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MPGA-Based Indoor Localization for Non Steady-State Gas Source

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Abstract

Traditional gas source localization algorithms are usually based on gas steady-state diffusion model which ignores the factor of the time, it is difficult to meet the practical application conditions. In order to solve this problem, we propose an effective gas source localization method based multiple population genetic algorithm(MPGA) to estimate the location of gas-leakage source via wireless sensor network. In this paper, we first build a gas unsteady-state diffusion model without wind based on the gas diffusion theory, and then we transfer the gas source location problem into a global optimization problem with the measured information of sensor nodes. Finally, we use MPGA to solve the optimization problem and obtain the location of the gas source. The simulation results show that the proposed method can quickly obtain the location of the gas source, and has the higher positioning accuracy as compared with tradition localization algorithms.

Keywords: *Gas source location, wireless sensor network, gas unsteady-state diffusion model, MPGA*

1. Introduction

Gas source localization (GSL) is an important and challenging task in environmental monitoring. Harmful gas leaks from unknown sites will cause the serious environment pollution, which is unexpected, critical, various and difficult to solve, and very different from other environmental incidents. The problem of source localization using sensor network was firstly formulated in the seminal work of Nehorai *et. al.,* [1]. Since then, wireless sensor networks (WSNs) have found their successful applications such as searching and positioning of toxic and hazardous gas leak source, dangerous environmental monitoring, detection and early warning of fire sources and other occasions in GSL, and it becomes an important research area [2-6].

Over the past decade, extensive studies focus on the location of gas-leakage source using WSNs. Nehorai and co-workers [7-9] proposed several methods for detection and localization of biochemical point sources, both static and moving, in the context of concentrated vs. distributed and batch vs. sequential processing. They modeled the dispersion of the contaminant in a rather simplistic manner using a diffusion mechanism and ignoring the turbulence. In 2005, Matthes *et. al.,* [10] proposed a two-step procedure where first the sets of points on which the source can be located is estimated for each sensor (based on the concentration measurements and the diffusion model), followed by the determination of the intersection of these sets of points. However, the gathering of concentration measurements at sink nodes was in conflict with the scheme of distributed models. In [11], Keats *et. al.,* solved the gas source localization problem for the case of transient release using the Markov chain Monte Carlo batch approach based on the adjoint diffusion model. Most of above GSL algorithms are based on gas steady-state diffusion model, because of ignoring the factor of the time, it is difficult to achieve the early warning and obtain rapid solution in practical applications. In this paper, we consider the

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time factor in the process of gas leakage and propose an estimation method of gas source location using multiple population genetic algorithm(MPGA) based on a gas unsteady-state diffusion model without wind. We first derive a gas unsteady-state diffusion model without wind based on the gas diffusion theory and build the gas concentration perception model of indoor environment for sensor nodes. Then the gas source location problem is transferred into a global optimization problem with the measured information of sensor nodes. We solve the optimization problem using the MPGA, and obtain the unknown parameters of the gas source. Since the logical shift cycle crossover operation is introduced to the algorithm which increases the diversity of individuals and improves the effectiveness of the algorithm.

The rest of this paper is organized as follows. In Section 2, we describe the diffusion model and measurement model. In Section 3, we present the proposed estimation method of the gas source location based on the MPGA. The performance of the proposed method is illustrated by the simulation experiments in Section 4. Conclusions are given in Section 5.

2. Problem Statement

We consider a WSN which consists of a data fusion center and sensor nodes $N_i, i \in [1,n]$, each sensor node evenly deployed within a square region in a windless indoor environment at location (x_j, y_j) , and there is only one gas leakage source which diffuses with constant velocity at an unknown location (x_s, y_s). Each sensor node can measure the gas concentration and communicate with the data fusion center. It is assumed that only when the gas concentration exceeds the threshold value T_h, the node can obtain the measurement of the gas concentration and transfer it to the data fusion center. Otherwise, the sensor node is scheduled to hibernate. All sensor nodes obtain the synchronization, and the gas concentration is measured synchronously in a period, $\forall k \in \{1,2,3...,T\}, T$ is total acquisition time.

