Detection and Tracking of an Odor Source in Sensor Networks Using a Reasoning System

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***Abstract*—This paper addresses the challenge of mapping the paths of particles originating from a chemical source using interpolation and extrapolation methods. Odor localization is the problem of identifying the source of an odor or another volatile chemical in an uncontrolled environment. Most localization methods require following an odor plume along its path by a mobile detector, that is time consuming and difficult in a cluttered environment. In this paper, physically separated multiple sensors and the dynamical behavior of fluids are used to predict the airflow pattern. A model of a particle path using an interpolation and extrapolation method, a framework of the reasoning systems, and results of odor source location process are presented. The method also demonstrates that an interpolation and extrapolation approach can be used to assist the odor localization search and shows that it is successful in reasoning about the surroundings in unstructured environments.**

***Index Term*—odor source localization, odor distribution map, sensor networks**

I. Introduction

The detection of the airborne chemicals presents a different type of challenge than the more traditional detection efforts, such as the visual-based detection or propagating signal detections [1]-[3]. The chemicals that are airborne tend to drift in various directions due to wind, up-draft, and obstacles. As a result, isolation of the source of such particles becomes considerable difficult and dependent on topography and environment. There has been some previous research on the detection and modeling of airborne particles, plume location and tracking [4]. However, most of such research is based on sensor information on moving robots that are guided by the detectors [5]. These types of sensing robots are assumed to move about freely following the trail of a chemical signature, while they're continuously sensing for the particles [6], [7]. Both of these assumptions are invalid in inaccessible and hostile environments with sensors that can either function once or need along rejuvenation time cycles. In our approach to the problem of chemical particle detection and source location, we use a small number of chemical sensors that are sparsely scattered around an area only known by a two-dimensional map. In real-world problems, we anticipate that a small unmanned aircraft would drop some of these sensors on the area of interest while taking some aerial pictures. We assume that the sensor data along with the map are transmitted to a nearby location perhaps to a vehicle that will be travelling through the area of interest. We would like to use the maximum available information content to generate first a model of the chemical particle distribution, and then locate the source of the particles based on the model.

II. Particle Paths Mapping and Odor Dispersal

A. Particle Path Algorithms Using Interpolation and Extrapolation

Using the sensors that can collect the sensors position, wind velocity, chemical concentration, we can determine the particle paths that describe the propagation in the environment. This map is a prerequisite for the detection the odor source.

In this paper, we start with the interpolation of two nodes points (x_0, y_0) and (x_1, y_1), where the points are the locations of two sensors with odor particle values of s_0 and s_1, respectively. Since a direct interpolation of a path between the two points would be inconsistent with the odor propagation and the air flow, we generate two more localizations, a propagation parameter "t" where $0 \le t \le 1$, and consistent interpolation functions H_x and H_y, such that

$$(x(t), y(t)) \approx (H_x(t), H_y(t)), \tag{1}$$

where $x_0 = H_x(0),\ x_1 = H_x(1),\ y_0 = H_y(0),\ y_1 = H_y(1).$

In this approximation, we use Hermite polynomials. In Equation (1), we match the boundary values of the location; however we also need to match the velocities $\partial x_0/\partial t,\ \partial x_1/\partial t,\ \partial y_0/\partial t, and\ \partial y_1/\partial t.$

From the sensor data, we can only collect the derivatives of y with respect to t, but we need the derivatives of x and y with respect to t. However, these derivatives aren't too hard to determine from using the identity

$$\partial y/\partial x = \frac{\partial y/\partial t}{\partial x/\partial t} \tag{2}$$

Consequentially, we chose

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$$\begin{aligned}
\frac{\partial x}{\partial t}\Big|_{t=0} &= \frac{\partial x_0}{\partial t} = \delta x_0, \\
\frac{\partial y}{\partial t}\Big|_{t=0} &= \frac{\partial y_0}{\partial t} = \delta y_0, \\
\frac{\partial x}{\partial t}\Big|_{t=1} &= \frac{\partial x_1}{\partial t} = \delta x_1, \\
\frac{\partial y}{\partial t}\Big|_{t=1} &= \frac{\partial y_1}{\partial t} = \delta y_1.
\end{aligned} \tag{3}$$

