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A 3-D Bio-inspired Odor Source Localization and its Validation in Realistic Environmental Conditions

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Abstract— **Finding the source of gaseous compounds released in the air with robots finds several applications in various critical situations, such as search and rescue. While the distribution of gas in the air is inherently a 3D phenomenon, most of the previous works have downgraded the problem into 2D search, using only ground robots. In this paper, we have designed a bio-inspired 3D algorithm involving cross-wind Lévy Walk, spiralling and upwind surge. The algorithm has been validated using high-fidelity simulations, and evaluated in a wind tunnel which represents a realistic controlled environment, under different conditions in terms of wind speed, source release rates and odor threshold. Studying success rate and execution time, the results show that the proposed method outperforms its 2D counterpart and is robust to the various setup conditions, especially to the source release rate and the odor threshold.**

I. Introduction

With the advances in robotics, embedded systems, and chemical sensors research in the last two decades, odor sniffing robots and sensor nodes have become an active research area. Finding sources of chemical compounds released in the air using mobile robots finds several applications in various critical situations such as security, safety, domestic, and medical domains. Canonical examples are represented by emergency scenarios such as oil spills or wild fires as well as more subtle search problems such as the localization of landmines in a humanitarian demining operation or the identification of dangerous leaks inside tunnels, mines, or production plants.

The main challenges in Odor Source Localization (OSL) are related to the intermittent structure of odor dispersion in the air [1]. Understanding how odor molecules disperse through an environment under naturally turbulent flow is the key to design and development of efficient olfactory search strategies. In outdoor or ventilated indoor environments, the dispersion of odor molecules is dominated by flow turbulence. Odor molecules move downwind due to mean flow velocity, forming an odor plume, while their net 3D motion is almost random, due to small-scale turbulence curls. As the flow carries patches of odor away from the source, the average concentration within a patch decreases and the average time between successive patches increases [1]. Due to the turbulent structure (over large scales) of the air flow, the plume has an irregular packet-like structure, whereby high and low concentrations are close in both time and space. The turbulent behavior of airflow, lack of smooth odor concentration gradients, patchiness of odor concentration, and meandering and time-variant characteristics of odor plumes imply that in real world conditions, classical search algorithms based on concentration gradient do not efficiently work. The inherent 3D structure of the plume also adds up to the complexity of the problem, requiring algorithms and systems capable of 3D planning and motion.

The OSL problem in robotics consists of three sub-problems (phases) [2], [3], although these actions might not be necessarily performed consecutively; (i) *Odor plume acquisition* refers to searching or sampling the environment in order to find an initial cue of the plume (i.e. a first odor patch). (ii) *Plume tracking* is the phase in which the sensing nodes attempt to remain in the plume while approaching the source. This phase typically requires self-locomotion capabilities and it is therefore carried out by robotic nodes. (iii) *Source declaration* is the decision process of localizing an odor source with a certain degree of confidence in its close vicinity. The later sub-problem is usually formulated as a separate problem, and the literature on that subject is far coarser than on plume tracking. Therefore, in this paper we focus on the first two phases (i.e. odor plume finding and tracking).

The solution for OSL starts with finding the odor plume (AKA plume acquisition). This sub-task is usually completed using coverage algorithms, as the task is to explore the environment until the plume is found without having any cues. Systematic casting, zigzagging, Lévy Walk and Correlated Random-walk are among typical solutions in this case. For instance, using the wind direction information Pasternak et al. [4] designed a bio-inspired algorithm called Lévy Taxis which performs a random walk biased by the local wind direction. While all previous works have simplified this search problem to a 2D plane, in this paper we tackle the problem in 3D.

The second sub-task, i.e. odor plume tracking, has been the main focus of most of the studies in robotics. Unlike the first phase, there is a large variety of strategies. In a wide perspective, we divide the previous works into four general categories, that often overlap, to classify odor plume tracking algorithms [5]: gradient-based algorithms, probabilistic and map-based, formation-based and bio-inspired algorithms.

Gradient-based algorithms try to reach to the source by climbing the concentration gradient using multiples samples taken at different positions in the environment. Due to the patchiness of odor plumes, a robot performing these algorithms may eventually reach the source, only if it moves slowly enough to measure the long-term average

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concentration level at each sampling point. Therefore, this type of algorithms, while being the most intuitive, needs relatively a lot of time and sampling to find the source. From a different point of view, probabilistic and map-based algorithms model the source location as a probability distribution function which is derived from the observations made by the agent in the environment [5]. After each new observation, the probability distribution modeling the source location is updated using recursive Bayesian estimation. This process continues until the probability distribution of the source reduces to a Dirac function. Infotaxis [6], Hidden Markov Models [7] and Kernel methods [8], are the main examples of this category. Although these techniques are very promising with a great potential in terms of research, they suffer from high computational costs and the need of accurate localization information for the sampling points. Formation-based algorithms are designed for multi-robot systems such that they can sample the odor concentration in different positions at the same time. The robots share their observations (i.e. odor concentration and wind direction) with other members of the group and determine their relative pose. The topology of the formation is adapted based on the observations and the whole group moves eventually towards the source [9]. Recently a 3D formation-based system has also been presented [10]. In general, these methods have low computational and memory requirements, while need at least two robots and a mean of inter-robot relative positioning.

