

# Virtual Cancellation Plume for Multiple Odor Source Localization

Gonalo Cabrita, Lino Marques, and Veysel Gazi

**Abstract**—This article presents a novel algorithm for multiple odor source localization by a multi-robot system based on a virtual cancellation plume approach. The proposed method is based on rendering a previously declared odor source invisible to the robots so that the declared source and the odor plume it generates do not interfere with the effects of other existing plumes, allowing the localization of the remaining sources. Exploration and plume tracking by the robots is achieved using a decentralized asynchronous particle swarm optimization algorithm. The divergence operator is used to declare the odor sources. A set of simulations and real world experiments are performed on two different scenarios on a controlled environment using a swarm of 5 robots to validate the proposed methodology. Results show that the virtual plume cancellation algorithm can be successfully used to find multiple odor sources, even when two plumes overlap. It can also extend the operation of many odor source localization algorithms developed for single source localization.

## I. INTRODUCTION

Robotic odor-sensing technology or simply robotic olfaction has attracted substantial interest by the research community in recent years [1]–[7]. This interest is driven by the developments in the robotics and sensing technologies along with the vast number of areas and applications of robot olfactory systems including safety, security, and environmental inspection to name a few. Robots equipped with chemical sensors can be used instead of humans in areas with odor contamination for purposes such as inspection, detection of leakages leading to the contamination source, providing continuous monitoring of the contaminated environment, for specific characterization of the odor, for building the chemical concentration map of the environment and others.

It is now well established that the process of odor source localization can be divided in three stages: (i) odor search and plume detection, (ii) odor plume tracking and (iii) odor source localization. In the past years, several algorithms have been proposed to address one or several of these stages, either using single or multi-robot systems, but in most cases, these algorithms assumed environments containing a single odor source. This observation is confirmed by a recent survey about robot algorithms for localization of multiple emission sources [8]. This survey addresses all types of sources, but gives particular focus to odor sources. A common procedure to localize multiple odor sources consists on generating an

odor map of the environment and later processing that map in order to identify areas with local concentration maxima [9]. There is also a wide range of work related to multiple odor source mapping without explicit source declaration [10]. Stochastic searching strategies, like Biased Random Walks (BRW) [5], Evolutionary Strategies (ES) [11], and Particle Swarm Optimization (PSO) [12], are more effective than mapping methods to localize a dominant source inside the search space, but tend to have problems dealing with other existing sources. Some strategies, e.g. Glowworm Swarm Optimization (GSO) [13], deal with multiple sources using a large number of searching elements that are separate into subgroups that move toward the nearest peak rather than toward a global maximum, on the other hand these methods have only been tested with smooth gradients, not with chemical plumes. In [11] and [12], the influence of localized sources was managed by collecting them, so their effect would disappear, however this mechanism might not always be possible or desirable. This work proposes a novel methodology, virtual cancellation plume, so each time an odor source is localized, its effect downwind is estimated and published to the searching robots, so they can take into account the expected effect of the known plume across the search space and proceed with the search process, eventually finding other existing plumes and sources.

## II. VIRTUAL CANCELLATION PLUME

Resorting to chemical cues while searching for an odor source is almost unavoidable. When looking for multiple odor sources it is likely that the plume generated by one source will get in the way of finding other sources. The idea behind the virtual cancellation plume algorithm is quite simple and naive, to cancel the effects of a declared odor source on the robot's gas sensor readings. In a nutshell, the goal is to make an odor source invisible to the robots.

In order to achieve this goal we propose that once an odor source is found a model of the plume being created by that source is generated. In order to do this the robot or robots must be able to estimate the necessary parameters. This

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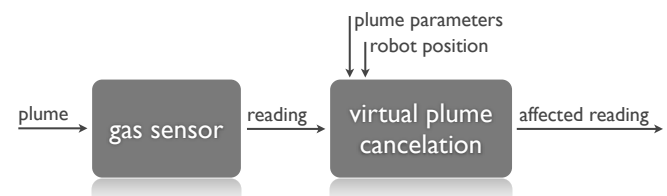


Fig. 1. Diagram representing the concept behind virtual plume cancellation.