We, then, proceed to construct the two Hermite polynomials in the usual way, such that

$$\begin{aligned}
H_x(t) &= ([1-2(t-0)L'_{1,0}(0)]L_{1,0}(t)^2)x_0 \\
&\quad + ((t-0)L_{1,0}(t)^2)(\delta x_0) \\
&\quad + ([1-2(t-1)L'_{1,1}(1)]L_{1,1}(t)^2)x_1 \\
&\quad + ((t-1)L_{1,1}(t)^2)(\delta x_1) \\
&= ([1-2(t-0)(-1)(\frac{t-1}{0-1})^2)x_0 \\
&\quad + ((t-0)(\frac{t-1}{0-1})^2)(x_0^+ - x_0) \\
&\quad + ([1-2(t-1)(1)](\frac{t-0}{1-0})^2)x_1 \\
&\quad + ((t-1)(\frac{t-0}{1-0})^2)(\delta x_1) \\
&= (1+2t)(t-1)^2 x_0 + t(t-1)^2(\delta x_0) \\
&\quad + (3-2t)t^2 x_1 + (t-1)t^2(\delta x_1)
\end{aligned} \tag{4}$$

where $L_{n,j}$ denotes the *jth* Lagrange coefficient of the $2n+1$ is the order polynomial.

Similarly, we have

$$\begin{aligned}
H_y(t) &= (1+2t)(t-1)^2 y_0 + t(t-1)^2(\delta y_0) \\
&\quad + (3-2t)t^2 y_1 + (t-1)t^2(\delta y_1)
\end{aligned} \tag{5}$$

As a test case, we consider a three sensor configuration system as in Fig. 1. In the figure, the thick black lines are the boundaries of the room, the red dots are the sensor locations, and the red dotted lines designate the border of the boundary zone.

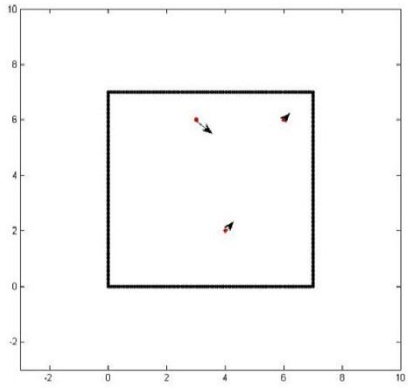

Figure 1. The location of three sensors in a square enclosure.

Some chemical sensors are designed to detect simply the existence of chemical particles and trigger a positive result when the concentration amounts are above a preset threshold level. In our design, instead of the threshold, we make use of the actual concentration levels that are detected. This approach along with some other data enables us to model the flow of the particles and the location of the source. Each sensor provides the co-located sensory information of the airflow information that is obtained not by an additional sensory device but by an off-centered multi-orifice detection hardware configuration. In our derivations, we assume that the differential information is perpendicular to the wind direction, but we can accommodate any non-zero known angular orientation simply by a coordinate transformation. Designating the location of the sensors by (x, y), we represent the flow of air by (δx, δy). Similarly, we represent the sensed particle concentration by s and the concentration gradient by δs.

Once we obtain the sensory information, we start with an approximation of the particle path. We configure paths that go through the sensor locations, such that the paths satisfy the locations as well as the differentials. This approach leads to a parametric cubic-polynomial representation of the path in terms of the variable t. We use the cubic Hermite splines with the end point differentials weighted three times, such that

$$\begin{aligned}
x(t) &= (2(x(0)-x(1)) + (\delta x(0) + \delta x(1)))t^3 + 3(x(1) \\
&\quad - x(0)) - (\delta x(1) + 2\delta x(0)))t^2 + \delta x(0)t + x(0), \\
y(t) &= (2(y(0)-y(1)) + (\delta y(0) + \delta y(1)))t^3 + 3(y(1) \\
&\quad - y(0)) - (\delta y(1) + 2\delta y(0)))t^2 + \delta y(0)t + y(0),
\end{aligned} \tag{6}$$

where the parametric curve starts at one sensor location at (x(0), y(0)) and ends at the other sensor location at (x(1), y(1)) as t goes from 0 to 1.

