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Environmental monitoring using autonomous vehicles: a survey of recent searching techniques☆

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Autonomous vehicles are becoming an essential tool in a wide range of environmental applications that include ambient data acquisition, remote sensing, and mapping of the spatial extent of pollutant spills. Among these applications, pollution source localization has drawn increasing interest due to its scientific and commercial interest and the emergence of a new breed of robotic vehicles capable of operating in harsh environments without human supervision. The aim is to find the location of a region that is the source of a given substance of interest (e.g. a chemical pollutant at sea or a gas leakage in air) using a group of cooperative autonomous vehicles. Motivated by fast paced advances in this challenging area, this paper surveys recent advances in searching techniques that are at the core of environmental monitoring strategies using autonomous vehicles.

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Introduction

Autonomous vehicles, such as flying, marine, and terrestrial robots, have made significant inroads into the area of source localization in the context of explosive and drug detection, sensing of leaking or hazardous chemicals, pollution monitoring, and in the specific case of the marine environment, hydrothermal vent source localization, plume tracing, and heat source seeking. Among others, localization of toxic pollutant sources is an important as well as a challenging issue in many environment related areas. In order to reduce the impact of pollutants on the environment, it is imperative to localize pollutant sources so as to devise an effective control strategy.

This problem has been approached in two distinct manners. In the first approach a fixed network of sensors collect and exchange measurements in order to estimate the location of the source. This localization scheme requires the use of reference nodes (nodes with known locations), thus implying expensive and time-consuming deployment, calibration, and recovery operations. For example, in the case of underwater applications, the nodes must be deployed at the surface and/or on the seabed, with consequent escalating costs. Furthermore, this strategy severely limits the coverage area, an undesirable, a practical limiting factor that can only be overcome by the approach described next.

The second approach involves the use of groups of vehicles equipped with appropriate sensor suites, moving collectively towards the source location in a cooperative manner. This approach is more dynamic, flexible, and suitable for multiple source localization, but requires resolving many challenging technical problems such as endurance, planning, coordination, communication, cooperation, and navigation of all the vehicles. In this context, there has been increasing interest in the development of methods for cooperative source localization using vehicles that have limited or no position information, thus dispensing with the need for expensive navigation systems.

This area of research is vast and defies a simple summary. Hence, in this article we focus on the key developments witnessed in the last five years. The reader is referred to [1] and the references therein for earlier developments in the area, with a focus on advancements and applications of robots for environmental monitoring over the period of twenty years preceding that publication. The presentation in [1] includes sections on marine and atmospheric plume detection and localization, as well as adaptive sampling. Interesting references in the area of biologically-inspired search algorithms can be found in [2], which surveys some of the strategies used, from single cells to

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higher level organisms and animals, as a means to answer extremely interesting questions in the fields of animal behavior, ecology, and evolution. A detailed survey of odor tracing methods and a review of autonomous underwater vehicle (AUV) autonomy and data-driven sample strategies can be found in [3,4]. Sensors are obviously an essential part of the source localization problem. However, sensing methods and platforms constitute a very broad field and are out of the scope of this paper. The interested reader is referred to the review articles [5,6] for sensing systems in air or water.

The organization of the paper is as follows. Section 'Robotic platforms and field experiments' discusses various experimental set-ups that include different robotic platforms. Section 'Source localization methods' provides a comprehensive discussion on recent source localization techniques developed in the last half a decade using single and multi-agents. Finally, Section 'Discussion' summarizes our findings and draws attention to some future directions.

Robotic platforms and field experiments

From a practical standpoint, the success of autonomous search methods hinges upon their performance during field experiments, which depends strongly on the types of platforms used and the operational conditions encountered. The choice of platforms depends in turn on a number of key issues that warrant close consideration. In what follows we briefly present recent advances in this topic, with a strong emphasis on marine robotic platforms.

