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RESEARCH ARTICLE

Integration of Bayesian Inference and Anemotaxis for Robotics Gas Source Localization in a Large Cluttered Outdoor Environment

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ABSTRACT Finding a gas source in a cluttered outdoor environment using autonomous robot is a complex challenge. The gas movement is difficult to predict as it is significantly affected by the wind and the shape of objects in the environment. In this paper, we propose a new probabilistic model and an integration of Bayesian inference and anemotaxis methods used for a robot to find a gas source in a large cluttered outdoor environment. An autonomous robot installed with a gas sensor is expected to find the location of the gas source after the gas leak occurs for a particular time. The advantage of the Bayesian inference technique has been presented previously so that a robot can find the gas source in an isolated indoor building without any significant wind flow. The large environment is divided into some particular regions. A set of probability density function was collected previously from a large amount of gas dispersion simulation to estimate the maximum likelihood of where the gas source is. The challenge gets more extensive if the Bayesian inference method is applied in an outdoor and cluttered environment. Instead of only measuring the gas concentration, the wind angle is also used as the wind profile significantly affects the gas dispersion. Therefore, the probability model is modified to allow the wind direction as a new variable. Moreover, an anemotaxis method is incorporated as the decision-making support as it may be more efficient to direct the robot explicitly to the upwind direction. Evaluations of the proposed method were carried out and its advantage was shown through simulation in a number of different scenarios.

INDEX TERMS Gas source localization, Bayesian inference, anemotaxis.

I. INTRODUCTION

Nowadays, unmanned ground or aerial vehicles are needed in a response to a chemical, biological, radiological, and nuclear (CBRN) leaks [1], [2]. The unmanned vehicles or robots are used to assist in a CBRN mitigation process as they are not affected by the CBRN contamination. The robots can carry some CBRN sensors to do a gas distribution mapping or gas source finding. The map and source location estimation can be useful for evacuation decisions or decontamination as the next phase of the mitigation process.

Research in gas source localization (GSL) by a robot are classified into reactive, heuristic, learning, and probabilistic methods [3]. The reactive methods are inspired by insect behaviors and they are classified into chemotaxis and anemotaxis methods. By using chemotaxis methods, the robot is driven along the gradient of the gas concentration [4]. By using anemotaxis methods, the robot finds a source by going against the wind direction [5]. [6]. However, the behavior of the reactive method is straightforward without considering previous information.

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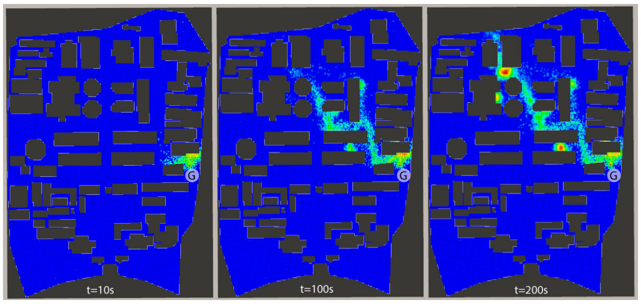

FIGURE 1. An illustration of time-variant gas dispersion in an outdoor cluttered environment with some turbulence points (G: gas source location).

Instead of using reactive methods, heuristic optimization may be a better alternative solution as historical samplings are used. [7], [8], [9], [10], [8]. They used a distributed nano multi-quadcopter in indoor cluttered GPS-denied environment. As the popularity of machine learning is significantly increased in the last decade, both supervised and unsupervised machine learning methods are adapted to solve the GSL problem. The deep learning architecture is used for odor source direction classification and gas source localization [11]. By adapting reinforcement learning methods [12], [13], a robot can autonomously find the optimal behavior for finding a gas source through trial and error with the environment.

A probabilistic method is another option as a learning method is data-hungry. Particle filter [14], [15], Information-driven [16], Entrotaxis [17], Bayesian inference [18], [19], [20], or Markov Decision Process (MDP) [21] based methods are some promising methods for GSL. Most of the works used a generalization of the plume model for estimating the likelihood probability. Realistically, a simple plume model does not consider the wind turbulence and the existence of obstacles. Near-realistic time-variant gas dispersion in a cluttered environment is depicted in Fig. 1. At first, the gas leaks in location (G) with small amount of gas particles. Eventually, the gas particles are distributed extensively to other regions by the wind advection, gravity, buoyancy, random movement and molecular diffusion.

The summary of the state-of-the-art related to GSL is shown in Table 1. Each research has its problem assumption, such as the existence of the obstacle, the wind turbulence and the size of the environment. The more the obstacle exists, i.e. in a cluttered environment, the more the wind turbulence spots exist. Moreover, the wind direction in an area which is very near to the obstacle is more irregular. The larger the environment is also more challenging as the robot may go far away from the source and cannot find the gas source because the robot repeatedly goes around the same track. Furthermore, how to evaluate the method is also very important. Some researchers have done the evaluation using real experiments; otherwise, the evaluation has been conducted in a simulated environment.

