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Abstract: In this paper, multiple fire source localization in building environments is approached based on energy distribution of fire by sensor array. A maximum likely-hood estimation method with genetic algorithm is proposed, that describes energy distribution of fire source as Gaussian distribution, and thus derives an energy multi-peak function model and an observation model of sensor nodes. The method facilitates the multiple fire source localization as a global optimization problem, which is explored by genetic algorithm with a global optimal solution. Finally, the simulation result shows the effectiveness of the proposed fire source localization method by the comparison of the traditional EM algorithm and genetic algorithm.

Key Words: fire source localization; global optimization

The research of the physical characteristics of fire source, fire point modeling, trend forecasting of building fire has

1 Introduction

With the development of economy and urbanization, the quantity of huge buildings with complex structure and function is increasing rapidly. This brings a stricter requirement for rescuing system in sudden disasters such as fire and blaster. Although the automation and fire alarm systems based on bus protocol have become an essential security device in modern buildings, it has been exposed many problems in the adversity. For example, the limited number of detectors prone to false information, misstatements and omissions. It can not accurately locate fire ignition point and make real-time prediction of disaster trends. In particular, since highly dependent on infrastructure, the traditional wired disaster relief system of building in the event of a disaster is very fragile, vulnerable to destruction of the line or power failure. Duo to these deficiencies, rescuers is difficult to accurately eligible site information, seriously hampered the rescue efficiency. While the most research for the tradition system at home and abroad is limited to local improvement system, it failed to resolve the fundamental problems at the system level.

As wireless sensor networks (WSN) have a dynamic selforganization, high reliability and data-centric features and take advantage of large-scale distribution node collaboration, it becomes the current hot topic of the research of building safety surveillance.

In previous studies, the spreading trend of fire is considered to be unpredictable, so monitoring and locating fire is transformed as sensor networks coverage optimization problems by densely deployed sensor nodes. FP Quintao et al. [1] proposed integer programming model on WSN node coverage, which is solved by genetic algorithms. Andrew Howard et al. [2] proposed the deployment configuration methods for mobile sensor network technology in unknown environment based on electromagnetic field. Huang and Tseng et al [3] proposed a polynomial time algorithm with a number of sensors, in which the coverage problem is abstractly expressed as a decision problem and the configuration of the k -th sensor coverage problem is verified.

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get a great of concern of the scientific community, but few achievements of fire model parameter estimation are appeared to now. Richard C.Rothermel [4] had proposed the methods to predict the spreading trend, spreading area as well as behavior of fire. M.F.Mysorewal and D.o.Popa[5] had proposed a fire elliptical Gaussian model and studied the problem of mobile robot adaptive sampling points for the fire, but the best estimate is get with single peak model of fire, under the condition of model parameters are known. However, we consider fire area of buildings as the Gaussian spatial multimodal model which is composed of a plurality of peaks, and derive multi-fire location method that can provide effective set information support to disaster relief with assistance of WSN.

2 Positioning principle

We suppose sensor nodes are random evenly distributed to detect environment of fire and acquits parameter of the building fire. When the fire spreads from a fire point, local temperature is perceived by sensor node at the corresponding location. With the fire spreads, more and more sensor nodes sense the temperature signal generated by the combustion flame. Therefore, by analysis of monitored temperature changes, we can locate source of ignition timely and know the boundaries of the fire by wireless sensor network node, determine the local situation of the fire, whether the fire is approaching, or began to burn, or complete combustion. Temperature changes of fire ambient approximately reflect the fire spreading situation. Hence, it is reasonable to consider the ignition point as a temperature source. Compared to the localization algorithm based on distance, localization algorithm based on energy is more suitable for ignition point. The basic steps for fire source localization as follows:

Almost all the flames spread outward from a fire source in

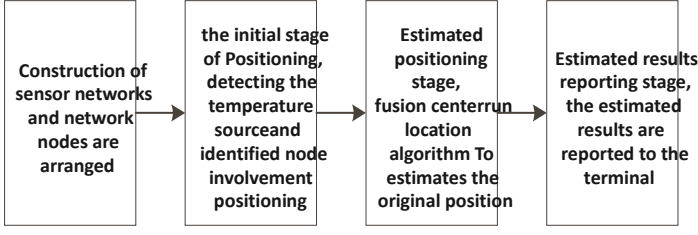


Fig. 1: The basic steps for fire source localization

the building fires. A compartment acts as the fire monitored area to facilitate the modeling, in which N sensor nodes and a fire source (high energy point) are randomly deployed on the ceiling. Each sensor node works with activation mechanism, so as to realize low power consumption, high realtime networked monitoring. Since the distance from the fire source to each sensor node is different, the data values of energy detected by each node are change in gradient type.

