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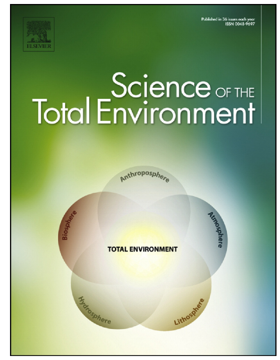

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A Comprehensive Review of Plume Source Localization Efforts Using Unmanned Vehicles for Environmental Sensing

Tyrell Lewis, Kiran Bhaganagar*

Abstract. Local atmospheric conditions including wind speed and turbulence significantly influence the dispersion of pollutant plumes, introducing severe difficulties in predicting its trajectory, potential evacuation sites, and ultimately containment efforts. Ongoing developments in estimating rapid contaminant dispersion include the combined use of local meteorological data along with plume-source localization and identification via autonomous data-driven mobile-sensing robotic/vehicular platforms. With a vast number of available environmental-sensing mobile platforms, contaminant dispersion scenarios, and source-finding algorithms, selection of the ideal configuration for autonomous source localization involves a great deal of opportunity alongside uncertainty. This paper aims to review the significant developments of unmanned ground-based mobile sensing network configurations and autonomous data acquisition strategies commonly used for the task of gaseous plume source localization.

Keywords: Autonomous plume source localization algorithms, mobile environmental sensing networks, unmanned ground vehicles, atmospheric dispersion modelling applications, source term estimation

1 Introduction

In hazardous situations involving the emission of Chemical, Biological, Radiological and Nuclear (CBRN) pollutants, containment of the release requires locating and neutralizing the source [87]. To characterise the nature of the release, information must be gathered through a process known as source term estimation (STE) that aims to estimate several parameters including the source location, emission strength, time of release, pollutant type, and dispersion behavior by generating a

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predictive model of the contaminant dispersion [17]. In realistic atmospheric conditions involving advection, the effect of turbulence on dispersion of pollutant plumes [56] introduces many difficulties in determining the source parameters based on its evolving trajectory [89, 21] which can develop in a range of environments including:

- *Above-ground terrains:* where chemical dispersion events [65] and forest fires [26] pose threatening hazards to nearby populations [36].
- *Subsurface terrains:* where gas leaks can cause the accumulation of a concentrated toxin [77]. Screening oil and gas reserves for hydrocarbon leaks is an additional slightly less threatening example [114].
- *Marine environments:* where applications include monitoring the dispersion of oil spills [29] and ocean temperatures [121] at the surface, along with underwater surveillance [58].

Emphasizing STE in above-ground terrains, current approaches for predicting the characteristics of contaminant dispersion include the combined use of local meteorological data collected from static sensing grids and weather stations / met. towers [50], mapping global weather conditions from satellite imaging [107], and the collection of environmental data from a range of sensors mounted to unmanned vehicles, termed mobile-sensing networks (MSN). The data collected from these measurements can then be used in two types of models:

- *Receptor models:* Given concentration data measurements, provide an estimation of the source parameters.
- *Dispersion models:* Given source parameters and known meteorological conditions, provide a prediction of contaminant concentration at some distance away from the source.

Measurements of meteorological data can be either fixed in location by a network of static sensors or collected at variable locations over time by mobile sensors. Static sensor networks provide a means of continuously collecting accurate meteorological data, however they are limited in applicability by their fixed locations [50], where data collection towers can be separated by a displacement of 50 meters. This is a crucial issue for the STE process, as the development of a reliable model is dependent upon known measurements near the site of release. To gather a larger set of data within a moving plume, mobile sensing devices are required, and can be carried by either a human or vehicle, guided remotely or autonomously. Due to the hazardous nature of exposure involved with the former handheld method, mobile-sensing offers the much needed safety to limit potential contact with noxious elements. The mobile-sensing approach is typically accomplished through the use of autonomous robots [27] and/or unmanned vehicles operating independently or cooperatively (swarm robotics). Unmanned vehicles are capable of reliably traversing harsh terrains [79] that are difficult or impossible for humans to explore due to the surface roughness belonging to many environmental landscapes. Their ability to navigate near the source location is therefore critical, and has been given significant attention in this field of research as a result.

Recent trends, ongoing developments, and associated difficulties in atmospheric environmental sensing using autonomous unmanned mobile ground robots for gaseous plume source detection and interface identification is the primary focus of this review. The scope of each effort as they relate to the primary task of source localization is examined in the following subsections, along with the associated areas of difficulty that they introduce. This paper is arranged as follows: in section 2.1, methods of sensing environmental variables are reviewed from past to present. The measurement data can be used as input to guidance algorithms that navigate the mobile platform towards its estimate of the source location. Before the implementation of mobile sensing algorithms is discussed, a brief outline of the different types of sensing devices and their functionality is examined, in addition to the difficulties associated with environmental monitoring. In order to predict the dispersion of contaminants in realistic atmospheric conditions, many Atmospheric Transport and Dispersion (ATD) Models are available that aim to represent the dispersion as specified by the type of source and ambient environmental conditions. The approach to modeling the dispersion of a contaminant within its environment is covered in section 2.2, where the dispersion characteristics are largely dependent upon the level of atmospheric stability.

In this review, attention is given primarily to unmanned land-based vehicles acting as autonomous mobile-sensing networks for the source term estimation problem. While this primarily includes unmanned ground vehicles (UGV) and unmanned aerial vehicles (UAV), a greater emphasis is placed on UGV's performing the task of source localization. The major aspects of autonomous mobile land-based robots used for source localization are reviewed in section 2.3 including vehicle localization, mapping, and corresponding areas of difficulty. One major component in determining pollutant source term parameters involves deploying autonomous unmanned vehicles that seek the location of the contaminant emission. Many strategic methods have been employed to develop a reliable source localization algorithm that gathers useful information about the nature of the dispersion. These strategies fall into several distinguishable methodologies including exploration-based, optimization, probabilistic, and hybrid approaches. In section 3, a review of source localization algorithms aims to cover several developing strategies for this crucial task.

Sharing the overall objective of obtaining accurate meteorological data to sufficiently estimate the nature of a contaminant plume's dispersion, the tracking of a plume's boundary/edge/interface can also be accomplished autonomously through the deployment of unmanned vehicles. Techniques developed for this purpose utilize measurements of concentration in the region of interest at individual points with a single vehicle or multiple points with cooperative vehicles in order to approximate the spatial extent of the contaminated area. In section 4, approaches to tracking the boundary (or interface) of a dispersing plume are listed and covered in brief detail to highlight the practical use of many unmanned robotic systems. Finally, the paper concludes by addressing the current limitations of source localization strategies using UGVs as mobile sensing networks, then provides an outlook on the emerging trends and expectations to accomplishing source term estimation using autonomous robots.