The ability to localize odor sources is crucial to many living species and plays an important role throughout the evolution process. Hence, OSL strategies used by animals are supposedly highly optimized, and constitute the most studied class of algorithm which tries to take inspiration from living organisms such as moth, bacteria, dung beetle, etc. [11]. In [12] and [13] Lochmatter presented a novel moth-inspired algorithm called Surge-Cast, tested along with two other algorithms of the same class, namely Casting and Surge-Spiral, with one wheeled robot. In our previous work [14], we adapted a Lévy Taxis algorithm to the plume tracking phase, by adjusting the key parameters of the algorithm during the run, using the odor concentration gradient sensed by the robot in the environment. The resulting method turned out to be more robust to a larger variety of environmental conditions when compared to typical bio-inspired algorithms such as Casting, Surge Cast, Surge Spiral. In general, bio-inspired algorithms usually define the behavior of the agent, using a finite state machine and are based on both chemotaxis and anemotaxis. They have the advantages of requiring small memory and computational resources for the agent and not requiring accurate localization. Moreover, they do not rely on any a priori information about the environment or its atmospheric conditions to operate, which makes them efficient for unknown areas.

Although most of the previous works are based on wheeled robots in 2D, recently there has been some attention towards 3D plume tracking. In 2006, Russell developed a robot with a sensor head capable of vertical movements in a limited range [15]. He used a simple algorithm based on zigzag path of the dung beetles to track the plume in 3D. Moth-inspired algorithms have also been adapted to 3D recently by Gao et al. [16] in simplified simulations, based on traditional 2D techniques. Having multiple sensors on the sides of the robot and measuring the local 3D gradient of odor concentrations, they have added a pitch angle to the heading of the robot. This modification is done only in the phase of upwind surge but not in the phase of plume retrieval. In another work, Edwards et al. [17] proposed a 3D moth-inspired algorithm that uses the plume edge (or the plume center-line in the modified version) to modify the timing of the crosswind movements. This algorithm was tested in a small realistic environment, using an ion source. Most of these algorithms are designed and tested in highly simplified environments.

The contribution of this work is the development of a 3D bio-inspired algorithm and its evaluation in a realistic environment, as well as the assessment of a 2D baseline method of the same category, in challenging conditions. To the best of our knowledge, none of the previous works has proposed a complete 3D bio-inspired algorithm that addresses plume acquisition and tracking in realistic environmental conditions. In the following sections of this paper, we present our proposed method in detail, then we explain the implementation and evaluation setups, along with the results and discussions.

II. Proposed method

The method that we propose in this paper covers the two first phases of the OSL problem, i.e. *plume acquisition* and *plume tracking*. In addition, in order to rigorously set the critical parameter of the algorithm, we perform an initial calibration phase before letting the robot start the actual process.

A. Plume acquisition: Lévy Walk on a crosswind plane

In the *plume acquisition* phase, the goal being to find the odor plume, the gas sensor of the robot has not detected any odor patch yet. Therefore, the robot needs to randomly or systematically scan the environment to find the first indication.

For this purpose, we chose Lévy Walk as a search algorithm, since it has been shown that the probability of returning to the previous position with Lévy Walk is smaller compared with other random walk mechanisms [18]. Lévy walk is performed by many living beings (e.g., Drosophilia [19] and honey bees [20]) for foraging, and has the advantage of allowing the searcher to maximize the number of visited targets, versus the traveled distance [20].

As we are addressing the problem of OSL in 3D, searching the entire space for the plume seems very time consuming, as the agent does not have any a priori information about the plume. On the other hand, performing a search on a 2D plane perpendicular to the wind direction allows the agent to find the plume in a quicker and more efficient way.

In this work, the wind orientation is not measured but assumed to be laminar and aligned with the X-axis. Therefore, as the crosswind plane would be Y-Z, the global process of the first phase of our algorithm is as follows: the agent starts

the search from a random position and moves only on the crosswind plane Y-Z according to the governing law of Lévy Walk, in order to encounter the plume. At each step, the robot moves to a point determined by a move length (M_l) (AKA step length) calculated based on a fixed probability distribution presented in Eq. (1), as well as a uniformly distributed random turning angle $T_a \in [0, 2\pi]$.

$$M_l = L_{min}.r^{\frac{1}{1-\mu}} \tag{1}$$

with M_l the move length, r a random variable uniformly distributed $r \in [0, 1]$, L_{min} the minimum move length, and μ (Lévy-index) the move length's key parameter $(1 < \mu \leq 3)$. In this work, in order to maximize the exploration of the area, we set μ to its maximal value 3 and chose a relatively long L_{min} of 50 cm.