model will then be used to affect the readings of the gas sensors equipped on the robots. This concept is represented in Figure 1. In this work virtual plume cancellation is achieved using a Gaussian plume model. The Gaussian model is probably one of the simplest plume models commonly used, allowing to prove the concept of virtual cancellation plume without introducing a high degree of complexity into the problem. Let  $\bar{c}$  be the mean chemical concentration at any given  $x$  and  $y$  given by equation (1) where  $Q$  is the emission rate of the source,  $\bar{u}$  is the mean transport velocity (the  $x$  axis is aligned with  $\bar{u}$ ) and  $\sigma_y(x)$  and  $\sigma_z(x)$  are the Gaussian plume dispersion parameters that for non-buoyant releases can be approximated by power laws in  $x$  as defined by equations (2) and (3) [14]. The three main requirements for a Gaussian plume model to hold are a continuous odor source, uniform wind flow and homogeneous turbulence. Notice that since the robots' gas sensors are located at a fixed height we assume that  $z = 0$  throughout this work, simplifying the Gaussian plume model to a 2D model without the last term of equation (1).

$$\bar{c}(x, y, z) = \frac{Q}{\pi \sigma_y(x) \sigma_z(x) \bar{u}} \exp\left(-\frac{y^2}{2\sigma_y^2(x)}\right) \exp\left(-\frac{z^2}{2\sigma_z^2(x)}\right) \quad (1)$$

$$\sigma_y(x) = ax^p \quad (2)$$

$$\sigma_z(x) = bx^q \quad (3)$$

As mentioned previously the robot or robots will have to estimate both the odor source position and the plume model parameters in order to properly cancel it. These parameters will depend on the type of model being used to generate the virtual cancellation plume, in this case the parameters of the Gaussian plume model. More complex plume models might require more information (e.g. a representation of the obstacles present in the environment). The odor source position is estimated by the divergence operator [15] used during the odor source declaration stage. The release rate  $Q$  is estimated using the principle of the integral mass-conservation condition in equation (4). The robots are also able to gather data regarding  $\bar{u}$  using anemometers. A non-linear least squares estimator using the gas readings sampled by the robots is used to estimate the remaining parameters. Non-linear least squares was chosen due to the fact that it is a cheap method from a computational point of view, this choice is related to the swarm approach in which the virtual cancellation plume algorithm was tested as we will see later in the article.

$$\int_0^\infty \int_{-\infty}^\infty \bar{c}(x_i, y, z) \bar{u} dy dz = Q \quad (4)$$

Since the idea is to envelope the plume generated by a declared source, the model used for cancellation should take into account the following factors (i) plume intermittency, (ii) the error in the estimation of the odor source position

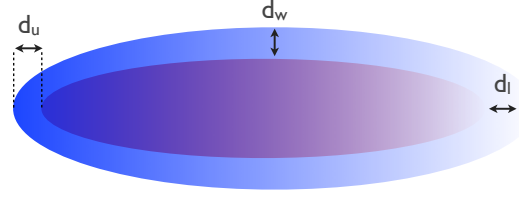


Fig. 2. The virtual cancellation plume should completely envelope the plume being canceled.

and (iii) the error in the estimation of the Gaussian plume model parameters.

Plume intermittency is one of the phenomena that can be observed in odor propagation. Practically speaking, if an observer is inside a stable plume at a certain position sampling the chemical concentration at a fixed rate, although the average of the sampled values will tend to a fixed value over time, certain readings will display values considerably higher or lower than the average. This might result in odor peaks being displayed inside the canceled plume which should present gas readings close to those of clean air.

Cancellation values generated by the virtual cancellation plume should be able to deal with the intermittency of the plume being cancelled. The cancellation plume will generate mean values of chemical readings whereas the plume being cancelled will provide instantaneous values. A simple solution to the problem would be to set every gas reading sampled inside the cancelling plume to a clean air value. This would however also cancel possible unfound sources located inside the cancelled plume. For this reason we propose that the cancelled gas readings are calculated using equation (5) where  $c$  is the cancelled gas reading,  $c_s$  is the gas sensor reading,  $\bar{c}_{vcp}$  is the mean cancellation gas reading generated by the virtual cancellation plume and  $c_a$  is the value for clean air sampled by the gas sensors. The value of  $\alpha$  can change over time and is calculated by the robot marking the odor source in order to ensure that the virtual cancellation plume can cope with the intermittency of the cancelled plume and the error in the estimation of the odor source release rate and flow rate.

