2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)
October 25-29, 2020, Las Vegas, NV, USA (Virtual)

A Bayesian approach for gas source localization in large indoor environments

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***Abstract*— The main contribution of this paper is a probabilistic estimator that assists a mobile robot to locate a gas source in an indoor environment. The scenario is that a robot equipped with a gas sensor enters a building after the gas is released due to a leak or explosion. The problem is discretized by dividing the environment into a set of regions and time into a set of time intervals. Likelihood functions describing the probability of obtaining a certain gas concentration measurement at a given location at a given time interval are assembled using data generated with GADEN, a three-dimensional gas dispersion simulator([1]). Given a measurement of the gas concentration is available, Bayes's rule is used to compute the joint probability density describing the location of the gas source and the time at which it started spreading. To illustrate the estimation process, a relatively simple motion planner that directs the robot towards the most likely gas source location using a cost function based on the marginal probability of the gas source location is used. The motion plan is periodically revised to reflect the latest posterior probability density. Simulation experiments in a large air-conditioned building with turbulence and wind are presented to demonstrate the effectiveness of the proposed technique.**

Keywords: gas source localization, robot olfaction, Bayesian estimation

I. Introduction

Over the past decade, the ability to use mobile robots to gather critical information has been recognised as an important aid to the first responders in search and rescue missions. The focus of this paper is to use a mobile robot to rapidly detect the location of an adverse event in which a harmful gas is discharged in an indoor environment. Significant progress in the field of odour source localisation has been made in recent times with different approaches to the problem [2], [3]. As widely accepted in the community, the gas source localisation problem is typically subdivided into three tasks [2] (a) gas plume finding (i.e. detecting the presence of gas) [4] (b) plume tracking (i.e. to follow a trail of plume to the gas source) [5], [6] (c) declaration of the location of the gas source [7].

There are two main approaches as to how gas concentration measurements are used to solve the gas source localisation problem. The first approach relies on a spatially distributed stationary sensor network to determine the location of a single gas source [8], [9]. The second approach uses a mobile robot equipped with suitable sensors to determine the location of the gas source [10], [11]. Methods involving a mobile robot to find the gas source given gas concentration measurements include gradient based, bio-inspired, multi-robot and probabilistic algorithms [3], [12]. The gradient based methods attempt to move the robot to the gas source location by computing the concentration gradient of the gas plume [3], [13], [14]. Biologically inspired algorithms have been proposed to track an odor plume up to its source by mimicking the behavior of moths and dung beetles. These algorithms have been implemented on mobile robots based on two principles [15] (a) movement of the robot is determined by the distribution of the gas (i.e. chemotaxis) [16] (b) movement of the robot is determined by the airflow (i.e. anemotaxis) [13]. For chemotaxis, already established concentration gradient techniques are popularly used. While most of the above algorithms have been implemented and tested using ground mobile robots, researchers have made advancements in using Unmanned Aerial Vehicles (UAV) to