While there are many topics relevant to source term estimation, some useful information specific to deploying UGV's for applications involving gas sensing can be found in [18, 19, 7, 30]. The topics of atmospheric dispersion modeling [49, 63] and simulation techniques for plume source localization [8] also share importance for the current discussion. Several applications of source localization algorithms using mobile sensors are reviewed in [93, 50, 95, 59].

2 Environmental Sensing Using Mobile Robots

2.1 Environmental Sensing and Data Acquisition

Sensor measurements of environmental parameters for pollutant source localization commonly include gas concentration [64], wind speed and direction [51], turbulent intensity, temperature, acoustics [103], humidity, mass flux [77], entropy [116], and radiation [42], depending on the nature of the plume and the ambient conditions. The data collected from these measurements can be used as input to autonomous guidance (source-finding) algorithms that navigate the mobile platform towards its estimate of the source location. Before the implementation of mobile sensing algorithms is discussed, a brief review of the different types of sensing devices is covered.

2.1.1 State of Gas Sensing for Point Measurements

Since the inception of pollutant source localization, methods involving the navigation along the direction of increasing concentration gradients by using gas sensing devices (chemotaxis) have remained at the forefront of plume tracking algorithms [50]. In general, gas concentration sensing devices function by responding to changes in the gaseous ambient environment through alterations in the sensor properties. Depending on the type of sensor and its composition, regulation of additional information from the environment is possible by adjusting the sensor's internal properties (e.g., voltage, temperature). These devices can be used passively (without being regulated) or actively [30], where the latter case often requires greater power consumption and introduces time delays.

Considering the physical method of ambient sensing for use in applications involving outdoor mobile robots, responses through conduction exist for several material types including metal oxides and various polymer composites and have been demonstrated to perform effectively while exposed to variable atmospheric conditions. Other responsive sensing methods that have been given less attention in this area include the use of optics, acoustics, quartz micro-balancing (QMB), and field effect transistors. In the context of mobile robotics, these are classified as exteroreceptive sensors that guide the responsive decision-making of the robot. The applicability and advantages of the more prominent gas sensing devices used in environmental mobile robotics are briefly discussed next.

- *Metal oxide (MOX)* based gas sensors provide a measure of concentration by correlating the presence of a particular gas to the resulting electrical resistance on the sensor's semiconducting surface [82, 83]. MOX sensors have an advantage of high sensitivity (for some gases), a useful lifetime of 3-5 years, and low-cost for thin films. Alterations in sensitivity occur based on several conditions, most influential of which are the thickness of the film (thinner films result in higher sensitivities), and the addition of catalytic metals to the oxide which increase the sensitivity for certain gases. Operating conditions require temperatures between 250-500°C [82], limiting the potential for gas detection unless they are preheated (a time-consuming process), and resulting in a greater power consumption. Additional disadvantages include delayed recoveries upon removing the surrounding gas [3], and their inability to perform in the presence of sulphur and ethanol [97].
- *Conducting polymer* gas sensors operate in a similar manner to MOX sensors, with the key

difference being a thin polymer film instead of a semiconducting film. The electrical resistance of the film is increased upon expansion in the presence of vapor, with response rates relying heavily on the rate of vapor diffusion [75, 7]. These sensors exist in two types: intrinsic and extrinsic, which are combined with doped and composite fillers respectively that increase conductivity [3]. Composite conducting polymers have been shown to offer higher sensitivity and reproducibility [80], the capability of synthesizing a wide range of materials for different organic gases, and functional operation at room temperature (an improvement over MOX, as power consumption is lower). Major disadvantages include a lower sensitivity than MOX sensors and aging effects resulting in sensor drift over their useful lifetime.

- *Quartz microbalance (QMB)* sensors utilize internal acoustic wave perturbations to sense the presence of gas, and can detect several different gases depending on the specific affinity of the coating over a piezoelectric substrate (typically quartz). These sensors offer rapid response times [43], low power consumption, a wide selection of gases, and increased lifetime compared to MOX sensors. Associated disadvantages include relatively low sensitivity, little protection against humidity, and poor signal to noise performance [7, 76].

With regard to the application of gas sensors in mobile robot sensing networks, their most common utility is to detect and measure the concentration of a known target gas (such as CO, CO2, Cl) in an outdoor environment so that the robot may autonomously locate its source with reliable accuracy in the shortest amount of time achievable, all while operating in the presence of ambient noise and fluctuating meteorological parameters. Specific to operation on land terrains, this objective can be accomplished using wheeled and/or aerial vehicles (drones) independently or cooperatively, through the use of intelligent guidance algorithms that ultimately aim to perform efficiently by using the least amount of energy and resources within the imposed test parameters and platform constraints. Accounting for these conditions, the most desirable gas sensor type would have the ability to detect multiple gases, a relatively high sensitivity, low power consumption, good performance in the presence of noise, and robustness to any possible weather conditions (humidity, high temperature, etc). Of the sensors reviewed, conducting polymer gas sensors may be the most useful for the described task, although MOX sensors have been used successfully in outdoor experiments [93].

2.1.2 Difficulties in Environmental Sensing

Additional difficulties facing meteorological data-driven guidance algorithms are introduced by the signal noise present in the ambient surroundings during data collection. For this particular system, the performance can be evaluated based on the signal to noise ratio (Eq. 1) [86] where the best performance corresponds to the highest ratio:

$$\frac{S}{N} = \frac{Required\ Signal\ Power}{Noise\ Power} \tag{1}$$

For mobile sensing networks that must communicate wirelessly, a theoretical maximum data rate in bits per second (known as the Shannon-Hartley Law, Eq. 2) exists for the surrounding medium that is directly related to the signal to noise ratio:

$$C = B(log_2(1 + \frac{S}{N})) \tag{2}$$

where C is the data rate and B is the bandwidth in Hz. It is worth noting that several filtering techniques (e.g, Kalman Filters, Washout Filters) have been used to effectively distinguish the actual sensor data from the background noise, essentially mitigating this problem for common environmental monitoring applications [47] where the noisy data is modelled by a linear Gaussian state-space model.

