# Odor Localization Sub Tasks: A Survey

*By* 01 NLH

# Odor Localization Sub Tasks: A Survey

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***Abstract*— This paper discusses about the sub tasks of odor localization research. Three steps of odor localization, i.e. Plume finding, plume tracking/tracing, and source declaration are explained. The difficulty of plume finding is discussed. Farrell's Filamentous and Pseudo-Gaussian plume models that have been analyzed by previous researcher are presented. Some approaches used in plume tracking/tracing based on advection/turbulent and the estimation of odors' distribution are provided. The advantages of source declaration are showed. Some problems occur in plume finding become a great consideration for the future research.**

***Index Terms*— Odor localization; Farrell's Filamentous; Pseudo-Gaussian; Plume models.**

## I. Introduction

Olfaction is very important for animals. Its roles include finding food, avoiding threats, coordinating behaviors in social animals [1], mating, and communicating [2]. Being more sensitive than human, animals' olfaction is widely used in various applications. Some animals are used for searching drugs or explosives material [3] and rescuing victims in the disaster location [4].

To emulate the olfaction of animals, static electronic nose was developed. It gives more advantages when employed in difficult places and situations, for instance in unreachable or poisonous area [5]. However, Static electronic nose only can detect and respond the objects that actually reached the reactive surfaces of the sensors [6]. To overcome this limitation, it was developed an integration of electronic nose to the robots that can move easily to the desired target.

Application of electronic nose on mobile robots in localizing odor is widely analyzed. Early pioneers, G. Kowadlo and R. A. Russell [7] and H. Ishida et al [6] provide detailed reviews about this.

## II. Localization Sub Tasks

In accomplishing odor localization task, the robots pass 3 steps: plume finding, plume transversal, and source declaration [8] or 4 steps: finding a plume, tracking in and/or out the plume, reacquiring the plume, and declaring the source [9]. In this paper, we use 3 terms, i.e. plume finding, plume tracking/tracing, and source declaration for representing the sub tasks existed on odor localization. ***Plume Finding*** (to come in contact with the odor) can be defined as the step which the robots still do not know or have no contact with the plume and try to contact it. ***Plume Tracking/Tracing*** (to follow the odor plume to its source) is the step that describes that the robots are already know the plume and try to maintain the connection while they are approaching the source. ***Source Declaration*** (to determine from odor acquisition characteristics that the source is in the immediate vicinity) is the step that lets the robots declare the location of the source that has been found [8]. In [10], the trends of researchers in the three sub tasks of localization using mobile robots are classified in table. Most of researchers focused on plume tracking/tracing while plume finding has little attention [10]. In Plume finding, some difficulties occur. One of them is the wind. It plays an important role on the shape of the plume, especially in the outdoor environment [11].

### *A. Plume Finding*

Plume is defined as the volume wherein odor concentration is generally above behavioral threshold, whereas Flume finding is to have contact with odor plume. This has been termed "searching", "questing", "wandering", and "appetitive" behaviors [12].

It is stated in [11] that the most common methods for finding plume are zigzag, casting, biased random walks, levy taxis, and spiral movement. However these methods are also used for other spatial search tasks. It makes the methods become inefficient for odor plume finding [11]. Thus, it encourages the researchers to develop new methods.

Designing and developing efficient olfactory robot that execute odor source localization task faces a problem on odor dispersion [13]. Odor plumes occur when the odor molecules are released from the source and are taken away by the wind. When the molecules move away from the source, the concentration decreases. Molecular diffusion and turbulent diffusion processes have the main role in determining the shape of plume in this state. Molecular diffusion causes random motion of the molecules to move gradually apart, while turbulent diffusion tears apart the cloud of molecules physically by air turbulence. [14]. Molecular diffusion effect on the plume shape can be neglected [11]. It is due to this diffusion is slow and small-scale phenomenon. The molecular diffusion of ethanol is only 1.32 x $10^{-5}$ $m^2$ $s^{-1}$ and hexadecanol (similar in size to many moth pheromones) is 2.5 x $10^{-6}$ $m^2$ $s^{-1}$ [12]. It's contradictive with turbulent diffusion that can change the shape of the plume, therefore the turbulent diffusion dominates the dispersion of odor molecules.

