Swarm Robotic Plume Tracking for Intermittent and Time-Variant Odor Dispersion*

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Abstract— **This paper presents a method for odor plume tracking by a swarm of robots in realistic conditions. In real world environments, the chemical concentration within an odor plume is patchy, intermittent and time-variant. This study shows that swarm robots can cooperatively track the odor plume towards its source by establishing a cohesive spatial sensor network to deal with the turbulences and patchy nature of odor plumes. The robots move together and maintain a distance margin between themselves in order to keep the cohesion of the constructed sensor network while the odor concentration and air-flow speed are considered in the equations of navigation of the robots in the network to more efficiently track the plume. The method is evaluated in simulation against various number of robots, the emission rate of the odor source, the number of obstacles in the environment and the size of the testing environment. The emergent behavior of the swarm proves the functionality, robustness and scalability of the system in different conditions.**

I. INTRODUCTION

Searching for olfactory targets with mobile robots has received much attention in the recent years. This problem finds applications in environmental monitoring, chemical leak detection, pollution monitoring, inspection of landfills, and search and rescue operations. Some of these tasks are done in scenarios extremely dangerous for humans, being desirable to use robots instead.

The effort to design and develop efficient robotic olfactory search strategies faces the problem of understanding how the odor molecules disperse through the environment under naturally turbulent flow. Odor patches released by an odor source are mainly transported by the airflow, forming an odor plume. As the plume travels away from the source, it becomes more diluted due to molecular diffusion and turbulence that mixes the odor molecules with the clean air [1]. Molecular diffusion is a slow process whose effect on the plume shape and the internal concentration can be neglected. The dispersion of odor molecules is dominated by flow turbulence in ventilated indoor or in outdoor environments. The odor molecules move downwind due to mean flow velocity $\vec{U}$ while their net motion is almost random, due to small scale turbulence curls. As the flow carries patches of odor, the average concentration within a patch decreases away from the source, and the average time between successive patches increases. The instantaneous odor concentration strongly fluctuates intermittently with peaks up to three orders of magnitude above the average concentration value [2]. Fig. 1 presents the nature of an odor plume from various exposures. Under these circumstances, a fast chemical sensor located far enough downwind of the odor source can only detect the odor peaks and will measure no odor concentration most of the time. The probability of encountering an odor patch at any given point is determined by the relative location of the sensor to the odor source, the statistics of the flow and the shape of the environment and obstacles [3], [4].

The problem of odor source localization in robotics is composed of three phases [5]: (i) odor plume finding, i.e., searching the environment randomly or systematically in order to find odor plumes, (ii) plume tracking, that is, following the plume toward the source; (iii) source declaration, that is, accurately localizing the source in close vicinity. We have already studied the first subproblem proposing a swarm robotics approach and found that the best strategy to find an odor plume is to line-up the robots while moving cross-wind [6]. This current paper extend that work by focusing on the second subproblem, assuming the plume was previously found and the robots should track it towards the source.

To state the problem, consider a swarm of N individual robots that are able to communicate with each other over a short distance Δ_d and are equipped with olfactory sensors for sensing the odor concentration C and airflow speed $\vec{U}$. Robots are limited in terms of memory capacity and there is no central station for the system so the robots should act separately and independently from the others. The problem is how the swarm can track an odor plume towards its source in an area. The approach should exploit swarming principles to track odor plumes in natural environments where the odor distribution may change over time. We assume that the plume is previously found so at least one robot is located inside the active area of the odor plume.

Concentration gradient climbing (chemotaxis [7], [8]) and up-wind directed search (anemotaxis [9], [10], [11]) are the most common approaches to track odor plumes by mobile robots. Several other methods have been proposed for plume tracking using swarm robotic concepts, namely, biasing expansion swarm approach (BESA) [12], biased random walk (BRW) [13], particle swarm optimization (PSO) [14], [15], glowworm swarm optimization (GSO) [16], gradient climbing techniques, swarm spiral surge [17], and physics-based swarming approach [18]. Researchers have developed methods that employ combinations and variations of plume acquisition and plume upwind following [19] using reactive control algorithms (comparisons of these kinds of methods