2.2 Atmospheric Transport and Dispersion Modeling

Atmospheric boundary layer (ABL) turbulence significantly influences the atmospheric dispersion processes. The ABL turbulence dynamics can be simulated using Numerical weather prediction (NWP) models such as Weather Research and Forecast model (WRF) [102], which have the capabilities to represent motions ranging from few meters to global scales of the atmosphere [73, 102]. WRF provides a powerful framework to capture the macro-scale features of the ABL. The micro-scale turbulence is well represented using the large-eddy-simulation (LES) formulation within WRF [12]. Recent studies have successfully used the concept of nesting of grids and demonstrated WRF-LES as an effective tool to simulate field-scale ABL processes [15, 13]. One way interaction between the ABL and the plume is achieved using passive tracer formulation in the WRF-LES [78, 16]. Alternatively, the existing transport and dispersion models use the model output from NWP models. Examples of such dispersion models include HYSPLIT (Hybrid Single

Particle Lagrangian Integrated Trajectory) (Stein et al. 2015 [106]), AERMOD (American Meteorological Society/Environmental Protection Agency Regulatory Model) [28], and FLEXPART (Flexible Particle dispersion) [108], to name a few.

An accurate representation of the atmospheric stability [40, 110, 25, 38] is important for a realistic model of plume dispersion in realistic scenarios. For example, Bhaganagar and Bhimireddy (2017) [11] demonstrated using the WRF model the significance of the role of atmospheric factors that influenced the dispersion of the chemical plume released on the fateful date of April 4, 2017, at 6.30 a.m. in the town of Khan Sheikhoun in northwestern region of Syria. Their study is one of the first studies to use WRF based dispersion models to estimate the short-term transport of plume subject to realistic dispersion processes. It should be noted that presence of surface roughness or irregularities complicates the dispersion processes [14, 10, 9], and most of these analysis ignores the surface roughness.

In order to predict the dispersion of contaminants in realistic atmospheric conditions, many Atmospheric Transport and Dispersion (ATD) Models are available that aim to represent the dispersion as specified by the type of source and ambient environmental conditions. Ranging from simple analytical models represented by a single equation with few inputs to complex numerical models made up of a series of equations, the computational time and effort involved increases substantially. Several of these models are frequently used for predicting dispersion, including box models [88], Gaussian plume models [21], Lagrangian models [108], Eulerian dispersion models [49], Dense gas models [46, 34], Computational Fluid Dynamics (CFD), and many recommended alternatives provided by the US Environmental Protection Agency (EPA). A comprehensive list of several popular models for STE applications is provided in table 1, followed by a description of the ATD model types.

In a review of ATD modeling techniques [49], it is shown that in general there is a strong correlation between gas and particle concentrations in open environments, while urban areas with large vertical structures show a disparity in the dispersion of gases versus particles. Only contaminants with particle diameters below 20 micrometers behave like gases (low settling velocities) and are commonly used in dispersion models [46, 34]. These constraints limit the selection of models for use with many source localization algorithms.

Table 1: ATD Model Types

Model Type	Model Name	Topography	Scale	Resolution	Types	Pollutants	Output
Box	AURORA VITO	Simple	L	NA	L	CO, NO2, SO2	1hr, 24hr, 1yr
	CPB GEOMET	Simple	L	NA	L	G (Inert)	1hr, 24hr, 1yr
	PBM	NA	R	NA	P,L,A	G	1hr, 24hr, 1yr
Gaussian Plume	CALINE 4	Simple	L	1m	L	CO, NO2, TSP	1hr, 8hr
	HIWAY2	Simple	L	1m	L	G (Non-reactive)	1hr
	AEROPOL	Simple	L	10-1000m	P,V	G,P	1hr
	ADMS	Complex	L,R	no limits	P,L,A	G,P	10mins-1yr
	AERMOD	Complex	L,R	no limits	P,L,A,V	G,P	1hr, 24hr, 1yr
Gaussian Puff	CALPUFF	Complex	R	no limits	P,L,A,V	G,P	1hr
Lagrangian	GRAL	Complex	L	100m-20km	P,L	G,P	10min-1hr
Eulerian	GATOR	Simple	L,R,G	NA	P,L,A,V	G,P	1hr-1yr
CFD	ARIA	Complex	L	1m+	P,L,A,V	G,P	Real-time
GP/Box (Hybrid)	OSPM	Simple	L	NA	L	NOx,NO2,O3,CO	1hr

Scale	L = local, R = regional, G = global
Source Types	L=line, P=point, A=area, V=volume
Pollutants	G=gases, P=particles

- *Box*: Given initial meteorological conditions as input, simulates the formation of pollutants within a 'box' based on the conservation of mass. Does not provide information on the local concentration of pollutants, but is capable of representing the chemistry and physics of particle interactions.
- *Gaussian Plume*: Simplest in complexity and least demanding on computational resources, the Gaussian Plume Dispersion model serves as a fundamental representation of the dispersion of a concentrated pollutant in open atmospheric environments. The Gaussian model provides gas concentration values at every point in three-dimensional space and is derived from the turbulent diffusion equation under assumed conditions of homogeneity and steady state flow. Dispersion in the vertical direction is governed by atmospheric stability (whose values are commonly determined based on Pasquill's atmospheric stability classes [81]), while dispersion in the horizontal plane is governed by molecular and eddy diffusion. The dispersion coefficients are used to account for atmospheric turbulence by considering the surrounding meteorological conditions (wind speed, solar radiation, and cloud cover) as defined for the stability classes in Table 2. Based on a Gaussian distribution of the plume concentration in the vertical and horizontal directions under steady state conditions, these models consider the effects of diffusion and advection on dispersion, and typically do not incorporate the physical processes of particle deposition or chemical reactions. They are best suited for quickly calculating pollutant concentrations at hourly intervals. They are not designed to model the dispersion under low wind conditions ($<$ 2 m/s) or at sites close to the source ($<$ 100 m), are unsuitable for far-field modelling, and are unable to predict the time required for pollutants to travel from the source to receptors.
- *Gaussian Puff*: A modification of the Gaussian Plume model that approximates the pollutant emission as a series of puffs over time, allowing for a time-variant wind speed to be implemented. Individual puffs follow a Gaussian dispersion, and the overall effect of

the emission is calculated by integrating the puffs with respect to time and summing their contributions at receptor sites.

- *Lagrangian*: Defines a volume ('box') region of air containing an initial concentration of pollutants, then follows the trajectory of the box as it moves downwind and incorporates changes in concentration due to the effects of dispersion, mean wind velocity, and turbulence. These models are suitable for simple and complex terrains with homogenous or heterogeneous/unstable meteorological conditions. Atmospheric turbulence is accounted for by the calculation of the random motion of particles.
- *CFD*: Computational fluid dynamics (CFD) models provide a dynamically sophisticated representation of fluid motion based on the conservation of mass and momentum by using finite difference and finite volume methods to resolve the Navier-Stokes equations. Although these models are able to represent the overall wind flow field, the model velocities and level of turbulence are highly sensitive to initial conditions.

