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A Survey on Gas Leakage Source Detection and Boundary Tracking with Wireless Sensor Networks

LEI SHU[1], (Senior Member, IEEE), MITHUN MUKHERJEE[1], (Member, IEEE), XIAOLING XU[1], (Member, IEEE), KUN WANG[2], (Member, IEEE), AND XIAOLING WU[3,4,5], (Member, IEEE)

[1]Guangdong Provincial Key Laboratory of Petrochemical Equipment Fault Diagnosis, Guangdong University of Petrochemical Technology, Maoming 525000, China
[2]School of Internet of Things, Nanjing University of Posts and Telecommunications, Nanjing 210003, China
[3]Guangdong University of Technology, Guangzhou 510006, China
[4]Guangzhou Institute of Advanced Technology, Chinese Academy of Sciences, Guangzhou 511458, China
[5]Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, Shenzhen 518055, China

Corresponding author: M. Mukherjee (mithun.mukherjee@outlook.com)

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ABSTRACT Gas leakage source detection and boundary tracking of continuous objects have received a significant research attention in the academic as well as the industries due to the loss and damage caused by toxic gas leakage in large-scale petrochemical plants. With the advance and rapid adoption of wireless sensor networks (WSNs) in the last decades, source localization and boundary estimation have became the priority of research works. In addition, an accurate boundary estimation is a critical issue due to the fast movement, changing shape, and invisibility of the gas leakage compared with the other single object detections. We present various gas diffusion models used in the literature that offer the effective computational approaches to measure the gas concentrations in the large area. In this paper, we compare the continuous object localization and boundary detection schemes with respect to complexity, energy consumption, and estimation accuracy. Moreover, this paper presents the research directions for existing and future gas leakage source localization and boundary estimation schemes with WSNs.

INDEX TERMS Wireless sensor networks (WSNs), diffusion model, source localization, boundary detection and tracking.

I. INTRODUCTION

With the rapid development of petrochemical industries in recent years, the interest in gas leak detection and localization has increased due the loss of life, injuries, and damaged equipment caused by the toxic gas leakage [1], [2]. Apart from the manufacturing and production point of view, real-time information about the distribution area of hazardous toxic gases in large-scale industry is needed to ensure safety precaution for the first-line working staff during various operations in production, storage, transportation, and usage. Thus, gas leakage source estimation continues to be a major part of intelligent industrial sensing systems. Gas leakage source localization and boundary tracking have been intensively investigated in the existing literature as follows:

1. Fixed Cable-Based Sensing: Traditional monitoring system consists of high-resolution sensors with fixed installation. The sensor data is sent to the control center through long-distance cables, which results very high cost. Deploying a large number of fixed cable-based sensing devices is not cost-effective in a very large monitoring area.

2. Big Mobile Robots: Expensive mobile robots are used to localize underwater gas leakage [3], [4]. Generally, these robots are designed in large size with good mobility, however, require very high cost for manufacturing

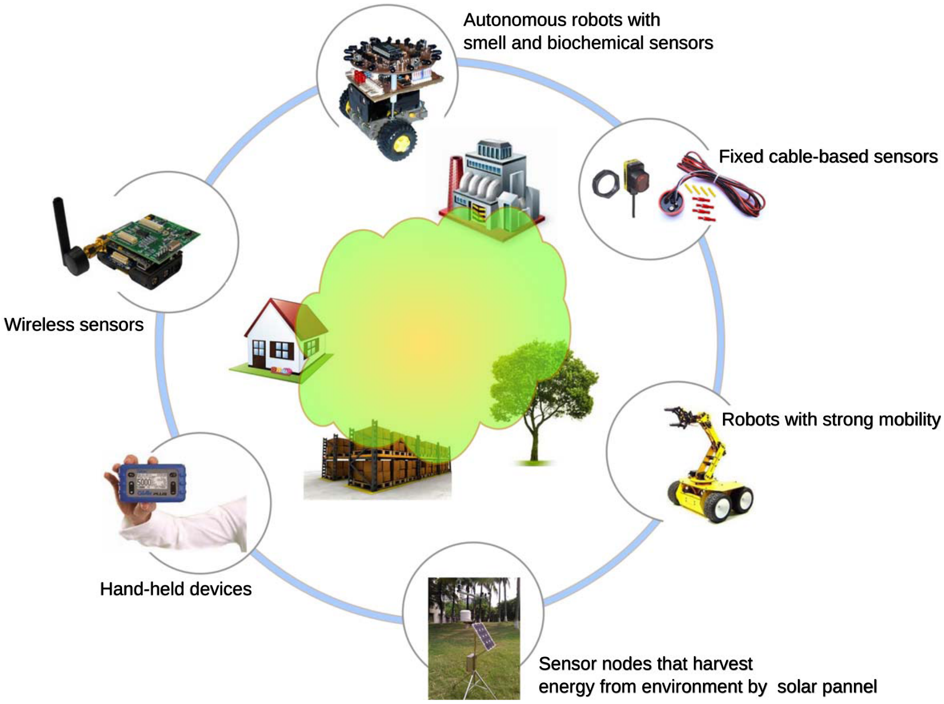

FIGURE 1. With the advantages of low cost, ease of deployment, and energy efficiency, various types of sensing elements[1] are used to monitor gas leakage in large-scale industries as well as in environments with WSNs.

as well as maintenance. Since the localization in robot-system is difficult due to its high degree of mobility, the high cost restricts further applicability in the large-scale monitoring.

3. Small Autonomous Mobile Robots, Called as Electronic Nose: Small size autonomous robots with low complexity and high mobility are widely used for sensing continuous objects. The smell and biochemical sensors in a single robot measure the gas density and estimate the direction as well as velocity of the gas diffusion. The collaborative biochemical gas source localization is based on adaptive swarm intelligence [4]. This localization scheme forms an autonomous group by more robots that have a wide coverage. However, the mobility of these robots is limited by the energy consumed by a long time in the large area. As the gas leakage source is estimated according to the wind field distribution, the localization accuracy is depends on the environmental factors, e.g., wind speed and wind direction.

4. WSN-Based Localization and Tracking: Wireless sensor networks (WSNs) are multi-hop systems with randomly deployed sensor nodes in the monitoring area. The gas concentration, diffusion direction, speed, and other physical parameters are measured by various senor nodes. Compared with previous *collaborative* localization and tracking systems, WSNs have the following advantages:

- Due to low-price sensor nodes, the self-organized WSNs perform better target estimation and localization than the robots which have higher cost and lack of cooperative movement.
- As the number of mobile robots is less, a long-time observation is required for the localization of objects. In contrast, the widely distributed sensor nodes can quickly estimate the location of the continuous objects,
- The sensor nodes are easily deployed in hard-to-reach areas where the robots have no-access for monitoring.

[1] The use of some images is for nonprofit educational purpose.

Along with various available high technologies in sensing devices, and also due to the advantage of low cost, ease of deployment, energy efficiency, and mobility (as illustrated in Fig. 1) compared to the traditional field bus, WSNs are evolving to become a promising approach for manufacturers as well as plant designers to solve many critical issues like gas leakage source localization and boundary tracking of continuous objects in large-scale industrial area as well as in environments.

This paper provides a comprehensive study on currently available gas diffusion models for localization of gas leakage sources. We further categorize the localization algorithms from the view of estimation accuracy and energy consumption issues. Since continuous objects are diffused in a wide region with the non-uniform diffusion velocity and the acceleration according to the surroundings, tracking of continuous objects is more difficult than an individual object tracking. Moreover, the study on boundary estimation of continuous objects has become popular in the last decade. We also present a detailed survey on boundary detection and tracking

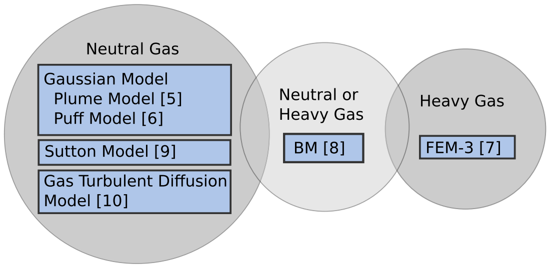

FIGURE 2. **Classification of gas diffusion models.**

algorithms proposed in the literature. In addition, this survey highlights the research issues of localization and boundary tracking of continuous objects in large-scale industries and environments.

