

Odor Source Localization based on Wireless Sensor Network

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The wireless sensor network, which has a low cost, low energy consumption and wide coverage, is currently involved in many interdisciplines, and becomes a hot research field with rich knowledge contents. It has more broad application prospects in the odor source localization research, and is of great significance to promote people's emergency response capacity. This paper studies the application of wireless sensor network in odor source location by plume model and locating algorithm, and carries out a simulation experiment. The experimental results show that the number of sensor nodes and the scope of environments influence the estimation of odor source location. Among them, as the number of sensor nodes increases, positioning errors decrease. However, when the number of nodes exceeds 20, the locating errors tend to be moderate. With the expansion of environmental ranges, the number of sensor nodes required to obtain stable estimation results is increasing, and errors occurred before the stability also tend to increase. When the number of nodes is limited, the sensor node can be combined with the autonomous mobile robot to carry out simple movement, and an effective estimation of odor source location can also be carried out.

1. Introduction

The wireless sensor network (Yang, 2018), which has a low cost, low energy consumption and wide coverage, is currently involved in many interdisciplines, and becomes a hot research field with rich knowledge contents (Arpan and Debashish, 2018; Sheng and Hu, 2004; Dong, 2017; Guan et al., 2018). The application of wireless sensor network in the odor source localization is typical in the field of environmental monitoring. The environmental concentration information of the location can be measured by sensor nodes distributed in different monitoring areas (Meng et al., 2008; Zlatkova and Lyubenova, 2017). It can give a warning timely about pollution sources and continuously improve people's ability to respond to emergencies, so that it has great significances and functions in the practical application (Niu et al., 2010).

Up to now, many domestic and foreign scholars and experts have conducted a lot of researches on the odor source localization based on the wireless sensor network with various methods, and formed an array of research results. Scholars adopt the maximum likelihood estimation algorithm (Xue et al., 2007; Shen et al., 2014; Chervenkov and Malcheva, 218), nonlinear least square method (Ma et al., 2010; Liu et al., 2012), and Bayesian estimation based on the distributed sensor network (Wang, 2011; Ampeliotis and Berberidis, 2010). This paper studies the application of wireless sensor network in odor source location by plume model and locating algorithm, which possesses an innovative significance (Wei and Liang, 2018).

2. Relevant Theories

2.1 Gas Sensors Selection

The common gas sensors are TGS2620 and MiCS-5135, which are mainly used to detect volatile organic compounds. The power consumption parameters of these two kinds of sensors are compared as shown in Table 1:

Table 1: Comparison of the main power consumption parameters of two kinds of sensors

	TGS2620	MiCS-5135
Heating circuit voltage(VH)	5.2V	3.0V
Detection circuit voltage(VC)	4.3V	4.3V
Heating circuit resistance(RH)	87	93
Heating circuit current(IH)	46mA	34mA
Heating circuit power consumption(PH)	220mW	105mW

2.2 Odor Source Estimation and Localization Algorithms

2.2.1 Plume Model

The rate of odor diffusion is generally slower than the wind speed, so the plume structure is determined by the air turbulence in breeze (Zhang et al., 2015). When the leakage source is continuous or the discharge time is greater than or equal to the diffusion time, the plume model is adopted. The model formula is:

$$c(x, y, z) = \frac{Q}{2\pi\mu\sigma_y\sigma_x} \exp\left[-\frac{y^2}{2\sigma_y^2} + \frac{-z^2}{2\sigma_z^2}\right] \quad (1)$$

When the wind speed is less than 1.5m/s, the standard plume model cannot ignore the diffusion on the X-axis (Lee et al., 2009). When the height is fixed (z is a fixed value), the concentration model is:

$$C_1(x, y) = \frac{2Q}{(2\pi)^{3/2}r_2\eta^2} G \quad (2)$$

$$G = \exp\left[-\left(\frac{u^2}{2r_1^2}\right)\right] \left\{1 + \sqrt{2\pi} \cdot s \exp\left(\frac{s^2}{2}\right) \cdot \Phi(s)\right\} \quad (3)$$

In general, the origin coordinates (0, 0) are set as the odor source location, and the wind direction is in the positive axis X (Tomic et al., 2015).

