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Review Article

A Survey on Pollution Monitoring Using Sensor Networks in Environment Protection

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Detecting pollution timely and locating the pollution source is of great importance in environmental protection. Considering advantages of the sensor network technology, sensor networks have been adopted in pollution monitoring works. In this paper, a survey on researches of pollution monitoring using sensor networks in environment protection is given. Firstly, sensors and pollution monitoring network systems are studied. Secondly, different pollution detection methods are analyzed and compared. Thirdly, an overview of state-of-art technologies on pollution source localization is given. Finally, challenges on pollution monitoring using sensor networks are presented.

1. Introduction

Pollution monitoring is of great significance to environment protection. Pollution events are mostly caused by pollutants which contaminate atmosphere and water. If the pollution source can be located when a pollution event is detected, it is helpful for solving the contamination accident timely. So, in pollution monitoring, the three problems, including environment status observation, pollution detection, and pollution source localization are always studied. In environment monitoring, the environmental data is sampled and transmitted to the data center in real time. The pollution detection problem is to ascertain whether there is a pollution event through sampling analysis. The pollution source localization problem is to locate the pollution source when a pollution event is ascertained.

As sensor networks have many advantages such as relatively dense distribution, large monitoring range, and being free from limiting by geographical locations, it is often adopted in environmental protection [1–3]. There have been many research works on environment monitoring, pollution detection, and pollution source localization using sensor networks. The research object is the pollution caused by diffusion sources in atmosphere and water. There are similar fluid characteristics in air and water, so many general monitoring network frames, pollution detection methods, and pollution source localization methods can be used in both environments. However, if special conditions in different environment cases are considered, different information detection systems and methods are necessary in pollution monitoring.

In this paper, a survey on researches about environment monitoring, pollution detection, and pollution source localization using sensor networks is given, and the problems and challenges are analyzed. The reminder of the paper is organized as follows: in Section 2, an overview on pollution monitoring works including sensors and network systems is given. In Section 3, pollution detection problems are discussed. In Section 4, different pollution source localization algorithms are studied and compared. In Section 5, the challenges in research works are presented. Finally, a brief conclusion is given.

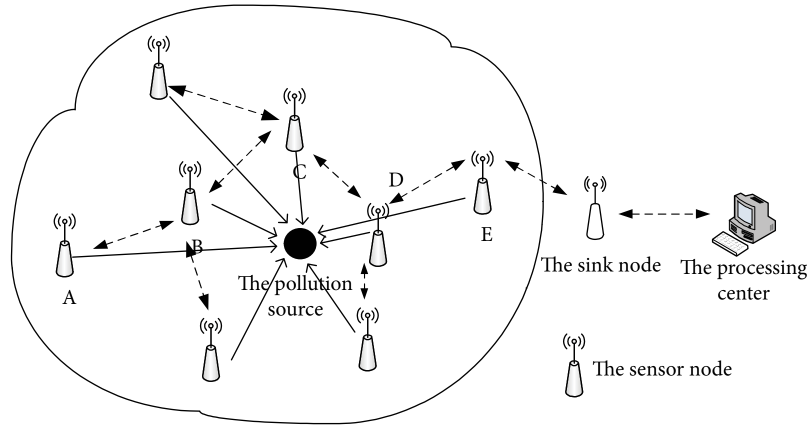

Figure 1: A network system for pollution monitoring.

2. Sensors and Networks in Environment Monitoring

2.1. Sensors. Sensor technology is a supporting technology in sensor networks. For air pollution monitoring, sensors detecting CO_2 [4], CO [5], NO_x ($x = 1, 2$) [6], SO_x ($x = 1, 2$) [7], H_2S [8], NH_3 [9], Cl_2 [10], O_3 [11] and particulate matter are frequently used. For water pollution monitoring, sensors monitoring heavy metal [12], pH value [13], conductivity [14], dissolved oxygen (DO) [15], turbidity [16], the content of carbon [17], chlorine [18], the content of phosphorus [19, 20], and the content of nitrogen [21] are used.

Some contaminants can be detected directly by sensors, especially in air environment, such as CO_x, NO_x, and SO_x, but some sensors can only detect a type of pollutants and cannot measure the content of a specific contaminant. For example, the dissolved oxygen (DO) sensor, the pH sensor, and the electrical conductivity sensor fall into this category. The dissolved oxygen (DO) sensor detects organic pollutants and is not for the measurement of explicit contaminants such as carbohydrate, axunge, and polycyclic aromatic hydrocarbons. The pH sensor detects corrosive and poisonous liquids, but the explicit chemistry acid or alkali contaminants are not indicated. The electrical conductivity sensor detects ionic pollutants and cannot distinguish whether the explicit contaminant is nitrate, sulfate, hydrochloride, or some other one. The measurement of many specific contaminants in water can only be implemented by sampling analysis in laboratory at present.

In environment monitoring, many sensors cost much, and the more precise the sensor measurement is, the higher the sensor costs. For example, in China a commonly used pH sensor costs about $18, and with the measurement accuracy rising, it may cost more than $159. A commonly used DO sensor costs about $33, and with the measurement accuracy rising, may cost more than $ 273. A cheap CO_2 sensor costs about $14, but a high precision one costs more than $130. So, different from dust sensor networks in theory [22], sensor nodes often cannot be deployed densely and nodes should be recycled when broken. Therefore, the advantages that monitor the environment using dense nodes cannot be realized in many practical applications.

2.2. Sensor Network Systems for Environment Monitoring. Environment monitoring is a data collecting and analyzing process actually. Many systems have been developed for environment monitoring, such as systems for gas pollution monitoring in [23–32] and systems for water pollution monitoring in [33–45]. The monitoring system always includes sensor nodes, a sink node, and a processing center. In some systems, the sink node is known as the gateway node [26, 27], the coordinator [35, 40], or the base station [25, 33, 34]. The processing center is known as the backend server [23, 24] or the external center [33, 39, 40] and always connected to the Internet. The basic structure of the network system is shown in Figure 1.

The monitoring systems are always hierarchical. The first layer is the monitoring networks. Sensor nodes sample environmental information and always transmit the data to the sink node in a wireless way. The second layer is the data uploading layer. The sink node uploads the data to the data center through wired networks or wireless ones. The data being transmitted to the data center is the raw data or the data preprocessed in advance by distributed nodes.

The main differences of different proposed monitoring systems are in nodes and networks, such as different sensing platforms, different network topologies, different communication protocols, wired networks, or wireless ones.

A sensor node is a sensing platform, which always includes a microprogrammed control unit (MCU), sensors, a communication module, and a power module. The MCU can be an ATmega single chip [23, 26, 38–40], an ARM (advanced RISC machine) chip [24, 27, 28, 41], and a PLC (programmable logic controller) chip [34]. The communication modules can be RF (radiofrequency) modules and GPRS modules [23]. In many works, sensing platforms are developed by the authors completely, while in some others, sensing platforms are refitted ones based on nodes such as Mica2Dot motes [46], Tyndall motes [47], and Fleck3 platforms [48], which are developed by corporations.

In monitoring systems, the star topology is always adopted in a small-size network [23, 25, 27, 34, 38]; large networks can be cluster topologies [26] or mesh topologies [24, 28, 33, 39–41]. The ZigBee/IEEE 802.15.4 wireless communication protocol is frequently used in monitoring networks [24, 26, 33, 35, 36], and then Bluetooth [27, 38] and

GPRS [23]. The sink node can communicate with the center via many ways, such as ZigBee, GSM, GPRS, 3G and even the wired network.

