CHEMICAL SOURCE LOCALIZATION IN UNKNOWN TURBULENCE USING THE CROSS-CORRELATION METHOD

Gail L. Rosen and Paul E. Hasler*

Integrated Computational Electronics Laboratory
Georgia Institute of Technology, Atlanta, GA 30332-0250
{gailr,phasler}@ece.gatech.edu

ABSTRACT

Estimating the direction of a diffusive source is a difficult problem, and little has been tried to estimate a chemical source subject to turbulence. Turbulence must be addressed if chemical localizer systems are to be effective. We look at how to quantify turbulence and develop a measure to locate a source in two different types of turbulence, modulated and unmodulated plumes. We show that a plume can be modeled linearly on a small-scale and that a wind measure for a stationary sensor array can indicate the direction of a chemical source with reasonable accuracy and time. This measure can be easily implemented in low-power computational electronics and applied to the detection of chemical leaks and illegal substances.

1. INTRODUCTION

Recently, engineers have begun addressing the hard task of diffusive source localization ([1], [2], [3]), but diffusive fields are rarely found in natural atmospheric conditions. Usually, turbulence is also a factor which further compounds the difficulty of the chemical localization problem. This is due to the fact that turbulent advection disperses a chemical and causes discontinuities in the flow. To attack this problem, most approaches use mobile sensing robots which can survey and sample a large plume. In [4], an intelligent plume mapping scheme based on HMM's for an autonomous vehicle is devised. In [5], a transient-response-based algorithm is used to in several modes, one being to track the plume upwind and another to switch into a local search.

Only mobile and multifaceted algorithms have been implemented because they are able to perform well for tracking sources in nonlinear, dynamical plumes. However, these solutions are complex and difficult to implement. In this paper, we show that an easy-to-implement stationary array can localize the direction of a source in two different turbulent scenarios in a matter of minutes.

Coherence spectra has been used to detect distance from a chemical source in plumes [6], but this measure loses all spectral phase information about the plume needed for source localization. In this paper, we will determine the flow of the plume by exploiting the sensor time delays. If a source releases a chemical at a constant rate and if we use an array small enough compared to the turbulent parcels (pockets of high concentration) in the plume, a rough estimate of the source location can be determined from computing the angle of arrival (AOA) of the wind direction.

* Funded in part by an AT&T Research Laboratories grant.

2. ASSESSING THE TURBULENT DATA

Fig. 1. An ideal von Kàrmàn vortex street with Reynold's number, $R = 73$. [7]

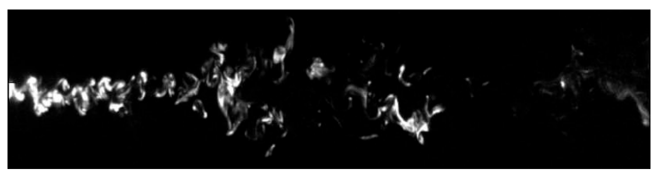


Fig. 2. Our modulated plume (von Kàrmàn vortex street) data with the Reynolds number above 1000. The modulated turbulence dissipates due to the effects of natural turbulence and diffusion.

Fig. 3. Our unmodulated plume data; the transitition from laminar to turbulent flow occurs due to natural turbulence and diffusion.

A simple model of diffusion can be written as:

$$C(r) = \frac{\mu}{4\pi D r} \tag{1}$$

where μ is the chemical release rate (moles/s), and D is the diffusion constant (cm^2/s). The r is the radius from the point source, and we assume $t \to \infty$) .

We do not only have effects from diffusion in our problem, but we also have unmodulated turbulence from a pure

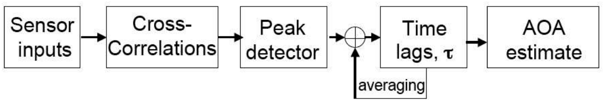


Fig. 4. Block diagram of the proposed wind AOA algorithm.

chemical flow at 5 cm/s in one case (Fig. 3). The unmodulated plume is subject to basic diffusion and turbulent advection. In the second case, we have a von Kàrmàn vortex street, or modulated turbulence, from a 5 cm/s chemical flowing over a 0.8 cm diameter cylinder (Fig. 2). This modulation compounds the normal turbulence to create more unpredictable effects. Our data was collected with planar laser-induced fluorescence (PLIF) technology which is a non-intrusive, optical measurement technique to obtain a sequence of instantaneous, high-resolution spatial concentration fields. The plume is sampled at a 10 Hz framerate, each pixel represents approximately $1\text{mm} \times 1\text{mm}$ in space, and the concentration values are normalized and quantized to values between 0 and 255.