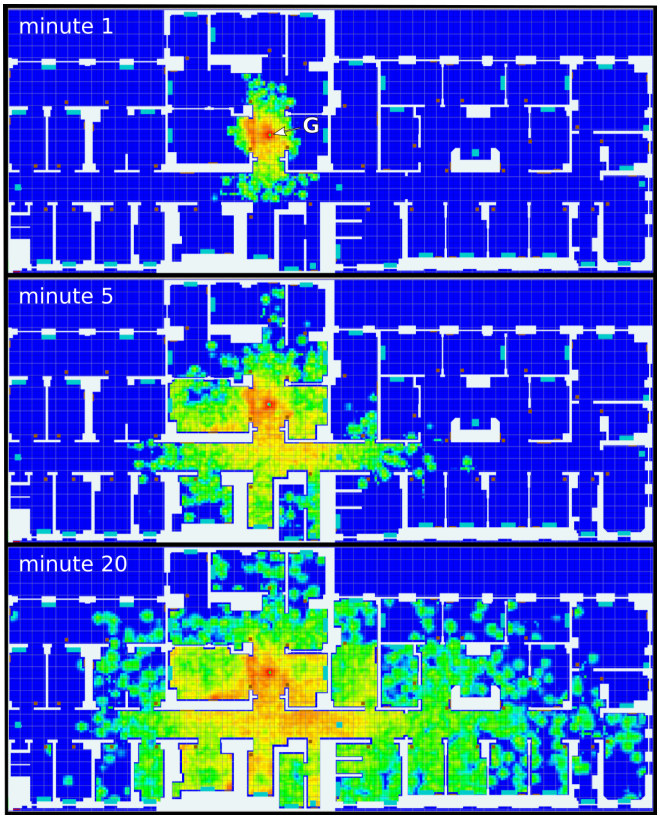

Fig. 1. Typical application scenario modelled using GADEN: The task is to guide a robot to the gas source location using an on-board gas sensor. In this example, although steady state is reached near the source that is denoted by G after five minutes, the gas concentration keeps changing with time in other parts of the building even after twenty minutes.

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locate the gas source, specially in outdoor environments. For example, the work reported in [17], proposes a gas-sensitive micro-drone with bio-inspired plume tracking algorithms.

As an alternative to these well-known gradient based algorithms, probabilistic algorithms to find gas source location have also been investigated [3]. Known as infotaxies, these methods use probability and information theory based search strategies. Typically the location of the source is modelled as a probability distribution using a large set of previously collected measurements [18], [19]. Using these precomputed models and the Bayes's rule, hypothesising on the most recent gas measurement, the next motion action of the robot is decided based on some criteria, for example minimising entropy. These models assume that gas distribution is in a steady state condition. As seen in Fig. 1 in a large building, this assumption is only satisfied near the gas source even after significant time has elapsed. The main contribution of this paper is a technique to deal with gas concentration measurements that change both in space and time, and compute the joint distribution of both the gas source location and the time at which the gas flow started in a Bayesian framework.

During the model development phase, a large number of simulations using a gas dispersion simulator [1] is used to collect a set of gas measurements over time in the building with gas sources placed at different locations. These are then used to build a set of likelihood functions that provides the likelihood of observing a gas concentration measurement at a given location in the building given the source location and a start time. As the robot enters and travels through the building, it takes gas concentration measurements with a constant time intervals using an on-board gas sensor. In order to terminate the search, it is also assumed that an appropriate visual or thermal sensor is available to quickly ascertain the presence or absence of a gas source when the robot enters a confined space such as a room. Beginning with a uniform prior, the robot periodically computes and updates the joint probability density of the gas source location and the start time. To illustrate the proposed algorithm a relatively simple motion planner, that combines the marginal posterior probability density of the gas source location together with the travel time in a cost function, is used to drive the robot to the potential location of the gas source. Target location is periodically updated to take the impact of the new measurements. Several simulation tests have been conducted to evaluate the proposed scheme and to demonstrate that it can effectively locate the source in a building with many rooms and long corridors.

The paper is organised as follows. Section II discusses the specifics of the problem to be solved together with the proposed Bayesian framework and the overall algorithm. Section II-C presents the details of how the joint probability density model describing the location of the gas source and the time at which it started releasing is developed. Section III discusses the results of several simulation experiments conducted. Section IV concludes the paper.

II. Methodology

A. Problem Description

Hazardous gas leak from a single stationary gas source at an unknown location inside a building eventually spreads throughout the building due to wind turbulence, gas diffusion and objects movement. It is assumed that the a priori knowledge of the building in the form of a map is available. A mobile robot installed with a suitable gas sensor enters the building and starts to sample the environment for presence of gas. The objective is to drive the robot to the gas source location. As the assumption that the system has reached the steady state is not used, both the gas source location and the time at which the gas leak started need to be estimated. The task is, therefore, to compute the joint probability density function (PDF) describing the gas source location and the start time. To illustrate the use of this PDF, a simple search strategy that guides the robot in the building is used in the experimental evaluations presented. It is important to note that the PDF generated could be of use in cost functions associated with other more complex search strategies proposed in the literature.