Source localization missions are often lengthy and require good vehicle maneuverability in order to explore large areas effectively. Thus, in this context, endurance and maneuverability are the two decisive factors in the selection of a robotic platform. Furthermore, because most pollution measurements are taken at discrete instants of time and the sensors used require some latency time to detect particles in air or water, the robots must have the capability to perform station keeping. Ground and marine vehicles have been the two types of robots of choice used in the past half-decade. In the early stages, there were attempts to use burrowing robots for underground gas leakage tracing [7], quadcopters for plume tracing [8], and unmanned aerial vehicles (UAVs) for microbe detection [9]. Unfortunately, the disturbance effect of drones on sensor measurements and their short endurance have severely limited their application. In what concerns ground operations, most robotic platforms are wheeled and in particular nonholonomic unicycle-modeled robots (two wheel differential drive with additional passive wheels) are popular, due to their simple design and superior maneuverability [10•,11–14,15•].

Among all types of vehicles, marine robots are probably the most challenging to build and operate in the adverse conditions imposed by the water medium. Factors such as cost, ease of deployment and recovery, energy limitations, and safety, have limited most existing AUVs to relatively small sizes (a few meters). Current AUVs are typically powered by propellers with low efficiency, driven by electric motors. Low efficiency, along with poor transient performance, have led to reduced AUV endurance capabilities. A comparative study on the use of underwater gliders, AUVs, and remotely operated vehicles (ROVs) for plume detection and tracking [16•], concludes that actively propelled AUVs are the most well suited platforms for such tasks due to their autonomy and sufficient payloads, despite their shorter endurance. The results of field tests with AUVs for source tracing purposes can be found in [17,18]. In this context, it is also worth mentioning other platforms such as the combination of Lagrangian drifters (an oceanographic floating device) and AUVs that are used in the context of environmental monitoring, which is indirectly related to plume tracing. The authors in [19] have presented a combination of a Lagrangian drifter and an AUV to map an area around it, once the drifter detects a patch of a desired substance.

In order to overcome the low efficiency of conventional AUVs and reduce substantially the disturbances caused by the propellers, there is a new breed of autonomous bio-inspired marine robots, which do not use propellers for vehicle thrusting. A robotic crayfish with two arms that mimic the maxillipeds of a crayfish [20], a swimming eel-like robot that uses body undulations for maneuvering [21], and robotic fishes that use caudal swimming to provide forward thrust [22,23] are a few examples of bio-inspired robotic platforms. In [20], the authors used the robotic crayfish for chemical source localization purposes in a small controlled aquatic environment. The robot uses its wheels for locomotion at the bottom of a water reservoir and moves the arms to improve the detection of chemical substances in water. The robotic fish developed in [22] is used in the applications of aquatic sampling and aquatic profiling of chemical substance diffusion reported in [24] and [25], respectively. The swimming eel-like robot [21] is designed for pollution localization [26••] with little disturbance of chemical substance distribution in water, while in [23] the authors use the robotic fish for estimating a scalar field over a region of interest.

Setting aside the platforms, the variability of operating conditions in a field experiment may lead to poor performance in the presence of external disturbances not taken explicitly into account during the design phase. Notice that experimental results such as odor tracing in a wind tunnel [10•,11–14,15•], underground gas leakage tracing in a and pool [7], and source tracing in a controlled water reservoir [20,23], were all carried out in controlled environments. As a notable exception, the underwater plume tracing mission reported in [17,18] was carried out in open waters.

Source localization methods

Some of the methods for source localization can be traced back to those described in [27], involving the use of classic search patterns (e.g. parallel line, creeping line, square, sector, and barrier patrol search patterns) inspired by the techniques used in the allied search for U-boats in the Bay of Biscay during World War II. From an historical perspective, an interesting survey of early search theory and applications can be found in [28], where the authors addressed a number of practical problems in the areas of search and rescue, mineral exploration, surveillance, and fishing. Each of these applications can be (in)directly related to environmental monitoring. In the following subsections, we present a categorized and concise review of recent autonomous search methods for environmental monitoring and/or pollution source detection.

Gradient-based (Chemotaxis) method

Intuitively, to trace a chemical plume or localize a pollutant source, one of the desirable features of any tracing or localizing algorithm is the ability to sense the concentration of a particular chemical. This is precisely the concept of *Chemotaxis*, first reported in 1881, which refers to the movement of an organism caused by a chemical stimulus [30]. In simple words, chemotaxis consists of following the local gradient of a chemical concentration. In this context plume concentration is viewed as a scalar map with a maximum at the source location and chemotaxis yields a procedure to solve a particular optimization problem. Since its inception, due to its simplicity, chemotaxis has been exploited by many researchers to develop source seeking strategies for single or multiple agents.

