Survey: Odor Source Localization

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Abstract: - This study aims to provide a brief overview for odor source localization and ongoing approaches taken to address the problem. To this aim, firstly the odor dynamics is introduced and models of odor diffusion mechanisms are discussed from different aspects. Next, forward and inverse problems are defined and demonstrated in relation to several applications. In the study, a discussion of commonly utilized estimation methods to solve the problem in the literature, is provided; Triangulation Method, Least Squares Method, Maximum Likehood Method, PQS, are briefly discussed. Finally, a case study for mobile odor tracking is presented with simulation results.

Key-Words: - odor**,** tracking, plume source localization, diffusion, estimation, PQS (Process Query System)

1 - Introduction

Odor detection studies have gained increased interest especially a result of terrorist attacks such as the one at the Tokyo Subway in 1995. As it is well-known, odor is one other sense like vision, hearing, and taste, a main difference being that it is based on chemicals [1]. Detection and tracking of odor when compared with sound using propagation based approaches, poses additional problems due to its very low dispertion rate as well as significant unpredictable external disturbances, such as wind effects [2]. Studies in this area are often classified under "Plume soure localization and tracking", and two main approaches: a) Forward problems, which estimate the state of odor (in terms of time and density) in advance, b) Inverse problems, which estimate the prior state of the odor based on current state information, hence perform localization and detection [3].

2 - Measuring Odor

Odor detection poses a major problem in practice in-and-of-itself: While a standard gas sensor measures the concentration of one gas only, an odor sensor has to detect more than one gas, which are the components of the odor, also known as odorants. Odor detection involves the measurement of several different gas concentrations, evaluation of these concentrations via a classification method to determine if the combination is an odor and finally, a decision process which concludes that the given concentration corresponds to a given odor. In this study, this problem will be addressed in terms of the detection and tracking of a single odorant, thereby reducing the problem to plume source localization. Although the problem complexity is reduced to a certain extent with the consideration of a "plume" as opposed to an "odor", complications still exist due to the stochastic nature of the problem. To address these issues approaches such as Process Query Systems (PQS) have been developed for the evaluation of binary data to decide whether the data is worthy of consideration as well as other resulting approaches, such as Factor 10, which increase the probability from 0 to 1 after a certain threshold is passed, and BAGEG which proposes a transition regime as given in Figure 1 [1].

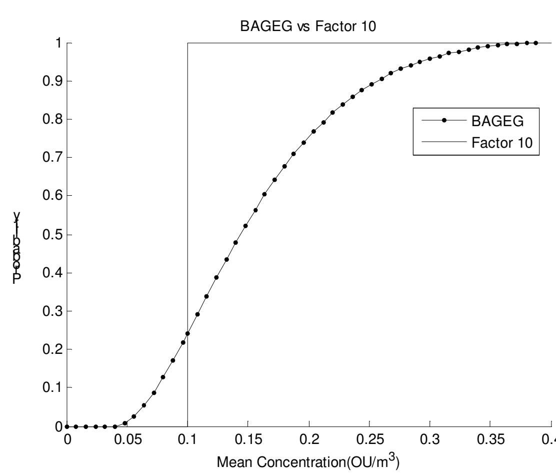

Figure 1: BAGEG vs Factor10 Concentration to Probability Curves

3 - Modeling of Plume Dynamics

Plume dynamics models are based on two major modeling approaches: Gaussian based models, and numerical models. Both approaches are based on the Navier-Stokes Equation given below [4,5]:

$$\frac{\partial}{\partial t^*}(\vec{u}^*) + (\vec{u}^*.grad)(\vec{u}^*) + grad^* p^* = \frac{1}{\mathrm{Re}}\Delta^* \vec{u}^* + \vec{g}^* \qquad (1)$$

where $\vec{u}^*$ represents wind speed field, p^* represents pressure, $\vec{g}^*$ represents external forces and Re represents the Reynold number.