B. Bayesian Framework

The floor map of the building is manually partitioned into N_R small regions $R = \{r_1, r_2, .., r_{N_R}\}$ taking geometrical restrictions into consideration such as walls, partitions etc. While relatively smaller and closed spaces are treated as individual regions, larger open spaces and regions along the corridors are divided into multiple regions. T, the time interval from the beginning of the gas leak is also partitioned into N_T time intervals $T = \{t_1, t_2, .., t_{N_T}\}$.

The goal of the gas source localization algorithm is to produce the probability that the gas source being positioned in any of the regions in R and started during any of the time intervals in T, given a sequence of gas concentration measurements $y(t)$ acquired at a constant sampling rate.

Consider the situation that the robot enters the building and takes a gas concentration measurement y in region r_b after a time t_{rob} has elapsed. The objective is to compute the the probability $P(r_a, t_{gas}|y(t_{rob}, r_b))$ that the gas source is located in a given region r_a and that it has been active for a time t_{gas} before the the robot entered the building. If the likelihood function describing the probability of acquiring such a measurement, given a gas source location and a start time, $P(y(t_{rob}, r_b)|r_a, t_{gas})$, is available, Bayes's rule as in Eq. (1) can be used for this purpose.

$$P(r_a, t_{gas}|y(t_{rob}, r_b)) = \frac{P(y(t_{rob}, r_b)|r_a, t_{gas})P(r_a, t_{gas})}{P(y(t_{rob}, r_b))} \tag{1}$$

$P(r_a, t_{gas})$ is the prior probability. The likelihood function $P(y(t_{rob}, r_b)|r_a, t_{gas})$ provides a model describing how the gas propagates in the building. Details on how the GADEN simulator can be used to build a set of functions that provides the likelihood of observing a particular gas concentration measurement y for all the measurement and source locations

R and start times T is presented below (Section II-C). Given such a set of functions, The joint probability density $P(r,t)$ that covers all the regions R and time intervals T, given a measurement y in any region after the robot has travelled for a time of t can be obtained by selecting the appropriate likelihood function an applying (1). Details of this process is presented in Section II-D.

C. Generating Likelihood Functions

This process starts with a three dimensional model of the building represents the walls, objects present in the environment, inlets and outlets of the building air conditioning system including the associated air pressures, speeds and flow rates as shown in Fig. 2. The CFD software Sim Scale is then used to compute the steady-state 3D wind vector profile.

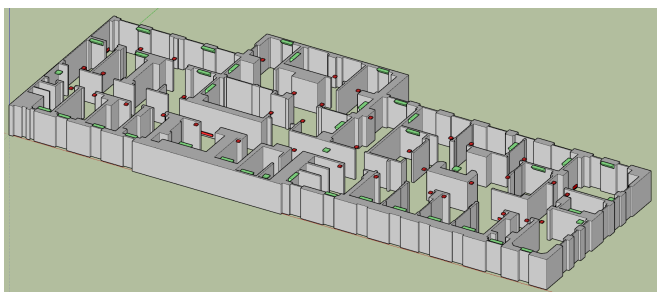

Fig. 2. Visualization of 3D building model. Objects with grey, green and red color are the walls, the inlets and the outlets respectively

The gas source is placed at multiple locations and gas concentration measurements y in each of the regions R at one time interval over the time period T is collected using the GADEN simulator that computes the distribution of gas inside the building as a function of time. To generate sufficient data to build a representative likelihood function, multiple locations inside each region is used to place the gas source and also to collect the measurements. Measurements y for each pair of gas source location and start time (r_a, t_{gas}) and measurement location and measurement time (r_b, t_{rob}) can then be assembled to generate the corresponding likelihood function using a kernel density estimator as in Eq. (2).

$$\hat{f}_h(x) = \frac{1}{nh}\sum_{i=1}^{n} K\Big(\frac{x - x_i}{h}\Big) \tag{2}$$

A Gaussian kernel K and a bandwidth h selected based on [20] were used in the resulted presented. Four typical likelihood functions are illustrated in Fig. 3.