The rest of this paper is organized as follows. Section II briefly overviews various gas diffusion models used in the literature. We present the gas source localization algorithms in Section III. The recent advancements and open challenges of boundary detection algorithms for the continuous objects are discussed in Sections IV. Finally, conclusions are drawn in Section V.

II. GAS DIFFUSION MODEL

Several research efforts were devoted to characterize basic theories of gas diffusion in the gas leakage area. Gas diffusion models are mainly classified into static and dynamic environment-based models. According to the spatial boundary, these models are further categorized into open space and limited space diffusion models. Various physical properties of gas-cloud further characterize these above models into heavy as well as light gas cloud-based models. Most of the toxic gases, e.g., liquid ammonia, liquefied petroleum gas, chloroethylene, and benzene belong to heavy gas category. Fig. 2 illustrates the classification of models based on heavy and neutral gases. Generally, Gaussian plume [5] and puff model [6], 3-D finite element (FEM-3) model [7], Britter and McQuaid (BM) model [8], Sutton model [9], and gas turbulent diffusion model [10] consider static environment characteristic of the gas diffusion. Since the gas diffusion is often affected by the wind and the barrier in real environment, therefore, present study mainly considers simple gas diffusion model, however, more practical conditions have yet to be addressed in the future.

A. GAUSSIAN MODEL

The Gaussian model [5], which is one of the oldest computational approaches, calculates the concentration of hazardous gas in an effective manner. This approach assumes a Gaussian distribution of the hazardous gas as follows. A hazardous gas diffusion has a normal probability distribution with the standard deviation that depends on the atmospheric turbulence, the distance from gas source to sensors, and the time duration of gas leakage. This model is more suitable for light gas diffusion which has a density similar to that of the air. In contrast, only theoretical analysis is possible in heavy gas category. However, this model is used for the prediction of the diffusion of non-continuous air pollution plumes. Generally, the Gaussian model is categorized into plume model and puff model, which are used to analyze continuous source diffusion and instantaneous source diffusion, respectively.

1) GAUSSIAN PLUME MODEL

Gaussian plume model [5] is used to simulate the concentration distribution of the neutral continuous gas at steady state. Assuming a static wind speed and direction, and atmospheric stability, the gas concentration can be expressed as

$$C(x,y,z) = \frac{Q}{2\pi\sigma_y\sigma_z u}\exp\left(-\frac{y^2}{2\sigma_y^2}\right) \times \left[\exp\left(-\frac{(z-H)^2}{2\sigma_z^2}\right)+\exp\left(-\frac{(z+H)^2}{2\sigma_z^2}\right)\right] \quad (1)$$

where $C(x, y, z)$ denotes the gas concentration in $\mathrm{mg\,m^{-3}}$ at point (x, y, z), Q is the leakage-rate in $\mathrm{mg\,s^{-1}}$, H is the effective gas source height in m, u is the average wind velocity in $\mathrm{m\,s^{-1}}$, σ_x, σ_y, and σ_z represent the diffusion parameters with wind in (x, y, z) direction, respectively, and x, y, and z denote the distance in (x, y, z) direction in m, respectively. Using (1), the isoconcentration curve is given by

$$y = \pm\left\{2\sigma_y^2 \ln\left(\frac{Q}{2\pi\sigma_y\sigma_z u C(x,y,z)}\left[\exp\left(-\frac{(z-H)^2}{2\sigma_z^2}\right) + \exp\left(-\frac{(z+H)^2}{2\sigma_z^2}\right)\right]\right)\right\}^{1/2} \quad (2)$$

The general assumptions in Gaussian plume model are as follows:

1) The gas is steadily and continuously released in a homogeneous atmospheric turbulence with a constant wind velocity.
2) The chemical conversion process and natural sedimentation are ignored.
3) The wind velocity is greater than or equal to $1\,\mathrm{m\,s^{-1}}$.
4) The maximum distance from leakage to source is 3000 m. However, the distance should be shorter in the horizontal direction with the homogeneous geographical conditions.

In recent years, Gaussian plume models [5] are widely used to estimate local pollution levels. Further, Fan et al. [11] improved this model by adding a terrain factor with geographic information system (GIS). Although, the accuracy of gas diffusion has been increased, the model parameters need to be frequently updated. Briant et al. [12] proposed a novel solution based on Gaussian plume model. This model reduces the error in a line source formula when the wind is not perpendicular to the line source. In addition, this model is suitable to simulate NO_x concentration[2] in large-scale.

[2]NO_x is a generic term for the mono-nitrogen oxides NO and NO_2 (nitric oxide and nitrogen dioxide).

Afterward, Ristic et al. [13] presented a theoretical analysis of best achievable estimation accuracy in estimation of the Gaussian plume model parameters. The numerical results illustrate that the parameter-estimation accuracy depends on the sensor measurement accuracy, the density of sensors, and the quality of prior meteorological advice.

2) GAUSSIAN PUFF MODEL

This model considers the diffusion of pollutants from an instantaneous point source. Assuming the axis of abscissae coincides with wind direction and the coordinate's initial point is located in the stack's socle, the concentration of pollutants to be emitted by a instantaneous point source in Gaussian puff model [6] is expressed as

$$\begin{aligned} C(x,y,z,t) = {} & \frac{Q}{(2\pi)^{3/2}\,\sigma_x\sigma_y\sigma_z}\exp\left(-\frac{(x-ut)^2}{2\sigma_x^2}\right) \\ & \times \exp\left(-\frac{y^2}{2\sigma_y^2}\right) \\ & \times \left[\exp\left(-\frac{(z-H)^2}{2\sigma_z^2}\right)+\exp\left(-\frac{(z+H)^2}{2\sigma_z^2}\right)\right], \end{aligned} \tag{3}$$

where $c(x, y, z, t)$ denotes the gas concentration at (x, y, z) point at time t in $\mathrm{mg\,m^{-3}}$.

This model is further improved to study the influence of uncertainties on the estimation of the parameters in a simple 3-D dispersion model. The issue of propagation uncertainty has been solved by using polynomial chaos method with a cost of additional computation [14]. In addition, the Gaussian puff model is used for the methane gas diffusion with an adjusted model parameters in coal-mine network topology [15]. This model estimates the safest and fastest escape routes for coal miners in a disaster. Further, the Gaussian puff model is extended to the social force model [16] that simulates the whole process and finds an efficient evacuation during a terroristic attack with toxic gas in a sub-way station. A stochastic extension of the Gaussian puff model helps to characterize atmospheric pollutant concentration with the multiple contaminant clouds [17].

B. 3-D FINITE ELEMENT MODEL (FEM-3)

The FEM-3 [7], which was first proposed in 1979, simulates the liquefied gas diffusion. It handles a variety of heavy gas diffusion. FEM-3 is composed of the momentum conservation equation, the continuity equation, the heat balance equation, the diffusion mass balance equation, and the ideal gas state equation [7]. Basically, this model is based on the Galerkin method. In addition, this model considers the turbulence problem using the gradient transporting theory and the mixing-length theory.

The discharging diffusion process of oxygen is dynamically simulated based on the FEM-3 [7] in a sealed space. Another diffusion process is described by the simplified 3-D diffusion model according to the characteristics of Chloroethylene [18] at stable as well as unstable atmospheres. Afterward, the relationship between diffusion concentration and diffusion distance is discussed. This model is widely applied in the gas leakage diffusion with continuous or limited time duration. For instance, Hu et al. [19] studied the changing nature of the gas concentration using the FEM-3 in the real conditions with a sealed space. High accuracy and low computation complexity are obtained for estimating the gas concentration. In addition, this model is also applicable for the gas leakage diffusion in a more complex terrain, e.g., diffusion near buildings. However, the estimation error increases due to many parameters that need to be properly estimated in this model.