2.1. Gas Unsteady-State Diffusion Model

It is assumed that the gas from the gas-leakage source is released to spread around with some diffusion coefficient. According to the Fick's law [12], we obtain:

$$\vec{f} = -k\nabla C \tag{1}$$

$$\frac{\partial C}{\partial t} = -\nabla \bullet \vec{f} \tag{2}$$

where $C = C(x,y,z;t)$ is the gas concentration at the location $l = (x,y,z)$ and time k , in units of $\mathrm{mg/m^3}$, $\vec{f} = \vec{f}(x,y,z;t)$ is the diffusion flux , in units of $m\mathrm{g/m^3}$, k is the diffusion coefficient , in units of $\mathrm{m^2/s}$. Then the diffusion equation can be written:

$$\frac{\partial C}{\partial t} = k\nabla^2 C \tag{3}$$

where $\nabla^2 C = \frac{\partial^2 C}{\partial^2 x} + \frac{\partial^2 C}{\partial^2 y} + \frac{\partial^2 C}{\partial^2 z}$.

It is assumed that the location of gas source is $l_s = (x_s, y_s, z_s)$, releasing gas at constant rate of $Q \ \ mg/s$, starting at time t_0. Then the gas concentration at location $l = (x,y,z)$ can be obtained:

$$C(x,y,z;t)=\frac{Q}{4\pi k\,|l-l_s|}erfc\left(\frac{|l-l_s|}{2\sqrt{k(t-t_0)}}\right) \tag{4}$$

where $erfc(x)=\left(2/\sqrt{\pi}\right)\int_x^{\infty}e^{-y^2}\mathrm{dy}$ is the complementary error function, $|l-l_s|$ is the Euclidean distance from the location l to the location l_s, when only considering the level of gas concentration, that is $z=0$. Then the Equation (4) can be converted to the following equation:

$$C(x,y;t)=\frac{Q}{4\pi k\,|l-l_s|}erfc\left(\frac{|l-l_s|}{2\sqrt{k\Delta t}}\right) \tag{5}$$

where $|l-l_s|=\sqrt{(x-x_s)^2+(y-y_s)^2}$, $\Delta t=t-t_0$, the other parameters is defined in the Equation (4).

2.2. Sensor Measurement Model

In actual measurement process, noise superposition of the measurements is inevitable. Therefore, the concentration r_j^k which the gas source obtained from the *jth* sensor node at time t_k based on the diffusion model discussed previous can be expressed by Equation (6).

$$r_j^k=c_j^k+v_j=\frac{Q}{4\pi k\,|l_j-l_s|}erfc\left(\frac{|l_j-l_s|}{2\sqrt{k(t_k-t_0)}}\right)+v_j \tag{6}$$

where $|l_j-l_s|=\sqrt{(x_j-x_s)^2+(y_j-y_s)^2}$ is the distance of the *jth* sensor node to the gas source location (x_s,y_s), t_0 is the time while gas source begin to leak, t_k is the sampling time, Q is the strength of gas leakage, and $v_j\sim N(u_j,\sigma_j^2)$ is the node measurement noise independent of time and space.

3. Gas Source Localization Method Based on MPGA

3.1. Optimization Objective Function

Assuming that the measurements of each sensor node transmission are independent of each other, the joint probability density function is written as

$$\begin{aligned} f(R^k\,|\,\theta)&=\prod_{j=1}^{n}p(r_j^k\,|\,\theta)\\ &=(2\pi)^{-\frac{n}{2}}\exp\left\{-\frac{1}{2}(R^k-C^k-u)^T\Sigma^{-1}(R^k-C^k-u)\right\}\end{aligned} \tag{7}$$

where $\theta=[\mathrm{x}_s,y_s,Q,\Delta t]$ is unknown parameters of gas source, $R^k=[r_1^k\ r_2^k...r_j^k...r_N^k]^T$, here r_j^k is the *jth* sensor measurements at t_k time, $C^k=[c_1^k\ c_2^k...c_j^k...c_N^k]^T$, here c_j^k is the theoretical value of the *jth* sensor measurements, $u=[u_1\ u_2\ u_\mathrm{j}...u_N]^T$, here u_j is the noise mean value of the *jth* sensor measurement, and $\Sigma=diag[\sigma_1^2,\sigma_2^2,\cdots,\sigma_j^2,\cdots,\sigma_n^2]$ is the diagonal matrix, here $j=\{1,2...,n\}$, σ_j^2 is the variance of the noise of *jth* sensor measurement.

