such a case, some organisms have the behavioral patterns to recapture or reenter the plume, i.e. the local search [37], including the casting of moths, the backtrack of lobsters, and the zigzag of dung beetles.

The upwind surge with certain local search behaviors forms the basis of chemotaxis-anemotaxis OSL methods, presenting as a repetitive combination of forward and turning. The differences between organisms' local search behaviors probably result from different natural factors, such as the odor-source types, the organisms' habitats, locomotion, and perception abilities. Besides, considering the massive gaps of locomotion and perception capabilities between robots and their biological counterparts, strictly mimicking biological behaviors seems to be of limited use [38]. On the contrary, these biological behaviors should be analyzed further to uncover the underlying principles before being applied in the robot OSL. Some progress has already been proposed in this respect through comparative analysis.

4.3. Comparative analyses *Parameters optimization* An obvious means of improving reactive OSL methods is to understand and optimize the parameters involved, mainly for the forward step size and the turning angle.

With respect to the underground OSL, Chen *et al.* [39] proposed a stage-wise zigzag strategy with adaptive turning angles according to the searching stages, which outperformed the standard zigzag algorithm with a constant turning angle. The proposed stage-wise zigzag algorithm adopts smaller turning angles in later stages (closer to the odor source), which resembles the use of a variable learning rate in the gradient descent to accelerate convergence.

Lu *et al.* [40] analyzed the influence of initial position and forward distance in the indoor environment through simulations. An adaptive principle named 'inverso surge chemo-anemotaxis' was used to determine forward distance, which varied forward distances inversely proportional to the detected chemical levels. Experiments demonstrated that the adaptive forward distance performed better than the fixed one in terms of total steps and success rates.

With similar ideas, Gao *et al.* [41] proposed an adaptive step control algorithm to optimize the forward step size. They argued that the robot should stride confidently (with large forward step size) when it is far away from the source for efficiency, and walk cautiously (with small forward step size) when it is close to the source for accuracy. A sigmoid function was employed as a control kernel to generate the adaptive forward step size, and its performance was validated through simulations under a diffusive environment only.

Performance comparison Russell *et al.* [42] conducted a series of comparisons between four reactive OSL methods, i.e. the *E. coli* algorithm, the silkworm moth algorithm, the dung beetle algorithm, and another gradient-based algorithm. The results showed that the bio-inspired methods were consistent with their corresponding biological behaviors in terms of applicable environments.

Voges *et al.* [32] provided another interesting comparison view, comparing three reactive OSL methods with a cognitive one. The robot platform was equipped with the living moth antenna as gas sensors. According to their results, the reactive searching is more efficient for higher pheromone doses whereas the cognitive searching works better for lower doses. They argued that zigzag could serve as a supplement for relocating the lost plume for the cognitive methods.

Statistical analysis As mentioned above, the reactive methods perform as a multiphase search with a state machine. Some statistical analyses were conducted from the state-action view.

Macedo *et al.* [43] conducted a statistical study of bio-inspired strategies. They first developed a 2D OSL simulator to collect different bio-inspired strategies' perception and action data, which were stored in an XML dataset. They designed five features to better describe the perceptual states during the OSL, including plume-lost, binary-odor-detection, discrete-odor-difference, and so on. Another feature named discrete-cos-target-upwind (the cosine of the robot's goal vector with respect to the upwind direction) was proposed to distinguish the robot actions, i.e. downwind, crosswind, and upwind. They tried to find out a meaningful set of state clusters to define the experiences of the robot through k-means clustering. State-action mappings were built for different strategies, and four state clusters were highlighted: never detected odor, sensed odor, recently lost plume, and lost for a long time.

Simulations [43] showed that: different strategies behaved differently in all perceptual states, and the most discrepant behaviors were seen under the state cluster of 'recently lost plume', confirming the importance of the local search again. Also, a small set of rules were derived from the results by combining the most consensual actions under each cluster. This research provides a statistical perspective for reactive methods analyses, through discretizing the inputs (states) and outputs (actions) of each strategy. The statistical optimal strategy may be different from all the current bio-inspired reactive methods, and may outperform them also, where further physical experiments are required to validate these viewpoints.

Focusing on indoor environments, Li *et al.* [44] evaluated the performances of 16 reactive behavior combinations, stressing the tracking of the wall plume induced by an odor source on or near a wall. They found an optimal combination through simulations, based on which an improved algorithm 'vallumtaxis' with an along-wall obstacle-avoidance method was put forward [44]. This research provides a problem-solving idea that best behavior combination could be inferred by comparisons, and improvements could be made based on the specific problem accordingly.

Strategy synthesis Based on simulations, Villarreal *et al.* [45] proposed a strategy synthesis method through genetic programming (GP). Some gradient-based OSL algorithms were decomposed into discrete action patterns as ingredients of strategy synthesis. The syntax tree was used to describe the OSL algorithms, whose leaves were action patterns and nodes were functions defining the relationships between the action leaves. A fitness function was designed to evaluate the performances, using a weighted sum of five criteria including distance reached, time used, etc.

For the GP process, the mutation probability was set to a small value (0.05) to ensure the stability of the generated algorithm, since a simple mutation may easily introduce an unreasonable behavior combination; the crossover probability was set to 0.5, enabling a 50% diversification and retaining the main structure at the same time. The process run on a simulator developed based on Netlogo and Matlab until the overall fitness was stabilized. The best final algorithm was a variation of the gradient-ascent algorithm, with different forward step size and measurement behaviors.

Summary of comparative analysis Through comparative analyses, we could explore the potential of reactive OSL methods by customizing the problem-specific parameters and the behavior combinations. Some modified or even synthetic methods may outperform the existing ones in a specific environment.

5. Heuristic Searching Methods

Reactive methods tend to locate the odor source using relatively straightforward behaviors with no or little historical information. Heuristic searching methods try to solve the robot OSL with heuristic optimization. When the OSL is viewed as a mathematical optimization problem, finding the odor source in the target area is equivalent to finding the best solution (i.e., the source) in the feasible region (i.e., the target area) depending on an objective function (e.g., the detected odor concentration).