Pollutants are not always above water. Underwater wireless sensor networks [49–51] are used to monitor underwater pollution. How to monitor the water environment using underwater wireless sensor network systems is mentioned in [42–45]. The main difference of the underwater sensor network compared with the sensor network above water is that acoustic wireless communication is widely used in the underwater monitoring system. However, in these systems there is often a sink node which floats on water, collects information of underwater sensor nodes, and forwards the data to the processing center.

Though many monitoring systems have been given, there are still problems such as those below:

(1) In wireless sensor networks, multihop and collaborative work are always mentioned. However, in consideration of packet losses, forwarding packets between nodes is inefficient and brings problems. Multihop (>3 hops) and collaborative work [52] in wireless sensor networks are mainly mentioned in theoretical studies; nevertheless, most wireless sensor networks are centralized processing systems with star topology in practical applications.

(2) The monitoring area is large, and the location of the pollution source is unknown. So, where to deploy sensor nodes is a problem needed to be considered properly in practical applications. In complicated environments like dynamic water, how to deploy sensor nodes and prevent them being washed away is a problem.

(3) The underwater wireless sensor network, especially the acoustic communication equipment of the network, costs much. So sensor nodes cannot be deployed densely under water. How electronic sensors are equipped properly on an underwater node in a waterproof package is also a problem in engineering.

3. Pollution Detection Using the Sensor Network

Pollution detection is a key technology in pollution monitoring, and it is an abrupt change detection problem actually [53]. There is the pollution detection problem of the network as

$$\begin{aligned}
\mathrm{H}_0 &: C(x_i, y_i, t_0) = f(x_i, y_i, t_0, \boldsymbol{\theta}_0), \quad i = 1, 2, 3, \ldots, I, \\
\mathrm{H}_1 &: C(x_i, y_i, t_0) = f(x_i, y_i, t_0, \boldsymbol{\theta}_0), \quad i = 1, 2, 3, \ldots, I', \\
&\quad C(x_i, y_i, t_0) = f(x_i, y_i, t_0, \boldsymbol{\theta}_1), \quad i = I' + 1, I' + 2, I' + 3, \ldots, I,
\end{aligned} \tag{1}$$

which is to detect whether there are nodes which find the pollution at time t_0, and the pollution detection problem of the node as

$$\begin{aligned}
\mathrm{H}_0^{(1)} &: C(x_i, y_i, t_l) = f(x_i, y_i, t_l, \boldsymbol{\theta}_0), \quad l = 1, 2, 3, \ldots, L, \\
\mathrm{H}_1^{(1)} &: C(x_i, y_i, t_l) = f(x_i, y_i, t_l, \boldsymbol{\theta}_0), \quad l = 1, 2, 3, \ldots, L', \\
&\quad C(x_i, y_i, t_l) = f(x_i, y_i, t_l, \boldsymbol{\theta}_1), \quad l = L' + 1, L' + 2, L' + 3, \ldots, L,
\end{aligned} \tag{2}$$

which is to determine whether the node (x_i, y_i) has detected the concentration information of the pollution source till time t_L. $\boldsymbol{\theta}_0$ and $\boldsymbol{\theta}_1$ are environment parameters when there is no pollution and when there is a pollution event. The specific detection nodes (x_i, y_i), $i = I' + 1, I' + 2, I' + 3, \ldots, I$, and detection time $t_{L'}$ are not needed to be known precisely because the purpose is only to find whether there is a pollutant event or whether a certain node has detected the pollution.

In most works, such as [13–45, 47, 54–66], the detection problem is not discussed analytically. It is assumed that $P(\boldsymbol{\theta} = \boldsymbol{\theta}_1 \mid C(x_i, y_i, t_l) > \alpha) = 1$; that is to say if the concentration value is larger than a given threshold α, it is determined that there is pollution. This is a coarse detection method.

In some works, the hypothesis-testing detection problems are studied [67–69]. Let the observation of the theoretical concentration $C(x_i, y_i, t_l)$ be $\tilde{C}(x_i, y_i, t_l)$, and the initial pollution concentration of normal production and life in the environment be C_0. Test problem (1) can be approximated as [67]

$$\begin{aligned}
\mathrm{H}_0^{(2)} &: \mu_1 = \mu_2, \\
\mathrm{H}_1^{(2)} &: \mu_1 \neq \mu_2,
\end{aligned} \tag{3}$$

or [68]

$$\begin{aligned}
\mathrm{H}_0^{(3)} &: \tilde{C}(x_i, y_i, t_0) = C_0 + e, \quad i = 1, 2, 3, \ldots, I, \\
\mathrm{H}_1^{(3)} &: \tilde{C}(x_i, y_i, t_0) = C(x_i, y_i, t_0) + C_0 + e, \quad i = 1, 2, 3, \ldots, I.
\end{aligned} \tag{4}$$

In (3), if there is no node that detects the pollution, $\mu_1 = \mu_2 = C_0$. In (4), e is the measuring noise, and when the node (x_i, y_i) does not detect the pollution, $C(x_i, y_i, t_l) = 0$.

Test problem (2) can be approximated as [67]

$$\begin{aligned}
\mathrm{H}_0^{(4)} &: \mu_3 = \mu_4, \\
\mathrm{H}_1^{(4)} &: \mu_3 \neq \mu_4,
\end{aligned}$$

$$\mu_3 = \frac{1}{L'} \sum_{l=1}^{L'} \tilde{C}(x_i, y_i, t_l),$$

$$\mu_4 = \frac{1}{L - L'} \sum_{L=L'+1}^{L} \tilde{C}(x_i, y_i, t_l). \tag{5}$$

If the distribution of monitoring noise values is known, the hypothesis-testing problems above can be solved by parameter test methods. Otherwise, the problems above should be solved by nonparameter test methods [70].

The advantage of the coarse detection method is simple and easy to be implemented. However, the water environment is often complicated, and there are plankton, garbage, aquatic animals, plants, and so forth, which bring disturbances to the monitoring data; the decision threshold which is used in determining whether there is pollution is difficult to be given.

In pollution monitoring, if the purpose is not to find the pollution timely, the coarse detection method is possible. For example, in the pollution source localization works, the data error can be compensated in the localization processing procedures, so the coarse detection method can be used.

In some monitoring works, such as environment status observation and pollution detection, whether there is pollution is often needed to be known correctly, so analytical detection methods should be considered seriously for a more rational result.

4. Pollution Source Localization

The pollutants migrate in flow fields, so the pollution source is located according to the pollution dispersion process in most works. In this part, the physical diffusion models usually mentioned in pollution source localization researches are introduced firstly, and different localization algorithms are given then.

