Survey: Detection, Recognition and Source Localization of Odor

Ahmet KUZU
Control Engineering
TUBITAK-MAM-BTE
PK21 41470 Gebze/Kocaeli
TURKEY
ahmet.kuzu@bte.mam.gov.tr

Seta BOGOSYAN
Electrical & Computer Engineering
University of Alaska Fairbanks
Duckering Building 221 Fairbanks
AK 99775-5915 USA
ffsob@uaf.edu

Metin GOKASAN
Electrical & Electronics Eng. Fac.
Istanbul Technical University
Maslak 34469, Istanbul,
TURKEY
gokasan@itu.edu.tr

Abstract: - This study aims to provide a review for odor detection, recognition and source localization and ongoing approaches taken to address the problem. To this aim sensor structures and chemical detection process are introduced. Next, recognition techniques of odor from detected chemicals are explained. To introduce source localization problem, the odor dynamics is introduced and models of odor diffusion mechanisms are discussed from different aspects. Next, forward and inverse problems for source location are defined and demonstrated in relation to several applications. A discussion of commonly utilized estimation methods to solve the localization problem in the literature is provided; Triangulation Method, Least Squares Method, Maximum Likelihood 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 dispersion rate as well as significant unpredictable external disturbances, such as wind effects [2]. Studies in this area are often classified under "Plume source 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 - Chemical Sensing

Chemical sensing can be achieved by several technologies can be grouped commonly by optic based sensing technologies, acoustic based technologies, mass spectrometry based technologies, surface stress based technologies, electrical based technologies and nanotechnology based technologies. Each of them has some advantages and disadvantages related by the application it is used. However we can define some common requirements such as rapid response time, lower power consumption, compact size, high selectivity and reliability. [4] Optic ones are the followings; Surface Plasmon Resonance (SPR), Colorimetric, Fluorescence and Chemiluminescence. SPR uses the phenomenon of total internal reflection (TIR) at the interface between two media sets up an exponentially decaying evanescent wave in the medium of lower refractive index. If the interface is coated with a thin of metals such as gold or silver, the evanescent wave penetrates the film and excites plasmon in it. The coupling between the incidents light at the interface with the surface plasmon waves (SPW) in the thin film makes a characteristic drop in the intensity of the reflected light which occurs at a particular combination of wavelength, incidence angle and refractive index of the medium. When selective odor's chemical reactions happen at this interface, changes in the surface properties alter the local refractive index at the interface. Then, the angle of the characteristic intensity drop changes supplies producing a response signal. [5]

However this system is not sufficiently sensitive to small molecules which are very common in odor sensing. Then, most SPR sensors are based on the measurement of SPR variations which are related with adsorption or a chemical reaction of an analyte with a transducing medium result in changes in its optical properties [6]. This transducing medium is the first factor which determines the selectivity and response time for these kinds of sensors. As an example polymer films like polyethylene glycol, polydimethylsiloxane is

used as transducing mediums for detection of organic vapors such as hydrocarbons, aldehydes and [6,7,8,9]. Most important disadvantages of this method are its difficulty to multiplex. Then this technology can not be used in an array format for improving sensor selectivity.

Colorimetric technology is second optic based technology used for odor detection. Colorimetric sensors include an indicator which changes its color if an analyte exists. This indicator can be organic or inorganic, but generally polymers are used for this purpose. For instance, amine-containing (poly)vinyl chloride membranes are used to detect 2, 4-dinitrotoluene (DNT) a compound commonly present in landmines [10].

Fluorescence technology which is the most popular because of the high quantum yields, well separated excitation and emission spectra and intrinsic sensitivity, is third optic based technology used for odor detection. The principle of this kind of sensors is that the target odor being sensed alters the fluorescence of the medium with which it interacts.[5]. Sensitivity, lifetime, reproducibility and stability of these sensor systems are their disadvantages. Their selectivity is also poor because of their weak interactions caused by the absorption of the odor in the polymer matrix containing the indicator medium. To overcome this problem about selectivity, indicators which are specific for particular analytes is developed. One interesting example of fluorescent conjugated polymer thin films that have a very high affinity for DNT and TNT for use in sensitive explosive detection [11]. While complex optical systems required like other optical sensors, multiplexing is also difficult.[5]

Chemiluminescence technology is the last optic based technology used for odor detection. Its implementation is easier because sensors employ chemically reactive species which are capable of directly emitting photons following oxidation, then no excitation source is needed and signals arise from initially dark backgrounds. [5] These sensors have been used generally for oxygen and metal-ion sensing and have been extended to detecting organic vapors such as chlorinated hydrocarbons, hydrazine and ammonia [12]. Although optic based technologies have some advantages like EMI unsensitivity, disadvantages of them are higher costs, complexity which make multiplexing difficult and material intensive processes when we compare with electrical based models which are easily mass produced with integrated circuit technology.

