Plume Source Position Estimation Using Sensor Networks

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***Abstract*— This paper proposes the use of a sensor network for estimating the location of a source that releases certain substance in the environment which is then propagated over a large area. More specifically, we use nonlinear least squares optimization to estimate the source position based on the concentration readings at the sensor nodes. Such a network can be of tremendous help to emergency personnel trying to protect people from terrorist attacks or responding to an accident. We show that in high uncertainty environments it pays off to use a large number of sensors in the estimation whereas in low uncertainty scenarios a few sensors achieve satisfactory results. We also show the importance of choosing the appropriate parameters for the least squares optimization especially the start position for our algorithm. We compare our results to the Closest Point Approach (CPA) where the source location is assumed to be the sensor node with the highest measurement.**

I. Introduction

Recent advances in wireless communications and electronics have enabled the development of low-cost, low-power, multifunctional sensor nodes that are small in size and communicate untethered in short distances. These tiny sensor nodes which consist of sensing, data processing, and communicating components, leverage the idea of sensor networks. A sensor network is composed of a large number of sensor nodes that are densely deployed either inside the phenomenon or very close to it. They have a wide variety of applications including military sensing, infrastructure security, environment and habitat monitoring, industrial sensing, building and structures monitoring and traffic control [1], [2], [3].

The proposed sensor network estimates the position of the source of a plume based on concentration readings from the sensor nodes. Tracing contaminant transport to source is a hot research topic internationally triggered by the terrorist attacks of September 11, 2001 in New York. After the attacks around the world there is an acknowledged need to protect military installations, government facilities, business enterprizes and private citizens from the occurrence and effects of terrorist related incidents. One of the most dangerous types of these attacks is contaminant transport by the releasing of chemical, biological or radiological substances. This requires immediate tracking of the source of contamination and action by the proper authorities to deal with the crisis. Various types of sensors can measure releases of potentially harmful chemical, biological and radiological materials. When networked together they can provide real-time detection, identification and assessment of the event. Apart from terrorist attacks, the proposed sensor network can also deal with a number of other applications. Examples include the accidental spillage of toxic waste by ships, factories etc. that contaminate the sea and the air, early detection of fires, other environmental monitoring and so on.

The main contribution of this paper is determining the source location of the plume using the nonlinear least squares optimization method [4]. In our simulations we vary the number of sensors in the sensor field and the variance of the noise at each measurement. We show that in high uncertainty environments it pays off to use a large number of sensors in the estimation whereas in low uncertainty scenarios a few sensors achieve satisfactory results. It seems that for every uncertainty level (measured as the variance of noise) there is an optimal number of sensors that need to be involved in the measurement in order to achieve satisfactory results while, at the same time, be energy efficient. We also show the importance of appropriately choosing the parameters for the least squares optimization especially the starting point of the optimization algorithm. Finally, we compare our results to the Closest Point Approach (CPA) where the source location is assumed to be the sensor node with the highest measurement.

The paper is organized as follows. First, in Section II, we look at related work in sensor networks and in plume tracking using unmanned vehicles. In Section III, we present the model we have adopted, the underlying assumptions and the way we approach the problem using the nonlinear least squares optimization. In Section IV, we present several simulation results using a number of randomly placed plume sources in the sensor field and varying the number of sensor nodes, the noise variance and the number of measurements at each sensor node. We conclude with Section V where we also present plans for future work.

II. Related Work

Shortly after the September 11, 2001 terrorist attacks in New York the Oak Ridge National Laboratory was formed in Tennessee, United States [5]. They are working to develop a sensor network that will serve as a national system for comprehensive incident management that will rapidly respond to a chemical, biological or radiological event. Also at Los Alamos National Laboratory they are working in developing a DSN (Distributed Sensor Network) that will be used to detect a motor vehicle carrying a RDD (Radiological Dispersion Device) [6].

Collaborative Signal Information Processing (CSIP) [7] deals with the energy constrained dynamic sensor collaboration, i.e., how to dynamically determine who should sense, what needs to be sensed, whom the information must be passed on to. Zhao et al. [8],[9], have addressed the problem of dynamically querying sensors and routing data in the network so information gain is maximized while latency and bandwidth consumption is minimized. They concentrate on selecting the next best sensor for a vehicle tracking application and updating the belief state in order to maximize information content. Our work is similar in that we start from the same estimation model (1) in our problem of finding the position of the plume source. We differ in that we use nonlinear least squares optimization at the sink to estimate the source position based on the readings from all available sensors. We are more interested in discovering the right number of sensors to use and the right parameters of the least squares estimation algorithm under various noise conditions so that estimation error and energy consumption are minimized.