This equation has no analytical solution under natural wind effects, thus solutions are sought, either under simplified boundary conditions, or by using numerical models. The numerical model approach solves the Navier-Stokes Equation using Computational Fluid Dynamics (CFD): In numerical models the system is divided into individual cells and instead of a closed-form solutions, equations are written and solved for each cell and time interval. The technique has the potential of providing high resolution solutions, but at the expense of high memory requirements and high computational complexity. [1]

The Gaussian based models involve simplified boundary conditions. One such example can be given as bellow;

$$\frac{\partial C}{\partial t} = D_x \frac{\partial^2 C}{\partial x^2} + D_y \frac{\partial^2 C}{\partial y^2} + \alpha \frac{\partial C}{\partial x} + \beta \frac{\partial C}{\partial y} \qquad (2)$$

where D_x and D_y are diffusion constants; α represents linear wind velocity in x direction and β represents linear wind velocity in y direction. The solution of this differential equation is the following [3]:

$$C(x,y,t) = \frac{A_1 A_2}{4\pi t\sqrt{D_x D_y}} e^{\left(-\frac{(x-\alpha t)^2}{4D_x t} - \frac{(y-\beta t)^2}{4D_y t}\right)} \qquad (3)$$

If diffusion is uniform (anisotropic diffusion) in x and y direction ,then $D = D_x = D_y$, which leads to

$$C(x,y,t) = \frac{A_1 A_2}{4\pi D} e^{-\frac{(x-\alpha t)^2 + (y-\beta t)^2}{4Dt}} \qquad (4)$$

A major assumption is made here based on environmental engineering concept, with the consideration of a plume's limits being within the 4σ portion of the material, or in other words, in the portion that contains the 95% of the material. Sensor readings are considered meaningless beyond this point [3]. Hence, in a wind-free environment, the biggest possible distance, L can be given as below:

$$L = 4\sigma = 4\sqrt{2Dt} \qquad (5)$$

Increased constraints give rise to more simplified models. By neglecting wind effects, the following solution becomes acceptable as an analytical solution for Fick´s 2nd law [6]:

$$C(t,d) = C_\Gamma .erfc\left(\frac{d}{2\sqrt{Dt}}\right) \qquad (6)$$

where C: dispersed gas amount, C_Γ: gas amount at source, d: distance from source, D: diffusion constant.

Some studies, such as [7,8] use the relative dispersion model of the odor (demonstrating decreasing concentration with increasing radius), instead of the time model of the odor. This results in the elimination of the exponential term and introduction of some curves approximating the physics. This model introduces a certain amount of unreliability, but since the more realistic model also considers no wind effect, simplicity offered by the new assumption overweighs the provided level of accuracy. One such model is given below along with the corresponding assumptions:

Assumption 1: The environment is uniform
Assumption 2: The plume source is assumed to have constant strength

The following equation can be given as an example:

$$R_i = \gamma_i \sum_{k=1}^{K} \frac{C_k}{\left\|\rho_k - r_i\right\|^\alpha} + \omega_i \qquad (7)$$

where R_i represents t-th sample of i-th sensor, γ_i represents gain factor, C_k represents k-th source intensity, ρ_k represents position of the k-th source, r_i represents position of sensor, α represents plume attenuation parameter, ω_i represents background noise which satisfies $N(\mu,\sigma^2)$. For single source K=1 and $C_k = C$

4 - Problem Statement

Detection and tracking of odor can be performed based on 4 different combinations of mobile or stationary sensors or targets. The problem assumes its simplest form for the detection of a fixed odor source with mobile sensors; i.e by mounting a minimum of two odor sensors onto a mobile robot [9,10,11] The robot moves left, right, or straight based on the direction of the odor and when no odor is sensed, it zig-zags in the environment searching for the odor [12].

In the case of multiple robots, the robots communicate and share the data with one another, hence shortening the duration of the detection/tracking process. In such multirobot systems, spiral robot trajectories are also proposed to reduce the wind effect [13,14].

