Exploration and Localization of a Gas Source with MOX Gas Sensors on a Mobile Robot - A Gaussian Regression Bout Amplitude Approach

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Abstract— **Mobile robot olfaction systems combine gas sensors with mobility provided by robots. They relief humans of dull, dirty and dangerous tasks in applications such as search & rescue or environmental monitoring. We address gas source localization and especially the problem of minimizing exploration time of the robot, which is a key issue due to energy constraints. We propose an active search approach for robots equipped with MOX gas sensors and an anemometer, given an occupancy map. Events of rapid change in the MOX sensor signal ("bouts") are used to estimate the distance to a gas source. The wind direction guides a Gaussian regression, which interpolates distance estimates. The contributions of this paper are two-fold. First, we extend previous work on gas source distance estimation with MOX sensors and propose a modification to cope better with turbulent conditions. Second, we introduce a novel active search gas source localization algorithm and validate it in a real-world environment.**

I. INTRODUCTION

Mobile Robot Olfaction (MRO) studies the combination of mobile robots with gas sensors to solve practical problems related to gas sensing. Among others, MRO systems perform gas discrimination, gas source localization (GSL), and gas distribution mapping. GSL can be of great importance for applications such as search and rescue missions, or environmental monitoring. Robotic solutions are especially favourable in dull, dirty or dangerous scenarios. When the gas of interest is harmful to humans, for example, it is indispensible to localize gas sources with a robot. The length of robot missions, however, is typically considerably limited by the available energy, both for ground and airborne robots. The challenges in GSL thus include importantly to find efficient navigation strategies that minimize the amount of time required for searching for a gas source.

In this paper, we present an active search GSL algorithm for a mobile robot, equipped with Metal-Oxide (MOX) gas sensors and a wind sensor. The robot searches a known environment (i.e., we assume that an occupancy map is given) for the gas source. The approach that we introduce estimates the gas source distance from the robot's position and aims to minimize it by exploiting a model of the wind flow and how it affects the gas distribution.

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This work was funded in part by H2020-ICT project SmokeBot (645101).

The problem of gas source localization has been studied in the past two decades and there are several methods to approach it. In general, plume-tracking algorithms make use of wind flows (anemotaxis) and/or gas concentration (chemotaxis) to find a direction for the robot to follow. A broad group of algorithms try to mimic odor source localization performed by insects in nature [3], [4]. In these approaches the robots follow the gas plume in the upwind direction by making use of both anemotaxis and chemotaxis principles, whereas in our work we include an explicit source distance estimation in the process. For this estimation we draw upon recent works, which showed that the information conveyed by MOX sensors can be used to estimate the distance to a gas source in wind tunnel conditions [1]. Li et al. [6], [7] approach the problem by estimating the source location inside an area and then try to minimize this area. Some more complex algorithms model the location of the gas source with a probability distribution and then try to reduce its entropy [5]. These algorithms model the source location probabilistically, while we search the environment and build a probabilistic model of the source distance.

The contributions of this paper are two-fold. First, we introduce and validate a novel active search GSL approach. Second, we extend the work on gas source distance estimation, which was carried out in a wind tunnel [1]. We show results of the source distance estimation technique presented in [1] in real-world environments and introduce a modified version better suited to the task.

II. PROBLEM DEFINITION AND APPROACH

We assume that the environment is known a priori and is not subject to change during a mission. The environment is represented as a Cartesian grid, thus obtaining a set M of N cells of identical size: $M = \{x_1, ..., x_N\}$. We also assume that only one source of gas is present in the environment.

The robot is equipped with an array of six in-situ sensors. In order to measure wind speed and direction, the robot is equipped with an ultrasonic anemometer.

The robot moves between the centers of the cells. After each movement it records measurements of gas concentration and wind information for a certain amount of time in order to compute the source distance estimation. We define a function $f : M \rightarrow \mathbb{R}^+$ to indicate the distance $f(x)$ from a cell $x \in M$. The function f is unknown a priori and is updated from noisy measurements. From the measurements made in visited areas, the robot estimates values of the function f in unvisited areas of the environment and uses this knowledge

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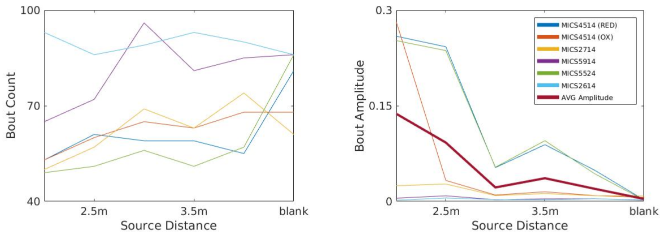


Fig. 1: Bout count and amplitude for each sensor vs. distance to the gas source at 0.1 m/s wind speed.

to decide where to navigate next in order to improve the estimation in an efficient way. The estimation of the source distance is thus performed online, as the robot visits the environment. The approach proposed in this paper consists in the repetition of the following steps: acquire sensor data from the current position, compute the source distance estimation, estimate $f(x)$, and finally move the robot to the next position selected by the search strategy. The two main modules of our system, namely source distance estimation and search strategy, are described in the following.

