Authors' accepted manuscript: Frontiers in Artificial Intelligence and Applications
(FAIA), IOS Press, 2018. doi: 10.3233/978-1-61499-929-4-110

Probabilistic Estimation of the Gas Source Location in Indoor Environments by Combining Gas and Wind Observations

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Abstract. This work deals with the problem of gas source localization by a mobile robot with gas and wind sensing capabilities. Particularly, we address the problem for the case of indoor environments where the presence of obstacles and the complex structure provoke the chaotic dispersion of the gases. Under these challenging conditions where traditional approaches based on mathematical modeling of the plume cannot be applied, we propose the use of numerical methods to solve the gas dispersion and its exploitation in a probabilistic formulation to estimate the likelihood of the gas source location from a set of sparse observations. We validate our approach with a simulated set of experiments in an office-like environment composed of multiple connected rooms. Two search strategies are compared (active and passive) demonstrating the suitability of our approach to infer the location of the source even when the robot is not actively searching for it.

Keywords. gas source localization, probabilistic localization, mobile robots, artificial olfaction

1. Introduction

The term *gas source* refers to any element in an environment with the property of releasing volatile substances (gases) into the air. This includes a large number of items like open waste containers, pipe leaks, explosives, or decomposing organic matter. The emitted gases from sources are dispersed in the environment following different physical principles, mainly diffusion and advection [2], which in turn depend on numerous environmental factors such as the wind direction and speed, the temperature, or the humidity, among others. This fact greatly hinders the accurate location of gas sources: the gases detected at large distances from their origin might have followed quite different, unpredictable paths, especially in complex scenarios where the presence of obstacles (walls, furniture, etc.) and inlets/outlets (doors and windows) cause turbulences and interferences with the path that largely modify the dispersion patterns [23].

Therefore, the location estimation of a gas source consists of inferring the position of the object releasing the gas from a series of observations (typically, gas concentration

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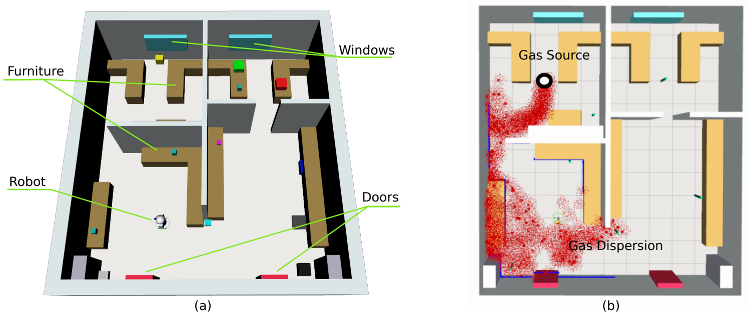

Figure 1. (a) Illustration of an office-like indoor environment with multiple objects that may potentially release gases. (b) Snapshot enlightening the complexity of the gas dispersal within indoor environments. As can be seen, there is not a straight and well formed downwind plume, but the collision with walls and furniture breaks it down into patches (image generated with GADEN [15]).

and wind vector) the position of the object releasing the gas (see Fig. 1). There are a variety of applications that would benefit from a system capable of locating sources of volatile substances, including: finding survivors in catastrophic areas, stopping a fire or leak in its initial stages, detecting explosives, drugs or dangerous agents, or monitoring landfills and chemical warehouses.

Traditionally, this problem has been addressed from two different perspectives: the deployment of fixed sensor networks [24], and the use of autonomous vehicles with olfactory capabilities [1] [20] [7]. Although the former approach enables the measurement of the gases dispersed in the environment at multiple locations simultaneously, in this work we opted for employing a mobile robot equipped with an "electronic nose" or "e-nose"[22] and an anemometer because they enable the measurement of gas concentration and wind velocity and direction at different spatial resolutions and in an adaptive way. Furthermore, a mobile robot brings the possibility of merging the chemical information with other sensory systems like laser scanners, cameras, etc., making it a very interesting and promising line of research.

Despite the advantages that a mobile robot brings, the estimation of the location of the gas source is not a simple task, particularly when carried out in indoor environments where the presence of obstacles contributes towards a chaotic gas dispersion. This is noticeable in the fact that most of the proposed works addressing this problem are accomplished under simplified and controlled scenarios [17], assuming the existence of laminar and/or homogeneous wind flows, and without accounting for obstacles that may interfere in the gas dispersion. As a consequence of relying on such strong premises, the proposed solutions are not applicable to most real environments.