$$c = \begin{cases} c_s - \alpha \bar{c}_{vcp} & \text{if } c_s - \alpha \bar{c}_{vcp} > c_a \\ c_a & \text{otherwise} \end{cases} \quad (5)$$

The error in the estimation of the odor source position will depend on the technique used during the odor source declaration stage. This will obviously have a major impact on the quality of the cancellation, as a wrong estimation of the position of the source might result in part of the plume not being cancelled. The error in the estimation of the Gaussian plume model parameters will in this case also depend on the odor source declaration algorithm, as the divergence is not only used to estimate the odor source position, but also its release rate. The estimation of  $\bar{u}$  will depend on the error of the anemometers used and the error of the remaining parameters will depend on the non-linear least squares method. To cope with these uncertainties we

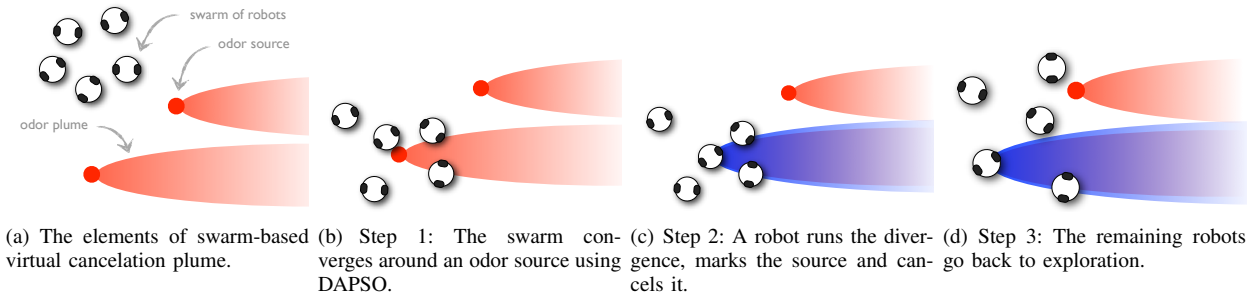


Fig. 3. Diagram representing the steps of the swarm-based virtual odor source cancellation algorithm.

propose to cancel the desired odor source using a plume whose source is placed slightly upwind and is slightly wider and longer. The diagram in Figure 2 illustrates this idea. The error in the estimation of the parameters needed to setup the virtual cancelation plume are reflected in the values of  $d_u$ ,  $d_w$  and  $d_l$ .

In order to inflate the plume width and length we must first present the definition of these plume characteristics according to the Gaussian model. We are looking for the values of  $x$  and  $y$  where the chemical concentration is equal to the minimum quantity measurable by the gas sensors equipped on the robots, i.e. the plume threshold,  $c_{th}$ . The plume width and length will thus vary with  $Q$  and  $\bar{u}$ . Higher release rates will generate wider and longer plumes whereas higher wind flows will result in shorter and thinner plumes. The chemical concentration along the centerline can be represented by equation (6). Solving for  $\bar{c}(x, 0, 0) = c_{th}$  we get the plume length  $l$  in equation (7). The length of the virtual cancelation plume is equal to  $l + d_u + d_l$ . In this work these values were chosen experimentally and are equal to the mean absolute error of the odor source position error.

$$\bar{c}(l, 0, 0) = c_{th} = \frac{Q}{\pi \bar{u} \sigma_y \sigma_z} \quad (6)$$

$$l = \sqrt[p+q]{\frac{Q}{\pi \bar{u} a b c_{th}}} \quad (7)$$

The average chemical concentration at a crosswind distance  $y$  from the plume axis can be calculated using equation (8). Solving for  $\bar{c}(x, y, 0) = c_{th}$  we get the plume width  $w(x)$  in equation (9). The width of the virtual cancelation plume is equal to  $w + 2d_w$ .