2.2.2 Trilateration Locating Algorithm

Taking the sensor node M1 in Fig. 1 as an example, the distance between the sensor node M1 and the odor source location is estimated to be N1 according to the Formula (1). The odor source location must be at the circle centered on M1 with a radius of N1 (Deng et al., 2017). By the same method, circles centered on sensor nodes M2 and M3 are obtained. In theory, the odor source should be at circles centered on M1, M2 and M3, and the location of the odor source is at the intersection of these three circles. However, in the actual operation, these three circles will intersect in a common area rather than at a point due to a lot of interference, and the odor source coordinates must be in this common area (Yan et al., 2010). In Fig. 1, the coordinates positions of three sensor nodes are M1, M2 and M3, and the location of the odor source must be in the shaded area.

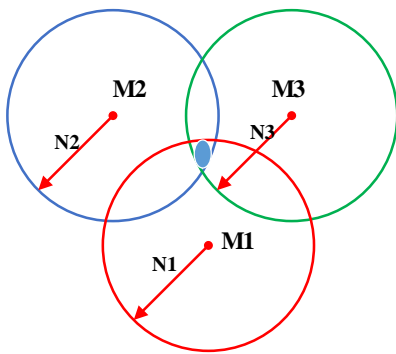


Figure 1: Trilateration locating algorithm

2.2.3 Nonlinear Least Square Method

The nonlinear least square method is mainly used to estimate parameters of the nonlinear static model by minimizing the error sum of squares. The hypothesis model is:

$$y=f(x,\theta) \quad (4)$$

More data $(x_1, y_1), (x_2, y_2) \dots (x_n, y_n)$ can be obtained through N experiments. The objective function is the error sum of squares, specifically:

$$Q = \sum_{k=1}^N [y_k - f(x_k, \theta)]^2 \quad (5)$$

It is assumed that the sensor node processes the gas concentration C_i of this position at a certain time, sends it to the central collection node, and establishes the objective function through the Formula (3) (Wang& Yang, 2007), which is specific to:

$$J = \min \sum_{i=1}^n \left\{ \frac{q}{2\pi K} \frac{1}{x_i} \exp \left[-\frac{U}{2K} (d - (x_i - \hat{x}_s)) \right] - C_i \right\}^2 \quad (6)$$

$$d = \sqrt{(x_i - \hat{x}_s)^2 + (y_i - \hat{y}_s)^2} \quad (7)$$

Formula (6) can achieve the minimum value and get the position of the odor source (\hat{x}_s, \hat{y}_s) through the nonlinear least squares method. In general, the optimization algorithm is the iterative method (Vaghefi and Buehrer, 2015).

3. Static Model Simulation Results and Analysis

The simulation model mainly adopts the static odor source, and sensor nodes are distributed in a rectangular area of 400cm x 500cm in space. The number of sensors is random and less than 100. If the location of odor source is (100,0), the gas concentration of sensor node can be calculated by Formula (2). In order to reduce the external interference, each experiment will be repeated 35 times. Fig. 2 shows the random distribution of sensor nodes in the simulation experiment, expressed in red dots.

