Implementation of a UAV-sensory-system-based hazard source estimation in a chemical plant cluster

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Abstract. Since there has been growing concern about the damage that atmospheric leakage and dispersion accidents may have done to human beings, researchers are dedicated to study effective and feasible source estimation methods in chemical plant clusters. In this paper, the safety monitoring of chemical production process is conducted via an unmanned aerial vehicle (UAV) monitoring system. Based on the observed data from this system, a source estimation method incorporating Bayesian inference and Particle Swarm Optimization (PSO) is proposed. Furthermore, the method is extended to discuss the source tracing algorithm using game theory in the UAV system. Finally, a practical case study is carried out to verify the feasibility and credibility of the proposed method. Results show that the method and system are helpful for safety monitoring and risk assessment in a chemical plant cluster.

1. Introduction

In chemical industry, plants tend to geographically cluster due to environmental and collaborative considerations [1]. Within such plant clusters, atmospheric by-products generated during the process of chemical production are often discharged to the surroundings without purification. Thus, technologies including air quality monitoring and source location estimation via a mobile inspection resource have been recently used to quickly locate the sources of contaminants and greatly mitigate the influence of dispersion.

The source estimation problem is the inverse of advection and dispersion, of which the methods can be basically divided into forward and backward modeling [2]. Most of them are based on Bayesian inference or optimization. Through Bayesian inference, the emission source can be estimated by calculating the posterior function. Some advanced filters (e.g., particle filter) and optimization methods (e.g., firefly optimization or particle swarm optimization) are also widely used in source estimation problems. Ma et al. [3] used the minimum relative entropy and Particle Optimization (MRE-PSO) method to locate and quantify the diffusion source with Gaussian model. However, these methods are only suitable for scenarios with a constant release rate.

Generally, the observed data of atmospheric pollutants is essential in source estimation. The traditional approaches which support such types of accurate source estimation mainly rely on the static monitoring stations. However, it can be prohibitively expensive to build an adequate number of monitoring stations, and the collection of invalid data often occurs when the limited station resources are located in the upwind of the emission source. As a result, a UAV monitoring system is thus developed to deal with this problem due to its flexibility in architecture and mobility [3].
The goal of this paper is to monitor and estimate the potential emission sources based on the UAV sensory system and source estimation methods. The UAV system is based on DJI M100 and the gas sensors is used for data collection. With the observed data, the source estimation method combining Bayesian inference and PSO is used to estimate the source parameters (i.e., the emission rate and the emission location). This work falls through providing practical patrolling routes for UAVs herein. Fortunately, according to Tambe et al. [4], game theory has the advantage of using a sound mathematical approach in modeling under limited resources deployment in a multiple stakeholders’ situation. Therefore, the method is extended to discuss the source tracing algorithm (e.g., bionic algorithms) with a UAV-system-based game-theory model. Finally, a practical case of chemical plant cluster was conducted.

2. UAV monitoring systems

Due to the fixed location, the measurements by static monitoring stations may be useless. Therefore, the UAV-based sensory system is developed to collect data. In the past, source estimation methods usually use concentration data from static monitoring stations. Thus, the accuracy of the estimation results largely relies on the distribution and the number of monitoring stations. Generally, insufficient monitoring stations and incorrect locations of monitoring stations may cause major errors, especially when the stations are not in the downwind direction of the contaminant source. The UAV monitoring system used in this paper overcomes the aforementioned demerits of static monitoring stations for its location information and flexible mobility, which significantly increases the probability of successfully finding the emission source. The monitoring system uses MATRICE 100 as a UAV platform, which can fly around 18 minutes at max. The maximum speed is 22 m/s, and the maximum flight distance is set at 10 km, which meets the requirement of inspecting a typical chemical cluster. The system contains gas sensors, GPS module, serial-USB converter, LTE transmitter, network connection module and a microcomputer. Moreover, the microcomputer (Raspberry Pi 2b) is used for receiving and sending measurements. In terms of data transmission, the aircraft sends measurements to a cloud database via an LTE transmitter.

In order to obtain high-quality data, the flight route is determined by the following basic rules. At the beginning, the aircraft moves in a circuit around the experimental area. When a peak appears in the measurement line (which means that the aircraft has just moved through the contaminant plume), the aircraft moves back and forth to sample the concentration data once again. After turning around several times, sufficient high-quality data have been obtained and the aircraft resumes its path along the original route.