Particularly, our interest is in indoor environments, with the presence of multiple rooms and obstacles, where a mathematical model of the gas dispersion is not available due to its inherent complexity. We model the environment as a 3D grid of cells, each one being free or occupied, and consider a set of gas source location candidates (e.g. a coarser tessellation of the grid map) on which to estimate the source probability. Then, our goal is to estimate the probability of this source-map, based on a Bayesian-probabilistic framework, from a sequence of wind and gas concentration measurements collected by a mobile robot. To overcome the lack of a mathematical model of the gas dispersion, we propose a solution based on computational fluid dynamics (CFD) and gas

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dispersal simulation tools. The goal is to generate a set of likely gas dispersal scenarios from which the probability distribution of the gas concentration and wind map can be estimated.

In this paper, after a summary of related works in Section 2, Section 3 introduces the graph representation of the problem (i.e. Bayesian network) and derives the probability of each cell in the map to contain the gas source from a sparse set of observations. After this, Section 4 outlines the implementation details and Section 5 presents an illustrative experiment in an office like environment to validate the proposal. We conclude this work in Section 6 with a discussion of the results and an analysis of future steps to improve the gas source localization process.

2. Related Work

The interest in estimating the location of gas sources by means of mobile robots endowed with olfactory capacities is not new, as shown by the diverse strategies proposed over the last two decades. The first works to appear were based on the concept of *chemotaxis* or orientation-reaction in response to a chemical stimulus. Examples are the works proposed by Rozas [19] using a single mobile robot, and by Genovese [6] or Buscemi [4] for the case of multiple robots. Also, bio-inspired methods were proposed relying on how moths search for their partners [12, 18], how lobsters seek food [8], or how bacteria Escherichia-coli locates nutrients [21], among others.

Exploiting the fact that the wind flow is the main factor in the dispersion of gases, different proposals were presented making use, not only of the gas concentration measurements, but also of the wind flow direction and strength [10, 13]. These works fall into the category of *fluxotaxis*, or orientation in response to the gas flow.

More recently, cognitive algorithms for solving the source location problem have gained importance in the scientific community. Their main contribution is the integration of probabilistic frameworks to estimate the source location. Examples are Infotaxis [26], a search method that proposes to move the robot in the direction of the places where more information exists in order to minimize the entropy of the source location and not directly to it, or [27], where expectation maximization is employed to determine the parameters of a probabilistic model based on unobservable variables.

However, most of these works have been designed and validated considering very simple laboratory environments (usually a room free of obstacles with laminar and constant wind flow), which limits their applicability to more realistic and complex environments where the presence of obstacles and the consideration of different rooms violate the assumptions they rely on. A notable exception are the methods based on the probabilistic modeling of the gas distribution [14, 3]. The main goal of these methods is to estimate a map of the gas dispersion from the set of observations, which can later be used to infer the source location. Yet, the main limitation of these algorithms is their low temporal efficiency, requiring many observations distributed throughout the environment in order to correctly estimate the source location.

The interested reader can find a more detailed review of different gas source search strategies with a mobile robot in [11, 9, 1].

3. Probabilistic Estimation of the Gas Source Location

The problem addressed in this work is the probabilistic estimation of a gas source location within a structured environment characterized by the presence of multiple rooms and obstacles, and where analytical models of the gas dispersion are not suitable. Specifically, our focus is on employing a mobile robot equipped with an electronic nose and an anemometer to enable the location of the gas source from a set of spatially distributed measurements of the gas concentration and wind vector in the environment.

Our approach stands on two main pillars: (i) the use of numerical methods to solve the dispersion of gases in the challenging conditions imposed by real, indoor scenarios, and (ii) a probabilistic modeling of the problem that accounts for the spatially distributed measurements gathered by the mobile robot during the search process. For the former pillar we rely on two different tools (see Fig. 2(a)), a computational fluid dynamics (CFD) platform to estimate the 3D wind flow conditions in the environment based on a set of contour conditions, and a gas dispersal simulator based on the filament dispersion theory (GADEN [15]) to derive the gas concentration (C) in the scenario. Given that numerical methods for gas dispersion simulation are computationally intensive and time consuming, we simplify the problem by assuming that there is a finite set of possible static wind flow conditions that can occur in the environment (W), as well as a set of candidate gas source locations (S) (e.g. cells of a grid-based map). Therefore, for each possible wind flow condition (w) and gas source location (s), we numerically estimate the gas concentration probability $p(c|s,w)$ as a multidimensional Gaussian distribution defined over the concentration grid map,

$$p(c|s,w) \sim \mathscr{N}(\mu^c, \Sigma^c), \;\; \mu^c = [\mu_n^c]_{n=1:N}, \tag{1}$$

where the mean vector μ^c contains the average gas concentration values for each of the N cells of the map and the $N \times N$ matrix Σ^c is the covariance matrix.

