Proceedings of the 9th International Conference of Control Systems, and Robotics (CDSR'22)
Niagara Falls, Canada – June 02-04, 2022
Paper No. 122
DOI: 10.11159/cdsr22.122

Optimal Gas Leak Localization and Detection using an Autonomous Mobile Robot

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Abstract **-** This paper investigates a problem of localizing a gas leak source based on the Hamiltonian approach. In general, it is difficult to accurately localize a gas leak source due to the fact that a sensor can only measure local information. To detect the location of a gas leak source using an autonomous mobile robot, an optimization problem is formulated, and the optimal control input is derived based on the Hamiltonian. This optimal control is calculated in a receding-horizon manner after each local measurement from the onboard sensor. The proposed method guarantees the optimality of the solution, and a simulation result is provided to validate the proposed method.

Keywords**:** Gas Leak Detection, Mobile Robot, Optimal Control, Hamiltonian

1. Introduction

The Bhopal gas tragedy that occurred on December 3, 1984, immediately claimed the lives of at least 3,800 people and exposed more than 500,000 people to methyl isocyanate gas that was leaked by a chemical plant in Bhopal, India [1]. This tragedy is one of the worst chemical disasters in history and its effects on the exposed people in the months following the tragedy were unpleasant to say the least: ocular, respiratory, and neurobehavioral health effects were observed in several epidemiological studies [1]. On March 23, 2005, an explosion caused by vapours being released from an overflowed blowdown drum and ignited by a heat source shook the BP Texas City refinery, killing 15 people and injuring 180 [2]. On October 23, 2015, a major natural gas leak of a well connected to the Aliso Canyon underground storage facility in California resulted in a large amount of natural gas being released into the atmosphere [3]. Processed natural gas is composed primarily of methane and ethane, which are a danger to the environment and their negative effects on air quality, climate, and human health could be detrimental [3]. These accidents [1] – [3] and countless others are testaments of the dangers of gas leaks throughout the decades; the impacts of gas leaks can be minimized if the source is localized in a timely manner and contained [4]. Considering not only these accidents but also the safety of human, there exists a need for an autonomous mobile robot equipped with some sensors that can easily, safely, and fast localize the gas leak source when compared to other means (e.g., stationary sensors, humans, etc.).

There have been several research studies [4] – [7] that aim at developing complex algorithms for mobile agents to localize the gas leak source. A nonparametric Bayesian-based motion planning algorithm for autonomous plume source term estimation and source seeking is presented [4]. In a Bayesian-based source term estimation process, robots coordinate and use a Gaussian-plume probability model, then concurrently search for, and navigate towards the source using model-based, bioinspired source seeking approaches like biased-random-walk and surge-casting. Rather than relying on direct or filtered sensor measurements, the algorithm developed makes use of coordination between several robots and the estimated plume model for faster and more reliable source seeking than other traditional motion planners. According to the simulations and experimental results presented, the proposed algorithms are faster and more robust than traditional methods. Authors in [5] developed a potential-field algorithm that integrates prior activities to provide collision-free monitoring in locations containing obstacles, such as urban and suburban environments. The experimental results, which used a drone fitted with an Enif system, demonstrate that chemical concentrations can be effectively mapped. A decentralized multi-agent information theoretic (DeMAIT) control algorithm is presented that leverages Bayesian and information theoretic motion planning for effectively and accurately estimating and localizing a gas leak source [6]. Experiments were conducted that involved a small autonomous fleet of robots equipped with chemical gas concentration sensors to search an area known to have a gas source leak and localize the source. Simulations confirmed the premise that the DeMAIT algorithm generated a higher average location success rate than the other two methods that were used for comparison in the study, specifically the raster-scanning [5] and clustering method [4]. A hybrid gas traceability algorithm consisting of modified versions of the Trilateration Method and Simplex Algorithm, and a combination method is designed [7]. Specifically, the algorithm takes advantage of the quick iteration capability from the Trilateration Method, the Simplex Algorithm's conservative optimization technique, and the combination method considerably enhances the success rate and search efficiency of gas traceability. According to the simulation results presented, the algorithm's traceability is 100 percent in most of the trials conducted within 100 to 500 minutes of the simulation.