Acoustic wave based sensors are second major technology group. Acoustic wave properties of the sensor can be changed by reaction and/or binding of an analyte onto the surface of a sensor or an intermediate sensing layer or into the bulk of an applied thin film. This is the transduction principle of these sensors. Acoustic wave devices can be developed and demonstrated for chemical sensing applications in both gas and liquid phases [13,14,15,16]. There are three main configurations for this technolgy. They vare quartz crystal microbalance (QCM), Surface Acoustic wave (SAW) devices, and Flexural Plate Wave (FPW) devices. All of them has thin film or metal electrodes used to convert electrical energy to mechanical energy in the form of acoustic waves and an interface that supplies reaction of an analyte and a piezoelectric substrate.
Array configuration of these devices is developed for use in conjunction with pattern recognition for improving sensor selectivity [17,18,19]. Their disadvantages are the relatively poor long term stability of the sensor coatings and also high sensitivity to humidity. Moreover acoustic coupling between the devices fabricated in array format cause cross talk and this cross talk increases errors. Also impedance mismatch is also an other error source when it is used in high frequencies. [5]

Mass spectrometry (MS) based technology is an other powerful analytical technique. It can permits to identify unknown compounds, to quantify known compounds and to elucidate the structure and chemical properties of molecules. IM sample is injected into the mobile phase and molecules are ionized. Then ions are accelerated in vacuum by the application of a voltage and last they are separated on the basis of their charge o mass ratio by a magnetic field. As it can easily be understood from the process that it is not suitable for field applications. Moreover getting quantitative information from this process is also difficult. In this technique mass accurate measure of concentration couldn't be taken, mass is the only information we can get. If it is used by a seperation process multiple components can be sensed. However it is not common.[5]

Surface stress technology is an other technology for detecting odor. Most commonly used surface stress sensors are microcantilevers [20,21]. A microcantilever is a highly sensitive mechanical element that deflects due to changes in surface stress, charge, mechanical force, IR radiation and heat flux. Optical, piezoresistive, piezoelectric, capacitive, or electron tunneling methods can be used to measure this deflection. [5] Microcantilevers can operate in the static mode in which we measure deflection itselfor in a dynamic mode in which we measure deflection's resonance frequency. In their chemical sensing usage the cantilever deflection caused by a differential surface stress change induced by the odor which interacts with the coating which is selectively applied to one side of the cantilever, is measured. An other common using configuration is micromembrane. Membranes can be read easier than microcantilevers. However they have lower sensitivity because they have larger form factors. Using low stiffness materials like polymers instead of silicon based materials can solve the sensitivity problem, but finding

microfabrication compatible polymers is difficult and also inserting them into the process is expensive. [5]

Chemoresistors are the first sensor group of electrical odor sensing technology. They used the change of conductivity in MOS (Metal Oxide Semiconductor) or organic polymers when chemical reaction with odor molecules occurs. By incorporating carbon black particles insulating polymers can get conductive. Then they can be used in composite chemoresistor array [22,23]. In the array usage each chemoresistor should contain different polymer. From one resistor we can not identify a unique odor, but using pattern recognition at the output of the array we can identify the odor. Also selectivity is proportional to number of array elements. However process fabrication limits that number. [22]. Also using sensor array require extensive computation power to handle pattern recognition. However selectivity is very poor when using one chemoresistor. [5]

ChemFETs are other sensor group of electrical odor sensing technology. Sensor coating material affects the Field Effect Transistor's (FET) physics. There exist both organic and inorganic coating material for this technology, and they can be used both for FETs and diodes. Using Conducting Polymer (CP) for coating material, supplies this sensor to be used with liquid and gas application. In that applications CP ban be used both as channel and gate. If ChemFETS are used as channel, they are called Thin Film Transistors (TFT) and if they are used as gate, they are called as Insulated Gate FET (IGFET). The current of TFT flows through the CP whose conductivity is modulated with odor and electrical field. However in IGFETS, CP is only gate conductor, and conductivity of the FET doesn't related with CP, that kind of sensor only depends only on the chemical modulation of the CP's work function. ChemFETs are so suitable for array technology, and microfabrication. Therefore they are commonly used in array applications. [5]