The probabilistic model from which to estimate the gas source location is depicted by the Bayesian network in Fig. 2(b). As can be seen, the hidden random variables are the source location S, the wind flow W and the gas concentration C, while two are the

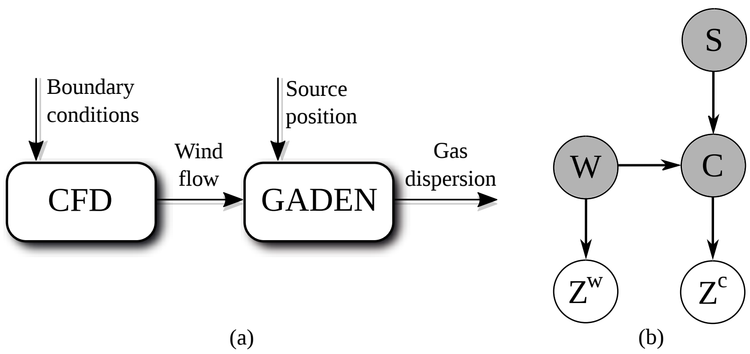

Figure 2. (a) Simulation process to obtain the gas dispersion in indoor environments. It is formed by two steps: first a Computational Fluid Dynamic tool (CFD) is used to get the wind flow from boundary conditions and then, with the use of gas dispersal simulation tool GADEN and a set of source positions we obtain the gas concentration in the search scenario. (b) Bayesian network of the gas source localization problem. Shaded nodes denote hidden random variables while white nodes represent observable ones.

observable variables: Z^c and Z^w, representing the gas concentration and wind vector measurements taken by the robot, respectively. From this model we first derive the source location probability of each candidate accounting only for the most current observation, and then, we introduce a Bayesian filter to improve robustness by integrating all the observations taken at different instants of time.

3.1. Estimation from a Single Observation

In this section we infer the source location probability by accounting only for the most current observation, that is, the current gas concentration and the wind velocity and direction vector taken at the corresponding robot location at instant of time k. We model both measurements as their respective current values (denoted here as c_k and w_k), corrupted by an additive Gaussian noise of variance $\sigma^2_{z^c}$ and Σ_{z^w}, respectively:

$$z^c_k = c_k + e_c, \quad e_c \sim \mathcal{N}(0, \sigma^2_{z^c}), \tag{2}$$

$$z^w_k = w_k + e_w, \quad e_w \sim \mathcal{N}(0, \Sigma_{z^w}). \tag{3}$$

From the Bayes network depicting our problem (see Fig. 2(b)) we can easily factor the joint probability given in Eq. (4), where $p(s)$ and $p(w)$ represent the prior knowledge about a gas source location and wind flow condition, $p(z^c_k|c) = \mathcal{N}(z^c_k; c_k, \sigma_{z^c})$ and $p(z^w_k|w) = \mathcal{N}(z^w_k; w, \Sigma_{z^w})$ are the gas and wind observation models, respectively, and $p(c|s,w)$ is the gas dispersion model which, in this work, is estimated by numerical methods as previously mentioned.

$$p(s,w,c,z^c_k,z^w_k) = p(s)p(w)p(c|s,w)p(z^c_k|c)p(z^w_k|w). \tag{4}$$

From this equation, we derive the source probability of each gas source candidate s given the observations collected by robot at the current instant of time ($p(s|z^c_k, z^w_k)$), as:

$$p(s|z^c_k,z^w_k) = \sum_w p(s,w|z^c_k,z^w_k) = \frac{1}{p(z^c_k,z^w_k)} \sum_w p(s,w,z^c_k,z^w_k), \tag{5}$$

where in the first step we applied the marginal probability theorem to include the discrete random variable representing the wind flow conditions, and then the conditional probability theorem to express it as a function of a joint probability. The term $p(z^c_k, z^w_k)$ represents the prior knowledge about observations and can be extracted from the summation since it does not depend on w. Applying once again the marginal probability theorem, we include the continuous random variable c representing the gas concentration in the joint probability as:

$$p(s|z^c_k,z^w_k) = \frac{1}{p(z^c_k,z^w_k)} \sum_w \int_c p(s,w,c,z^c_k,z^w_k)dc, \tag{6}$$

where we can now substitute Eq. (4) and extract from the integral the terms that do not depend on c:

$$p(s|z_k^c, z_k^w) = \frac{p(s)}{p(z_k^c, z_k^w)} \sum_w p(w) p(z_k^w|w) \int_c p(c|s,w) p(z_k^c|c) dc. \tag{7}$$