Taking log of the joint probability Function (7), we can obtain the following likelihood function:

$$\begin{aligned} L(\theta) &= \ln f(R^k \mid \theta) \\ &= -\frac{n}{2}\ln(2\pi) - \sum_{j=1}^{n} -\frac{1}{2\sigma_j^2}(r_j^k - c_j^k - u_j)^2 \end{aligned} \tag{8}$$

If the number of sensor nodes and measurement samples tends to infinity, the estimated parameter θ is consistent estimation of unknown parameters quantity θ [13]. The maximum problem is equivalent to the following minimization:

$$\begin{aligned} \min J(\theta) &= \sum_{j=1}^{n} \frac{1}{\sigma_j^2}(r_j^k - c_j^k - u_j)^2 \\ &= \sum_{j=1}^{n} \frac{1}{\sigma_j^2}\left(r_j^k - \frac{Q}{4\pi k \mid l_j - l_s \mid} erfc\left(\frac{\mid l_j - l_s \mid}{2\sqrt{k(t_k - t_0)}}\right) - u_j\right)^2 \end{aligned} \tag{9}$$

There is the same Gaussian noise in all the sensor nodes, that is $u_j = 0$, and $\sigma_j^2 = \sigma^2$. Then the Formula (9) is equal to:

$$\begin{aligned} \min J(\theta) &= \sum_{j=1}^{n} (r_j^k - c_j^k)^2 \\ &= \sum_{j=1}^{n} \left(r_j^k - \frac{Q}{4\pi k \mid l_j - l_s \mid} erfc\left(\frac{\mid l_j - l_s \mid}{2\sqrt{k(t_k - t_0)}}\right)\right)^2 \end{aligned} \tag{10}$$

We impose some constraints in the practical applications and obtain the following optimization problem:

$$\begin{aligned} \min J(\theta) &= \sum_{j=1}^{n} (r_j^k - c_j^k)^2 \\ &= \sum_{j=1}^{n} \left(r_j^k - \frac{Q}{4\pi k \mid l_j - l_s \mid} erfc\left(\frac{\mid l_j - l_s \mid}{2\sqrt{k(t_k - t_0)}}\right)\right)^2 \\ & s.t.\ x_{\min} < x_s < x_{\max} \\ & \quad y_{\min} < y_s < y_{\max} \\ & \quad 0 < Q < Q_{\max} \\ & \quad 0 < \Delta t \end{aligned} \tag{11}$$

Taking the partial derivative with respect to each component of the unknown parameters θ, and taking partial derivative equal to 0, we can get:

$$\sum_{j=1}^{n} (r_j^k - c_j^k)\frac{\partial c_j^k}{\partial \theta_m}\Big|_{\theta=\theta} = 0 \tag{12}$$

where θ_m is the mth element of θ, $m = \{1,2,3,4\}$.

$$\frac{\partial c_j^k}{\partial \theta_m} = \frac{Q[l_j(m) - l_s(m)]}{4\pi k \mid l_j - l_s \mid^2}\left[\frac{erfc\left(\frac{\mid l_j - l_s \mid}{2\sqrt{k(t_k - t_0)}}\right)}{\mid l_j - l_s \mid} + \frac{\exp\left\{-\frac{\mid l_j - l_s \mid^2}{2\sqrt{k(t_k - t_0)}}\right\}}{\sqrt{\pi k(t_k - t_0)}}\right] \tag{13}$$

3.2. Steps for Gas Source Localization Method Based on MPGA

The basic genetic algorithm easily captures the local optimal solution and has a low speed rate. However, MPGA can obtain the global optimal solution and has a high speed rate, and can avoid the deficiency. The flow chart of MPGA is shown as Figure 1.