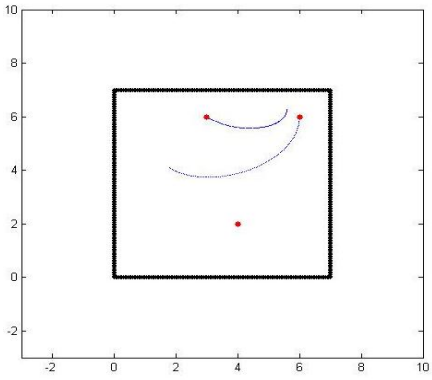

Figure 2. Consistent air-borne particle paths between two sensors.

We compute the expected concentration values along the computed path and compare them with the actual sensed concentration values Based on the errors and the measured gradient concentrations; we determine new locations perpendicular to the initial paths, where the expected and the sensed concentration values match. We, then, compute the corrected paths going through one of the sensors and the new location. When we repeat this process forwards from one sensor and backwards from another, we end up getting two consistent paths with correct concentration values. We will refer to these paths as primary paths. Fig. 2 shows the two paths generated by matching the expected and the sensed concentration values.

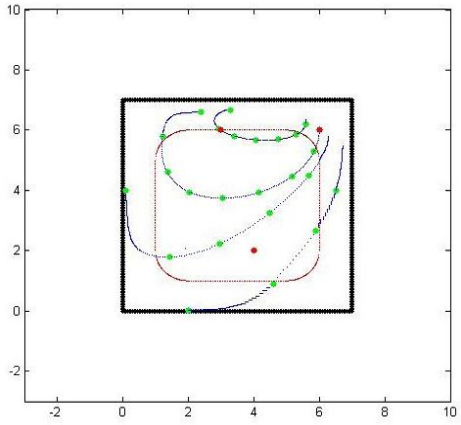

Figure 3. Primary and secondary air-borne particle paths going through two sensors.

In the next step of the extrapolation, we complete the particle propagation paths by generating secondary paths for the whole area. The secondary paths are between two adjacent primary paths. To generate these secondary paths, we determine the perpendicular lines to the tangents of the paths, and use the intersection points of these perpendicular lines. We assign the average values of the particle concentrations and the concentration gradients on the secondary paths. For the paths that are on the external regions of the primary paths, we use perpendicular normal extensions, but we extrapolate the particle concentrations and the concentration gradients. Fig. 3 shows the path extensions as well as the whole room coverage with primary and the secondary paths.

B. Chemical Particle Distribution by the Continuous Releasing

Particle-laden flow refers to a class of two phase fluid flow, in which one of the phase is continuously connected (referred to as the continuous or carrier phase) and the other phase is made of small, immiscible and typically dilute particles (referred to as the dispersed or particle phase) [8]-[10]. The problem of detecting odor source is typically about the particle-laden flow. The chemical particle is the dispersed phase, and the air is the carrier phase.

If the mass fraction of the dispersed phase is small, the one-way coupling between the two phases is a reasonable assumption; that is, the dynamics of particle phases are affected by the carrier phase, but the reverse is not the case. In our case, the particles are very small and occur in low concentrations; hence the dynamics are governed by the carrier phase. The particle phase is typically treated in a Gaussian distribution along the flow direction, such that

$$C(x,y)=\frac{q}{2\pi K d_s}e^{[-\frac{u}{2K}(d_s-\Delta x)^2]} \tag{7}$$

where,

$$d_s=\sqrt{(x_s-x)^2+(y_s-y)^2}$$
$$\Delta x=(x_s-x)\cos\theta+(y_s-y)\sin\theta \tag{8}$$

C is the concentration, q is the emitted rate, u is the wind speed, K is turbulent diffusion coefficient, θ is the angle from the x-axis to the upwind direction, and the subscript "s" denotes the odor source.

III. Reasoning System and Algorithm

We use a reasoning system that uses the airflow model effectively to reason about the odor dispersal. It's able to navigate the sensor around the environment to gather relevant information and then successfully predict the region from which the odor originated, without moving the sensor.