D. The Algorithm

Until the first measurement indicating the presence of gas is obtained, information as to the gas source location and the start time is not available. Therefore, the prior $P_{prior}(R,T)$ can be initialized to a uniform distribution with the magnitude $1/(N_R \times N_T)$. This prior is updated as measurements $y(t_{rob}, r_b)$ are gathered to produce the posterior PDF, $P_{post}(R,T)$. The region r_b where the robot has taken the observation is determined using the current

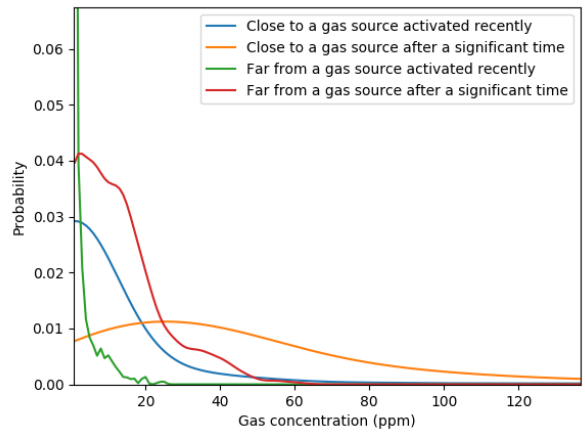

Fig. 3. Four likelihood functions of obtaining a gas concentration measurement in a specific region at a specific time. It is seen that these curves follow intuition, showing a low probability of observing a strong gas concentration measurement far from a gas source that has been activated recently where as the probability is high if the gas source is nearby and has been active for a significant time

robot pose. The posterior probability $P_{post}(R,T)$ is then used as the prior probability for the next iteration.

It is important to note that information on t_{gas} is not available once the gas concentrations reach the steady state. However, considering the impact of time on the gas concentration measurements is important as the robot needs to travel through regions where the gas concentration is changing.

As the objective is to find the gas source location, the marginal PDF $P(R)$ that describes the probability that the gas source present in each of the rooms R is used for decision making. As discussed previously, a simple strategy that uses an objective function which compensates for the time required to travel given by Eq. (3) is used to illustrate the algorithm presented in this paper.

$$r_{goal} = \arg\max\Big(P(R) + \frac{\alpha}{distance(x, center(r_a))}\Big) \tag{3}$$

Where r_{goal} is the room to which the robot is directed, $P(R)$ is the marginal posterior PDF of location updated using the latest measurement received at location x, and α is a constant that governs the relative importance between the probability and travel time.

III. Experimental Results

A. Simulation Setup

The simulation is set up using a one-level hospital building which has a long corridor with many rooms as shown in Fig. 2. Specific details of the parameters used are as follows.

The size of the building is $(54 \times 22)m^2$. This was manually partitioned to 50 small regions (i.e. $N_R = 50$). Grid cell size $(0.2 \times 0.2)m^2$ were selected for use in the simulation. The simulation time, T, is 20 minutes, and N_T was chosen to be 20 making each small time interval to be 1 minute. A hundred Gaussian-shaped filaments emerge from the source and spread out every step of time with initial standard deviation is $0.1m$ with the gas concentration at the

Algorithm 1 Main Program

Require: R, T
  collect set of $PDF(y(t_{rob}, r_b)|r_a, t_{gas})$
  set $P_{prior}(R,T) = \{1/(N_R N_T), ..., 1/(N_R N_T)\}$
  for sensor sample time **do**
    get $y(t_{rob}, r_b)$ observation in region r_b at t_{rob}
    for $r_a := r_1 \longrightarrow r_{N_R}$ **do**
      for $t_k := t_1 \longrightarrow t_{N_T}$ **do**
        $L = PDF(y(t_{rob}, r_b)|r_a, (t_k + t_{rob}))$
        $P_{post}(r_a, (t_k + t_{rob})|y(t_{rob}, r_b)) =$
        $L \cdot P_{prior}(r_a, (t_k + t_{rob}))$
      end for
    end for
    normalize $P_{post}(R,T)$
    $P_{prior}(R,T) = P_{post}(R,T)$
    compute $P(R)$ and estimate r_{goal} using (3)
    if no gas source in region r_{goal} **then**
      $P_{prior}(r_{goal}) = 0$
    end if
  end for

centre is $5000ppm$. In the simulation experiments, CO_2 was chosen as the gas and as suggested in [21], CO_2 diffusion coefficient and mass parameter were set to $0.16cm^2/sec$ and $44.01g/mol$ respectively. The building temperature and pressure were assumed constant with 298 Kelvin and 1 atm respectively. A random white noise was used to approximate difficult to model phenomena such as human motion and opening and closing doors. In the corridors and near to the door, white noise was set to $0.3m$ while other places were set to $0.1m$.