A few GSL works have considered realistic gas dispersion. The most frequently used gas dispersion simulators is GADEN [22]. In [19], a Bayesian filtering technique was used for localizing a gas source. The likelihood is estimated from a set of likely gas dispersal simulations. This work was extended by considering the time factor in the Bayesian model by [20] in a more complicated indoor environment. Another work in [12] used deep reinforcement learning. It used a 10×10 grid environment in the training phase. The result was also evaluated in GADEN, but some experiments were not more efficient than simple bio-inspired methods.

The challenge is become more complex for finding the gas source in outdoor cluttered environment. Many papers used anemotaxis as it is effective in an environment with strong wind flow. However, other methods were also proposed. Computational Fluid Dynamics (CFD) simulation and LSTM-RNN method are utilized by [11] to allow a robot predicts the source location in a chemical plant that has complex terrain. Simulated annealing method was used by [9] in a multi-building environment. However, there is no comprehensive evaluation as it only used one simple wind profile. In this paper, we use an outdoor environment that contains some buildings. In that kind of environment, the wind flow is chaotic, and the distribution can be different depending on the current weather. We proposed a new probabilistic method and integrating Bayesian inference with anemotaxis to more efficiently find the gas source location.

In a Bayesian framework, the most challenging thing is how to estimate the likelihood. In this case, the likelihood probability can be estimated by utilizing a set of gas simulations with different wind profiles. The likelihood probability means the probability of the robot observing the gas and the wind direction at a specific time and region, given a set of probability density functions (PDF). As in the Bayesian inference technique, the estimated likelihood updates the posterior probability of each region whether it is more likely to contain a gas source or not. The decision of each iteration is not only based on Bayesian inference but also incorporates an anemotaxis method. We named it as Bayesian+anemotaxis method. The anemotaxis method is used as a local search. The robot will move to a neighbor region where the smallest difference between the robot's heading to the region with the highest posterior and the angle of the wind direction is.

Several simulations are conducted to evaluate the efficiency of the proposed method. A comparison among other methods such as chemotaxis+anemotaxis and Bayesian inference only is analyzed. Robot Operating System (ROS) and GADEN simulator are used as the robot and gas simulator. The robot used in this paper is an Unmanned Aerial Vehicle (UAV) installed with a gas sensor. The UAV estimates the wind direction by using a method in [23].

The paper is organized as follows. Section II describes the formulation of the problem addressed. Section III elaborates the methods used to solve the problems. Section IV shows the

TABLE 1. Summary of some relevant GSL literatures.

Reference	Method	Obstacle	Environment size	Wind turbulence	Evaluation
[4]	Chemotaxis	No	Small	Yes	Simulation with simple plume model
[5]	Anemotaxis	No	Small	Yes	Simulation with simple plume model
[6]	Bio-inspired (Spiral, Surge-cast, etc.)	No	Small	No	Real experiment
[7]	Probability-PSO	No	Small	Yes	Simple odor plume simulation
[8]	Particle Swarm Optimization (multi-robot)	Yes	Small	Yes	Real experiment with nano drones
[9]	Simulated Annealing (Using TDLAS gas sensor)	Yes	Small	No	Simulation with simple plume model in outdoor
[10]	Artificial Bee Colony (multi-robot)	No	Small	No	Simulation with simple plume model
[11]	LSTM-RNN (using static wireless sensor network)	Yes	Large	Yes	Simulation with CFD
[12], [13]	Reinforcement Learning	No	Small	No	Indoor simulation (with GADEN)
[14], [15]	Particle filter	No	Small	No	Real outdoor experiment
[16]	Information-driven	Yes	Small	Yes	Indoor simulation
[17]	Entrotaxis	No	Small	Yes	Simulation with simple plume model
[18]	Probabilistic model-based (multi-robot)	No	Small	No	Real indoor experiment
[19]	Bayesian	Yes	Small	Yes	Indoor simulation (with GADEN)
[20]	Bayesian (with discretized time)	Yes	Large	Yes	Indoor simulation (with GADEN)
Proposed method	Bayesian+Anemotaxis	Yes	Large	Yes	Outdoor simulation (with GADEN)

results and discusses the comparison among other methods. A conclusion and some future works are written in Section V.

II. PROBLEM FORMULATION

The strong airflow rapidly distributes a gas leak from a single gas source in a cluttered outdoor environment. It is assumed that the 3D map building is available apriori. A robot installed with an appropriate gas sensor is driven to find the location of the gas source. The gas dispersion is time-variant and the wind distribution varies. Therefore, a joint PDF of gas source location and time should be computed, given the measurement of gas and wind direction. The use of PDF is to estimate the maximum likelihood of where the gas source is. The likelihood is used to update the posterior probability in a Bayesian inference framework.

The contribution of this paper are a novel probability model and a goal decision-making strategy combining Bayesian and anemotaxis methods for GSL. A novel probability model is presented, in which some wind profiles are joined to construct the PDF. The anemotaxis method, an oriented movement in response to a current of wind flow, is expected to increase the efficiency of the GSL.