$$\bar{c}(x, w, 0) = c_{th} = \frac{Q}{\pi \bar{u} \sigma_y \sigma_z} \exp\left(-\frac{w^2}{2(ax^p)^2}\right) \quad (8)$$

$$w^2(x) = 2ax^{2p} \left( \ln \frac{\pi \bar{u} c_{th}}{Q} + \ln(ab) + (p+q) \ln x \right) \quad (9)$$

The results in equations (9) and (7) are integrated into the Gaussian expression in (1) (for  $z = 0$ ) to provide the model for the virtual cancelation plume found in equation (10). This is the virtual cancelation plume model that we propose to be used to cancel plumes that can be represented by a Gaussian model. From a sensitivity analysis, we conclude that the main

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**Algorithm 1:** The pseudocode for the virtual odor source cancellation algorithm.

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while true do
  // Step 1: Run the DAPSO algorithm
  initialization;
  repeat
    runDAPSO()
  until end conditions are met or new odor source is found;
  if end conditions are met then
    // Step 2: Declare the odor source
    source_x source_y ← divergence(samples);
    // Step 3: Mark the source
    moveTo(source_x, source_y);
    // Step 4: Generate the VCP
    plume ← gaussian(); // Equation (10)
    broadcastVCP(plume);
  else
    subscribe to VCP;
  end
end

```

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parameters influencing the plume shape are  $a$  and  $Q$ , so we generate a virtual cancelation plume, larger than the real one, using the following  $a_{vcp}$  and  $Q_{vcp}$  as given by equations (11) and (12). Notice that by changing the plume width the value of  $Q_{vcp}$  will also be influenced.

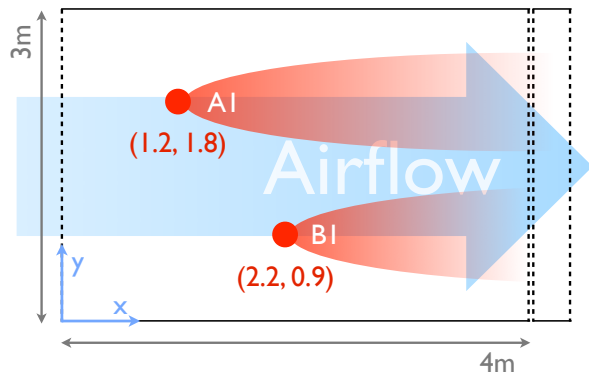
$$\bar{c}_{vcp}(x, y) = \frac{Q_{vcp}}{\pi \bar{u} a_{vcp} x^p} \exp\left(-\frac{y^2}{2(a_{vcp} x^p)^2}\right) \quad (10)$$

$$a_{vcp} = \frac{a + 2d_w}{w_{max}} a \quad (11)$$

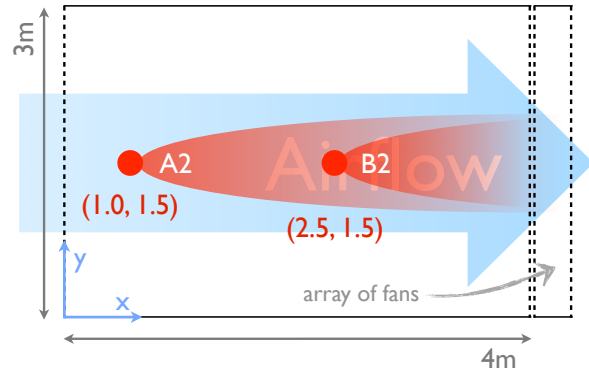
$$Q_{vcp} = \left( \frac{l + d_u + d_l}{l} \frac{w_{max} + 2d_w}{w_{max}} \right)^{p+q} Q \quad (12)$$

#### A. Swarm-based Virtual Cancellation Plume

The proposed algorithm can be applied to different odor source localization algorithms after the stage of odor source declaration. These algorithms can be single robot, multi-robot or swarm based. In this work a swarm-based approach is used since our previous work consisted on swarm-based odor mapping. The algorithms tested proved to be appropriate for the proposed task, however odor source declaration was performed by the user by interpreting the odor maps. Furthermore the algorithms used are not prepared



(a) Scenario 1 - Diagram of the setup for the first scenario containing two separated odor plumes.



(b) Scenario 2 - Diagram of the setup for the second scenario containing two plumes propagating on the same axis.

Fig. 4. The two scenarios used in this work.

to work with multiple sources, hence the need for the virtual cancellation plume algorithm.

