Experimental Analysis of the Impact of Sensor Response Time on Robotic Gas Source Localization

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***Abstract*—Robotic olfaction is a promising application of volatile-sensing technologies with many potential uses, such as gas leak detection or rescue missions. The effectiveness of any proposal to cope with this task is partially limited by the characteristics of the sensors employed. Most of the small, low-power sensing devices that are appropriate for mobile robotics suffer from problems like slow response time, long recovery, or low selectivity; and this makes the search process slower and less robust. In this work, we seek to provide a preliminary quantification of the effect of these issues in the results of a state-of-the-art gas source localization method. By using high-fidelity gas dispersion simulations, we compare the behaviour of the robotic agent when attaining measurements from a realistic sensor, with modelled response delay and inaccuracy, versus an idealized one that returns the ground-truth gas concentration value instantly. We find that, for slow-response sensors, there is a clear improvement of the results as the robot is allowed to gather measurements for a longer period of time, giving the sensor time to stabilize. A fast-responding sensor, on the other hand, does not benefit from very long measurement steps, needing only a small time window to account for instantaneous instabilities in the spatial dispersion of the gas.**

I. Introduction

The field of robotic olfaction presents many challenges that need to be solved before the technology is mature enough for real-world applications. Beyond the intrinsic difficulties that the deployment of robotic agents in real-world scenarios carries (navigation, localization, *etc.*), one of the most prominent hurdles comes from the slow reaction of the gas sensors that are used.

The sensors that are utilized in mobile robotics need to be light and compact, and have a relatively low power consumption, since all of these are limiting factors to the mobility and autonomy of the robots. The most common type of such gas sensor is the chemiresistor [1], a device whose electrical resistance varies as a result of chemical reactions when it is exposed to certain substances (*e.g.* metal oxide, *MOX* sensors). These are single-point sensors, so they can only measure the gas concentration at the exact location of the robot, and have a slow response time [2], [3], taking a noticeable amount of time to achieve an accurate gas concentration reading when being exposed to it, and often an even longer time to become de-excited when being exposed to clean air after a high-concentration reading.

Despite these disadvantages, chemiresistors also feature some advantages that mean they are still common tools. Since a given chemiresistor will react differently to each substance, and different models of chemiresistors have their own response curves, it is possible to use an array of them (what is usually referred to as an *electronic nose* [4]) to discern what volatile is being measured (gas classification [5], [6]), or even to filter out the effect of interfering substances that happen to exist in the environment when searching for the gas source or generating a gas distribution map. This selectivity, combined with their low cost and size, make them more appropriate for many applications than faster, more accurate sensors like photoionization detectors (*PID*), which would otherwise be preferable.

When searching for the source of a gas emission, this slow response of the sensor means the robot is forced to remain still several seconds at sampling positions to let the sensor readings stabilize before the next decision can be made. This is particularly problematic in changing, turbulent airflow conditions, where the spatial distribution of the gas is time-dependent, and a clear gas plume might not exist [7]. For this reason, when developing new GSL techniques, researchers often resort to using faster sensors under carefully controlled conditions where no interfering gases exist and there is no need for substance classification. As such, the results obtained do not necessarily reflect the applicability of the techniques to real-world scenarios, where those assumptions are not true.

In this work, we seek to quantify the effect of having realistic, slow-response sensors on the results of a state-of-the-art GSL algorithm [8]. We compare the behaviour of the robot and the accuracy of the predicted source location when using simulated *MOX* sensors versus having immediate access to the ground-truth concentration value, and study to what degree the limitations of the sensors can be corrected by extending the measuring time when the gas dispersion is a time-dependent phenomenon. We rely on GADEN[9], a gas dispersion simulator fully integrated in the Robotic Operating System (*ROS*), to carry out these experiments.

II. Experiment Description

Figure 1 shows the environment in which the experiments were carried out (10m x 10m). The airflow through the environment was simulated using OpenFoam, with a setup that features multiple inlets and outlets in order to increase the complexity of the search process. Two different gas dispersion instances were simulated with this airflow.

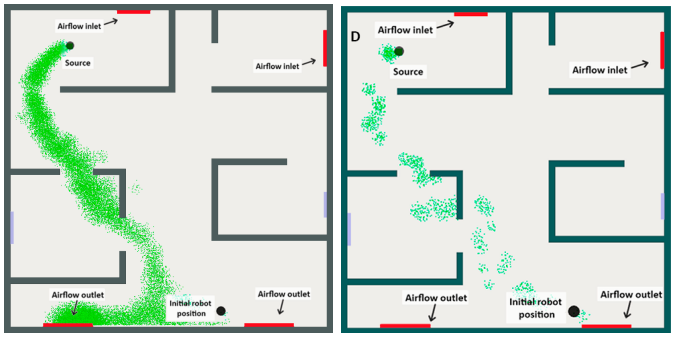

Fig. 1: The environment in which the experiments were carried out. Experiment 1 features a continuous release of gas forming a clear plume, while the intermittent source of experiment 2 creates a patchy distribution of gas that never quite forms a plume.