When considering mobile sensors and mobile odor sources, the odor source can be treated as fixed if the velocity of the mobile sensors is higher than that of the dispersion rate of the odor; however, the inverse problem must be solved otherwise.

The solution is slightly more complicated with fixed sensors, in which case the sensors must perform data fusion to localize the odor. This requires the solution of the inverse problem [3]. The inverse problem can be avoided with the use of a very high number of sensors, but this approach may not always be practical. However, in the case of mobile odor souces,solving the inverse problem becomes unavoidable, and might require tracking other sources with the use of algorithms developed for i.e seismic, passive infra red, sound sensors etc. [2].

5 – Localization Algorithms

The simplest method to estimate location is by using weighted averages. As indicated by all models, sensors far from the odor source sense the odor at lower levels. This implies that the odor source localization can be performed to some extent by taking the weighted product of the sensed odor amount and the corresponding coordinates. It is apparent that resolution will improve with increased number of sensors. It can also be said that, although not very feasible for fixed sensor systems, the algorith may be considered simple and fast for systems using multiple mobile sensors. The algorithm will give rise to a large initial error with both sensor types, but the error will continuously get smaller as mobile sensors move towards the odor source.

Triangulation method is the next in simplicity in terms of computational complexity. Considering the system in Figure 2 and taking equation (7) for α =2, and by organizing sensor distances on one side of the equation and ignoring the noise, ω_i, the following 3 equations are obtained [8].

$$(x_1 - x_s)^2 + (y_1 - y_s)^2 = R_1 /(\gamma_1 C) \tag{8}$$

$$(x_2 - x_s)^2 + (y_2 - y_s)^2 = R_2 /(\gamma_2 C) \tag{9}$$

$$(x_3 - x_s)^2 + (y_3 - y_s)^2 = R_3 /(\gamma_3 C) \tag{10}$$

It is apparent that an analytical solution exists for the solution of the above equations for the 3 unknown coordinates.

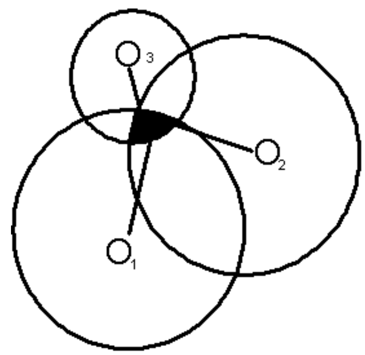

Figure 2: Triangulation geometric representation [8]

The least squares method (LSM) is a slightly more complicated approach than direct triangulation [7]. Below is the LSM version of the model given by equation (7), with the output equation given as below:

$$R_{i,t} = \gamma_i \frac{C}{\|\rho_k - r_i\|^2} + \omega_i = \gamma_i \frac{C}{d_i^2} + \omega_i \tag{11}$$

where $d_i = \sqrt{(x_i - x_s)^2 + (y_i - y_s)^2}$ represents the Euclidean distance between the node and the plume source. For simplification $\zeta_i = (\omega_i - \mu_i)/\sigma_i \sim N(0,1)$

The main difference offered in this method is that the noise, ω_i neglected in the direct triangulation method is now to be taken into consideration and the squared error is to be minimized by solving the nonlinear least square estimation problem, hence yielding a higher accuracy solution than that provided by triangulation.

$$J = \sum_{i=1}^{N} \left(\frac{C}{\left[(\hat{x}_s - x_i)^2 + (\hat{y}_s - y_i)^2\right]^{\frac{\alpha}{2}}} - \bar{z}_i \right) \tag{12}$$

where $(\hat{x}_s, \hat{y}_s)$ is estimated source location and $\bar{z}_i$ is the computed mean of M measurements at sensor i

$$\bar{z}_i = \frac{1}{M}\sum_{t=1}^{M} z_{i,t} \quad (13)$$

Another popular estimation approach related with this topic is Maximum Likehood Estimation (MLE). Before discussing the MLE technique, let's model the system using Equation (11).