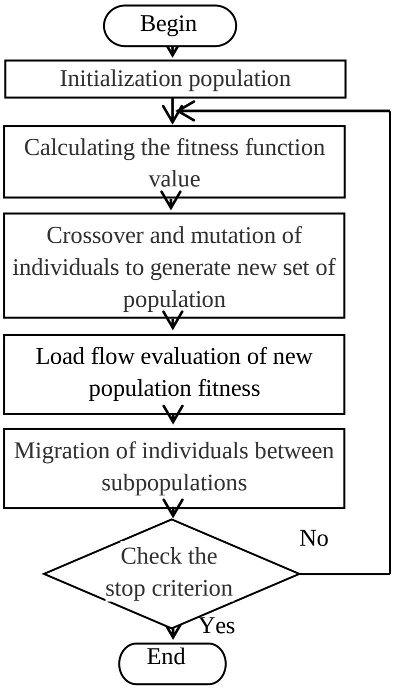

Figure 1. Flow Chart of MPGA

The steps of gas source localization method based on MPGA can be described as follows:

Step 1: collect the measurement data

When the gas concentration is greater than the threshold, the sensor node is activated, and the collected data is uploaded to the data center.

Step 2: According to node measurement data from multiple sensor nodes, Data center can locate the gas source based on MPGA. It is as follows:

(a) The objective function is built based on gas diffusion model by selecting the maximum measurement value. We can determine the search scope of unknown parameters $[x_s, y_s, Q, \Delta t]$.

(b) Initialize parameters of various populations. The population size is M, the maximum generation of optimal individual preservation is $MAXgen$, the maximum evolution generation is N. Meanwhile, each population will be endowed with different control parameters.

(c) Set different crossover probability (Pc) and mutation probability (Pm) with each population, which can be crossover and mutation independently.

(d) Contact immigration between various populations with every fixed generation ($immigrant\_gen$). Exchange information between populations using immigrant operator, and select optimal parameters $[x_s, y_s, Q, \Delta t]$ of each generation by artificial selection operator and save it to optimal individual of the essence in population.

(e) Check the stop criterion. Whether the optimal individual generations of the essence in population is reached $MAXgen$ or the population is reached the maximum iterations of N, it will stop. Otherwise, go to Step 3, else re go to Step (c).

Step 3: Output the parameter value

If the optimization process is over, the best individual in the essence of population is the optimal solution which consists of the location of gas leakage source, the gas source strength and the time.

4. Simulation Results

For all subsequent experiments, we assume that the monitoring region is $50m \times 50m$ in a windless warehouse where evenly distributed 64 sensor nodes arranged in 8×8. The location of each node is known as (x_j, y_j), and the coordinate of gas source is assumed of $(8m, 11m)$. It is assumed that gas source began to leak at $t = 0$. Figure 2, shows that the location of sensor node and gas leakage source. Here, '○' represents sensor nodes, '△' represents a hypothetical leak gas source.

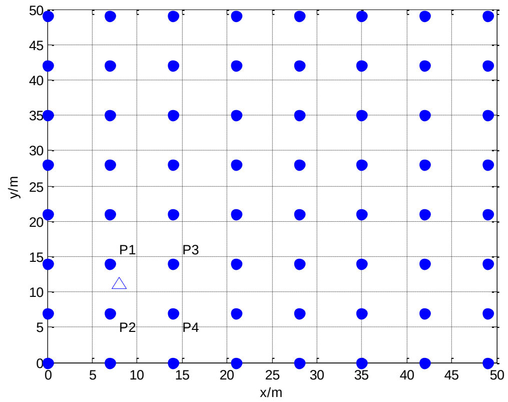

Figure 2. Localization Scenario

The specific parameters of simulation experiment are assumed as shown in the following table

Table 1. Experimental Parameters

The Parameters	Select value
Measurement of noise	$\omega \sim N(0, 0.001)$
Gas source strength	Q=1000mg/s
Sensor threshold	ε=5mg/s
Diffusion coefficient	k=0.08m^2/s
Population size	M=10
Individuals in each population	n=20
Maximum iterations	N=400
Maximum generation of optimal individual preservation	$MAXgen$=10
Maximum crossover probability	$Pc\_\max = 0.9$
Minimum crossover probability	$Pc\_\min = 0.7$
Maximum mutation probability	$Pm\_\max = 0.07$
Minimum mutation probability	$Pm\_\min = 0.001$