In the first one, the gas source has a constant release rate, allowing for the formation of a clear, uninterrupted gas plume, with the only distortions in its shape being due to the geometry of the environment. Under these conditions, the concentration of gas at a fixed spot within the plume only varies slightly over time, with the main difference in values registered by the sensor corresponding to the movement of the robot.

In the second one, an intermittent release of gas causes a patchy plume to form, so that the gas concentration at any given spot within the plume varies greatly over time depending on the position of each of the gas patches. This poses an extra difficulty for sensors with a slow response time, as it is likely for the sensor to be exposed to very different concentration values during a fixed-position measuring phase.

The experiments were carried out using two *MOX* sensors with different values of the response-time τ constant. *MOX1* has $\tau_{rise} = 8.4$ and $\tau_{decay} = 24.5$; *MOX2* has $\tau_{rise} = 4.5$ and $\tau_{decay} = 15.7$. Both were tested against an idealized *PID* that measures the ground-truth gas concentration and has instant response to changes in the concentration value. Under each set of environmental conditions, the algorithm was tested with 4 values for the length of the stop-and-measure phase: 1s, 2s, 5s and 10s. The gas concentration value used by the search algorithm to make decisions is the average of the values reported by the sensor during this phase. This practice of taking average measurements over a period of time is necessary even with fast sensors, as the intrinsically transient nature of gas dispersion means that a single concentration reading might not be enough to determine if the robot is inside of a gas plume or not.

For the *MOX* sensors, an additional setting was tested for each of these configurations, comparing the effect of averaging all the measurements of the sensor during the stop-and-measure phase versus only taking into consideration the concentration values reported during the second half of the measuring phase, to avoid using measurements corrupted by the slow response of the sensor. The data shown in the figures is the average and standard deviation over 30 runs for each configuration.

III. Results

Figures 2 and 3 show the results for each of the sensors under the first set of environmental conditions, where the gas forms a continuous plume. Figures 4 and 5 show the results for the second experiment, with an intermittent source.

In the first experiment, it can be observed that the length of the measuring phase ($t_{measure}$) shows little to no effect on the effectiveness of the algorithm when using the idealized sensor. This is consistent with what was expected, as averaging many sensor readings is not beneficial when the gas concentration is near-constant over time.

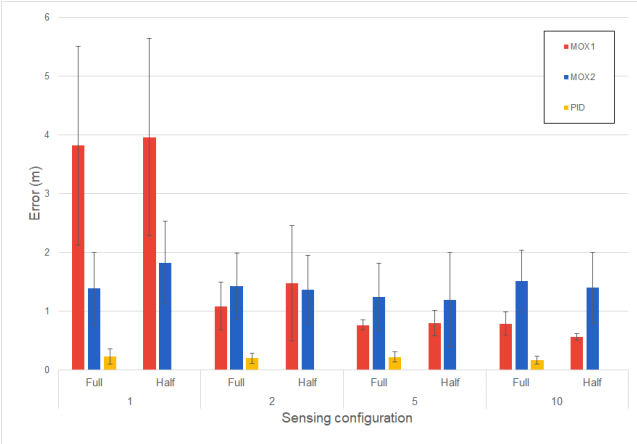

Fig. 2: Error in the final declared source position in experiment 1, with a constant gas release forming a clear plume.

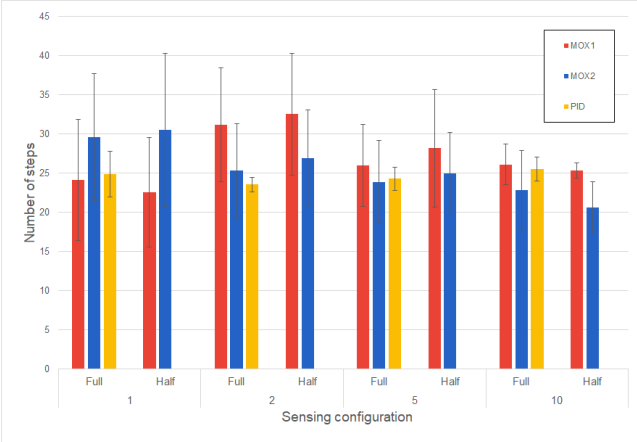

Fig. 3: Number of steps before the algorithm declares the search finalized in experiment 1. Note that this includes all runs, regardless of how accurate the predicted source location is.