The detection of odor source is finding the highest concentration in the considered area, although we have limited number of sensors in the this area. Each sensor can provide some information that contributes the decision about the location of the source.

Definition 1: When the sensor's location is (x_n, y_n), $n=1,\cdots,N$ and the odor source location is (x_s, y_s), we use $\|(x_n,y_n)-(x_s,y_s)\|_2$ to indicate the distance. Then the closest two sensors from the minimization ($\arg\min_n \|(x_n,y_n)-(x_s,y_s)\|_2$) to the odor source, are called the critical sensors.

Definition 2: If a critical sensor is on the upstream of the chemical source, we call it the upstream critical sensor. Otherwise, it's called the downstream critical sensor.

Through these definitions, the problem of odor source detection is transformed to the problem of detecting upstream critical and downstream critical sensors. The odor source is located in the region between the two critical sensors.

The detection process is based on the sensitivity of the interpolation with respect to individual sensors. In a system with N sensors, we first generate a set of particle paths based on all of the sensors. Then, we successively reduce an individual sensor data one at a time and generate another set of particle paths. The differences between these two sets of particle paths provide us the necessary information to identify and locate the source.

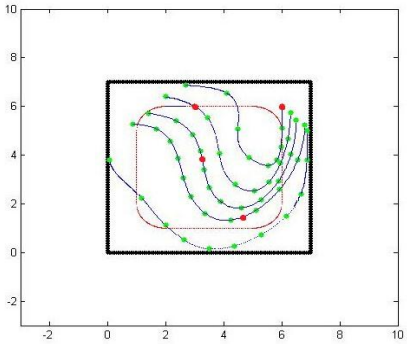

Figure 4. The particle path map using 4 sensors.

To demonstrate the reasoning process, we assume there are 4 sensors in the room, as shown in Fig. 4. Based on the method described in Section 2, we conclude that the airflow is in from left to right direction. In other words, the particle paths go through Sensor 1 first, then Sensor 2 and 3, and lastly Sensor 4.

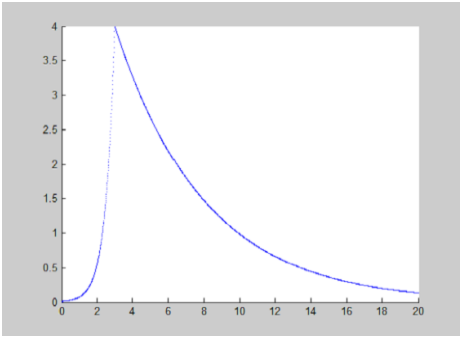

Figure 5. The chemical concentration on the particle path.

As part of the method, we can approximate the particle paths, the position, the velocity, and the concentration of every point on the particle paths. Fig. 5 shows the concentration distribution along the particle path for this case. The horizontal axis denotes the motion distance of the particles along the path, and the vertical axis shows the value of the chemical concentrations. The odor source is located between Sensor 1 and Sensor 2. In downstream flow, the chemical concentration is decayed smoothly with a small rate, but in the upstream, the chemical concentration is decayed drastically, because the air flow blows most of particles downstream.

Case 1: ($S_n > S_0$ **or** $S_n < S_0$ **case)** After removing one sensor, we get a new particle and a new chemical dispersal map. If the new chemical concentration S_n on at the location of the removed sensor is higher (or lower) than the actual valve S_0, then we conclude that the removed sensor is upstream (or downstream) of the odor source. In this case, the removed sensor is called critical sensor.

Case 2: ($S_n \approx S_0$ **case)** After removing one sensor, we get a new particle and a new chemical dispersal map. If the new chemical concentration (S_n) at the location of the removed sensor point is close to the actual valve (S_0), then we conclude that the removed sensor is far from the odor source, and this sensor is not a critical sensor.