Given that the gas measurement z_k^c depends only to the c_k cell (i.e. the e-nose is a point sampling device), we can factorize the above integral in N integrals corresponding to each cell in the gas concentration map:

$$p(s|z_k^c, z_k^w) = \frac{p(s)}{p(z_k^c, z_k^w)} \sum_w p(w) p(z_k^w|w) \int_{c_1} \dots \int_{c_N} p(c_n|s,w) p(z_k^c|c_n) dc_1 \dots dc_N. \tag{8}$$

Taking into consideration that the integrals for $c_n \neq c_k$ simplify to 1 (i.e. integral of a probability density function), we can express the source probability of candidate s as:

$$p(s|z_k^c, z_k^w) = \frac{p(s)}{p(z_k^c, z_k^w)} \sum_w p(w) p(z_k^w|w) \int_{c_k} p(c_k|s,w) p(z_k^c|c_k) dc_k. \tag{9}$$

where $p(c_k|s,w)p(z_k^c|c_k)$ corresponds to the product of two Gaussian distributions which outcome is also a Gaussian function given by:

$$\mathcal{N}(c_k; \mu_k^c, \sigma_k^c) \mathcal{N}(z_k^c; c_k, \sigma_{z^c}) = \eta \mathcal{N}\left(\frac{\mu_k^c \sigma_{z^c}^2 + c_k \sigma_k^{c2}}{\sigma_k^{c2} + \sigma_{z^c}^2}, \frac{\sigma_k^{c2} \sigma_{z^c}^2}{\sigma_k^{c2} + \sigma_{z^c}^2} \right), \tag{10}$$

where η is the scale factor that relates it to a normal distribution and can be obtain as in [5] as:

$$\eta = \frac{1}{\sqrt{2\pi(\sigma_k^{c2} + \sigma_{z^c}^2)}} exp\left(-\frac{(\mu_k^c - c_k)^2}{2(\sigma_k^{c2} + \sigma_{z^c}^2)} \right). \tag{11}$$

3.2. Accounting for Multiple Observations: Bayes Filtering

To estimate a more robust posterior taking into account all the observations gathered by the robot since the search began, we formulate the recursive version of the Bayes filter which defines the posterior or belief at the current instant of time $Bel_k(s) = p(s|z_{1:k})$ as a function of the belief at the previous instant of time $Bel_{k-1}(s)$ and the most recent observation z_k:

$$\begin{aligned} Bel_k(s) = p(s|z_{1:k}) &= \frac{p(z_k|s, z_{1:k-1})\ p(s|z_{1:k-1})}{p(z_k|z_{1:k-1})} = \frac{p(z_k|s)\ p(s|z_{1:k-1})}{p(z_k|z_{1:k-1})} \\ &= \frac{p(s|z_k)\ p(z_k) p(s|z_{1:k-1})}{p(s)\ p(z_k|z_{1:k-1})}, \end{aligned} \tag{12}$$

where we assumed $z_k \perp\!\!\!\perp z_{1:k-1}$ given the gas source location s.

To get rid of the terms that do not depend on s we apply *log-odds* [25], obtaining an alternative expression of the filter that simplifies the update process when we take a new observation:

$$lod_k(s) = log\left(\frac{Bel_k(s)}{Bel_k(\neg s)}\right) = log\left(\frac{p(s|z_k)}{p(\neg s|z_k)}\right) + log\left(\frac{p(\neg s)}{p(s)}\right) + log\left(\frac{p(s|z_{1:k-1})}{p(\neg s|z_{1:k-1})}\right). \tag{13}$$

Three terms compose the resulting expression: the first one makes reference to the posterior given the current observation (calculation is detailed in Section 3.1). The second term corresponds to the log-odds at instant of time 0 ($lod_0(s)$). In this work we assume that there is no a priori knowledge about the source location, that is $p(s) = 1/(range(S))$. Finally, the last term refers to the log-odds at an instant of time $k-1$, which allows us to obtain the recursive equation of the filter:

$$lod_k(s) = log\left(\frac{p(s|z_k)}{1-p(s|z_k)}\right) + lod_0(s) + lod_{k-1}(s). \tag{14}$$

Lastly, to recover the gas source probability of each candidate s at a given instant of time k the following expression can be employed:

$$p(s|z_{1:k}) = 1 - \left(e^{lod_k(s)}\right)^{-1}. \tag{15}$$

4. Implementation Details

This section describes a direct and intuitive implementation of the proposed probabilistic framework, constituted by the phases illustrated in Fig. 3: (i) the collection of a new observation, (ii) the estimation of the posterior source probability given the current observation, (iii) the update of the Bayes filter, and (iv) an evaluation phase to determine whether the source has been found or not. The latter leads, if successful, to (v) the source declaration, or else, to (vi) the navigation of the robot to a different location to gather a new observation.