4.1. Analysis of Convergence and Error for this Method

We can verify performance of the proposed method under the conditions of the unknown strength, the location and the leakage time of the gas source in MATLAB platform simulation environment. In order to describe the impact of various factors on location results clearly and evaluate the error of location, the root mean square error (RMSE) is considered. The RMSE is a key performance indicator to evaluate the accuracy of the localization method

$$RMSE = \sqrt{\frac{1}{m}\sum_{t=1}^{m}((x_s^{\,t} - x_s)^2 + (x_s^{\,t} - y_s)^2)} \tag{14}$$

where m is the number of Mote Carlo simulation experiment, (x_s^t, y_s^t) is the predicted gas source location information obtained from the t times simulation results, and (x_s, y_s) is the real location of gas leakage source.

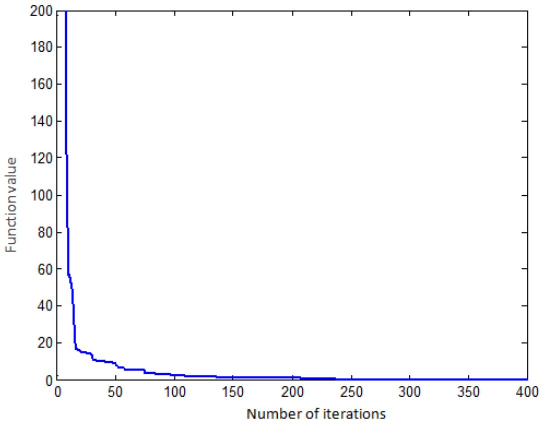

Figure 3. Convergence Result of Function Value

Figure 3, shows the convergence of function value, versus the number of iterations. From the figure the optimal value of function is gradually close to the theoretical optimal value 0.

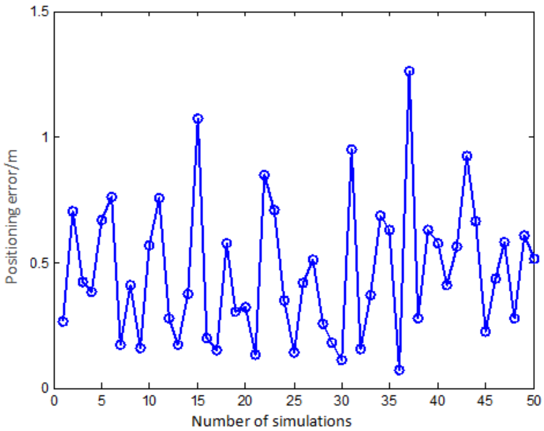

Figure 4. Location Errors

Figure 4, shows the positioning error results of simulation 50 times. As shown from the figure, the average localization error is about 0.7m.

In order to eliminate the difference caused by this process on the performance of the algorithm, the statistical analysis of 50 simulation results was as shown in Table 2.

Table 2. Simulation Experiment Results

The parameters	The real value	The maximum deviation value	RMSE	The average operation time
Xs	8m	1.77m	0.67 m	17.313s
Ys	11m	1.25m		
Q	$1000mg/s$	$283.1mg/s$		
Δt	40s	14.7s		

Table 2, shows that the unknown parameters of the gas source can be estimated exactly by our proposed method. From the simulation results, we can see that the average running time of the proposed method in this paper is small.

4.2. Performance Comparison between MPGA and Genetic Algorithm (GA)

In order to verify the performance of MPGA, we compare the performance of MPGA and GA. The total number of GA is 200 which are same as the MPGA, and other simulation parameters set as shown in Table 1.

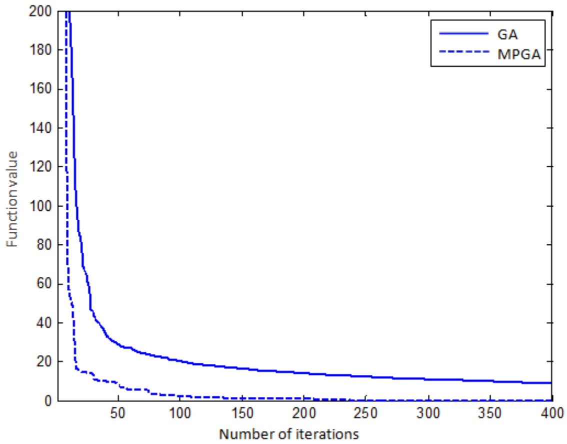

Figure 5. Convergence Comparison of GA and MPGA

Figure 5, shows the convergence of MPGA and GA. From the Figure 5, we can see that the global convergence and stability of MPGA are better than those of GA. Therefore， we use MPGA to solve complex optimization problems involved in the function of this paper.