Chemocapacitors are other sensor group of electrical odor sensing technology and despite of other electrical based odor sensing technology insulating polymers whose volume and/or dielectric properties has the capability of changing by odor concentration, are used in this technique. This technology has some disadvantages like long time constant and hysteresis. Moreover AC excitation and impedance bridge is generally needed for measuring capacitance. However fabrication process is easier then ChemFETs. [5]

Last electrical technology based sensors are Amperometric Sensors which are the most popular sensors for sensing toxic gases like CO2, H2S and SO2. The working principle of amperometric gas sensors (AGS) is measuring the current between working and counter electrodes and which is a function of analytes concentration. The analyte is reacted electrochemically and while this process occurs, in terms of Faraday's law either it produces or consumes electrons at the working electrode. This method is complement of the other two electrochemical sensors. First one is potentiometric sensors which measure Nernst potential at zero current. Other one is conductometric sensors that measure changes in impedance [24]. Response time varies milliseconds to minutes with respect to odor type. Good sensitivity and selectivity properties with related to their low cost, small size and long stable lifetimes are their advantages. However when they are implemented by microfabrication, some problems with lifetimes, long term stability and multiplexing start to begin. [25]

Nowadays nanotechnology is an other improving technology in the sensor era. Nano structures like nanoparticles, nanotubes, and nanobelts have significant properties to be a chemical sensing element. The properties of small size and high surface to volume ratio, supplies this materials have rapid response time and high selectivity. [5] There are some interesting examples in the literature. These are; a palladium based chemoresistor using electrochemically deposited palladium nano wires for hydrogen sensing [26]; single-walled carbon nanotubes (SWNTs) chemoresistors for NO2 and NH3 sensing [27] and tin-oxide nanobelts chemoresistors for DMMP (nerve gas simulant) sensing [28]. Disadvantages are difficultness of array fabrication and multiplexing of these sensors. But technology is very recent, and probably these disadvantages can be canceled soon. [5]

There are also biosensing techniques for odor detection. These techniques use protein or enzymes, which are sensitive to odor particles, as a sensing material and used above expressed techniques to identify odor. [29,30,31]

An other important issue about detection is drift effect and drift correction. Drift effect means sensor response to an odor may change over a period of time. There are two main types of drift effect long term drift effect and short term drift effect. Short time drift effect's period is in terms of days or weeks and it can be solved by using a reference gas and it is compensated by reference gas values from other sensor measurements [4]. Long term drift's period is in terms of months or years [32]. It is difficult to model this phenomenon.

Taking large amount of sample within short period of time; is other problem. Then a memory effect occurs and samples are influenced by the previous samples. There should be put enough time (approx. 3 minutes) to permit sensors go to steady state value. [4]

3 - Recognition of 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.

The biggest problem of recognition of the odor is determining the relationship between independent measurements. [33] This multivariable process can be done by two major view. One view uses statistical methods, and other one uses heuristic methods. [33]. Although there are lots of statistical methods can be used in this problem we will explain most used ones. [4]

First of them is Multiple Linear Regression (MLR). This technique uses independent variables to predict the dependent variable by using least squares fit of the data to a function of the following form. [4]

$$c_{sj} = b_{1j}x_{1j} + b_{2j}x_{2j} + \ldots + b_{ij}x_{ij} + \ldots + b_{nj}x_{nj} \quad (1)$$

where bij are the partial regression coefficients, the discrepancy between the observed and calculated values is described by the residual e, xij is the sensor output and predicted component concentration values csj. In this case independent variables are sensor measurements. Our aim is to calculate the regression coefficients for csj as close to the real component concentration values [4]. Detailed description of the MLR has been outlined in [34]. however, we should say that it is mentioned, this method has some drawbacks at the sensitivity to noise, and the treatment of co-linearity in the gas sensing array. [4, 34]

Other statistical technique is Partial Least Squares (PLS). This technique gets its basics from MLR and principal component analysis. Instead of representing between relation of regression coefficient between sensor outputs (X = {x1j, x2j, . . . , xij}) and predicted component concentration values (csj) as MLR a new function is used which contains variables W, P, and csj . W is the set of coefficient weights and P is a set of loadings to describe the relationship between the variables. Much in the same way as a mean value gains precision as the more measurements are made. [4] However PLS gives more precise solution. Because in MLR, X should be orthogonal. However in PLS it is not needed, and it can also contain partly same information, because PLS algorithm extracts latent structures in the data which have the character of weighted averages. The amount of collinear variables included in the calculations improves the precision of latent structure. [4,35]