On the other hand, the MOX sensors do exhibit an increase in performance when allowed to gather measurements for a prolonged time. In both cases, the extremely high variance in the results when the measurement phase is short demonstrates that the algorithm cannot function properly with those configurations. When using the faster MOX sensor (*MOX2*, $\tau_{rise} = 4.5$; $\tau_{decay} = 15.7$), the number of iterations of the algorithm required to achieve convergence and declare an estimated source location descends steadily as $t_{measure}$ is increased.

When using the slower MOX sensor (*MOX1*, $\tau_{rise} = 8.4$; $\tau_{decay} = 24.5$) the reduction of the number of iterations is only observable beyond a certain threshold of $t_{measure}$. This can be explained by looking at the error in the final estimation of the source location: when the measurement phase is too short, the sensor does not have time to adapt to changes in concentration as the robot moves, and the algorithm ends up converging too soon and declaring the source to be in the wrong area of the map. It can be observed that the error in the estimated source position descends as $t_{measure}$ increases, which is an effect that is not observed in the results of the faster MOX sensor. It cannot be inferred from this data that slower sensors produce better source location estimations, however; rather, it is likely that this is linked to the higher number of iterations that the algorithm does with the slower sensor.

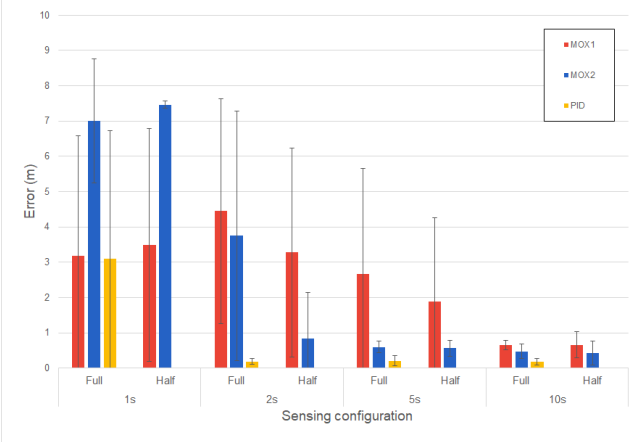

Fig. 4: Error in the final declared source position in experiment 2, with an intermittent gas release.

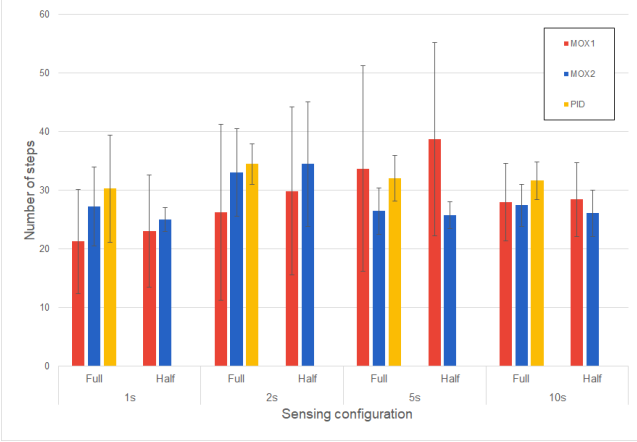

Fig. 5: Number of steps before the algorithm declares the search finalized in experiment 2. This includes all runs.

The author's hypothesis is that slightly delayed convergence helps refine the final prediction by gathering more information before an estimation is produced. Further research would be necessary on this idea, as if this effect is confirmed, it may be recommendable to increase the requirements for convergence, or to add an extra "refinement phase" after a first estimation is produced.

In the second experiment, we can observe very similar trends to those discussed in the previous case. It is notable that the idealized sensor now exhibits a clear improvement in its effectiveness when $t_{measure}$ is increased from 1s to 2s. This is due to the more pronounced transient nature of the gas dispersion in this case. Even with access to perfect sensory readings, it is still possible for the algorithm to misjudge whether a given position is "inside the plume" if its readings only encompass a brief period when no gas patch happened to be close enough to be detected.

In neither experiment can we observe a significant improvement from having the algorithm disregard the first half of the MOX sensors measurements. In fact, the results of this technique are worse when $t_{measure} <= 5s$, and only show improvement in some cases for $t_{measure} = 10s$.

IV. Conclusions and Future Work

We have analyzed the effect of sensor response time on the effectiveness of source localization with a mobile robot. The results show that, as was expected, gathering measurements over a longer period of time can mitigate the slow response of sensors; and it is a necessary technique even with idealized instant-response sensors when the gas dispersion is time-dependent. Even though the results shown in this work cannot be generalized to any case, as we tested only one specific algorithm under a limited range of conditions, we hope the data obtained and our analysis of it may offer some insight into the topic, and be useful to guide further research.

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