Thus, for a robot located at (x_0, y_0, z_0) that needs to take a step, once M_l and T_a are calculated, the target position to move towards will be as presented in Eq. (2).

$$\begin{aligned} x &= x_0 \\ y &= y_0 + M_l \ . \ \sin(T_a) \\ z &= z_0 + M_l \ . \ \cos(T_a) \end{aligned} \tag{2}$$

Bio-inspired algorithms usually use an odor concentration threshold O_{th} beyond which they consider the agent being in the plume and out otherwise. Even though it is a crucial parameter of the algorithm, in the literature, this value is usually set empirically and kept fixed for multiple runs, during which the shape and other characteristics of the plume might change. In order to systematically determine the appropriate value for each run, we have developed a mathematical approach based on the Advective-Diffusive Equations (ADE) presented in [14]. Using a data set of samples taken before each run along the crosswind section of the experimental environment, the cumulative distribution function is established. Then a constant probability threshold P_{th} is chosen based on the distribution of the data. The concentration value which corresponds to the probability threshold P_{th} on the cumulative distribution function is therefore set as odor concentration threshold O_{th}.

B. Plume tracking: up-wind surge and 3D spiralling

Once the plume is encountered, the *plume tracking* phase begins. We design two alternating behaviors to address this phase; "upwind surge" and "spiralling on the 3rd dimension". The details of the two behaviors are explained in the following.

In nature, although the behavior of different species (e.g., crab, lobster, moth, salmon) are not exactly the same, they all seem to pursue the upstream path while in contact with the plume [21]. This behavior is used in many bio-inspired robotic OSL works as well (e.g., [16], [15]). Therefore in this work also, the robot goes upwind with a constant speed once in contact with the plume.

However, if the robot loses the plume, either due to the plume's conic shape or patchiness, or an error in the wind direction estimation, it needs to search the environment in order to reacquire the plume once again. This search should

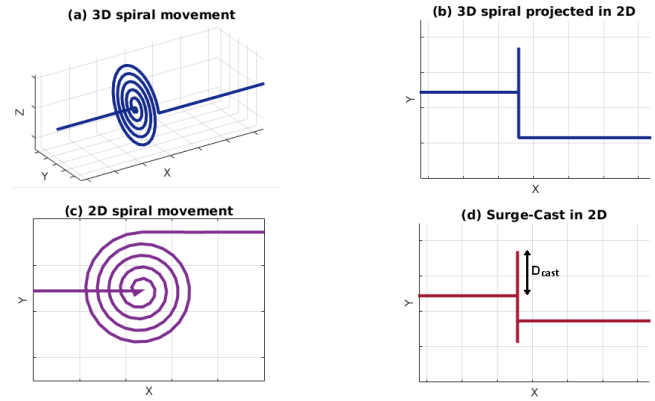

Fig. 1. Trajectories of different behaviors: (a) and (b) 3D spiralling, (c) 2D spiralling, (d) 2D Surge-Cast.

not necessarily be a random walk as the first phase, since the robot is most probably very close to the plume and thus a local search would be more efficient to find the plume back.

For re-finding the plume, in similar works (e.g., [15], [16]), different bio-inspired behaviors have been developed. One of the behaviors that has always shown outstanding performance in terms of success rate in 2D scenarios, is the spiralling movement [5], [22]. Therefore, we take advantage of this particular algorithm and upgrade it to 3D (which is closer to the reality in nature). This behavior is inspired by the spiralling movement of moths while searching for an odor plume [23], [24].

Moths' behavior being in 3D, the spiralling movement is performed on a crosswind plane where the chance of plume reacquisition is the highest. Thus in this work, we implemented the spiralling movement on the crosswind Y-Z plane. Ultimately, all 3 dimensions are covered by the combination of the upwind surge (along X-axis) and the spiralling (on Y-Z plane). Therefore, in this local search, the coordinates of a target position for a step are expressed in Eq.(3).

$$\begin{aligned} x &= x_c \\ y &= y_c + s_d \ . \ t \ . \ \cos(2\pi t) \\ z &= z_c + s_d \ . \ t \ . \ \sin(2\pi t) \end{aligned} \tag{3}$$

with (x_c, y_c, z_c) the position where the robot loses the plume and thus needs to search the surroundings, s_d the spiral drift which determines the distance between the laps of the spiral movement, and t the iteration of the local search. As shown by the Eq. (3), the movement on the X-axis stops until the plume is retrieved.

Even though mimicking the natural models is the most common idea in bio-inspired robotics, this behavior of moths has never been previously implemented in 3D for OSL.