Third statistical technique is Cluster Analysis (CA) whose purpose is finding natural grouping in the individual observations. Cluster Analysis can be realize by different ways. Usage of both agglomerative algorithms and divisive algorithms are used. [36]. Agglomerative algorithms start from many groups and join them with neighbor groups and make larger groups and divisive algorithms is the opposite of agglomerative algorithms, they start from one big group and divide them into small groups. [4]

Principal Component Analysis (PCA) is the last statistical technique express in this paper. It performs a principal component or eigenvector analysis of data and projects the observations into a new co-ordinate system. The most advantageous property of PCA is it describe the major trend in data reduces the size of data. [4] This property of PCA also supplies it to be used as a preprocessing technique. PCA is often used as input of non-linear type classification algorithms [37].

Despite those statistical algorithms as mentioned before there also exist heuristic algorithms. Artificial Neural Networks (ANN), which model human neural system, is the most common used pattern recognition techniques in heuristic world. They are also the most commonly used algorithms for classifying odor sensor arrays output. In the literature there are lots of example of using Artificial Neural Networks with eNoses like detecting of odor of coffees [38], odor of wines [39], odor of other food sources [40, 41], odor of toxicity for medical applications [15_42]. One of their advantageous is that they permit to use different type of sensors, which supplies using more selective more expensive sensors with less selective less expensive sensors. Other advantageous of them is that after training process, their recognition process occur rapidly and efficiently [4]. Detailed explanation of the ANNs can be found from the [42].

Other heuristic techniques are fuzzy based techniques. The principle of the fuzzy logic is enabling machines to deal with human linguistic terms in order to describe data that may not be exact or crisp. Fuzzy algorithms are generally built by four blocks called fuzzification block, fuzzy inference block, rule base block and defuzzification block. In fuzzification block sensor measurements are converted to linguistic terms like very low concentration, low concentration, medium concentration, high concentration, very high concentration with some membership weights like sensor A measures 3.5V that means 0.8 high concentration 0.2 medium concentration. Moreover in rule based block there are some if then cases like if sensor A says low concentration and sensor B says high then odor is red wine. In inference block rules in rule base block is processed with the inputs of outputs of fuzzification block by using fuzz logic. Finally defuzzification block again converts fuzzy items to real values like 10ppm red wine. Fuzzy algorithms are used in several types of classifying systems. It is also used for

olfactory classifying; for instance entire odor recognition architecture called a "Fuzzy logic-based Recognizer of Olfactory Signals" (FROS) was presented in the literature. [43]

In the following part of 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].

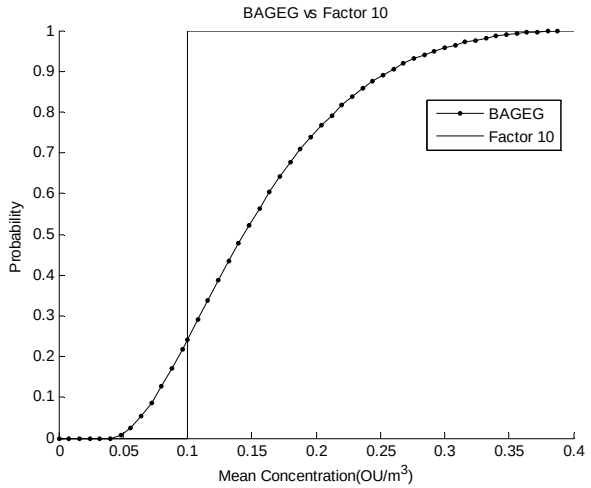

Figure 1: BAGEG vs. Factor10 Concentration to Probability Curves

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 [45, 46]:

$$\frac{\partial}{\partial t^*}(\vec{u}^*) + (\vec{u}^*.grad)(\vec{u}^*) + grad^* p^* = \frac{1}{\mathrm{Re}}\Delta^*\vec{u}^* + \vec{g}^* \quad (2)$$

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 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;

$$\frac{\partial C}{\partial t} = D_x \frac{\partial^2 C}{\partial x^2} + D_y \frac{\partial^2 C}{\partial y^2} + \alpha \frac{\partial C}{\partial x} + \beta \frac{\partial C}{\partial y} \quad (3)$$

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]:

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

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

$$C(x,y,t) = \frac{A_1 A_2}{4\pi t D} e^{-\frac{(x-\alpha t)^2 + (y-\beta t)^2}{4Dt}} \quad (5)$$

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:

$$L = 4\sigma = 4\sqrt{2Dt} \quad (6)$$

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 [47]:

$$C(t,d) = C_\Gamma . erfc\left(\frac{d}{2\sqrt{Dt}}\right) \quad (7)$$

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

Some studies, such as [48,49] 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:

$$R_i = \gamma_i \sum_{k=1}^{K} \frac{C_k}{\left\| \rho_k - r_i \right\|^{\alpha}} + \omega_i \qquad (8)$$

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 [50,51,52] 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 [53].