3. Methods

3.1 Bayesian inference model

This section will explain how to use the measurements \( d = \{d_i\}_{i=1}^n \) from the UAV monitoring system to estimate the source parameters (the release location \( l \) and the release rate \( q(t) \)) will be explained. The dataset \( d \) is collected by the UAV system at location set \( z \) in wind field \( W \). We assume that the emission source (source parameter \( \theta = \{l, q(t)\} \)) starts release at time \( t_{\text{start}} \) and ends at time \( t_{\text{end}} \). Thus, the theoretical concentration value \( c_i(t) \) at time \( t \) and location \( z \) can be computed through a dispersion model \( c_i(t) = f(t, z, l, q, t_{\text{start}}, t_{\text{end}}) \). In this paper, Gaussian multi-puff model is selected to simulate the dispersion process of gaseous pollutants. In this model, the function \( f \) is used to calculate the concentration value of plume wherein the release rate and the wind are variants. Further, the \( i^{th} \) record of measurements contains information about location of UAV \( z_i \), time \( t_i \) and the value of observed concentration \( c_i(\omega_i = \{z_i, t_i, c_i \mid z_i \in z\}) \). As a result, the following formula can be obtained:
\[ c_i \approx c_i'(t_j) = f(t_j, z_i, \theta) + e_j \]
\[ \approx \sum_{j=1}^{n} q_j \cdot f(t_j, z_j, l, 1, t_{\text{start}}) + (j-1) \cdot \delta = \sum_{j=1}^{n} q_j \cdot f_j. \]

Among which, the measurement error \( e = \{e_j\} \) obeys the condition \( e_j \sim N(0, \sigma^2) \); \( q_j \) denotes the release rate of the \( j^{th} \) puff; \( n \) is the total number of puff; and \( \delta \) is the interval between each puff.

For the dispersion model \( c_i(t) = f(t, z, l, q, t_{\text{start}}, t_{\text{end}}) \), it is impossible to obtain analytic solution through inverse derivation because it is a nonlinear equation. Fortunately, we can utilize maximum likelihood estimation (MLE) method to estimate the release rate of the puff. According to the maximum likelihood estimation (MLE) method, we assume the release rate of each puff satisfies.

\[ p(\theta | d) \propto p(d | \theta) \cdot p(\theta), \]

where \( p(\theta | d) \) is posterior probability density function, \( p(\theta) \) is the prior function and \( p(d | \theta) \) denotes the likelihood function. Moreover, the likelihood function can be expressed as follows:

\[ p(d | \theta) \propto \exp \left\{ -\frac{1}{2\sigma^2} \sum_i [f(t_i, z_i, \theta) - c_i]^2 \right\}. \]

The key of computing posterior PDF is to determine prior PDF and likelihood function. The prior PDF is usually obtained from historical data or empirical information. Though there is little information about the diffusion source in this paper, we can still use a uniform distribution to denote the prior PDF.

As for the likelihood function, since the release rate is hard to estimate accurately, it may be feasible to use the maximum likelihood estimation of \( \theta \) (\( \theta = \{l\} \)) to substitute \( \theta \) and estimate \( p(\theta | d) \) instead of \( p(\theta | d) \). According to the maximum likelihood estimation (MLE) method, we assume the release rate \( q_m(t) \) that maximizes the likelihood function in formula (3) as actual release rate. In previous research, we utilize ridge regression method to estimate the release rate. As a result, location \( l \) is the only parameter that needs to be estimated here. Then we use PSO to find the optimal location with maximum posterior probability.

### 3.2 PSO algorithm

The essence of PSO is to give random solutions to a set of particles initially and find optimal solution through iteratively updating location and velocity of particles. The concrete process is illustrated as follows: (1) first, the positions \( x_i \) of each particle are initialized uniformly; (2) then, assign the best known position \( x_i^p \) of a particle as its current position \( x_i^0 \); (3) If the posterior PDF of \( x_i^p \) is greater than that of the best known position \( x_i \), that is, the inequality \( p(x_i^p | d) > p(x_i | d) \) satisfies, the best known position \( x_i \) will be updated; (4) randomly initialize the velocity of each particle; (5) keep the particle moving until the number of iteration reaches the given value. The process is shown as below,

\[ v_i^{(t+1)} = w \cdot v_i^{(t)} + c_1 \cdot r_1 \cdot (x_i^p - x_i^{(t)}) + c_2 \cdot r_2 \cdot (x_g - x_i^{(t)}) \]
\[ x_i^{(t+1)} = x_i^{(t)} + v_i^{(t)}, \]

where \( v_i^{(t)} \) denotes velocity of the \( i^{th} \) particle at \( t \) step; denotes location of the \( i^{th} \) particle at \( t \) step; \( r_1 \) and \( r_2 \) are random number obeying uniform distribution \( U(0,1) \); parameter \( c_1 \) and \( c_2 \) are accelerate ratio and they are set at 2 here; parameter \( w \) is named as momentum term and is set at \( 2/t \).