4.1. Physical Models. The pollution sources are always point sources. If advection and chemical reactions as well as fate models are ignored, the transport of substances from a diffusive source can be illustrated by the diffusion equations below [71, 72].

$$\frac{\partial C}{\partial t} = D_x \frac{\partial^2 C(\mathbf{r}, t)}{\partial x^2} + D_y \frac{\partial^2 C(\mathbf{r}, t)}{\partial y^2} - u_x \frac{\partial C}{\partial x} - u_y \frac{\partial C}{\partial y}, \tag{6}$$

$$C(\mathbf{r}, t) = \int_{t_0}^{t} \mu(\tau) C'(\mathbf{r}, t - \tau) d\tau, \tag{7}$$

$$C|_{t=0} = M\delta(x - \varepsilon)\delta(y - \eta), \tag{8}$$

$$\lim_{x\to\infty} C = 0, \quad \lim_{y\to\infty} C = 0, \tag{9}$$

where $\mathbf{u} = (u_x, u_y)$ is the velocity of the fluid, $\mathbf{D} = (D_x, D_y)$ is the diffusion coefficient, (ε, η) is the source position, $\mathbf{r} = (x, y)$ is a site in the flow field, and $C(\mathbf{r}, t)$ is the concentration (content) at position $\mathbf{r}$. In general, diffusion coefficients in air are larger than those in water. Equation (8) is the initial condition, and (9) is the boundary condition which is with no constraint. The solution of (6)–(9) is

$$C(\mathbf{r}, t) = \frac{M}{4\pi\sqrt{D_x D_y} t} \cdot \exp\left[-\frac{(x - u_x t - \varepsilon)^2}{4D_x t} - \frac{(y - u_y t - \eta)^2}{4D_y t}\right]. \tag{10}$$

Equation (10) is a general dispersion model discussed in most research works. In addition, the diffusion influenced by impermeable boundaries and permeable boundaries is also considered in some pollution source localization works [73], and in some works the diffusion model is also extended to 3D environments. Diffusion model (10) in the 3D case is

$$C(x, y, z, t) = \frac{M}{8\left(\pi\sqrt{D_x D_y D_z} t\right)^{3/2}} \cdot \exp\left[-\frac{(x - u_x t - \varepsilon)^2}{4D_x t} - \frac{(y - u_y t - \eta)^2}{4D_y t} - \frac{(z - u_z t - \delta)^2}{4D_z t}\right]. \tag{11}$$

In general, the farther the source is from the sensor node, the smaller the monitoring value is. So, in some works, if $\mathbf{u} = (u_x, u_y) = (0, 0)$ and the fluid field is static, physical diffusion model (10) is simplified as [54, 55]

$$C(\mathbf{r}, t) = \frac{M}{\left((x - \varepsilon)^2 + (y - \eta)^2\right)^{\alpha/2}}. \tag{12}$$

In a static environment, the concentration contours approximate circles when there is no boundary constraint, like the diffusion process depicted by (6)–(9) and as shown in Figure 2, and when there is a boundary constraint or symmetrical boundary constraints, the concentration contours are often symmetric, like the case shown in Figure 3.

4.2. Different Localization Algorithms. If the pollution source location is denoted by $\mathbf{x} = (\varepsilon, \eta)$, the theoretical concentration monitoring value of node (x_i, y_i) provided by the diffusion model is denoted by $C(x_i, y_i, t_l, \mathbf{x})$, the monitoring noise is denoted by e_{il}, and the measurement obeys

$$\tilde{C}(x_i, y_i, t_l) = C(x_i, y_i, t_l, \mathbf{x}) + e_{il}. \tag{13}$$

The pollution source localization problem is to get the pollution source $\mathbf{x}$ based on known information such as the diffusion model, monitoring values $\tilde{C}(x_i, y_i, t_l)$, and node locations (x_i, y_i), $i = 1, 2, 3, \ldots, I$.

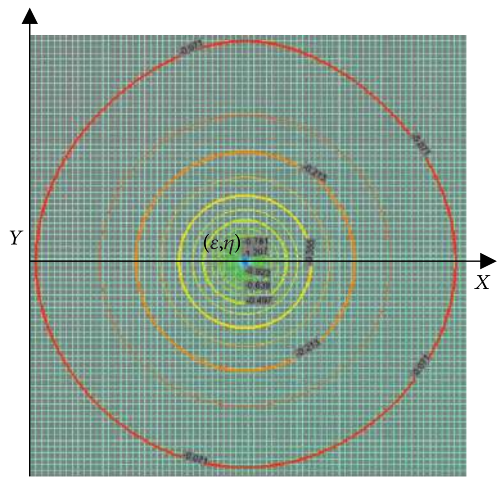

Figure 2: The concentration field without boundary constraints.

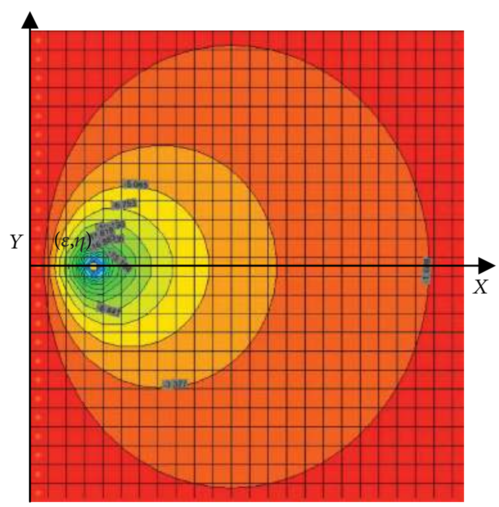

Figure 3: The concentration field with a boundary constraint.

4.2.1. The Localization Algorithms Independent of Diffusion Models
(1) The Coarse Localization Methods

(a) The maximum monitoring value point approach (MPA): as the sensor node with the maximum monitoring value is always very close to the pollution source, the location of the sensor node with the maximum monitoring value in the network is the source position.

(b) The earliest detection point approach (EPA): the source position is the location of the sensor node which detects the pollution the earliest.

The MPA and EPA methods belong to the CPA (closest point approach) methods [54]. In [54, 69], these methods are compared with other localization methods in the experiments, and some advantages are improved.

(c) The centroid localization algorithm: the centroid of the area where the pollution source exists is the source location. In [74], a centroid algorithm for pollution source localization is given. The specific method is as follows.

Sort (x_i, y_i, T_i), $i = 1, 2, 3, \ldots, I$ by pollution source detection time T_i firstly, and get the results $T_1 < T_2 < T_3 < \cdots < T_I$. Then, the estimation of the source location is obtained as

$$\widehat{\varepsilon} = \frac{\iint_D x\,dx\,dy}{A}, \qquad \widehat{\eta} = \frac{\iint_D y\,dx\,dy}{A}, \tag{14}$$

where $A = \iint_D d\sigma$, the boundary condition of the source location is $(\varepsilon, \eta) \in B$, and

$$D = \left\{ (\varepsilon,\eta) \,\middle|\, \begin{bmatrix} 2(x_2 - x_1) & 2(y_2 - y_1) \\ 2(x_3 - x_1) & 2(y_3 - y_1) \\ \cdots & \cdots \\ 2(x_I - x_1) & 2(y_I - y_1) \end{bmatrix} \begin{bmatrix} \varepsilon \\ \eta \end{bmatrix} < \begin{bmatrix} x_2^2 + y_2^2 - x_1^2 - y_1^2 \\ x_3^2 + y_3^2 - x_1^2 - y_1^2 \\ \cdots \\ x_I^2 + y_I^2 - x_1^2 - y_1^2 \end{bmatrix} \right\} \cap B. \tag{15}$$

The effectiveness of the algorithm is tested in some practical experiments.