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 [54,55].

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 sources, 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 algorithm 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 (8) 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 [49].

$$(x_1 - x_s)^2 + (y_1 - y_s)^2 = R_1 / (\gamma_1 C) \qquad (9)$$

$$(x_2 - x_s)^2 + (y_2 - y_s)^2 = R_2 / (\gamma_2 C) \qquad (10)$$

$$(x_3 - x_s)^2 + (y_3 - y_s)^2 = R_3 / (\gamma_3 C) \qquad (11)$$

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

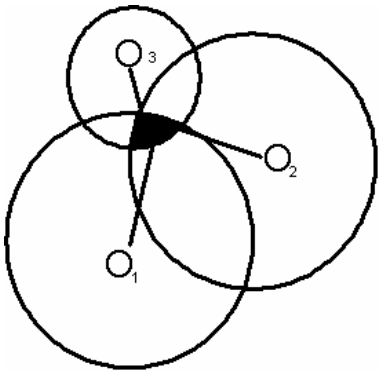

Figure 2: Triangulation geometric representation [49]

The least squares method (LSM) is a slightly more complicated approach than direct triangulation [48]. The LSM version of the model given by equation (8), with the output equation is given below:

$$R_{i,t} = \gamma_i \frac{C}{\left\|\rho_k - r_i\right\|^2} + \omega_i = \gamma_i \frac{C}{d_i^2} + \omega_i \qquad (12)$$

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.

$$J = \sum_{i=1}^{N} \left(\frac{C}{\left[(\hat{x}_s - x_i)^2 + (\hat{y}_s - y_i)^2\right]^{\frac{a}{2}}} - \bar{z}_i \right) \qquad (13)$$

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

$$\bar{z}_i = \frac{1}{M} \sum_{t=1}^{M} z_{i,t} \qquad (14)$$

Another popular estimation approach related with this topic is Maximum Likelihood Estimation (MLE). Before discussing the MLE technique, let's model the system using Equation (12).

Then, it can be said that

$$\frac{(R_i - \mu_i)}{\sigma_i} \sim N\left(\frac{\gamma_i}{\sigma_i} \frac{C}{d_i^2}, 1\right) \qquad (15)$$

And by defining the following matrices,

$$Z = \left[\frac{(R_1 - \mu_1)}{\sigma_1}, \frac{(R_2 - \mu_2)}{\sigma_2}, \cdots, \frac{(R_N - \mu_N)}{\sigma_N} \right] \qquad (16)$$

$$G = diag\left[\frac{\gamma_1}{\sigma_1}, \frac{\gamma_2}{\sigma_2}, \cdots, \frac{\gamma_N}{\sigma_N} \right] \qquad (17)$$

$$D = \left[\frac{1}{d_1^2}, \frac{1}{d_2^2}, \cdots, \frac{1}{d_N^2} \right] \qquad (18)$$

$$\zeta = \left[\zeta_1, \zeta_2, \ldots, \zeta_N\right] \qquad (19)$$

Then the model can be expressed with the following equation.

$$Z = GDC + \zeta \qquad (20)$$

At this point, let's apply the Maximum Likelihood Method. The Joint Probability Density Function can be formulated as [48]

$$f(Z \mid \theta) = (2\pi)^{-(N/2)} e^{-\frac{1}{2}(Z-GDC)^T (Z-GDC)} \qquad (21)$$

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

$$L(\theta) \sim -\frac{1}{2} \sum_{i=1}^{N} \left\| Z_i - \gamma_i \frac{C}{d_i^2} \right\|^2 = -\frac{1}{2} \sum_{i=1}^{N} \left(\frac{R_i - \mu_i}{\sigma_i} - \gamma_i \frac{C}{d_i^2} \right)^2 \qquad (22)$$

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

$$I(\theta) = \sum_{i=1}^{N} \left(\frac{R_i - \mu_i}{\sigma_i} - \gamma_i \frac{C}{d_i^2} \right)^2 \qquad (23)$$

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

$$\frac{\partial I(\theta)}{\partial x} = 0, \frac{\partial I(\theta)}{\partial y} = 0 \qquad (24)$$

Moreover, there is the Process Query System (PQS) technique, which is based on solving the inverse problem. The method developed by Dartmouth 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 algorithm uses this information in a probabilistic 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]

$$P(B \mid A) \tag{25}$$

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

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)} \tag{26}$$

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 these 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.