At each step, the best-known position of each particle \( x_i^p \) would be updated if the condition \( p(x_i^{(t+1)} | d) > p(x_i^{(t)} | d) \) satisfies. Then, if the inequality \( p(x_i^p | d) > p(x_g | d) \) satisfies at each step, the best-known position \( x_g \) will be updated. When the iteration ends, the final \( x_g \) will be the best estimated location of emission source.
4. **Source tracing algorithm using game-theory**

The use of UAV monitoring system in aforementioned sections can also be considered as resource monitoring with mobility. However, the ability of the UAV monitoring system and the information of the measurements are not fully utilized. Therefore, we add fluid flow sensors to the UAV system and carry out study in plume-tracing algorithm in a 3D framework.

In this framework, the search strategy of UAVs follows three stages: plume searching, plume tracing and plume source location. However, most recent studies on plume-tracing algorithm neglected the prior background information. Meanwhile, they used to set the mobile vehicles in downwind direction of the source. For these reasons, we believed that there was not solid proof of the current plume tracing algorithms having the ability to locate the emission source in complicated environments or under different initial search positions by these experiments.

![Figure 1](image-url)

**Figure 1.** The illustrative tracing trajectory of the UAV.

Schedule patrolling (i.e., a traveling act of mobile resource at different locations and intervals) is one of the applications of game theory in the security domain \[7\], and it is also introduced in some other domains. Using game theory, the background information of the research area can be modeled into a combined algorithm (the plume-tracing algorithm and the game-theory algorithm). In this way, a robust algorithm can be proposed to fit in with different complicated environments and different initial search positions of UAVs. Figure 1 shows an illustrative tracing trajectory (i.e., the yellow line) of the UAV.

5. **Practical case study**

To verify and validate the feasibility of the UAV-based monitoring system and the source estimation method, a practical case study of a chemical plant cluster in Shanghai was carried out. The research area is shown in figure 2 and the yellow circles denote potential SO\(_2\) emission spots. Information like coordinates of the potential emission sources is listed in table 1.

| No. | X      | Y      | Height | Explanation                                    |
|-----|--------|--------|--------|-----------------------------------------------|
| 1   | -132.575 | -1317.63 | 50     | Waste incinerator for acrylonitrile (AN)       |
| 2   | -302.901 | -1483.42 | 68     | Chimney of sulfuric acid recovery (SAR) system |
| 3   | 267.1415 | 0.359916 | 27     | Furnace No.1                                  |
| 4   | 861.3643 | 147.0462 | 27     | Furnace No.2                                  |
| 5   | 1532.017 | -142.542 | 30     | Hazardous waste incinerator                    |

The field experiment was conducted at 11 a.m. local time in 23\(^{rd}\) July 2017. Based on the field scene, the UAV flight path is represented as the red line in figure 2 and the concentration of SO\(_2\) along the flight path is shown in figure 3. The flight process inspected a higher concentration of SO\(_2\) in the south-east section of the research area, when the emission spot of SAR system was found working at the same time. This information was used as empirical estimation.
Based on the SO$_2$ concentration data collected from the UAV sensory system, the source location was identified by PSO algorithm. Figure 4 exhibits the distribution of particles in step 10 and 15 with the observed concentration data along trajectory. The source location would be estimated by computing the weighted average sum of particles, which was (-305.6, -1445.4). Based on empirical estimation and real locations of potential emission spots, the estimated location was further confirmed as the SAR system.

6. Conclusions
This paper focuses on safety monitoring and accurate estimation of emission sources in one chemical plant cluster. To tackle these problems, this paper introduced a UAV monitoring system, an estimation method as well as an improved tracing algorithm, and implement them into a practical case. Results of the case study imply that the proposed system and method are able to estimate the source location accurately. In the future, more experiments will be conducted to verify the improved UAV-monitoring-system-based plume-tracing algorithm in more complicated environments.

7. References
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