C. Source identification

In the *source identification* phase, the robot has to identify the source and declare success. In this work, as we focused on the two first phases of the problem, we consider the source localized if the robots reaches an area of $20 \times 20 \times 20\ cm^3$ around the source while still being in the plume (see Fig. 2).

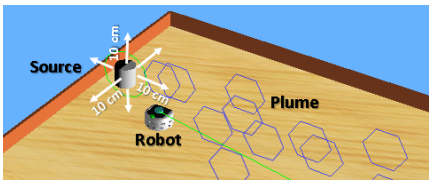

Fig. 2. Margin of the source area in simulation

This identification, however, could have been done more rigorously using existing algorithms such as [25] which is an idea for a future work.

III. Performance Evaluation

In the present section, we explain the evaluation methodology of the algorithmic performances.

A. Baseline 2D method

Despite the similarity, the projection of the 3D method in 2D would not be the Surge-Spiral, but the Surge-Cast algorithm [5] which performs a local search on the crosswind dimension (see Fig. 1). Therefore we chose the Surge-Cast algorithm [13] as reference in terms of performances. We have adapted this algorithm to the procedure of our 3D proposed method in order to have a fair comparison.

Assuming that the X-axis is towards the down-wind direction, the strategy of this reference method would be the following: after establishing the odor concentration threshold O_{th} at the fixed altitude, the robot moves to a random position on the Y-axis, at the beginning of the experimental environment. At this point, it performs Lévy Walk on the Y-axis (crosswind) in order to find the plume, while maintaining constant its position on the X and Z axes.

Once the plume is retrieved, the robot moves upwind (i.e. towards the X-axis), while remaing in the plume. As soon as the plume is lost, the robot moves crosswind for a distance of D_{cast} (here 43 cm based on [5]). If the plume is found during this movement, the upwind surge is resumed, otherwise the robot performs another crosswind surge, in the opposite direction, for a distance of $2 \times D_{cast}$ (see Fig. 1d). This local search continues by exploring more either sides each time, until the plume is reacquired.

B. Essential parameters of the setup

The performances of our method and the reference algorithm have been verified in different setups involving different parameters. In the present section, we describe the parameters that we varied as well as their potential impact on the experiment and simulation results. The chosen values for each parameter correspond to the ones of a realistic and challenging environment. Table I provides a list of these parameters and their values. The description of each parameter is provided thereafter.

1) Odor source release rate: The release rate of the source has a significant impact on the algorithms performance, since it shapes the structure of the plume. The higher the release rate of the source for a given wind speed, the richer the plume, and thus the easier the task of the robot to track it to the source. Theoretically, the structure of the averaged plume depends on the ratio between the wind speed and the source release rate. However, in this work, we found it interesting to verify the impacts of both parameters separately in realistic experiments.

TABLE I

Setup parameters used in the experiments and simulations

Setup	Wind speed	Source rate	Odor threshold
A	0.2 m/s	low	70%
B	0.2 m/s	low	90%
C	0.2 m/s	high	70%
D	0.2 m/s	high	90%
E	0.9 m/s	low	70%
F	0.9 m/s	low	90%
G	0.9 m/s	high	70%
H	0.9 m/s	high	90%

In this paper we conducted the simulations and experiments while setting the odor source release rate to two different (low and high) values. Further details are provided in Section III-E.3.

2) Wind speed: In a strong air flow the plume becomes very narrow. In this case, the first phase of the problem, i.e. *plume acquisition*, becomes as difficult as the size of the environment to be searched. However, once the plume is found, tracking it towards the source is supposedly easier than the case of a wide plume. As opposed to this case, when the wind speed is low, the plume gets wider, which can be found very easily, but does not give the robot a strong clue to follow in order to reach the source. Therefore, the robot might lose the plume multiple times and thus lose a lot of time, which may lead to a failure. As the time penalty caused by multiple local searches is most likely higher than that of a long plume acquisition phase, we expect a better performance for our algorithms in the case of a stronger wind and high source release rate.

In this paper, we verify the impact of this parameter on the algorithms, while keeping the direction of the laminar air flow fixed in the experiments and simulations. We set its speed to 0.2 and 0.9 m/s, in order to have both narrow and wide plumes.

3) Odor threshold: While the two previous parameters depend on the environment of the experiment and directly affect the structure of the plume, the odor threshold determines how the robot captures the plume. In other words, the odor threshold is the value beyond which the robot is considered being inside the plume, and outside otherwise. Therefore, if this value is chosen too high, the plume seen by the robot is very narrow and patchy. On the other hand, a very low value yields a misleading large plume seen by the robot.

As the shape of the plume might vary from one run to another in the same setup, we decided to determine the odor threshold in a way that respects the fairness between runs, as explained in Section II-A. The probability threshold P_{th} is however a design choice and can be set to different values impacting the performance of the algorithm on various

environmental conditions.