A lot of research has been done in the area of plume tracking using unmanned vehicles. They use bio-mimetic robotic plume-tracing algorithms based on olfactory sensing. Usually a single sensor on the robot is capable of sensing the chemical and sensing or estimating fluid velocity. Subsequently, this information is used to determine the speed and heading direction of the vehicle such that the motion of the vehicle is likely to locate the odor source. Farrell [10] has done significant work in locating a chemical source underwater using an autonomous vehicle operating in a fluid flow. Using sensor networks in plume tracking offers a lot of advantages but also poses several challenges when compared to unmanned vehicles:

1) Sensor networks can cover a large area and immediately discover the presence of a plume whereas a robot has to spend a significant amount of time searching for the plume and maintaining contact until it finds the source.
2) Sensor networks can cover areas where the use of unmanned vehicles is not possible- among people, around buildings or other obstacles.
3) On the other hand, a robot can move close to the source to get a better measurement whereas static sensor nodes have to cooperate to remotely estimate the location of the source. In our future plans we plan to investigate the possibility of identifying a small area where the plume source is located and subsequently use measurements from sensors that are positioned on moving platforms to pinpoint the exact location of the source.
4) Energy is a major constraint for sensor networks so efficient estimation algorithms and routing techniques need to be employed which is the major topic of our current research.

III. Simulation Model

For the initial implementation of our sensor network that traces the contaminant transport to source we are going to make the following assumptions:

1) A set of N sensor nodes are stationary, randomly placed in a rectangular field R at positions (x_i, y_i), $i = 1, \cdots, N$. Their locations are known through the use of a combination of GPS and localization algorithms.
2) We use a centralized approach where all sensor readings are gathered at the sink (base station) using a communication paradigm like directed diffusion [11] and at the sink the nonlinear least squares [4] is employed to estimate the source position. The sink is stationary at a pre-determined position.
3) The contaminant source is located at a position (x_s, y_s) which is also randomly placed inside the rectangle R.
4) The propagation of the contaminant transport is uniform in all directions and there are no environmental changes throughout the propagation.

Assumptions 1 and 2 are quite common and reasonable for sensor networks. On the other hand, assumptions 3 and 4 although simplifying, will serve as a starting point for the investigation of a difficult problem. For our future work we plan to extend our model to situations where the source is outside the sensor field and consider the effects of wind and turbulence in the propagation of the plume. For this paper, we assume that the measured intensity at the source is c and as we move away from the source, the measured intensity is inversely proportional to the distance from the source raised to some power $\alpha \in \mathcal{A} \subset \mathbb{R}$ which depends on the environment. As a result, the measured intensity at any sensor i is given by (1).

$$z_{i,t} = \frac{c}{r_i^{\alpha}} + w_{i,t}, \tag{1}$$

$i = 1, \cdots, N$, $t = 1, \cdots, M$. Measurement $z_{i,t}$ is the t-th sample at sensor i while r_i is the radial distance from the source, i.e.,

$$r_i = \sqrt{(x_i - x_s)^2 + (y_i - y_s)^2}$$

Finally, $w_{i,t}$ is additive Gaussian noise with zero mean and variance $\sigma_{i,t}$. We point out that such a model, though common in the literature, may not be accurate for the

problem at hand, and thus we are also investigating the possibility of adopting different noise models such as log-normal and chi-square.

As already mentioned earlier, we assume that sensor i knows its location (x_i, y_i) through GPS or the use of some localization algorithm (e.g., triangulization). The sensor node can either send all measurements $z_{i,t}$, $t = 1, \cdots, M$ directly to the sink or take M measurements and send the computed mean back to the sink. We chose to first take a number of discrete measurements M at each sensor node over a time interval T and take the mean of these measurements $\overline{z_i}$ before communicating this information back to the sink. This choice is well justified in the context of sensor networks. Such an approach reduces the communication overhead because we only require the sensor nodes to send just the mean (a single value) every time interval T and not their entire measurement set. Calculating the mean at each sensor node is a simple operation that consumes minimal energy whereas communicating all the discrete measurements has a very high energy cost. By reducing the amount of data flowing in the sensor network we save both bandwidth and energy and therefore prolong the lifetime of the sensor network.