The first three phases correspond to the estimation of the source posterior probability as depicted in the previous section. In particular, the estimation process starts by gathering a new observation at instant of time k ($z_k = \{z_k^c, z_k^w\}$), then, the probabilistic weighing is performed for each of the source candidates s given this new observation (recall Section 3.1), and finally we update our belief about the source probability by integrating all the observations gathered so far (see Section 3.2). To illustrate these phases, we provide in Algorithm 1 the pseudo code of the estimation procedure.

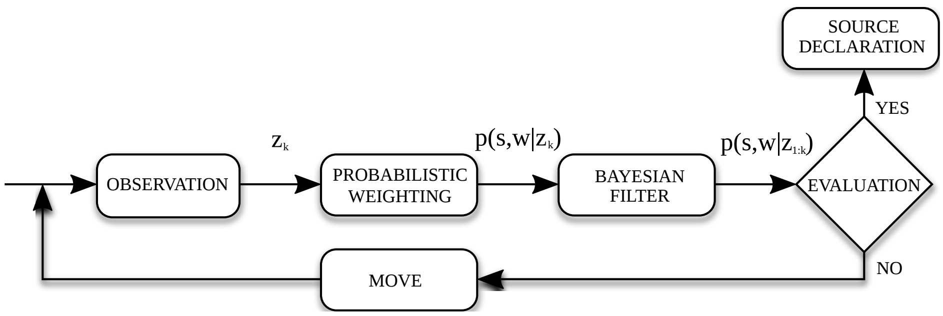

Figure 3. Diagram of the phases involved in the search and localization of the gas source.

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Algorithm 1 Estimation of Gas Source Location

procedure GSL($Bel_0(S)$) ▷ *Input:Prior of source location*
  while Source not declared **do**
    $k++$
    $z_k = \{z_w^c, z_k^w\}$ ▷ *Take a new observation*
    for each s **do**
      $p(s|z_k)$ ▷ *Probabilistic weighting*
      $Bel_k(s) = p(s|z_{1:k}) = 1 - \left(e^{lod_k(s)}\right)^{-1}$ ▷ *Bayesian Filter*
      if $Bel_k(s) \geq p_{th}$ **then** ▷ *Evaluation*
        t_s++
      else
        $t_s = 0$
      if $t_s \geq t_{th}$ **then**
        Source declaration ▷ *Source Declaration*
    Robot Movement ▷ *Move robot*
  return $(p(S|Z))$

Once the posterior probabilities of the gas source locations have been estimated, we evaluate if the obtained solution converges to a particular s. For this, we empirically set a threshold over the source probability (p_{th}) that must be exceeded over a temporal window of length (t_{th}) in order to declare convergence, that is, we impose the condition $p(s|z_{1:k}) \geq p_{th}$ for a period of time t_{th}. When this condition is fulfilled, the source is declared at location s. It is important to notice that our approach does not require navigating to s in order to declare the source (i.e. our probabilistic approach is not a plume tracking algorithm), but is able to declare the source from a distance.

Finally, until there is enough information to declare the source, the robot can move within the environment to collect observations at different locations. There are diverse movement strategies that can be implemented according to $p(s|z_{1:k})$. In this work we implement two different solutions, a passive strategy where the robot follows a predefined path (as is the case with the patrolling robot), and an active search proposing a displacement of the robot towards the most likely source location at each instant of time:

$$s^* = \underset{s}{\operatorname{argmax}}\ p(s|z_{1:k}). \tag{16}$$

In the future we intend to implement more elaborate search strategies (e.g. Infotaxis[26]) and to analyze their impact on search performance.

4.1. Pre-computation of Wind and Gas Concentration Maps

Our approach can be considered a model-free method since we do not assume any particular dispersion model (which would reduce its applicability as discussed in Section 3). Instead, we rely on CFD and gas dispersion simulation tools to derive $p(c_k|s,w)$, that is, we need to carry out the gas dispersal simulation given the wind flow condition w and the source location s. Since simulation is, in general, a time consuming process, we propose to pre-compute all the wind and gas concentration maps, and store them in a look-up table.