C. BRITTER AND McQUAID (BM) MODEL

In 1988, Britter and McQuaid estimated the heavy gas diffusion that was continuously and instantaneously released from area sources. Basically, Britter and McQuaid (BM) model is an empirical model where the gas leakage diffusion phenomenon is described through a series of simple graphs and relational expressions [8]. This method provides a high computational efficiency with simple and intuitive expressions, however, it has a very low precision and poor extensibility. It is observed that this model is mainly suitable for neutral and heavy gas diffusion in large-scale gas leakage area. Afterward, Hanna et al. [8] performed a non-dimensional analysis. Agreement between this analytical, and Britter and McQuaid experimental curves is observed.

However, BM model, a benchmark of a screening model, is not suitable for city and industrial area with large surface roughness due to its limitation of derived ranges. Since the advanced simulation model demands accurate and precise estimation, this model has been gradually replaced by other gas diffusion models as discussed next.

D. SUTTON MODEL

Sutton model [9], which was widely used for pheromone dispersion model, considers the diffusion problem using turbulent diffusion statistical theory. It estimates the gas concentration at any point (x, y, z) downwind of a point source as

$$\begin{aligned} & C(x,y,z,h) \\ & \quad = \frac{Q\exp\left(-\frac{y^2}{C_y^2x^{(2-n)}}\right)}{\pi C_yC_zux^{(2-n)}} \\ & \qquad \times\left[\exp\left(-\frac{(z-h)^2}{C_z^2x^{(2-n)}}\right)+\exp\left(-\frac{(z+h)^2}{C_z^2x^{(2-n)}}\right)\right], \end{aligned} \tag{4}$$

where Q denotes the release rate, C_y and C_z are the respective horizontal and vertical diffusion coefficients, respectively, n is a parameter $(0 < n < 1)$ dependent on the vertical profile of wind velocity, and h is the height of the source above ground with an assumption that all sample locations are at the same height as the source, i.e., $z = h$. However, this model is less applicable for the combustible gas due to the significant error in leakage estimation.

TABLE 1. Feature comparison of gas diffusion models.

Model	Application	Complexity	Computing Power	Accuracy	Relevant Parameter	Characteristic	Disadvantage
Gaussian Plume [5]	Large-scale and long time	Easy	Few	Bad	Density, explosion limits, air temperature, wind velocity and direction, and atmospheric stability	Simulate instantaneous or continuous leakage	Only applicable to neutral gas, low accuracy
Gaussian Puff [6]	Large-scale and short time	Easy	Few	Bad	Density, explosion limits, air temperature, wind velocity with direction, and atmospheric stability	Simulate instantaneous point source	Only applicable to neutral gas, low accuracy
FEM-3 [7]	Un-constrained	Difficult	Large	Good	Air temperature, and wind velocity with direction	Continuous and limited time gas source leakage	Huge computations and difficult computer simulations
BM [8]	Large-scale and long time	Easy	Few	Normal	The average concentration of gas cloud transverse section,	Used continuous leakage experimental data	Empirical model, poor extensibility
Sutton [9]	Large-scale and long time	Easy	Few	Bad	Diffusion parameters associated with meteorological conditions	According to the turbulent diffusion theory	Simulation error with combustible gas leakage diffusion
Gas Turbulent Diffusion [10]	Large-scale and long time	Easy	Few	Bad	Density, explosion limits, air temperature, wind velocity and direction, and atmospheric stability	Continuous gas leakage	Only applicable to neutral gas, low simulate accuracy

E. GAS TURBULENT DIFFUSION MODEL

Turbulent diffusion model is a static plume model based on turbulent diffusion theory. It was first applied for static gas source localization. The gas diffusion is estimated in a horizontal-flow of the wind according to the distribution of gas concentration in the 2-D plane. This model is one of the widely used mathematical models in the static gas source localization. The gas concentration C at coordinate point (x, y) at time t is expressed as [10]

$$C(x, y, x', y', t) = \frac{q \exp\left(\frac{V(x-x')}{2K}\right)}{\pi^{1.5} Kd} \times \int_{(d/2\sqrt{Kt})}^{\infty} \exp\left(-\zeta^2 - \frac{V^2 d^2}{16K^2\zeta^2}\right) d\zeta \tag{5}$$

where q is gas leakage velocity, t is gas leakage time, V is the wind speed with the positive direction of x-axis, K is gas diffusion coefficient, and d is Euclidean distance from arbitrary point (x, y, z') to gas source point (x', y', z') in z axis. Let $C \equiv 0$ at $t \leq 0$, then we rewrite (5) at $t \to \infty$ as

$$C(x, y, x', y', \infty) = \frac{q \exp\left(-\frac{V}{2K}(d - (x - x'))\right)}{2\pi Kd} \tag{6}$$

It is observed that the gas concentration is higher near the gas source than anywhere else at $t \to \infty$. Moreover, the gas diffusion has the same direction as wind-flow.

An odor source localization approach [10] was proposed based on the turbulence model to identify the static odor source in a stable wind-field. The spatially distributed sensor-array is used to monitor odor concentration. Afterward, the performances of these algorithms are discussed using static plume model [20]. Although, the positioning accuracy and the source localization trends are demonstrated under the static plume environment, the localization accuracy is low in dynamic environment. Recently, Qiuming *et al.* [38] studied gas diffusion theory and further derived a universal function of gas diffusion model with and without wind-field. Table 1 summarizes the feature comparison between gas diffusion models. Since the localization error increases due to the nonlinearity in the gas diffusion model, the study of particle filter would be a future research work.

III. GAS SOURCE LOCALIZATION

Continuous target localization and tracking are two major research issues in WSNs applications. Target tracking is applied to various applications, e.g., military, anti-terrorism, anti-riot, industrial and environmental monitoring, and the like. Here, we focus on gas leakage source localization, which belongs to the continuous target localization based on WSNs. However, constrained by physical size of sensor nodes, hard-to-reach area, and short distance wireless charging due to high interference, limited battery-powered sensor nodes bring major challenges in localization and tracking operations. A summary of existing gas source localization algorithms with WSNs is provided in Fig. 3. We present a detailed overview on gas leakage localization and tracking problem from the view of precision, robustness, and energy consumption issues.

The gas leakage source localization algorithms with WSNs are categorized as follows: *acoustic signal*- and *gas diffusion model*-based localizations. Acoustic signal-based localization method, which uses acoustic signal

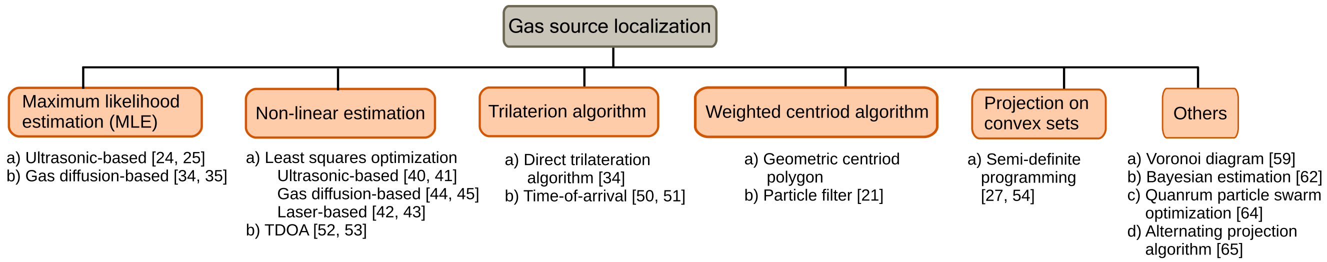

FIGURE 3. **Summary of gas source localization algorithms.**

for localization, provides instantaneous leakage information. In addition, this method consumes a small amount of communication energy due to low sampling rate [22]. The source location is obtained through analyzing and processing the acoustic information of each node in the gas leakage area. Ushiku et al. [23] discussed another type of localization algorithm based on gas diffusion model. The gas source location was estimated in a map based on the specific strength at each observation-point for every cells using a turbulent diffusion model of gas distribution. Such leakage source localization algorithms are realized based on the detected status of deployed sensor nodes without any additional acoustic sensors.

