# Towards a Semantic Gas Source Localization under Uncertainty

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**Abstract.** This work addresses the problem of efficiently and coherently locating a gas source in a domestic environment with a mobile robot, meaning *efficiently* the coverage of the shortest distance as possible and *coherently* the consideration of different gas sources explaining the gas presence. The main contribution is the exploitation, for the first time, of semantic relationships between the gases detected and the objects present in the environment to face this challenging issue. Our proposal also takes into account both the uncertainty inherent in the gas classification and object recognition processes. These uncertainties are combined through a probabilistic Bayesian framework to provide a priority-ordered list of (previously observed) objects to check. Moreover the proximity of the different candidates to the current robot location is also considered by a cost function, which output is used for planning the robot inspection path. We have conducted an initial demonstration of the suitability of our gas source localization approach by simulating this task within domestic environments for a variable number of objects, and comparing it with an greedy approach.

**Keywords:** mobile robotics, semantics, gas source localization, e-nose

## 1 Introduction

The fusion of different sensing modalities can empower service robots operating in human environments (*e.g.* for elder care at homes or as assistants at offices, airports or hospitals) with new abilities and the possibility to efficiently accomplish complex tasks. With this aim, in this work we focus on the senses of vision and olfaction, and face a challenging task: gas source localization, *i.e.* the finding of the object releasing a particular smell. In this context, *olfaction* is understood as the sensing of volatile chemical substances by means of an electronic nose (e-nose)[1], while *vision* is interpreted as the perception of the environment through a camera capturing light intensity [2,3].

Given the volatile nature of gases and the complex processes involved in their dispersion (*i.e.* dominated by turbulent flows [4]), after the perception of

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an unusual gas concentration it is necessary to carry out a search of the object that is releasing it in the environment, process commonly referred as gas source localization (GSL). For the case of domestic environments it includes the location of methane or butane leaks from the home heating system, the presence of smoke, or unpleasant smells coming from spoiled food, the toilet, or the pet sandbox, among others. An efficient localization of these gas sources would permit the robot to act consequently and in time, for instance alerting a human (*e.g.* notifying the presence of smoke from the oven) or suggesting different actions to be carried out (*e.g.* replacing the pet sandbox).

GSL is usually addressed by mimicking animal behaviors through bio-inspired algorithms, assuming the existence of a downwind gas plume (*i.e.* plume tracking) [5,6], or by exploiting other information sources like dispersion models or windflow data [7,8]. However, most of these methods are prone to fail in human-like environments due to the important assumptions they rely on (*e.g.* existence of a gas plume, the predominance of laminar and uniform windflows, or the absence of obstacles in the environment that can interfere with the gas dispersion). Thereby, their success heavily relies on how well the given algorithm adjust itself to the environmental conditions, which determines the way in which gases are dispersed. A way to overcome this issue is to employ artificial vision systems to detect gas source candidates and inspect them, reducing the complexity of the search process. For example, if the e-nose detects an abnormal concentration of a gas classified as smoke, a visually recognized oven is a good candidate to check, while a chair is not. This approach, not being novel, has only been superficially explored under very simple scenarios where the robot exploited knowledge about the source physical characteristics to reduce the locations to search [9]. Yet, what is still needed is a principled way to set the nature of the objects and their possible gas emissions – in other words, their semantics –, from which we can infer what objects in the environment are prone to be the gas source.

Moreover, traditional GSL approaches work, in most cases, with gas classification systems that produce an exact outcome, for example, a detected smell is smoke or not. However, the classification of gases is not extent of uncertainty sources (*e.g.* the cross-sensitivity of gas sensors or the environmental conditions), being mandatory their consideration for a coherent robot operation. For example, an ambiguous gas classification result between smoke and spoiled food (probability of 0.55 vs. 0.45) could end up with the robot only searching for smoke when indeed a dish with fish was forgotten in the kitchen counter. The same holds for the uncertainty inherent to the object recognition process: an object can be recognized as a heater with probability 0.60 or as a fan with 0.40, so it must be also considered.