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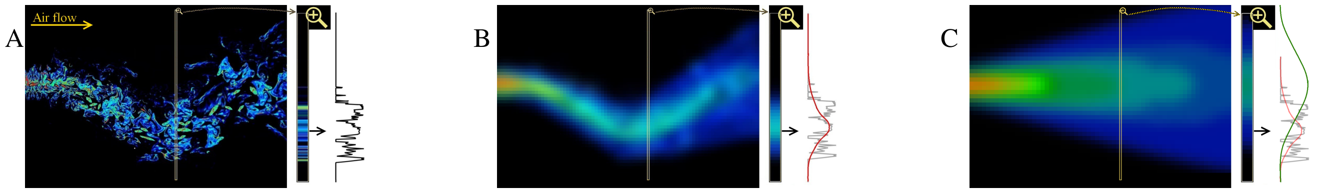

Fig. 1. Odor plume structure in various exposures. A. instantaneous structure (adapted from [2]), B. The spatial average of the odor plume, and C. The time (and spatial) average of the odor plume. The black signal in A shows the instantaneous measurements of a fast gas sensor while moving cross-wind, the red signal in B shows the output of a slow sensor (that acts like a low-pass filter) that moves cross-wind, the green signal in C shows the average of the measurements during a long time period.

are in [7]). We have previously proposed another swarming approach for olfactory swarm navigation [20] that was based on gradient climbing but it fails in environments under turbulent airflow where the concentration of odor does not change gradually. A common drawback of most of these methods is that they do not consider the conditions of the real world odor plumes where the flow is turbulent and the odor distribution is patchy and time-variant.

Turbulent behavior of airflow, lack of smooth odor concentration gradient, patchiness of odor depression, meandering and time variant characteristics of odor plumes imply that neither concentration gradient climbing methods nor up-wind directed search alone can efficiently localize odor sources in an environment under turbulent flow. Given this time variant and patchy behavior, we believe that in the real world conditions, a mobile sensor network can be advantageous in comparison to a single robot that can measure only the odor concentration of its own place. Robots in a swarm can speared out in the environment and construct a dynamic spatial sensor network. The swarm robots can move together and maintain a distance margin between themselves in order to keep the cohesion of the established moving sensor network. Despite most of other works in this area that propose centralized approaches and address the problem in simplified conditions, this paper presents a distributed method in which robots track an odor plume in an unknown environment where the odor distribution is time-variant and patchy, the flow is turbulent, and there are obstacles in the environment. The main contribution in this method is that the motion of swarm robots is not only based on the robot-to-robot virtual forces; the olfactory sensory data (the stochastic concentration gradient and airflow direction) affects the formation of the swarm. The performance of the method is evaluated against various number of swarming robots, the emission rate of the odor source, the number of obstacles in the environment and the size of the testing environment. The emergent behavior of the swarm proves the functionality, robustness and scalability of the system in different conditions.

II. Proposed method

A. Tracking the plume locally

Based on the nature of odor distribution, the following fact should be considered [21]: when a robot observes an odor patch, it is obvious that the best strategy is to make a step in the direction from which the patch has arrived. Since the wind carries the odor patches, if a patch is observed at position $P(x_0, y_0)$, one should visit the places close to this position and toward the upwind direction. Each odor patch observation reduces the uncertainty about the odor source position. Therefore, a goal vector can be defined by a linear combination of the concentration gradient and the upwind vector [13]:

$$\vec{G}_i(t) = k_1 \vec{\nabla} \bar{C}_i(t) - k_2 \vec{U}_i(t) \quad (1)$$

Where k_1 and k_2 are two positive constant coefficients, $\vec{\nabla} \bar{C}_i(t)$ is the direction of the gradient of odor concentration measured at the position of robot i at the current time t, and $\vec{U}_i(t)$ is the airflow direction measured by robot i. The first term in the above equation applies a force towards the higher odor concentrations to the robot, whereas the second term applies a force towards up-wind direction.