Although these studies show promising results and most have been verified by experimental results, these methods lack the optimality in their solutions. In this research, we thus plan to develop an optimal solution of the gas leak source localization problem. For this purpose, an optimization problem is formulated, and the Hamiltonian is constructed to derive an optimal control for a mobile agent. To verify the soundness of the result, a simulation result is provided.

2. Problem Description

In this paper, we propose a method of localizing a gas leak source by means of a mobile robot, where a sensor can only detect a local gas plume. An illustrative example for this problem is visualized in Fig. 1.

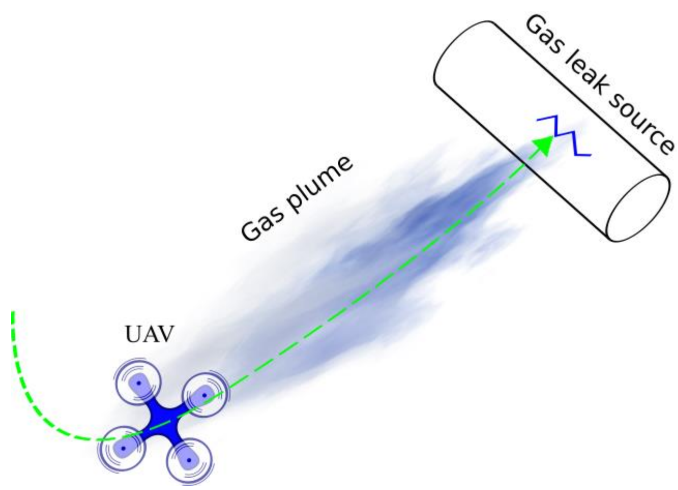

Fig. 1: Shows the UAV traveling towards the gas plume to localize the gas source leak.

For simplicity, we consider a mobile robot platform, which has a simple first-order, discrete-time dynamics given by $x(k+1) = x(k) + u(k)$, where $x(k)$ is the current position of the robot, $u(k)$ is a control input, and k is a discrete-time index.

The main problem to be tackled in this paper can be mathematically formulated as follows:

$$\begin{gathered} max \sum_{k=t_k}^{t_k+T_h} \left(I^{obt}\left(x(k), u(k)\right) - \frac{1}{2} \parallel u(k) \parallel^2\right) \\ \text{subject to} \\ x(k+1) = x(k) + u(k) \\ \parallel u(k) \parallel \le u_{max} \end{gathered} \tag{1}$$

where $I^{obt}\left(x(k), u(k)\right)$ is expected obtainable information (or gas plume concentration) at time k, T_h is a fixed length of time horizon (or window), and u_{max} is a maximum control input. Since the objective function in (1) has a time frame from the current time t_k to a future time $t_k + T_h$, the solution of this optimization problem will guide a robot moving to an area where a high gas plume is expected. Thus, our major goal is to obtain an optimal control input u^* for the optimization problem (1). To this end, a Hamiltonian is constructed, and the optimal control input will be derived in the next section.

3. Main Results

For the obtainable information function, it is defined by

$$I^{obt}(x_k, u_k) \triangleq \int_{\Omega} g(x(k), u(k)) dA \tag{2}$$

where $g(x_k, u_k)$ is a measured intensity of the gas plume, which depends on the current position of the robot x_k and control input u_k. The obtainable information function is then calculated by an area integral with a pre-defined domain Ω according to a given sensor model.

Then, we formulate the Hamiltonian using (2) as follows.

$$\mathcal{H}(x(k), u(k), k, \lambda(k)) = I_k^{obt} - \frac{1}{2} \parallel u(k) \parallel^2 + \lambda^T(k)(\Delta x(k)) \tag{3}$$

where the superscript ^{T} denotes a transpose operator.

Taking the partial derivatives,

$$\frac{\partial \mathcal{H}}{\partial x(k)} = -\Delta\lambda(k) = \frac{\partial}{\partial x(k)} \int_{\Omega} g(x(k), u(k)) dA \tag{4a}$$

$$\frac{\partial \mathcal{H}}{\partial \lambda(k)} = \Delta\, x(k) \tag{4b}$$

$$\frac{\partial \mathcal{H}}{\partial u(k)} = \frac{\partial}{\partial u(k)} \int_{\Omega} g(x(k), u(k)) dA - u^*(k) = 0 \tag{4c}$$

Finally, solving for the optimal control from (4c), which gives the control input that maximizes the information gain

$$u^*(k) = \frac{\partial}{\partial u(k)} \int_{\Omega} g(x(k), u(k)) dA \tag{5}$$

The optimal control (5) will drive the robot to head toward a location where the highest intensity of gas plume is expected. This optimal control u^* will be calculated in a receding-horizon fashion [8-13] with a given horizon length T_h, meaning in each time step, the robot measures the gas plume using an onboard sensor, constructing a function $g(x_k, u_k)$, followed by u^* as shown in (5).