Then, it can be said that

$$\frac{(R_i - \mu_i)}{\sigma_i} \sim N\left(\frac{\gamma_i}{\sigma_i}\frac{C}{d_i^2}, 1\right) \quad (14)$$

And by defining the following matrices,

$$Z = \left[\frac{(R_1-\mu_1)}{\sigma_1}, \frac{(R_2-\mu_2)}{\sigma_2}, \cdots, \frac{(R_N-\mu_N)}{\sigma_N}\right] \quad (15)$$

$$G = diag\left[\frac{\gamma_1}{\sigma_1}, \frac{\gamma_2}{\sigma_2}, \cdots, \frac{\gamma_N}{\sigma_N}\right] \quad (16)$$

$$D = \left[\frac{1}{d_1^2}, \frac{1}{d_2^2}, \cdots, \frac{1}{d_N^2}\right] \quad (17)$$

$$\zeta = [\zeta_1, \zeta_2, \ldots, \zeta_N] \quad (18)$$

Then the model can be expessed with the following equation.

$$Z = GDC + \zeta \quad (19)$$

At this point, let's apply the Maximum Likehood Method. The Joint Probability Density Function can be formulated as [8]

$$f(Z \mid \theta) = (2\pi)^{-(N/2)} e^{-\frac{1}{2}(Z-GDC)^T(Z-GDC)} \quad (20)$$

where θ represents the estimated source position ρ, and its log likehood function of θ is

$$L(\theta) \sim -\frac{1}{2}\sum_{i=1}^{N}\left\| Z_i - \gamma_i \frac{C}{d_i^2}\right\|^2 = -\frac{1}{2}\sum_{i=1}^{N}\left(\frac{R_i-\mu_i}{\sigma_i} - \gamma_i\frac{C}{d_i^2}\right)^2 \quad (21)$$

The Maximum Likehood Parameter Estimation of the θ can be evaluated by minimizing

$$I(\theta) = \sum_{i=1}^{N}\left(\frac{R_i-\mu_i}{\sigma_i} - \gamma_i\frac{C}{d_i^2}\right)^2 \quad (22)$$

Hence, the accurate position of the odor source can be estimated using the following expressions:

$$\frac{\partial I(\theta)}{\partial x} = 0, \frac{\partial I(\theta)}{\partial y} = 0 \quad (23)$$

Moreover, there is the Process Query System (PQS) technique, which is based on solving the inverse problem. The method developed by Dartmunth University has been used by Nofsinger (from the same university) to solve the inverse problem of plume source localization by using this framework. Nofsinger chooses a model which is different from the others previously discussed in this article. The study uses the concept of binary sensors, which means that the sensor gives true or false as output; i.e. it smells odor or not, respectively. The system focuses on the state transition of the sensors, and makes an event at every state transition. The agorithm uses this information in a probolastic way. For instance, let P(A) be the probability of an odor existing at sensor A, and P(B) , the probability of an odor existing at sensor B near sensor A. A forward diffusion solution can be defined easily, if we know that A is released, then P(B can be defined as [3]

$$P(B \mid A) \quad (24)$$

In the same way, the inverse probabilty can be calculated using Bayes Rule as following

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)} \quad (25)$$

The probabilities are calculated reverse in time;hence, the estimation of the odor location leads to the most probable source location. The use of binary sensors in this algorithm also reduces the time required for data conversion [3]

6 - Case Study

The case study uses the weighted averages approach to locate and track a mobile odor target. In the simulation, a hub unit and randomly deployed fifty sensor modules are considered in a 10 by 10 square meter area. The area is assumed to have no air draft, no boundaries, hence no reflection effects. The environment temperature and the velocity of sound throughout the simulations are assumed to be constant. It is also assumed that the 2 humans (one carrying the odor source) are emitting sound waves periodically.