Since the odor dispersal is patchy and intermittent, the main challenge is how to measure the odor concentration gradient $\vec{\nabla} \bar{C}_i(t)$. Due to intermittency and patchiness of odor dispersal, a problem is that the instantaneous concentration fluctuations is bigger then the average concentration differences between the two close sensors (see Fig. 1.A). A solution found to this problem is to use the mean concentration values gathered during the motion of the robot to estimate the local concentration gradient [13]. Applying a low-pass filter on the instantaneous sensor measurements of different places provides a smooth data that its local gradients is towards the current plume center line and also towards the source (see Fig. 1.B). This will address the problem of dealing with fluctuation and the patchiness of odor dispersal. If another low-pass filter is applied to this data during the time, a pseudo-Gaussian plume is obtained that its gradient is smooth and it is towards the source (see Fig. 1.C). This addresses the problem of dealing with plume meandering in large and real world environments. Therefore, to obtain a smooth gradient we need to apply two low-pass filters on the sensory measurements:

- temporal filter,
- spatial filter.

To obtain these two filters, this paper take the advantages of swarming approaches. The basic idea is that the distributed swarm robots can cooperatively act as a spatial filter and each agent can also have its own temporal filter. Each robot measures its own mean odor concentration (temporal-filter) and communicates with its neighbors and computes the maximal difference quotient of the mean odor concentration to calculate the gradient (spatial-filter). The estimate of the

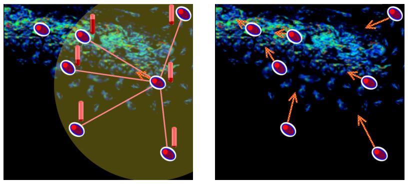

Fig. 2. The concept of swarm gradient estimation. The arrows represent (only) the gradient estimated by each robot using equation (4). The picture in the left shows the the communication range of one sample robot and the vertical gauges present the odor concentration that the robots sense at the moment.

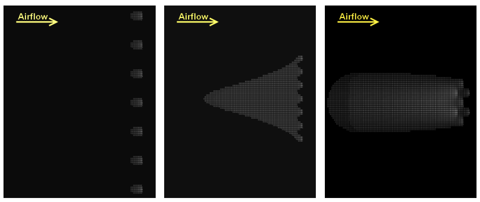

Fig. 3. Sensor coverage area of seven sensors in three different spatial configurations. When the sensors get close to each other the covered area expands toward the opposite direction of the air flow [6].

gradient at each robot is the vector in the corresponding direction with norm equal to the maximal difference quotient. The difference quotient of mean odor concentration ($Q_{ij}(t)$) at the position of robot i relative to robot j is given by:

$$Q_{ij}(t) = \frac{\bar{C}_j(t) - \bar{C}_i(t)}{\|P_j(t) - P_i(t)\|} \tag{2}$$

Where $P_i(t)$ and $P_j(t)$ denote the position of robot i and j respectively, and $\bar{C}_i(t)$ and $\bar{C}_j(t)$ represent the mean (temporal-averaged) odor concentration calculated by the robots. The mean odor concentration gradient between robot i and j is given by:

$$G\vec{rad}_{ij}(t) = Q_{ij}(t)\Big(\frac{P_j(t) - P_i(t)}{\|P_j(t) - P_i(t)\|}\Big) \tag{3}$$

Where the first term is the difference quotient of mean odor concentrations of robot i and j, and the second term is the unit direction vector between the two robots.

Considering N robots in the neighborhood, the concentration gradient in the position of robot i is given by:

$$\vec{\nabla}\bar{C}_i(t) = \sum_{j=1;j\neq i}^{N} G\vec{rad}_{ij}(t) \tag{4}$$

Taking a lot of measuring points (robots) into account gives higher accuracy in the estimation of gradient. This formula is used in equation (1) for the navigation of the robots. Fig. 2 show the concept of these equations in a patchy and intermittent plume.

B. Maintaining formation of the swarm sensor network

We have previously shown that when multiple robots get close to each other, their coverage area gets expanded toward the opposite direction of the air-flow [6]. Fig. 3 compares the coverage area of three different configurations of seven sensors in an environment. The right figure that is a mesh configuration shows the longest sensor coverage towards upwind direction. Maintaining a mesh-like topology the swarm will detect the odor patches coming from very further possible locations. Therefore, not only the robots should navigate towards higher concentrations and upwind direction, they should also establish a spatial mesh topology and maintain its cohesion.