This work presents, to the best of our knowledge, the first attempt towards a system performing an efficient and coherent gas source localization under uncertainty exploiting semantics. For that, it is built and maintained a semantic representation of the robot environment that provides the GSL task with valuable prior information (see Fig. 1). Concretely, an *ontology* [10] is used to encode the semantic knowledge of the domain at hand (e.g. ovens can give off smoke with

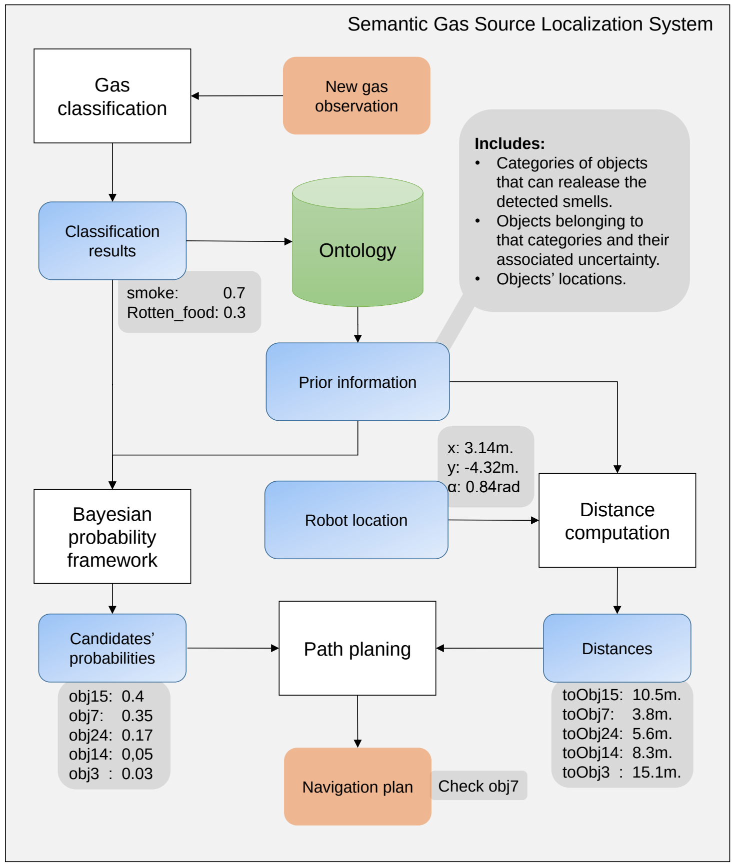


**Fig. 1.** Overview of the proposed Semantic Gas Source Localization System: from a new gas observation with a detected gas until the the generation of the navigation plan for localizating the source. White boxes are processes, while blue shapes are generated/consumed data.

probability $P_a$, cocked meal smell with probability $P_b$, and no smell with $P_c$), and also to store information about previously perceived objects: their probability of belonging to the considered categories (e.g. heater, cigarette, fish, etc.), and their locations. In this work we assume that the robot workspace has been already visually inspected and a number of objects have been recognized and codified into the ontology. In this way, when a gas emission is perceived and classified as belonging to a number of gas classes with their respective uncertainties, a semantic request is submitted to the ontology which returns: the object categories that can release those gases, and the instances (objects) of that categories already observed in the environment, also with their recognition uncertainty. A probabilistic Bayesian framework is then in charge of fusing this information and assigning to each object (*i.e.* candidate) a probability of being the gas source. Finally, a cost function is introduced to weight the probability of each candidate by the distances from the current robot location to them, and a path planning module processes its output to provide the navigation plan to be executed by the robot.

A demonstration of the system suitability has been carried out within complex simulated scenarios using GADEN [11]. The obtained results were promising, suggesting that our probabilistic approach is suitable for efficient gas source localization within complex environments, such as domestic ones.

## 2 Related Work

Gas source localization strategies are many and varied [12]. In this section we focus on two particular approaches: the fusion between the chemical data provided by the e-nose with vision systems in order to boost the GSL task efficiency, and works that consider uncertainty during the search process.