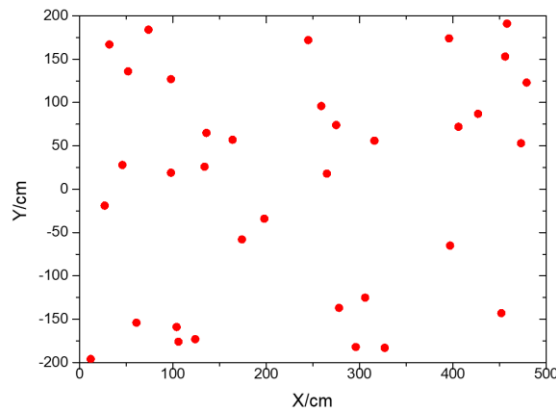


Figure 2: Random distribution diagram of sensor nodes

3.1 Influence of the Number of Sensor Nodes on Locating Estimation

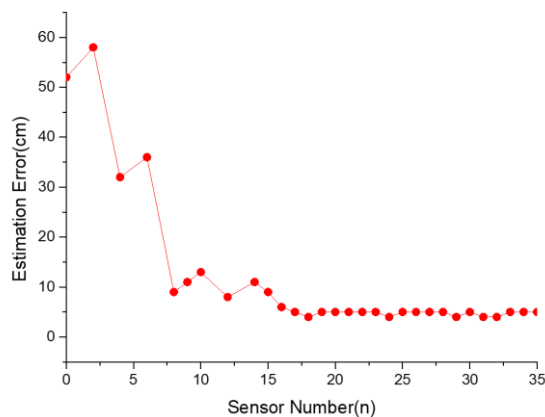


Figure 3: Influence of the number of sensor nodes on locating estimation

In the experiment, the odor source would spread continuously. The measured value obtained from nodes far away from the overflow source would be noisier than that close to the overflow source. If these noisy nodes are not removed, the actual locating estimation will be greatly affected. The number of sensor nodes has an effect on the locating estimation. As shown in Fig. 3, the locating error decreases with the increase of the number of nodes. However, when the number of nodes exceeds 20, locating errors tend to be moderate. Therefore, the number of nodes in the locating estimation is not as large as possible. A threshold value will be set in the experiment, and the nodes exceeding the threshold will be selected for the locating estimation.

3.2 Influence of Environmental Ranges on Locating Estimation

A large number of sensor nodes cannot be set up in all environmental ranges due to the limitation of energy consumptions and costs. From the previous analysis, it is found that when the number of sensor nodes exceeds 20, the accuracy of the estimation of odor source location would tend to be stable. Therefore, the corresponding number of nodes should be set in different environments.

Table 2: Estimation of estimated location error under different environments

Environmental dimensions(m)	5*6	9*9	12*15	20*15
Environmental area(m ²)	30	81	180	300
Appropriate number of nodes(n)	20	32	45	57

The number of sensor nodes required to obtain stable estimation results is increasing with the expansion of environmental ranges as shown in Table 2. In addition, the error occurred before the stability of estimation results is also increasing. Therefore, the appropriate number of nodes should be selected in different environments, in order to accurately, efficiently and cost-effectively estimate the odor source location.