We start our review with the single agent framework. In [8], a pseudo gradient-based method for the application of gas source localization was reported and validated in an open air field with the aid of a quadcopter. Inspired by [31], the vehicle attempts to find the plume by sweeping crosswind and then switching to the pseudo gradient-based method by comparing the odor concentration at its current position with that at a previous position and moving towards the larger concentration region.

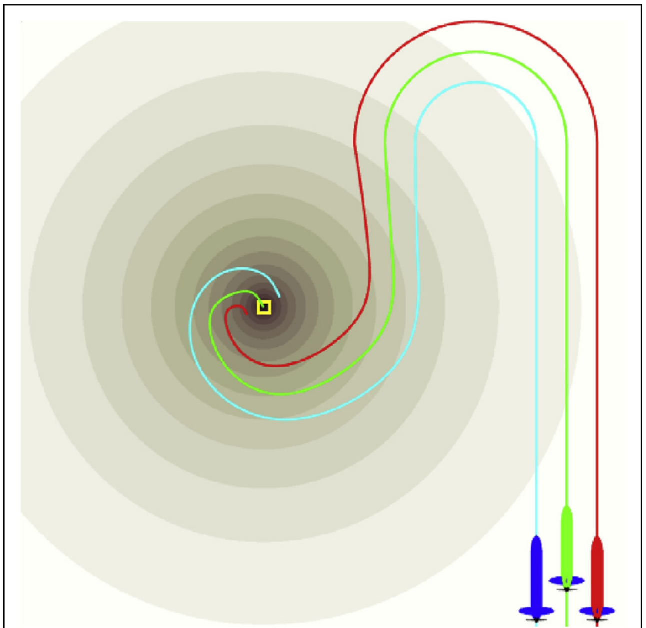
Comparative studies reported in [13] and [7] described experimental results of different chemotaxis algorithms in an in-air and underground source seeking scenario, respectively. In both scenarios, the algorithm inspired by *Escherichia coli* movement resulted in inferior quality of source seeking. This was mainly due to its nature of random change of direction of movement and its sensitivity to added measurement noise. In [13], algorithms inspired by the motion of silkworm moths and dung beetles achieved a better success rate compared to a purely gradient-based method, but at the expense of traveling for a longer distance. In [7], the presented Hex-path algorithm (discretizing the search area by hexagonal cells and move along edges) outperformed the bio-inspired planarian behavior (changing direction of movement based on consecutive measured concentrations) in a scenario of underground chemical leak localization using a burrowing robot.

An interesting approach to three dimensional (3D) environmental extremum seeking navigation of a mobile robot is described in [32]. This study is complemented by experiments using a wheeled ground robot for a smooth scalar field, reported in [33]. The strategy proposed for extremum seeking does not require the direct computation of gradients. However, it is not evident from simulations or experiments if the proposed method can be applied to the localization of a pollution source with a diffusion process in a turbulent medium, e.g. pollution sources modeled in [26••] and [34••]. In spite of the progress done on the use of single agents for source localization, the latter have a number of limitations. For this reason, there has been a flurry of activity on the use of multiple agents, as explained in the sequel.

Moving to a multi-agent framework, there are two possibilities; fixed and flexible formations of group of agents. In [35] the authors proposed a fixed formation of mobile sensor platform for in-air chemical plume tracing in the presence of a time-varying airflow environment. For a given formation speed, the desired formation heading is given as a function of the estimated plume direction. The algorithm was validated through simulations of a large-scale advection-diffusion airflow environment with an achieved success rate of 80%. In [36], the authors proposed a plume tracking and localization algorithm in a turbulent flow using a fleet of agents. The key idea of this algorithm was to transform the detected turbulent flow field into a smooth scalar field in order to make the gradient well defined. The transformation is derived by thresholding the large concentration scalar field values and considering the occurrence of large concentrations, that is a function of distance to the source. The derived control law was such that the direction of the movement of the agents converges to the gradient direction of the smooth scalar field, thereby moving towards the source. However, the required sampling interval is high and choosing smaller sampling intervals leads to longer or unsuccessful source tracing. Further, the results were demonstrated through simulations only.