The former approach enables robots to identify candidates from a distance, thus dramatically diminishing the effective search space and greatly enhancing the ability to locate an odor source. It must be noticed that opposed to vision, which is a range sensing modality, most of the gas sensors are point-sampling devices, measuring only the gas that is in contact with them. Despite the notable advantages of considering vision in the GSL task, only very basic algorithms have been proposed so far, most of them relying on strong assumptions about the gas-source shape or color for the visual detection of candidates [9,13]. An exception is the work proposed by Loutfi *et al.* [14], where the authors proposed a symbolic reasoning technique for fusing vision and olfaction. However, focus is placed on object recognition, where gas sensing is only employed for object disambiguation, not to locate the source releasing the volatiles.

Related to works considering some type of uncertainty in the search process, we can highlight some engineered plume-tracing strategies such as infotaxis [7], a gradient-free method exploiting the expected entropy of future samples to guide the robot search towards the gas source, probabilistic approaches based on particle filters [8,15], or strategies based on gas distribution mapping [16]. The latter do not rely on the presence of a plume, neither on strong assumptions about the environmental conditions, however, their limitation resides in the time necessary to sweep the entire environment, and their bad scalability as the environment enlarges.

## 3 The Semantic Gas Source Localization System

Fig. 1 shows an overview of the processes and data involved in the proposed system. In a nutshell, if an unusual gas concentration is detected (e.g. while the robot is exploring the environment or while performing other non gas-related tasks) (see Section 3.1), the Semantic Gas Source Localization (SGSL) System is triggered for detecting the object releasing that odor and acting consequently. For that the system performs a semantic query to an ontology to get prior information with different flavors (see Section 3.3), which is introduced into a probabilistic framework that yields an ordered list of objects candidates according to their probability of being the source (see Section 3.3). This list is the input to a cost function, which is also feed with the distance from the robot current location to the source candidates. A path planning algorithm exploits this function to re-order the candidates list and produce a navigation plan to check them (see Section 3.4). For checking if an object candidate is the gas source (process know as validation), the robot will sample the air in the object's proximity, measuring concentration and carrying out a new gas classification. By comparing these values with the ones that triggered the search, the robot is able to discern if the object is or not the gas source it is looking for. The main components of the SGLS system are described next.

### 3.1 Starting Point: Gas Detection & Classification

In this work we assume that an assistance robot deployed in a home environment is equipped with an e-nose that is sampling the environment on a regular basis. This implies that while the robot is performing its duty tasks (*e.g.* patrolling, assistance, cleaning, etc.), it is also monitoring the gases present in the air. When an abnormal gas concentration level is detected, that is, when the gas concentration observed exceeds a predetermined threshold, the SGSL system triggers the search.

Once the search has been triggered, and in order to determine which objects in the environment are susceptible for releasing the observed gas, we carry out a gas classification. As in many other disciplines, classification corresponds to the process of determining which of a set of classes a new sample belongs. In this work we account for the uncertainty in this process by considering probabilistic classifiers. The output of such classifiers is not a class label, but a set of probabilities representing the belief of the gas observation to belong to each considered gas-class [17,18]. Therefore, any gas classifier giving as output a probability distribution over the set of classes can be employed, *e.g.* Support Vector Machines, Naive Bayes (the one considered in this work), Decision Trees, etc.

### 3.2 Exploiting Semantic Knowledge: The Ontology

Once a gas has been detected and classified with a certain belief, *e.g.* 0.6 of being smoke and 0.4 rotten food, the first step towards the localization of its source is to obtain valuable prior information to assist the process. With *prior information* in this context we mean: i) knowledge about the categories of objects that can release such gas, *i.e.* in the case of smoke and rotten food smells, ovens, ashtrays or bins are candidates, and ii) information regarding the objects already detected in the environment which can belong to that categories. As a reminder, we are assuming that the gas source is between a set of object candidates previously recognized in a visual inspection of the robot workspace. The chosen recognition method must be able to provide confidence values about its results, and although this task is simulated in the experiments conducted in this paper, we plan to use