When a chemical flow passes around a cylinder, a von Kàrmàn vortex street results, and an ideal one is seen in Fig. 1. Figures 2 and 3 are single frames captured from the turbulent plume data. In Fig. 2, there is slight von Kàrmàn vortex shedding in the modulated plume, but it is subject to many diffusive and additional unknown turbulent forces. In Fig. 3, the unmodulated plume is subjected solely to diffusion and natural turbulence. These images are a cropped version of the full 401×940 pixel (y-dimension $\times$ x-dimension) images. The centerline of the plume is 205 pixels (20.5cm) down on the image.

While we have a model for the diffusion, we do not know the exact models for the turbulence or the Reynold's number of the vortex shedding. This makes attacking the problem challenging because we are blind to the turbulence involved. Therefore, we desire to localize the source of the plume using $only$ the following knowledge:

- Intermittent "events" occurring in the plume due to turbulence
- Constant flow rate
- Diffusion dissipating the events after a certain distance

3. CROSS-CORRELATION METHOD FOR WIND AOA

Suppose we have N sensors and a source signal, $s(t)$ propagating through air. Due to Fick's second law, an unknown nonlinear turbulence function, $f(\ )$, and sensor noise, the signal received by the ith sensor can modeled as:

$$x_i(t) = f\left(\frac{s(t)}{r_i}\right) + n_i(t)$$

where r_i is the distance from the source to the ith sensor and $n_i(t)$ is additive white Gaussian noise.

In eq. 2, we test to see if linear correlations exist between sensors in a window of size T, assuming that the $f(\ )$ signal and n are not correlated.

$$r_{1i}(t) = \sum_{k=0}^{T} x_1(t)x_i(t+k) \tag{2}$$

Then the delay that maximizes the peak of the function is stored in τ_i. Column vector, τ, contains all the peak delays between the N sensors.

If the array has a 2-D symmetrical geometry, τ can be used to estimate the wind direction by weighting the coordinates with the delays. We now represent the array center with cartesian coordinates $\mathbf{x} = [x, y]^T$, and the sensor coordinates in reference to the center are:

$$\mathbf{X} = \begin{bmatrix} x_1 - x & x_2 - x & \dots & x_N - x \\ y_1 - y & y_2 - y & \dots & y_N - y \end{bmatrix}.$$

Next, the direction of the wind from the centroid of the array is estimated as:

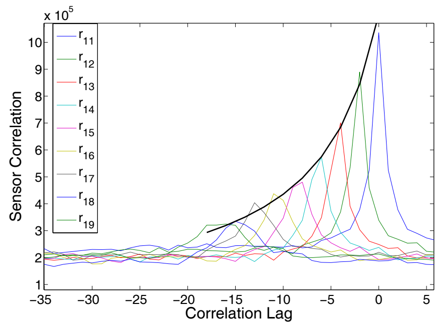
$$\begin{aligned} &[d_x\, d_y]^T = \mathbf{X} \cdot \tau \\ &\theta_{wind} = \text{atan}\left(\frac{dy}{dx}\right) \quad \theta_{source} = \text{atan}\left(\frac{-dy}{-dx}\right) \end{aligned} \tag{3}$$

We denote θ_{source} as the angle of arrival (AOA) and $\tau[n]$ as the sensor delays for each window. $\tau[n]$ is averaged over time by $\hat{\tau} = \frac{1}{N}\sum_{n=0}^{N-1} \tau[n]$ to smooth the delay estimates where L is the entire data length, and $N = L/T$. Then, using equation 3, a time-averaged $\hat{\theta}_{source}$ is determined.

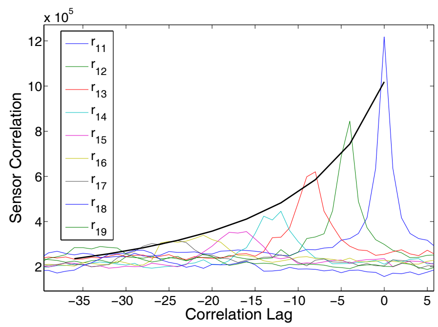
A block diagram of the algorithm can be seen in Fig. 4.

4. PLUME CHARACTERIZATION WITH A LINEAR SENSOR ARRAY

In Fig. 5, cross-correlations of a nine-sensor linear (on the x-axis) array using just equation 2 for the whole 600 second modulated plume data are shown. The peak at time 0 is always the first sensor's autocorrelation. The negative time lags are then the correlation of the first sensor with the successive sensors, spaced 1cm, and 2cm apart respectively in the graphs. In the graphs, there is an $1/r$ drop-off in the magnitude of the correlation peaks due to the effects of diffusion (see equation 1). For the 1cm case, we see that even when the sensors are 9cm apart for r_{19}, there is still a slight correlation. Each time lag corresponds to 0.1 seconds, and a pixel is approximately 1mm of distance. So, from Fig. 5 (a), we can infer the plume covers 1cm in 2 time lags or 0.2 seconds, and this corresponds to the 50mm/s flow rate in the experiment. In Fig. 5 (b), the r_{17} is practically in the noise floor representing that there is very little noticeable correlation left in the plume after a distance of 14cm. In fact, the $\frac{1}{r}$ curvefit is not as precise in this case because a few of the correlation peaks are buried in noise.