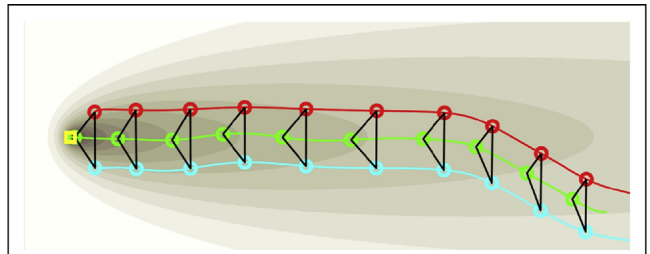
In order to avoid the local maxima issues of gradient algorithms, [37] proposed an adaptive searching scheme called *theseus gradient search* (TGS) for localizing an unknown radio transmitter in indoor environments using received signal strength (RSS). The strategy combines the gradient of the RSS and the exploration of regions that are not traveled in order to ensure that the robot will not get stuck in the local maxima.

Figure 1



(adapted from [29]): Example of chemotaxis of three agents using a leader-follower approach. The brown heat map represents the spatial distribution of expected pollution level. The red, blue, and green tracks indicate movements of the agents in a group formation. The agents start from bottom right without any knowledge about the source location. The strategy starts with a lawn mowing sweeping trajectory. Whenever the agents sense an increase in the intensity of the source signal (e.g. pollution level), they follow the gradient towards the source indicated by the yellow square.

Figure 2



(adapted from [10•]): Example of source localization and tracing with a triangular formation of three agents against the wind direction that is from left to right. The brown heat map represents the spatial distribution of expected pollution level. Agents start from the bottom right without any knowledge of the source location. The green, red, and blue tracks represent movements of the agents, and the corresponding circles show a time lapse of their location as the mission unfolds. Black lines represent the formation of the agents at each time lapse, and the black yellow shows the location of the source.

A simulated leader-follower approach was presented in [29] for source localization using autonomous surface vehicles (ASVs) and AUVs based on gradient information from a scalar field of interest (see Figure 1). The control law that is applied to the agents is determined by an approximation to the gradient of the particular scalar field of interest obtained by collecting measurements taken by the agents. The strategy starts with a predefined search pattern, for instance, a lawn mower sweeping trajectory. Whenever the measured intensity of the scalar field is above a certain threshold, the agents will follow the gradient towards the source.

Wind detection (anemotaxis)

Anemotaxis is the response of an organism to wind. Many insects show a positive anemotactic response (turning or flying into the wind) upon exposure to an airborne stimulus cue from a food source. In simple words, anemotaxis-driven agents focus on the advection portion of the flow. The agents navigate upstream within the plume by measuring the direction of the fluid's velocity. Moths are fascinating examples of anemotaxis agents. As early as 1983, a review of zigzagging and casting as a programmed response to follow wind-borne odor was presented [38]. Later, a study [39] investigated the search strategies of male moths to find female ones by following their scent. More specifically, the authors showed that the male moths balance counterturning and flying upwind depending on the plume structure and frequency of odor encounters, leading to faster and/or straighter upwind motion.

Inspired by search methods taken from male moths flying upwind, similar control laws based on a behavior-based state machine have been implemented on Remote Environmental Monitoring UnitS (REMUS) AUV [40] to trace, reacquire, and localize a plume [17]. Further on a different study [41], the authors used the same idea to install a pair of separated chemical sensors on an AUV for plume tracing in a marine simulated environment. In [42], the authors extended the moth-inspired plume tracing using a single vehicle to multiple vehicles. Although the multi-vehicle algorithm was validated through simulations, experimental results were performed with a single vehicle in [18].