(2) The Localization Algorithms Based on Diffusion Contours. Information on pollutant transport is implied in concentration contours, and the pollution source location can be obtained according to contour features.

In an ideal situation like the case shown in Figure 2, the concentration contours approximate circles. The nodes $(x_i, y_i), i = 1, 2, \ldots, I$ in the same contour have the same distance to the source. One can obtain

$$\begin{aligned} (x_1 - \varepsilon)^2 + (y_1 - \eta)^2 &= r^2, \\ (x_2 - \varepsilon)^2 + (y_2 - \eta)^2 &= r^2, \\ (x_3 - \varepsilon)^2 + (y_3 - \eta)^2 &= r^2, \\ &\cdots \\ (x_I - \varepsilon)^2 + (y_I - \eta)^2 &= r^2. \end{aligned} \tag{16}$$

The overdetermined equations can be solved by least squares.

If the source location is at the symmetry axis of the contours and there are two nodes with the same unidirectional coordinate value on the same contour, the coordinate value in one direction can be obtained at least. For example, in the case shown in Figure 3, if there are two nodes (x_1, y_1) and (x_1, y_2) in the same contour, one has

$$\hat{\eta} = \frac{y_1 + y_2}{2}. \tag{17}$$

In [56, 69], the localization algorithms based on contours are proposed and compared with other methods. If the contours have distinguishing features, rather precise results can be obtained.

(3) Inverse Problems Based on Diffusion Process Observation. In some works, source localization problems are disposed by solving inverse problems. In these works, the numerical pollutant transport process is studied firstly, and then posteriori probabilities $p(\mathbf{x} = (\varepsilon, \eta) \mid \tilde{C}(x_i, y_i, t_l), i = 1, 2, 3, \dots, I, l = 1, 2, 3, \dots, L)$ are calculated and a site (ε_0, η_0) where the posteriori probability is the highest is the source location. In [57], the posteriori probability is calculated by the Monte Carlo Markov chain method. In [58], the posteriori probability is calculated based on a BN (Bayesian network) capturing a Hidden Markov process.

(4) Multiple Diffusion Source Localization Using the Methods Independent of Models. The multiple diffusion source localization problem is to locate diffusion sources $\mathbf{x}_i = (\varepsilon_i, \eta_i), i = 1, 2, 3, \dots, I$.

For the coarse localization methods, the difficulty in this case is that individual information of different sources is hardly distinguished from the monitoring value. So the monitoring values which are close to a pollution source are always used to locate the source. In multiple-diffusion source localization, the earliest detection point approach is more applicable than the maximum monitoring value point approach.

In the fields where there are multiple pollution sources, the contours are influenced by multiple sources and are irregular. So, there are often no obvious contour centers and the localization algorithms based on diffusion contours are not used in multiple-diffusion source localization generally.

A multiple-diffusion source localization problem disposed by solving the inverse problem is also discussed in [57]. However, the same as the coarse localization methods, this method is hard to be applied if pollution sources are close to each other.

4.2.2. Parameter Estimation Based on Diffusion Models. In these localization problems, the solving methods are related to diffusion models closely.

(1) Source Location Estimation Using Maximum Likelihood Estimation. The posterior probability is

$$p(\mathbf{x}|\mathbf{D}) = \frac{p(\mathbf{D}|\mathbf{x})p(\mathbf{x})}{p(\mathbf{D})}, \tag{18}$$

where $\mathbf{D} = \{\tilde{C}(x_i, y_i, t_l), i = 1, 2, 3, \dots, I, l = 1, 2, 3, \dots, L\}$. As the elements in $\mathbf{D}$ are observation values, $p(\mathbf{D}) = 1$. If there is an assumption that the prior probability is $p(\mathbf{x}) = 1$, one can obtain $p(\mathbf{x} \mid \mathbf{D}) = p(\mathbf{D} \mid \mathbf{x})$. Then, the maximum likelihood estimation method can be used, and the estimation problem is

$$\arg \max_{\mathbf{x}} \quad p(\mathbf{D}|\mathbf{x}) = \prod_{(i,l)=(1,1)}^{(I,L)} p\left(\tilde{C}(x_i, y_i, t_l)|\mathbf{x}\right). \tag{19}$$

In general, it is assumed that $e_{il} \sim N(\mu_{il}, \sigma_{il}), i = 1, 2, 3, \dots, I, l = 1, 2, 3, \dots, L$ are noises with normal distribution [60, 69], so based on diffusion equation (14), the likelihood function is always

$$p\left(\tilde{C}(x_i, y_i, t_l)|\mathbf{x}\right) = \left(\frac{1}{2\pi\sigma_{il}^2}\right)^{1/2} \cdot \exp\left[-\frac{\left(\tilde{C}(x_i, y_i, t_l) - C(x_i, y_i, t_l, \mathbf{x}) - \mu_{il}\right)^2}{2\sigma_{il}^2}\right], \tag{20}$$

and the result can be obtained by solving the partial differential equation as below:

$$\frac{d \ln\left(\prod_{(i,l)=(1,1)}^{(I,L)} p\left(\tilde{C}(x_i, y_i, t_l)|\mathbf{x}\right)\right)}{d\mathbf{x}} = 0. \tag{21}$$

In [55], CH_4 source localization is discussed. Firstly, a CH_4 propagation model is given, and the inner part $(\tilde{C}(x_i, y_i, t_l) - C(x_i, y_i, t_l, \mathbf{x}) - \mu_{il})^2$ in (20) is rewritten as a linear model. Then, maximum likelihood estimation is used and the theoretical lower bound of the source estimation error is given. In [59], a linear gas propagation model which is similar to (13) is given, the inner formula $(\tilde{C}(x_i, y_i, t_l) - C(x_i, y_i, t_l, \mathbf{x}) - \mu_{il})^2$ is also rewritten as a linear one, and the result is obtained by solving problem (21). In the work, the maximum likelihood estimation result is compared with the results obtained by the nonlinear least square method, and some advantages are improved.

(2) Source Location Estimation Using Bayesian Estimation. The Bayesian estimation problem is as (22) and (23) shown below:

$$p(\mathbf{x}|\mathbf{D}) = \frac{\left(\prod_{(i,l)=(1,1)}^{(I,L)} p\left(\tilde{C}(x_i, y_i, t_l|\mathbf{x})\right) p(\mathbf{x})\right)}{\int_{\mathbf{x}} \left(\prod_{(i,l)=(1,1)}^{(I,L)} p\left(\tilde{C}(x_i, y_i, t_l|\mathbf{x})\right) p(\mathbf{x}) d\mathbf{x}\right)}, \tag{22}$$

$$\hat{\mathbf{x}} = \mathrm{E}(\mathbf{x}|\mathbf{D}) = \int \mathbf{x} p(\mathbf{x}|\mathbf{D}) d\mathbf{x}. \tag{23}$$

Different from the background assumption in (18) and (19), in many cases the prior probability $p(\mathbf{x})$ and the likelihood probability $p(\tilde{C}(x_i, y_i, t_l) \mid \mathbf{x})$ cannot be known precisely in advance, so $p(\mathbf{x} \mid \mathbf{D})$ cannot be obtained directly.