The energy signal point received in the time-interval n is expressed as:

$$x_i(n) = s_i(n) + v_i(n), i = 1, 2, \dots, N, \quad (1)$$

where

$$s_i(n) = \gamma_i \frac{a(n - t_i)}{\|\rho(n - t_i) - r_i\|} \quad (2)$$

is the energy density receive from the fire source by nodes, $v_i(n)$ is background Gauss white noise (AWGN). $\gamma_i(n)$ is the gain factor of i -node, r_i is the position vector of the i -node, $a(n - t_i)$ is the measured energy intensity that spreads one meter away from the source of fire (temperature sources), ρ is position vector of the source of fire (temperature source).

Here, $s_i(n)$ and $v_i(n)$ are assumed uncorrelated, that is $E\{s_i(n)v_i(n)\} = E\{v_i(n)s_i(n)\} = 0$. The energy intensity of temperature received by i -node is expressed as:

$$E[s_i^2(n)] = \gamma_i^2 \frac{E(a^2(n - t_i))}{\|\rho(n - t_i) - r_i\|^2} = g_i \frac{S(n - t_i)}{\|\rho(n - t_i) - r_i\|^2} \quad (3)$$

The average energy $y_i(t)$ in the time window $[t - T/2, t + T/2]$ can be divided into two parts, that is the node energy intensity and energy intensity noise, and $y_i(t)$ can be expressed as:

$$\begin{aligned} y_i(t) &= \frac{1}{f_s T} \sum_{n=(t-T/2)f_s}^{(t+T/2)f_s} x_i^2(n) \\ &= \frac{1}{f_s T} \sum_{n=(t-T/2)f_s}^{(t+T/2)f_s} s_i^2(n) + \frac{1}{f_s T} \sum_{n=(t-T/2)f_s}^{(t+T/2)f_s} v_i^2(n), \end{aligned}$$

where the sampling frequency is f_s , M is the sampling number of points in the sampling interval $T = M/f_s$.

For the propagation delay of received signal between the nodes is so small that can be ignored, the formula (4) can be simplified as:

$$y_i(t) = \mathbf{y}_{si}(t) + \varepsilon_i(t) = g_i \frac{S(t)}{d_i^2(t)} + \varepsilon_i(t) \quad (5)$$

where $d_i(t) = \|\rho(t) - r_i\|$ is the Euclidean distance, $v_i^2(n)$ follows χ^2 distributed and $E[v_i^2(n)] = \zeta_i^2$, variance is $2\zeta_i^4/M$. If M is large enough ($M \geq 30$), according to the central limit theorem $\varepsilon_i \sim N(\zeta_i^2, 2\zeta_i^4/M)$. For convenience, we define

$$\mu = \zeta_i^2, \quad \sigma_i^2 = 2\zeta_i^4/M. \quad (6)$$

3 Location model

Fire area is installed with sensor nodes, that is approximately a Gaussian spatial model to fire situation sampling.

Suppose the function of fire point is two-dimensional, composed by one or more Gaussian function. The mathematical expressions of each Gaussian function is

$$f^l(\mathbf{x}_i) = K^l * \exp\left(-\frac{1}{2}(\mathbf{x}_i - \mathbf{x}_0^l)^T \Sigma_l^{-1}(\mathbf{x}_i - \mathbf{x}_0^l)\right), \quad (7)$$

where \mathbf{x}_i is the position vector (x_i, y_i) of wireless sensor nodes, K^l is the intensity of peak function at fire center. \mathbf{x}_0^l is the vertex coordinates of ignition point. Σ_l is the variance (assumed to be a known quantity, which can be obtained based on experience). Multiple peaks function (assuming that the number of peaks is L) can be represented as:

$$f^{(L)}(\mathbf{x}_i) = \sum_{l=1}^L f^l(\mathbf{x}_i) \quad (8)$$

Based on the peak function, observation model for sampling of i -node can be expressed as:

$$Z_i = f^{(L)}(\mathbf{x}_i) + v_i, i = 1, 2, \dots, N \quad (9)$$

where \mathbf{x}_i is the position of i -nodes, v_i is Gaussian white noise, and follows Gaussian probability distribution $N(0, \sigma_i^2)$. Suppose there are M sampling points, and the number of peaks L is known. Parameters of peak function are estimated by sampling data.