III. Source Distance Estimation

One of the crucial steps of our approach is the detection of the *bouts* of the signal, i.e., portions of the filtered signal where the amplitude is rising. In [1], it is reported that there is a strong correlation between the number of bouts and the distance to the gas source: the higher the bout count, the closer the sensor to the gas source.

To detect the bouts, a cascaded filtering approach is used to detect fast transients in the sensor signal [1]. A low-pass filter is first used in order to remove high-frequency noise. This is done by applying a Gaussian convolution with $\sigma_{smooth} = 0.3s$. On the smoothed signal, a differential convolution is applied to show differences between pairs of samples and see the amplitude changes. Finally, the signal undergoes an exponentially-weighted moving average filter with a half life $\tau_{half} = 0.4s$. The operation that yields the filtered time series y_t from the low-pass filtered z_t can be expressed by the following equation:

$$y_t = (1 - \alpha) * y_{t-1} + \alpha * z_t \qquad (1)$$

where $\alpha = 1 - \exp \frac{log(0.5)}{\tau_{half} \Delta t}$ and Δt is the time step in the equation. Bouts of rising amplitude can be identified on the differential of the filtered signal (y'_t). The presence of a bout is characterized by y'_t being equal to or greater than zero.

The bout method in [1] was evaluated only inside a wind tunnel, while we are considering open environments. The gas plume was generated through evaporation of propanol placed inside an open plastic container. A constant wind flow was generated with a fan placed near the gas source. The bout detection was tested with low wind speeds (0.1 m/s to 0.4 m/s). The propanol container was placed in between the robot and the fan at different distances from the robot in 6 different locations in the range from 2 to 4 meters. The sampling rate of the sensors was set to 74 Hz and the sensing time of the robot was 135 seconds, obtaining a gas concentration signal

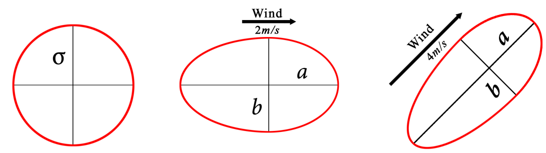


Fig. 2: Influence of the wind speed and direction on the shape of the kernel. The ellipse is rotated according to the wind direction. The semimajor axis a is stretched in the upwind direction and shrunk in the downwind direction according to the wind speed. σ represents the spatial scale of the kernel.

with a total of $10,000$ samples per location for the bout detection algorithm. Experiments were repeated 6 times.

Our experiments show that the bout count gives mixed results in this scenario and cannot be used to reliably estimate the distance to the gas source. In some cases it can be seen that the bout count even increases with distance. From the analysis of the gas concentration signal, we noted, however, that the amplitude of the bouts tends to decrease with distance, making it possible to estimate the source distance. The distance is thus estimated for each sensor as the mean value of the amplitudes of all the bouts. Our results (Fig. 1) actually show that the average bout amplitude is a good indicator of the distance to the gas source. In some cases, when moving away from the source by 0.5 m the average amplitude slightly increases. However, in most cases, the average bout amplitude decreases when moving away from the source for more than 1 m.

In the experiments performed in outdoor environments the wind flow conditions were not stable, resulting in the wind changing direction very often. Moreover, the wind speed was much higher than in indoor environments (about 1 m/s). Because of the high wind speed, the transients of the signal are too short and the sensors cannot resolve them, resulting in failure to detect the bouts. Overall, the sensors used in our experiments were able to reliably estimate the source distance in wind speeds up to 0.3 m/s.

IV. Search Strategy

A. Algorithm

We model the average bout amplitude function $f(x)$ (which is related to the distance from the robot to the gas source) as a Gaussian process with kernel function $k : M \times M \to \mathbb{R}^+$. Since, in realistic environments, advection dominates gas dispersal we use the upwind direction to direct $f(x)$ towards the gas source. This then favors exploration in upwind directions. We include wind information using a radial kernel, stretched according to the wind speed and rotated according to the wind direction as in [2], see Fig. 2:

$$k(x, x') = \exp - \sqrt{(x - x')^T \Sigma^{-1} (x - x')} \qquad (2)$$

where Σ is the 2D covariance matrix of the Gaussian.