In some works, $p(\mathbf{x} \mid \mathbf{D})$ is obtained by approximation methods firstly, and then the estimation result is calculated according to (23). For example, in [72], two methods, a Gaussian density approximation and a LPG function (linear combination of polynomial Gaussian density functions) approximation, are used in the approximation of $p(\mathbf{x} \mid \mathbf{D})$, and in [60, 61], $p(\mathbf{x} \mid \mathbf{D})$ is computed by Markov Chain Monte Carlo (MCMC) numerical method. While in some other works, $\mathrm{E}(\mathbf{x} \mid \mathbf{D})$ is calculated directly by using the Monte Carlo numerical method [62].

(3) Source Location Estimation Using Sequence Filter. The pollution source localization can be implemented by using time-varying concentration measurements $\tilde{C}(x_i, y_i, t_l, \mathbf{x})$, $i = 1, 2, 3, \ldots, I$.

Let $\hat{\mathbf{x}}_l^-$, $\hat{\mathbf{x}}_{l-1}$, and $\mathbf{w}_{l-1}$ be the priori state estimate at t_l, the posteriori state estimate at t_{l-1}, and the state noise respectively. When the observation equation is (13), and the time-varying relation of the states is

$$\hat{\mathbf{x}}_l^- = \mathbf{A}\hat{\mathbf{x}}_{l-1} + \mathbf{w}_{l-1}, \tag{24}$$

the methods based on sequence filters can be used. In [63], the source localization problem is solved based on Kalman filter. A localization method based on PF (particle filters) is proposed in [64]. In [65], source localization methods based on unscented Kalman filter are presented. Considering that the mathematical expression of $C(x_i, y_i, t_l, \mathbf{x}_I)$ is often nonlinear, and the specific distribution parameters are often unknown even when the distribution of measuring noise is normal, PF localization methods have more applicability.

(4) Source Location Estimation Using Least Squares. The usually used localization method is the least square as follows:

$$\begin{aligned} \min_{\zeta,\eta} \quad & \sum_{i=1}^{n} \left[\tilde{C}_i - C(x_i, y_i, t_l, \mathbf{x})\right]^2, \\ \text{s.t.} \quad & f_j(\mathbf{x}), \quad j = 1, 2, 3, \ldots, J, \end{aligned} \tag{25}$$

where $f_j(\mathbf{x}), j = 1, 2, 3, \ldots, J$ are constraints of the location parameters. This method is comparatively simple and often applied in practical applications when the distribution of e_{il} is unknown.

In works [54, 65, 66, 73], least square methods are adopted to solve the pollution source localization method. In some works, there is no constraint, and the mathematical problem can even be rewritten as linear cases. In most cases, (25) is a nonlinear problem, and methods such as Levenberg-Marquardt [75], reflective Newton [76], and interior trust region [77] can be adopted to solve the nonlinear least square problem.

(5) Multiple Diffusion Sources Localization Based on Diffusion Models. In ideal conditions, the concentration monitoring value in flow fields when there are multiple sources is

$$\begin{aligned} \tilde{C}(x_i, y_i, t_l, \mathbf{X}) = {} & C(x_i, y_i, t_l, \mathbf{x}_1) + C(x_i, y_i, t_l, \mathbf{x}_2) \\ & + C(x_i, y_i, t_l, \mathbf{x}_3) + \cdots \\ & + C(x_i, y_i, t_l, \mathbf{x}_I) + \theta_{il}, \end{aligned} \tag{26}$$

where $\mathbf{X} = (\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_I) = (\varepsilon_1, \eta_1, \varepsilon_2, \eta_2, \ldots, \varepsilon_I, \eta_I)$.

The above localization algorithms based on diffusion models can be extended to locate multiple diffusion sources if each theoretical $C(x_i, y_i, t_l, \mathbf{x}_i)$ has an explicit expression. Nevertheless, localization problems are high-dimensional and coupling interferences in the estimation of multiple location parameters are unavoidable.

4.2.3. Performances of Different Pollution Source Localization Methods. For the localization algorithms independent of diffusion models, localization is based on observations of the network, rather than the pollutant migrating laws, so the precision of many methods is susceptible to node observations.

For the localization based on diffusion models, as the diffusion models are all proposed under ideal assumptions and cannot depict the diffusion process very precisely, the accuracy of many localization algorithms is limited by diffusion models. In many cases, there are even no explicit diffusion models. In analytic water pollution source localization methods related to diffusion models, error-prone numerical iteration computations are also often involved.

In particular, comparisons of different pollution source localization methods are shown in Table 1.

Furthermore, even if there are many pollution source localization methods, it should be realized that as the pollutant migrating process is complicated, in order to simplify the research backgrounds, advection and chemical reactions as well as transport and fate models of pollutants are ignored in most works.

5. Challenges in Pollution Monitoring

5.1. Challenges in Environment Monitoring and Pollution Detection

5.1.1. Sensor Technology. More sensors which can detect specific pollution material are needed, so the sensor technology is a challenge.

5.1.2. Robust Networks. Higher-efficiency power supplies and lower-power consumption devices are needed, especially in wireless sensor networks. To realize multihop and collaborative work in practical applications, more robust communication technologies are needed.

5.1.3. Pollution Detection. There are many statistical distributions of measurement noises, parameter test methods, and different nonparameter test methods. Which one is the most proper solving method for a particular hypothesis testing problem is a problem to be discussed further.

In node deployment, the number of sensors in any subregion is generally considered to be Poisson distributed [78, 79]. Only when the node closes to the pollution source, the node does detect the pollution timely. If the Poisson

Table 1: Comparison of different pollution source localization methods.

Methods	Advantages	Deficiencies	Feature properties
The coarse localization algorithms	The coarse localization methods are easily to be implemented in engineering.	The localization result is affected easily by a node's measurement and nodes' deployment. Localization precision is comparatively low.	Theoretically, this method can be used to locate a pollution source even when there is only one node. This method is rarely used in multiple-pollution-source localization.
The localization based on contours	An accurate result can be obtained easily if concentration contours has obvious characteristics.	The diffusion contours are irregular in many cases, and the localization methods based on contours cannot be always used.	At least 5 nodes are needed to estimate the plane contour's shape [74]. This method is not used to locate multiple sources.
The localization methods by solving inverse problems	Even if the pollutant dispersion model is not used, an analytic result is obtained.	The accuracy is determined by the sampling methods of sites (ζ_k, η_k), $k = 1, 2, 3, \ldots, K$ which are potential pollution source locations in the field.	At least 3 nodes are needed to locate a pollution source. If pollution sources are far away from each other, this method can be used to locate multiple sources.
The maximum likelihood estimation	The estimation accuracy is improved with the increase in the sample size. The method is a statistical inference method with a comparatively smaller computational complexity.	The likelihood function is hard to be obtained if the prior distribution of the concentration is not known. If the diffusion model is of strong nonlinearity, a globally optimal solution is difficult to be obtained.	Node number requirement is related to the number of unknown parameters and the nonlinear complexity of the diffusion equation. This method can be used to locate multiple pollution sources if an explicit propagation expression can be given.
The Bayesian estimation	Accurate localization results can be obtained more possibly.	The computational complexity in this method is high.	Similar feature properties as the maximum likelihood estimation
Localization methods using a sequence filter	Time-varying characteristics of observations are considered. The computational complexity is not high comparatively.	Choosing proper noise parameters is a problem.	Theoretically, one node's monitoring values in different times are enough to locate a source. This method can be used to locate multiple pollution sources if an explicit propagation expression can be given.
Localization methods based on least squares	In the least square, there are no complicated statistical calculations. This method has a strong universality.	If the diffusion model is of strong nonlinearity, a globally optimal solution is hard to be obtained.	Node number requirement is related to the number of unknown parameters. In a linear least square problem with two unknown parameters, no less than 3 nodes are needed. This method can be used to locate multiple pollution sources if an explicit propagation expression can be given.

density λ is small, there are few nodes in the nearest neighbor region, and the node number could even be 0. So, the performance of the detection methods is always related to the node density. A high-precision detection method with a sparse node density is a problem to be studied further.