III. METHODOLOGY

A. PROBABILISTIC MODEL

In this paper, the environment is divided apriori into N_R regions $R = \{r_1, r_2, .., r_{N_R}\}$ using a Voronoi partition in a non-convex area [24]. The time is also divided into N_T periods $T = \{t_1, t_2, .., t_{N_T}\}$. As an outdoor building is used, the wind distribution can vary in order that there are N_W wind profiles $W = \{w_1, w_2, .., w_{N_W}\}$. For example, four different wind profiles are depicted in Fig. 2.

A gas source is located in one of the regions (r_a). The gas leakage starts at (t_{gas}). The gas sensor measures the gas concentration (y_{gas}) at a particular time (t_{robot}) in a particular region (r_b) with a specific wind profile (w_i). It is assumed that the wind profile is time-invariant. Therefore, the wind (y_{wind})

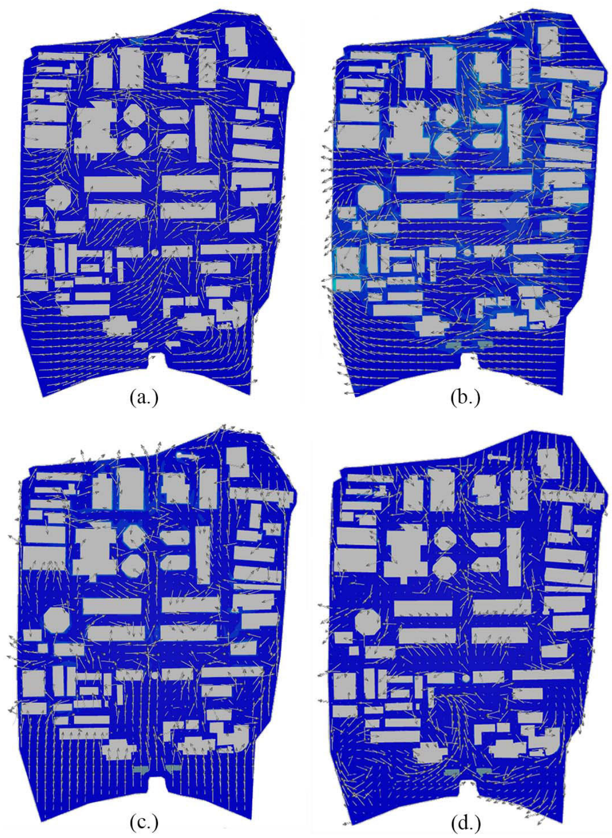

FIGURE 2. Different wind profiles generated in a campus building: (a.) West to East, (b.) East to West, (c.) South to North, and (d.) North to South.

is measured in a particular region (r_b) with a specific wind profile (w_i).

$$P(r_a, t_{gas}|y_{gas}(t_{robot}, r_b, w_i), y_{wind}(r_b, w_i)) = \frac{P(y_{gas}(t_{robot}, r_b, w_i), y_{wind}(r_b, w_i)|r_a, t_{gas})P(r_a, t_{gas})}{P(y_{gas}(t_{robot}, r_b, w_i), y_{wind}(r_b, w_i))} \quad (1)$$

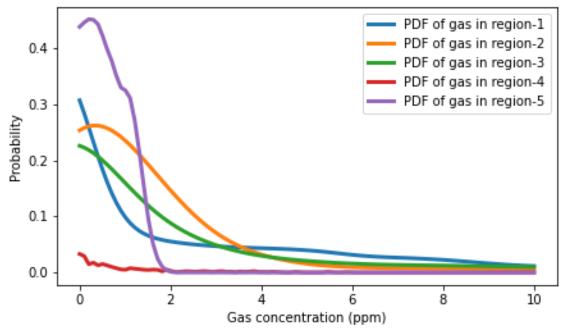

FIGURE 3. Several PDFs of gas that are taken with wind profile as in Fig. 2.c if the gas source is located in region-1 in a particular time.

Eq. 1 is a Bayes rule which models the probability of the joint PDF of the gas source location and the start time given the measurement of gas concentration and wind angle. The prior probability, $P(r_a, t_{gas})$, is initialized equally depend on the number of region, time period and wind profile. The posterior probability, $P(r_a, t_{gas}|y_{gas}(t_{robot}, r_b, w_i), y_{wind}(r_b, w_i))$, will be continually updated and assigned to prior probability in the next iteration. Moreover, the posterior can only be updated if the likelihood, $P(y_{gas}(t_{robot}, r_b, w_i), y_{wind}(r_b, w_i)|r_a, t_{gas})$, can be estimated.

B. GENERATING A SET OF GAS SIMULATIONS

To estimate the likelihood, a set of gas distribution data is needed. At least a simulation of a gas source in each region is done for each wind distribution. Therefore, the minimum number of simulations is $N_R \times N_W$. For each simulation, the time is divided into N_T periods. The gas concentration readings for each period of gas simulation in each region are assembled using Kernel Density Estimator (KDE) in Eq. 2.

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

A Gaussian kernel K and a bandwidth h are selected based on [25]. The KDE equation is formulated in Eq. 2. The number of gas concentration readings is n.

There are two PDFs (PDF of gas and wind) which are useful for estimating the likelihood of gas and wind separately. For a such clarity, illustration of the PDF of gas and wind are depicted in Fig. 3 and 4 respectively.