Alongside ATD models, Numerical weather prediction (NWP) models such as the Weather Research and Forecast model (WRF) [102] provide a powerful framework to capture the macro-scale features of the Atmospheric Boundary Layer (ABL) with the capability to represent motions ranging from few meters to global scales of the atmosphere [102]. The micro-scale turbulence is well represented using the large-eddy-simulation (LES) formulation within WRF. Alternatively, the existing transport and dispersion models can use the model output from NWP models, or in some instances, the NWP models can contain Eulerian or Lagrangian atmospheric dispersion models.

Table 2: Pasquill Stability Classes and Criteria

Stability Class	**Definition**	**Surface Wind Speed**		**Daytime Solar Radiation**			**Nighttime Cloud Cover**	
A	*Very Unstable*	m/s	mi/h	Strong	Moderate	Slight	> 50%	< 50%
B	*Unstable*	< 2	< 5	A	A - B	B	E	F
C	*Slightly Unstable*	2 - 3	5 - 7	A - B	B	C	E	F
D	*Neutral*	3 - 5	7 - 11	B	B - C	C	D	E

E	*Slightly Stable*	5 - 6	11 - 13	C	C - D	D	D	D
F	*Stable*	> 6	> 13	C	D	D	D	D

2.2.1 Characteristics of Source Emissions

Sources of air pollutant emission belong to particular types that can be characterized based on several factors, including source shape, motion characteristics, level of urbanization, and release duration. The geometric shape of the emission source is one of the most influential factors on the behavior of the plume.

- *Point*: a single identifiable source of emission approximated as a localised release from a zero-dimensional point that can be at ground-level or elevated (e.g., a combustion furnace / gas stack [21])
- *Line*: one-dimensional array of emissions (e.g., exhaust from vehicles along a roadway)
- *Area*: emissions from a forest fire [26], evaporated vapors from a chemical spill of a volatile liquid
- *Volume*: an area source with a third dimension representing height (e.g., dust emissions from wind erosion / gaseous emissions from oil refineries [69])

Contaminant sources are not limited to a single stationary position, and can be attached to a moving body (exhaust from automobiles). The duration over which they are emitting a pollutant is categorized into two separate classes:

- *Puff / intermittent source*: emissions that consist of a series of instantaneous pollutant releases
- *Continuous source*: emissions that continuously exhaust a pollutant

The level of urbanization is dictated by the presence of human populations and large city infrastructures. Highly urbanized areas with high population densities (cities) can form a heat island that produces more heat than the surroundings causing the air to rise above the urban area resulting in more turbulence (and therefore instability) in the atmosphere than adjacent areas. Rural areas, on the other hand, have low population densities and typically do not have large-scale infrastructures that affect the level of turbulence in the atmosphere.

In many instances where studies are focused on testing the performance of a source localization algorithm using mobile sensing robots, attention is given to stationary continuous point source emissions at ground-level in rural areas. The Gaussian Dispersion model is used most often to predict the dispersion of contaminants due to its simplicity.

2.3 Autonomous Ground-Based Mobile Robots

In this paper, attention is given to unmanned land-based vehicles acting as autonomous mobile-sensing networks for the source term estimation problem. While this primarily includes unmanned ground vehicles (UGV) and unmanned aerial vehicles (UAV), a greater emphasis is placed on UGVs performing the task of source localization [19]. UAVs are more ideal for attempting to track the interface of a plume and are briefly reviewed in the corresponding section on interface tracking. Considering the use of autonomous ground-based mobile platforms for plume source localization, two significant efforts dependent upon data from multiple sensors exist: simultaneous vehicle localization and mapping (SLAM) [33] and meteorological data-driven guidance [27]. Because these efforts are performed concurrently during operation, the amount of data being received is significantly large, resulting in several difficulties when attempting to interpret, transmit, and utilize the data gathered.

2.3.1 Mobile Robot Localization and Mapping

For a mobile robot to operate autonomously in an unknown environment, it must be able to simultaneously identify the presence of any obstructions immediately surrounding it (mapping) and determine its own position relative to its surroundings (localization). Mapping requires the use of perception systems that allow the robot to extract multi-modal information from the environment [61]. Perception systems can include vision-based imaging equipment (e.g., light or thermal cameras) [2] and/or optical sensors such as LIDAR [79]. Vision systems have the added benefit of allowing external operators to view the robot's surroundings and take over vehicle guidance if necessary (tele-operation). Optical sensors offer the ability to create a map of the environment and detect any nearby objects, which is crucial for efficient navigation when planning the vehicle's trajectory. While a combination of the two sensor types can ultimately increase the perceptive capabilities of the robot, the computational efficiency acts as a harsh constraint, and a trade-off between the two is often required.

Vehicle localization is accomplished by incorporating sensors that measure internal values of the robot (e.g., robot heading, wheel speeds, wheel loads) to provide an estimate of the robot's position relative to its previous states and any surrounding landmarks. A myriad of devices can be used simultaneously for this effort including GPS and Inertial Measurement Unit (IMU) sensors [74], and wheel encoders. Typically, with regard to mobile platforms, localization efforts to determine the robot's current position historically include reading the wheel encoder values that count wheel rotations over time to update the vehicle's position, a technique known as dead reckoning [6]. This basic method can prove unreliable however, as any slip that occurs between the wheel and ground surfaces will not be read by the encoders, resulting in a position estimate that drifts as the vehicle navigates. To prevent the accumulation of drift, GPS can be used to update the known position of the robot in combination with sensor estimation techniques (e.g., Kalman filtering [66]) that effectively improve the accuracy of the position estimate.

2.3.2 Difficulties in Mobile Robot Sensing

For a mobile-sensing network operating in outdoor environments, it is clear that a considerable amount of sensing devices are required (in addition to environmental sensors) to accomplish the overall goal of autonomously localizing a pollutant source [71]. An increasingly complex configuration of multi-modal sensing networks requires reliable integration of sensor data (data fusion) so that the robot's perception of its environment is both accurate and computationally efficient [109]. Once the data from multiple sensors gets combined into a point cloud, it often must be compressed and transmitted wireless to a separate server for faster computational processing, which can become a significant difficulty depending on the bandwidth limitations imposed by the particular operating environment and the total number of sensors involved. These physical constraints limit the real-time capability of many proposed MSN architectures that attempt to incorporate a large number of sensing devices or additional mobile robots.

It is necessary in practice to simulate the expected environment for a mobile sensor network so that the performance of its source-finding ability can be evaluated [8, 35]. The most ideal scenario used for simulation testing includes a flat homogeneous terrain without obstructions, multiple sensors excluding signal noise, a single continuous contaminant release, and the exclusion of turbulence in the diffusion process. These ideal conditions are often far from realistic, resulting in poor performance when experimentally testing in the field using real-time systems.