4. Simulation

In this section, we provide a simulation result for the verification of the proposed method. In Fig. 2, the concentration of the gas increases linearly and diagonally from the bottom left corner to the top right corner. The mobile robot is equipped with a sensor to detect the gas concentration, where a square represents the sensing measurement range. The sensor model determines how much new information can be gained if the robot were to move in a particular direction. Our algorithm prioritizes moving in directions of higher information gain. In this case, it prioritizes moving to areas with a higher gas concentration. The robot with three different initial locations shown in Fig. 2A illustrates how the robot will move towards the gas leak source on the top right of the map. Fig. 2B illustrates four (labeled A-D) of the many possible choices the robot can travel to maximize the concentration. Based on the ground truth map we know that if the robot moves in the direction of choice D, then the robot will get closer to the gas leak source.

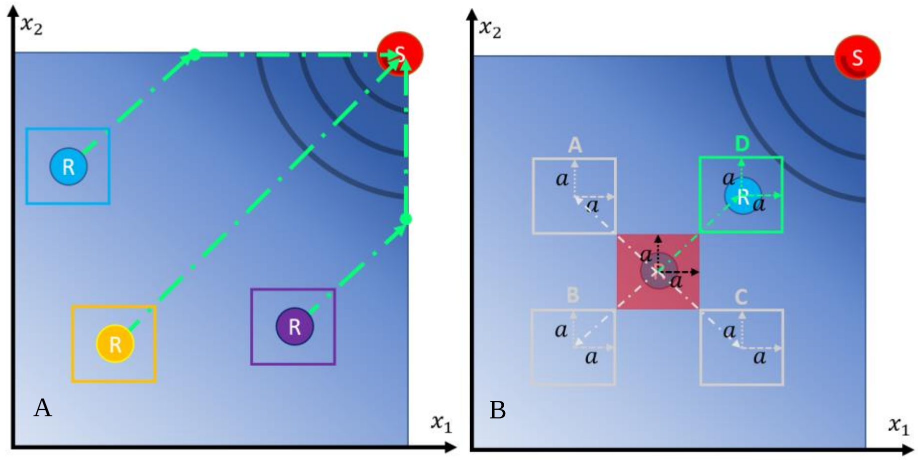

Fig. 2: (A) Illustration shows the path that the unmanned vehicle takes to locate the gas leak source. The concentration of gas varies linearly and diagonally from the lower left corner to the top right corner of the map. (B) Illustration shows where the robot was initially placed in the environment, indicated by the red box. It shows four possible locations that the robot could travel to, locations denoted by A, B, C, and D, but only D will result in getting closest to the source: therefore, maximizing the information gain.

The weight function for Fig. 2 is the sum of the robot coordinates and is given by

$$g(x_1, x_2) = x_1 + x_2,$$

where x_1 and x_2, respectively, denote a direction along x and y axis in a Catesian coordinate.

This means that the highest information will increase as the robot travels diagonally from left to right. Notice that in real environments, the robot does not have information about $g(x_1, x_2)$ which, however, can be induced at each time step from the local measurement by the onboard sensor. The optimal control input is then obtained by applying (5). Letting $(x_1^R(1), x_2^R(1))$ indicate the position of the robot at the next time step with a given initial position $(x_1^R(0), x_2^R(0))$. From the control dynamics constraint, we know that $x_1^R(1) = x_1^R(0) + u_1(0)$, and a similar equation can be written for $x_2^R(1)$. Then, with a unit horizon length $T_h = 1$, we have

$$u^*(k) = \frac{\partial}{\partial u(k)} \int_{x_2-a}^{x_2+a} \int_{x_1-a}^{x_1+a} [(x_1^R(k) + u_1(k)) + (x_2^R(k) + u_2(k))] dx_1 dx_2 \tag{6a}$$

$$= \frac{\partial}{\partial u(k)} [2ax_1^R(x_2^R + a) + a(x_2^R + a)^2 - 2ax_1^R(x_2^R - a) - a(x_2^R - a)^2] \tag{6b}$$

$$= \frac{\partial}{\partial u(k)} [4a^2(x_1^R(1) + x_2^R(1))] \tag{6c}$$

Substituting control dynamics constraints into **(**6c**)** yields,

$$\frac{\partial}{\partial u(k)} \left[4a^2 \left(x_1^R(0) + u_1(0) + x_2^R(1) + u_2(0)\right)\right]. \tag{6d}$$