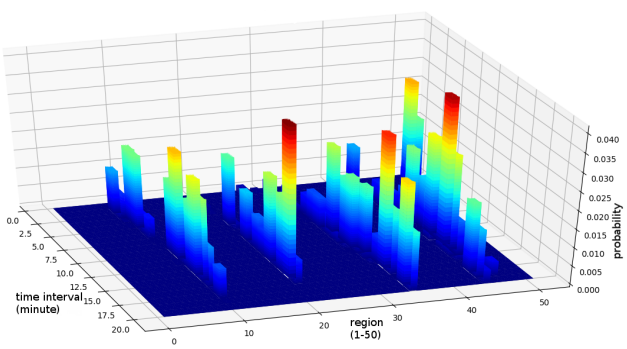

Fig. 4. The plot of joint probability density function of region 1 to 50 and 20 time intervals as soon as the robot detects a gas

The placement of inlets and outlets were set to follow the ventilation building standard. For the selected hospital building, one inlet at the ceiling and two outlets (one at the ceiling and the other one at the floor) were set in every room with the magnitude of the airspeed from the inlets was set to $0.4m/s$. The inlets and outlets are also installed in the corridors. Fig. 4 illustrates the joint probability density function of 50 regions and 20 time intervals computed using the proposed algorithm immediately after the robot detects the presence of gas near region 2 for the example presented in Fig. 5.

B. Result and Discussion

The proposed Bayesian algorithm to estimate the joint distribution of both the gas source location and the time at which the gas flow started has been evaluated using several simulation experiments.

1) Performance Evaluation: Comprehensive result from four different gas source locations are presented: a gas source in arbitrary location in the middle of building (region 50 in Fig. 5a), activated short time before the robot enters and placed near entry (region 39 in Fig. 5b), activated short time before the robot enters and placed near entry (region 3 in Fig. 5c) and far away from the robot (region 37 in Fig. 5d). Gas source locations were selected to be different from those used during the process of building the likelihood functions. The robot starts the mission 5, 4, 20 and 5 minutes after the gas source was activated respectively. The robot starts from the left-end of the corridor (region 15).

a) Gas source in region 50: It is shown in Fig. 5a that the robot was first directed to move along the corridor in the absence of any information until it detects a gas at location 2. The robot does not turn to the left as expected, due to the fact that the PDF is not yet sufficiently accurate. It travels straight until it reaches location 3. At location 3, the robot estimates that most likely gas source location to be in region 41 and turns around to move towards region 41. However, when the robot reaches location 4, it makes the decision to go to region 42. The time estimation in location 3 and 4 are 2-3 minutes before the robot entered the building as the robot expects that the gas source is nearby. In region 42, the visual/thermal sensors on the robot does observe a gas source so that it revises the PDF accordingly and enters the region 50 and then finds the gas source. The gas leak is estimated to have started six minutes before the robot entered the building.

b) Gas source in region 39: In the experiment depicted in Fig. 5b, as soon as the robot enters the building, it detects the presence of gas. It estimates that the region 2 or region 26 as the potential regions where the gas dispersion originated from. As it moves towards region 26, at region 3 it estimates that the gas source is potentially in region 39. While moving towards region 39, at location 4, robot estimates that the gas source is in region 38 and finally enters the region 39.

c) Gas source in region 3: In this experiment, focus is on a scenario where gas source is located near the robot but the gas dispersion started long time before the robot enters the building. In this case, even though the gas source is located near the robot's initial position, finding the location appears to be quite challenging. Furthermore, as the gas concentration has reached steady state by the time the robot visits this region, the measurements do not contain information about the start time. Therefore, the time estimate in this case is inaccurate.