We use the Decentralized Asynchronous Particle Swarm Optimization (DAPSO) algorithm developed earlier as a high-level exploration and plume tracking algorithm [7], [16], [17]. Furthermore we employ the divergence operator for odor source declaration [15] taking advantage of the behavior of the DAPSO algorithm as the robots usually aggregate around a maximum of the chemical concentration or basically in the vicinity of an odor source. The estimation of the odor source position along with the estimation of the Gaussian plume parameters are used by the robot who performed the divergence to generate and broadcast the virtual cancellation plume. Each robot keeps a buffer of odor readings that are used for calculating the divergence that will provide an estimation of the odor source position and also for estimating the Gaussian plume parameters using non-linear least squares. Algorithm 1 shows the pseudocode of the proposed algorithm for multiple odor source declaration using the swarm-based virtual cancellation plume. The algorithm is also schematically illustrated in Figure 3.

### III. EXPERIMENTAL SETUP

The experiments described next were performed inside a controlled environment, an arena designed specifically for odor experiments represented by the schematics in Figure 4



(a) The miniQs.

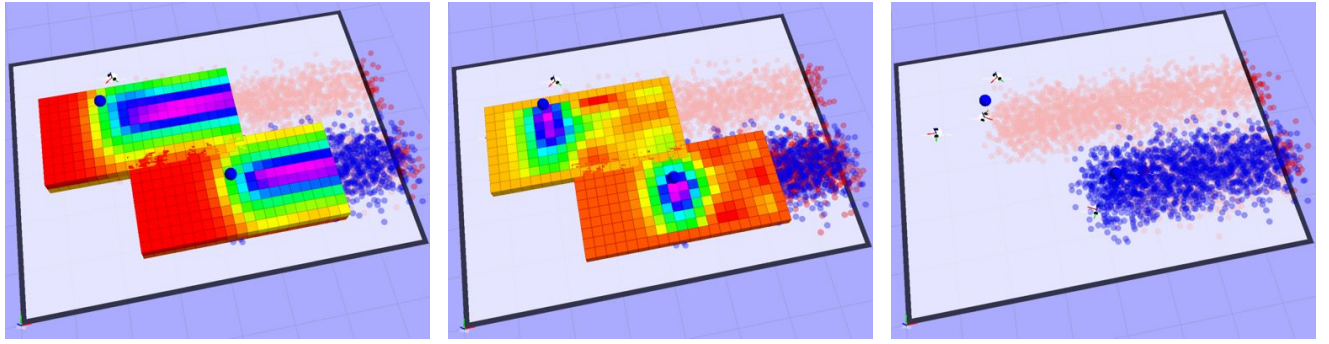


(b) The test arena.

Fig. 5. The miniQ robots used in the experiments and the test environment.

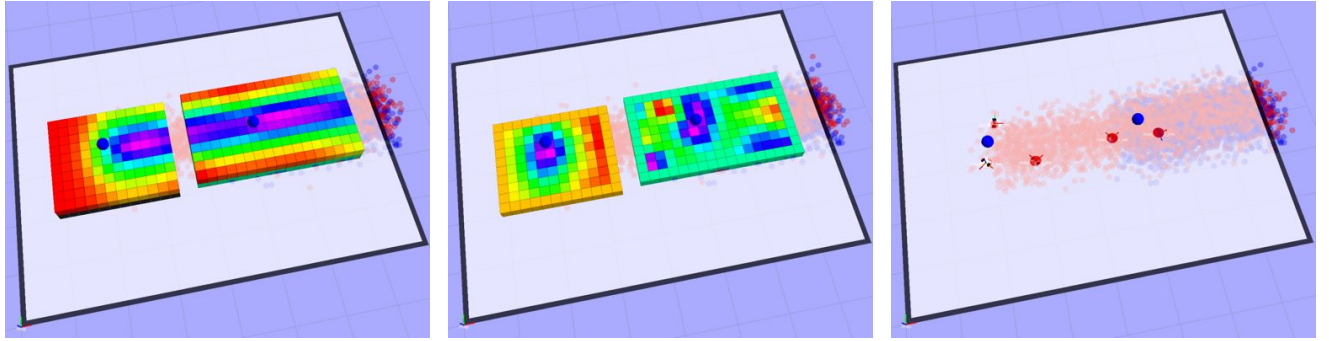
and shown in Figure 5(b). The  $3m \times 4m \times 0.5m$  arena is an enclosed environment delimited by four walls where two extremities are made of honeycomb-like plastic, allowing for the air to circulate. It includes an array of controllable fans thus making it possible to control the airflow inside the arena. The top is covered by a large transparent acrylic cover. This setup allows to generate laminar and constant wind-flow. As a result the requirements for the Gaussian plume to be applicable are met. This arena was used for both simulations with its virtual representation and for the real world experiments. As illustrated by Figures 4(a) and 4(b) two different scenarios were used for the experiments. In the first scenario two odor sources were placed so that their plumes would propagate parallel to each other. The second scenario consisted in two odor sources placed on the same downwind axis. In this scenario the plume generated by the source placed further downwind is completely covered by the plume of the source placed upwind. Notice that the odor sources were named A1 and B1 for scenario 1 (Figure 4(a)) and A2 and B2 for scenario 2 (Figure 4(b)), this convention will be used throughout the results and discussion sections.

A set of simulations was performed on the virtual representation of the experimental arena in Figure 4. The proposed algorithm was tested on a swarm of 5 robots, the goal was to verify the virtual odor source cancellation algorithm. A set of 10 simulations was performed on each scenario on a total of 20 simulations. A Gaussian Puff model was used for simulating the plumes in both scenarios. The reason for this is twofold. First, given a perfect odor source declaration the odor source cancellation would be perfect if the exact



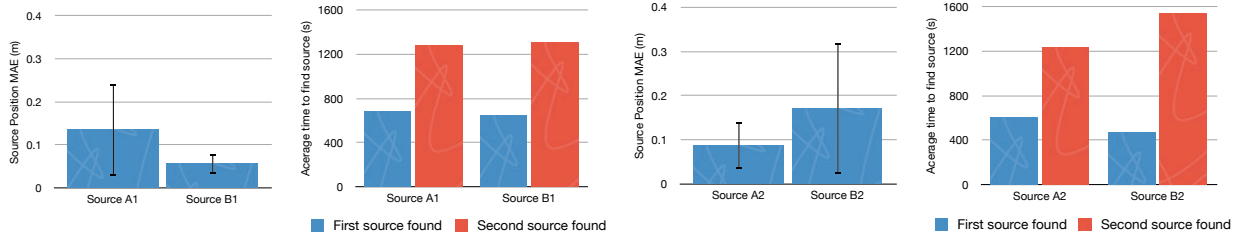
(a) The estimations for the odor distribution around the possible sources. (b) The divergences for the possible sources. (c) The virtual cancelation for odor source B1 which was the first source to be found.

Fig. 6. Example of a simulation performed on scenario 1. The plumes in red are the plumes generated by A1 and B1, the plume in blue is the virtual cancelation plume. The blue spheres indicate the sources localized by the robots.



