Simulation implementation of air pollution traceability algorithm based on unmanned aerial vehicle

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1. Introduction

With the rapid development of industrialization in China, the problem of air pollution is becoming more and more serious. In recent years, haze weather frequently occurs in some densely populated cities and industrial areas, and the bad air environment seriously affects people's daily life. When sudden air pollution accidents occur, if the environmental protection department cannot quickly trace the air pollution sources and prevent the pollution accidents from worsening, it will cause serious harm to the ecological environment and people's health [1].

At present, the research of air pollution traceability algorithm is mainly divided into static traceability algorithm and active olfactory algorithm [2]. The static traceability algorithm mainly monitors pollutant data in real time by ground monitoring stations, and estimates the location of pollution sources by means of cross location or model calculation [3]. However, due to the influence of the number and distribution of ground monitoring stations, the ground monitoring stations do not have access to high-quality air pollution data, and the results obtained by static tracing algorithm have significant uncertainties [4]. The active olfactory algorithm takes the ground mobile robot as the monitoring platform, installs the gas monitoring sensor on the robot, and tracks the pollution sources through the set search strategy [5]. However, in practical application, the ground mobile robot is affected by the complex ground environment, and its search scope is small and limited to the laboratory stage [6].

Unmanned aerial vehicle (UAV) has high mobility and rapid response ability. As a mobile monitoring platform, UAV can realize the monitoring and tracking of air pollution source in a large area [7]. Aiming at the problem of air pollution traceability, this paper combines the existing UAV...
technology and hill climb algorithm to trace the air pollution sources accurately and quickly. A gas sensor is added to the outside of the UAV to collect information on the concentration of pollutants in the current environment, and the concentration parameters are transferred to the drone autopilot. The coordinates of the next point are obtained through the processing of hill climb algorithm imported into the drone autopilot, thus approaching the pollution source gradually.

2. Simulation

2.1. Hill climb algorithm

The algorithm is a local search algorithm [8], which moves continuously in the direction of value increase, so as to find the best way to solve the problem. The algorithm terminates when the value reaches a peak or when there is no higher value in the neighborhood. When the algorithm satisfies the optimization condition, the position will be updated according to formula (1).

\[ x_i(t+1) = x_i(t) + \frac{\text{rands}(1,2)}{\text{eps} + \text{norm} \left( \text{rands}(1,2) \right)} \times \text{step} \]  

In the formula, \( t \) is the current number of iterations, \( x_i(t) \) is the coordinates of the UAV in iteration \( t \), \( x_i(t+1) \) is the coordinates of the UAV in iteration \( t+1 \), step is the distance the UAV moves each time, \( \text{rands}(1,2) \) is a random matrix with values between 0 and 1.

Framework of hill climb algorithm:

1. Set the maximum number of iterations \( \text{MAX}_\text{GEN} \), number of explorations \( \text{N} \) and step;
2. While \( t<\text{MAX}_\text{GEN} \);
3. For \( i=1 \) to \( \text{N} \);
4. If \( f(x)<f(x_i) \);
5. Update the position according to formula (1);
6. \( t++ \);
7. end if;
8. end for;
9. end While;

2.2. Construction of air pollution concentration field

The diffusion data of air pollutants is not easy to obtain, and the field test cost is high, but the diffusion scene of air pollutants can be accurately simulated by MATLAB. Based on the gaussian plume model and the two-dimensional k-ε model, the gaussian and turbulent concentration fields are constructed in MATLAB.

Gaussian plume model formula [9]:

\[ C(x, y, z, H) = \frac{Q}{2\pi u \sigma_y \sigma_z} \exp \left( -\frac{y^2}{\sigma_y^2} \right) \times \left[ \exp \left( -\frac{(z-H)^2}{2 \sigma_z^2} \right) + \exp \left( -\frac{(z+H)^2}{2 \sigma_z^2} \right) \right] \]  

In the formula, \( C(x, y, z, H) \) is the concentration value of each coordinate point in three-dimensional space, kg/m³; \( \sigma_y \) is the transverse diffusion parameter, m; \( \sigma_z \) is the lead diffusion parameter, m; \( H \) is the effective height of the pollution source, m; \( Q \) is the leakage rate of pollutants, kg/s; \( u \) is the average wind speed in horizontal direction, m/s.