d) Gas source in region 37: The fourth experiment illustrates locating a gas source situated far away from where the robot enters the building. The most important aspect of

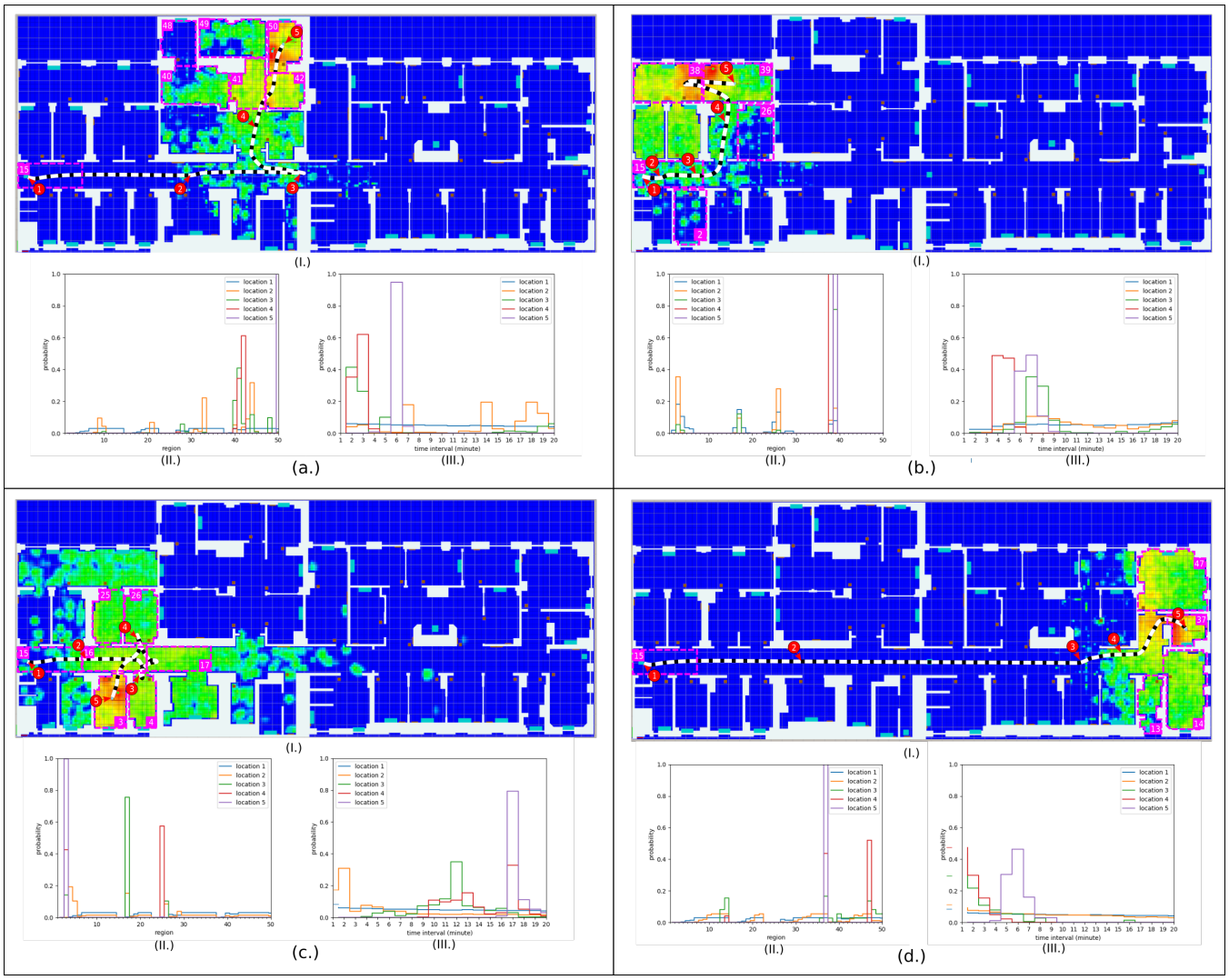

Fig. 5. Experiments from four different gas sources: (a.) a gas source in arbitrary location in the middle of building (region 50), (b.) activated short time before the robot enters and placed near entry (region 39), (c.) activated short time before the robot enters and placed near entry (region 3) and (d.) far away from the robot (region 37). Gas source locations were selected to be different from those used during the process of building the likelihood functions. Each experiment contains: (I.) robot trajectory, (II.) marginal posterior probability of region, (III.) marginal posterior probability of time

this case is that robot requires a significant amount of time before it detects the presence of gas. When the sensor does not detect any gas, it is simply directed to move forward along the corridor as during this period the PDF remains uninformative.