The problem of choosing the most suitable dispersion model becomes a big challenge to the researchers. Moreover, another matter that occurs is lacking of correct and exact information about the concentration measurements [15].

Mathematical equations can overcome dispersion model problems. The model can be used to analyze the process happened in the dispersion of the plume and to count the concentration of the substance released from the source[15].

Some of researchers on plume dispersion models used Gaussian plume model [16] that was introduced by Sutton. The formula on this model assumes the meteorological condition and plume emission are stationary. The concentration field is made in the 3 dimensional, and , while the source is in the form of a point.

Jay Farrell et al used farrell's filamentous plume model [17]. This model also adopts the dispersion model of Gaussian distribution. The purpose of that plume is to enhance the performance of navigation strategies. It was designed using a simplified plume simulation so that computational simulation can be feasible. The research analyzed 3 simulated plume data: long-term time averages, amplitude statistic, temporal statistic. Farrell's filamentous plume model is still widely used nowadays [6].

Farrell's filamentous model used Gaussian distribution [17] is represented as follow:

$$\overline{C}(x,y,z)=\frac{Q}{2\pi S_y S_z \sigma}\left(-\left(\frac{y^2}{2S_y^2}+\frac{z^2}{2S_z^2}\right)\right) \quad (1)$$

where the concentration in the *x,y,z* position is symbolized as $\overline{C}(x,y,z)$. $Q$ represents the release rate and $\overline{U}$ represents the wind speed, whereas $S_y$ represents standard deviations in the *y* and $S_z$ represents the standard deviations in direction.

For the long-term time averages simulation, the threshold was set $0.04x10\,molecules/cm^3$, parameters $n=1$, $Q=20$, $C_y=0.4$, $C_z=0.2$, $S_y=0.5C_y x^{2-n/2}$, and $S_z=0.5C_z x^{2-n/2}$ [17]. Plume finding requires a suitable exploration strategy in order to define a threshold value above which the plume is assumed to be present. This threshold should be able to counterbalance the variation of environmental condition and to adapt sensor digression [18].

From the research [17], it was found that the 3-minute time average has almost similar contour with the Gaussian contour. It follows the rule of time duration, i.e. when the duration of time-average increases, the width of a given contour also increases.

In the amplitude statistic and temporal statistic simulation [17], J. Farrell compared the data of simulation with Jone's statistic data [19]. For amplitude statistic, the mean concentration [17] is defined as:

$$\Gamma(\mathrm{P})=\frac{1}{T}\int_0^T C(\mathrm{P},\tau)d\tau \quad (2)$$

From the result, it concluded that the amplitude statistic was successful in determining mean sensed concentration and conditional mean of the simulated plume as a function of downwind distance from the source. Besides that, the statistic temporal was also successful in analyze the experiment duration using this equation [17]:

$$T \approx \sum_{i=1}^{n_{pi}} t_{pi} = \sum_{i=1}^{n_{gi}} tgi \quad (3)$$

where $T$ is the experiment duration, $\tau_{pi}$ is the width of the i-th peak, $\tau_{pi}$ is the width of the i-th gap, $n_{pi}$ and $\tau_{gi}$ are the number of pulses and gaps in the experiment.

Ali Marjovi in [11] used pseudo-Gaussian plume models in determining the probability density function of odor mean concentration in position *(x, y, x)*. The formula can be seen in Equation 4.

$$C(x,y,z)=\frac{Q}{2\pi\overline{U}\sigma y(x)\sigma_{z(x)}}\exp\left\{\frac{-y^2}{2\sigma_y^2(x)}+\frac{-g^2}{2\sigma_z^2(x)}\right\} \quad (4)$$

The position of odor source is assumed in the position (0, 0, 0). The downwind, crosswind, and vertical coordinates are symbolized as $x, y$. The deviations used in Equation 4 are based on the standard deviation found by Brigg experimentally [11]. The research was successful in determining the best formation of robot in discovering the plume.