Taking the partial derivative with respect to $u(k)$ yields,

$$u^*(k) = [4a^2 \; 4a^2]^T \tag{6e}$$

Finally, the normalized optimal control input is obtained by

$$u^*(k) = u_{max}\frac{[4a^2\ 4a^2]^T}{\| [4a^2\ 4a^2]^T \|} = u_{max}\,[\frac{1}{\sqrt{2}}\ \frac{1}{\sqrt{2}}]^T \tag{7}$$

The result indicates that if the robot is given the same control input for its x_1^R and x_2^R coordinate, then it will optimally locate the gas concentration leak.

The algorithm was simulated in MATLAB with an initial robot position of [20, 5] and the results are presented in Fig. 3. Fig. 3A shows the ground truth map of the leak concentration, Fig. 3B shows the egocentric map, and Fig. 3C shows the poses of the robot taken to locate the gas leak source on the top right corner. From Fig. 3C we can observe that the robot travels in a diagonal direction from left to right until it reaches the top boundary, and then it moves strictly to the right until it reaches the coordinates for the gas leak source.

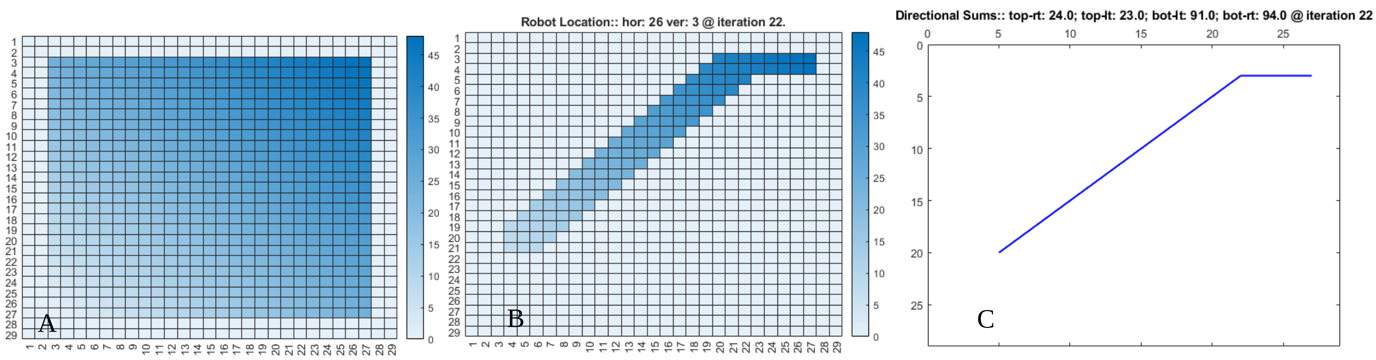

Fig. 3: The ground truth map (A) shows that the gas leak concentration varies diagonally, with high concentration in the top right corner where the gas leak source is located and low concentration in the bottom left corner. The egocentric map (B) shows the cells that were explored by the robot. The poses of the robot (C) are shown to indicate the path that the robot took to locate the source.

4. Conclusion

This paper investigated an optimal control strategy of an autonomous mobile robot to localize a gas leak source. Based on the Hamiltonian formulation, the optimal solution is derived in a receding-horizon fashion, guaranteeing the optimality of the solution. This approach can be beneficial especially compared to greedy-based approaches, which are commonly used methods in gas leak detection problems.

As future research, we plan to investigate an integrated approach to take care of more complicated scenarios such as environments filled with obstacles as well as the gas concentrations being more sophisticated, which will lead to more usefulness and practicality of the proposed method.

Acknowledgements

This research is partially supported by New Mexico Consortium Collaboration Grant with Dr. Steven J. Buelow as a prime contractor PI.

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