From the Fig. 3, it can be observed that the PDF of gas in region-1 has the highest probability of measuring high gas concentration. The curves of PDF of gas in region 2 and 3 are almost the same. In region-5 only contains low gas concentration and there is almost zero gas concentration in region-4.

The statistics of wind in region 1, 2 and 3 with the wind profile as in Fig. 2.c is depicted in Fig. 4. As it is seen from the PDFs, the wind flow in region 1 and 3 are laminar but region 1 has lower standard deviation. In region-2, it is observed that there is two dominant wind angles around 0 and 100 degrees. A turbulence flow has occurred in region 2.

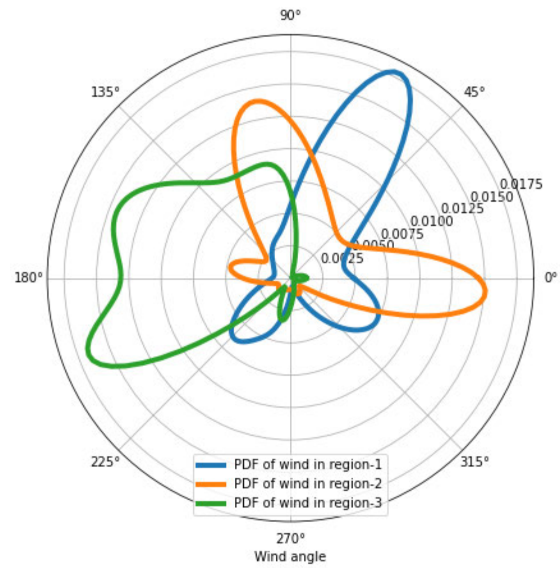

FIGURE 4. Several PDFs of wind that are taken with wind profile as in Fig. 2.c.

C. ANEMOTAXIS

The movement of gas particles is highly affected by the wind vector $\vec{w}_i$. Intuitively, the robot can drive to the upwind direction to find the gas source. However, in a complex environment, the wind profile is not laminar. Wind turbulence may occur in some places. Therefore, $\bar{\theta}_w$, the circular mean of n sample before current time t of wind vectors is used instead of a single wind sample, which may be fluctuated as in Eq. 3.

As there are many goal candidates of r_a, each angle between the robot position x and the center of each region r_a, $\theta_x^{r_a}$, should be obtained as in Eq. 4. It is used to define a region that has the slightest difference between $\theta_x^{r_a}$ and the upwind angle.

$$\bar{\theta}_w = \mathrm{atan2}(\sum_{i=t-n}^{t} \sin \angle\vec{w}_i, \sum_{i=t-n}^{t} \cos \angle\vec{w}_i) \tag{3}$$

$$\theta_x^{r_a} = \angle(x, center(r_a)) \tag{4}$$

In the place where wind turbulence exists, the wind direction is more uncertain. In consideration of that, the circular standard deviation of n sample of wind angle is needed to detect whether an area has a turbulence flow or not. The circular standard deviation (σ_{θ_w}) of a wind angle measurement set is calculated using Eq. 5. If an area has a turbulence flow, the wind measurement of that particular area will be neglected. Therefore, the decision is only depend on the gas concentration measurement.

$$\sigma_{\theta_w} = \sqrt{\left(\frac{1}{n}\sum_{i=t-n}^{t} \sin \angle\vec{w}_i\right)^2 + \left(\frac{1}{n}\sum_{i=t-n}^{t} \cos \angle\vec{w}_i\right)^2} \tag{5}$$

Algorithm 1 Bayesian+Anemotaxis GSL

Require: R, T, W
  collect set of $P(y_{gas}(t_{robot}, r_b, w_i), y_{wind}(r_b, w_i)|r_a, t_{gas})$
  set $P_{prior}(R, T) = \{1/(N_R N_T), \ldots, 1/(N_R N_T)\}$
  for sensor time sampling **do**
    get $y_{gas}(t_{robot}, r_b)$ gas observation in region r_b at t_{robot}
    get $y_{wind}(r_b)$ wind observation in region r_b
    for $r_a := r_1 \longrightarrow r_{N_R}$ **do**
      for $t_k := t_1 \longrightarrow t_{N_T}$ **do**
        $L_{GW} = \{\}$
        for $w_i \in W$ **do**
          $L_{gas} = PDF(y_{gas}(t_{robot}, r_b, w_i)|r_a, (t_k + t_{robot}))$
          $L_{wind} = PDF(y_{wind}(r_b, w_i)|r_a)$
          $L_{GW} = L_{GW} \bigcup \{L_{gas}.L_{wind}\}$
        end for
        $L = max_{w_i}(L_{GW})$
        $P_{post}(r_a, (t_k + t_{robot})|y(t_{robot}, r_b)) = L \cdot P_{prior}(r_a, (t_k + t_{robot}))$
      end for
    end for
    normalize $P_{posterior}(R, T)$
    $P_{prior}(R, T) = P_{posterior}(R, T)$
    compute $P(R)$
    estimate r_{goal} using (6)
    if no gas source in region r_{goal} **then**
      $P_{prior}(r_{goal}) = 0$
    end if
  end for