The mesh formation is obtained by implementing virtual attraction/repulsion forces between the robots. The robots which sense more odor patches (higher odor concentration), attract other robots with stronger forces to cover the region. As an emergent result, the swarm moves toward the consensus direction of all the swarm members.

It is required that the robots aggregate together to keep a specific distance margin between each other and try to virtually push and pull each other. If a robot goes toward a specific direction, the robots in behind, to maintain the sensor network's cohesion, go toward the same direction and the robots in front also go to that direction in order to keep their distance. Therefore, the swarm always moves toward the direction that more robots tend to go while keeping the formation of established sensor network. For instance if ten robots try to go to the left and five robots to the right, the whole swarm (maybe with lower speed) will move to the left because the resultant virtual forces that is applied to each robot from the other robots is in that direction. To implement this behavior, the virtual forces applied to robot i from another robot j is defined as:

$$\vec{F}^{co}_{ij}(t) = \begin{cases} \frac{\mu_1 q_j(t)}{\|\vec{P}_{ji}(t)\|^2}\big(\frac{\vec{P}_{ji}(t)}{\|\vec{P}_{ji}(t)\|}\big), & \|\vec{P}_{ji}(t)\| < R_1 \\ 0, & R_1 \leq \|\vec{P}_{ji}(t)\| \leq R_2 \\ \frac{-\mu_2 q_j(t)}{\|\vec{P}_{ji}(t)\|^2}\big(\frac{\vec{P}_{ji}(t)}{\|\vec{P}_{ji}(t)\|}\big), & \|\vec{P}_{ji}(t)\| > R_2 \end{cases} \tag{5}$$

where μ_1 and μ_2 are two positive coefficients, $\vec{P}_{ji}(t) = P_j(t) - P_i(t)$, and R_1 and R_2 define a distance margin between each two neighboring robots ($0 < R_1 < R_2 < \Delta_d$). If two neighboring robots are farther than the defined threshold R_2 the equation acts like an attraction force, however, if the neighboring robots are closer than R_1 the formula acts like a repulsion force. This equation maintains the swarm in a cohesive form. $q_j(t)$ is defined as:

$$q_j(t) = \beta_j \frac{\bar{C}_j(t) - C_0}{C_{max} - C_0} \tag{6}$$

where C_{max} is the maximum odor concentrations that the swarm robots have reported so far, and C_0 denotes the minimum value that the olfactory sensors report in clean-air conditions. β_j is a constant that is predefined by the system designer as the effectiveness of the robot j on the other robots.

In most previous studies in swarm formation, force formula is the inverse function of the distance between the agents and other parameters such as q_j are ignored. However, we used q_j as a parameter of effectiveness of the robots on each other and defined a formula for that based on the problems' modality (i.e. olfactory) to increase the efficiency of the method. Each robot has a parameter q so that the force that the robots apply to each other will be dependent on that. Robots with higher q apply bigger forces to the neighboring robots. In contrast, a robot that does not sense high odor, does not apply significant forces to its neighbors.

By the above equations, the total cohesion force $\vec{F}_i^{co}(t)$ for robot i is determined as:

$$\vec{F}_i^{co}(t) = \sum_{j=1;j\neq i}^{N} \vec{F}_{ij}^{co}(t) \tag{7}$$

C. Obstacle avoidance

The low level of autonomous navigation of a robot relies on the ability of the robot to simultaneously achieve its target goal and avoid the obstacles in the environment. Similar to our previous work [9], to avoid the environmental obstacles, a reactive potential field control method [22] is used. Considering M range sensors, we define the forces applied to robot i by its surrounding environment as:

$$\overrightarrow{F}_i^{obs}(t) = \sum_{j=1}^{M} \frac{c_1}{\left|d_i(j)\right|^n} \overrightarrow{(Vec_i j)} \tag{8}$$

Since $d_i(j)$ is simply the distance between robot i and an obstacle that is reported by the range sensor j, the force is an inverse function of the distance of the robot to the surrounding obstacles. $\overrightarrow{Vec_i j}$ is a predefined vector whose magnitude is set to one and its direction is from sensor j toward the center of robot i. c_1 is a positive coefficient and n is an even integer parameter. For more details of obstacle avoidance see [9].