(a) The estimations for the odor distribution around the possible sources. (b) The divergences for the possible sources. (c) The virtual cancelation for odor source B2 which was the first source to be found.

Fig. 7. Example of a simulation performed on scenario 2. The plumes in red are the plumes generated by A2 and B2, the plume in blue is the virtual cancelation plume. The blue spheres indicate the sources localized by the robots.



(a) The MAE (mean absolute error) of the odor sources position for scenario 1. (b) The average time that took each source to be found on scenario 1 since the start of the simulation. (c) The MAE of the odor sources for scenario 2. (d) The average time that took each source to be found on scenario 2 since the start of the simulation.

Fig. 8. Results for the simulations performed on scenarios 1 and 2.

same model was used for both the environment and the cancelation plumes, something that is impossible in the real world, thus rendering the simulations useless. Second this allows to simulate the effects of intermittency on the virtual cancelation algorithm as the Gaussian Puff model provides instantaneous concentrations in contrast to the mean concentrations provided by the Gaussian model. For a given source let  $c$  denote the instantaneous chemical concentration,  $Q'$  the mass of the source and  $\sigma'_x$  and  $\sigma'_y$  the puff-diffusion coefficients (note that these have different meanings from the  $\sigma_y$  and  $\sigma_z$  of the Gaussian model). Then one can use the Gaussian expression in (13) to generate a concentration of the

effect of that source at time  $t$  and position  $(x, y)$ . All simulations were implemented under the ROS [18] framework using Stage for simulating the robots and PlumeSim [19] for the plumes using the models in (13) for the simulated plumes and in (10) for the virtual cancelation plumes. The parameters of the Gaussian Puff plumes used during the simulations were extracted experimentally to mimic the real odor plumes that they simulate ( $Q' = 100$ ,  $\sigma'_x = 0.1$  and  $\sigma'_y = 0.0005$ ).

$$c(x, y, t) = \frac{Q'}{4\pi\sqrt{\sigma'_x\sigma'_y}t} \exp\left(-\frac{1}{4t}\left(\frac{x^2}{\sigma'_x} - \frac{y^2}{\sigma'_y}\right)\right) \quad (13)$$

On the second phase of the work real world experiments were performed in order to validate the proposed methodology with real odor sources. Experiments were performed using a swarm of 5 miniQ robots (shown in Figure 5(a)). The miniQs are small and cheap robots based on the popular Arduino platform. They were modified to achieve olfactory swarming mainly due to the e2v MiSC5524 gas sensors that they carry. Moreover, two LEDs (one red and one blue) were also integrated to the robots for usage with an Arecont MegaVideo IP camera for correcting the odometry of the robots and to provide global localization. Odometry correction and global localization is achieved using SwisTrack, a software designed for tracking robots. Once again ROS was the framework used. A set of 2 experiments were performed on each environment, on a total of 4 experiments. All experiments were performed under an average wind speed of  $0.1\text{ m/s}$  with a chemical release rate of approximately  $1\text{ mg/s}$  at a height of approximately  $0.07\text{ m}$  (about  $0.04\text{ m}$  above the height at which the gas sensors are located).