A. MAXIMUM LIKELIHOOD ESTIMATION (MLE)

Maximum likelihood estimation (MLE) algorithm uses the distance between a source and each beacon node to obtain the nonlinear equations according to 2-D space-distance formula. This method approximates the source coordinate using the minimum mean square error (MMSE) estimation method. As MLE is a centralized method, the detected values from all the nodes must be sent to the fusion center for estimation.

1) ULTRASONIC-BASED LOCALIZATION

At present, many literatures implemented some improvements for the localization algorithm such as localization accuracy, computational complexity, and energy consumption. Masazade et al. [24] proposed an energy efficient iterative method to improve MLE algorithm. This method reduces the energy consumption in a network because the sensor data is quantized before transmission. Actually, the network uses anchor nodes to obtain the coarse location estimates, then employs a few additional sensor-data to refine ML estimates through an iterative algorithm with an update in posterior Cramér-Rao lower bound (PCRLB). Since in real applications, MLE is effected by the noise, Liu et al. [25] proposed a model combined with Gaussian and impulse noise model that consider the contamination of outliers in these acoustic measurements.

Afterward, a noise-aware MLE [26] was proposed to achieve source localization with the Cramér-Rao bound (CRB). This model was provided to show how the estimation performance is improved with a location estimator using quantized binary data and channel statistics. In addition, the distributed source localization is formulated as a convex feasibility problem (CFP). Then, consistent and inconsistent CFP for the MLE has been solved by diffusion-based parallel and sequential projection methods [27], respectively. Low complexity and global optimal solution are obtained without any fusion center. Furthermore, this non-convex problem was relaxed as a convex semi-definite programming (SDP) for a better estimation with a randomization [28]. Recently, particle swarm optimization (PSO) [29], [30], is extensively used to solve this above problem. For instance, MLE uses the light-weight dynamic population in PSO-based grid strategy method [29] to accurately estimate the source location with reduced energy consumption.

For the multi-source localization, MLE determines the source-to-sensor distance using acoustic sensors. An acoustic energy attenuation model was designed to derive CRB. The impact of various deployment strategies was investigated in [26] for localization accuracy. To overcome the drawbacks of the centralized EM algorithm, Meng et al. [31] proposed distributed expectation maximization (EM) algorithm. Since energy consumption-based MLE is non-convex, a global solution is rarely obtained without a good initial estimates. At this point, it is difficult to localize multi-source with lower computational complexity. An improved scheme is proposed in [32] that reduces complexity of the algorithm by applying the decay factor. Afterward, an efficient sequential dominant source (SDS) initialization scheme was discussed with an incremental parameterized search scheme for better estimation accuracy and lower computation complexity. In addition, Zhang et al. [33] proposed the advanced multiple resolution (MR) alternative method that adopts Tabu heuristic algorithm for global optimal values in a distributed multiple source localization.

2) GAS DIFFUSION-BASED LOCALIZATION

The location estimation of a plume source using the MLE algorithm was studied in [34]. Mitra et al. [35] proposed CH_4 source localization using MLE, which estimates the related explosion-threat in an indoor environment. It is observed that this localization method estimates more accurate location when a subset node is selected. Thus, the error estimation in the above algorithm is satisfactory for various single source points. However, considering the high computational complexity in MLE, a real-time approximated ML estimator (RTAMLE) is discussed in [36] where the diffusion of a gas source is estimated based on a binary observation. The estimation performance of the RTAMLE is close to MLE with a significant reduction in computational complexity when the node density tends to infinity. Levinbook and Wong [37] showed an excellent estimation performance by using MLE and RTAMLE with binary observation made by the active sensor nodes. Thus, this approach is suitable for the real-time processing due to its reduced complexity.

Qiuming et al. [21] proposed a novel gas source localization method that combines the weighted centroid algorithm and the particle filter. The convergence-rate is improved by the proper estimation of its initial values. Afterward, Martinez et al. [39] presented a preliminary characterization of the custom wind tunnel designed for an experiment on the volatile gas source localization with a mobile robot. The results conclude that the gas diffusion behavior strongly depends on gas injection rate, position of the mobile robot, and wind flow.

B. NONLINEAR LEAST SQUARES (LS) OPTIMIZATION

Nonlinear least squares (LS) optimization estimates the nonlinear static-model parameters based on minimum sum of squared error. It uses a sophisticated optimization algorithm to solve the nonlinear location estimation problem.

1) ULTRASONIC-BASED

To estimate the distance between a leakage-source and sensors, Li and Hu [40] designed an acoustic micro-sensor array with an energy-decay model. The source locations are realized by the MLE. After that, the energy readings are compared to solve this nonlinear LS problem. Although, this method is robust against localization errors and energy-decay factors, is more sensitive to the sensor-gain calibration. A variety of LS optimization using Monte Carlo simulation is discussed in [41]. The results illustrate that the weighted one-step least squares (WOS) algorithm with an optimal weighting achieves a tradeoff between the esrimation performance and computational complexity. In addition, the weighted direct LS method with a correction technique can estimate the same location leading to further estimation performance gain without any computation of energy-ratios as in conventional nonlinear LS optimization [40].

2) LASER-BASED

The laser-based algorithms found in the literature mainly exploit top-down visual attention mechanism (TDVAM) [42] combined with shape analysis to localize gas sources in the large-scale outdoor environments. Mobile robots capture images at different horizontal angle with an on-board tilted camera. In each image three salient regions are computed using this TDVAM. One plausible gas source is identified after the shaping analysis on these salient regions. A laser-range scanner is used to determine the position of recognized plausible gas source. After that, a compact surface representation of gas distribution map [43] was generated with an inspection robot equipped with a 3-D laser-range finder, and gas sensor which returns an integral of the concentration measurements. The state-of-the-art mapping algorithm gives a very accurate estimation of the laser-beam path compared to other previous methods in an open-field environment.

3) GAS DIFFUSION-BASED

Many researchers used gas diffusion model to solve nonlinear LS optimization for the plume source localization. Such a method is discussed in [44] which assumes an uniform propagation of the plume in environment. To minimize the least squares error, a two-step approach is discussed with a known homogeneous wind field and isotropic diffusion [45]. The concentration measurement is performed based on the turbulent diffusion model and the advection model to estimate the source position. Further, Wang et al. [46] performed the nonlinear LS localization experiments with different node distribution and background noise in Gaussian plume dispersion model. It is shown by simulation that high accuracy is observed at larger node density. Thus, this approach could be widely used in environment monitoring. Recently, semi-definite programming (SDP) relaxation is used to solve the approximate weighted least squares (WLS) using the energy-decay model [47]. The accuracy can be further improved with a randomization, however, this approach suffers from local minima at higher noise level.

C. TRILATERATION ALGORITHM

Trilateration algorithm, which is an another type of localization algorithms, calculates the location according to the coordinates of three beacon-nodes and the distance between the beacon-node and the target.

1) DIRECT TRILATERATION (DT)-BASED

Kuang and Shao [34] studied the direct trilateration (DT)-based source localization algorithm that provides better accuracy compared to the MLE in a plume source localization at low noise level. To handle a stronger background noise than conventional DT algorithm [34], a robust plume source localization algorithm is designed based on an weighted combination in trilateration algorithm [48]. Afterward, an effective source localization algorithm called equilateral triangular distribution trilateration algorithm (ETDT) is proposed in [49] where the beacon nodes are deployed in the equilateral triangles. The ETDT algorithm that combines trilateration measurement with weighted centroid method considers an angular-weighted function to further reduce the localization error.

2) TIME-OF-ARRIVAL (TOA)

A time-of-arrival (TOA) method calculates the distance between nodes according to the signal propagation time. The trilateration method is used to estimate the source position with a known signal propagation speed. As a centralized scheme, this method has low energy efficiency and low scalability due to the excessive radio transmissions. In addition, as the sink node is overloaded with the data traffic in the centralized scheme, the network lifetime becomes a critical issue. To prolong the network lifetime, a distributed processing is proposed in [50] where many intermediate estimates (IEs) are used in some of the active nodes. Another flexible distributed method is proposed in [51]. It emphasizes on the data fusion strategies that are introduced to process the raw and intermediate data, which result in an improved estimation in TOA-based localization.