3 Plume Source Localization

One of the major components to determining pollutant source term parameters involves deploying autonomous unmanned vehicles that seek the location of the contaminant emission. Many strategic methods have been employed to develop a reliable source localization algorithm that gathers useful information about the nature of the dispersion. This information is continuously collected in an attempt to reach a suitable dispersion model prediction, a process which is outlined in figure 1.

Figure 1: STE Components Diagram

Testing source localization algorithms within a realistic simulation environment has remained a key objective in validating their actual/expected performance when tested experimentally or compared to experimental datasets [85, 23], where the accuracy and resolution of sensors in real-time is limited. In attempting to validate any simulated results of this case in a real environment, the effects of turbulence on the concentration's dispersion creates a large disparity in source seeking performance, often resulting in the localization of local maximum concentration values, a major difficulty when implementing gradient-based chemotaxis methods [68, 105]. Thus, developments in source-seeking approaches currently aim to increase the accuracy and speed of localization under conditions involving both dispersion and advection, and are largely dependent on accurately simulating the aforementioned scenario using a variety of Atmospheric Transport and Dispersion (ATD) modeling techniques [49]. An example of combining CFD and MATLAB simulation for evaluating plume source localization techniques within a complex indoor geometry (modeling contaminant propagation) is demonstrated in [8].

Source localization techniques have been widely tested for uniform, steady-state chemical plumes moving solely due to diffusion. The most outdated yet fundamental form of source localization is based around reactive global exploration, where mobile sensing networks follow pre-defined pattern trajectories while sampling concentration measurements across the entire area (domain) being searched. Aimed at improving the reliability, speed and efficiency of source localization by autonomous mobile platforms, current plume tracking algorithms typically take two main approaches, either through the use of optimization [101] or probabilistic techniques [20]. The more recent trend of combining the aforementioned strategies into a single hybrid algorithm is discussed in the final subsection. At the end of each of the following sections, a table containing referenced applications of the major algorithms pertaining to each particular methodology is listed. Shown below, table 3 provides convenient abbreviations for several parameter descriptions.

Table 3: Algorithm Parameter Descriptions

Sensors:	C = concentration, W = wind velocity, M = mass flux, E = entropy, T = temperature, En = Electronic Nose, L = light
STE Parameters:	x,y,z = source location coordinates, Q = source emission strength, t0 = time of release, t = duration of release, n = source quantity, wd = surface wind direction, s = turbulent diffusion parameters

3.1 Exploration Methods

First reviewing the fundamental strategies that have been developed to trace the source of a gas/chemical leak, reactive exploration-based methods aim to deploy path-following robots that measure concentration values across the entire (global) search-space, adjusting their path in response to detected concentration levels. The process is essentially performed in three phases [94]:

1. Initially deployed outside of the contaminant area, follow a preliminary search direction until contact with the plume is made
2. Using measured concentration values, trace the source of the chemical release by performing a unique exploration strategy
3. After finding a global peak concentration value, confirm the predicted location of the emission

While this approach will theoretically always find the source location (after the entire domain is explored), it is often too time-consuming to have real practical value in many cases. The more successful global-searching reactive exploration-based strategies have attempted to mimic the behavior of biological organisms that sense the concentration and wind in their immediate surroundings and use this information to follow the direction of increasing concentration (termed chemotaxis and anemotaxis). Relying heavily on the assumption of smooth, positive concentration gradients in the source direction, chemotaxic-only methods tend to fail in the presence of turbulent conditions. Combining the use of biologically-inspired anemotaxis methods such as those in table 4 (Zigzag [51], upwind searching [92], silkworm moth [93]) has offered improvements and new localization techniques altogether, but not definitive success.

Table 4: Exploration / Direct Search Method Algorithms

Algorithm	Date	Parameters	Sensors	Gradient	References
Zig-zag	1994	x,y,z	W,C	Yes	[51]
Upwind Search	1995	x,y,z	W	No	[92]
E. coli	1996	x,y,z	C	No	[48]
Silkworm Moth	1992	x,y,z,n	W,C	Yes	[55]
Braitenberg-Style	1993	x,y,z,Q	C	Yes	[96]

3.2 Optimization Methods

The objective of optimization is to minimize a cost function that can represent a number of different objectives (minimization of the total energy cost, source location estimate error, etc.). Reviewed in [50], when applied to source localization, optimization approaches aim to estimate a single source location by minimizing an objective/cost function that aims to match the measured and predicted concentration values of an Atmospheric Dispersion Transport (ATD) model through an iterative process. Listed in order of increasing complexity, several subcategories exist: direct-search methods [123], gradient-climbing methods [100], and meta-heuristic methods [4, 44, 45].

The simplest category, direct-searching, involves guiding the mobile robot along a pre-planned path trajectory until the gas concentration is detected, followed by re-initializing the path at the location of the highest detected concentration while aiming to minimize the objective function. Because of its simplicity, this algorithm works well (albeit rather slowly) for steady dispersion models, but fails to navigate in rapidly changing turbulent conditions. However, this method does not require an initial estimate of the source location, benefiting from its global searching strategy to reduce the chance of converging in a local maximum. Gradient-climbing approaches (listed in tables 4 and 5) have shown success in localizing steady plumes driven by diffusion where smooth concentration gradients exist throughout the plume. Regarding implementation in conditions with advection, these approaches require a highly approximate initial estimate of the source location and are otherwise revealed to have issues in converging at sites of local maximum concentrations. Strategies avoiding the need for good initial estimates, classified as Meta-heuristics, prove to excel over gradient-climbing methodologies.

An example cost function used in Least Squares Estimation that aims to iteratively minimise the sum of the squared residuals of the observed and predicted concentration measurements is shown in Eq. 3:

$$J = \sum_{n=1}^{N}(C_n - D_n)^2 \tag{3}$$

To minimize this function (which is dependent on the spatial locations during measurement), the gradient of J (cost) is computed and set equal to zero, allowing for an estimate of the direction of highest increasing concentration. This process is repeated until a single optimized solution (in this case, the estimated source location) is found. Thus, optimization algorithms are a useful tool for gradient-climbing approaches.

Two common optimization-based gradient-climbing techniques that are reliant upon measurements of chemical concentration include Re-normalization [52] and the Brodyen-Fletcher-Goldfarb-Shanno algorithm (BFGS) [24, 37, 41, 98]. Renormalization is an extension of the more basic Least Squares Estimation optimization strategy while concurrently utilizing weighted measurements of a concentration monitoring network based on its arrangement to reduce the total search space [52]. This is a fundamental improvement in attempting to avoid convergence at sites of local maximum concentration, however its success has not been definitive. The BFGS algorithm belongs to the family of quasi-Newton optimization techniques [98] that offers improvements over Newton's method for this particular application by approximating the inverse of the Hessian matrix, thereby improving computational efficiency and increasing the speed at which the function extrema can be estimated. Again, the algorithm is subject to converge incorrectly when used independently.