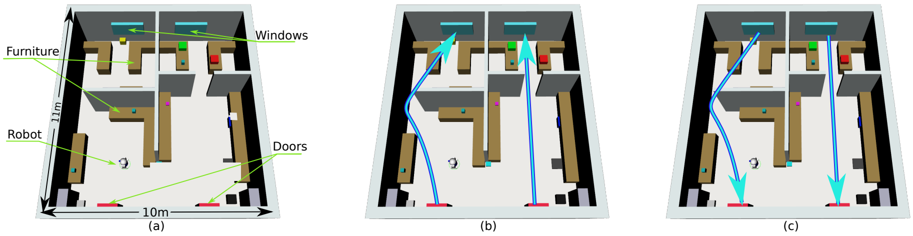

Figure 4. (a) 3D geometric map of the office-like environment employed in the experiments. As can be seen, it is a challenging scenario composed of multiple rooms and containing furniture (e.g. tables and cabinets) and physical elements (e.g. walls, doors and windows) that affect the dispersion of gases. (b-c) Illustration of the two wind flow conditions considered where the blue arrows depict the wind's main flow.

In this work we make use of two different tools, the SimScale platform (`https://www.simscale.com`), and the gas dispersal simulator GADEN [15].

The former is used to simulate the wind flow conditions w in the 3D environment, giving access to sophisticated fluid dynamics simulation capabilities, and enabling the specification of parameters like the Reynolds number of the fluid flow, the selection of laminar or turbulent models or the numeric solver to be employed. The resulting wind maps approximate the wind vector in each cell of the environment, taking into account the boundary conditions, the presence of obstacles and a series of restrictions based on fluid mechanics. Notice that simpler tools can also be employed in this step as described in [16] at the cost of accuracy. Finally, once the set of w maps has been simulated, we obtain the gas concentration maps c with the GADEN gas dispersion simulator[2].

5. Validation Experiments

This section present a set of illustrative experiments to evaluate and validate the proposed approach. First we present a full trace of a gas source estimation to analyze how the posterior probabilities vary over time, and how the source is finally declared without needing to physically reach it. Then, we compare the passive and active search strategies, that is, estimation of the source location by following a fixed path and by navigating towards the most probable source, demonstrating the suitability of our estimation algorithm to both approaches.

All experiments are carried out in the simulated environment shown in Fig. 4(a), corresponding to an office-like environment with multiple rooms and the presence of furniture. We consider two different wind flow conditions in the environment (see Fig. 4(b-c)), and a total of 110 different source locations, corresponding to a grid of $(1 \times 1)m$ over such environment. A mobile robot is then commanded to inspect the environment and locate the gas source location by estimating, on each new observation, the probability of the considered source candidates.

[2]The current version of GADEN is not probabilistic, providing only a value for the gas concentration at each cell of the specified grid map. In this work we consider a set of consecutive maps over time (assuming that a semi-permanent state of the gas dispersion has been reached) to estimate the mean and variance concentration of each cell.

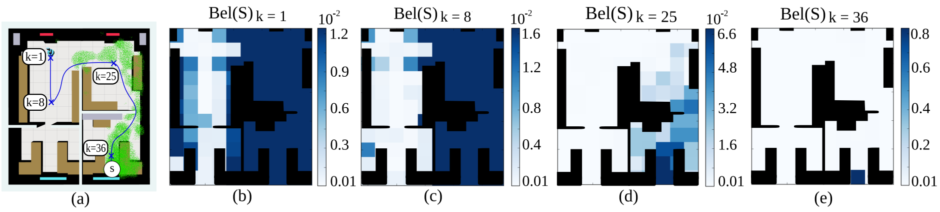

Figure 5. Illustration of the estimation process when locating a gas source in an indoor environment. (a) 3D geometric map of the office-like environment depicting the path followed by the robot when actively searching for the gas source location (blue line). (b-c) Estimated probabilities for each source candidate at different instants of time (k). Objects in the environment are marked in black.

5.1. Experiment 1: Full Trace

The objective of this experiment is to validate and exemplify the probabilistic estimation carried out by the proposed algorithm when locating a gas source. Fig. 5(a) depicts the environment, the ground-truth gas source location, and the gas dispersal as a colored point cloud, while Fig. 5(b-e) shows four different instants of time of the search process, illustrating for each one the probabilities of all the gas source candidates considered.

The algorithm starts with an uniform prior where all the gas source candidates are equally probable, and as the robot moves and gather new observations, this probability converges towards the real gas source location. As can be seen, after just a few observations (k=8) the algorithm is able to discard all the source candidates in the left side of the environment, focusing the search in a more narrowed area. Also, it is important to notice that given the potential to estimate the source probability at far locations, the algorithm is able to pinpoint the source location in the bottom-right room at step k=25.

5.2. Experiment 2: Passive and Active Search Strategies

In this experiment we compare two different search strategies, a passive one where the robot is not driven by the results of the search process but it follows a predefined path (e.g. performing another task not related with gas source localization), and an active search strategy where the robot moves, at each instant of time, towards the most probable location containing the gas source.