In the simulations and experiments of this paper we set P_{th} empirically to 0.7 and 0.9. These values mean that we consider the robot inside the plume if it reads an odor concentration higher than respectively 70 or 90% of the preliminary calibration phase. However, the absolute threshold value O_{th} corresponding to the odor concentration might change between the runs of a single setup.

4) Initial position of the robots with respect to the source: The position where the robot starts the operation has a high impact on the performance of the algorithms. In order to be fair between the runs of both algorithms, we chose to place the robot on a random initial position on the crosswind section, and 10 m far from the source in the X-axis (downwind direction). As the 2D algorithm needs to be restrained on a fixed altitude, we have chosen to set it at a certain altitude z of 10 cm below the one of the source (in this paper placed at 50 cm from ground).

C. Metrics

The performances of both algorithms have been evaluated using two metrics: success rate and execution time.

A run is considered successful if the robot reaches the source area while being inside the plume, within the time window of 12 minutes. This time out is an arbitrary value that is twice longer than most of usual successful runs. Therefore, for each setup, the number of successful runs over the total number of runs is called success rate s_r as expressed in Eq. (4).

$$s_r = \frac{\#success}{\#runs} \tag{4}$$

The other metric would simply be the time spent by the robot in the experiment. It is calculated from the moment when it starts the search from its initial position, until it declares success by reaching the source. As the robot travels with a constant speed of 50 mm/s, and no turnings are required in the movements, it is fair to simply consider the time instead of the traveled distance. This metric is not taken into account for failed runs.

D. Simulations

Before evaluating the proposed method in real-world experiments, we have developed and tested the algorithm in simulation.

1) Webots environment: We used Webots [26] which is a high-fidelity submicroscopic robotic simulation software. An odor dispersion simulator plugin [27] has also been developed which allows a realistic simulation of wind and odor plume, based on the filament-based atmospheric dispersion model proposed in [28], as well as using olfaction and anemometry sensors on robots. Using these tools, we have been able to simulate a realistic odor plume in a large environment of $20 \times 4 \times 2\ m^3$ (see Fig. 3).

2) Simulated robot: By removing the gravity in the experiment, we were able to use a simulated Khepera robot, equipped with an olfactory sensor, as an aerial robot. The behavior of the agent was implemented as explained in the previous section.

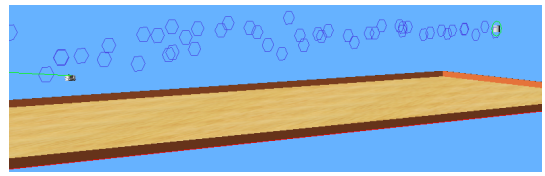

Fig. 3. Simulation setup; the blue hexagons represent the odor patches, the robot is in left and the source in the right side.

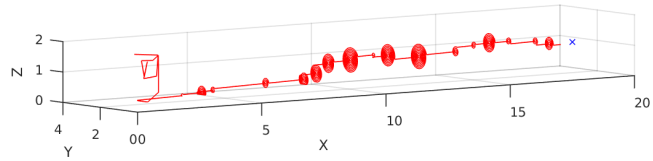

Fig. 4. Trajectory of the proposed 3D algorithm in simulation

3) Simulation results: An example trajectory of the agent is shown in Fig. 4. For every setup exposed in Tab. I, the method has been run 20 times and the results are summarized in Fig. 5. As expected, the performance of the algorithm is outstanding even in complex environmental conditions such as the setup A. In the lower wind-speed the general performance in terms of success rate is not affected, however in terms of execution time, setups with lower wind-speeds took about 100 s more for a given threshold P_{th} and source release rate. This is due to the time the robot has to spend on local search when it loses the plume. The two other parameters, i.e. source release rate and odor threshold, did not have a significant impact on the performance. This implies that the algorithm is robust to these parameters.

E. Realistic Experiments

1) Wind tunnel setup: In order to evaluate the performance of the algorithms in a repeatable fashion, our real-world experiments are carried out in a wind tunnel of volume $18 \times 4 \times 1.9\ m^3$, which provides a controllable laminar wind flow.

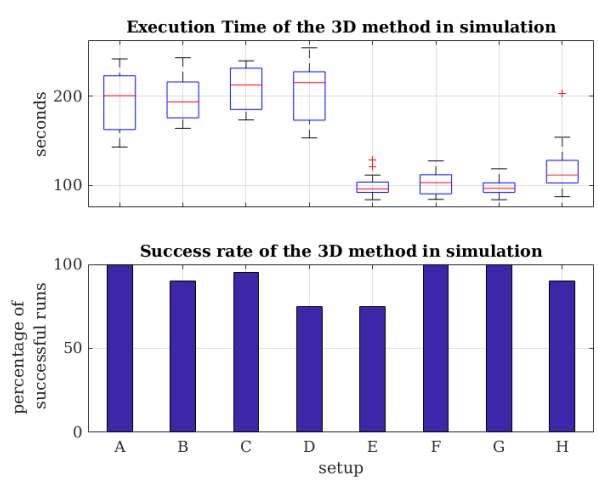

Fig. 5. Performances of the proposed 3D algorithm in simulation in different setups