The addition of environmental sensing beyond solely gas concentration has resulted in the development of more sophisticated meta-heuristic algorithms built off of the fundamental concepts established with chemotaxis. An improvement to global pattern searching, the simulated annealing (SA) algorithm [60] introduced by Kirkpatrick et al. [60] aims to bring the system from an initial state to a convergent state of minimum possible energy where accepted state changes are based on a Boltzmann probability Distribution [114]. Implementing the SA algorithm for the purpose of source localization, Thomson et al. [114] aimed to determine the location of a source and its emission rate while measuring gas concentration and wind velocity. Newman et al. [39]

used SA to determine contaminant zones in underground water, and compared its performance with a Minimum Relative Entropy (MRE) method [67], ultimately arriving at an optimal solution being a hybrid of the two, where MRE followed SA to provide confidence limits of a refined solution.

Another popular technique used in many STE processes is known as the Genetic algorithm (GA). Representative of the natural evolution process [39], this evolutionary computation method is a global optimization technique (stochastic search method) that generates new solution candidates after multiple iterations (generations) so as to avoid the issue of local maximum convergence. With regard to source localization, the algorithm optimizes a combination of source parameters (location, strength, surface wind direction) that provide the best fit between measured concentration data and model-predicted concentration values as determined by an objective function, such as Eq. 4:

$$Cost = \frac{\sqrt{(ln(\alpha C_r + 1) - ln(\alpha R_r + 1))}}{\sqrt{ln(\alpha R_r + 1)}} \tag{4}$$

where C_r represents the model-predicted concentrations, R_r represents the measured concentration data for an individual receptor r, and α is a scalar value. In one of its most successful implementations [5], the GA was used to estimate the source terms of multiple releases with a better estimate compared to several optimization and probabilistic-based approaches [84]. The process functions as follows:

1. Represent the problem variable domain as a chromosome of fixed length representing a combination of source term parameters.
2. Define a fitness function to measure the performance of an individual chromosome (Eq. 4).
3. Randomly generate an initial population of chromosomes of size N.
4. Calculate the fitness of each individual chromosome.
5. Select a pair of chromosomes with the highest fitness probabilities for mating.
6. Create offspring chromosomes to replace the original chromosomes.
7. Recalculate individual fitness and repeat the process until convergence

Another popular optimization algorithm for detecting multiple emission sources with multiple cooperative robots is known as Glow-Swarm Optimization, although its use of large numbers of sensing platforms is infeasible for practical applications.

Several modifications to these fundamental gradient-based optimization algorithms aimed at improving source term estimates include the use of wind velocity data within the simulation environment [4], using known prior information and null sensor readings to limit the global search space, and more complex ATD models beyond the simple Gaussian dispersion model [17]. Many of the more successful optimization methods showed a large discrepancy between simulation and experimental results, owing to reliance on the ATD model and knowledge of the atmospheric conditions/stability, which includes a wide range of meteorological parameters that are subject to noise during measurement. Appeal can be seen in the comparative simplicity of optimization and global-searching methods as they often have the benefit of reduced computational requirements. However, a large portion of these algorithms (table 5) utilize gradient calculations that have demonstrated a severe shortcoming in their tendency to converge towards areas of local maximum concentration. Because optimization techniques only produce a single optimized solution by their design, they cannot reliably be used as a standalone approach.

Local observations of meteorological data are typically conducted within tens of kilometers from the source of emission, capturing data that is heavily influenced by the surrounding environmental weather conditions [32]. Global forecast observations do not aim to capture the smaller localised regional effects of the environmental conditions, but instead make predictions over hundreds of square kilometers.

Table 5: Optimization Method Algorithms

Algorithm	**Date**	**Params**	**Sensors**	**Grad**	**Evaluation Method**	**Domain**	**Refs**
Least Squares Estimation (LSE)	2012	x,y,z,Q,n	C	Yes	Data from IIT diffusion experiment conducted at Delhi for surface release of tracer SF6 in low-wind conditions.	-	[99]

Re-normalization	2009	x,y,z,Q	W,C,T	Yes	Observations taken in the tracer diffusion experiment conducted for surface releases of tracer SF6 in February 1991 at IIT Delhi in low-wind conditions.	-	[100]
Pattern Search Method (PSM)	2010	x,y,z,Q	C	No	Synthetic: Gaussian Puff Model	Local	[123]
Limited-memory BFGS	2015	x,y,z,Q	C	Yes	Synthetic: SCIPUFF, Gaussian Plume. Experimental data: FFT07	Local	[17]
Simulated Annealing (SA)	2007	x,y,z,Q	C,W	Yes	Multiple surveys in the Middle East, each of which covered multiple hundreds of	Global	[114]

					square kilometres.		
Genetic Algorithm (GA)	2007	x,y,Q	C,W	No	Synthetic: Gaussian Plume model. Twin experiments data.	Global	[4]

3.3 Probabilistic Bayesian-Inference Methods

Unlike optimization methods that provide a single estimated solution of the source location, Bayesian Inference-based STE methods produce a probability density function (PDF) of the estimated source parameters with associated confidence levels to account for any uncertainties obtained from the observed data, which is modelled as high-dimensional and non-Gaussian. Bayes theorem estimates the probability (or uncertainty) of an assumption or hypothesis being correct given new observed information [113]. With regard to Bayesian Inference applied to STE, the interpretation of Bayes Theorem can be written as Eq. 5:

$$Posterior\,\alpha\,\frac{Prior\ x\ Likelihood}{Evidence} \Rightarrow P(\theta \mid D, M, I)\,\alpha\,\frac{P(\theta \mid I)\,x\,P(D \mid \theta, M, I)}{P(D \mid M, I)} \tag{5}$$

Where θ is the hypothesis (inferred source parameters) being estimated, given observations of data (measured concentrations or other parameters treated as random variables) D, the ATD model M, and any related prior information I. The prior distribution expresses what is known about the hypothesis before collecting any data measurements. If there is no known prior information, this probability becomes a uniform distribution. The likelihood function, also known as the sampling distribution [23], quantifies the probability of the data (measured concentration) being correct assuming that the hypothesis (predicted concentration) is true. The reverse statement is true for the posterior distribution, which expresses the probability of the hypothesis being true, assuming that the given data, model, and prior information is correct. Lastly, the evidence, or marginal likelihood, measures the support for a particular hypothesis. For the typical case of only a single source, this term is dropped, simplifying equation 5:

$$Posterior\ \alpha\ Prior\ x\ Likelihood \Rightarrow P(\theta \mid D, M, I)\,\alpha\,P(\theta \mid I)\,x\,P(D \mid M, I) \tag{6}$$

When applied to STE, each term can be updated sequentially via sampling methods, and the posterior distribution is of primary interest. The use of sequential Monte Carlo (MC) sampling techniques [31] can be applied to the Bayesian-based STE approach to feasibly produce an estimate of the posterior PDF for the given source parameters in real-time, which allows for an accurate representation of the parameter estimates and uncertainty. In the presence of many high-dimensional parameters being estimated, Markov Chain Monte Carlo (MCMC) and Sequential Monte Carlo (SMC) sampling techniques offer reliable computational efficiency and are not subject to linearity or Gaussian constraints.