D. TIME DIFFERENCE-OF-ARRIVAL (TDOA)

Time difference-of-arrival (TDOA) method, which locates the emission signal source by measuring the time lag between the radio signals transmitted to different monitoring centers, is a nonlinear localization method. As relative time is used for localization, the time synchronization issue can be relaxed. Wang and Chen [52] suggested a localization method based on the TDOA scheme that considers the non-convex optimization problem. Monte-Carlo sampling method is used to achieve an approximate global solution of the ML estimation in a line-of-sight (LOS) environment. It is noted that this method outperforms several existing methods with the CRB accuracy. A robust source localization with TDOA method in presence of errors was proposed by Yang et al. [53]. In particular, this method analyzes both second-order cone programming (SOCP) relaxation and alternative semidefinite program (SDP) relaxation. These computationally efficient convex relaxation methods provide optimal performance predicted by the CRLB.

E. WEIGHTED CENTRIOD ALGORITHM

The geometric centroid of polygon is treated as a source localization by the weighted centriod algorithm. The polygon is the overlapping area of the beacons where the unknown nodes are within the scope of communications. This algorithm is designed to be simple, however, is not widely used due to low estimation accuracy. In addition, this algorithm cannot accurately estimate the source location with the nonlinear gas diffusion model in a windy condition. Qiuming et al. [21] proposed a localization method that combines the advantage of particle filter with the weighted centroid algorithm. An improved position estimation is observed by the rigorous simulation results.

F. PROJECTION ON CONVEX SETS (POCS)

A distributed source localization method is proposed based on convex sets. Assume that the communication link between the nodes as a geometric constraint of the node location, whole network is modeled as a convex set. Thus, the localization problem is converted into a convex-constrained optimization problem which can be solved with a projection on convex sets (POCS) method. The algorithm uses linear programming and SDP method to obtain a global optimized solution for the source location. The anchor nodes continuously update the position based on circles and lines according to the energy-ratio.

The POCS method is widely used for consistent as well as inconsistent source localization. Then, a diffusion-based projection method is applied to the distributed source localization as a convex feasibility problem. Since full data-set from each node is not required for processing, the algorithm has few computation and communication cost compared to weighted least squares method [27]. When this algorithm solves a local optima and saddle points in the convex feasibility problem, estimation performance is better than MLE [54]. Thus, an unique solution to true source location is obtained based on intersection of convex sets, however, assuming infinite samples without any measurement noise.

G. OTHERS

Apart from the above-mentioned algorithms, there are a few other source localization methods as follows. For instance, Ho and Sun [55] discussed an accurate algebraic closed-form solution for source localization using the acoustic-energy model. It reaches the CRLB accuracy under Gaussian noise. To handle non-Gaussian noise, a sequential method based on acoustic-energy attenuation model with particle filter was discussed in [56]. It tracks the unknown number of the targets. In addition, this method dramatically reduces the computational complexity with an improved localization accuracy. It is true that the beamforming algorithm with an acoustic wave provides better accuracy in relatively sparse network, however, needs high energy requirement [57]. Kim [58] designed a functional quantizer to minimize the localization error by transmitting the quantized acoustic sensor data to a fusion center. To reduce the complexity as well as to improve the accuracy, You et al. [59] proposed a distributed algorithm with a Voronoi diagram that reduces the size of estimation area with a Voting-grid to achieve the essential event region (EER) with less complexity.

An data compression and sensor selection are performed to select the most informative sensors before the communication in an iterative Monte-Carlo source localization [60]. This method significantly reduces the communication overhead due to message-exchange between nodes. Yong et al. [61] proposed the distributed sequential minimum mean squared error (MMSE) estimation with node scheduling and node cooperation for a random gas diffusive source localization. This method provides an advantage in terms of energy consumption and communication latency issues. This method is further improved by the Bayesian estimation in the scheme proposed in [62]. First, the physical and statistical measurement models of the substance dispersion are derived by solving the diffusion equations. Then, this model is integrated into distributed processing techniques. At last, the optimal nodes are selected to meet the low communication overhead and accurate estimation. Meanwhile, two parametric belief representation methods, which are suitable for various source types in different environments, are proposed for the distributed processing.

Taylor expansion is used in [63] to design a linear model. Then, the best linear unbiased estimator (BLUE) is employed

TABLE 2. **Comparison between source localization algorithms.**

Algorithms	Application scope	Localization accuracy	Computational complexity	Advantages	Disadvantages
Maximum likelihood estimation (MLE) [24]–[26]	Small-scale	Low	General	Multiple source localization and robust in noisy environment	Poor scalability, large communication requirement, and sensitive to parameter perturbation
Nonlinear least squares optimization [40], [41]	All	High	General	Better precision than MLE at low noise power	Limited to single source estimation and low localization accuracy at higher noise levels
Direct trilateration (DT) [34], [49]	Large-scale	Low	Low	Very low hardware requirements	Large localization error
Time difference-of-arrival (TDOA) [52], [53]	Small-scale	High	Low	Time synchronization is not required	Multipath effect and limited by ultrasonic propagation distance
Time-of-arrival (TOA) [50], [51]	Small-scale	High	Low	High estimation accuracy with few sensor nodes	Time synchronization is required and multipath effect
Weighted centriod [21]	All	Low	Low	Low communication overhead	Localization accuracy depends on node density and distributions
Projection on convex sets (POCS) [27], [54]	All	High	General	Low hardware requirement	Local optimum, localization failure, and high energy consumption

to estimate gas leakage position. This method obtained more accurate localization through many iterations based on the Gaussian model and the BLUE. Based on the attenuation model of a plume source, Liao et al. [64] applied a quantum particle swarm optimization (QPSO) to solve the plume source localization problem in windy condition. According to the fact that the plume source only can be detected when the sensor measured concentration is larger than a threshold, the sensors exert the virtual forces to affect the updated position of each particle in QPSO based on the force-directed heuristics. Further, this method makes the particles to roam more purposive, which directs the updating of particles to improve the convergence speed.

For multiple gas source detection and localization, an alternating projection (AP) algorithm was considered when the advection and diffusion change with time [65]. The complexity, localization performance, and cost function are analyzed in a distributed sensor networks. However, the performance is only similar to that of ML estimator in some cases. A lumped-parameter state-space model for the advection diffusion of atmospheric gas concentration is proposed in [66]. The two-tiered detection strategy, dynamic sensor selection, and a threshold-based approach are used to extend the network lifetime with an increase in active sources. The mean and covariance data are provided to Kalman filters to accurately estimate the source location. To simultaneously detect and localize multiple sources, Kalman filter [67] is extensively used. To decrease localization error, a greedy approach is suggested to iteratively detect the potential sources based on the measurement of sensors.

A qualitative comparison of the above-mentioned source localization algorithms is provided in Table 2. In general, these algorithms are categorized into centralized and distributed source localization algorithms. Centralized algorithm provides better estimation, however, energy consumption is more compared to the distributed algorithms. Based on the above discussion, we have reached the following conclusions:

1) Since autonomous mobile robot can move towards the target as close as possible to obtain more accurate measurements, localization estimation is better than static node-based WSNs. In addition, measurement precision increases in higher node density, however, increasing the number of sensor nodes results in higher deployment cost.
2) Most of localization algorithms are gas diffusion model-specific, thus the localization error varies with diffusion model.

Although the aforementioned studies provide a useful overview on source localization methods, these algorithms are still in their infancy and should be carefully redesigned with high accuracy as well as low energy consumption.

IV. BOUNDARY DETECTION AND TRACKING IN WSNs

Continuous objects such as wild fire, radio-active contamination, toxic gas leakage, and hazardous biochemical material are diffused in a wide region with non-uniform diffusion velocity and acceleration according to the surroundings. Fig. 4 shows a typical boundary detection of continuous objects. These objects also dynamically change their shape and size. Thus tracking of continuous objects is more difficult than an individual object tracking. To overcome this problem, many methods are designed with reduced energy consumption and higher accuracy in estimation as discussed next.

A. DYNAMIC CLUSTER-BASED ALGORITHMS

A dynamic cluster structure for object detection and tracking (DCSODT) [68] is one of the widely used approaches. There are two important phases in DCSODT as follows: *collaborative data management* and *object localization reporting*.