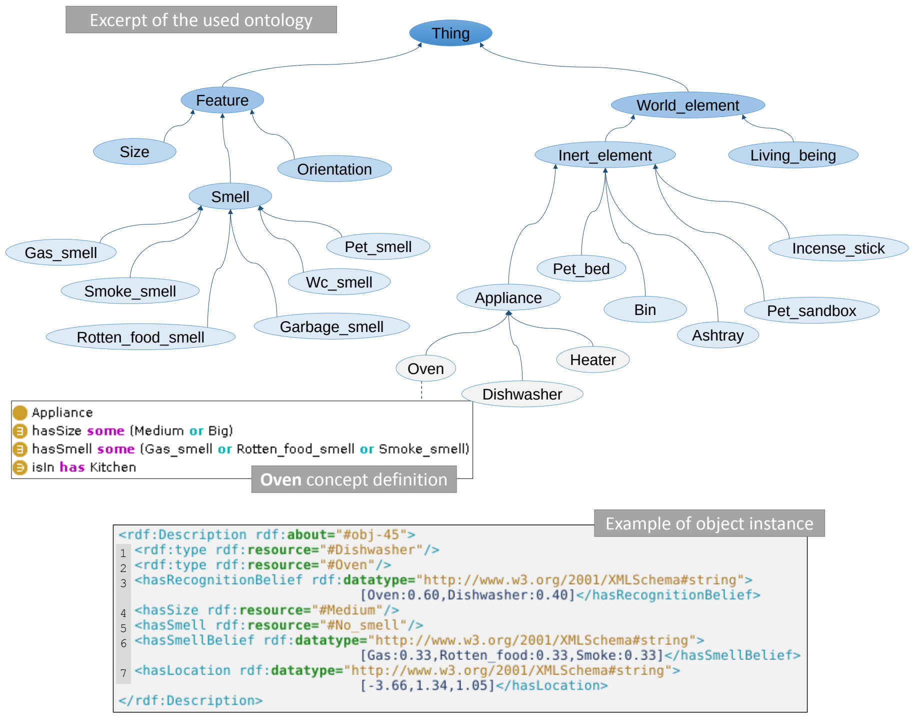


**Fig. 2.** Excerpt of the ontology used in this work, showing part of the hierarchy of encoded concepts, the definition of the concept `Oven`, and an example of object instance.

Conditional Random Fields (CRFs) [19] given their high recognition rates and proved suitability to this end [20,21].

For codifying the previous information, which is clearly a form of Semantic Knowledge (SK), we have resorted to an ontology [10]. An ontology is a principled way to naturally represent and update SK about a domain of discourse, employing for that a set of concepts arranged hierarchically, properties of that concepts, and instances of them.

As an illustrative example, let us consider an excerpt of the ontology used in this work, shown in Fig. 2. The root concept is `Thing` with two children: `Feature` and `World_element`, the latter establishing the elements that could be found in the robot surroundings and the former their features, *i.e.* `Size`, `Orientation`, and `Smell`. The elements can be `Inert_elements` or `Living_beings`, although in this work we are interested in the first one, which is the parent of concepts like `Oven`, `Astray`, `Dishwasher` or `Bin`. The concepts within this hierarchy are defined by their properties, as it is shown in the same figure for the `Oven` case. From that definition we can retrieve that ovens usually exhibit a medium or big size, that can release different smells: gas, rotten food, or smoke, and that they are placed in kitchens.

This ontology is also populated with instances of concepts, whose in this case are objects in the robot workspace previously detected to the SGSL process. The bottom part of Fig. 2 shows an instance that, according to the output of an object recognition method, could be an oven with belief 0.6 or a dishwasher with 0.4. This is specified in the three first lines of the instance definition. The fourth one tell us that the object has a medium size, and the next one that, at the time of its detection, it did not release any smell. The sixth line expresses that the object could release three different smells: gas, rotten food, or smoke, and also their associated believes. By now, these beliefs are set uniformly, although we are studying how to update them according to the robot experience in a certain workspace. The last line stands for the object position (coordinates) in the environment metric map.