The length and width of the simulation environment are set to 150m and 80m, the coordinate of the pollution source is \( (20,0) \), the leakage rate of pollutants \( Q \) is 0.002kg/s, the effective height of the pollution source \( H \) is 0.3m, the average wind speed \( u \) is 0.5m/s, the transverse diffusion parameter \( \sigma_y \) is 0.08x/(1+0.0001x)^0.5, the lead diffusion parameter \( \sigma_z \) is 0.06x/(1+0.0001x)^0.5. Figure 1 shows the 3D gaussian concentration field and Figure 2 shows the 2D gaussian concentration field.

The color indicator diagram on the right in Figure 1 represents the correlation between pollutant concentration and color. The concentration of pollutant ranges from 0kg/m³ to 1kg/m³, and the corresponding color changes from blue to yellow. Figure 2 and Figure 3 are the same as Figure 1.
Two-dimensional k-ε model [10]:

\[
\frac{\partial}{\partial y} \left[ \frac{1}{\rho} \left( \mu + \frac{\mu_t}{\sigma} \right) \frac{\partial \varepsilon}{\partial y} \right] + \frac{\varepsilon}{k} \left( C_{\varepsilon} G_k - C_{\varepsilon} \varepsilon \right) = 0
\]  

(3)

In the formula, \( \rho \) is the density of air, kg/m\(^3\); \( \mu \) is fluid molecular viscosity, Pa\cdot s; \( \mu_t \) is turbulent dynamic viscosity, Pa\cdot s; \( G_k \) is turbulent kinetic energy generation term; turbulence model constant, \( \sigma_{\varepsilon} = 1.3, C_{\varepsilon} = 1.44, C_{\varepsilon2} = 1.92 \).

The length and width of the simulation environment were set as 80m and 50m, the coordinate of the pollution source is (20,25), the pollutant emission speed is 4m/s, the wind speed is 0.2m/s, and the temperature was 300K. Figure 3 shows the turbulent concentration field.
2.3. Experimental design
We set up four experiments in the gaussian concentration field, the leakage rate of pollution in each group was 0.002kg/s, 0.004kg/s, 0.006kg/s and 0.008kg/s, respectively. The initial position coordinates of the UAV in each group of experiments are (50,-20), (60,30), (80,20), (100,0) and (130,-30). In the turbulent concentration field, the initial coordinate points of the UAV are set as (60,20), (50,30), (65,15), (50,35), (45,35), (70,30), (40,30), (55,35), (28,15) and (65,35).

Table 1. Simulation results in gaussian concentration field.

| Leakage rate of pollution (kg/s) | Starting point coordinates | End point coordinates | Location error(m) | Operation time(s) |
|----------------------------------|-----------------------------|-----------------------|-------------------|-------------------|
| 0.002                            | (50,-20)                    | (19.5971,-0.0155)     | 0.4032            | 0.936             |
|                                  | (60,30)                     | (19.6201,0.0202)      | 0.3805            | 1.029             |
|                                  | (80,20)                     | (19.5129,-0.1835)     | 0.5205            | 1.056             |
|                                  | (100,0)                     | (20.2790,-0.2771)     | 0.3932            | 0.868             |
|                                  | (130,-30)                   | (20.0944,0.5734)      | 0.5811            | 0.884             |
|                                  | (50,-20)                    | (20.0006,-0.2306)     | 0.2306            | 0.935             |
|                                  | (60,30)                     | (19.3874,-0.4370)     | 0.7525            | 1.060             |
| 0.004                            | (80,20)                     | (19.6618,0.1791)      | 0.3827            | 1.056             |
|                                  | (100,0)                     | (19.6574,-0.1888)     | 0.3911            | 1.129             |
|                                  | (130,-30)                   | (19.8777,0.2749)      | 0.3008            | 0.925             |
|                                  | (50,-20)                    | (19.8735,-0.5395)     | 0.5542            | 0.894             |
|                                  | (60,30)                     | (20.3250,-0.1413)     | 0.3544            | 1.023             |
| 0.006                            | (80,20)                     | (19.8861,0.0265)      | 0.1169            | 1.091             |
|                                  | (100,0)                     | (20.1042,-0.1318)     | 0.1680            | 1.078             |
|                                  | (130,-30)                   | (19.7192,0.3213)      | 0.4267            | 0.892             |
|                                  | (50,-20)                    | (19.5362,0.2753)      | 0.5393            | 1.102             |
|                                  | (60,30)                     | (19.7098,0.0679)      | 0.2980            | 1.145             |
| 0.008                            | (80,20)                     | (19.2393,-0.0613)     | 0.7632            | 1.069             |
|                                  | (100,0)                     | (19.9859,-0.0389)     | 0.0413            | 1.084             |
|                                  | (130,-30)                   | (20.2382,0.5735)      | 0.6210            | 0.863             |
3. Results and discussion