5.2. Challenges in Pollution Source Localization Using Sensor Networks

(1) The environment is not always static, especially in dynamic water, the sensor nodes always drift, and localization methods based on nonfixed sensor nodes should be considered [80]

(2) In complicated water, for example the velocity field, the pollutant migrating is influenced by shear flow, turbulent flow, dispersion, degradation, etc.; effective localization algorithms are still hard to be given actually [80]

(3) The pollutant migrating process is complicated; in order to simplify the research problems, advection and chemical reactions as well as transport and fate models of pollutants are ignored in most pollution monitoring works using sensor networks. Localization methods considering the factors are hard to be given

(4) In some cases, the pollutant migration has no regularity, and characteristics of the pollution source even change with time. How the sensing values are used to locate the pollution source in these cases is a problem

(5) Because the sensors are valuable, the sensor nodes cannot be deployed densely. How to get a precise localization result when sensor nodes are deployed sparsely is a challenge

(6) The diffusion models are always complicated. If the pollution source localization problem is a strong

nonlinearity problem, there are many local extremum points in the domain. So, a precise result is often hard to be obtained in analytic localization algorithms based on diffusion models

6. Conclusions

Pollution monitoring is of great importance to environmental protection. In this paper, a survey on air and water environment monitoring, pollution source detection, and localization using sensor networks is given. Firstly, the sensors and monitoring systems are investigated. Secondly, the pollution detection methods using sensor networks are studied. Subsequently, different pollution source localization methods are discussed. Finally, challenges in pollution monitoring and diffusion source localization are presented.

Disclosure

Some problems and challenges in water pollution monitoring using sensor networks have been discussed and presented in reference [80], which is an early conference paper. In this paper, problems and challenges in pollution monitoring in both water and air environments are discussed. Details of the research status on pollution monitoring using sensor networks are only given and analyzed in this review paper.

The founding sponsors had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; and in the decision to publish the results.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

Authors' Contributions

There is a long-term cooperation between the two authors in the research of pollution monitoring using sensor networks. This review paper is based on the authors' previous works. In this paper, Sections 2, 3, 4, and 5 are written by Xu Luo, and other parts are contributed by Jun Yang.

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References

[1] H. Karl and A. Willig, *Protocols and Architectures for Wireless Sensor Networks*, John Wiley & Sons, Ltd, Chichester, 2005.

[2] Y. Wang and Z. Wang, *Wireless Sensor Network*, Publishing House of Electronics Industry, Ltd, Beijing, 2005.

[3] Z. E. Kamal and M. A. Salahuddin, "Introduction to wireless sensor networks," in *Wireless sensor and mobile ad-hoc networks*, Z. E. Kamal, B. D. Driss, and A. Al-Fuqaha, Eds., pp. 1–18, Springer Press, New York, NY, USA, 2015.

[4] S. Yao, S. Hosohara, Y. Shimizu, N. Miura, H. Futata, and N. Yamazoe, "Solid electrolyte CO_2 sensor using NASICON and Li-based binary carbonate electrode," *Chemistry Letters*, vol. 20, no. 11, pp. 2069–2072, 1991.

[5] H. Yamaura, T. Jinkawa, J. Tamaki, K. Moriya, N. Miura, and N. Yamazoe, "Indium oxide-based gas sensor for selective detection of CO," *Sensors and Actuators B: Chemical*, vol. 36, no. 1–3, pp. 325–332, 1996.

[6] N. Koshizaki and T. Oyama, "Sensing characteristics of ZnO-based NO_x sensor," *Sensors and Actuators B: Chemical*, vol. 66, no. 1–3, pp. 119–121, 2000.

[7] R. Akila and K. T. Jacob, "An SO_x (x = 2, 3) sensor using β-alumina/Na_2SO_4 couple," *Sensors and Actuators*, vol. 16, no. 4, pp. 311–323, 1989.

[8] Y. Wang, H. Yan, and E. Wang, "Solid polymer electrolyte-based hydrogen sulfide sensor," *Sensors and Actuators B: Chemical*, vol. 87, no. 1, pp. 115–121, 2002.

[9] V. Srivastava and K. Jain, "Highly sensitive NH_3 sensor using Pt catalyzed silica coating over WO_3 thick films," *Sensors and Actuators B: Chemical*, vol. 133, no. 1, pp. 46–52, 2008.

[10] H. Zhang, X. Liang, J. Li, and G. Lu, "NASICON-based potentiometric Cl_2 sensor combining NASICON with Cr_2O_3 sensing electrode," *Sensors and Actuators B: Chemical*, vol. 180, pp. 66–70, 2013.

[11] T. Takada, K. Suzuki, and M. Nakane, "Highly sensitive ozone sensor," *Sensors and Actuators B: Chemical*, vol. 13, no. 1–3, pp. 404–407, 1993.

[12] D. Vlascici, E. Fagadar-Cosma, E. Pica et al., "Free base porphyrins as ionophores for heavy metal sensors," *Sensors*, vol. 8, no. 8, pp. 4995–5004, 2008.

[13] A. Richter, G. Paschew, S. Klatt, J. Lienig, K. F. Arndt, and H. J. Adler, "Review on hydrogel-based pH sensors and micro-sensors," *Sensors*, vol. 8, no. 1, pp. 561–581, 2008.

[14] P. M. Ramos, J. M. D. Pereira, H. M. G. Ramos, and A. L. Ribeiro, "A four-terminal water-quality-monitoring conductivity sensor," *IEEE Transactions on Instrumentation and Measurement*, vol. 57, no. 3, pp. 577–583, 2008.

[15] F. J. Machuca, K. W. Montgomery, and R. P. Chiarello, "Dissolved oxygen sensor," 2017, US Patent 9541539 B2.

[16] R. E. Taylor and D. W. Bull, "Turbidity sensor," 1998, US Patent US5828458 A.

[17] L. Campanella, T. Ferri, M. Pia Sammartino, P. Sangiorgio, and G. Visco, "Development of a new sensor for total organic carbon (TOC) determination," *Sensor Review*, vol. 22, no. 1, pp. 57–61, 2002.

[18] M. Belz, W. J. O. Boyle, K. F. Klein, and K. T. V. Grattan, "Smart-sensor approach for a fibre-optic-based residual chlorine monitor," *Sensors and Actuators B: Chemical*, vol. 39, no. 1–3, pp. 380–385, 1997.

[19] Z. L. Liu and Y. J. Peng, "Study and production of organic phosphorus sensor fast pesticides detection," *Food Science*, vol. 25, no. 2, pp. 130–134, 2004.

[20] Y. Bai, "The study on MEMS based electrochemical micro-sensor for total Phosphorus determination. PHD dissertation," University of Chinese Academy of Sciences, 2013.