Recently, in [10•,11] a range-based formation control scheme was employed for odor source localization and tracing in a two dimensional (2D) wind tunnel via Laplacian feedback formation control [43] of multiple cooperative robots in a variety of formations (see Figure 2). Source localization was done by plume centering of the formation based on odor measurements obtained from all the robots in the formation. With an extension to a 3D scenario, another study presents simulation and experimental results for 3D distributed plume tracking with a group of land and air robots measuring odor concentration in a wind tunnel [12]. In [44], the authors simulated a group of MEDUSA class of marine vehicles [45] measuring conductivity in a fresh water stream. The work reported in [12,44] exploited the integration of three behaviors: upstream movement, plume centering, and Laplacian feedback formation control.

In a more recent study [46], the authors extended the source localization problem to multiple odor sources and showed the results of source localization with multiple robots in simulation. From an optimal point of view, the formation of swarm robots that maximizes the probability of finding an odor plume in an unknown environment was studied [14]. The authors analytically showed that the optimal configuration is a diagonal upwind moving formation, facing the wind direction. This was validated through simulations and indoor experimental tests.

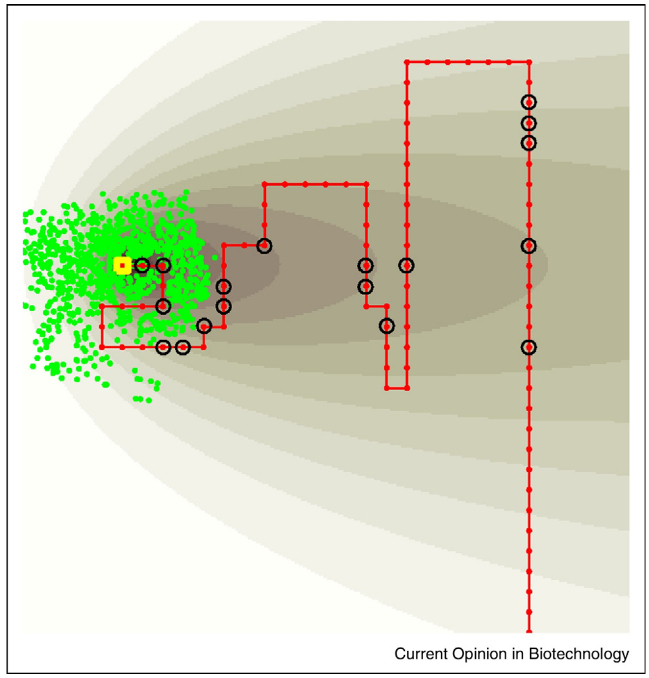
Entropy reduction (infotaxis)

In a turbulent medium like air or water, turbulent flow causes random and disconnected patches of odor or pollution which makes the gradient of information too uncertain to be used for guidance in source seeking. *Infotaxis* [47], a gradient-free method, is a recent addition to the search methodology. From a theoretical standpoint, this method is based on information principles to maximize the entropy reduction. Several studies exploited this method as reported in [34••], see Figure 3, and references therein. In a different study [15•], inspired by moths, the authors attached an electroantennogram of a moth to a robot to indirectly control it. They compared four search strategies, three reactive (combination of upwind surge, spiral casting and crosswind [zigzag] casting) [48], and infotaxis [47]. They concluded that reactive searching is more efficient (yielding shorter trajectories) for higher pheromone doses while infotaxis does a better job in cases with lower doses of pheromones but with more computational cost. In [49], the authors investigated the performance of the infotaxis algorithm on a simulated 3D turbulent channel air flow for two different Reynolds numbers.

The authors in [50] have presented information theoretic search strategies based on [47] for a planar case but also extended the source localization for a group of robot(s) in a turbulent flow, in a 2D [50] and 3D [51] scenario. The clear contribution and advantage are the use of a multi-robot system which is explored in a lossless communication framework communication without any loss of information. In reality, however, underwater communications are severely affected by packet losses and delays.

The infotaxis search problem on a two-dimensional grid but in a distributed form and with agents that are almost memoryless is studied in [52]. The author emphasizes that a good search strategy does not necessarily consist in always trying to approach the source, but also to move orthogonally to the estimated direction of the source, which has been shown analytically in a different application in [53]. In this strategy, which is introduced as *amoebae-infotaxis* model, each agent performs a random walk on the grid and when it makes a detection, it triggers a reaction-diffusion wave in the grid to attract other agents towards itself. In the long term, this will move the group towards the source. The search strategy benefits from a simple implementation for multi-agent systems, but its success is not guaranteed and it might fail in some situations.