3.1. Simulation results in gaussian concentration field
The results of four groups of simulation experiments are shown in Table 1. Figure 4 and Figure 5 shows the 3D and 2D traceability path of the UAV when the pollutant leakage rate is 0.002kg/s and the starting coordinate is (130, -30).

![3D traceability path in gaussian concentration field](image1.png)

**Figure 4.** 3D traceability path in gaussian concentration field.

![2D traceability path in gaussian concentration field](image2.png)

**Figure 5.** 2D traceability path in gaussian concentration field.

3.2. Simulation results in turbulent concentration field
The results of 10 groups of simulation experiments are shown in Table 2: Figure 6 and Figure 7 show the traceability path of the UAV when the starting coordinates are (65, 15) and (50, 35).
Table 2. Simulation results in turbulent concentration field.

| Starting point coordinates | End point coordinates | Location error(m) | Operation time(s) |
|---------------------------|----------------------|-------------------|-----------------|
| (60,20)                   | (19.3701,25.0747)    | 0.6344            | 4.037           |
| (50,30)                   | (21.0146,24.2509)    | 1.2612            | 3.946           |
| (65,15)                   | (19.4090,25.5649)    | 0.8175            | 4.245           |
| (50,35)                   | (19.5704,24.4879)    | 0.6684            | 4.276           |
| (45,35)                   | (19.6500,25.1869)    | 0.3968            | 4.570           |
| (70,30)                   | (20.5213,25.0321)    | 0.5223            | 4.123           |
| (40,30)                   | (20.3502,24.1361)    | 0.9322            | 4.280           |
| (55,35)                   | (20.0385,25.5113)    | 0.5127            | 4.187           |
| (28,15)                   | (19.0825,25.1722)    | 0.9335            | 3.987           |
| (65,35)                   | (20.8412,25.4593)    | 0.9584            | 4.094           |

Figure 6. Traceability path in turbulent concentration field when the coordinates is (65, 15).

Figure 7. Traceability path in turbulent concentration field when the coordinates is (50, 35).

3.3. Discussion

According to the data in Table 1, the location error obtained from the 20 experiments in the Gaussian concentration field are all less than 1m, and the average location error is 0.41096m, less than 0.5m. According to the data in Table 2, the maximum value of location error in the 10 experiments is 1.2612m, and the minimum value is 0.3968m. Among them, the error of 9 groups of experiments was less than 1m, and the average location error was 0.76374m, less than 1m. It can be seen that the hill climbing algorithm can be more accurate in the search for air pollution sources.

4. Conclusions

Aiming at the precise location of air pollution sources, this paper proposes a hill climbing traceability algorithm. This algorithm innovatively combines the UAV and intelligent search algorithm to realize the monitoring and tracking of air pollution source in a large area. Pixhawk drone autopilot selected in this paper is an open source drone autopilot that researchers can modify by themselves. Therefore, we added the search mode in drone autopilot and wrote the code of hill climbing traceability algorithm. The added gas sensor on the outside of the UAV can collect the concentration information of air pollutants, and then control the UAV to approach the air pollution sources through the processing of hill climbing traceability algorithm. Gaussian concentration field and turbulent concentration field are built by MATLAB, and simulation experiments are conducted in these two concentration fields.
respectively. According to the simulation results, it is found that the average location error in both concentration fields is less than 1m, which proves that the hill climbing traceability algorithm has high accuracy and high efficiency.

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