Heuristic, derived from the Greek expression of 'to discover' [46], represents a set of optimization methods that try to solve the problem through heuristic means, resorting to information of historical samplings and spatially distributed samplings. Heuristic OSL methods usually share the following characteristics:

1) An objective function is designed to evaluate solutions;
2) Relative long-term historical information is involved;
3) Next position of the robot is dynamically generated;
4) The robot(s) need to get to the source, which means at least one robot needs to approach the source by itself during the search.

In general, the heuristic searching methods resort to two techniques to obtain improved performance: (i) a well-designed objective function to ensure efficient global searching (and to avoid falling into local optimums); (ii) collaboration of multiple robots to enable efficient spatially distributed samplings.

Heuristics methods cover genetic algorithm, formation searching, particle swarm optimization (PSO), simulated annealing, ant colony optimization, artificial bee colony algorithm, cuckoo search, firefly algorithm, etc. Most of these heuristic algorithms are designed based on multiple agents, thus as to the robot OSL, they are probably implemented in some form of swarm robotics.

Simply applying some single-robot reactive methods to the multi-robot situation can in no way guarantee a performance improvement. Multiple robots conducting the same reactive OSL method are likely to hinder each other and compete for space along the way to the source, especially in narrow plumes [47]. Thus, cooperative mechanisms are required to support more intelligent collective behaviors for multiple robots. In the multi-robot OSL, two main problems are how to share information between agents and how to plan the path for each agent. Some heuristic algorithms have provided solutions for these problems, and this section

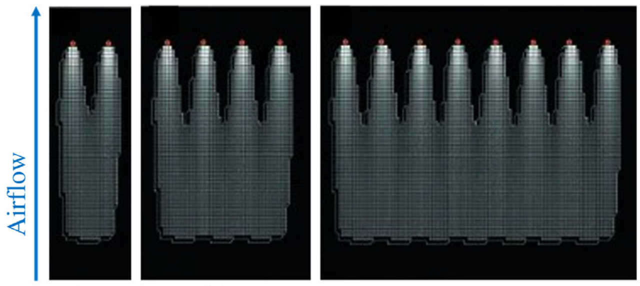


Fig. 4. Optimized configurations of 2, 4 and 8 gas sensors [48]

reviews two representative ones, namely formation searching and PSO.

5.1. Formation searching The formation searching based OSL drives a group of robots to search the odor source while maintaining a desired spatial pattern. Here we focus on three perspectives of the formation searching in the multi-robot OSL.

From the gas sensing perspective in situ sensors (e.g., MOS sensors) are widely used in the OSL research. Searching with a well-designed formation could expand the sensing area coverage, thus improving the search efficiency.

Marjovi *et al.* [48] raised two questions of swarm robots in plume finding: What is the best spatial formation? and What is the best movement strategy? They proposed a probability model of gas sensor coverage, and then optimized the formation to obtain the largest sensing area. They concluded that the optimal formation in plume finding is a line configuration along cross-wind direction with equal distance between sensors, as shown in Fig. 4. It is important to note that according to the gas sensor coverage model presented in Ref. [48], the overall coverage (the gray regions in Fig. 4) of appropriately distributed sensors could be larger than the sum of individual coverage of each sensor, producing an effect of 'a whole greater than the sum of the parts'. This is also a crucial reason why the formation is important in the multi-robot OSL.

From the chemotaxis perspective Some chemotaxis-based formation searching methods were proposed with a similar behavior mechanism to the single-robot based chemotaxis reactive methods. The main difference is that the formation searching could obtain concentration gradient with multiple robots.

Zhang *et al.* [49] proposed a searching algorithm based on multiple robots with regular polygon formations (e.g., triangle for three robots, quadrangle for four robots, and so on). A virtual robot was located at the center of the polygon, serving as the leader. The robots cooperated through virtual-physics forces, including the goal force, structure formation forces, and obstacle-avoidance forces. The goal force was set to the direction from the center of the polygon to the highest chemical concentration detected, and only acted on the virtual center-robot. The other real robots followed the virtual center-robot according to structure formation forces. This formation search method seems like installing multiple gas sensors at large intervals on a giant robot, thus increasing the coverage of the sensors.

From the anemotaxis perspective Also, the fluid information and the plume shape are considered in some formation searching methods, i.e. anemotaxis-based formation searching methods.

Soares *et al.* [50] proposed a graph-based formation searching method to follow the odor plume. A center-robot was assigned to follow the centerline of the plume, and the remainder robots were deployed on the left and right sides of the center robot to follow the plume edges. All the robots had an upwind tendency based on the measured wind direction. This method is similar to the plume-centered upwind search method proposed by Russell [51], but gets rid of the cross-wind casting through robots deployed on the edges of the plume, thus having a better real-time performance.

Due to the turbulence of realistic dispersion environments, even a small subarea may contain complex information (such as intermittent plumes), and it is easy to miss some crucial cues if only one robot is assigned there. Spreading all robots in service to search separated areas might result in loss of some odor plume cues because of the limited sensing area of one single robot. The formation searching method may serve as a basic tool for considering the cooperation of a small group of robots in a sub-area.

5.2. Particle swarm optimization Particle swarm optimization (PSO), which simulates animals' social behavior, is a computational method that optimizes a problem by iteratively improving a candidate solution with regard to a given measure. This section starts with reviewing the introduction of standard PSO (S-PSO) [52] to the robot OSL, and then focuses on several problems and the corresponding variants, as shown in Table I.