In this study, it is also assumed that the location of each sensor module and hub unit is known. Each module in the 50-sensor network consists of an odor sensor, microphone, accelerometer and pressure sensor. In this simulations, due to the similarities of their physics, sound sensors and accelerometers are assumed to have the same model.The total simulation time is 50 seconds, with the sampling times for sound/pressure/ accelerometers taken as 100 μsec and that of odor sensors (with a slower response) taken as 1 sec. In these results, data fusion is performed using a Least Square Estimation algorithm, which fuses all motion signals separately combining data coming from sensors of the same type. Moreover odor signals are fused with weighted average algorithm. However, a decision-making process which evaluates odor and motion signals together is also performed in determining the motion of the "mobile" explosive and separating it from the trajectory of the unarmed human.

The results presents the performance of the odor sensor based algorithm, which is used to distinguish the explosive carrying human from the innocent one. In the figures, the *'s indicate the location of the sensor modules; the light grey triangles represent the estimated trajectory of the innocent human and dark grey triangles represent that of the explosive-carrying human; finally the black circles indicate the trajectory of the "mobile" explosive estimated based on data collected from the odor sensors only. It is easily seen that odor based tracking of mobile targets is not adequate just itself. However when it is supported with other techniques, it supplies separating intruder from the public. Figure 3(a) represents the performance of the algorithm fusing data from odor sensors with the other sensors in case of spinal paths. It can be noted that the algorithm detects and tracks the intruder quite well. The performance of the algorithm is also observed to be adequate in Figure 3(b), where the two humans are walking in parallel, and in Figure 3(c) and 3(d), where the paths cross.

7 - Conclusions

Although it is well known that odor source localization is very important topic in security area, there haven't been a vital improvement in that topic yet. The reason is not just the complexity of dynamic equations of odor. The reason is the high sensitivity of the system on wind. Especially in outdoor applications wind causes big problems. Moreover, if the odor become mobile, the problem is grown dramatically. If also sensors become mobile and they move faster than odor source, the problem can be solve, but then mobile sensors make system consume more power. By looking the odor source localization problem from these sides, it is still a huge problem ,waiting to be solved, of the comunity.

In spite of many technical difficulties, some of which were summarized in this paper, it is the authors' belief that odor source localization techniques will find increased applications, particularly in relation to critical operations involving security/surveilance in public places with enclosed and air-controlled space, such as airports. Some potential applications subject to ongoing research are detection of explosives, drugs, or various other types of target tracking. It is also possible to forsee earlier applications of odor tracking, such as odor source voting, and mostly in combination with other more mature tracking types, such as motion tracking, sound tracking, seismic tracking etc.

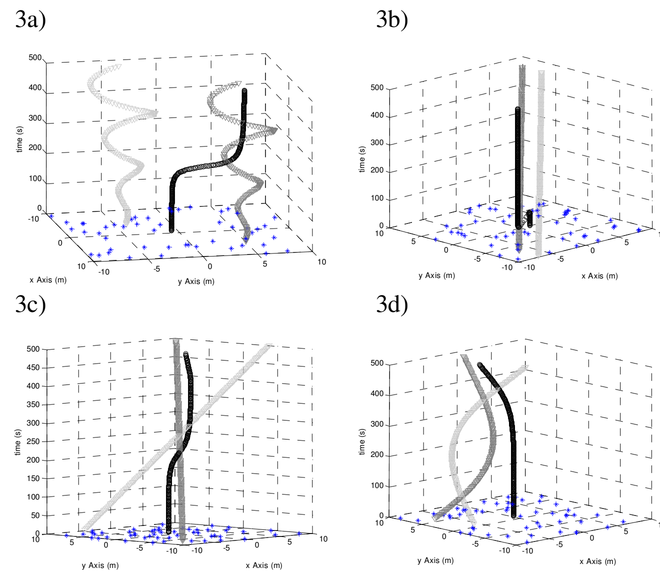

Figure 3: Simulation of the system for various trajectories

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