After the sink receives the information from all sensor nodes, it employs the nonlinear least squares method [4] using the received information. It computes an estimate of the source location $(\hat{x}_s, \hat{y}_s)$ by minimizing the following function:

$$J = \sum_{i=1}^{N} \left(\frac{c}{[(\hat{x}_s - x_i)^2 + (\hat{y}_s - y_i)^2]^{\frac{\alpha}{2}}} - \overline{z_i} \right)^2 \quad (2)$$

where $\overline{z_i}$ is the computed mean of M measurements at sensor i,

$$\overline{z_i} = \frac{1}{M} \sum_{t=1}^{M} z_{i,t}.$$

IV. Results

For all subsequent experiments we used a square sensor field of $1km \times 1km$ and assume that the sensor measurements were given by:

$$z_{i,t} = \frac{10^6}{r_i^2} + w_{i,t} \quad (3)$$

where $i = 1, \cdots, N$, $t = 1, \cdots, M$, $r_i^2 = (x_s - x_i)^2 + (y_s - y_i)^2$ and $w_{i,t} = N(0, \sigma^2)$, $\forall i$, $\forall t$. The error reported is the average over K experiments where we assume that the plume source is randomly placed at points $(x_{s,k}, y_{s,k})$ and we solve the problem (2) K-times to obtain $(\hat{x}_{s,k}, \hat{y}_{s,k})$, $k = 1, \cdots, K$. In other words, the error shown in our results is given by

$$Error = \frac{1}{K} \sum_{k=1}^{K} \sqrt{(x_{s,k} - \hat{x}_{s,k})^2 + (y_{s,k} - \hat{y}_{s,k})^2} \quad (4)$$

At the beginning of these K experiments we randomly initialize the sensor field but it remains fixed for all K experiments. A typical $1km \times 1km$ sensor field with 100 sensors is shown in Figure 1. For the following experiments we used the Matlab package and assumed $K = 100$.

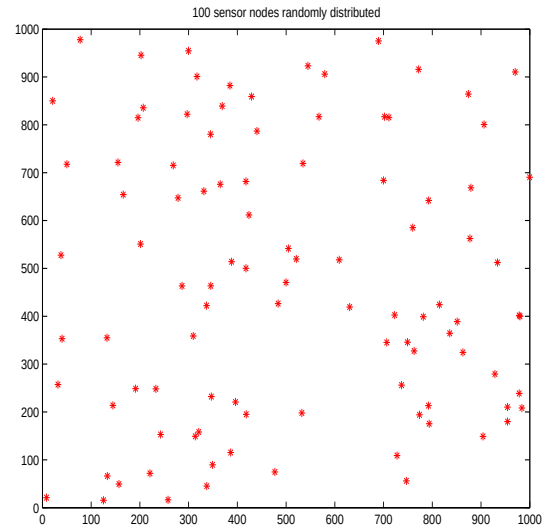

Fig. 1. A field with 100 randomly placed sensor nodes

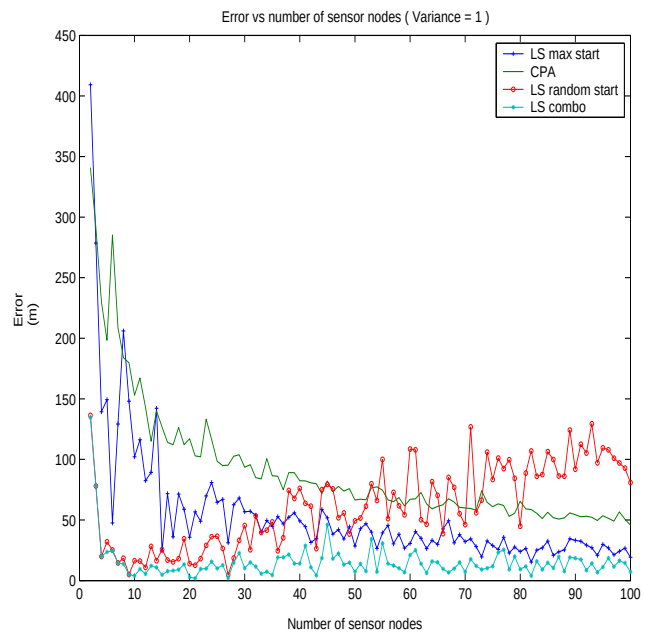

Fig. 2. Error vs number of sensor nodes for $\sigma = 1$

A. Effect of varying the number of sensors

In the first set of experiments we investigated the effect of the number of sensors N used in the calculation and compared the results against the CPA. We varied the number of sensor nodes in the sensor field from 2 to 100 and used three different approaches for evaluating the start point of the least squares algorithm. In the first approach, for the