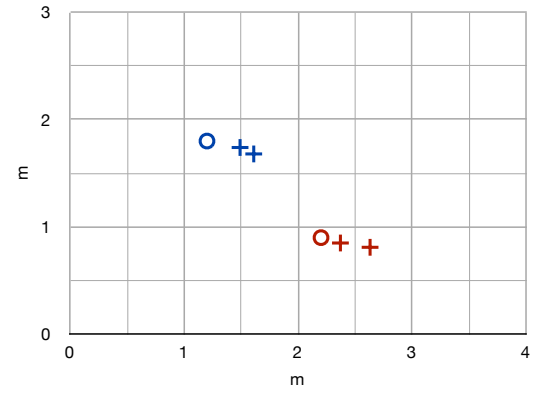
For simulations the values of  $d_u$ ,  $d_w$  and  $d_l$  were set to  $0.1\text{ m}$  which is the MAE (mean absolute error) of the estimation of an odor source using the divergence. For real world experiments these values were set to  $0.2\text{ m}$ . These errors were determined experimentally. A simulation or experiment was considered finished once two odor sources were declared.

#### IV. EXPERIMENTAL RESULTS

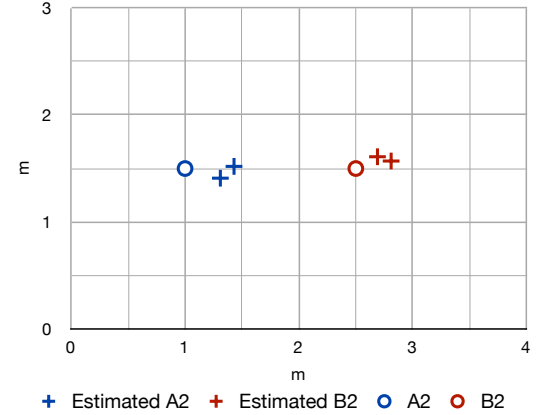
The screenshots in Figures 6 and 7 show examples of the results for the virtual cancelation plume running on scenarios 1 and 2 respectively. The visualization software is rviz. Examples of the simulations were chosen instead of the real experiments since in the simulations it is possible to visualize the plumes generated by the sources A1, B1, A2 and B2. All the screenshots were taken after the simulations were finished.

Figure 6(a) shows the estimations of the odor distributions used to calculate the divergences in Figure 6(b). In Figure 6(c) it is possible to see the virtual cancelation plume for cancelling B1 represented by the blue particles. The plumes generated by A1 and B1 are represented by the red particles. The odor sources declared by the robots are represented by the blue spheres in all three Figures. Figure 7 contains the same information regarding scenario 2.

The graphics in Figure 8 contain the results for the simulations. Figure 8(a) shows the MAE of the estimation of the position of A1 and B1. The same can be found on Figure 8(c) for A2 and B2. The graphics in Figures 8(b) and 8(d) contain information regarding the average time each source took to be found since the start of the simulation for both possible outcomes, when found first and when found last (e.g. for scenario 1 source A1 can be found first or second as there are 2 sources, A1 and B1). For both scenarios both sources were found first during half of the simulations (each source was found first 5 times out of 10 simulations for each scenario).



(a) The sources estimated by the robots for 2 experiments.



(b) The sources estimated by the robots for 2 experiments.

Fig. 9. Results for the real world experiments performed on scenarios 1 and 2.

Figures 9(a) and 9(b) contain the results for the real world experiments. These plots present the position of the declared sources for scenarios 1 and 2 respectively where the circles mark the sources A1, B1, A2 and B2 and the crosses mark the declared sources.

This article is accompanied by a video attachment showing the virtual cancelation plume algorithm running during one of the simulations performed during this work.

#### V. DISCUSSION

Although the errors in graphics 8(a) and 8(c) result from the divergence operator they are also a product of the virtual cancelation plume algorithm in the sense that after a source was found the second source was always found without an increase in the error of the estimation of the odor source position, independently of the source that was found first. The graphics in Figures 8(b) and 8(d) reinforce the idea that after a source is found the virtual cancelation plume algorithm performs its task as intended. The time it takes to find the second source after the first source is found is identical to the time it takes to find the first source. This data indicates that finding the second source is a task that the robots undertake without the interference of the previously declared source and its plume. The fact that in scenario 2