S-PSO based OSL The S-PSO provides velocity and position updating rules for each robot. Equations (1) and (2) are the ith robot's velocity and position updating rules, respectively, where $x_i^{(t)}$ and $v_i^{(t)}$ represent the position and velocity at the time t, respectively; $x_{isb}^{(t)}$ and $x_{ab}^{(t)}$ stand for the robot's personal best solution and the swarm's global best solution at the time t, respectively. r_1 and r_2 are random numbers in the range (0, 1).

$$v_i^{(t+1)} = wv_i^{(t)} + c_1 r_1 (x_{isb}^{(t)} - x_i^{(t)}) + c_2 r_2 (x_{ab}^{(t)} - x_i^{(t)}) \tag{1}$$

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \tag{2}$$

Each particle's velocity is influenced by two types of learning, including learning from its own experience (the self-learning term, i.e., the second term) and from other particles (the social-learning term, i.e., the third term). c_1 and c_2 refer to the corresponding learning factors. The first term in the velocity update equation can be thought as the inertial term (and w is the inertial weight), preventing particles from drastically changing directions.

Marques *et al.* [71] first applied the S-PSO in the OSL context. The algorithm regards the odor source as the best solution, and takes each robot as a particle searching in the feasible region. The measured time-averaged concentration [71] or some statistical indexes (e.g., the proximity index [54]) are used as the fitness function or the objective function. The S-PSO method performed better than the multi-robot gradient-based search and biased-random walk search.

Problem 1: Avoiding being trapped in local optima Due to the time-varying odor dispersion in realistic environments, a problem faced by S-PSO methods is being trapped in local optima [72]. Several variant PSO methods were introduced to maintain diversity of the positional distribution of robots and prevent them from being trapped in local optima, including the detection and responding PSO (DR-PSO) [53], the charged PSO (C-PSO)

Table I. Problems in the PSO based OSL and the corresponding variants

Problems	Variants	Principles	Validations	Compared algorithms
Avoiding being trapped in local optima	DR-PSO [53]	Performs a random spread when the global best has not changed for a period of time.	Simulation	S-PSO
	C-PSO [53]	Introduces mutual repulsive forces between robots by charging some robots.	Simulation	S-PSO
	E-PSO [54]	Forbids samplings that are too close, ensuring more widespread samplings.	Simulation	S-PSO
	RR-PSO [55]	Requests some robots with low fitness leave current positions, and resets the rest to search any possible areas with higher fitness scores.	Simulation	non-hybrid PSOs
Utilizing wind information	PSO-WUI [56]	Sets the updated velocity to zero if the velocity points to the downwind direction.	Simulation	C-PSO, DR-PSO
	PSO-WUII [56]	Modifies the velocity with a control function to adjust it to the upwind direction.	Simulation	C-PSO, DR-PSO
	RW-PSO [57,58]	Dynamically adjusts two learning factors of self-learning and social-learning in the velocity update equation based on the wind direction.	Simulation	S-PSO, PSO-WU
	IgB-PSO [59]	Deviates the global best position according to the wind direction by adding a wind term in the velocity equation (IgB1) or modifies the social-learning term (IgB2).	Simulation	RSPSO, RMNPSO
	U-PSO [60]	Adds an upwind term in the velocity update equation.	Experiment	S-PSO, PSO-WU
	UR-PSO [61]	Adds a random disturbance term in the self-learning term and an additional upwind term in the velocity update equation.	Experiment	S-PSO, PSO-WU
Locating multiple odor sources	RS-PSO [62]	Modifies PSO with the niche or parallel search characteristic, and a ranged subgroup method is used to cope with the double searching problem.	Simulation	Parallel MPSO
	N-PSO [63]	Robots located at a neighbor form a dynamically changing niche, and different niches are employed to localize different odor sources synchronously.	Simulation	PSO-WU, RS-PSO
	GD-PSO [64]	Group behaviors: group formation, limiting group size, group merging and dismantling; Inside group behaviors: diverse tracking a plume centerline.	Simulation	N-PSO, RS-PSO
Combining with probability estimation	P-PSO [65,66]	Estimates the probability distribution map of the odor source via Bayesian rules and fuzzy inference, and the estimated distribution is used as the fitness function.	Experiment	C-PSO
	PPSO-IM [67]	Introduces an information-sharing mechanism to estimate the probability distribution of the source. Next position is updated via the estimated distribution.	Simulation	S-PSO, C-PSO
	L-PSO [68]	Builds a source probability map for each robot based on concentration information, wind information and swarm information. Next position is estimated by uniformly sampling the source probability map.	Simulation	C-PSO, PSO-WU
Hybrid optimization methods	IWOA [69]	Locates the odor source by encircling and approaching the global maxima location. Adds an upwind term in the velocity update equation.	Simulation	S-PSO, U-PSO
	HTLPSO [70]	Combines TLBO with PSO, performing PSO updating and TLBO teaching in parallel. Merges the best halves of TLBO and PSO as TLBO learning's input.	Simulation	TLBO, S-PSO

[53], the explorative PSO (E-PSO) [54], the ignore global best PSO (IgB-PSO) [59], the request and reset PSO (RR-PSO) [55], and so on.

Problem 2: Utilizing wind information Wind direction provides a useful cue for the robot OSL, so how to utilize wind information with multiple robots is another problem for the PSO based OSL. Inspired by the upwind movement in reactive anemotaxis methods, some researches improved S-PSO methods through incorporating the wind information, such as the PSO with wind utilization (PSO-WUI and PSO-WUII) [56], the PSO based on repulsive and wind (RW-PSO) [57,58], the PSO with upwind term (U-PSO) [60] and the PSO with Upwind term and Random term (UR-PSO) [61].

Problem 3: Locating multiple odor sources In realistic environments, there may exist more than one odor source in the target area. When considering multiple odor sources localization, swarm robotics is particularly gifted. Aiming at this problem, some grouping based PSO methods were proposed, including the ranged subgroup PSO (RS-PSO) [62], the Niching PSO (N-PSO) [63], the group-based diverse PSO (GD-PSO) [64], and so on.

Problem 4: Combining with probability estimation Instead of using the best measurements as criteria for velocity update, some algorithms combine the probability distribution of the odor source with the PSO framework, leading to some probabilistic variants of PSO. Representative methods include the probability based PSO (P-PSO) [65,66], the probability PSO with information-sharing mechanism (PPSO-IM) [67], and the learning PSO (L-PSO) [68].