This representation allows us to make semantic requests about the concepts (concerning objects) that could release a certain smell, as well as the instances of that concepts already detected. Notice that these instances come with uncertainty measurements about their belonging to the posed concepts, while the concepts that can give off that smell define an uniform probability distribution, information that is probabilistically propagated by the framework in the next section, along with the initial information about the detected gas.

### 3.3 Handling Uncertainty and its Propagation: The Probabilistic Framework

Our probabilistic Bayesian model for uncertainty propagation aims to, given the gas classification results and the prior information from the ontology, provide the probability for each candidate being the source. For that it considers four random variables:

- $Z$ is the gas observation (*i.e.* a measurement of the e-nose ($z_g$)).
- $G = \{G_i,\ i = 1 : N_G\}$ models the gas class and takes values on the set of $N_G$ possible gases.
- $C = \{C_i,\ i = 1 : N_C\}$ stands for the category of a candidate object, assigning to it a value from the set of $N_C$ categories.
- $S = \{O_i,\ i = 1 : N_O\}$ stands for the gas source, taking values on the set of $N_O$ objects perceived in the environment.

Thus, the probability of a certain candidate object $o_i$ being the gas source, given a gas observation $z_g$, is modeled as:

$$P(S = o_i|Z = z_g) = \sum_{j=1}^{N_C} P(S = o_i|Z = z_g, C_j)\ P(C_j|Z = z_g) \tag{1}$$

$$P(C_j|Z = z_g) = \sum_{k=1}^{N_G} P(C_j|Z = z_g, G_k)\ P(G_k|Z = z_g)$$

Such source probability is calculated by marginalizing first against the object categories $C_j$, and second against the gas classes $G_k$. It allows us to model the probability of each object in the environment of being the gas source as the product of three conditional probability distributions. The first one, $P(S = o_i|Z = z_g, C_j)$, represents the probability of object $i$ being the gas source conditioned on both the gas observation and knowledge about the object category of the gas source (*e.g.* bin, oven, toilet, etc.). Assuming independence with the gas observation given the object category $C_j$, this probability can be defined as the likelihood of the object belonging to that category (*i.e.* object recognition probabilities), information provided by the ontology (recall line 3 in the bottom part of Fig. 2).

The second probability distribution $P(C_j|Z = z_g, G_k)$, models the likelihood of the source to belong to a certain category $C_j$ conditioned on the gas observation and knowledge of the gas class $G_k$ that has ben released. Again, we can safely assume that this distribution is independent of the gas observation given the gas class, computing its value from the semantic knowledge encoded in the ontology about the object categories that can give off the gas $G_k$. For example, if $G_k =$ `Smoke` and the defined object categories that can release smoke are `Oven`, `Heater` and `Ashtray`, then: $P(C_{Oven}|G_{Smoke}) = P(C_{Heater}|G_{Smoke}) = P(C_{Ashtray}|G_{Smoke}) = 0.33$, while for the rest of object categories it takes a value of 0, *e.g.* $P(C_{Pet\_sandbox}|G_{Smoke}) = 0$.

Finally, $P(G_k|Z = z_g)$ is interpreted as the probability of the gas release belonging to gas of class $G_k$ conditioned on the gas observation, which corresponds to the output of the probabilistic gas classifier (recall Section 3.1). Given the three described probability distributions, the computation of Eq. (1) can be accomplished in short time, enabling a real time operation.