(a)



(b)

Fig. 5. Time correlations of a 9-sensor linear array placed parallel to plume with the center located $50cm$ away from from the source on the centerline, placed at $(20.5, 50)$cm, and a sensor separation of (a) 1 cm and (b) 2 cm. The correlation window length is $T = 600$ seconds. The propagation delays between sensors can be computed from the correlation lag between peaks, and there is a $\frac{1}{r}$ amplitude decay in the successive peaks due to diffusion; we curvefit the peaks with a $\frac{1}{r}$ function represented by the black curves.

5. NUMERICAL EVALUATION FOR 2-D STATIONARY ARRAYS

Now, we want to expand our sensor array from a linear to a symmetric 2-D array in order to estimate the direction of a source. Using a linear array for this task is difficult since this is not a wavefield; only intensity information is available. We design a square array of $N+1$ sensors where N is the number of sensors that maximize the perimeter of the array, and one sensor is placed at the centroid of the array. In equation 2, we assign this middle sensor as the first sensor, and compute the correlation of it with the surrounding i sensors to obtain τ. τ can help us determine the AOA (see Fig. 6).

With our algorithm, there are a few parameters to take into consideration with each plume:

- The distance between sensors / array size
- The sensor array placement in the plume

First, we examine the array size, or the distances between sensors, to localize a source; see Fig. 7 to get an idea of the scale of a "large" array that we used in the plume. We also

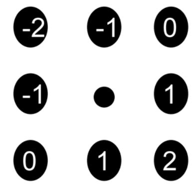


Fig. 6. Illustration of a $135°$ source localization scenario for an $N = 8$ sensor array. The numbers on the sensors are the τ_i's corresponding to the time delay with respect to the center sensor. Weighting the coordinates with these values, gives us a wind localization of $-45°$. The opposite direction is taken as the source direction.

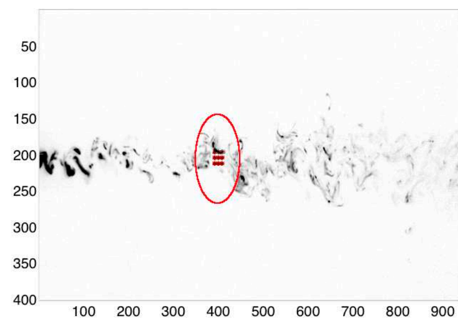


Fig. 7. An $N = 8$, 1.6cm $\times$ 1.6cm array placed at $(20.5, 40)$cm in the modulated plume.

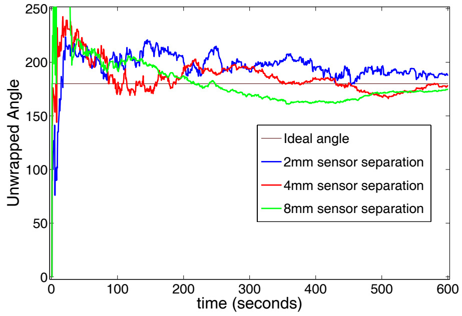
want to examine the difference between localizing the unmodulated vs. modulated turbulence. Visually, the plumes do not look considerably different, but the AOA estimate converges much slower for the modulated plume. The comparison of the modulated vs. unmodulated effects can be seen in Fig. 8.

Ideally, we want to be able to blindly locate a turbulent source despite the sensor array orientation in the plume. Two strenuous array placements are tested. One tests the array's ability to track the plume while being placed a bit outside the flow (see Fig. 9). The second tests the ability of the array to localize the wind direction while being far downstream from the source (see Fig. 10).

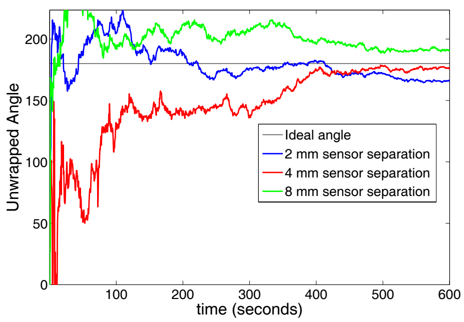
Finally, distance and plume-type comparisons are shown in Table 1.

Position	Unmodulated/ Modulated	Avg. Final Angle Error (in °)	Avg. Time to 90% of Final Angle
(20.5,40) cm	Unmod	6°	120s
(20.5,40) cm	Mod	10°	225s
(20.5,80) cm	Mod	13°	420s

Table 1. A table summarizing the average final angle error and the convergence time to reach 90% of the final angle. Here, $N = 8$, the correlation window length is 0.5 seconds, and the results from the 2mm, 4mm, and 8mm sensor separations are averaged for each placement/plume. The convergence time doubles in a modulated plume over an unmodulated plume. Placing the array twice the distance from the source, the convergence time again almost doubles. The angle error also has a linear increase with these scenarios.