2) Repeatabillity: Due to the sensor noise and the stochasticity of the gas propagation, a further experiment was conducted by repeating the experiment five times with the same configuration as in Section III-B.1.a. As expected, this results in several slightly different trajectories as seen in Fig. 6.

3) Evaluation of the impact of different gas source strengths: In the proposed algorithm, the impact of the gas source strength was not considered. To evaluate the robustness of the estimation to changes in the gas source strength, experiments were conducted to compare the performance of the algorithm when a gas source with 50%, 75%, 100%, 125% and 150% of the strength of the source used for building the likelihood functions. It is clearly seen in both in

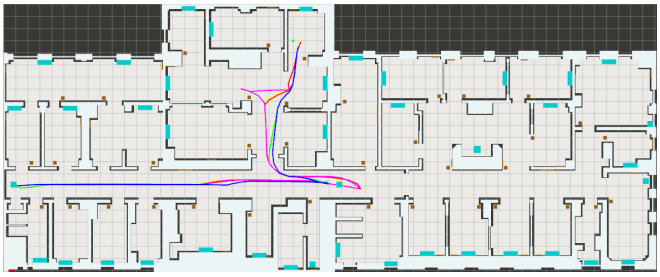

Fig. 6. Trajectories generated by repeating the experiment five times with the same configuration as in Section III-B.1.a

Table I and Fig. 7 that the performance is degraded. Although the estimates of the PDFs are inaccurate, the search algorithm is able to locate the source in all these situations. The potential for improving the accuracy of the PDF estimation exists though incorporating a third variable in the joint PDF to represent the gas source strength.

TABLE I

IMPACT OF A GAS SOURCE STRENGTH THAT IS DIFFERENT FROM THE ONE USED FOR GENERATING THE LIKELIHOOD FUNCTIONS

Gas strength (%)	***Trajectory length (m)***	***Spent time (s)***
50	45.92	90
75	49.5	83
100	24.08	64
125	51.52	92
150	46.4	73

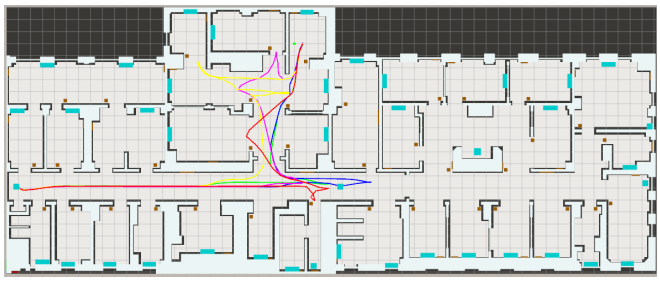

Fig. 7. Robot trajectory as a result of experiment using 5 different gas strengths. (magenta: 50%, blue:75%, green:100%, yellow:125%, red:150% gas strength)

IV. CONCLUSION

This paper presented a framework suitable for estimating the location of a gas source in a large indoor environment. By using Bayesian inference, joint probability density of the gas source location and the time at which the gas leak was initiated was estimated from repeated measurements of gas concentrations measured from a sensor on board a robot. A simple search strategy based on the most likely location and the travel cost to chosen candidate location was used to illustrate the effectiveness of the proposed strategy. The performance of the proposed approach was evaluated by simulation in a large air-conditioned building, as the main assumption that the wind profile is near constant limits the applicability of this work to such environments. It was observed that incorporating the strength of the gas source as an additional variable is required for improved performance. An optimal motion planning strategy based on the information generated by the estimation algorithm is also a clear avenue for further research. Future work will also involve experiments in real life environments.

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