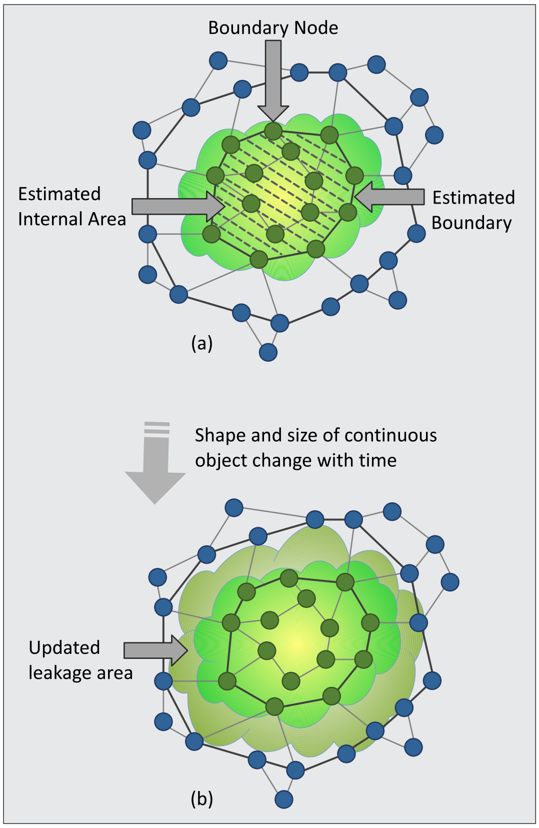

FIGURE 4. **(a) The boundary of the continuous objects is estimated by the boundary nodes. The area covered by the boundary nodes is reported to the sink. (b) However, the continuous objects are diffused in a wide region with non-uniform diffusion velocity and acceleration according to the surroundings. In addition, these objects also dynamically change their shape and size, which make it more difficult than an individual object tracking.**

A node that contains one of more adjacent normal nodes is called as a reporter. According to the location of the object, all reporters are organized into cluster in a distributed manner. Cluster-head (CH) aggregates the collected data in a cluster, and broadcasts the information to the sink using a geographic routing method. Then, the target boundary is estimated by the sink. The CH selection process is simple since a node, which is close to cluster center, is always selected as a CH. However, this type of CH selection process yields traffic overhead when the number of reporters increases. In addition, this method does not consider the power consumption issue of the reporter. Han et al. [69] proposed a mobile anchor-assisted localization algorithm based on regular hexagon (MAALRH), which covers the whole monitoring area with a boundary compensation method. The unknown nodes calculate their positions by the trilateration method. It is shown by simulation that the MAALRH achieves high estimation accuracy when the communication range is within the trajectory resolution.

A distributed, light-weight, and dynamic clustering algorithm is proposed by Chen et al. [70]. A node, which is close to the target, is selected as CH using the Voronoi diagram. When the acoustic signal strength exceeds a pre-determined threshold, an active CH broadcasts the information about solicitation packet according to the two-phase broadcast mechanism. After that, the CK requests nodes to join its cluster for the boundary estimation. However, this method is limited by the hardware resource the node. To relax the hardware constraint, Yang et al. [71] proposed a multi-sink architecture which consists of a *static* sink and a *mobile* sink guided by geographic information system (GIS). The mobile sink calculates the optimized position and collects the information from boundary nodes with less energy consumption. This sink also moves to a adaptive position relative to the static sink. Then, the static sink reduces data transmission as well as energy consumption based on the centroid algorithm. Wang et al. [72] proposed a task allocation algorithm based on score incentive mechanism (TASIM) with an reward or punish policy. CHs are responsible for task allocation and score calculation. The uncompleted tasks on failed nodes can be timely migrated to other cluster members for further execution. In addition, the uncompleted tasks on death nodes are reallocated by CHs. The performance of the TASIM is better than conventional task allocation algorithms in terms of both network-load balance and energy consumption. It is observed by simulation that the energy consumption is reduced upto 30% compared to previous methods.

Continuous object detection and tracking algorithm (CODA) [73] allows each sensor node within the scope of sensing to detect and track moving continuous object. In each cluster, any sensor that is near to the detected object directly send the status to the CH. After receiving the information, the CH performs local boundary estimation to determine the boundary of the continuous object within the scope of cluster. Then, a dynamic cluster sends the continuous target boundary information to the sink. Since the number of boundary nodes is reduced, communication cost is minimized. However, this process leads to cluster construction and maintenance overhead because the clusters are proactively formed to wait for a continuous object. Furthermore, a convex-hull algorithm is used to detect boundary of a continuous object to overcome the limitation of CODA on the detection of convex forms of continuous objects [74]. The broadcasting strategy is similar to the single target tracking (SAT) algorithm. Most importantly, this algorithm prolongs the network lifetime and achieves a good balance between tracking accuracy and energy consumption. However, this algorithm assumes uniformly distributed nodes in homogeneous WSNs which sometime is far away from practical application. Another scheme is proposed termed as static cluster and dynamic cluster head mechanism (SCDCH) [75] to forwards the data collected from active node to the CH without changing cluster border within the network lifetime.

B. THE TOPOLOGY CONTROL AND ROUTING PROTOCOL

Topology control protocol is found to be an interesting extension to dynamic cluster-based algorithms. For example, Tu et al. [76] proposed scalable continuous object detection and tracking based on a cluster-based approach (DCSODT), which has two phases as collaborative data processing and object location reporting. These phases determine whether an event node is helpful to estimate the position of the object in a collaborative data processing stage. If the local information of an event node is not useful for locating the object, the opportunity for this node to be selected as a reporter is very less. Chintalapudi et al. [77] proposed three qualitatively different approaches to select boundary nodes for localized boundary. A boundary node is defined as the sensor node that detects the object in its sensing area, however, has one or more one-hop neighbors that do not detect the same object. The statistical approach is used to gather data from the nodes in probing neighborhood and to determine the boundary node. Image processing techniques are used for an edge detection. Also, a classifier-based approach is used to partition the similar data gathered from its neighbor in a classifier, thereafter, solves the false detection problem. A tradeoff between energy consumption and estimation accuracy is observed. However, this method is not capable to handle a random distribution that also changes with time in the networks.

For a moving phenomenon over the area, real-time edge tracking is difficult. Liu et al. [78] discussed a distributed position-based adaptive quantization scheme to choose a thresholds of the quantizer. Each sensor node dynamically adjusts its quantization threshold, then sends its one-bit quantized version of the original observation to a fusion center. The signal intensity received at local sensors is modeled as an isotropic signal intensity attenuation model. Numerical results show that the position-based MLE is more accurate than the classical fixed-quantization MLE and the position-based CRLB is less than its fixed-quantization-based CRLB.

Zhang et al. [79], proposed two novel algorithms for boundary detection where only one-hop information is available. Two novel computational geometric techniques as localized Voronoi polygon (LVP) and neighbor embracing polygons (NEP) are developed. The LVP algorithm detects all the boundary nodes, and gives perfect estimation on coverage boundaries with low energy consumption. Most importantly, these algorithms are topology independent.

C. CONTINUOUS TARGET DETECTION AND TRACKING MECHANISM

An energy-efficient algorithm is proposed for continuous target detection [80]. The proper selection of monitoring nodes significantly reduces the size of reporting messages. However, the method ignores the energy consumption due to the communication between representative nodes and boundary nodes. Hong et al. [81] focused on the nodes-state scheduling and used the minimum set of active sensing node to obtain a predictive continuous object tracking scheme before an acceptable tracking accuracy. The scheme predicts the next boundary by measuring the diffusion speed and direction of the current boundary line. This process suggests a wake-up mechanism to decide which sleeping nodes need to be activated for future tracking. Adjusting the sensing range of active nodes using boundary node identification mechanism (BNIM) [82] is another way to save communication energy. An accurate boundary estimation is possible by controlling the sensing range of the active nodes. Another wake-up mechanism for future boundary tracking is proposed in [83]. This method minimizes the number of boundary nodes, however, precise boundary estimation is less possible due to low computing ability of these boundary nodes. A grid-based asynchronous selective wake-up protocol is discussed in [84]. This simple and asynchronous protocol is suitable for WSNs, however, results inaccurate estimation. Based on the cluster-based structure, a selective wake-up scheme is presented in [85]. Basically, this method forecasts the next location by the selective wake-up scheme with grid-based clusters. Such a technique does not require any complex computations on massive data. Most importantly, this asynchronous algorithm is suitable for real-time WSNs.