### 3.4 Giving Coherence to the Localization Process: The Path Planning Algorithm

Once computed the probability of each object in the environment of being the gas source, the robot must plan and inspect the different objects in order to locate the one that is the gas source. For this step we rely on a path planning module that in addition to the referred probabilities also takes into account the distance between the current robot location and the objects. For doing that a cost function is used:

$$\mathcal{L}(o_i) = -\ln\big(P(S = o_i|Z = z_g)\big)\, distTo(o_i) \tag{2}$$

where $distTo(o_i)$ is the distance between the robot location and the candidate object $o_i$. This cost function models a trade off between source probability and distance, giving lower values for objects with high probability and/or close to the robot. On each iteration, the path planning module calculates these costs to retrieve the *best* object to check $\hat{o}$ through the optimization:

$$\hat{o} = \underset{o_i,\, 1 \leq i \leq N_O}{arg\min}\ \mathcal{L}(o_i) \tag{3}$$

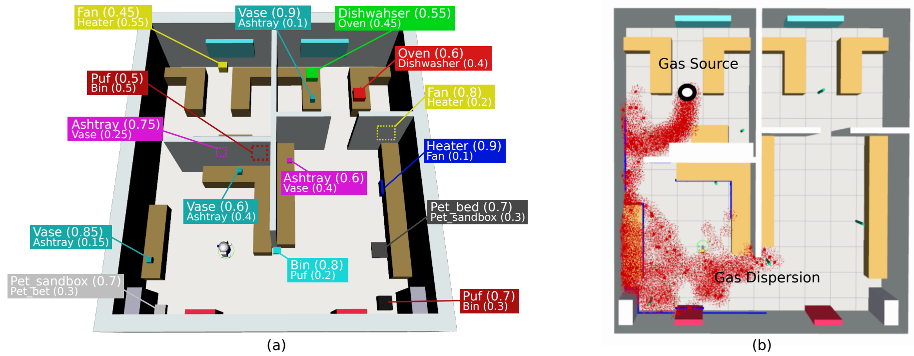


**Fig. 3.** Experimental setup. (a) 3D simulated environment composed of four rooms and fifteen objects. Objects are shown as 3D colored boxes specifying their location in the environment and their category probabilities. (b) Illustration of a gas dispersion simulation within the environment using GADEN [11]. When the robot is exposed to a gas concentration higher than a set threshold, the search is triggered to locate the source. As can be seen, gas dispersion is chaotic and spreads over multiple rooms, which implies that the robot may be far from the source when the search is triggered.

Once $\hat{o}$ has been calculated, the robot checks if it is the gas source releasing the gas trhough a process commonly referred as *source validation*. If it is, we are done. If not, the object is removed from the list of candidates, and the optimization in Eq. (3) is carried out again (since the distances from the robot to the remaining candidates have changed), obtaining a new target candidate. Recall that we are assuming that the gas source is among the objects already present in our system, otherwise a more sophisticated search must be implemented for example by performing object recognition along the search process to find new candidates. We will explore that approach in a future work.

## 4 System Demonstration

This section presents a simulated experiment where a mobile robot equipped with an e-nose must locate a gas emission source in a home environment (see Fig. 3). For this scenario we consider 3 gas classes, namely: `Smoke_smell`, `Gas_smell` and `Rotten_food_smell`, 11 object categories (`Vase`, `Bin`, `Ashtray`, `Oven`, `Heater`, `Dishwasher`, `Fan`, `Puf`, `Incense_stick`, `Pet_sandbox` and `Pet_bed`), and model $P(C_j|Z=z_g, G_k)$ as an uniform probability distribution (see Table 1). Furthermore, we set up fifteen different objects in the environment, which we assume have been previously detected by the robot with the probabilities shown in Fig. 3. All this information is managed by the ontology by means of associations between the objects, categories, gases, the robot and the environment itself.

For demonstration purposes we compare our approach with a deterministic case where there is no uncertainty consideration neither in the gas classification, nor in the object recognition. It must be noticed that this second approach

**Table 1.** Conditional probabilities of each object category given the gas class being released by the source: $P(C_j|G_k)$. As can be seen, some categories do not release any of the gas classes considered in the experiment ($P(C_j|G_k) = 0$), aspect to be exploited by our system, together with the object recognition uncertainty, to locate the gas source.