Table 1
Standard Deviations for Urban Environment in Various conditions [11]

| Env. | $\sigma_y(x)$ | $\sigma_z(x)$ |
|---|---|---|
| A-B | $0.32x(1+0.0004x)^{-0.5}$ | $0.24x(1+0.0004x)^{-0.5}$ |
| C | $0.22x(1+0.0004x)^{-0.5}$ | $0.20x$ |
| D | $0.16x(1+0.0004x)^{-0.5}$ | $0.14x(1+0.0003x)^{-0.5}$ |
| E-F | $0.11x(1+0.0004x)^{-0.5}$ | $0.08x(1+0.0015x)^{-0.5}$ |

### *B. Flame Tracking/Tracing*

According to its surrounding environment, A. J. Lilienthal [20] in [21] divided the plume tracking/tracing step into two groups: first based on advection/turbulent and second based on the estimation of odors' distribution.

The first group uses concentration to localize odor source [21]. Besides concentration, sometimes, it also uses wind information [21]. Such applications include biology simulating methods, fluxotaxis-based methods, infotaxis-based methods, etc. Using these methods, the response to environment change can be increased, however, it forces the robots to arrive at the center of an odor source [21].

The second group estimates the position of an odor source by forcing the robots to move in the workspace to update the odor distribution model [21]. Some approaches of this group areodors' distribution grid map methods, naive physics models of airflow, and particle/Bayesian filtering methods [21]. These methods can estimate the position of an odor source remotely according to the odor distribution model with condition the prior distribution of an odor source has been given in advance [21].

Plume tracking/tracing of the first group has been observed in various researches. H. Ishida made some experiments related to odor localization that took the benefits of wind direction using odor compass [4, 23], wind direction sensor [22], robotic system [24], and Olfactory assist mask [25]. The information of wind direction along with the concentration gradient was used to determine the odor source direction in order to achieve plume tracking in uncertain condition. The uncertainty of the odor localization is caused by the difficulty of tracking an airborne odor to its source. Due to the diffusion rate of odor molecules is generally slower than the wind velocity, the odor molecules is dragged to the downwind direction (the dragged odor molecules are named odor plume) [4]. This affects the odor concentration gradient along wind direction becomes very small. Besides that, the air turbulence makes the plume shape become irregular. This is the reason why the instantaneous concentration gradient does not always point to the odor source.

H. Ishida [4] made an experiment using sensors that mimicked a male silkworm moth. The sensing probe was equipped with two gas sensors and a small fan instead of two antennae and wings of a silkworm moth. These gas sensors have function to determine the direction of the source.

DimitriZarzhitsky [26] introduced an approach to the odor localization based on physics. His algorithm utilized the principles of the flow of the fluid (fluxotaxis) [27, 28]. The robots used the information of fluid flow in navigating toward the chemical emitter.

LinoMarquest developed 3 algortims that based on: 1. bacteriachemotaxis, 2. male silkworm moth, and 3. estimation of odor geometry and gradient tracking [29]. In [30], LinoMarquest used 4 local search strategies, i.e. gradient search, biased random walk, particle swarm optimization (PSO), and PSO-based robotic searching. Using PSO method, when the agents detect no chemical cue exists in the neighborhood, the agents tend to avoid each other, leading to the emergence of exploration behavior. This leads to the improvement of global searching performance. WisnuJatmiko et al also used PSO [31, 32], modified PSO [33], and ranged subgroup PSO [34] in localizing the odor source. Up to now, PSO still has many attractions for other researchers, that's why some authors still develop it [21, 35]. On the other hand, some authors also still investigate the plume tracking/tracing using silk-moth approaches, i.e. jouhYeong et al [36].

Adam T. Hayes et al [2, 8] used the principles of swarm intelligent, a computational and behavioral metaphor. The research described that a group of real robots under fully control can successfully transverse a real odor plume [2]. This leads to the conclusion that group performance is better than single robot.

On the other research, Thomas Lochmatter [5] tried to make a comparison between casting and spiraling algorithms. They tested the same robot with the same sensors in the same type of plume. The parameters, such as environmental condition and wind characteristics were made the same. The result of those casting and spiraling algorithms were then compared each other. They concluded that the spiral surge algorithm has good performance.

Researchers in [37, 38] worked in the area of the first group. While, on the second group, there are Qiang Lu [39], G. Kowadlo [40], and Li ji Gong [41].