[21] Y. Li, "The study on MEMS based electrochemical micro-sensor for total Nitrogen determination. PHD dissertation," University of Chinese Academy of Sciences, 2012.

[22] Y. Mashalkar and A. Kazi, "Wireless sensor network (MOTES): smart dust," *International Journal of Computer and Electronics Research*, vol. 3, no. 4, pp. 308–312, 2014.

[23] A. Kadri, E. Yaacoub, M. Mushtaha, and A. Abu-Dayya, "Wireless sensor network for real-time air pollution monitoring," in *2013 1st International Conference on Communications, Signal Processing, and their Applications (ICCSPA)*, pp. 1–5, Sharjah, United Arab Emirates, February 2013.

[24] C. Becher, P. Kaul, J. Mitrovics, and J. Warmer, "The detection of evaporating hazardous material released from moving sources using a gas sensor network," *Sensors and Actuators B: Chemical*, vol. 146, no. 2, pp. 513–520, 2010.

[25] R. Shepherd, S. Beirne, K. Lau, B. Corcoran, and D. Diamond, "Monitoring chemical plumes in an environmental sensing chamber with a wireless chemical sensor network," *Sensors and Actuators B: Chemical*, vol. 121, no. 1, pp. 142–149, 2007.

[26] A. Somov, A. Baranov, A. Savkin, D. Spirjakin, A. Spirjakin, and R. Passerone, "Development of wireless sensor network for combustible gas monitoring," *Sensors and Actuators A: Physical*, vol. 171, no. 2, pp. 398–405, 2011.

[27] M. Rossi and D. Brunelli, "Ultra low power wireless gas sensor network for environmental monitoring applications," in *2012 IEEE Workshop on Environmental Energy and Structural Monitoring Systems (EESMS)*, pp. 75–81, Perugia, Italy, September 2012.

[28] M. Gao, F. Zhang, and J. Tian, "Environmental monitoring system with wireless mesh network based on embedded system," in *2008 Fifth IEEE International Symposium on Embedded Computing*, pp. 174–179, Beijing, China, October 2008.

[29] W. Tsujita, H. Ishida, and T. Moriizumi, "Dynamic gas sensor network for air pollution monitoring and its auto-calibration," in *Proceedings of IEEE Sensors, 2004*, pp. 56–59, Vienna, Austria, 2004.

[30] W. Tsujita, S. Kaneko, T. Ueda, H. Ishida, and T. Moriizumi, "Sensor-based air-pollution measurement system for environmental monitoring network," in *TRANSDUCERS '03. 12th International Conference on Solid-State Sensors, Actuators and Microsystems. Digest of Technical Papers (Cat. No.03TH8664)*, pp. 544–547, Boston, USA, 2003.

[31] W. Tsujita, A. Yoshino, H. Ishida, and T. Moriizumi, "Gas sensor network for air-pollution monitoring," *Sensors and Actuators B: Chemical*, vol. 110, no. 2, pp. 304–311, 2005.

[32] L. Sun, K. Wong, P. Wei et al., "Development and application of a next generation air sensor network for the Hong Kong marathon 2015 air quality monitoring," *Sensors*, vol. 16, no. 2, p. 211, 2016.

[33] P. Jiang, H. Xia, Z. He, and Z. Wang, "Design of a water environment monitoring system based on wireless sensor networks," *Sensors*, vol. 9, no. 8, pp. 6411–6434, 2009.

[34] E. V. Hatzikos, N. Bassiliades, L. Asmanis, and I. Vlahavas, "Monitoring water quality through a telematic sensor network and a fuzzy expert system," *Expert Systems*, vol. 24, no. 3, pp. 143–161, 2007.

[35] J. Wang, X. Wang, X. Ren, and Y. Shen, "A water pollution detective system based on wireless sensor network," *Journal of Guilin University of Electronic Technology*, vol. 29, no. 3, pp. 247–250, 2009.

[36] B. O'Flynn, R. Martinez-Catala, S. Harte et al., "SmartCoast: a wireless sensor network for water quality monitoring," in *32nd IEEE Conference on Local Computer Networks (LCN 2007)*, pp. 815-816, Dublin, Ireland, October 2007.

[37] T. Le Dinh, W. Hu, P. Sikka, P. Corke, L. Overs, and S. Brosnan, "Design and deployment of a remote robust sensor network: experiences from an outdoor water quality monitoring network," in *32nd IEEE Conference on Local Computer Networks (LCN 2007)*, pp. 799–806, Dublin, Ireland, October 2007.

[38] F. J. Tiausas, M. L. Guico, J. C. Monje, and C. Oppus, "Design and development of a wireless sensor network framework for water quality remote monitoring," in *Mobile and Wireless Technology 2015*, K. Kim and N. Wattanapongsakorn, Eds., vol. 310 of Lecture Notes in Electrical Engineering, pp. 99–106, Springer, Berlin, Heidelberg, 2015.

[39] Z. Rasin and M. R. Abdullah, "Water quality monitoring system using Zigbee based wireless sensor network," *International Journal of Engineering & Technology*, vol. 9, no. 10, pp. 14–18, 2009.

[40] J. Wang, X. L. Ren, Y. L. Shen, and S. Y. Liu, "A remote wireless sensor networks for water quality monitoring," in *2010 International Conference on Innovative Computing and Communication and 2010 Asia-Pacific Conference on Information Technology and Ocean Engineering*, pp. 7–12, Macao, China, 2010.

[41] G. Tuna, B. Nefzi, O. Arkoc, and S. M. Potirakis, "A real-time remote monitoring of water quality by means of a wireless sensor network," *Sensor Letters*, vol. 12, no. 9, pp. 1414–1421, 2014.

[42] A. Khan and L. Jenkins, "Undersea wireless sensor network for ocean pollution prevention," in *2008 3rd International Conference on Communication Systems Software and Middleware and Workshops (COMSWARE '08)*, pp. 2–8, Bangalore, India, January 2008.

[43] X. Yang, K. Ong, W. Dreschel, K. Zeng, C. Mungle, and C. Grimes, "Design of a wireless sensor network for long-term, in-situ monitoring of an aqueous environment," *Sensors*, vol. 2, no. 11, pp. 455–472, 2002.

[44] G. Xu, W. Shen, and X. Wang, "Applications of wireless sensor networks in marine environment monitoring: a survey," *Sensors*, vol. 14, no. 9, pp. 16932–16954, 2014.

[45] J. Lloret, S. Sendra, M. Garcia, and G. Lloret, "Group-based underwater wireless sensor network for marine fish farms," in *2011 IEEE GLOBECOM Workshops (GC Wkshps)*, pp. 115–119, Houston, USA, December 2011.

[46] Crossbow, "Mica 2Dot datasheet," July 2017 http://www.datasheetarchive.com/MICA2DOT-datasheet.html.

[47] P. Sikka, P. Corke, and L. Overs, "Wireless sensor devices for animal tracking and control," in *29th Annual IEEE International Conference on Local Computer Networks*, pp. 446–454, Tampa, USA, 2004.

[48] B. O'Flynn, S. Bellis, K. Mahmood et al., "A 3D miniaturised programmable transceiver," *MicroElectronics International*, vol. 22, no. 2, pp. 8–12, 2005.