To reduce the energy consumption through decreasing redundant information and communications, Park et al. [86] considered a two-tier grid structure that relies on location information of beacon node and a grid cell size value when the nodes are aware of their locations to achieve flexible and reliable detection as well as tracking. A coarse-grained grid structure for flexibility is constructed proactively, and the fine-grained grid structures of minute grid cells provide the detailed boundary shape of the continuous object for reliability according to the continuous objects movement or alteration. It reduces the amount of data from boundary nodes to the sinks to get better performance. Peng et al. [95] developed a distributed multiple-sensor cooperative turbo coding (DMSCTC) scheme for a large-scale WSN with sensor grouped in a cooperative cluster. Along with a simple forward error correction (FEC) coding in each sensor nodes, the CH performs a simple multi-sensor joint coding. The complicated joint iterative decoding is implemented only at the data collector. The WSNs achieve the target error performance with less power consumption, thus prolong its lifetime. The analytical and simulation results show that the DMSCTC can substantially improve the energy efficiency of the clustered WSN. Hong et al. [87] presented a small set of candidates using neighbors descriptor table (NDT). The candidates provide a well-balanced representative nodes selected from the small set that is independent of node density. Another method is discussed in [88] where the sensing field is divided into cells like the TV pixels. The sampling and reporting time are estimated based on the pixel density. The boundary traverse algorithm (BTA) in space domain is used to obtain the boundary information. The redundant information is reduced with the help of a sampling method based on the virtual-grid in the static cluster-based WSNs.

Chen et al. proposed an energy-efficient boundary estimation for unsmoothed continuous object called as EUCOW [89] that considers the Voronoi-based network to simplify node selection in the WSNs. This algorithm monitors both interior and exterior boundary of unsmoothed object by selecting only the nodes that are within transmission range and far from event boundary, respectively. A minimum set

TABLE 3. Comparison between boundary detection and tracking algorithms in WSNs.

	Algorithms	Key Issues	Solution	Advantages	Disadvantages
Dynamic cluster-based algorithm	Ji et al. [68]	Dynamic infrastructure	A dynamic cluster-based structure	The reduction of communication cost	Not adjust adaptively the size of clusters. Low accuracy and the lack of scalability
	Chen et al. [70]	Only one CH considering communication collision	Voronoi diagram	Better quality data collected and less collision incurred	No routing protocol, energy consumption of CH is not considered
	Yang et al. [71]	Reduced energy consumption	Multi-sink architecture	Less energy consumption	Not precise enough with movement of the mobile sink
	Chang et al. [73]	Precise boundary tracking and reduced energy consumption	A hybrid static-and-dynamic clustering mechanism	Less energy consumption	Does not provide boundary detection of convex forms
	Xu et al. [74]	Heavy data traffic and time consumption	Scheduling with adaptive node selection	Tradeoff between accuracy and energy consumption	Consider only uniform node distribution
Routing and topology	Tu et al. [76]	The number of reporters	A scalable, topology control-based protocol	Reduces number of reporters	Sleep scheduling
	Chintalapudi [77]	Edge node detection	Three edge detection approaches	Generates the phenomenon edges	Not consider the objects that randomly change their shape
	Zhang et al. [79]	Boundary node detection	A deterministic method based on localized Voronoi polygons	Coverage boundary was identified correctly, applied to arbitrary topology	Low precision due to one-hop information
Continuous Target Detection and Tracking Mechanism	Kim et al. [80]	Selection of boundary node set	Energy-efficient algorithm for moving phenomena boundaries	Reduces the data traffic between nodes	Ignores the communication between representative nodes and boundary nodes
	Hong et al. [81]	Sensor state scheduling	Using minimum set of active nodes and wake-up mechanism	Dramatically reduces the energy consumption	Not precise predictive boundary line
	Jin et al. [82]	Selection of boundary node set	Adjusting sensing range, representative node selection	Size of the communication and report message is reduced	Not precise boundary estimation
	Hong et al. [83]	Scheduling the sensor state	The future boundary line and the wake-up mechanism	Reduces the energy consumption	Boundary estimation is not accurate
	Park et al. [84]	An asynchronous prediction protocol	A grid-based asynchronous selective wakeup protocol	Simple asynchronous protocol	Inaccurate boundary estimation
	Lee et al. [85]	An asynchronous method	An asynchronous selective wakeup scheme	Simple computation and accuracy tracking	Prediction accuracy becomes lower with faster target speed
	Park et al. [86]	Flexible and reliable detection and tracking	The coarse-and fine-grained grid structures	Reduces data from boundary nodes to the sinks	Ignores the long-range transmission
	Hong et al. [87]	Selection of a small set of candidates	Selection of representative boundary node	Reduces a large amount of data	Small set of representative nodes sometime results in reduced accuracy.
	Kim et al. [88]	Reducing the redundancy, adaptive sampling scheme	Diffusion area is divided into several cells with virtual grid	Reduces the number of boundary nodes as well as redundant boundary information	The diffusion velocity directly affect the boundary tracking accuracy
	Chen et al. [89]	Monitoring unsmoothed continuous object	Selecting a minimum set of representative nodes	Simple and efficient selection process	Low boundary accuracy
	Ding et al. [90]	Faulty sensor identification	Fault-tolerant event boundary detection	High accuracy and a low false alarm rate	Depends on sensor fault probability.
	Liao et al. [91]	The high noise environment	Data fusion and decision fusion for edge node detection	Low computational complexity and communication cost	Short tolerance range
	Sun et al. [92]	Tracking with uncovered holes	Directional antenna	Uncovered holes is considered with less energy consumption	Low estimation accuracy
	Hong et al. [93]	Void area problem	Selective wakeup scheme	More accurate tracking	Pays more attention to estimation accuracy than energy efficiency
	Lee et al. [94]	Multiple objects tracking with changing shape	Dynamic rectangular zone-based mechanism	Minimizes the energy consumption in data collection	Low accuracy due to diffusion speed

of representative nodes near event boundary is reported to the sink. To decrease the false alarm-rate, faulty node identification is most essential. A boundary detection algorithm with fault-event disambiguation is proposed to detect several faulty nodes [90]. However, this algorithm is highly sensitive to the threshold settings. Two distributed approaches with composite hypothesis test in WSNs are developed in [91]. One-level decision method is used to collect and process the data from its neighbors with a low false-alarm probability, whereas the two-level decision method determines the edge nodes with reduced the false alarm-rate of local decision. The algorithm has a low computational complexity as well as low power consumptions due to message exchange among nodes. It is important to note that the detailed information about the whole continuous object is required for rescue operations to estimate the nature of the damage. However, none of these above methods discuss in-depth research on this issue, hence, more study into this direction is needed in the future.

Since most of the above methods do not able to estimate near void area, which is a serious issue in uniformly deployed WSNs, the messages sometimes are not able to reach to the sink. To overcome this problem, the directional antenna is used to tracking continuous objects in void area [92]. Hong et al. [93] proposed a selective wake-up scheme for smart-cluster continuous object tracking protocol (SCOP) with a void area around the boundary of the objects. Since the data collection with a void-area is more important in such a situation, SCOP pays attention to the estimation accuracy than energy efficiency when compared with the other schemes.

For multiple continuous objects tracking, dynamic rectangle zone-based collaboration mechanism is introduced according to the dynamic change of objects [94]. Basically, this method contains three phases as: 1) selection and collection of sensing data, and construction of a dynamic rectangle zone, 2) reselection of the node and reconfiguration of the dynamic rectangular zone based on the diffusion of continuous object, and 3) construction of an updated dynamic rectangular zone when continuous objects are merged together. In addition, the split behavior of the continuous object is discussed in [96]. The corresponding center nodes in the rectangular zone are updated when the continuous objects split into several continuous areas. Moreover, the total energy consumption issue is discussed in [97]. Table 3 provides a qualitative comparison of the existing boundary detection and tracking algorithms for continuous objects in WSNs.