Qiang Lu [39] used Learning Particle Swarm Optimization (LPSO) for odor localization. They combined concentration magnitude information with wind information to build an efficient search algorithm. LPSO is used to update the source probability map by learning the combination information got from the concentration magnitude, the wind, and the swarm. After new position for the robot generated, a distributed coordination architecture established. The proposed LPSO algorithm was not only useful in determining the new position of robot but also give advantages in controlling the robot to move to the new position.

### *C. Source Declaration*

Some reseachers were interesting in analyzing the third step of odor localization, i.e. source declaration [42-45]. Odor source declaration according to A. Lilienthal [42] is the step that establishing that the odor source is in the nearby surrounding. Two advantages offers from source declaration [42] are: It is absolutely necessary. This task can be applied in clearing up the mine or supervising, 2. It is able to be use for rescue and security missions. A. Lilenthal [42] used ANN and SVM to evaluate the declaration data of the experiment.

G. Carbita in [44] used divergence operator in declaring the odor source. Three algorithms (DAPSO, BFO, and ACO) were used. The experiment was done in the simulation and real world experiment. The simulations were used to generate odor map. The odor maps were useful as the input of the Cartesian operator. The result of divergence operator was compared to the maximum odor concentration. From the experiment, it concluded that the divergence is an excellent odor source declaration estimator. In real world experiment, 5 miniQs robot were used. The 30 random sets of chemical reading that were generated were interpolated using Nadaraya-Watson estimator as Equation 5.

$$\overline{C}_{i,j} = \frac{\sum_{n=1}^{N} K_{i,j,n} c_n}{\sum_{n=1}^{N} K_{i,j,n}} \tag{5}$$

where $K_{i,j,n}$ is the advection-diffusion kernel, is chemical concentration. The result showed that the odor source has trend to notice downwind of its real position.

Table 2 shows that sub task research on odor localization in recent year starting 2013 until now. Plume tracking/tracding dominates the researches. This is caused that making experiment in plume finding is very difficult due to the uncertainty of the plume concentration and shape as the effect of wind diffusion and turbulence. On the other hand, making experiment on source declaration also faces difficulties on airflow of the wind.

Table 2
Sub Task Research on Odor Localization in Recent Year

| No. | SubTask | Researchers | Method |
|---|---|---|---|
| 1 | Plume Finding | Ali Marjovi [11] | Line configuration toward cross wind direction [11] |
| | | HaiFengJiu [46] | Effective olfactory based planning and search [46] |
| | | Jianhua Zhang [21] | Niching particle swarm optimization |
| 2 | Plume Tracking/Tracing | Jie Yuan [47] | Petri net based chemical plume tracing [47] |
| | | JouhYeong Chew [48] | Hierarchical classification method [48] |
| | | Li Ji Gong [49] | Estimation-based plume tracing [49] |
| | | SitiNurmaini [50] | Cooperation between fuzzy logic control and particle swarm [50] |
| | | Siqi Zhang [51] | Swarm olfactory search [51] |
| | | Qiang Lu [39] | Learning particle swarm optimization [39] |
| | | Patrick P. Neumann [43] | Novel pseudo gradient plume tracking and particle filter based [43] |
| 3 | Source Declaration | G. Cabrita [44] | Swarm Based Algorithm [44] |
| | | Meng Li Cao [45] | Adapted ant colony optimization and divergence based idea [45] |

## III. CONCLUSION

The research on odor localization has developed so fast. The area of researches moves forward in various sub tasks. Some new methods/techniques are proposed in order to increase the robot's performance in localizing the odor. Although only have a little attraction in past researches, the subtask of plume finding and also source declaration are still important to be analyzed. It still gives chance that the dream of achieving good performance on odor localization will be clear in some more years. For further research, we are interested in analyzing plume finding using plume dispersion model.

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# Odor Localization Sub Tasks: A Survey

ORIGINALITY REPORT

23%

SIMILARITY INDEX

MATCH ALL SOURCES (ONLY SELECTED SOURCE PRINTED)

★Ali Marjovi, Lino Marques. "Optimal spatial formation of swarm robotic gas sensors in odor plume finding", Autonomous Robots, 2013 — 3%

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