(a) Unmodulated plume.



(b) Modulated plume.

Fig. 8. The effect of the array size/lateral sensor separation on the convergence time of the source AOA. The array's center was placed at $(20.5, 40)$cm ($180°$ angle from the source), the window correlation length is 0.5 seconds, and the array has $N = 8$ (8 sensors on the perimeter and one in the middle). Clearly, the algorithm converges slower in the modulated plume compared to the unmodulated plume.

6. CONCLUSIONS

This paper demonstrates that nonlinear turbulent plumes can be linearized on a small-scale and that we can exploit the time delays between sensors with the cross-correlation method to obtain wind direction and chemical source AOA estimates from the plume. With a stationary array placed 80cm away from the source in modulated turbulence, the algorithm converges to within 90% of the AOA in approximately 400 seconds (and to 80% of the AOA in about 200 seconds). Localization time in unmodulated turbulence takes about half the time of the modulated convergence time on average. In the future, more controlled turbulent scenarios should be explored. For now, this stationary solution is a simple measure compared to mobile implementations and can be easily implemented in low-power computational electronics for many security applications.

7. ACKNOWLEDGEMENTS

We thank Prof. Jiri Janata's laboratory in the Georgia Tech Chemistry department for providing the turbulent plume data.

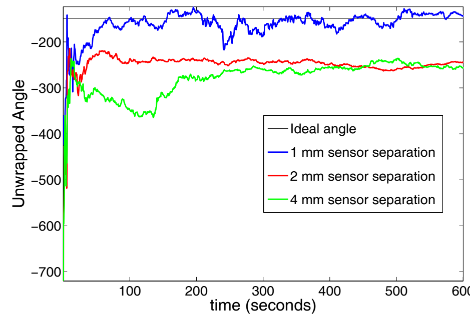


Fig. 9. (a) The sensor array placed at $(17.5, 5)cm$ in the modulated plume, with the source $-150°$ from the array. $N = 16$ in this case, and the correlation window length is 0.5s. In this case, the larger the sensor array, the worse the performance of the localization. This is due to the fact that pockets of concentration are closely spaced when near the source, and if the sensors are too far apart, they are uncorrelated.

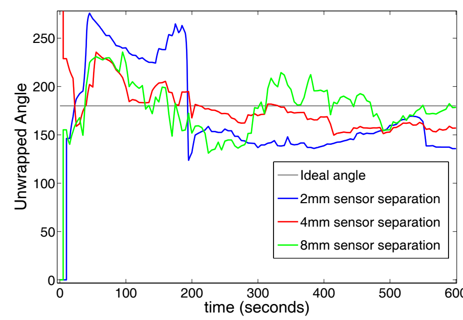


Fig. 10. (b) The sensor array placed at $(20.5, 80)$cm, a $180°$ angle from the source, in the modulated plume. $N = 8$ in this case, and the correlation window length is 0.5s. In this case, enlarging the array size improves the array's localization time and estimate of the source angle, due to the fact that the pockets of concentration are dispersed and greater in size.

8. REFERENCES

[1] A. Nehorai, B. Porat, and E. Paldi, "Detection and localization of vapor-emitting sources," *IEEE Transactions on Signal Processing*, vol. 43, no. 1, January 1995.

[2] G. L. Rosen, M. T. Smith, and P. E. Hasler, "Circuit implementation of a 2-d gradient source localizer," in 3^{rd} *IEEE Conference on Sensors*, Vienna, Austria, October 2004.

[3] S. Vijayakumaran, Y. Levinbrook, and T.F. Wong, "Maximum likelihood localization of a diffusive point source using binary observations," *Preprint, http://www.wireless.ece.ufl.edu/~twong/Preprints/mldif.pdf*, 2005.

[4] J.A. Farrell, S. Pang, and W. Li, "Plume mapping via hidden markov models," *IEEE Transactions on Systems, Man, and Cybernetics - Part B: Cybernetics*, 2003.

[5] H. Ishida, G. Nakayama, T. Nakamoto, and T. Moriizumi, "Controlling a gas/odor plume-tracking robot based on transient responses of gas sensors," *IEEE Sensors Journal*, vol. 5, no. 3, pp. 537–545, 2005.

[6] T. Kikas, P. Janata, H. Ishida, and J. Janata, "Chemical plume tracking. 2. multiple-frequency modulation," *Analytical Chemistry*, vol. 73, pp. 3669–3673, 2001.

[7] G.K. Batchelor, *An Introduction to Fluid Dynamics*, Cambridge University Press, Cambridge, UK, 1967.