3.3 Discussion on Locating Estimation of Sensor Nodes Movement

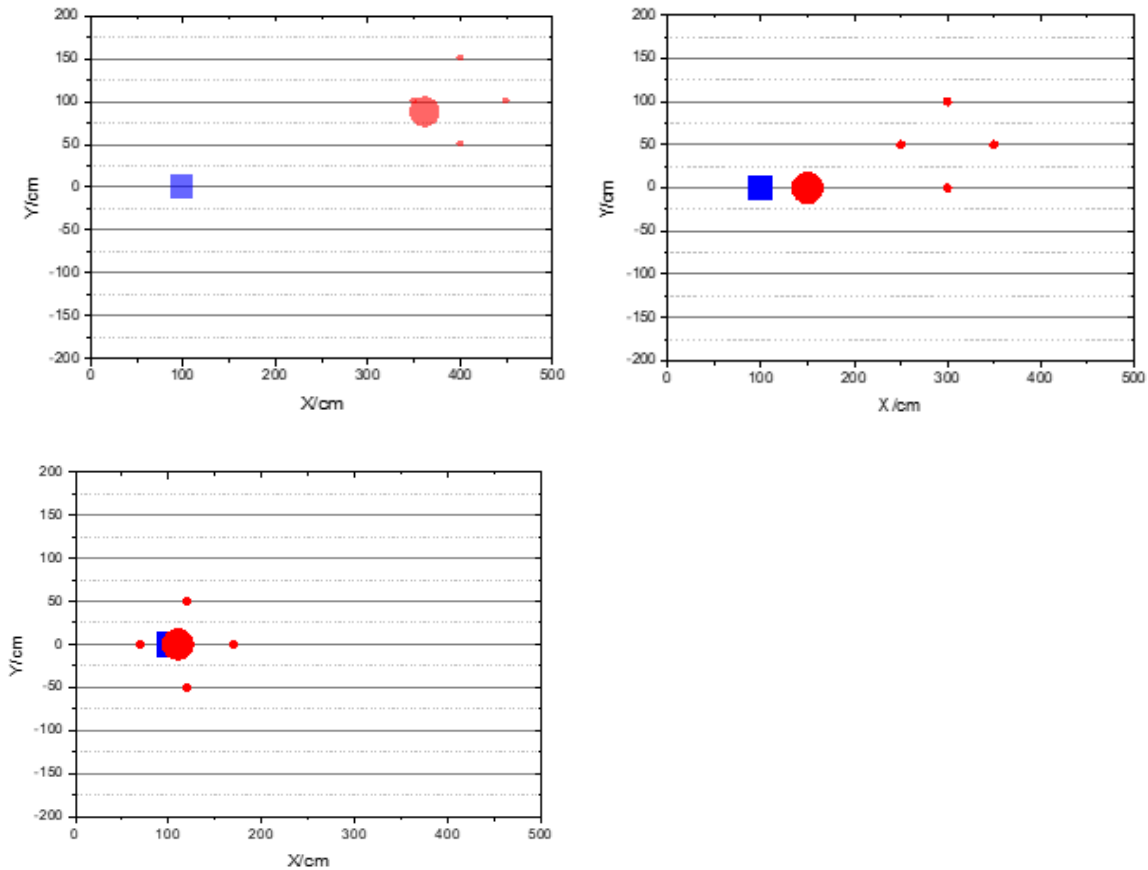


Figure 4: Initial coordinates (400, 100), circle radius 50cm, locating effect

The accurate locating estimation can be made through a large number of sensor nodes in an appropriate environment. But in the actual experiment, due to the limitation of funding, it is impossible to provide enough sensor nodes for experiments, which will have adverse effects on the final locating estimation. Therefore, when the number of nodes is limited, the sensor node can be combined with the autonomous mobile robot to carry out simple movement, and an effective estimation of odor source location can also be carried out.

In Fig 4, the blue square represents the odor source location with the coordinates (100,0), the red dots four sensor nodes at the circle centered on the coordinates (400,100) with a radius of 50cm, and the large red circle the locating estimation. After obtaining the locating estimation, the sensor network will conduct a new layout centered on the above estimation and repeatedly start a new estimation.

Three estimations are shown in Fig. 4. It can be found that when sensor nodes have not surrounded the odor source, the locating result can reflect the direction of odor source and the increasing trend of concentration in general.

How about dynamically changing environmental ranges of sensor network instead of increasing the number of nodes to improve the accuracy of locating estimation? Through the simulation experiment, it can be found that this method can obtain a more accurate locating effect with high adaptability and precision.

4. Conclusion

Firstly, both the number of sensor nodes and environmental ranges influence the estimation of odor source location. Among them, as the number of nodes increases, the locating error decreases. However, when the number of nodes exceeds 20, the locating error tends to be moderate. With the expansion of environmental ranges, the number of sensor nodes required to obtain stable estimation results is increasing and the error occurred before the stability of estimation results also tends to increase.

Secondly, in the actual experiment, due to financial constraints, it is impossible to provide enough sensor nodes for experiments. Therefore, when the number of nodes is limited, the sensor node can be combined with the autonomous mobile robot to carry out simple movement, and an effective estimation of odor source location can also be carried out.