Fig. 6 shows the probability of the real gas source as estimated by our algorithm at different instants of time, and compares how this probability varies according to the new gathered observations. From these results we can conclude that our algorithm represents a very suitable solution for estimating the gas source location in a complex indoor environment, even when the robot is not actively searching for the gas source.

6. Conclusions

In this work we have reviewed the problem of gas source localization with a mobile robot endowed with the ability to measure gases. We have seen how model-based solutions relying on the simplification of the dispersion model are not suitable for complex and structured environments (e.g. indoor environments), and proposed a model-free probabilistic approach. Specifically, we have derived the posterior probability of the gas source location based on a single observation, and then, improved the robustness and efficiency

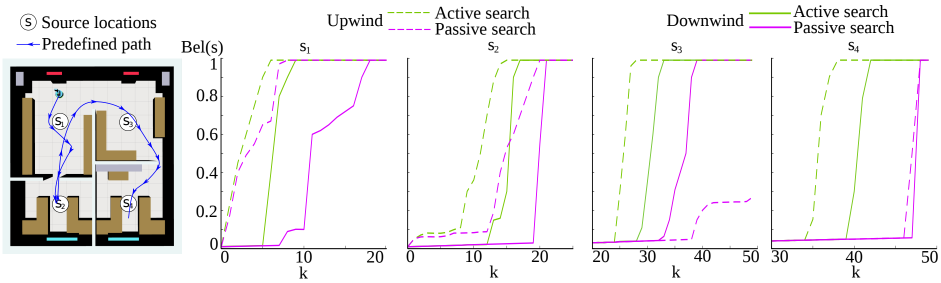

Figure 6. Comparison between the passive and active search strategies when locating a gas source in an indoor environment. The map shows the predefined robot path used in the passive search, and the source location for four different instances ($s_1 - s_4$). Each graph plots the source probability as estimated by both strategies for two different wind conditions.

of the system by implementing a recursive Bayes filter to estimate the source posterior probability according to all gathered observations since the search started.

We exploited this framework by implementing a search algorithm composed of six different phases, ranging from the collection of new observations to the source declaration, and validated it by presenting two experiments in an office-like simulated environment composed of four rooms and with the presence of multiple obstacles. Results demonstrated the suitability of the proposed method for locating gas sources in complex indoor environments even when the estimation is carried out passively. Furthermore, we have proved an interesting feature of our approach, its ability to declare the source location from a distance without requiring to track the gas plume. The latter is fundamental for indoor environments where tracking the gas plume is not always feasible due to the obstacles.

As a natural continuation of this work, we plan on integrating further sources of information that may contribute towards locating the gas source more efficiently, such as vision or semantic information. Also, as discussed in this work, a study of different robot movement strategies (e.g. moving in the direction of maximum information or in the direction that minimizes entropy) is necessary in order to attain a functional and effective search method.

Acknowledgements: Work partially funded by the Spanish Ministry of Industry, Energy and Tourism (project [DPI2017-84827-R]), and the Andalusian Regional Government (project [TEP2012-530]), both financed by European Regional Development's funds (FEDER).

References

[1] Bayat, B., Crasta, N., Crespi, A., Pascoal, A. M., and Ijspeert, A. (2017). Environmental monitoring using autonomous vehicles: a survey of recent searching techniques. *Current Opinion in Biotechnology*, 45:76–84.
[2] Bird, G. A. (1976). Molecular gas dynamics. *NASA STI/Recon Technical Report A*, 76.
[3] Blanco, J.-L., Monroy, J., Gonzalez-Jimenez, J., and Lilienthal, A. (2013). A kalman filter based approach to probabilistic gas distribution mapping. In *Proceedings of the 28th Annual ACM Symposium on Applied Computing*, pages 217–222. ACM.
[4] Buscemi, L., Prati, M., and Sandini, G. (1994). Cellular robotics: behaviour in polluted environments.
[5] Fernández-Madrigal, J.-A. and Blanco, J.-L. (2012). *Simultaneous Localization and Mapping for Mobile Robots: Introduction and Methods*. IGI Global.
[6] Genovese, V., Dario, P., Magni, R., and Odetti, L. (1992). Self organizing behavior and swarm intelligence in a pack of mobile miniature robots in search of pollutants. In *Intelligent Robots and Systems, 1992., Proceedings of the 1992 lEEE/RSJ International Conference on*, volume 3, pages 1575–1582. IEEE.

[7] Gongora, A., Monroy, J., and Gonzalez-Jimenez, J. (2017). Gas source localization strategies for teleoperated mobile robots. an experimental analysis. In *2017 European Conference on Mobile Robots (ECMR)*.