First examining MCMC, the sampling process begins by constructing a Markov Chain from an initial starting point (which may be a random walk in the absence of prior information), proposing inferences from this current 'link' and evaluating their likelihood of being the next link based on established acceptance criteria (commonly generated by the Metropolis-Hastings (MH) algorithm [72]). MCMC has been tested in real environmental applications, with its success being highly dependent on correctly specifying dispersion model errors [120]. SMC methods are simulation-based approaches that essentially perform the same routine as MCMC with an advantage in computational efficiency as inference proposals are generated in parallel. With SMC, new data can be incorporated into the algorithmic process immediately upon availability and assigned a weight (known as importance sampling) to update the posterior distribution.

For Bayesian-based approaches to STE, a disparity exists between results from simulation and experiments (which is true for optimization approaches as well), in this case due to the inaccuracy of the model's likelihood function and random sensor noise. By requiring a back-propagation of the plume model based on the measured concentration values to compute the likelihood function, many of these algorithms prove to be too demanding of computational resources for real-time applications [90]. To mitigate the issues arising from the unknown likelihood function, Lane et al. [62] used Approximate Bayesian Computation (ABC) as a likelihood-free rejection sampling method for data approximation to successfully estimate the source strength, location, and time of a single release with the SMC process.

Some Bayesian-based approaches to STE that incorporate additional algorithmic strategies include Differential evolution Monte Carlo (DEMC), Polynomial Chaos Expansion (PCE), and Polynomial Chaos Quadrature (PCQ). DEMC uses the genetic algorithm in combination with MCMC to determine the jump proposition for multiple Markov chains [112]. PCE and PCQ combine the Bayesian approach to STE with concepts extended from homogeneous evolutionary chaos [118]. PCE is a non-sampling based method that suffers from difficulties in evaluating nonlinear integration steps, while PCQ uses Monte Carlo sampling to overcome this pitfall. DEMC and PCQ have both been used for attempting STE with experimental data as described in Table 6.

Ultimately, probabilistic methods (table 6) often have an advantage over optimization in that they provide a measure of uncertainty along with the estimate for the source term, which can overcome the major issue of convergence at sites of a local maximum concentration. This uncertainty estimate, which can be produced by a probability distribution function, allows for sequential update-based algorithms to determine the desirable choice of direction at each iterative step in the source-seeking process. Because many of these algorithms require an initial estimate of the source location, a poor first choice can consequently lead to failure. To improve the accuracy of the initial estimate, incorporating meteorological data acquired by external sources such as static sensor networks, satellites, and weather stations allows for the reduction of the designated search-space and provides a general idea of where the source is located.

Table 6: Probabilistic Bayesian-Inference Method Algorithms

Algorithm	**Date**	**Params**	**Sensors**	**Likelihood**	**Evaluation Method**	**Refs**
MCMC	2007	x,y,Q	C	Yes	Mock urban setting test (MUST), full-scale field experiment (joint Urban 2003)	[57]
MCMC	2012	x,y,z,Q,s	C	Yes	Synthetic: Gaussian Plume	[20]
SMC	2013	x,y,z,Q,s	C	Yes	SCIPUFF, Gaussian Puff	[117]
DEMC	2009	x,y,t,Q	C	Yes	Gaussian Plume	[91]
PCE	2013	x,y	C	Yes	SCIPUFF	[68]
PCQ	2012	x,y	C	Yes	Numerical Simulation	[1]
ABC	2009	x,y,z,n,t0	W,C	No	Bar-sensor model, Gaussian Plume	[62]

3.4 Hybrid Source Localization Methods

Combining multiple approaches into a single 'hybrid' algorithm (table 7) is certainly an ongoing trend that aims to handle the many difficulties produced by turbulence in real-world experiments. The spectrum of current methods used for improving source seeking algorithms embody the combination of traditional gas-sensing techniques (which have proven successful for the steady state case) with additional sensing of other environmental parameters. Additional measurable parameters that have inspired new localization techniques include wind velocity (anemotaxis) [17], mass flux (fluxotaxis) [77], and entropy (infotaxis) [67]. With an increasing amount of available sensors and data-fusion efforts offering improvements in the perceptive capabilities of mobile sensing platforms, along with a vast collection of ongoing weather observations, autonomous source localization strategies continue to evolve in both complexity and capability.

Table 7: Hybrid Algorithms

Algorithm	**Date**	**Params**	**Sensors**	**Evaluation Method**	**Refs**
Minimum Relative Entropy (MRE) + Particle Swarm Optimization (PSO)	2014	x,y,z,Q	C	Gaussian Plume, Prairie Grass emission experiment (Barad, 1958)	[67]
Nelder-Meade Downhill Simplex (NMDS) + Genetic Algorithm (GA)	2007	x,y,Q,wd	C,W	Synthetic: Gaussian Plume, field data.	[44]
Approximate Bayesian Computation (ABC) + Sequential Monte Carlo (SMC)	2015	x,y,z,s	C	Experimental datasets collected by COANDA Research & Development Corporation. Dataset 1 was collected in the absence of any obstacles mimicking a rural terrain. Dataset 2	[90]

				was collected in the presence of mm high obstacles mimicking an urban terrain.	

4 Plume Interface Tracking

Sharing the overall objective of obtaining accurate meteorological data to sufficiently estimate the nature of a contaminant plume's dispersion, the tracking of a plume's boundary/edge/interface can also be accomplished autonomously through the deployment of unmanned vehicles. Useful applications include monitoring oil spills [29], nuclear radiation levels [115], growth of harmful algae [70], and estimating the spread of contaminant pollutants and volcanic ash clouds [107]. Similar in strategy to source localization, techniques developed for this purpose utilize measurements of concentration in the region of interest at individual points with a single vehicle [22] or multiple points with cooperative vehicles [58] in order to approximate the spatial extent of the contaminated area. For the task of tracking the interface of a developing plume, many strategies require the use of multiple cooperative (swarm) robots. Because of the three-dimensional nature of the dispersion in open environments, unmanned aerial vehicles (UAVs) offer a practical solution to measuring many points along the contour when compared to UGVs alone, which cannot feasibly collect data at variable altitudes.