Figure 3



(adapted from [34••]): Example of source localization and tracing using infotaxis method. An agent starts from the bottom right without any knowledge of the source location. The brown heat map represents the spatial distribution of expected pollution level. The red track represents movements of the agent, the black circles are pollution detection, the yellow square shows the location of the source, and the green dots show hypotheses of source locations which are close to the true location. Since the current flow is to the right, the agent first sweeps cross-current and approaches the source when detections occur more often.

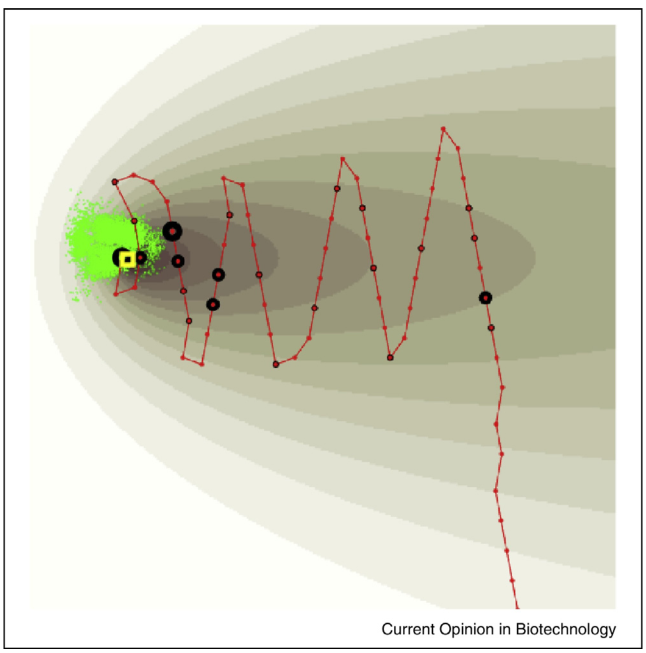
The infotaxis approach is very promising, but as pointed out in [54•], it only remains robust as long as the estimated parameters of the source are within a neighborhood of their true values. If the searcher agent severely underestimates or overestimates the real environment parameters, the success rate quickly drops, making infotaxis no longer feasible.

Information maximization (FIM)

The concept of using the model of an acoustic sensor carried by a mobile agent to decide on the best course of action of that agent so as to maximize the information available for localizing an underwater target using range measurements has been explored in [53,55]. By adopting an estimation-theoretical setting, the key idea exploited is to maximize, by a proper choice of the agent's motion, the information available for source localization. This is done by maximizing the determinant of an appropriately defined Fisher information matrix (FIM), which yields a measure of the minimum covariance of the target estimation error that can possibly be achieved with any unbiased estimator. In practice, as described in [55], this leads to an integrated strategy for target localization that involves motion planning, motion control, and target estimation in sequence over a sliding horizon.

Contrary to infotaxis, where the agent actions are limited to a predefined set of actions, the FIM based approach optimizes a sequence of control actions (that satisfy the vehicle constraints such as bounds on speed and yaw rate) by maximizing a scalar function of an analytically computed FIM over a sliding horizon. Inspired by this approach, the authors in [26••] exploited this concept for the sensor model adapted from [47] and analytically derived the FIM associated to a pollutant source localization problem. Figure 4 shows an example of source localization and tracing using the new methodology proposed.

Figure 4



(adapted from [34••]): Example of source localization and tracing using the information maximization (FIM) method. An agent starts from bottom right without any knowledge about the source location. The red track represents movements of the agent, black circles are pollution detections (diameters proportional to pollution levels), the yellow square shows the location of the source, the green dots show hypotheses of source locations, which are close to the true location. The flow direction is to the right and the brown heat map represents the spatial distribution of expected pollution level.