the two plumes are overlapping does not seem to influence the outcome of the experiment. This is probably one of the most important results.

The results for the real world experiments are consistent with those of the simulations. The robots were able to find both odor sources in both scenarios. The main difference is that the errors in the estimation of an odor source position during real world experiments are over 4 times greater than during a simulation. This can however be explained by the height at which the sources were positioned in the arena which might have resulted in the odor only being detected a certain distance downwind of the actual source. Although the sources were placed only 3 cm above the odor sensors this can account for the fact that the biggest component of the error is along the x axis, downwind of the source. Furthermore in the real world experiments the robots take over twice as much time to find a source. This was also expected as the real robots take more time to reach a goal due to the uncertainties in their localization.

## VI. CONCLUSIONS

The results of this work prove that the virtual cancelation plume algorithm is suitable for multiple odor source localization. This is also true for situations where two plumes overlap. Furthermore it might be able to provide multiple odor source capabilities to a wide range of existing odor source localization algorithms that only work with a single odor source.

Although the Gaussian plume model was used in this work to avoid introducing a high degree of complexity into the problem this implementation is not far from real world applications. The Gaussian plume model is commonly used in the meteorological sciences for studying the propagation of pollutants in the atmosphere. The method presented in this article can be used for example by a group of aerial robots to localize factory emissions in a city that are not following air pollution regulations.

A Gaussian plume model was used in our case as the environment contained no obstacles with constant and laminar wind flow. However this will not work on complex or realistic environments such as a warehouse. The virtual cancelation plume algorithm can however be used with different plume models, including numerical models. A more complex plume model can be generated using Computer Fluid Dynamics (CFD) software. That would require robots with good computational capabilities as well as a perception of the obstacles present in the environment as that information would be necessary. In spite of the fact that this is not suited for swarming applications, it can be implemented on a multi-robot or even a single robot system. The virtual cancelation plume algorithm is intended to work with all odor source localization algorithms that treat the problem as a global optimization problem.

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