Define the following matrix (ignoring t):

$$Y = \begin{bmatrix} Z_1 & \dots & Z_N \\ \sigma_1 & \dots & \sigma_N \end{bmatrix}^T, \quad (10)$$

where vector matrix G shows the effect of background noise on the environment sensor signal, that is:

$$G = \text{diag} \left[\frac{1}{\sigma_1}, \dots, \frac{1}{\sigma_N} \right]. \quad (11)$$

Matrix E represents energy changes with the different distance between sensor nodes and target source, that is

$$E = \begin{bmatrix} e_{11} & e_{12} & \cdots & e_{1L} \\ e_{21} & e_{22} & \cdots & e_{2L} \\ \vdots & \vdots & \vdots & \vdots \\ e_{N1} & e_{N2} & \cdots & e_{NL} \end{bmatrix},$$

$$e_{il} = \exp\left(-\frac{1}{2}(\mathbf{x}_i - \mathbf{x}_0^l)^T \Sigma_l^{-1} (\mathbf{x}_i - \mathbf{x}_0^l)\right). \quad (12)$$

The observation model (9) can be represented as a matrix equation:

$$Y = GEK + \xi = HK + \xi, \quad (13)$$

Where $K = [K^1, \dots, K^M]^T$, $\xi =$

$$\sim C^{N \times L}, h^{(i)} = [h_1^i, \dots, h_N^i]^T$$

$$[\xi[1, \dots, \xi_N]^T, \xi]_{i \in \in v_i / \sigma_i N(0, 1)}, H = GE, H = h^{(1), \dots, h^{(L)}}$$

Getting the joint probability density function by the formula (10), that is

$$f(Y|\Theta) = (2\pi)^{-(M/2)} \exp\left(-\frac{1}{2}(Y - HI)^T (Y - HI)\right), \quad (14)$$

where $\Theta = [\mathbf{x}_0^1 \dots \mathbf{x}_0^i \dots \mathbf{x}_0^N; K^1 \dots K^i \dots K^N]$ is the unknown parameter vector. Further simplified, formula (14) is equivalent to

$$\ell(\Theta) = (Y - HI)^T (Y - HI) \quad (15)$$

By the maximum likelihood estimation theory, parameters are calculated by the following formula:

$$\Theta = \text{b argmin}((Y - HI)^T (Y - HI)) \quad (16)$$

The formula (16) can be solved by multi-resolution MR algorithm and EM algorithm etc. Compared with those methods, the global search method is more computation complexity, however it is able to obtain a more accurate solutions.

4 Genetic Algorithms

Therefore, this paper uses genetic algorithms to minimize the objective function and obtain the fire point position. Specific steps are as follows: 1) Randomly generate the initial data for (x_0^l, y_0^l) , $l = 1, \dots, L$.

2) Generate initial population by real number coding x_0^l and y_0^l [7][8], which is shown as Figure 2 where length of each code strings is $2L$.

x_{01}	x_{02}			x_{0L}	y_{10}	y_{02}			y_{0L}
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Fig. 2: The way of Chromosome encoding

3) Calculate the fitness expressed as fitness function taken as the inverse of error. The fitness of the j -chromosome is:

$$fitness(j) = \frac{1}{(Y - HI)^T (Y - HI)} \quad (17)$$

4) Calculate the MSE (mean square error) to determine whether it meets the error requirement, satisfied then end, otherwise continue.

5) Use the roulette wheel selection method. We select the corresponding individual according to the size of fitness. The fitness of j -th individual is $fitness(j)$, then the probability of being selected is

$$P(j) = \frac{fitness(j)}{\sum_{q=1}^Q fitness(Q)}, q = 1, 2, \dots, Q, \quad (18)$$

where Q is the population size [9].