Problem 5: Hybrid optimization methods Heuristic optimization is a booming research direction with new heuristic algorithms emerging in an endless stream. Hybrid methods combining two or more heuristic optimization methods have been turned out to outperform all components. Some hybrid optimization methods were also introduced in the robot OSL research, such as the improved whale optimization algorithm (IWOA) [69] and the hybrid teaching-learning PSO (HTLPSO) [70].

5.3. Summary of heuristic searching methods

Heuristic searching is a fast-growing direction, where a series of algorithms based on metaphors of certain natural processes have been proposed. As a result, heuristic searching methods represented by PSO have also been becoming one of the most thriving directions in the robot OSL. Simply introducing some newly emerging complex heuristic algorithms in the robot OSL would not guarantee improvements, since what is reasonable in one set of circumstances may be far-fetched in others. But the heuristic searching methods have indeed provided several practical frameworks for the multi-robot OSL.

We argue that the robot OSL research and heuristic optimization should reinforce each other in a virtuous cycle. For example, from the multi-robot perspective, PSO provides an effective tool to solve the robot OSL problem, and in return, the OSL also provides a suitable test bench for the PSO algorithms in view of practical applications. Applying heuristic searching methods in the robot OSL encourages researchers to actively adapt the algorithm to realistic environments, which means the delicate algorithm must take a back seat to the intrinsic characteristics of the specific application, and simulations must give way to real experiments.

6. Probabilistic Inference Methods

Probabilistic inference is the task of deriving the probability distribution of random variables from probabilistic models based on known data. Due to the chaotic characteristics of fluid environments, most gas dispersion models are represented in statistical views, making probabilistic methods appropriate for the robot OSL.

Two distribution maps The location of the odor source could be regarded as a parameter of the gas dispersion model, so we could estimate the distribution of the odor source via probabilistic methods based on measurements. Another view focuses on the distribution of the released odor molecules, or say the distribution of plumes. Therefore, two probabilistic distributions are involved:

1) The probability distribution of the odor source;
2) The probability distribution of the released odor molecules.

Since the target area is usually discretized into grid cells, the probability distribution to be inferred is in the form of probability mass function (PMF) rather than probability density function (PDF). The gas concentration distribution could be seen as an example of PMF of the odor molecules, since the integration of concentrations against the target area is the total number of released odor molecules. Furthermore, the odor plume distribution could also be regarded as a PMF of the odor molecules in an extended meaning.

Bayesian inference framework Since the target area is usually discretized into a grid map with a number of N cells (take the 2D case as example), the problem becomes an N dimensional Bayesian inference problem. Taking the probability distribution of a single odor source as an example, the inference process could be described based on Bayes theorem, as shown in (3):

$$P(l_s|D) = \frac{P(l_s, D)}{P(D)} = \frac{P(l_s) \times P(D|l_s)}{\sum_{i=1}^{N} P(l_i) \times P(D|l_i)} \tag{3}$$

Equation (3) represents the inference of the probability that the odor source is located at the cell $l_s (1 < s < N)$ given history measurements D. $P(l_i)$ stands for the prior probability that the odor source is located at the cell $i (1 < i < N)$. $P(D|\, l_s)$ describes the probability of obtaining measurements D given that the odor source is located at l_s, which could be deduced from the gas dispersion model and the odor sensing model. The resulted posterior distribution $P(l_s|\, D)$ against all cells is the full solution to the odor source distribution estimation, from which we could infer the most likely location of the odor source.

The design of $P(D|\, l_s)$ is a forward problem which tries to calculate the odor concentration distribution or the odor plume distribution given a certain odor source location based on the gas dispersion model and the odor sensing model. The inference of $P(l_s|\, D)$ is an inverse problem which tries to estimate the odor source distribution given history measurements and the models.

A series of probabilistic inference algorithms have been proposed based on the Bayesian theorem with different problem descriptions, and some representative ones are discussed here.

6.1. Hidden Markov methods (HMM)

Farrell *et al.* [73] proposed an HMM based OSL method, describing the robot OSL problem under the HMM framework, which may be the first work bringing a complete probabilistic framework into the robot OSL.

They put forward three assumptions (abbreviated as *Asm*):

Asm1: The air flow is uniform over the searching area; thus, every grid cell has the same flow velocity (denoted as u) at the same time, which could be measured by a single robot;

Asm2: Odor molecules are transported in a cluster form (named odor parcel) along with the airflow;

Asm3: An odor parcel moves a distance less than one cell width in an updating time interval $\mathrm{d}t$.

Asm1 could be called the wind uniformity hypothesis, which is satisfied in a uniform wind field. *Asm2* and *Asm3* provide a simplified gas dispersion model from the Lagrangian view [74], and in this view, the research focuses on the movement of relatively long-lived odor parcels, thus a binary odor sensing mechanism (detection vs. non-detection in a cell) could be applied. These assumptions are widely used in the probabilistic OSL methods.

Hidden states: The target area is discretized into $m \times n$ grid cells, then the system state is made up of each cell's state — whether there is detectable odor parcel in that cell or not.

Observation probability distribution **B**: Based on *Asm2*, for each cell, a binary odor detector is applied, i.e. two possible observation results for each cell — detection event and non-detection event. The observation depends on the state with a constant probability coefficient $\mu(1 > \mu > 0)$, the probability of detecting the odor parcel if there is indeed one parcel in the cell.

State transition distribution **A**: The state transition distribution describes the transportation of odor parcels, which is a matrix whose element a_{ik} denotes the probability of an odor parcel moving from the cell C_i to C_k.

According to *Asm3*, each odor parcel may only move to the cells around its current places (including its own cell), so each row of **A** has only nine non-zero elements. The transition probability a_{ik} is calculated as the probability of whether an odor parcel at C_i could be transported to C_k with a displacement $u\mathrm{d}t$. The initial position is picked in C_i randomly, which could be regarded as an effect of turbulence and diffusion.