After calculating the circular mean and standard deviation of the wind angles, the robot's destination (r_{goal}) can be calculated by using Eq. 6. The r_{goal} considers the circular standard deviation of the angle. If the value is less than a particular threshold (σ_{thr}), the upwind angle is used to weight the posterior probability obtained by the Bayesian inference method. Otherwise, the r_{goal} is calculated only from the posterior probability.

$$r_{goal} = \begin{cases} \arg\max\left(\frac{P(R)}{|(-\pi+\bar{\theta}_w)-\theta_x^{r_a}|}\right), & \text{if } \sigma_{\theta_w} \leq \sigma_{thr} \\ \arg\max(P(R)), & \text{otherwise} \end{cases} \quad (6)$$

D. THE ALGORITHM (BAYESIAN + ANEMOTAXIS)

In this paper, we address a combination of the Bayesian and anemotaxis methods for gas source localization. The anemotaxis mechanism is expected to support the Bayes decision to allow the robot finds the gas source location more efficiently.

The proposed method is illustrated in Algorithm 1. This algorithm needs three important sets: set of region (R), time (T) and wind (W). The set of probability density functions also needs to be obtained to estimate the likelihood of the Bayesian inference.

According to the common procedure for performing the Bayesian inference, a set of prior probabilities is equally initialized. The likelihood of gas (L_{gas}) and wind (L_{wind}) are estimated based on the PDF. The posterior probability is updated for each iteration based on the maximum likelihood and the prior probability. Then, the new posterior probability will be used for the next prior probability after normalizing the posterior probability.

After obtaining the new posterior probabilities, then, the joint posterior probabilities of a region $P(R)$ are computed. It is used to decide where the robot should go. However, rather than only using the $P(R)$, the circular mean and standard deviation of the wind angle are used (See: Eq. 6). If there is no gas source in the region, then the prior probability in that region is assigned to zero. The gas declaration can be done using visual check or using a particular gas concentration threshold as in [26].

IV. EXPERIMENTAL RESULTS

A. SIMULATION SETUP

A large cluttered outdoor campus environment with approximately 500m× 700m area is used in the simulation. The building is divided into 50 regions. The division of regions is conducted using non-convex Voronoi tesselation as it is used in [27] to allow an equal area discretization. The robot actuators and sensors model, including GPS, LIDAR and gas sensors, that are used to do the navigation, localization and mapping are simulated in ROS platform. The GADEN simulator is used as the gas dispersion simulator.

B. RESULT AND DISCUSSION

Four scenarios with different gas source locations, initial robot locations and wind profiles are carried out. For each scenario, the length of the trajectory of using three different strategies: (1) Bayesian+anemotaxis, (2) Bayesian only and (3) chemotaxis+anemotaxis are statistically compared. The chemotaxis+anemotaxis, a conventional reactive method, is formulated in Eq. 7. The anemotaxis part is weighted by α and the chemotaxis part is weighted by β. The objective of the anemotaxis is to search the region which has the slightest difference in upwind angle. The objective of the chemotaxis is to decide which region has the neighbor where the average of the gas concentration ($\bar{y}_{gas}$) is maximum. To test the repeatability, each strategy is conducted five times.

$$\begin{aligned} r_{goal} = \arg\min_{r}(\alpha|(-\pi + \bar{\theta}_w) \\ -\theta_x^r| - \beta \max(\bar{y}_{gas}(neighbor(r))) \end{aligned} \quad (7)$$

1) SCENARIO 1

In this scenario, the robot's initial position and gas source location can be seen in Fig. 5 by the symbol S and G, respectively. Our proposed method, the Bayesian+anemotaxis method, results in the shortest trajectory as it is seen in Fig. 6. Compared to the Bayesian method without anemotaxis, a Bayesian+anemotaxis method is slightly more straightforward and directed to the source (See: Fig. 5 red

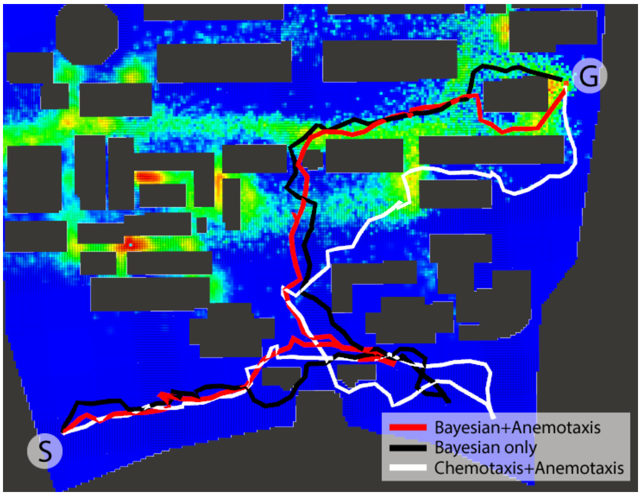

FIGURE 5. Trajectory comparison by different strategies in scenario 1.