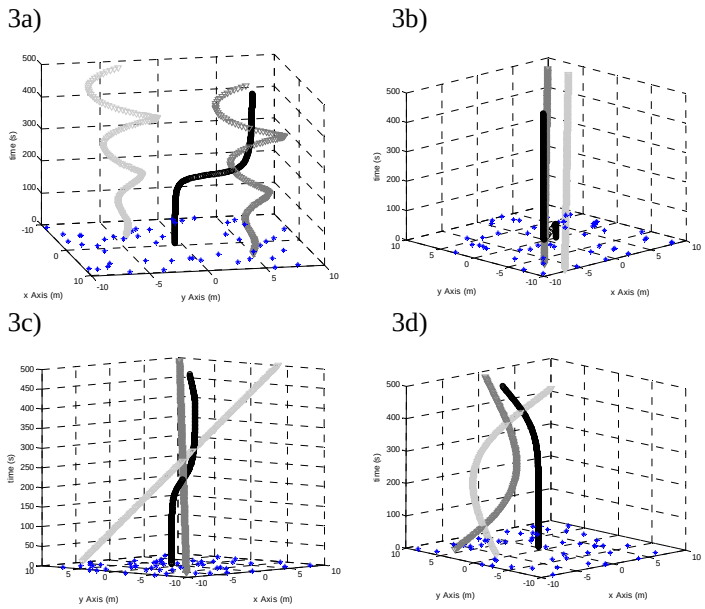

Figure 3: Simulation of the system for various trajectories

References:

[1] P. Boeker, O. Wallenfang, et al., The Modelling of Odour Dispersion with Time-Resolved Models, *Agrartechnische Forschung*, Vol.6, 2000, pp.84-89.

[2] A. Kuzu, S. Bogosyan, M. Gokasan. Detection and Tracking of an Explosives-Carrying Human with Odor-Sensor Based Multisensor Networks, *6th WSEAS International Conference on System Science and Simulation in Engineering (ICOSSSE)*, Italy, 2007.

[3] G. Nofsinger, G. Cybenko, Distributed Chemical Plume Process Detection, *MILCOM*, 2005.

[4] A. Loutfi, Odour Recognition using Electronic Noses in Robotic and Intelligent Systems, *Phd Thesis at AASS*, 2005.

[5] S. Satyanarayana, Surface Stress and Capacitive MEMS Sensor Arrays for Chemical and Biological Sensing, *Phd Thesis at University of California Berkeley*, 2005.

[6] J. Homola, S.S. Yee, and G. Gauglitz, Surface plasmon resonance sensors: review, *Sensors and Actuators B: Chemical*, Vol.54 (1-2), 1999, pp.3-15.

[7] S. Miwa and T. Arakawa, Selective gas detection by means of surface plasmon resonance sensors, Thin Solid Films, Vol.282 (1-2), 1996, pp.466-468.

[8] A. Abdelghani, J.M. Chovelon, N. Jaffrezicrenault, C. Ronottrioli, C. Veillas, and H. Gagnaire, Surface plasmon resonance fibre-optic sensor for gas detection, *Sensors and Actuators B-Chemical*, Vol. 39 (1-3), 1997, pp.407-410.

[9] M. Niggemann, A. Katerkamp, M. Pellmann, P. Bolsmann, J. Reinbold and K. Cammann, Remote sensing of tetrachloroethene with a micro-fibre optical gas sensor based on surface plasmon resonance spectroscopy, *Sensors and Actuators B-Chemical*, Vol.34 (1-3), 1996, pp.328-333.

[10] D.T. Mcquade, A.E. Pullen and T.M. Swager, Conjugated polymer-based chemical sensors, *Chemical Reviews*, Vol.100 (7), 2000, pp.2537-2574.

[11] T.M. Swager, The molecular wire approach to sensory signal amplification, *Accounts of Chemical Research*, Vol.31(5), 1998, pp.201-207.

[12] G.E. Collins, and S.L. Rosepehrsson, Chemiluminescent chemical sensors for inorganic and organic vapors, *Sensors and Actuators B-Chemical*, Vol.34(1-3), 1996, pp.317-322.