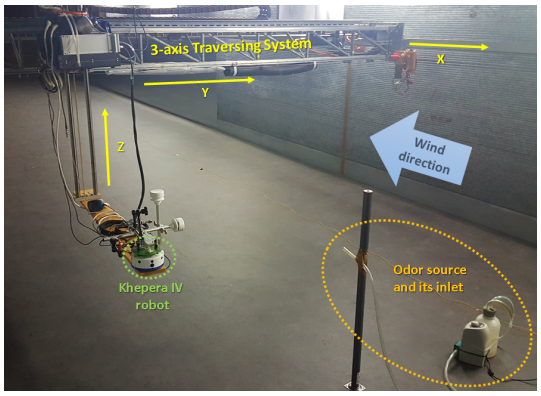

Fig. 6. Wind tunnel equipped with a 3-axis traversing system, the Khepera IV robot and an odor source

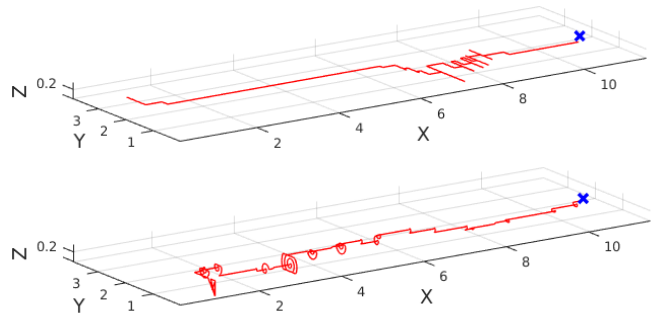

Fig. 7. Trajectory of two successful runs of both algorithms (2D on top and 3D on bottom) in the wind tunnel, with the wind speed of 0.9 m/s towards -X, source release rate of 18% and P_{th} of 0.7. The blue cross shows the position of the source.

2) Robot: Our wind tunnel is also equipped with a controllable 3-axis traversing system, on which we mounted a wheeled Khepera IV robot equipped with an olfaction sensor MiCS-5521 CO/VOC [29] (see Fig. 6). The system composed by the traversing system and the Khepera robot represents an emulated aerial robot, able to move in 3 axes. Thus, given a position $p(x, y, z)$, the aerial robot moves towards p with a constant speed. A similar system has been used in [10].

3) Emulated odor source: The odor source used in this work is an stationary electric pumping device vaporizing liquid acetone. While the exact amount of released gas in ppm is not controllable with this device, a percentage of the pump power can be set in order to adjust the release rate. For this work, we have carried out experiments with 8% (low) and 18% (high) . In both cases, human nose is not able to detect the acetone smell in the environment.

4) Robot Trajectories: Fig. 7 shows two sample trajectories performed by the 2D and 3D algorithms, respectively. Both trajectories start with a crosswind search, on Y-Z plane for the 3D algorithm and on Y-axis for the 2D method. In the rest of the trajectories, upwind surge and local search are performed sequentially. It should be noted that the movement of the traversing system is limited to its working area borders, therefore some trajectories, such as the spiralling, are truncated at the margins of this area. The blue cross shows the position of the source and the wind is oriented towards -X.

5) Experimental results: Fig. 8 summarizes the results of the 2D baseline method for sets of 5 runs for each setup. The group of results corresponding to conditions with high speed wind have better performance in terms of success rate and spent time. The 2D algorithm does not yield satisfactory results in case of a low-speed wind, and is less efficient is general.

Since the plume gets wider (in cross-wind plane) as it travels far from the source, the robot can sense the plume at the beginning of the experiment even if it is located in a lower altitude with respect to the source. However, by tracking the plume towards the upwind direction and getting closer to the source where the plume is narrower, it becomes harder to sense the plume and thus the robot has to perform multiple local searches in the process. This is why a 2D algorithm results in not a reliable performance, even in case the source is located only 10 cm higher than the operation plane of the robot.

We have also evaluated the presented method 10 times for each setup described in Table I, and the results are shown in Fig. 9.

The 3D method shows, as expected, outstanding performance in case of high-speed wind and high release rate, since the amount of information transmitted from the source to the robot is sufficient to guide it correctly. Even in low wind speed, the 3D method's performance are satisfactory compared to the 2D baseline algorithm.

It is also interesting to note that, in the setup F (i.e. wind speed = 0.9 m/s, source rate = low and P_{th} = 90%), even though the source release rate is not high, the higher odor threshold, compared to the case E, has compensated for the environmental conditions and the 3D algorithm remained totally successful. However, this did not happen for the cases B and D, where the wind speed was very low. This proves that the wind speed is more significant than the other two parameters and thus the proposed method, while being generally successful in different environmental conditions, is sensitive to the cases where the wind speed is too low.