Optimization methods similar to those described for source localization have also been used with mobile sensors for boundary tracking by minimizing a cost function representing the difference between the desired and measured concentration values at the estimated contour. In its most successful application, a collaborative algorithm was used that aimed to minimize the centroid distance of the plume. Implemented by Srinivisan et al. in [104] and renamed Adaptive Contour Estimation (ACE), the centroid location of the contour was estimated by utilizing information about the concentration gradient to guide the mobile sensors using an adaptive sampling algorithm. Several other estimation and control approaches have also been used for boundary tracking using mobile sensors, and the more successful methods are discussed next. In most cases, the simulation tests were performed with clearly defined boundaries and no account for sensor noise, limiting their practicality in field experiments.

First examining the fundamental control algorithms, perhaps the simplest is known as bang-bang control. For boundary tracking there exist only two system states that alternate when the vehicle crosses the contour edge. In a basic implementation, Kemp et al. [58] used bang-bang control requiring a single concentration sensor with an unmanned underwater vehicle (UUV) to track an underwater boundary. Several sources of error exist with this method, where failure to consistently track the boundary can occur due to large redirection angles, sensor noise, and narrow bottlenecks along the edge. Improvements proposed by Bertozzi et al. [53] aimed at correcting the turning (redirection) angle which has been extended to cases involving multiple vehicles [54], along with the addition of a cumulative sum algorithm for the purpose of reducing the effects of noise. This particular control algorithm has been used for the purpose of monitoring an oil spill, a radiation field [115], and even a dynamic plume [22] (with the addition of a static-sensor network). With the exception of the latter application, this method has seen greater success in regions of quasi-static contaminant fields, where the movement of the boundary is much slower than that of the vehicle's speed. An extension of bang-bang control, sliding mode control acts in a similar manner, redirecting the vehicle at a 'sliding distance' away from the boundary with a threshold value specified by the concentration density near the edge. Several common applications of boundary tracking showed that this algorithm was particularly robust to typical uncertainties seen with bang-bang control.

At the peak of control law tracking algorithms, multiple cooperative robots have been used in formation to track level sets of a moving field [122]. The fixed-shape formation control of multiple Newtonian particles allowed for many additional steering control laws to be developed using differential geometric approaches that controlled the center of formation to detect and track curvatures based on the estimated concentration gradient at multiple points simultaneously. Additionally, this method has been extended to track 3-D surfaces using multiple UAVs [119]. Other developments attempt to estimate and visualize the boundary curvature [26]. Demonstrating the diversity of mathematical approaches to boundary tracking, Neural Networks (NN) have also been combined with a robust controller to allow a mobile robot to track a moving boundary and estimate the unknown model parameters [111].

5 Conclusion

Regardless of the strategic approach taken by mobile sensing networks, there are still many limitations associated with accurately testing the source localization algorithm's performance in simulation against field trials due to constraints on CPU capabilities including processing, available memory, and wireless data communication for testing in both simulation environments and real-time field experiments. As computational efficiency stretches even further alongside technological developments, and the above limitations are made less restrictive, then the overall capabilities of mobile sensing networks can feasibly extend to include more complex hybrid data-fusion algorithms and additional sensors and sensing platforms (cooperative robots). Emerging trends that follow these expectations include:

- Combining several algorithms into a hybrid method to utilize their individual benefits and increase reliability.
- Increasing the complexity of the atmospheric dispersion model beyond the simple Gaussian Plume case by using CFD model generated plumes that incorporate the effects of turbulence.
- Utilizing other meteorological sensor data in addition to gas concentration (wind velocity and direction, mass flux, entropy, turbulent intensity), within the bounds of wirelessly transmitting a larger amount of data at a high enough frequency.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Highlights

- For dynamic tracking of plume in space-and time, the data collection using mobile sensing increases the detection accuracy compared to meteorological towers.
- Conducting polymer gas sensors are most efficient for autonomous robots to locate the source in the least amount of time.
- Atmospheric turbulence influences the dispersion processes, hence, obtaining data using Large-eddy-simulation framework within numerical weather prediction models increases the accuracy of the dispersion models significantly.
- Optimal multi-sensor fusion algorithms are critical to accomplish the goal of autonomously localizing the pollutant source.
- Bayesian, Optimization, and Hybrid source-finding methods are reviewed.

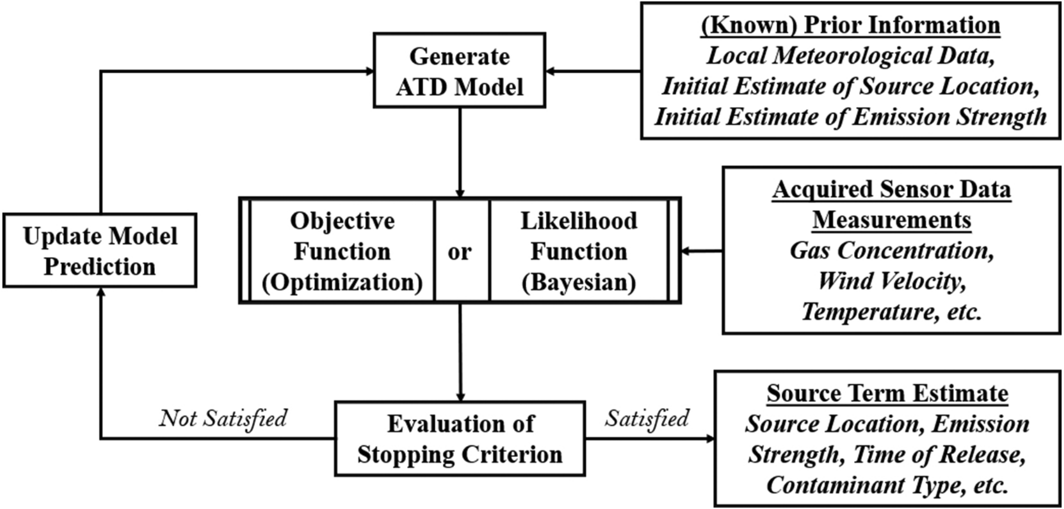
Generate
ATD Model
(Known) Prior Information
Local Meteorological Data,
Initial Estimate of Source Location,
Initial Estimate of Emission Strength
Update Model
Prediction
Objective
Function
(Optimization)
or
Likelihood
Function
(Bayesian)
Acquired Sensor Data
Measurements
Gas Concentration,
Wind Velocity,
Temperature, etc.
Not Satisfied
Evaluation of
Stopping Criterion
Satisfied
Source Term Estimate
Source Location, Emission
Strength, Time of Release,
Contaminant Type, etc.

Figure 1