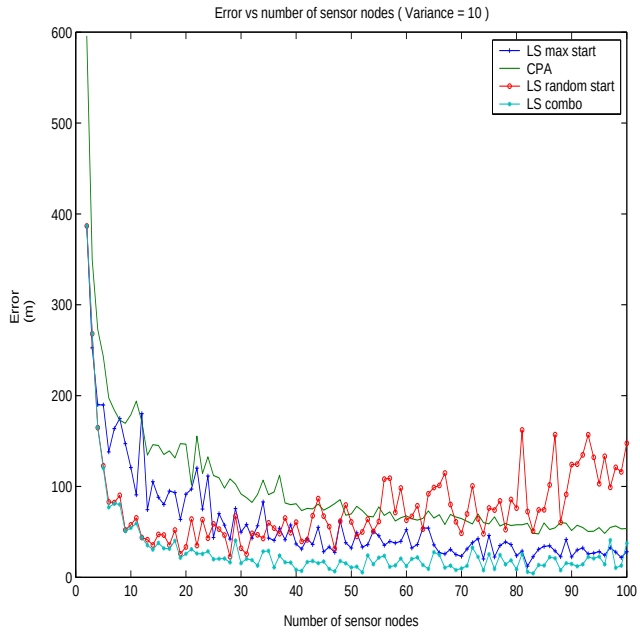

Fig. 3. Error vs number of sensor nodes for $\sigma = 10$

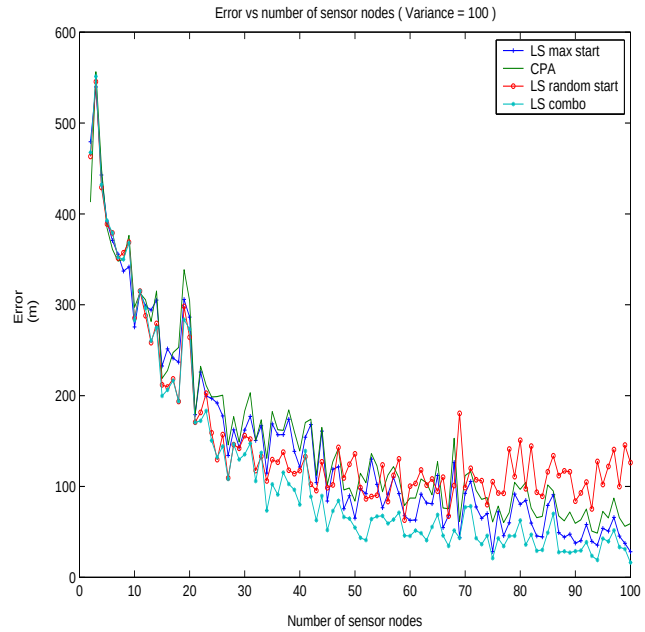

Fig. 4. Error vs number of sensor nodes for $\sigma = 100$

starting point, we used a point close to the sensor node with the highest measurement. This plot is denoted as `LS max start`. In the second approach, the initial point is randomly selected. Specifically, we randomly picked 10 different starting positions and chose the one that minimized the squared 2-norm of the residual (`resnorm`) in the least square results. This plot is denoted as `LS random start`. In the third approach we took the better of the two approaches as the one that minimized the overall `resnorm` and we denoted this by `LS combo`. The results are shown in Figures 2-4 for noise variance 1, 10 and 100 respectively. There are several things to observe from these plots:

1) The `LS random start` performs quite well for small numbers of sensor nodes whereas for sensor numbers greater than 50 the `LS max start` performs better. This is expected because the success of the least squares algorithm depends greatly on the starting point of the algorithm and having a starting point close to the actual plume source position enhances the probability of correctly converging to the correct minimum. When there are only a few sensors in the field using the `LS max start` often results in starting points that are far away from the source and so it is a better approach to randomly search for the start position. When the number of sensor nodes increases above a certain threshold this guarantees good coverage of the whole sensor field and starting at the sensor node with the highest measurement results in starting the optimization in the local neighborhood of the source. In situations like these, `LS random start` performs even worse than the CPA approach. This is due to the large number of sensor nodes which allows several starting positions that are far away from the neighborhood of the source and as a result, the optimization algorithm ends in some local minimum other than the global one. The `LS combo` approach combines the best of both worlds and performs very well for all numbers of sensor nodes so we decided to adopt it for all subsequent experiments and discussions and will simply refer to it as LS.
2) Increasing the number of sensor nodes does not always produce better results. For low variance conditions the error decreases until we reach the number of 10 sensor nodes to a value of less than 10m and from there on it follows steady state behavior with unpredictable fluctuations. These are very encouraging results because we want to use as few sensors as possible in the computations to save energy. This way the sensors that are not involved in the sensing or communication process can go to sleep to conserve energy. In higher variance conditions we need more sensor nodes to obtain similar results. For variance 10 we need 25 sensor nodes and for variance 100 we need all 100 sensors.
3) The least squares approach performs better than the CPA for all numbers of sensor nodes. The benefits are more obvious for a few sensor nodes where there is as much as 1500 percent more error in using the CPA. The difference between CPA and LS gradually decreases with increasing numbers of sensor nodes This is expected because increasing the number of sensors allows for a better coverage of the sensor field.

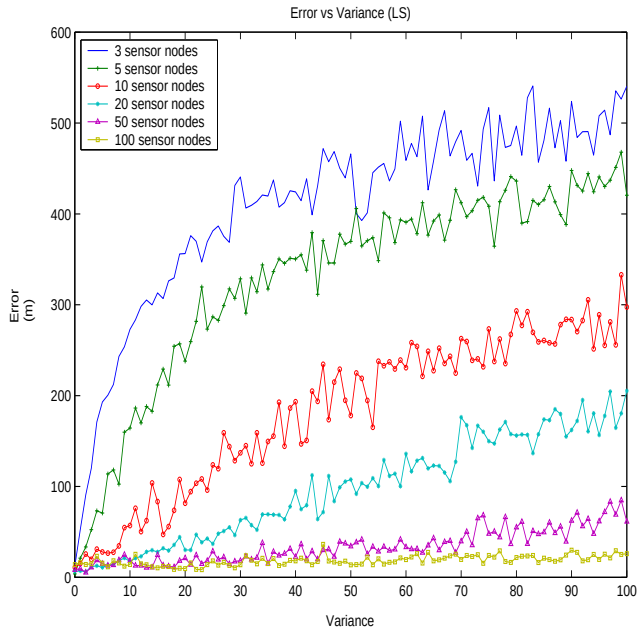

Fig. 5. Error vs noise variance using least squares

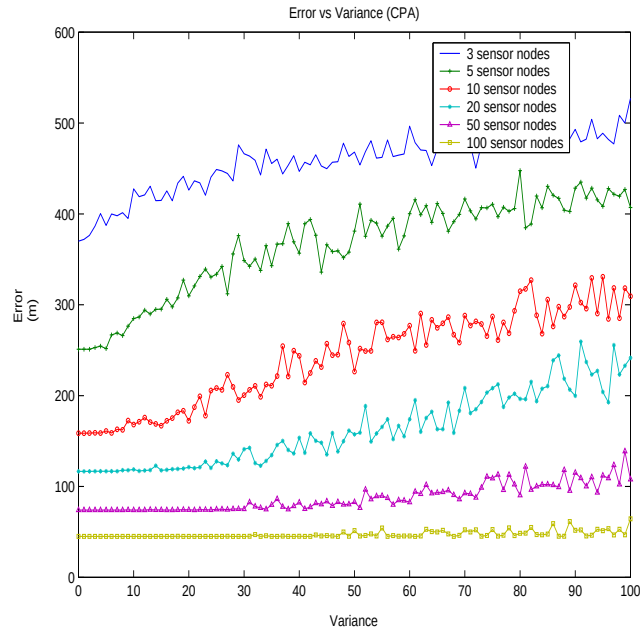

Fig. 6. Error vs noise variance using closest point approach

B. *Effect of varying the noise variance*

In the second set of experiments we investigated the effect of variance for six different sensor networks with 3, 5, 10, 20, 50 and 100 sensor nodes. The results are shown in Figure 5 for the least squares approach and Figure 6 for the closest point approach. From these results we make the following observations:

- The 100 sensor network is the only one that is robust to the noise variance. For the rest of the sensor networks the error increases with variance increase and for high variances it asymptotically approaches the CPA curves. The least squares approach performs better than the CPA for all variance conditions. The benefits are more obvious for low noise variance conditions but seem to diminish for variance 100. At this point, it is worth pointing out that variance 100, implies that for a significant portion of the sensors, the measurements are dominated by noise, which explains the poor performance of the least squares approach. In our future work, we investigate the use of log-normal and/or chi-square distributed noise which is expected to have better data fit.
- The rate of increase of error with variance increase is dependent on the number of sensor nodes. The 3 sensor node network exhibits the highest rate of increase with the error reaching 50 m for noise variance of just 1. The 5 sensor node network reaches the same error for variance 5, the 10 sensor network for variance 10, the 20 sensor network for variance 30 and the 50 sensor network for variance 75. The 100 sensor network has an error of about 10m for all variance conditions. Based on these results we conclude that for correctly determining the number of sensor nodes to use in the calculation to achieve certain accuracy in the results we need to take this decision based on the noise variance of the propagation model.

C. *Effect of varying the number measurement samples*

For all the previous experiments the number of measurements was fixed to $M = 10$. In this set of experiments we investigated the effect of the number of measurements M for six different sensor fields of fixed variance and number of sensor nodes. These where chosen from the previous sets of experiments as the threshold values for which the error was around 50m. This time the number of measurements was varied from 1 to 100 and part of the results are displayed in Figure 7. From the plot we see that all six of the sensor networks follow a similar behavior. The error decreases exponentially as the number of measurements increases until a certain threshold value of measurements. After this threshold there is no real benefit for taking more measurements as the plots reach a steady state behavior. For the 100 sensor network this threshold is 5 measurements and for the rest of the sensor networks it is around 25 measurements. It is worthwhile to observe the sudden increase in error if we decide to take fewer than 10 measurements.

V. Conclusions and Future Work

Our proposed sensor network estimates the plume source location in a constrained sensor field using least squares optimization techniques assuming a uniform propagation of the plume. Before performing the least squares we perform

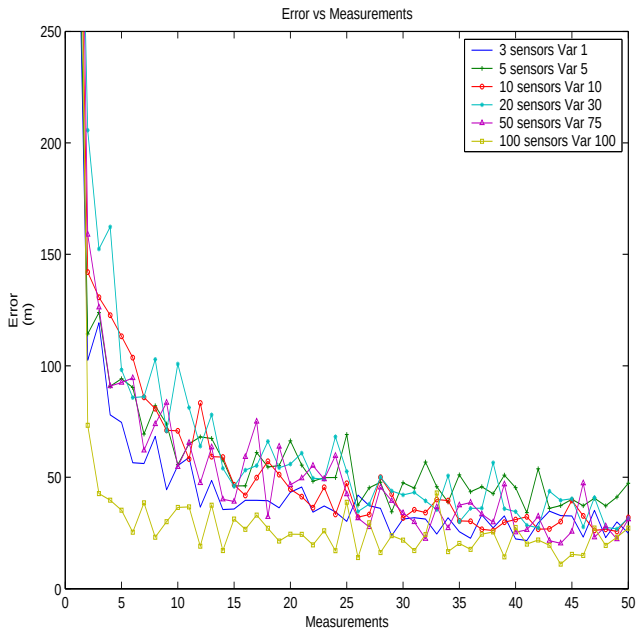

Fig. 7. Error vs number of measurements

time averaging of the measurements at the sensor nodes. Our algorithm performs better than the CPA (Closest Point Approach). We investigate the effect of using more sensors in the estimation and show that this is dependent on the noise variance of our sensor model. In situations with high noise variance it is necessary to increase the number of sensors or the number of measurements to achieve satisfactory results.

For our future work we plan to investigate a number of different propagations models, both static and dynamic. For static models, we will assume noise with different distribution characteristics. Furthermore in the real world the plume does not have a uniform distribution mainly because of turbulence and the changing environmental conditions (wind), so we plan to use a more realistic model for the plume propagation like the one described in [12]. Furthermore, we plan to investigate different estimation techniques including, direct triangulization, maximum likelihood, Bayesian estimators [13]- to find the plume source location and compare the results to the least squares method. In addition, we also plan to investigate the possibility of having multiple simultaneous plume sources in the sensor field. Finally, we are currently in the process of setting up a test-bed with Berkley modes for the testing of the proposed algorithms.

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