The kernel in Eq. 2 corresponds to the assumption that positions in upwind direction have a bout amplitude similar to the measurement point. It also expresses the exploitation component of the exploration strategy, which leads the robot to follow a gas plume. The bout amplitude estimation at an unvisited location x_* and the a posteriori variance are computed respectively as:

$$\bar{f}_* = k_*^T[K + \sigma_n^2 I]^{-1} y$$
$$V[f_*] = k(x_*, x_*) - k_*^T[K + \sigma_n^2 I]^{-1} k_* \tag{3}$$

where k_* and K are abbreviations respectively for $k(x_*, X)$ and $k(X, X)$ and X is the set of visited cells.

The direction towards the next sensing position is computed as a trade-off between exploration of unvisited areas (following the variance gradient) and exploitation (following the direction to the highest bout amplitude estimate). The robot moves to the next position by following a direction θ for a step size ρ. The direction θ is sampled from the following Gaussian distribution:

$$p(\theta) = \begin{cases} \exp \frac{-(\theta - \theta_m(s))^2}{\sigma_m^2} & \text{if } R > \tau \\ \exp \frac{-(\theta - \theta_v(s))^2}{\sigma_v^2} & \text{otherwise} \end{cases} \tag{4}$$

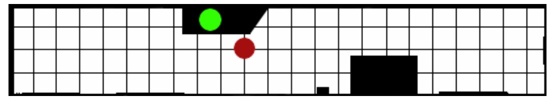
where s is the iteration step, $\theta_m(s)$ is the direction to the highest bout amplitude estimation, $\theta_v(s)$ is the direction to the highest variance, τ is the trade-off parameter and $R \in [0, 1]$ is a random variable. At the beginning τ is set to 1. During the first steps of the mission the trade-off favors exploration and the robot moves towards unknown areas. After each step of the algorithm, the trade-off parameter decays to slightly lean more towards exploitation. If exploitation is favored, the robot follows the direction to the highest bout amplitude estimation. When the a posteriori variance is low enough (i.e., τ goes under a threshold), the algorithm terminates by declaring the position where the highest bout amplitude estimate is found as the final one.

B. Experimental results

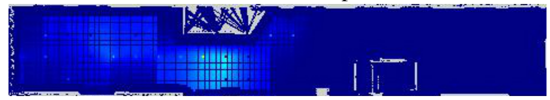
Experiments with a Clearpath Husky A200 robot were performed in a 22m x 4m indoor corridor.

The sensory function for Gaussian regression was derived from the bout amplitudes of the all signals of the sensor array. The estimation of the source distance is not always accurate if derived from a single sensor, especially the low resistance sensors were found to be not very reliable. The bout amplitude from the high resistance sensors, on the other hand, showed only small changes with distance. Therefore, the distance was estimated using all sensors. More specifically, for each sensing operation, the average bout amplitude for each sensor is calculated, then the six values are averaged together to have the final value. In this way, the effects of the sensors are balanced in order to get a good estimation. The occupied cells in the occupancy grid are considered to have a bout amplitude equal to zero.

We consider an experiment successful if the robot chooses as the final position the reachable cell nearest to where the gas source is placed, along the wind direction (Fig. 3). From a total of 12 complete experiments that were run, 8 were successful in identifying the proper final position, giving our method a 67% success rate. Reasons that could explain the failed experiments include the high wind speeds (which lead to bouts that cannot be resolved) and that the plane in which the robot sampled gas concentrations was at a substantially lower height than the gas source.



(a) Grid map of the environment: The black cells indicate obstacles. The green circle indicates the gas source and the red circle the final position of the robot.



(b) The mean estimate map: The dark blue regions map areas with low bout amplitude estimates, whereas the light blue indicates high mean values.

Fig. 3: Results of an experiment in which the wind was flowing towards the south-east direction.

V. Conclusions

In this paper we introduced an integrated GSL and exploration approach that uses a mobile robot equipped with MOX sensors and a wind sensor. The proposed solution exploits the bout amplitude of the concentration signal and drives the robot towards areas where its value is expected to be maximized. Experimental results show that the bout amplitude of the signal is a good estimator of the source distance. The proposed search strategy performed with a success rate of 67% in indoor environments, identifying reachable areas near the gas source.

A possible improvement of the work done in this paper would be to consider scenarios with multiple gas sources. The robot then estimates the number of sources and the distance to the closest one. Possible extensions would be to study the bout amplitude response of different gases and try to learn detection thresholds in order to declare the presence of a gas source.

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