Total force:

The total force applied to robot i during plume tracking is given by:

$$\vec{F}_i(t) = \vec{G}_i(t) + \vec{F}_i^{co}(t) + \vec{F}_i^{obs}(t) \tag{9}$$

As an emergent result, the robots tend towards upwind direction and higher odor gradients (due to $\vec{G}_i(t)$, equation 1), while maintaining their sensor network formation (due to $\vec{F}_i^{co}(t)$, equation 5) and avoid obstacles (due to $\vec{F}_i^{obs}(t)$, equation 8). If some robots tend to go to one direction and others to another direction the whole swarm will actually move toward resultant summation of virtual forces of all the robots. It should be noted that not all the robots in a swarm are always located in an area of active odor plume. At a given moment, some of them may sense high odor concentrations and air flow while others do not sense any odor clues. Equation 9 implies if a robot does not sense air-flow and high odor concentrations, it follows the swarm to maintain the sensor network's cohesion.

III. Experimental results

1) Testing environment: The model of the testing environments were given to ANSYS Fluent CFD[1] software to simulate ethanol gas sources and provide concentration data. One of the environments designed for these experiments is

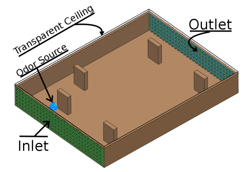

Fig. 4. The model of a testing environment with 4×6 m^2 dimensions.

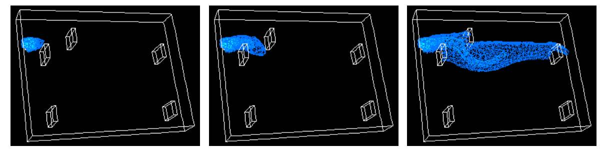

Fig. 5. ANSYS Fluent three dimension simulations; contours of mass fraction of ethanol propagated in the testing environment of Fig. 4 during the time. The odor source is placed at the left side and the wind is set to be left to right.

depicted in Fig. 4. The dimension of designed arenas for simulations was varied from 4×6 m^2 to 30×40 m^2. Laminar airflow was ventilated from the inlet side (left) with constant speed of 0.5 m/s. In the environments with obstacles, the flow velocity varies in different parts of the arena. Fig. 5 shows several snapshots of 3-D odor plume propagation during the time in one of the tested scenarios. As it is shown in the simulation snapshots, the odor propagation is time variant and under turbulent flow and the odor concentration does not change gradually. We extracted the odor concentrations and airflow velocities of 10 centimeters height from the 3-D odor plumes and fed it to the robots in the simulations. The olfactory data generated by ANSYS Fluent were exported to GNU Octave[2] to be used in simulations.

2) Robots: Robots were simulated in GNU Octave as independent entities with no shared variables. The environmental data including odor concentrations, wind speeds and obstacles locations are shared with the robots such that the robots can measure the odor concentration and air-flow speed of their places. Each robot can send and receive small messages to its neighbors. Robots are able to measure their distances to the obstacle and to the other neighboring robot. In each test the initial positions of the robots are the results of the "odor plume finding" method explained in [6], so the robots are initially located downwind the odor source and at least one of them is inside the odor plume.

3) Evaluation: Fig. 6 demonstrates a series of snapshots during a simulation that shows the functionality of the method. The first frame of this figure shows that 10 robots are released randomly in one part of the environment. To better explain the functionality of the method, we have colored the robots based on their status in these simulations. If the mean odor concentration that a robot senses is less than a certain threshold, the color of that robot is black, but, if the robot senses more odor concentrations the robot turns to red. In the first frame, only one robot (the red one) is inside the plume and senses high odor concentration. Therefore

[1]http://www.ansys.com

[2]http://www.gnu.org/software/octave

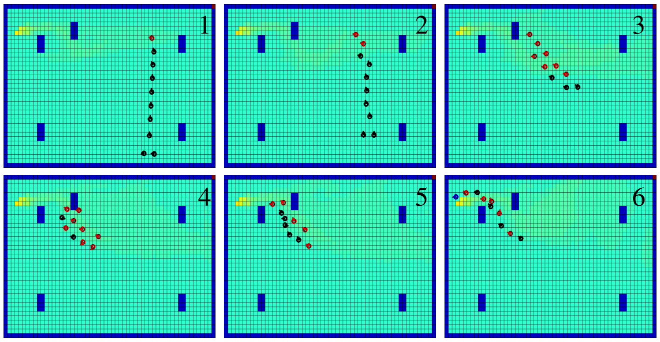

Fig. 6. Swarm of 10 robots searching the 4×6 m^2 environment of Fig. 4 for an odor source. The emission rate of odor source is 0.01 g/s. The red color means that the robot senses high odor concentration.