The optimization problem consisted of finding a sequence of the agent's course angle that maximized a scalar valued function of the FIM, i.e. its determinant. Maximizing the information about the source location resulted in steering the searcher towards the source. One can balance between gathering new knowledge versus exploiting existing knowledge by choosing the sliding time horizon. The FIM approach could possibly suffer from overestimation or underestimation as stated by [54•] for infotaxis. To the best of our knowledge, the successful implementation of the FIM method was reported for the first time in [53], where the objective is to localize a moving underwater target using a surface vehicle that measures its range to the target.

Discussion

The source localization problem has attracted enormous interest over the years and many methods have been proposed with various degrees of sophistication and complexity. In this article, we provided an overview of recent developments in this area that included various applications, different search methods, and platforms employed. Aerial applications have been investigated very extensively due to their early development, ease of deployment, and the use of wind tunnels to simulate an odor source [14]. In contrast to aerial applications, the marine technology is relatively new and still facing challenges such as long sensor response time, low bandwidth underwater communications, and limited vehicle capabilities for cruising and hovering.

Among the search methods, chemotaxis and anemotaxis are model-independent, which is a drawback if the medium is turbulent [15•]. The latter causes disconnected patches of chemical substances with low or high dose, thus making it more difficult to get a good gradient estimation of the scalar field. Moreover, in chemotaxis or anemotaxis there is no feedback mechanism to minimize the uncertainty in the source location. Information based approaches, FIM and infotaxis, use a model of the pollutant in turbulent medium to minimize the uncertainty about the source location. This may lead to poor performance if there is a severe model mismatch [54•]. It is worth mentioning that foraging strategies in nature may exhibit differently, such as the one reported in [56], which showed that mice can efficiently track odor sources with limited prior experience of source locations and consistent with a gradient ascent algorithm. Although, with more experience, they shifted from a sensory driven approach to a more efficient and stereotyped foraging approach that varied little in response to sensory data. Interestingly in [26••] one can notice that the optimal trajectory obtained has a close resemblance with the moth trajectory as reported in [56].

To summarize, we have provided the state-of-art in the domain of various search methods using different search

Figure 5

Graphical abstract.

platforms for source localization, as shown graphically in Figure 5. Although there is less freedom to pick a platform, there are mainly four methods, namely chemotaxis, anemotaxis, infotaxis, and FIM, depending on the application, and each of these methods has its own advantages and disadvantages. The gradient method is simple to implement compared to others but can be troublesome in the presence of turbulence. However, turbulence can be more effectively dealt by using the infotaxis method, which is a gradient-free method. From a conceptual point of view, information maximization seems to be very promising and may prove to play a significant role in many applications in the near future. We next discuss future directions that warrant some attention.

In contrast to single-agent approaches that may require the agent to undergo complicated motions and may take a larger time to converge, multi-agent systems with complementary sensor suites offer a better way to approximate the gradient of signal measured by individual agents and shared among the agents in a centralized or distributed fashion. This helps to drive the formation of agents towards the source [10•,12,23,35,42,50,51,52,57,58,59,60]. Since multi-agent systems provide flexibility, maneuverability to explore regions, and more information, we envision that they hold a great potential and will likely dominate future research directions in the source localization problem. However, from a theoretical standpoint this requires solution to a much harder problem but there are still challenges that needs to be addressed such as testing in open environments, hardware implementation and system integration, and cooperative localization and tracing.

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A range-based formation control scheme was employed for odor source localization and tracing in a 2D wind tunnel via Laplacian feedback formation control of multiple cooperative robots in a variety of formations. Source localization was done by plume centering of formation based on odor measurements obtained from all the robots in the formation

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Inspired by moths, the authors attached an electroantennogram of a moth to a robot to indirectly control it. They compared four search strategies, three reactive (combination of upwind surge, spiral casting and crosswind [zigzag] casting), and infotaxis. The key conclusion was that the reactive search methods are more efficient (yielding shorter trajectories) for higher pheromone doses, while infotaxis performed better under lower doses of pheromones but with a more computational cost.

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This article provides a comparative study of using underwater gliders, AUVs, and remotely operated vehicles (ROVs) for plume detection and tracking. The highlight of this work was that actively propelled AUVs are the most well suited platforms for such tasks due to their autonomy and sufficient payloads, despite their shorter endurance

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