With this HMM framework, inferring the source distribution is an HMM training problem that tries to obtain the initial states according to observations, and inferring the most likely odor paths given the estimated odor source distribution is a combination of HMM evaluating and decoding problems that try to estimate the most likely state sequences. These problems could be solved based on classical HMM solutions, such as the forward and backward algorithms, and the Viterbi algorithm. The source distribution map is used to estimate the odor source location, and the plume distribution map is used to plan the optimal path.

6.2. Standard Bayesian inference

Pang and Farrell [75] put forward an odor-source likelihood mapping approach based on the standard Bayesian inference framework. The core idea of this method is to iteratively update the source probability map based on detection and non-detection events.

In the proposed framework [75], the target area discretization and the measurement binarization are similar to Ref. [73]. They introduced the filament-based gas dispersion model [26] to describe the odor parcels' movements, which contains a determinate portion (induced by advection) and a random portion (induced by fluctuation).

A basic probability unit is the probability of there being an odor source in the cell C_i that released one odor filament at time t_1, given that the filament is detected in the cell C_k at time t_s, which is denoted as $S_{ik}(t_1, t_s)$. The probability set of $S_{ik}(t_1, t_s)$ against all cells describes the posterior probability of the source map upon a single detection event given a single release. The continuous release version of this map could be derived by adding $S_{ik}(t_1, t_s)$ of all the possible release times, which are uniformly generated by a local time-window. The final posterior probability of the source map is obtained by incorporating multiple sequential events, which is a product of the continuous release version of the source distributions upon all detection and non-detection events, based on an assumption of conditional independence of measurements (CIM). The CIM assumes that the current measurement is independent of all the other measurements, which is usually incorrect since the gas sensor output may be affected by multiple cells. But this assumption simplifies the updating of the final posterior source probability. With the final posterior probability updating formula, the source distribution map is updated iteratively according to the newly obtained measurements.

Some variants have been proposed, which improve this algorithm by introducing certain prior information or assumptions.

Bayesian occupancy grid mapping Instead of estimating the likelihood map of a single odor source, another inference method is to consider the probabilities that each discrete cell contains a source. A Bayesian occupancy grid mapping based OSL method was proposed in Ref. [76], which is suitable for locating multiple odor sources. The occupancy grid mapping is the process of estimating the likelihood of each cell being either occupied or empty (here it refers to be occupied by an odor source), considering the successive noisy and uncertain measurements. An adaptive updating rule was proposed which uses the prior source distribution inferred in the last step as the prior distribution in the current step. This rule is derived under an assumption named independence of posteriors (IP), which interprets new measurements in the light of the current state.

The IP assumption is inexact since a cell with detectable odor is likely to influence the measurements of nearby cells. However, for environments with low prior probabilities, this method does tend to produce maps that are more consistent with the true maps, which shows a better performance especially in multiple odor source localization according to experiments.

Sparse Bayesian learning Wiedemann *et al.* [77] proposed a sparse Bayesian learning (SBL) method for multi-robot OSL, with physical knowledge and model uncertainties incorporated. The diffusion process is modeled using a partial differential equation. The only assumption involved in the proposed method is a sparse constraint: there are only a few spatial sources in the target area, and SBL is used to deal with the sparse prior. SBL applies a hierarchical prior calculation which parameterizes the actual prior distribution by an additionally introduced hyper-parameter. The marginal probability of the source distribution is calculated based on a factor graph representation of the posterior probability.

This method permits an efficient distributed implementation. Experiments showed that this method accelerated the identification of the source parameters and outperformed systematic samplings.

6.3. Infotaxis

In Ref. [78], Vergasolla *et al.* proposed a method based on information-driven principles, named Infotaxis, which highlights the importance of information during searching.

Infotaxis follows the basic idea of Bayesian inference, updating the source probability distribution upon new measurements, but makes a novel improvement by proposing an information-driven path planning strategy. Instead of the binary sensing model, a criterion of odor encounter rates is presented to deduce the posterior probability of odor source according to measurements. The mean number of odor encounters at a position given a source location is modeled as a random variable subject to a Poisson distribution.

Shannon's entropy is employed to describe the uncertainty of the odor source location, which could be calculated according to the inferred odor source distribution. The problem of the 'exploration versus exploitation trade-off' is stressed, where exploration means searching more unknown areas to accumulate more information, while exploitation tends to direct the robot towards the estimated odor source. They put forward an expression for the variation in entropy of the inferred source distribution, which contains two terms: the first term represents the direct gain of finding the source, and the second one stands for the knowledge gain from receiving additional cues. Then all that remains is to take whatever action — making a move or staying still — that maximizes the expected reduction in entropy of the inferred source distribution [79].

Infotaxis provides an information-driven path planning method for the robot OSL, through calculating the expected entropy variation of different movements according to the inferred source distribution. Several other researches have been conducted to further evaluate and improve the performance of Infotaxis.

Evaluation and assessment As noted by the authors in Ref. [78], simulated infotactic paths share qualitative similarities with the classical casting and zigzagging pattern observed in the bio-inspired reactive methods. Voges *et al.* [32] conducted a comparative analysis, comparing four strategies (three reactive methods versus Infotaxis) based on the same robotic platform with living moth antennae as gas sensors. According to their experiments, reactive methods are more efficient (yielding shorter trajectories) in the high doses environment whereas cognitive searching works better in the low doses. A similar conclusion was drawn in Ref. [80] by Moraud *et al.*, which indicates that Infotaxis is both effective and robust in dilute conditions according to experiments and simulations.

Ristic *et al.* [81] implemented the information-driven idea under the particle filter (PF) framework. Three reward functions for navigation were compared, including an Infotaxis II reward, which removes the Infotaxis' bias towards the source (the direct gain), and a reward based on the Bhattacharyya distance. The Infotaxis II reward slightly outperformed the others in numerical simulations.

