Authors' accepted manuscript: International Conference on Applications of Intelligent Systems (APPIS), Las Palmas de Gran Canaria, Spain, 2018.

Probabilistic Localization of Gas Emission Areas with a Mobile Robot in Indoor Environments

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Abstract.

This work deals with the problem of gas source localization by a mobile robot with gas-sensing capabilities. Particularly, we address the problem for the case of indoor environments, where the presence of obstacles and the possibly complex structure with multiple rooms, inlets and outlets provoke the chaotic dispersion of the gases. Under these challenging conditions, where traditional approaches based on tracking or mathematical modeling of the plume cannot be applied, we propose a two-stage methodology to split the search into coarse and fine localization. Focusing on the broad localization, we contribute with a novel approach to estimate, from a set of sparse observations, the likelihood of different regions in the environment to hold a gas source. Experiments demonstrate that our approach is suitable to locate gas emission sources.

Keywords. gas source localization, olfactory robots, indoor environments

1. Introduction

The search of gas sources (e.g. chemical leaks, fires, hidden explosives, etc.) is an important and challenging task for many real applications, including citizen security, early leak detection, landfill monitoring or environmental control, among others.

From the different approaches to tackle this problem, we focus on the use of a mobile robot with the ability to detect and recognize volatile chemicals. This enables a dynamic search and lower cost of maintenance than the traditional setup of deploying a network of fixed sensors [3]. More concretely, our interest lies in realistic indoor environments where the commonly complex structure of the search area (i.e. multiple rooms, presence of obstacles) contributes to a chaotic dispersion of the released chemicals, making very difficult to apply traditional methods relying on mathematical plume models [1].

Under these challenging conditions, we propose a top-down methodology that first determines a broad area containing the gas source to later refine the search, accurately pinpointing its location. In this work we focus on the first phase, the identification of the broad area within the environment from which a volatile gas emission exists. This phase is very challenging given that natural indoor environments usually have multiple rooms, corridors and other physical structures that heavily condition the gas dispersion, therefore, making the localization of the source (even a broad search) a complex problem.

The proposed approach is rooted in a probabilistic Bayesian framework, dividing the environment in a series of emission areas (i.e. regions of the environment from which a gas source would theoretically generate a very similar gas dispersion), and evaluating on each new measurement (i.e. gas concentration and wind vector measured by the robot) the probability for each of these areas to hold the gas source. This novel approach not only makes possible the search and location of emission sources in complex and structured environments, but also allows a remote localization, that is, the robot does not need to physically travel to the gas source location, but it can declare the source from a distance (a critical point for scenarios where the robot cannot reach all the locations in the environment, e.g. disaster areas).

2. Method

The proposed approach can be decomposed in two main phases: a preliminary offline phase consisting of the generation of the necessary data crucial for the algorithm, and an online phase where the robot actively searches for the gas source.

- **Offline phase**: Here, from the geometrical map of the environment a set of N_r emission areas is declared, $\mathbf{r} = \{r_i\}_{i=1}^{N_r}$. In this work we assume that the set of emission areas is given, leaving for a future work the automation of this process. Then, doing use of computational fluid dynamic tools and gas dispersion simulators [2] we define N_v wind conditions that may take place in the environment, and generate a set of dispersion maps ($N_r \times N_v$). Fig. 1 illustrates this phase where $\mathbf{m} = \{\boldsymbol{m}_{i,j}\}_{i=1:N_r}^{j=1:N_v}$ is the set of generated maps.
- **Online phase**: Once the set of dispersion maps has been generated, the robot starts the active search to declare the emission area containing the gas source. Fig. 2 depicts the five steps in which this phase is sub-divided: observation, probabilistic weighting, Bayesian filtering, evaluation and robot movement.

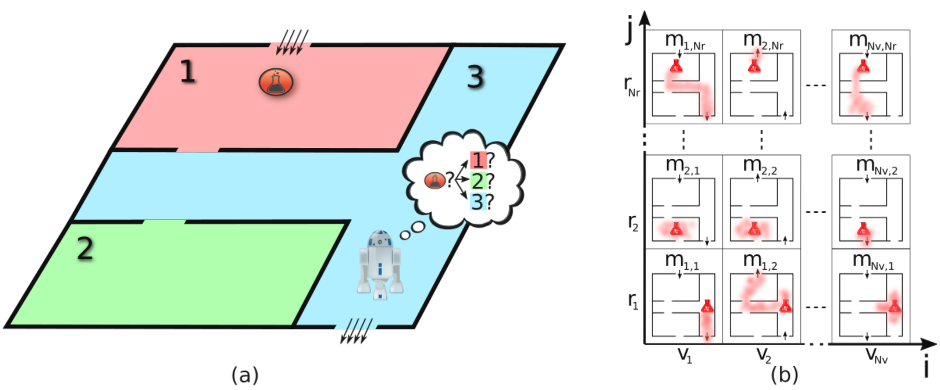

Figure 1. (a) Example of an indoor environment with 3 emission areas (1-3) (b) Set of simulated distribution maps ($\mathbf{m}$) result of considering N_r emission areas and N_v wind conditions.