| Category | Smoke_smell | Gas_smell | Rotten_food_smell |
|---|---|---|---|
| Vase | | | |
| Bin | | | **0.33** |
| Ashtray | **0.25** | | |
| Oven | **0.25** | **0.5** | **0.33** |
| Heater | **0.25** | **0.5** | |
| Dishwasher | | | **0.33** |
| Fan | | | |
| Puf | | | |
| Incense_stick | **0.25** | | |
| Pet_sandbox | | | |
| Pet_bed | | | |

will fail when the gas or the objects are misclassified (*i.e.* when uncertainty is relevant), being necessary to check all the objects in the environment one by one using only the distance between the robot and the objects to optimize the search. Fig. 4 shows the averaged distance traveled by the robot and the number of objects checked before locating the gas source for three setups with different number of objects: 7, 11 and 15. In order to obtain statistically representative results, for each case we run the experiment 1000 times varying (i) the initial robot pose, randomly selecting a pose from within the environment, (ii) the gas source, randomly selecting an object to be the gas source from the list of objects, and (iii) the class of the released gas, generating a gas dispersion in accordance with the types of gases the selected source can emit (see Table 1). As can be seen our approach improves both magnitudes considerably, not only reducing the total distance traveled (which is directly related to the exploration time), but also reduces the number of objects visited before locating the source. The latter is important since the *validation* of a gas source is also an expensive task in terms of time. Furthermore, it can be noticed that the improvement seems to increase with the number of considered objects, something reasonable when comparing with the greedy approach that visits all the objects one by one.

## 5 Discussion

This work contributes a gas source localization system for mobile robots that aims to find the object releasing a smell efficiently and coherently by exploiting semantic information. On the one hand, it is efficient in the way that selects a set of candidate objects to be the source, and checks them according to their source probability and their distance from the current robot location. On the other hand, its coherence comes from the consideration of the uncertainty coming from both the gas classification and object recognition processes, as well

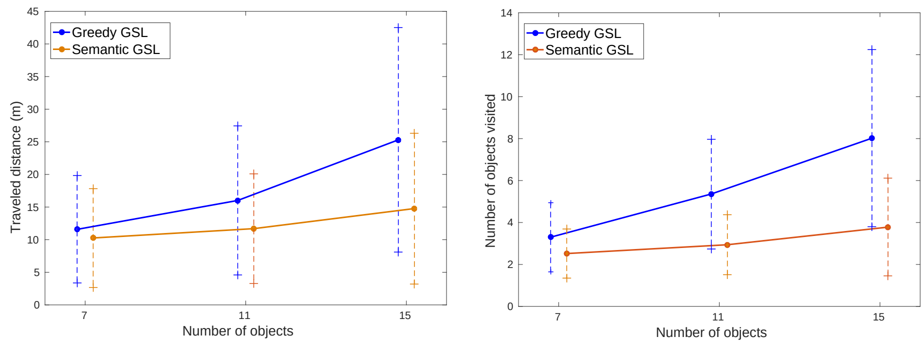


**Fig. 4.** Traveled distance (left) and number of objects visited (right) during the gas source localization experiments for three different set of objects. In each case, the average ± one standard deviation are plotted. As can be seen our approach improves both magnitudes substantially, specially for a high number of objects.

as semantic information providing valuable prior information, like the possible smells that a type of object can release. The system relies on an ontology to naturally encode this prior knowledge in a principled way, and also serves to codify information about the objects already detected in previous explorations of the robot workspace, including the belief concerning their classification as belonging to a certain object category.

We have proposed a probabilistic Bayesian framework to fuse such information, and implemented a simple cost function to derive a path planning algorithm that completes the localization system. The suitability of our approach has been demonstrated in a simulated home-like scenario with multiple objects and with realistic uncertainties. Comparison with a greedy approach based only on distance to the objects has been provided, suggesting that the consideration of semantics and uncertainty represents an interesting approach for tackling this complex problem.

The proposed system has significant room to explore. First of all, experiments in real environments must be carried out in order to find possible limitations and face them. We also plan to replace the simulated object recognition system by one based on Conditional Random Fields. Another certainly interesting point is how to update the beliefs about the smells of objects with the robot experience in a certain environment, which could further improve the search efficiency.

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