[13] T.C. Pierce, S.S. Schiffman, H.T. Nagle and J.W. Gardner, J. W., *Handbook of Machine Olfaction*, Wiley-VCH Verlag GmbH & Co, Weinheim, 2003.

[14] M. Thompson and D.C. Stone, Surface-launched acoustic wave sensors, *ed.,Wiley-Interscience*, , Vol.144, 1997.

[15] H. Baltes, W. Gopel ,and J. Hesse, *Sensors update*, VSH, Weinheim, 1996

[16] J. W. Grate, Acoustic wave microsensor arrays for vapor sensing, *Chemical Reviews*, 2000, Vol.100(7), 2000, pp.2627-2647.

[17] W.P. Carey, K.R. Beebe, and B.R. Kowalski, Multicomponent Analysis Using an Array of Piezoelectric Crystal Sensors, *Analytical Chemistry*, Vol.59 (11), 1987, pp.1529-1534.

[18] W.P. Carey, and B.R. Kowalski, Chemical Piezoelectric Sensor and Sensor Array Characterization, *Analytical Chemistry*, Vol.58(14), 1986, pp.3077-3084.

[19] W.P. Carey, K. R. Beebe, B.R. Kowalski, D.L. Illman, and T. Hirschfeld, Selection of Adsorbates for Chemical Sensor Arrays by Pattern Recognition, *Analytical Chemistry*, Vol.58(1), 1986, pp.149-153.

[20] T. Thundat, P.I. Oden, and R.J. Warmack, Microcantilever sensors, *Microscale Thermophysical Engineering*, Vol.1(3), 1997, pp.185-199.

[21] N.V. Lavrik, M.J. Sepaniak, and P.G. Datskos, Cantilever transducers as a platform for chemical and biological sensors, *Review of Scientific Instruments*, Vol.75(7), 2004, 2229-2253.

[22] N.S. Lewis, Comparisons between mammalian and artificial olfaction based on arrays of carbon black-polymer composite vapor detectors, *Accounts of Chemical Research*, Vol. 37(9), 2004, pp.663-672.

[23] S.M. Briglin, M.S. Freund, P. Tokumaru and N.S. Lewis, Exploitation of spatiotemporal information and geometric optimization of signal/noise performance using arrays of carbon black-polymer composite vapor detectors, *Sensors and Actuators B-Chemical*, Vol.82(1), 2002, pp.54-74.