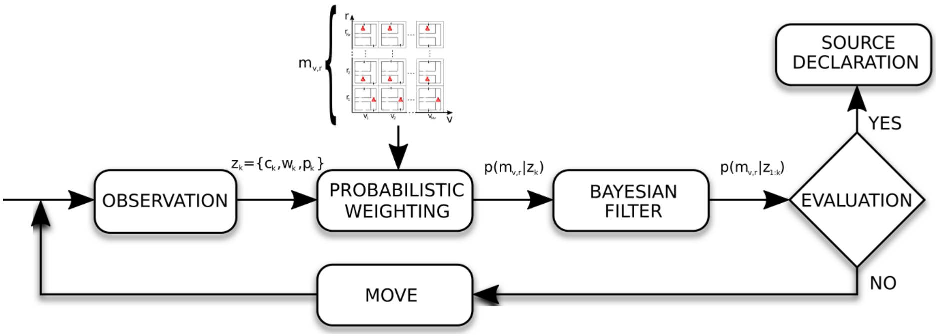

Figure 2. Diagram of the method for locating the area in which the gas source is located.

As the robot proceeds it continuously gathers new observations $\mathbf{z}_k$, understood as random variables with Normal distribution $\mathbf{z}_k = \mathcal{N}(\bar{\mathbf{z}}_k, \Sigma_z)$ at time instant k. Then, we estimate the likelihood of such observations to belong to the previously generated distribution maps $p(\boldsymbol{m}_{i,j}|\mathbf{z}_k)$, from which the probability of each emission area can be derived. To do this, for each dispersion map, we calculate the distance between the taken observation and the corresponding value in the simulated map (modeled in this case as a scalar vector). This corresponds to calculate the Mahalanobis distance, given by: $DM(\boldsymbol{m}^k_{i,j}, \mathbf{z}_k) = \sqrt{(\bar{\mathbf{z}}_k - \boldsymbol{m}^k_{i,j})^T \; \Sigma_z^{-1} \; (\bar{\mathbf{z}}_k - \boldsymbol{m}^k_{i,j})}$, from which the probability of each dispersion map is calculated as:

$$p(\boldsymbol{m}_{i,j}|\mathbf{z}_k) = \frac{1}{\sqrt{|2\pi\Sigma_z|}} \exp\left(\frac{-DM(\boldsymbol{m}^k_{i,j}, \mathbf{z}_k)^2}{2} \right) \tag{1}$$

In order to give robustness to the system, we integrate the information of all the observations gathered until the current time by means of a recursive version of the Bayes filter, obtaining that $Bel_k(\boldsymbol{m}_{i,j}) = p(\boldsymbol{m}_{i,j}|\mathbf{z}_{1:k})$. Finally, after probability evaluation in each iteration, a new robot movement direction is estimated towards the area r_i corresponding to the map $\boldsymbol{m}_{i,j}$ with hightest probability, or the search is finished if there is sufficient certainty of gas source location (source declaration).

3. Experiments and Results

To validate the proposed approach we have designed a set of experiments where a mobile robot is commanded to determine the most probable emission area containing a gas source within a multi-room environment. We assume that the emission areas have been estimated (6 for the current experiment), and consider 36 different wind conditions, which result in 216 different simulated distribution-maps. Evaluating the likelihood of the gathered observations to belong to these distribution-maps, we estimate the probability of each emission-area and control the robot movement.

Fig. 3 illustrates an example of such experiments where it can be observed how the volatiles, emitted by a gas source located in area 2 (see (a)), spread over the environment.

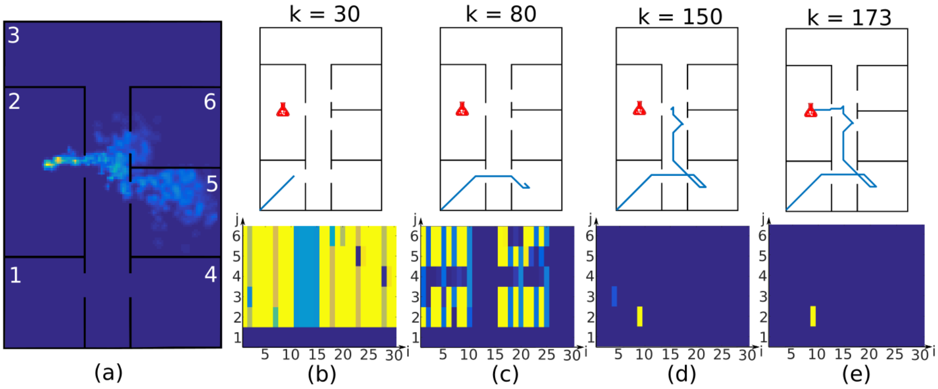

Figure 3. (a) Geometric map of the environment showing the division in emission areas (1-6), and the gas dispersion generated from a source located in area 2. (b-e) Evolution of the search process for different time instants *k*, depicting (top) the robot's current path and (bottom) the estimated probabilities for each of the simulated distribution maps.

Fig. 3 (b-e) show the evolution of the search process for different time instants (k), depicting (top) the robot's current path and (bottom) the estimated probabilities for each of the simulated maps. From these probabilities, we estimate the likelihood of each emission area, and command the next robot movement, which for this experiment consists in moving towards the area of maximum probability.

To evaluate the efficiency of the proposed method we compare our approach against a sequential search (i.e. visiting all the emission areas in a fixed order), measuring the execution time until the robot declares or reaches the gas source. Results show an average improvement of 62%.

Acknowledgements: Work partially funded through the national plan, government of Spain (project DPI2014-55826-R) and by the Junta de Andalucia (project of excellence TEP2012-530).

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