6) Use adaptive genetic algorithm to adaptive select crossover and mutation rate[6][7]. The crossover rate P_c and mutation rate P_m are adaptive adjustment according to the following formula:

$$P_c = \begin{cases} P_{c \max} - \frac{(P_{c \max} - P_{c \min})(f' - f_{avg})}{f_{\max} - f_{avg}}, & f' \geq f_{avg} \\ P_{c \max}, & f' < f_{avg} \end{cases} \quad (19)$$

$$P_m = \begin{cases} P_{m \max} - \frac{(P_{m \max} - P_{m \min})(f' - f_{avg})}{f_{\max} - f_{avg}}, & f' \geq f_{avg} \\ P_{m \max}, & f' < f_{avg} \end{cases} \quad (20)$$

where $P_{c \max}$ and $P_{c \min}$ are the upper and lower cross rate, respectively. $P_{m \max}$ and $P_{m \min}$ are the upper and lower mutation rate, f is the larger fitness value of the two individual crossovered, f_{avg} is the average fitness of population, f_{\max} is the fitness value of largest population.

7) Adopt the improved elitist selection method to ensure quality and the evolution of the population. If contemporary fitness of the optimal solution is less than the previous generation, it indicates that the optimal solution of the previous generation is destructed. That is the population evolved better. Then, current optimal solution is duplicated to the next generation intact. Conversely, there is no need to duplicate when contemporary fitness is larger than the previous generation.

5 Simulation

Suppose that a fire scenario of $20 \times 20 \text{ m}^2$, fire point number $N = 3$, a number of simulations of 1000. The EM method and genetic algorithm is used to estimate the parameters of the experiment, and the accuracy of the estimation error and the amount of calculation are compared and analyzed respectively. Observation noise meets $N(0,1)$. Figure 3 depicts the estimation error of the mean value with different number of sampling points. It is easy to find that the estimated error of EM method is close to genetic algorithm. With the increase of sampling points,

the estimation precision of the genetic algorithm is better than the EM method.

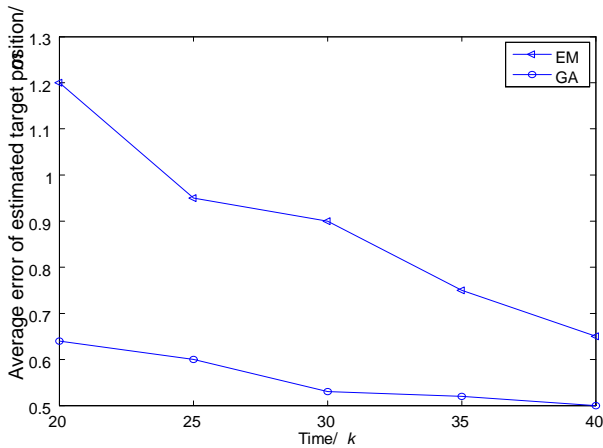


Fig. 3: Sampling point number and estimation error

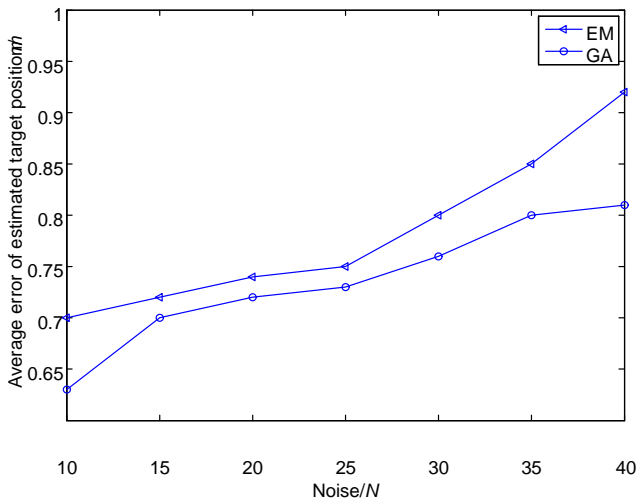


Fig. 4: Noise and estimate error

The number of sensor nodes $L = 30$. EM and genetic algorithm is adopted to estimate parameters respectively with the changes of observation noise. Figure 4 reflects the influence of observation noise on estimation error. With the increase of the observation noise, that is the decrease of signal-tonoise ratio, parameter estimation error is enlarged. However, the affection of genetic algorithm is minimal by observation noise.

6 Conclusion

In this paper, a new location method of the building fire ignition point based on genetic algorithm is proposed. Firstly, the peak model of temperature energy distribution is established, and thus established a measurement model. By considering the measurement noise, the locating of ignition point is reformulated as global optimization problem, solved with genetic algorithms. The simulation verifies the correctness and effectiveness of the proposed method and

gets better accuracy than the classical EM method. From the idea of this paper, further studies will consider the specific spatial structure of buildings, obtain more practical engineering methods.

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