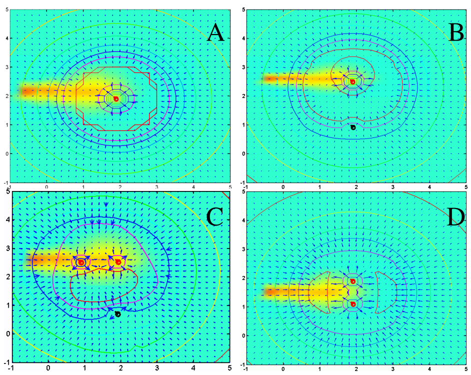

Fig. 7. Virtual forces during tracking the plume. (A) One robot sensing high odor concentration. (B) Only the upper robot senses high odor concentrations. (C) Only the two upper robots sense high odor concentrations. (D) Two robots sense equal high odor concentration.

the other neighboring robots estimate the odor concentration gradient towards this robot. The next frames show that the robots aggregate to the plume and track it towards higher concentrations while upholding sensor network's cohesion. The robots dynamically (and automatically) change their colors in this behavior and the emergent result is that the swarm is able to pass through the obstacles by changing its shape and travel towards the odor source.

In this experiment, the coefficient parameters of the method were set as following: $\Delta_d = 1m$, i.e. the range of communication between the robots is considered to be 3 meters, $\beta_i = 1$ for all the simulated robots since they are all equivalent, $R_1 = 0.1m$ and $R_2 = 0.5m$ for keeping the cohesion of the sensor network in plume tracking behavior and keep the neighboring robots in range of 10 to 50 centimeters apart, $k_1 = 50$ and $k_2 = 0.5$ to rationally correlate the odor gradient, the wind and the forces applied to the robots, and $\mu_1 = \mu_2 = 1$, and $c_1 = 1$.

Fig. 7 shows the virtual forces that the swarm robots generate in various conditions. Each arrow in a place shows the magnitude and the direction of virtual forces that would be applied to another robot if it was located in that place. By adding (or removing) robots to these scenarios the configuration of forces will change, however these figures only show the virtual forces in the current setup of the figures before adding another robot. These forces are obtained by

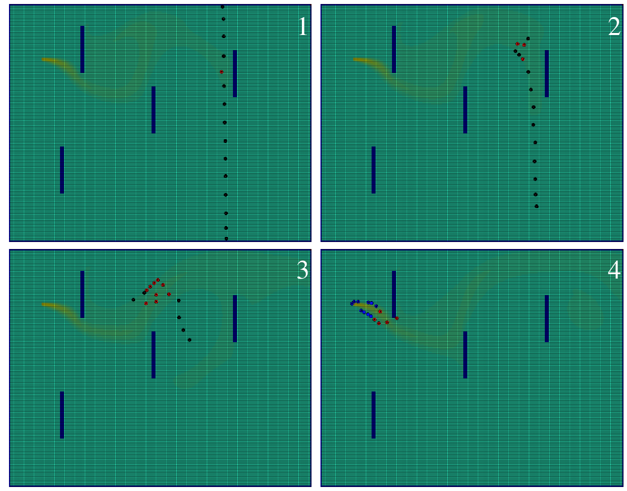

Fig. 8. Swarm robots searching for an odor source in a 30×40 m^2 environment.

implementing the equations (5) and (6). As shown in these figures, each robot implies repulsive forces in its close surrounding area and attractive forces far from it. The robots which sense higher odor concentrations imply stronger forces in their neighborhood (e.g. Fig. 7.(B)). As a result, if there was any other robot near these robots, the virtual forces would attract it toward these robots (until a certain margin). This margin can be adjusted by modifying the parameters R_1 and R_2 in the equation (5). It must be mentioned that the movements of the robots in this behavior is not only based on these cohesive virtual forces, due to (1) each robot tends to go toward higher odor concentrations and up-wind direction while being affected by the swarm virtual forces. The direction and amplitude of navigation forces depend on the amount odor concentration and the air-flow direction in any specific location.