IV. Conclusion

We proposed a bio-inspired 3D algorithm which involves cross-wind Lévy Walk, upwind surge and crosswind spiralling for the problem of odor source localization. The algorithm was validated in simulation and evaluated in a realistic controlled environment under different environmental conditions. Since the algorithm is inspired from nature, it needs very little a priori data and computational resources. The comparison between the 3D method and its 2D counterpart shows that unless the source is located on the ground, an aerial vehicle and a 3D algorithm are needed to robustly find the source. Studying three main parameters, the experiments showed that the wind speed is more significant than the other two parameters and thus the proposed method, while being generally successful in different environmental conditions, is sensitive to the cases that the wind speed is too low.

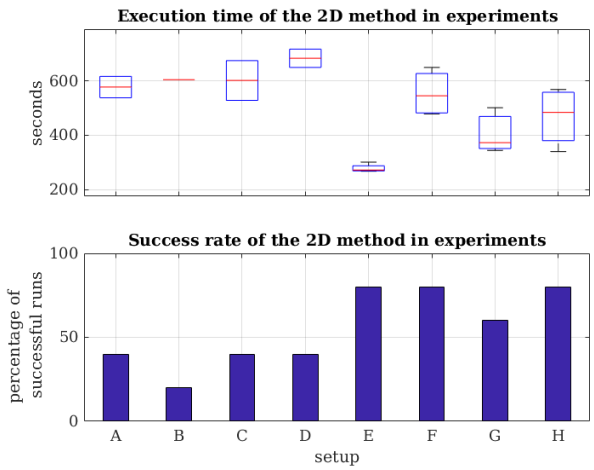

Fig. 8. Performances of Surge-Cast algorithm in real-world experiments in different setups

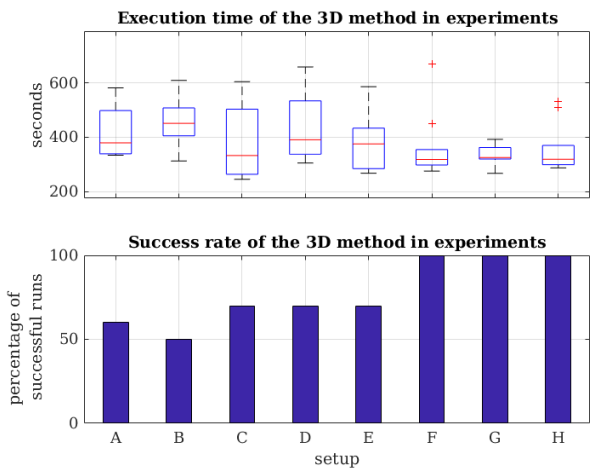

Fig. 9. Performances of proposed 3D algorithm in real-world experiments in different setups

References

[1] J. A. Farrell, J. Murlis, X. Long, W. Li, and R. T. Cardé, "Filament-based atmospheric dispersion model to achieve short time-scale structure of odor plumes," *Environmental fluid mechanics*, vol. 2, no. 1-2, pp. 143–169, 2002.

[2] R. A. Russell, D. Thiel, R. Deveza, and A. Mackay-Sim, "A robotic system to locate hazardous chemical leaks," in *IEEE Conf. on Robotics and Automation*, vol. 1, 1995, pp. 556–561.

[3] A. T. Hayes, A. Martinoli, and R. M. Goodman, "Distributed odor source localization," *IEEE Sensors Journal*, vol. 2, no. 3, pp. 260–271, 2002.

[4] Z. Pasternak, F. Bartumeus, and F. W. Grasso, "Lévy-taxis: a novel search strategy for finding odor plumes in turbulent flow-dominated environments," *Journal of Physics A: Mathematical and Theoretical*, vol. 42, no. 43, p. 434010, 2009.

[5] T. Lochmatter, "Bio-inspired and probabilistic algorithms for distributed odor source localization using mobile robots," *PhD Thesis 4628, EPFL*, 2010.

[6] M. Vergassola, E. Villermaux, and B. I. Shraiman, "Infotaxis as a strategy for searching without gradients," *Nature*, vol. 445, no. 7126, pp. 406–409, 2007.

[7] J. A. Farrell, S. Pang, and W. Li, "Plume mapping via hidden markov methods," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 33, no. 6, pp. 850–863, 2003.

[8] M. Reggente and A. J. Lilienthal, "The 3d-kernel dm+ v/w algorithm: Using wind information in three dimensional gas distribution modelling with a mobile robot," in *IEEE Sensors*, 2010, pp. 999–1004.

[9] T. Lochmatter, E. A. Göl, I. Navarro, and A. Martinoli, "A plume tracking algorithm based on crosswind formations," in *Distributed Autonomous Robotic Systems*, 2013, pp. 91–102.