In the example case, when we remove \ Sensor 1, the updated chemical concentration at the location of Sensor 1 is higher than the original value. We observe this result in Fig. 6. As a result, we conclude that Sensor 1 is an upstream critical sensor. Applying same reasoning on Sensor 2, we observe that the chemical concentration at the location of Sensor 2 is lower than the original value, as seen in Fig. 7. As a result, we conclude that Sensor 2 is a downstream critical sensor. Similarly applying same method on Sensor 3 and Sensor 4, we observe that the chemical concentrations at the locations of Sensor 3 and Sensor 4 are almost equal to the original values. Consequentially, we conclude that Sensor 3 and Sensor 4 are not close to the source and they are not critical sensors. From the above analysis, we conclude that the odor source should be located between Sensor 1 and Sensor 2.

The accuracy in the odor source detection is directly related to the amount of sensors and the placement of the sensors. Since the concentration on an upstream of the odor source cannot decrease more than a know rate, we get a large error, when the concentration on the upstream critical sensor is higher than the concentration on the downstream critical sensor. If the value of the upstream critical sensor is larger than the value of the downstream critical sensor, then we conclude that the source is located further upstream of the upstream critical sensor. As a result, we can choose a wrong region as the odor source in such circumstances.

In the above analysis, we concluded that the source is in the region between Sensor 1 and Sensor 2 as shown in Fig. 8. In most cases, we need to improve the detection by reducing the region. To achieve this reduction, we utilize the secondary paths as described in the previous section.

Similar to the primary path approach, we generate consistent chemical concentration at the points on the perpendicular lines to the paths going through the critical sensors. We, then, compare these concentrations and indentify the two paths with the highest concentrations as the critical paths. Fig. 9 shows how the region that the odor source is located is narrowed using the secondary path analysis.

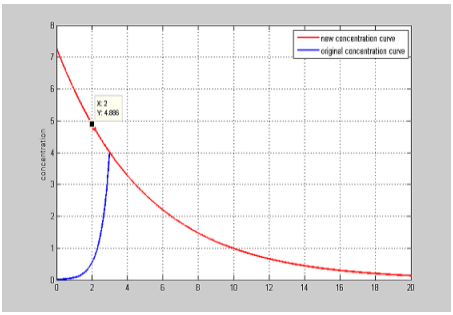

Figure 6. Concentration curves using all sensors and using 3 sensors.

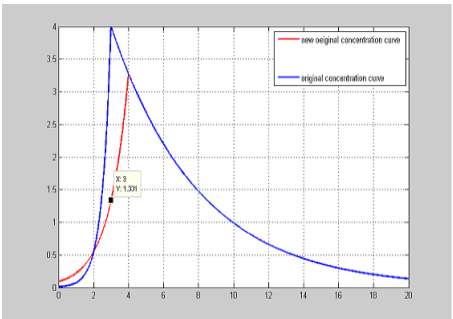

Figure 7. Concentration curves using all sensors and using 3 sensors.

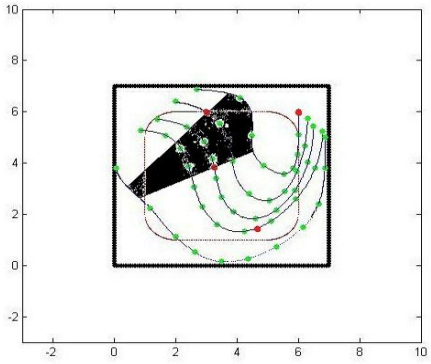

Figure 8. The region selected by critical sensors.

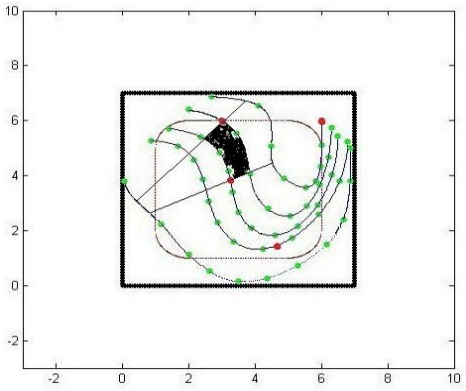

Figure 9. The most-likely region selected by critical sensors.

IV. Experimental Evaluations

In this section, we apply the method presented on the previous section to a real world problem. First, we obtained a real map of Missouri University of Science and Technology campus. Second, we use an edge detection technology to process the map to eliminate all the features except the main buildings. Fig. 10 shows the real map after the edge detection process. Third, we place 8 sensors on the surveyed region and generated the primary paths as shown in Fig. 11.