3D Infotaxis Ruddick *et al.* [82] extended Infotaxis to 3D environments, which has a maximum of 26 possible targets (one cell's adjacent neighbors in 3D environments) for the next movement, compared with nine in 2D environments.

Continuous-space Infotaxis Barbieri *et al.* [83] presented a continuous-space version of Infotaxis, and analyzed its behaviors in both 2D and 3D environments. They pointed out the problem of the greedy nature of the continuous Infotaxis: moving to directions maximizing the immediate gain in information, rather than considering what could be gained on a long-time horizon. They suggested a possible extension to non-greedy Infotaxis by considering the total expected gain of next several steps.

Limited space perception Masson *et al.* [84] proposed a mapless OSL method following the basic idea of Infotaxis, but focusing on more realistic conditions: searching with limited space perception and no accurate model of the environment. The estimated posterior probability of source distribution is projected on a standardized form due to the limited space perception. A new criterion, the free energy, is used to replace the entropy during path planning, since the entropy requires a precise environment model and tends to shift the exploration-exploitation balance towards exploration.

Multi-robot and multi-sources Masson *et al.* [85] also proposed a collaborative Infotaxis, which is a multi-robot version of Infotaxis. n robots were applied during searching, and decision making was coordinated through evaluating all joint movements available to the whole swarm. Since the number of possible actions for n searchers in 2D environments is 5^n (each robot has five optional movements), a fast-cooling simulated annealing procedure was applied to heuristically choose the coordinated movement rather than making a time-consuming exhaustive evaluation. This multi-robot Infotaxis outperforms a group of independent infotactic searchers without information and decision sharing.

Hajieghrary *et al.* [86] came up with a Kullback–Leibler (KL) divergence based collaborative Infotaxis method, which relies on a relative entropy of the system to synthesize a suitable search strategy for the team. Park *et al.* [87] proposed another multi-robot Infotaxis, where a decentralized coordination approach was employed for sharing sensor measurements and decisions among the team. Song *et al.* [88] presented a different collaborative method, which applied the weighted social Bayesian estimation to make full use of all the measurements at each step. The measurements were fused according to a cognition-difference criterion measured by KL-divergence. The PF and Gaussian fitting were employed to bound the computation and communication burden.

6.4. Particle filter PF is a sequential importance sampling filter, which could be applied for Bayesian inference. Since the posterior model may be unknown or hard to sample, PF uses a set of particles to empirically represent the posterior distribution given noisy or partial observations. Each particle has a likelihood weight that represents the probability of the particle being sampled from the target PDF. In the resampling step, particles with high weights are multiplied while particles with low weights are discarded, to avoid weight degeneracy.

The first PF-based OSL framework was proposed by Li *et al.* in Ref. [89]. In this framework, weighted particles are distributed in the searching area (no overlap), each of them represents the probability of the odor source located near the particle's position. A likelihood function is used to directly generate particles based on measurements. The most possible area of the odor source upon a binary measurement event (detection or non-detection) is estimated based on the history airflow vector, in a similar way as Ref. [75]. Instead of directly updating the corresponding probabilities in the source likelihood map [75], this PF-based method updates particles' weights based on the likelihood information provided by new measurements. A resampling step is introduced to avoid degeneracy, deleting low weight particles, and reproducing high weight particles according to the normal distribution. The weighted mean of the particles could be seen as the most possible location of the odor source for now. The convergence of the particles is used as a termination condition. During the whole process, particles' weight updating and resampling are conducted recursively while the robot conducts a spiral surge strategy in the area and collects new measurements, until the termination condition is satisfied.

Anemotaxis-PF Since the fluid flow plays an important role in the robot OSL, several methods that combine wind information with PF have been proposed, which is noted as anemotaxis-PF here.

Neumann *et al.* [90] implemented the PF-based OSL method on a gas-sensitive microdrone. The airflow is estimated online through a wind triangle method. The concept of patch-path envelope is put forward to describe the outline of an area where the odor patch has passed with high probability, which also considers the wind direction uncertainty induced by the wind estimation.

Chen *et al.* [91] proposed an anemotaxis–PF method for smoke plume path tracing. They equipped a laser particle-counter based smoke sensor on a ground robot to trace particulate plumes. A noteworthy improvement is that they introduced a modified firefly algorithm in the resampling step to mimic the anemotaxis behavior. Each particle is regarded as a firefly, and the fireflies' position update equation has an upwind term to guide the fireflies move upwind. This method offers an idea that the particles' updating process could be combined with other heuristic searching methods, thus bringing in the improvement of heuristic optimization.

6.5. Entrotaxis

Hutchinson *et al.* [92] proposed an OSL method: Entrotaxis, which models the OSL as a partially observable Markov decision process (POMDP) and builds a solution based on the PF estimation and information-driven navigation.

Similar to Infotaxis, the number of odor encounters during a given time interval is used as the measurement. The distributions of source terms (including source location and release rate) are estimated using the PF. New samples are drawn from a proposal distribution: the estimated posterior distribution of the last step.

Distinct from Infotaxis, Entrotaxis employs a navigation reward function based on the maximum entropy sampling principle for movement decisions, which maximizes the information gain of the next measurement. This principle holds that maximizing the entropy of the next measurement is equivalent to minimizing the pre-posterior entropy (used by Infotaxis), thus avoiding the use of conditional distributions [93]. In Entrotaxis, considering a certain moving direction for the next step, all possible measurements (odor encounters) are predicted based on the current source distribution, and a corresponding entropy gain is calculated. The direction with the maximum entropy gain is chosen as the next moving direction.

Compared with Infotaxis, Entrotaxis performed better in simulations in terms of average search time. Some variants of Entrotaxis were proposed to improve its searching performance.

Reward function modification Zhu *et al.* [94] put forward a new navigation reward function for Entrotaxis, which considers the expected entropy gain of the next measurement as well as the repeated exploration scores. They pointed out that repetitively searching the same area would reduce efficiency. Therefore, they added a punishment item in the navigation reward function, corresponding to the repetition scores of the candidate direction.