Current research efforts have provided a good understanding of the boundary tracking of continuous object. However, studies on time synchronization, void-area problem, 3-D space tracking, and robust interference-aware routing protocol are limited in the complex environments. Hence, more in-depth research in these issues is expected in the future.

V. CONCLUSION

This survey provides a comprehensive overview of the existing and emerging work on gas leakage source detection and tracking of continuous objects with WSNs. We have highlighted the inherent features of the various well-known gas diffusion models used in localization and tracking algorithms. With the advancement in sensing technologies, the gas source localization techniques are discussed from the view of precision, robustness, and energy consumption issues. In addition, we also categorized the state-of-the-art algorithms to estimate the boundary of the continuous objects that change their shape and size with time.

Although a significant amount of research has been carried out on source localization and boundary tracking of continuous objects, there are still many issues to be addressed as follows:

- As the detection characteristic of nodes directly affect the localization and tracking estimation, the choice of sensor is much more crucial than the choice of the optimization algorithms in real environment.
- Multiple gas source localization is less discussed in the existing literature. The current approaches may be further explored for robust multi-source identification under the noise due to hardware impairments, interference, and channel estimation errors.
- Since turbulence effects, obstacles, and wind speed greatly influence the localization accuracy, these are the main issues to be properly addressed in future. For more accurate localization, gas diffusion models need to be combined with gas temperature that strongly depends on large-scale temperature fluctuations.
- In the context of energy-efficient localization and boundary detection algorithms, *redundant nodes* generate a massive amount of data transmission, which also reduces the network efficiency. An algorithm should be designed based on data fusion technology to solve this problem.
- Considering the fact that the research on continuous object detection and tracking in a 3-D space is in an early stage under strong assumptions, further studies are needed to handle these issues in the 3-D space.

As localization of continuous object and boundary tracking become serious issue in large-scale industrial area as well as environment, in-depth research on the development of localization and tracking technology is expected to become fundamental task with several new problems to solve and challenges to overcome in factory automation, fault diagnosis, surveillance, and gas consumption monitoring systems.

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LEI SHU received the Ph.D. degree from the National University of Ireland, Galway, Ireland, in 2010. Until 2012, he was a Specially Assigned Researcher with the Department of Multimedia Engineering, Graduate School of Information Science and Technology, Osaka University, Japan. Since 2012, he has been with the Guangdong University of Petrochemical Technology, Maoming, China, as a Full Professor. Since 2013, he has been a Ph.D. Supervisor with the Dalian University of Technology, Dalian, China, and a Master Supervisor with the Beijing University of Posts and Telecommunications, Beijing, China. He has also been the Vice Director of the Guangdong Provincial Key Laboratory of Petrochemical Equipment Fault Diagnosis with the Guangdong University of Petrochemical Technology. He is the Founder of the Industrial Security and Wireless Sensor Networks Laboratory. He has authored over 300 papers published in related conference proceedings, journals, and books. He has an H-index of 25. His research interests include wireless sensor networks, multimedia communication, middleware, security, and fault diagnosis. He served as a Co-Chair for more than 50 various international conferences/workshops, e.g., the IEEE International Wireless Communications and Mobile Computing Conference (IWCMC), the IEEE International Conference on Communications (ICC), the IEEE Symposium on Computers and Communications (ISCC), the IEEE International Conference on Computing, Networking and Communication, and the International Conference on Communications and Networking in China (Chinacom). He also served/will serve as a Symposium Co-Chair for IWCMC 2012 and ICC 2012, as a General Chair for Chinacom 2014 and the 2015 International Conference on Heterogeneous Networking for Quality, Reliability, Security, and Robustness (Qshine), as a Steering Chair for the 2015 International Conference on Industrial Networks and Intelligent Systems, and as the Technical Program Committee Member of more than 150 conferences, including the IEEE International Conference on Distributed Computing in Sensor Systems, the IEEE International Conference on Mobile Ad hoc and Sensor Systems, ICC, Globecom, the IEEE International Conference on Computer Communications and Networks, the IEEE Wireless Communications and Networking Conference, and ISCC. He currently serves as the Editor-in-Chief of the *European Alliance for Innovation Endorsed Transactions on Industrial Networks and Intelligent Systems*, and the Associate Editor for a number of renowned international journals. He received the 2010 IEEE Global Communications Conference and the 2013 IEEE International Conference on Communications Best Paper Awards. He is a member of the IEEE Communication Society, the European Alliance for Innovation, and the Association for Computing Machinery.

MITHUN MUKHERJEE (S'10–M'16) received the B.E. degree in electronics and communication engineering from the University Institute of Technology, Burdwan University, India, in 2007, the M.E. degree in information and communication engineering from the Indian Institute of Science and Technology, Shibpur, India, in 2009, and the Ph.D. degree in electrical engineering from IIT Patna, India, in 2015. He is currently a Specially Assigned Researcher with the Guangdong Provincial Key Laboratory of Petrochemical Equipment Fault Diagnosis, Guangdong University of Petrochemical Technology, China. He was a Faculty Member with the Department of Electronics and Communication Engineering, National Institute of Technology Hamirpur, India (2014–2015). His research interests include wireless sensor network, wireless communications, sensor network middleware, dynamic spectrum sharing, and cloud computing.

XIAOLING XU received the B.S. and M.S. degrees from the Department of Automation, School of Electrical Engineering and Automation, Henan Polytechnic University, China, and the B.S. degree from the Department of Electric Power engineering, School of Electrical Engineering and Automation, Henan Polytechnic University, in 2008 and 2006, respectively. She has served for four years as a Teacher of measurement technology and instrument specialty with the Guangdong University of Petrochemical Technology, China. Her current research interests are wireless sensor networks and intelligent control.

KUN WANG (M'13) received the B.Eng. and Ph.D. degrees from the School of Computer, Nanjing University of Posts and Telecommunications, Nanjing, China, in 2004 and 2009, respectively. From 2013 to 2015, he was a Post-Doctoral Fellow with the Electrical Engineering Department, University of California at Los Angeles (UCLA), CA, USA. In 2016, he was a Research Fellow with the School of Computer Science and Engineering, University of Aizu, Fukushima, Japan. He is currently an Associate Professor with the School of Internet of Things, Nanjing University of Posts and Telecommunications. He has published over 50 papers in referred international conferences and journals, including the IEEE Transactions on Industrial Informatics, *ACM Transactions on Multimedia Computing, Communications and Applications*, *ACM Transactions on Embedded Computing Systems*, the *IEEE Wireless Communications Magazine*, the *IEEE Communications Magazine*, *IEEE Network*, the IEEE Access, and the IEEE Sensors Journal. His current research interests are mainly in the area of big data, wireless communications and networking, smart grid, energy Internet, and information security technologies. He is a member of ACM.

XIAOLING WU received the B.S. and M.S. degrees from the Harbin Institute of Technology, Harbin, China, in 2001 and 2003, respectively, and the Ph.D. degree from the Department of Computer Engineering, Kyung Hee University, Korea, in 2008. From 2008 to 2012, she was a Senior Engineer with the R&D Center, AT Lab Inc., Korea. Since 2012, she joined the Guangzhou Institute of Advanced Technology, Chinese Academy of Sciences, as an Associate Professor. She is currently an Associate Professor with the Guangdong University of Technology and an Evaluation Expert both in Guangdong and Guangzhou Bureau of Science and Technology. Her research interests include wireless sensor networks, touch sensing, and IoT. She has authored over 10 SCI indexed journal papers and over 30 EI indexed papers, granted seven international patents and more than 15 Chinese invention patents. She has been serving as an Area Editor of *EAI Endorsed Transactions on Industrial Networks and Intelligent Systems* and a Lead Guest Editor of IJDSN special issue. Besides, she has been a Reviewer of multiple SCI/EI international journals and a TPC Member/Session Chair for many international conferences.