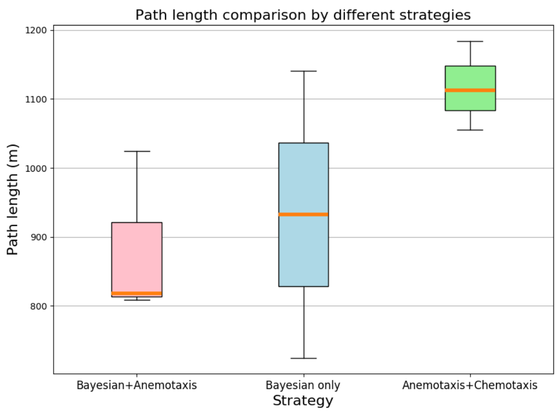

FIGURE 6. Path length comparison by different strategies in scenario 1.

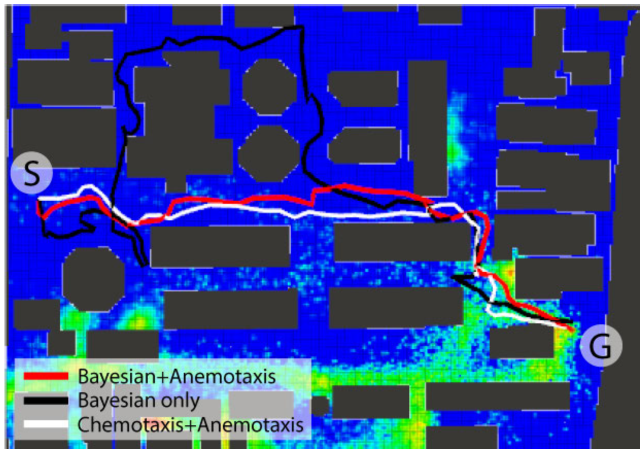

FIGURE 7. Trajectory comparison by different strategies in scenario 2.

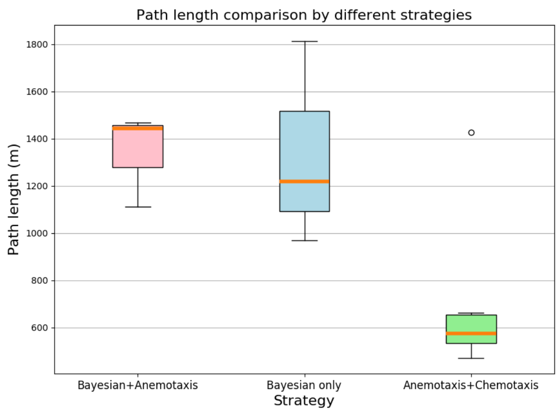

FIGURE 8. Path length comparison by different strategies in scenario 2.

and black trajectories) as this method not only considers the posterior probability $P(R)$ but also the upwind angle.

Another strategy is using the reactive method named chemotaxis+anemotaxis method. The chemotaxis+anemotaxis method is more consistent than the others as it is deterministic. However, the average trajectory length produced is the least efficient. This is reasonable as the average of the wind direction is to the west, and the robot tends to check all regions to the east.

2) SCENARIO 2

The second scenario depicted in Fig. 7 illustrates the exact gas source location and wind profile as the previous scenario but different robot's start location. This scenario is more straightforward for the robot as the difference in wind angle is small. As expected, the chemotaxis+anemotaxis method results in the most efficient trajectory. For the chemotaxis+anemotaxis method, this scenario is effortless as the robot just follows the upwind and then finally finds the gas source.

The trajectory result by using only the Bayesian method is inefficient. Sometimes the robot chooses a wrong path, as the black line in Fig. 7, as it does not consider the wind. By combining the Bayesian with anemotaxis method, the result is slightly better. However, the Bayesian+anemotaxis method cannot be more efficient than the chemotaxis+anemotaxis method. Bayesian+anemotaxis also considers the posterior probability of all regions, makes the robot may want to check another region.

3) SCENARIO 3

This scenario is aimed to analyze the trajectory differences if there are some turbulence flows between the robot and the gas source. The chemotaxis+anemotaxis method is too greedy, as is expected. There are back-and-forth movements in certain areas, which result in a very inefficient robot path.

The Bayesian+anemotaxis and Bayesian only method result in almost the same path at first. However, by using only Bayesian, the robot sometimes travels in the opposite direction to where the gas source is (see: black path in Fig. 9). This behavior may indicate that the region with the largest posterior probability is in the opposite of the gas source location. The robot may be more confident with the gas measurement and the likelihood estimation