6.6. Summary of probabilistic inference methods

The above-mentioned probabilistic inference methods provide a unique opportunity to solve the robot OSL in an analytical view. The two basic components involved are inferring the posterior probability based on the measurements, and planning the robot movements based on the inferences. For the first part, different probabilistic methods (HMM, PF, POMDP, and so on) and different odor sensing models (binary measurements, number of encounters, or the concentration) have been introduced to develop more accurate and efficient inference schemes. For the second part, information-driven (Infotaxis) and entropy-driven (Entrotaxis) strategies have been proposed to make full use of the inferences.

Probabilistic methods are always devised along with assumptions, which are usually deviated from the reality to some extent. Some of these assumptions are validated, such as the wind uniformity hypothesis [89], while some are not. The assumptions used by these probabilistic methods need to be treated with caution. Calm analyses and experiments would prompt algorithms to develop more reasonable assumptions that fit the corresponding application conditions well. With the deepening understanding of the gas dispersion principles, new probabilistic approaches will certainly continue to appear in the robot OSL research.

7. Learning Methods

Machine learning, referred to as learning methods in the following paragraphs, focuses on improving task executing performance through training experience [95]. Learning methods are first introduced into the robot OSL for solving odor source declaration problems [96]. Although machine learning plays a meaningful auxiliary means in OSL researches, it does not provide many straightforward solutions yet. As deep learning (DL) is prompting a brand-new implementation of 'artificial intelligence' recently, some DL-based methods stand out in the context of robot OSL, which are highlighted in this section.

7.1. Learn from gas sensor array: DL-classification

Odor-source location classification The DL-based OSL is first employed based on the static sensor network. Kim *et al.* [97] proposed a model to predict the leakage source, based on a recurrent neural network (RNN) with long short-term memory (LSTM) module. RNN is effective to extract features of sequence data by re-inputting worthy data, and the selective re-inputting is determined by LSTM. The training data is generated by CFD simulations.

Bilgera *et al.* [98] presented a convolutional LSTM network for OSL based on time series data measured from a gas sensor array and an anemometer. A 5×6 MOS sensor array with an anemometer in the center was deployed to collect data for training and testing.

The above-mentioned two methods treat the OSL task as a classification problem, since either the target area is discretized into grid cells [98] or the source is located at finite known locations [97]. LSTM is used to learn the intrinsic patterns in the time series data.

Both the methods hold the assumption that the odor source is inside the gas sensor array, that is to say, the gas sensor array should cover the possible area of the source. Considering the case where the odor source may be outside the array, it is more reasonable to predict the source direction rather than to locate it in this situation.

Odor-source direction classification Thrift *et al.* [99] put forward a new odor compass based on a surface-enhanced Raman scattering (SERS) sensor array, which combines a convolutional neural network (CNN) and a support vector machine (SVM) classifier to identify directions of multiple odor sources. Transfer learning is introduced to enable faster model training. This system was then used to identify the location of an *Escherichia coli* biofilm via the volatile organic compounds it released.

Summary of DL based classification These methods provide an enlightening idea to learn odor-source information (location or direction) directly from data of simulations or experiments. The target information is discretized into finite states so that a classification DL network or other machine learning classifiers (such as SVM) could be applied. Since the measured data are time series, LSTM is commonly involved to process these inputs.

Even though these methods are designed based on the static gas sensor array, it is quite straightforward to extend them to a multi-robot version, which supports multiple spatial samplings as well. Although the mechanical motion of the robots may introduce more complexities for data analysis and network design, it also provides more active searching capacity.

7.2. Learn from interactions: Reinforcement learning

Reinforcement learning (RL) means training models upon which the agent could make a sequence of decisions autonomously. The robot OSL is a standard decision-making problem, during which the robot needs to take a series of actions (sampling, waiting, moving, and avoiding obstacles) to reach the odor source finally. RL enables a robot to autonomously discover the optimal behavior through trial-and-error interactions with the environment.

However, due to the dynamic and turbulent environment in the robot OSL, which leads to a high dimensional state and action spaces, previous RL-based approaches are of limited applications. Recently, deep reinforcement learning (DRL) has achieved impressive achievements and solved a series of previously intractable problems. Some DRL-based OSL methods coming into view recently have constructed a pioneering research framework by training the model with customized simulators.

Hu *et al.* [100] proposed a DRL-based method for underwater plume tracking. The RL framework follows the actor-critic structure, using the LSTM-based deterministic policy gradient (DPG) algorithm to learn a tracking strategy. The actor-network inputs the observable state sequence and outputs the corresponding action sequence, while the critic-network evaluates the rewards of the action sequence. The actor-critic model updates the tracking strategy progressively through interactions with a simulator. The reward function has a crucial influence on the convergence of the algorithm. In Ref. [100], the reward function is adapted to the OSL background: positive rewards are gained if approaching the plume, while negative rewards are assigned if leaving the plume. Simulation results show that the proposed LSTM-based DPG outweighs the standard DPG in efficiency and accuracy, and the resulted searching trajectory is a quite smooth one.

Another DRL-based method was presented in Ref. [101] by Wang *et al.* The reward function is a fusion of the source distribution map and the plume distribution map, and these two maps are estimated through a POMDP model and an HMM model. The fusion of the two maps is conducted by a fuzzy inference approach with a dynamic weight, which is learned by a DRL process: optimizing the weight through interactions with the simulator.

Both the DRL based methods adapt the OSL to a POMDP model, construct context-relevant state space and action space, and try to find the optimal policy with maximum rewards through a training process. Since the RL training relies on interactions with the environment, both methods build a compatible simulator to train the model. Actually, the simulator is a crucial constraint for the DRL-based OSL research, mainly due to the complexity of the gas dispersion. A lifelike and accurate simulator requires a great amount of calculation, which may be unwieldy in the DRL training process that usually possesses thousands of epochs or more.