[24] N.Barsan, M.S. Berberich, and W. Gopel,

Fundamental and practical aspects in the design of nanoscaled SnO2 gas sensors: a status report, *Fresenius Journal of Analytical Chemistry*, Vol.365(4), 1999, pp.287-304.
[25] W.J. Buttner, G.J. Maclay, and J.R. Stetter, An Integrated Amperometric Microsensor, *Sensors and Actuators B-Chemical*, Vol.1(1-6), 1990, pp.303-307.
[26] F. Favier, E.C. Walter, M.P. Zach, T. Benter and R.M. Penner, Hydrogen sensors and switches from electrodeposited palladium mesowire arrays, Science, 2001, 293 (5538), 2227-2231.
[27] J. Kong, N.R. Franklin, C.W. Zhou, M.G. Chapline, S. Peng, K.J. Cho, and H.J. Dai, Nanotube molecular wires as chemical sensors, *Science*, Vol 287(5453), 2000, pp.622-625.
[28] C. Yu, Q. Hao, S. Saha, L. Shi, X.Y. Kong and Z.L. Wang, Integration of metal oxide nanobelts with microsystems for nerve agent detection, *Applied Physics Letters*, Vol.86 (6), 2005
[29] G. Macbeath, and S.L. Schreiber, Printing proteins as microarrays for highthroughput function determination, *Science*, Vol.289(5485), 2000, pp.1760-1763.
[30] D. Guschin, G. Yershov, A. Zaslavsky, A. Gemmell, V. Shick, D. Proudnikov, P. Arenkov and A. Mirzabekov, Manual manufacturing of oligonucleotide, DNA, and protein microchips, *Analytical Biochemistry*, Vol.250(2), 1997, pp.203-211.
[31] B. Schweitzer, P. Predki and M. Snyder, Microarrays to characterize protein interactions on a whole-proteome scale, *Proteomics*, Vol.3(11), 2003, pp.2190-2199.
[32] K. Ihokura and J. Watson, *The stannic oxide gas sensor*. CRC Press, Florida, 1994.
[33] J. Gardner and P. Bartlett, *Electronic Noses, Principles and Applications*, Oxford University Press, 1999.
[34] J. Gardner, E. Hines, and C. Pang, Detection of vapours and odours from a multisensor array using pattern recognition: selforganizing adaptive resonance techniques, *Measurement and Control*, Vol.29, 1996, pp.172–178.
[35] E. Kalman, Gas-Sensors for Automobile Interiors, *PhD Thesis at Linkoping University*, 2000.
[36] M. Penza, G. Cassano, F. Tortorella, and G. Zaccaria, Classification of food, beverages and perfumes by WO3 thin-film sensors array and pattern recognition techniques, *Sensors and Actuators B Chemical*, Vol.73(1), pp.76–87, 2001.
[37] K. Esbensen, S. Schonkopf, and T. Midtgaard, *Multivariate Analysis in Practice*, Camo, Trondheim, 1994.
[38] A. Larkin, E. Hines, S. Thomas, and J. Gardner, Supervised learning using the vector memory array method, *In Proceedings of the Workshop on Neural Network Applications and Tools*, 1994, pp.6–10.
[39] A. Guardarrama, J. Fernandez, and M. Iniguez, Discrimination of wine aroma using an array of conducting polymer sensors in conjunction with solid-phase micro-extraction (SPME) technique, *Sensors and Actuators-B Chemical*, Vol.B77(1-2) , 2001, pp.401–408.
[40] M. O'connell, G. Valdora, and G. Peltzer, A practical approach for fish freshness determinations using a portable electronic nose, *Sensors and Actuators-B Chemical*, Vol.B80(2), 2001, pp.149–154.
[41] T. Borjesson, H. Sundgren, and T. Eklov, Grain odour classification with an electronic nose, *In 8th International Congress on Solid State Sensors and Actuators and Eurosensors*, vol.3, 1995, pp.11–12.
[42] P. Wide, F. Winquist, and D. Driankov, An air-quality sensor system with fuzzy classification, *Measurement and Science Technology*, 1998.
[43] H. Abdel-Aty-Zohdy, Artificial neural network electronic nose for volatile organic compounds, *In Proceedings of the 8th Great Lakes Symposium on VLSI*, 1998, pp.122–125.
[44] B. Lazzerini, A. Maggiore, and F. Marcelloni. Fros: a fuzzy logic-based recogniser of olfactory signals. *Pattern Recognition*, Vol.34(11), 2001, pp.2215–2226.
[45] G.T. Dornseifer, T.Neunhoeffer, Numerical Simulation in Fluid Dynamics, a Practical Introduction. *SIAM*, 1998.
[46] J.H. Seinfeld, *Atmospheric chemistry and physics: From air pollution to climate change*, John Wiley & Sons, 1998.
[47] J. Crank, *The mathematics of diffusion*, Oxford University Press, 1956.
[48] M.P. Michaelides, C.G. Panayiotou, Plume Source Position Estimation Using Sensor Networks. *Proceedings of the 13th Mediterranean Conference on Control and Automation Limassol*, Cyprus, 2005.
[49] X. Kuang, H. Shao, Maximum Likelihood Localization Algorithm Using Wireless Sensor Networks, *Proceedings of the First International Conference on Innovative Computing, Information and Control (ICICIC'06)*, 2006.
[50] M. Kiatweerasakul, T.J. Stonham, Odour Plume Tracking Robot Using Semiconductor Gas Sensors, *Seventh International Conference on Control, Automation, Robotics and Vision (ICARCV'O2)*, Singapore, 2002.
[51] A. Lilienthal, A. Zell, M. Wandel, U. Weimar, Sensing Odour Sources in Indoor Environments Without a Constant Airflow by a Mobile Robot, *IEEE International Conference on Robotics and Automation*, Korea, 2001.
[52] J. Cai, D.C. Levy, Source Direction Detection based on Stationary Electronic Nose System, *Transactions on Engineering, Computing and Technology*, Vol.15, 2006,

pp.115-119, WES.
[53] E. A. Gonzalez, F. M. G. Mascenon, et al., An Autonomous Mobile Olfactory Robot for the Localization of a Chemical Leak, *ECE Student Conference De La Salle University*, Philippines, 2003.
[54] A.T. Hayes, A. Martinoli, R.M. Goodman, Distributed Odor Source Localization, *IEEE Sensors Journal*, Vol.2, 2002, pp.260-271
[55] A. Farina, Target tracking with bearings - Only measurements, *Signal Processing*, Vol.78, 1999, pp.61-78.