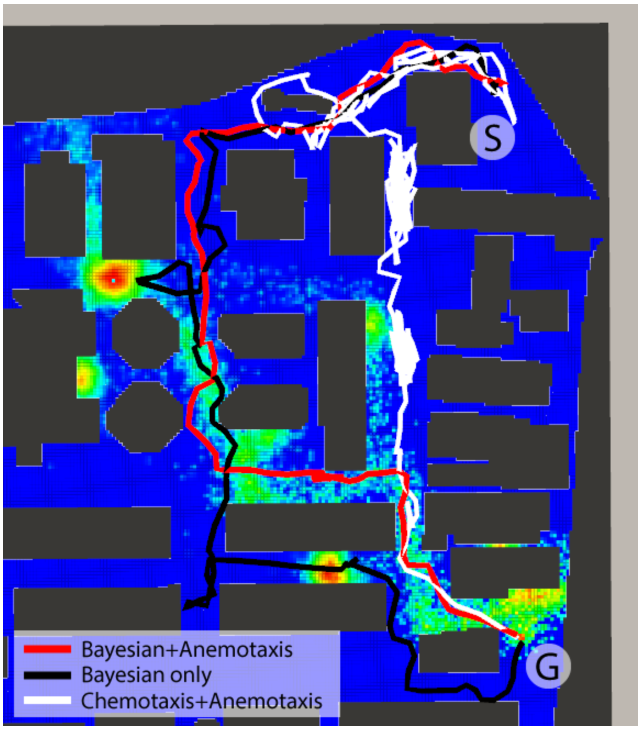

FIGURE 9. Trajectory comparison by different strategies in scenario 3.

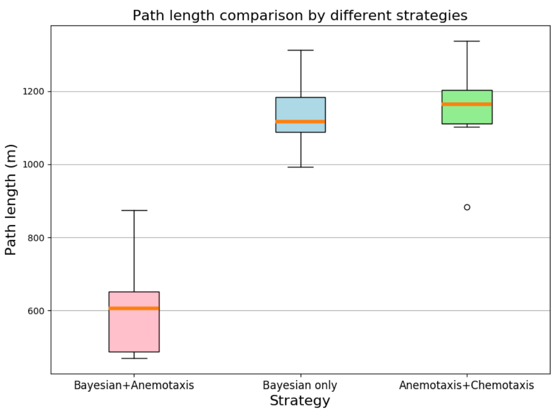

FIGURE 10. Path length comparison by different strategies in scenario 3.

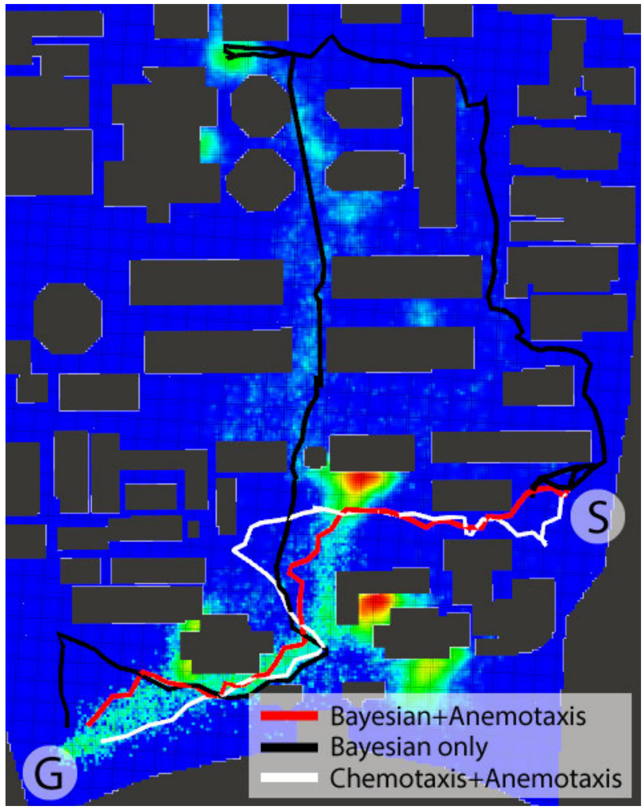

FIGURE 11. Trajectory comparison by different strategies in scenario 4.

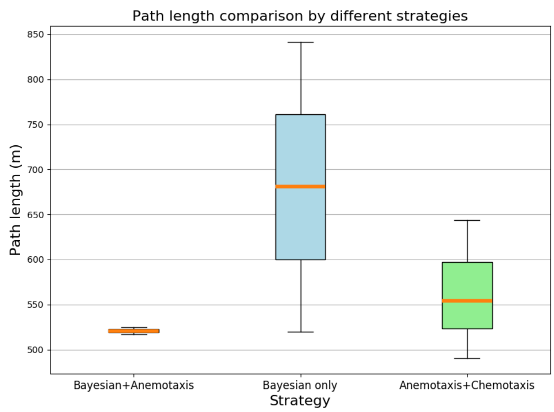

FIGURE 12. Path length comparison by different strategies in scenario 4.

than the wind information. Therefore, incorporating the wind information in the goal decision-making process as the Bayesian+anemotaxis method may become an alternative solution. The Bayesian+anemotaxis method considers the wind information but is not as greedy as the chemotaxis+anemotaxis method.

4) SCENARIO 4

In this scenario, the gas source is placed in the north-west of the environment and the wind is flown to the east (see Fig. 11). Although this scenario seems to be easier than the previous scenario, however, by using only the Bayesian method, the robot travels far from where the gas source is. It is also statistically proven by the Fig. 12 that the Bayesian only method in a very large environment is inefficient.