8. Outlook

The robot OSL is an interdisciplinary field, which involves robotics, bioscience and bionics, mathematical optimization, swarm intelligence, probability theory, machine learning, control theory, signal processing, and so on. These involved fields either provide straightforward solutions, or help to remove some barriers for the OSL study. Thus, developments in these related research fields will probably bring a breath of fresh air to the robot OSL research.

The robot OSL is also an engineering-associated field, which stems from the practical needs of toxic gas leakage prevention, environment monitoring, natural resources searching, and so on. Newly emerging social needs will give rise to new research directions, e.g. the contaminant monitoring promotes the research of 3D OSL [102] under the background of increasing haze days.

As stated by previous surveys [7–10], the robot OSL has made progress in several focal directions over the past decades, represented by extending the algorithms to 3D environments, multi-robot situations, and hybrid versions. Here we will try to highlight some other recent trends and future directions as a conclusion.

8.1. Learn more from animals Bioscience and bionics have been serving as unfailing sources of inspiration for the robot OSL research. While micro-organism chemotaxis is relatively well understood, in larger animals the algorithms and mechanisms of olfactory search remain mysterious. Larger organisms have more computational resources, neurons, and complex sensory systems, enabling them to overcome more complex problems. Highlighting that larger animals' ability to modulate behaviors with environmental complexity is beneficial for the OSL research [103].

Baker *et al.* [3] present recent understandings of olfactory search in flies and rodents, focusing on their behaviors for solving problems such as navigating in turbulent environments, optimizing olfactory information sampling actively, and so on.

In Ref. [3], the effect of memory in olfactory search is discussed. Strong evidence implicates that memory plays an important role in olfactory search at multiple timescales. Short timescale memory enables the tracking of rapid changes in odor concentration. At the intermediate time scale, the memory of a history of odor encounters over tens of seconds enables creating a model of source locations in a turbulent environment. Long-term memory allows organisms to create odor-informed maps, utilizing prior information to narrow the range of odor-guided searches. These memory patterns could also provide instructions for the robot OSL research.

Many questions [3] remained in neuroscience and bioscience also exist in the robot OSL area, such as 'How is odor information combined with wind information?', 'How do brains exploit odor concentration dynamics?', 'How do animals integrate olfactory sensation with sampling strategies?', and 'How do animals use other sensory cues and memory to navigate in the larger areas?' Keeping ongoing attention on the progress in neuroscience and bioscience will surely provide more inspiration for the robot OSL.

8.2. New sensing modality Biological evidences have proved that other sensing modalities also play important roles in olfactory searching, especially vision [104] . Several methods have been proposed in vision-based OSL.

The current vision-based methods focus on the visual features of objects associated with the target odor (suspected source objects, such as bottles, pipelines, and so on), and obtain vision cues based on certain object detection algorithms [105,106]. Thanks to the development of DL-based computer vision, more powerful object detection tools have arisen, which possess more robust and adaptable detection abilities [107]. A few researches have already resorted to these DL-based vision tools [108], which may set off a new wave of vision-based OSL research. In odor to integrate the disparate sensing modalities of vision and olfaction, different fusion methods are introduced, such as the multi-variable fuzzy control system [109] and the probabilistic Bayesian framework [108].

The widely used optical gas imaging devices, which produce video streams of leaking gases based on the thermal contrast between the background and the gas, may also open a new gate for the vision-based OSL [102].

8.3. Gas sensor information mining A consensus among OSL researchers is that the gas sensors used by robots are far less effective than the biological counterparts, especially for the *in situ* ones, like MOS gas sensors.

A direction of improvement is to employ live olfactory organs as gas sensors in the robot OSL [32,110]. And another idea is to dig more information based on current gas sensors. The odor compasses discussed in Section 2 present a way of information mining upon current gas sensors. The successful applications [19,111,112] of the 'bout' feature [17] in the robot OSL indicate that the transient response is still a valuable feature to be further studied. Considering the combination of multiple different gas sensors (i.e., e-nose) will provide more powerful selectivity sensing during the robot OSL [113]. The Tunable Diode Laser Absorption Spectroscopy (TDLAS) sensor, as a remote gas sensing device, constitutes an alternative to *in situ* gas sensors [114]. Although some methods [11,114] based on TDLAS have been reported, there are still some challenges in data processing due to the peculiar line integral measurement pattern.

To exaggerate a bit, gas sensor information mining will be an eternal theme along with the robot OSL research [9].

8.4. Standardized simulators As mentioned in Section 3, simulation has been more and more popular in the robot OSL research. Most of the recently published methods use simulation as one of the validation measures, if not only.

Since each method has its own characteristics and lays emphasis on different aspects, it is unattainable to expect a general hardware platform that supports all-purpose experiments. Whereas, computer simulation is expected to provide a common tool for further evaluation and comparison among the numerous methods due to its inherent outstanding expansibility and portability.

A promising candidate is the GADEN proposed in Ref. [21], which provides the first-class expansibility based on ROS. But as a comprehensive or perhaps complex simulator, it is not befitting for some applications such as DRL-based OSL, where a large number of iterative simulations are required.

Hence, we may consider a second-best choice, expecting standardized simulators for each specific research direction. With the help of the open-source community, we will surely witness some simulators emerging as common test benches in the long run.

9. Conclusion

As an interdisciplinary and engineering-associated research field, the developments in the robot OSL provide immense academic values and practical benefits. Recent years have witnessed obvious increases in the number of new research groups and new directions in the robot OSL. This paper reviews the recent progress from the view of the algorithm principle, and divides existing works into four categories: reactive methods, heuristic searching methods, probabilistic inference methods, and learning methods.

Several current trends and future directions are discussed at the end. Large animals' olfactory searching behaviors, new sensing modalities, and novel data mining methods may serve as new motivations for the robot OSL. And standardized and widely spread simulators will be very beneficial, which is worthy of the efforts of the whole community. Despite the promising results reported so far, with the developments of the related fields and practical needs, we believe that more methods are still to come, and the OSL robots widely used around us will no longer be a remote scene.

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