[49] J. Heidemann, M. Stojanovic, and M. Zorzi, "Underwater sensor networks: applications, advances and challenges," *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, vol. 370, no. 1958, pp. 158–175, 2011.

[50] I. F. Akyildiz, D. Pompili, and T. Melodia, "Underwater acoustic sensor networks: research challenges," *Ad Hoc Networks*, vol. 3, no. 3, pp. 257–279, 2005.

[51] L. Lanbo, Z. Shengli, and C. Jun-Hong, "Prospects and problems of wireless communication for underwater sensor networks," *Wireless Communications and Mobile Computing*, vol. 8, no. 8, pp. 977–994, 2008.

[52] S. Rani and S. H. Ahmed, "Multi-hop reliability and network operation routing," in *Multi-Hop Routing in Wireless Sensor Networks: an Overview, Taxonomy, and Research Challenges*, S. Rani and S. H. Ahmed, Eds., pp. 471–490, Springer Press, New York, 2015.

[53] M. Basseville and I. M. Nikiforov, *Detection of Abrupt Changes: Theory and Application*, Prentice Hall, Englewood Cliffs, NJ, 1993.

[54] M. P. Michaelides and C. G. Panayiotou, "Plume source position estimation using sensor networks," in *Proceedings of the 2005 IEEE International Symposium on, Mediterrean Conference on Control and Automation Intelligent Control, 2005*, pp. 731–736, Limassol, Cyprus, 2005.

[55] S. Mitra, S. P. Duttagupta, K. Tuckley, and S. Ekram, "3D ad-hoc sensor networks based localization and risk assessment of buried landfill gas source," *International Journal of Circuits, Systems and Signal Processing*, vol. 1, no. 6, pp. 76–85, 2012.

[56] X. Luo, J. Yang, and L. Chai, "Water pollution source localization based on the contour in sensor networks," in *2016 Chinese Control and Decision Conference (CCDC)*, pp. 3433–3437, Yin Chuan, China, May 2016.

[57] M. Ortner, A. Nehorai, and A. Jeremic, "Biochemical transport modeling and Bayesian source estimation in realistic environments," *IEEE Transactions on Signal Processing*, vol. 55, no. 6, pp. 2520–2532, 2007.

[58] G. Pavlin, P. D. Oude, and F. Mignet, "Gas detection and source localization: a Bayesian approach," in *Proceedings of the 14th International Conference on Information Fusion*, pp. 406–413, Chicago, USA, 2014.

[59] X. H. Kuang and H. H. Shao, "Application of sensor networks in plume source position estimation," *Journal of East China University of Science and Technology (Natural Science Edition)*, vol. 32, no. 7, pp. 780–783, 2006.

[60] C. Huang, T. Hsing, N. Cressie, A. R. Ganguly, V. A. Protopopescu, and N. S. Rao, "Bayesian source detection and parameter estimation of a plume model based on sensor network measurements," *Applied Stochastic Models in Business and Industry*, vol. 26, no. 4, pp. 331–348, 2010.

[61] M. Borysiewicz, A. Wawrzynczak, and P. Kopka, "Stochastic algorithm for estimation of the model's unknown parameters via Bayesian inference," in *Proceedings of the Federated Conference on Computer Science and Information Systems*, pp. 501–508, Wroclaw, Poland, 2012.

[62] A. Gunatilaka, B. Ristic, A. Skvortsov, and M. Morelande, "Parameter estimation of a continuous chemical plume source," in *Proceedings of the 11th International Conference on Information Fusion*, pp. 1–8, Cologne, Germany, 2008.

[63] M. Zoumboulakis and G. Roussos, "Estimation of pollutant-emitting point-sources using resource-constrained sensor networks," in *GeoSensor Networks. GSN 2009*, N. Trigoni, A. Markham, and S. Nawaz, Eds., vol. 5659 of Lecture Notes in Computer Science, pp. 21–30, Springer, Berlin, Germany, 2009.

[64] X. H. Kuang and H. H. Shao, "Plume source localization based on Bayes using wireless sensor network," *Acta Armamentarii*, vol. 12, no. 29, pp. 1474–1478, 2008.

[65] X. Luo, L. Chai, and J. Yang, "Offshore pollution source localization in static water using wireless sensor networks," *Acta Automatica Sinica*, vol. 40, no. 5, pp. 849–861, 2014.

[66] H. Wang, Y. Zhou, X. Yang, and L. Wang, "Plume source localizing in different distributions and noise types based on WSN," in *2010 International Conference on Communications and Mobile Computing*, pp. 63–66, Caen, France, April 2010.

[67] X. Luo and J. Yang, "Water pollution detection based on hypothesis testing in sensor networks," *Journal of Sensors*, vol. 2017, Article ID 3829894, 8 pages, 2017.

[68] T. Zhao and A. Nehorai, "Detecting and estimating biochemical dispersion of a moving source in a semi-infinite medium," *IEEE Transactions on Signal Processing*, vol. 54, no. 6, pp. 2213–2225, 2006.

[69] J. Yang and X. Luo, "A study on water pollution source localization in sensor networks," *Journal of Sensors*, vol. 2016, Article ID 9528050, 11 pages, 2016.

[70] R. E. Walpole, R. H. Myers, and K. Ye, *Probability and Statistics for Engineers and Scientists*, Pearson Prentice Hall, Upper Saddle River, NJ, 8th edition edition, 2011.

[71] Z. Z. Peng, T. X. Yang, X. J. Liang, and Z. S. Gu, *Mathematical Model of Water Environment and Its Application*, Chemical Industry Press, Beijing, 2007.

[72] T. Zhao and A. Nehorai, "Distributed sequential Bayesian estimation of a diffusive source in wireless sensor networks," *IEEE Transactions on Signal Processing*, vol. 55, no. 4, pp. 1511–1524, 2007.

[73] J. Yang, X. Luo, and L. Chai, "The localization of pollution source in steady diffusion state in river based on wireless sensor networks," *Chinese Journal of Sensors and Actuators*, vol. 27, no. 10, pp. 1423–1430, 2014.

[74] X. Luo and J. Yang, "A centroid algorithm for water pollution source localization in sensor networks," *Chinese Journal of Sensors and Actuators*, vol. 27, no. 10, pp. 1423–1430, 2018.

[75] S. D. Shan, "A Levenberg-Marquardt method for large-scale bound-constrained nonlinear least-squares [Master. dissertation]," Acadia University, 2006.

[76] T. F. Coleman and Y. Li, "On the convergence of interior-reflective Newton methods for nonlinear minimization subject to bounds," *Mathematical Programming*, vol. 67, no. 1-3, pp. 189–224, 1994.

[77] T. F. Coleman and Y. Li, "An interior trust region approach for nonlinear minimization subject to bounds," *SIAM Journal on Optimization*, vol. 6, no. 2, pp. 418–445, 1996.

[78] C. Bettstetter, "On the connectivity of *ad hoc* networks," *The Computer Journal*, vol. 47, no. 4, pp. 432–447, 2004.

[79] B. Wang, *Coverage Control in Sensor Networks*, Computer Communications and Networks, Springer, London, 2010.

[80] X. Luo and J. Yang, "Problems and challenges in water pollution monitoring and water pollution source localization using sensor networks," in *2017 Chinese Automation Congress (CAC)*, pp. 5834–5838, Jinan, China, October 2017.