From this experiment, it can be argued that if the robot has not yet measured gas concentration more than zero, the Bayesian only method will greedily check the farthest area. Although the wind likelihood is estimated from the PDF, it does not seem enough to drive the robot more straightforward to the gas source. Incorporating the anemotaxis method is way more promising than only considering the wind in the probability model, as it may not stand with the turbulence flow.

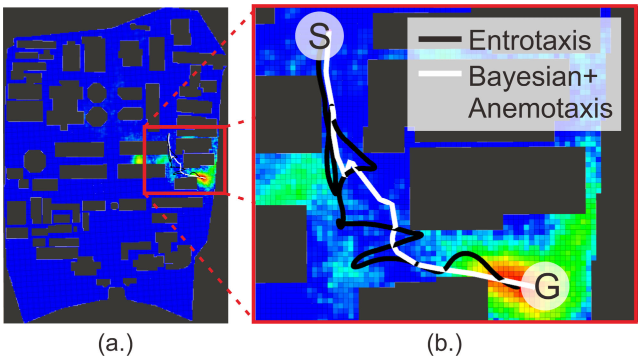

FIGURE 13. Initial robot (S) and gas source location (G) for Entrotaxis (black path) and Bayesian+anemotaxis (white path) comparison testing in a small area. (a.) The whole building used (b.) Small part of the building zoomed.

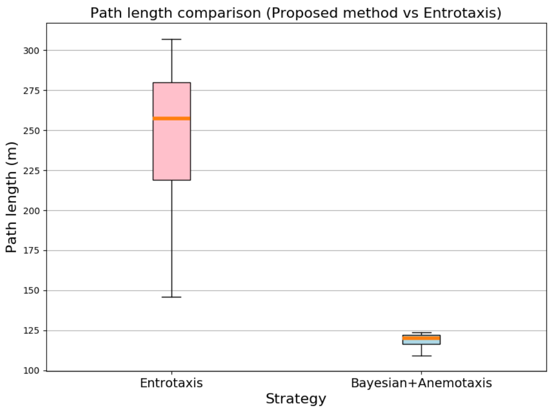

FIGURE 14. Path length comparison of Entrotaxis and Bayesian+anemotaxis.

C. COMPARISON WITH ENTROTAXIS

The Entrotaxis method is a GSL method which assumes that the source strength is unknown and the gas distribution is turbulence [17]. It causes an irregular gradient of the gas concentration. The idea of this method is how the robot counts the appearance of the gas particle rather than measuring the continuous gradient value. The particle is calculated in a specific area once the gas sensor senses a relatively high concentration.

The Entrotaxis method utilizes the particle filter method. Each particle weight is updated according to a Poisson probability distribution involving the particle encounters. The Poisson probability distribution will also be used to calculate the entropy for each action candidate. The optimal action is the action with the maximum entropy.

In this section, the efficiency of the Entrotaxis will be compared with the Bayesian+anemotaxis method. In [17], a small free area (without any obstacle) is used to evaluate the efficiency of the Entrotaxis method. It is different from the problem that this paper wants to solve: a GSL in a large cluttered environment. The implementation and testing of Entrotaxis in a large cluttered area have been conducted. However, it is challenging to find the gas source if the initial robot position is too far from where the gas source. The robot does not have a piece of information in an area with no gas contamination. Therefore, a combination with anemotaxis may improve the efficiency of the Entrotaxis method.

As Entrotaxis also utilizes a particle filter method. A larger number of particles is needed in a large area. It may cause inefficiency in time computation. Moreover, the wind turbulence caused by the obstacles is more irregular than in free space. The original Entrotaxis method cannot deal with that kind of environment. With all of those conditions, we can only compare the efficiency of Bayesian+anemotaxis and Entrotaxis if the robot location is initially near the gas source, as seen in Fig. 13. Bayesian+anemotaxis show more efficiency according to the trajectory length illustrated in Fig. 14.

V. CONCLUSION

This paper presented the advantage of the anemotaxis method, which can be incorporated with the Bayesian method in a robotics gas source localization in a large cluttered outdoor environment. The Bayesian method estimates the likelihood of where is the region which most likely contains a gas source by considering a set of PDFs from simulations. The anemotaxis method seeks a gas source by driving the robot to the upwind direction. Our proposed algorithm combines those two methods and shows a promising result from several evaluations. Without enough gas information, the Bayesian method cannot efficiently decide where the gas source is located. Using only the reactive method such as chemotaxis+anemotaxis results in greedy behavior, which is not efficient in a complex environment with some turbulence flows. Thus, combining those two methods cause the robot drives to the gas source more efficiently.

Besides evaluating the proposed method using the real robot, modifying the Entrotaxis method in a large cluttered environment is also one of the future research that seems promising. The Entrotaxis method has a more realistic assumption, whereas we do not need to depend on the low accuracy of the gas sensor. Moreover, the disadvantage of our proposed method is that prior information about the building structure is mandatory. A pre-processing phase is also needed to construct the robot's knowledge about gas distribution. Modifying other heuristic GSL methods may allow a robot to find a gas source in a large cluttered environment.

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