[10] J. M. Soares, A. Marjovi, J. Giezendanner, A. Kodiyan, A. P. Aguiar, A. M. Pascoal, and A. Martinoli, "Towards 3-d distributed odor source localization: an extended graph-based formation control algorithm for plume tracking," in *IEEE/RSJ Int. Conf. on Robots and Systems*, 2016, pp. 1729–1736.

[11] G. Kowadlo and R. A. Russell, "Robot odor localization: a taxonomy and survey," *The Int. Journal of Robotics Research*, vol. 27, no. 8, pp. 869–894, 2008.

[12] T. Lochmatter and A. Martinoli, "Simulation experiments with bio-inspired algorithms for odor source localization in laminar wind flow," in *Int. Conf. on Machine Learning and Applications*, 2008, pp. 437–443.

[13] ——, "Tracking odor plumes in a laminar wind field with bio-inspired algorithms," in *Experimental robotics*, 2009, pp. 473–482.

[14] R. Emery, F. Rahbar, A. Marjovi, and A. Martinoli, "Adaptive Lévy Taxis for Odor Source Localization in Realistic Environmental Conditions," in *IEEE Int. Conf. on Robotics and Automation*, 2017, pp. 3552–3559.

[15] R. A. Russell, "Tracking chemical plumes in 3-dimensions," in *IEEE Conf. on Robotics and Biomimetics*, 2006, pp. 31–36.

[16] B. Gao, H. Li, W. Li, and F. Sun, "3d moth-inspired chemical plume tracking and adaptive step control strategy," *Adaptive Behavior*, vol. 24, no. 1, pp. 52–65, 2016.

[17] S. Edwards, A. J. Rutkowski, R. D. Quinn, and M. A. Willis, "Moth-inspired plume tracking strategies in three-dimensions," in *IEEE Int. Conf. on Robotics and Automation*, 2005, pp. 1669–1674.

[18] G. M. Viswanathan, V. Afanasyev, S. V. Buldyrev, S. Havlin, M. G. E. da Luz, E. P. Raposo, and H. E. Stanley, "Levy flights in random searches," *Physica A: Statistical Mechanics and its Applications*, vol. 282, no. 1, pp. 1–12, 2000.

[19] A. M. Reynolds and M. A. Frye, "Free-flight odor tracking in Drosophila is consistent with an optimal intermittent scale-free search," *PLoS ONE*, vol. 2, no. 4, p. e354, 2007.

[20] D. K. Sutantyo, S. Kernbach, V. a. Nepomnyashchikh, and P. Levi, "Multi-Robot Searching Algorithm Using Levy Flight and Artificial Potential Field," in *IEEE International Workshop on Safety, Security, and Rescue Robotics*, no. July, 2010, pp. 26–30.

[21] N. J. Vickers, "Mechanisms of animal navigation in odor plumes," *Biological Bulletin*, vol. 198, no. 2, pp. 203–212, 2000.

[22] G. Ferri, E. Caselli, V. Mattoli, A. Mondini, B. Mazzolai, and P. Dario, "SPIRAL : A novel biologically-inspired algorithm for gas / odor source localization in an indoor environment with no strong airflow," *Robotics and Autonomous Systems*, vol. 57, no. 4, pp. 393–402, 2009.

[23] R. Kanzaki, N. Sugi, and T. Shibuya, "Self-generated zigzag turning of Bombyx mori males during pheromone-mediated upwind walking (physology)," *Zoological science*, vol. 9, no. 3, pp. 515–527, jun 1992.

[24] A. J. Rutkowski, R. D. Quinn, and M. A. Willis, "Three-dimensional characterization of the wind-borne pheromone tracking behavior of male hawkmoths , Manduca sexta," *Journal of Comparative Physiology A: Neuroethology, Sensory, Neural, and Behavioral Physiology*, vol. 195, no. 1, pp. 39–54, 2009.

[25] G. Cabrita and L. Marques, "Divergence-based odor source declaration," in *9th Asian Control Conf.*, 2013, pp. 1–6.

[26] O. Michel, "Webots TM : Professional Mobile Robot Simulation," *Int. Journal of Advanced Robotic Systems*, vol. 1, no. 1, pp. 39–42, 2004.

[27] Wikibooks, "Webots odor simulation — wikibooks, the free textbook project," 2010, [Online; accessed 7-November-2016]. [Online]. Available: https://en.wikibooks.org/w/index.php?title=Webots_Odor_Simulation&oldid=1966420

[28] J. A. Farrell, J. Murlis, X. Long, W. Li, and R. T. Cardé, "Filament-Based Atmospheric Dispersion Model to Achieve Short Time-Scale Structure of Odor Plumes," *Environmental Fluid Mechanics*, vol. 2, no. 1, pp. 143–169, 2002.

[29] SGX Sensortech technologies, "MiCS-5521 CO/VOC sensor," url: http://www.sgxsensortech.com.