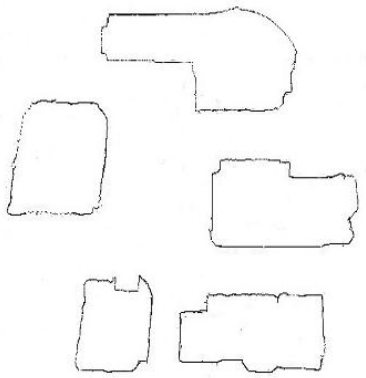

Figure 10. A real map of Missouri University of Science and Technology processed by edge detection method.

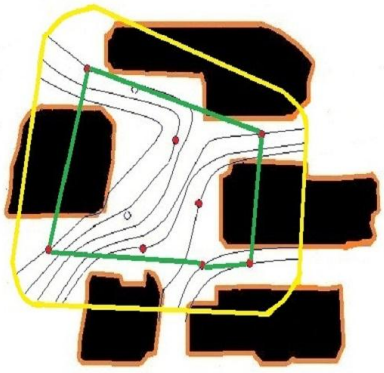

Figure 11. A particle path map of Missouri University of Science and Technology.

As we explained in the previous sections, we removed the data of every sensor one at a time and determined the critical sensors. Based on the critical sensor data and the secondary path analysis, we obtained the region for the source of the odor particles as shown in Fig. 12.

For comparison purposes, we also used fluid dynamics simulation to study the airflow characteristics in an environment. We used the COMSOL software that is used to analyze complex flow of fluid dynamics. We set the wind to flow from southwest to northeast and the configuration is set to be the same. The COMSOL software utilizes a finite element method that incorporates the fluid dynamics of the air flow. Fig. 13 shows the steam lines of airflow as produced by the COMSOL software. Comparing the results, we verify that the most-probable region that contains the odor source determined by the proposed method is consistent with the COMSOL software results.

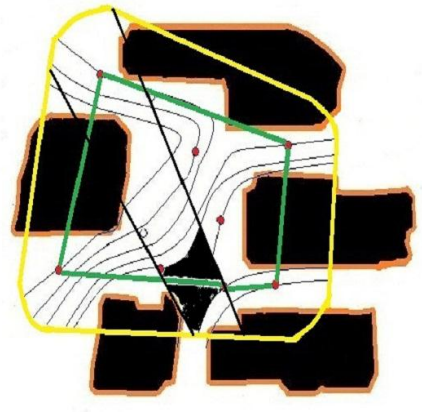

Figure 12. The most-likely region contains odor source in the real map.

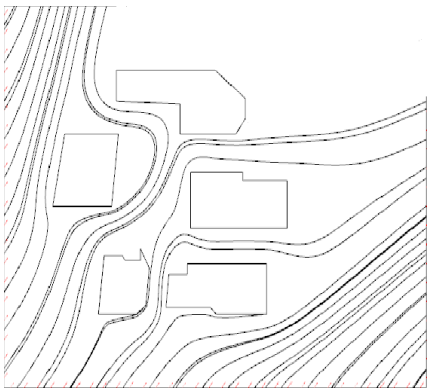

Figure 13. Air-borne particle paths going through ten sensors in a real map processed by COMSOL.

When we compare the particle flow paths in Fig. 12 and the air flow paths in Fig. 13, we verify the close consistency of the presented interpolation method, even though the interpolation method requires and uses at least a couple of magnitude less computational and storage resources than COMSOL software.

V. Conclusions

There are many useful and humanitarian reasons to locate the source of a chemical odor source. Generally, the majority of work in this area uses reactive control schemes that track an odor plume along its entire length.

This type of an approach is slow and difficult in cluttered environments. In this paper, we presented an interpolation and extrapolation method to model odor generating particle flow in an environment with distributed sensors. We used particle paths of the model to narrow down the location of the odor source. The presented method has the advantage of utilizing at least couple of magnitude less resource than a finite element based commercial software analysis.

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