[8] Grasso, F. W., Dale, J. H., Consi, T. R., Mountain, D. C., and Atema, J. (1996). Behavior of purely chemotactic robot lobster reveals different odor dispersal patterns in the jet region and the patch field of a turbulent plume. *The Biological Bulletin*, 191(2):312–313.

[9] Hutchinson, M., Oh, H., and Chen, W.-H. (2017). A review of source term estimation methods for atmospheric dispersion events using static or mobile sensors. *Information Fusion*, 36:130–148.

[10] Ishida, H., Hayashi, K., Takakusaki, M., Nakamoto, T., Moriizumi, T., and Kanzaki, R. (1995). Odour-source localization system mimicking behaviour of silkworm moth. *Sensors and Actuators A: Physical*, 51(2-3):225–230.

[11] Kowadlo, G. and Russell, R. A. (2008). Robot odor localization: a taxonomy and survey. *The International Journal of Robotics Research*, 27(8):869–894.

[12] Kuwana, Y., Shimoyama, I., and Miura, H. (1995). Steering control of a mobile robot using insect antennae. In *Intelligent Robots and Systems 95.'Human Robot Interaction and Cooperative Robots', Proceedings. 1995 IEEE/RSJ International Conference on*, volume 2, pages 530–535. IEEE.

[13] Lilienthal, A. J., Reimann, D., and Zell, A. (2003). Gas source tracing with a mobile robot using an adapted moth strategy. In *AMS*, pages 150–160.

[14] Monroy, J., Blanco, J.-L., and Gonzalez-Jimenez, J. (2016). Time-variant gas distribution mapping with obstacle information. *Autonomous Robots*, 40(1):1–16.

[15] Monroy, J., Hernandez-Bennetts, V., Fan, H., Lilienthal, A., and Gonzalez-Jimenez, J. (2017a). GADEN: A 3D gas dispersion simulator for mobile robot olfaction in realistic environments. *MDPI Sensors*, 17(7: 1479):1–16.

[16] Monroy, J., Jaimez, M., and Gonzalez-Jimenez, J. (2017b). Online estimation of 2d wind maps for olfactory robots. In *International Symposium on Olfaction and Electronic Nose (ISOEN)*, pages 1–3.

[17] Pang, S. and Farrell, J. A. (2006). Chemical plume source localization. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 36(5):1068–1080.

[18] Pyk, P., Bermúdez i Badia, S., Bernardet, U., Knüsel, P., Carlsson, M., Gu, J., Chanie, E., Hansson, B. S., Pearce, T. C., and J. Verschure, P. F. (2006). An artificial moth: Chemical source localization using a robot based neuronal model of moth optomotor anemotactic search. *Autonomous Robots*, 20(3):197–213.

[19] Rozas, R., Morales, J., and Vega, D. (1991). Artificial smell detection for robotic navigation. In *Advanced Robotics, 1991.'Robots in Unstructured Environments', 91 ICAR., Fifth International Conference on*, pages 1730–1733. IEEE.

[20] Ruiz-Sarmiento, J. R., Galindo, C., and Gonzalez-Jimenez, J. (2017). Robot@home, a robotic dataset for semantic mapping of home environments. *The International Journal of Robotics Research*, 36(2):131–141.

[21] Russell, R. A., Bab-Hadiashar, A., Shepherd, R. L., and Wallace, G. G. (2003). A comparison of reactive robot chemotaxis algorithms. *Robotics and Autonomous Systems*, 45(2):83–97.

[22] Sanchez-Garrido, C., Monroy, J., and Gonzalez-Jimenez, J. (2014). A configurable smart e-nose for spatio-temporal olfactory analysis. In *IEEE Sensors*, pages 1968–1971.

[23] Shraiman, B. I. and Siggia, E. D. (2000). Scalar turbulence. *Nature*, 405(6787):639–646.

[24] Shu, L., Mukherjee, M., Xu, X., Wang, K., and Wu, X. (2016). A survey on gas leakage source detection and boundary tracking with wireless sensor networks. *IEEE Access*, 4:1700–1715.

[25] Thrun, S., Burgard, W., and Fox, D. (2005). *Probabilistic Robotics (Intelligent Robotics and Autonomous Agents)*. The MIT Press.

[26] Vergassola, M., Villermaux, E., and Shraiman, B. I. (2007). Infotaxis as a strategy for searching without gradients. *Nature*, 445(7126):406–409.

[27] Vijayakumaran, S., Levinbook, Y., and Wong, T. F. (2007). Maximum likelihood localization of a diffusive point source using binary observations. *IEEE Transactions on Signal Processing*, 55(2):665–676.