4.3. Comparison of Gas Localization Based on MPGA and Centroid Algorithm (CA)

Under the same conditions of noise, we compare the positioning errors of gas source localization based on MPGA and CA. In the experiment, we select four sensor nodes which the measured concentration value is the maximum to participate location and carries on 50 times of simulation experiment, and other simulation parameters as shown in Table 1.

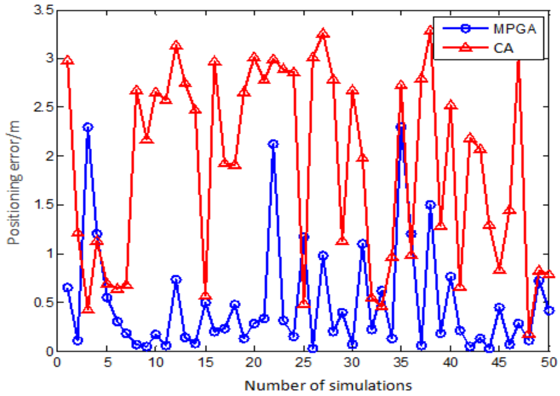

Figure 6. Comparison for Location Errors of two algorithms

Figure 6, shows the positioning error curve of two algorithms. From the Figure 6, we can see that the position error of the gas source localization based on MPGA is significantly less than the error of CA.

4.3. Influence of Environmental Noise

Noise in practical application is inevitable, so we analyze the impact of environmental noise to this algorithm. For each scenario, 50 simulation runs are used to obtain each simulation point. The noise is assumed that $\omega_1 \sim N(0,0.01)$, $\omega_2 \sim N(0,0.1)$, $\omega_3 \sim N(0,0.5)$, $\omega_4 \sim N(0,1)$, $\omega_5 \sim N(0,5)$, $\omega_6 \sim N(0,10)$, and other simulation parameters as shown in Table 1.

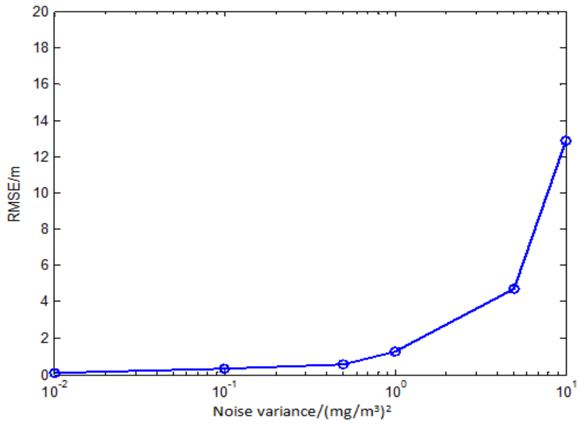

Figure 7. Impact of Environmental Noise on the Performance of Algorithm

Figure 7, shows the positioning error curve with the noise intensity changed. From Figure 7, the increasing of the measurement noise, the positioning accuracy decrease. In the same noise, the larger the value of node measurements is, the higher signal-to-noise ratio is. Therefore, we use as far as possible the nodes with large measurement value to participate location.

5. Conclusions

In this paper, we investigate the gas source localization method using wireless sensor network. Most gas source localization algorithms are based on stable-state gas diffusion model which ignores the factor of the time, it is difficult to meet the practical application conditions. Account for this problem we propose a novel gas source localization method based on MPGA. The unsteady-state gas diffusion model without wind based on the gas diffusion theory and gas concentration perception model of indoor environment for sensor nodes are first built, and the gas source location problem is transferred into a global optimization problem with the measured information of sensor nodes, we use MPGA to solve the global optimization problem.

The simulation experiments results show that the proposed method can effectively estimate the unknown parameters of the gas source, and the convergence speed of this algorithm is fast, the average running time is short. As compared with the traditional algorithm the proposed method enjoys a significantly improved performance.

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