Reference

- Ampeliotis D., Berberidis K., 2010, Sorted order- k , voronoi diagrams for model-independent source localization in wireless sensor networks, *IEEE Transactions on Signal Processing*, 58(1), 426-437, DOI: 10.1109/tsp.2009.2029724
- Arpan H., Debashish C., 2018, Wireless relay placement optimization in underground room and pillar mines, *Mathematical Modelling of Engineering Problems*, 5(2), 67-75, DOI: 10.18280/mmep.050203
- Chervenkov H., Malcheva K., 2018, Statistical modelling of extremes with distributions of Fréchet and Gumbel: Parameter estimation and demonstration of meteorological applications, *International Journal Bioautomation*, 22(1), 21-38.
- Deng F., Guan S., Yue X., Gu X., Chen J., Lv J., 2017, Energy-based sound source localization with low power consumption in wireless sensor networks, *IEEE Transactions on Industrial Electronics*, 64(6), 4894-4902, DOI: 10.1109/tie.2017.2652394
- Dong T., 2017, Assessment of data reliability of wireless sensor network for bioinformatics, *International Journal Bioautomation*, 21(3), 241-250.
- Guan F.W., Zhang F., Cao N.L., Liu Q., Liu J., Yu S.M., Guan H.Y., 2018, Thermal control design and experimental verification of light off-axis space optical remote sensor in the sun-synchronous orbit, *International Journal of Heat and Technology*, 36(1), 125-132, DOI: 10.18280/ijht.360117
- Lee H., Lee S., Kim Y., Chong H., 2009, Grouping multi-duolateration localization using partial space information for indoor wireless sensor networks, *IEEE Transactions on Consumer Electronics*, 55(4), 1950-1958, DOI:10.1109/tce.2009.5373755
- Liu Y., Hu Y.H., Pan Q., 2012, Distributed, robust acoustic source localization in a wireless sensor network, *IEEE Transactions on Signal Processing*, 60(8), 4350-4359, DOI: 10.1109/tsp.2012.2199314
- Ma D., Meng J.E., Wang B., 2010, Analysis of hop-count-based source-to-destination distance estimation in wireless sensor networks with applications in localization, *IEEE Transactions on Vehicular Technology*, 59(6), 2998-3011, DOI: 10.1109/tvt.2010.2048346
- Meng C., Ding Z., Dasgupta S., 2008, A semidefinite programming approach to source localization in wireless sensor networks, *IEEE Signal Processing Letters*, 15, 253-256, DOI:10.1109/lsp.2008.916731
- Niu R., Varshney P.K., Keskinoz M., 2010, Energy aware iterative source localization for wireless sensor networks, *IEEE Transactions on Signal Processing*, 58(9), 4824-4835, DOI: 10.1109/tsp.2010.2051433

- Shen H., Ding Z., Dasgupta S., Zhao C., 2014, Multiple source localization in wireless sensor networks based on time of arrival measurement, *IEEE Transactions on Signal Processing*, 62(8), 1938-1949, DOI: 10.1109/tsp.2014.2304433
- Sheng X., Hu Y.H., 2004, Maximum likelihood multiple-source localization using acoustic energy measurements with wireless sensor networks, *IEEE Transactions on Signal Processing*, 53(1), 44-53, DOI: 10.1109/tsp.2004.838930
- Tomic S., Beko M., Rui D., 2015, Rss-based localization in wireless sensor networks using convex relaxation: noncooperative and cooperative schemes, *IEEE Transactions on Vehicular Technology*, 64(5), 2037-2050, DOI: 10.1109/tvt.2014.2334397
- Vaghefi R.M., Buehrer R.M., 2015, Cooperative joint synchronization and localization in wireless sensor networks, *IEEE Transactions on Signal Processing*, 63(14), 3615-3627, DOI: 10.1109/tsp.2015.2430842
- Wang G., 2011, A semidefinite relaxation method for energy-based source localization in sensor networks, *IEEE Transactions on Vehicular Technology*, 60(5), 2293-2301, DOI:10.1109/tvt.2011.2142204
- Wang S., Yang J., 2007, Decentralized acoustic source localization with unknown source energy in a wireless sensor network, *Measurement Science & Technology*, 18(12), 3768-3776, DOI: 10.1088/0957-0233/18/12/011
- Zhai W., Shen L., 2018, Application of wireless communication technology in chemical production process, *Chemical Engineering Transactions*, 66, 823-828, DOI: 10.3303/CET1866138
- Xue W., Bi D.W., Liang D., Sheng W., 2007, Agent collaborative target localization and classification in wireless sensor networks, *Sensors*, 7(8), 1359-1386, DOI: 10.3390/s7081359
- Yan K., Wu H.C., Iyengar S.S., 2010, Robustness analysis and new hybrid algorithm of wideband source localization for acoustic sensor networks, *IEEE Transactions on Wireless Communications*, 9(6), 2033-2043, DOI: 10.1109/twc.2010.06.090515
- Yang G., 2018, Data acquisition technology of chemical equipment based on wireless sensor network, *Chemical Engineering Transactions*, 66, 943-948, DOI: 10.3303/CET1866158
- Zhang Y., Lou Y., Hong Y., Xie L., 2015, Distributed projection-based algorithms for source localization in wireless sensor networks, *IEEE Transactions on Wireless Communications*, 14(6), 3131-3142, DOI: 10.1109/twc.2015.2402672
- Zlatkova A., Lyubenova V., 2017, Dynamics monitoring of fed-batch E. coli fermentation, *International Journal Bioautomation*, 21(1), 121-132.