The method was evaluated against: (i) the number of swarming robots, to test the scalability of the method in different conditions, (ii) the emission rate of the odor source, to evaluate the sensitivity of method in different amount of odor in the environment, (iii) the number of obstacles, to measure the performance of the method against airflow turbulences caused by obstacles, and (iv) the size of the testing environment, to study the effect of meandering phenomenon that happens in large environments.

Three environments similar to the one shown in Fig. 4 with 0, 5 and 10 obstacles have been tested with 5, 15, 20 and 30 robots, while the emission rate of the odor source in the left side of the testbed was set to 0.01, 0.02 and 0.05 g/s. Each experiment was repeated for ten times. The end of each experiment was considered to be when at least one robot gets closer than 20 cm from the odor source. In each experiment the other parameters were kept constant and the search time is measured. Fig. 9 shows the average search times in the mentioned conditions. The charts show that a bigger swarm finds the odor source faster than a small swarm specially when there are more obstacles and the emission rate of the odor source is low. The swarm was able to deal with the

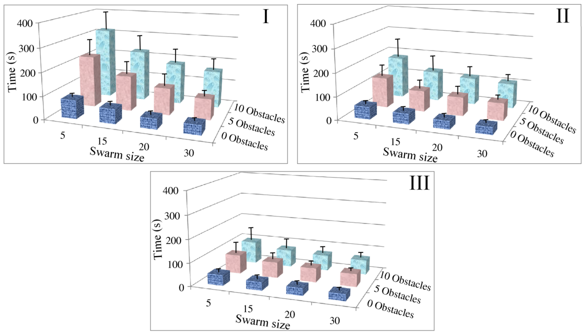

Fig. 9. Search time in different environment with different number of robots while the emission rate of odor source was I: $0.01g/s$, II: $0.02g/s$, and III: $0.05g/s$

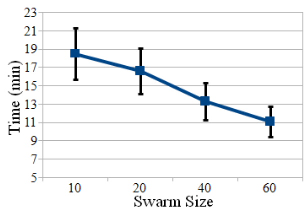

Fig. 10. The results of simulation in GNU Octave using 10, 20, 30 and 60 robots in a large (30×40 m^2) environment.

obstacles, turbulences and local maximums.

To evaluate the proposed method in large environments where the odor plumes highly meander, simulations were carried out in $30 \times 40 \times 5m^3$ environment. The emission rate of the odor source was set to $0.05g/s$. Fig. 8 demonstrates the movements of 10 swarming robots in the large environment. In this experiment, the coefficient parameters of the method were set to the same values of previous simulations except following parameters: $\Delta_d = 6m$, $R_1 = 2.2m$ and $R_2 = 3.3m$. As shown in Fig. 8, when the plume meanders, the shape of the swarm automatically changes and the robots track the plume toward its source. Fig. 10 presents the results of the tests of the method with 10, 20, 40 and 60 robots in the mentioned conditions. This chart shows that a big swarm shows better results to track a meandering plume and finding the odor source.

IV. Conclusions

This paper presented an approach for tracking odor plumes by a swarm of robots in near real world conditions where the environments is under flow turbulent and the odor distribution is time-variant and patchy. The method was designed based on the swarm robotics principles of simplicity of individuals, distributed control and minimum communications. The swarm robots establish a dynamic sensor network by maintaining a cohesive formation between themselves to overcome the problems of local maximums, patchiness and turbulences in the odor plumes. The odor concentration and air-flow speed were considered in the swarm formation virtual forces' equations to more efficiently preform the tasks. The method has been simulated in GNU Octave and the results prove functionality, robustness and scalability of the proposed approach in different conditions. The swarm shows acceptable performance for reduced swarm sizes and provides increasing performance with increasing swarm sizes specially when there are more obstacles in the environment and the emission rate of the odor source is low.

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