Mapping odour sources with a mobile robot in a time variant airflow environment

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This paper focuses on the problem of mapping odour sources using a mobile robot in a time-variant airflow environment, and provides a localization method which uses the Dempster-Shafer (D-S) theory to reason the possible locations of odour sources. In the proposed method, the robot carries out the D-S inference and iteratively updates a grid map, using the successive measurements from a gas sensor and an anemometer when the robot is cruising in the given search area. Simulations are carried out and the results in a time-variant airflow environment show that the locations of the multiple odour sources can be estimated online with the proposed method.

1. Introduction

Odour information is widely used by many animals for searching for food, finding mates, exchanging information, and evading predators. Inspired by the olfaction abilities of many animals, in the early 1990s, people started to try building mobile robots with similar olfaction abilities to replace trained animals (Sandini and Lucarini et al., 1993; Consi and Atema et al., 1994; Ishida and Suetsugu et al., 1994; Russell and Thiel et al., 1994). It is expected that mobile robots developed with such olfaction capability will play more and more roles in such areas as judging toxic or harmful gas leakage location, checking for contraband (e.g., heroin), searching for survivors in collapsed buildings, humanitarian de-mining, and antiterrorist attacks.

The methods of odour source localization (OSL) realized using an individual or multiple mobile robots can be classified into tracing-behavior-based methods and analytical-model-based methods (Lilienthal and Loutfi et al., 2006). In the tracing-behavior-based group, the source location is often determined by the final position of the mobile robot doing plume tracing and successfully arriving at the source. An alternate name for OSL, chemical plume tracing (Farrell and Pang et al., 2005; Zarzhitsky and Spears et al., 2005), reflects the importance of the plume-tracing strategy in these methods. Some biologically inspired approaches have been designed for mobile robot based plume tracing, such as gradient-following-based algorithm in low Reynolds number (Berg, 1990) and up-wind algorithm in a wind tunnel (Belanger and Willis, 1996), which intended to mimic the behaviors of chemotaxis and anemotaxis of a few biological entities, respectively. Moreover, some engineered plume tracing strategies have also been proposed, such as fluxotaxis (Zarzhitsky and Spears et al., 2005) and infotaxis (Vergassola and Villermaux et al., 2007) algorithms. A combination of the biomimetic and engineered strategies can be found in (Li and Farrell et al., 2006).

Comparatively, only a few analytical-model-based methods have been reported, such as modeling the wind field using naive physics (Kowadlo and Russell, 2006; Kowadlo and Russell, 2009), remote gas source localization (Ishida and Nakamoto et al., 1998),

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building gas distribution grid maps (Lilienthal and Duckett, 2004), a source-likelihood mapping approach based on the Bayesian inference method (Pang and Farrell, 2006), mapping multiple odour sources using Bayesian occupancy grid map (Ferri and Jakuba et al., 2011), and localizing via Particle Filter (Li and Meng et al., 2011) in our earlier work, etc. Kowadlo et al. (Kowadlo and Russell, 2006; Kowadlo and Russell, 2009) tried to obtain the location of the odour source by mapping the search area in environments with a stable airflow field. Ishida et al. (Ishida and Nakamoto et al., 1998) intended to identify the source location based on a time-averaged gas distribution model in conditions with stable airflows and stable odour release rate. Lilienthal et al. (Lilienthal and Duckett, 2004) demonstrated that the position of the average maximum concentration can often be used to estimate the source location in environments with no strong airflow. Pang et al. (Pang and Farrell, 2006) localized the odour source offline using Bayesian inference in near-shore ocean conditions with an autonomous underwater vehicle. Ferri, G., et al. (Ferri and Jakuba et al., 2011) located multiple odour sources by a Bayesian occupancy grid mapping based method in an uncontrolled indoor environment. In our earlier work (Li and Meng et al., 2011), a PF-based OSL algorithm was presented to localize an odour source in outdoor airflow environments.

For tracing-behavior-based methods, it is difficult for the robot to automatically provide the source location with its final position because the robot cannot know whether it arrives at the source. Therefore, to automatically obtain the source location by the robot itself, an analytical-model-based method is necessary. However, the methods proposed in (Kowadlo and Russell, 2006; Kowadlo and Russell, 2009) and (Ferri and Jakuba et al., 2011) might not work in real outdoor environments because the required conditions, i.e., stable airflow field or weak airflow, are hardly satisfied in outdoor environments where the airflow is almost always turbulent, time varying, and strong. And the methods presented in (Pang and Farrell, 2006) and (Li and Meng et al., 2011) only suit the cases with a single odour source. Unfortunately, large amount of OSL problems not only happen in environments with turbulent flow, but also involve multiple odour sources.

This paper presents a multiple odour sources localization (MOSL) method via D-S inference to estimate the locations of the odour sources while the robot performs exploratory behavior in an outdoor environment with time-variant airflow. The purpose of the exploratory behavior is to collect information associated with the locations of the odour source, such as odour concentrations and airflow directions/velocities, and the collected information is exploited by the D-S Inference to obtain the solution to the MOSL problem. In current study, the exploratory behavior of the robot is by following a predefined path shaped like rectangular wave to cover the given search region. To exploit the collected information, belief mass functions is constructed and used in the proposed MOSL algorithm, even though the belief mass functions are sometimes inaccurate.

The remainder of this paper is organized as follows. Section 2 introduces the D-S inference for MOSL. The belief mass function for MOSL is presented in section 3, and the simulation setup and results are presented in section 4. The conclude is presented in the final section.

2. D-S Inference for MOSL

2.1 Introduction of D-S Theory

D-S theory has established itself as a promising and popular approach to data fusion especially in the last few years (Khaleghi and Khamis et al., 2013). It can be considered as a generalization to the Bayesian theory that deals with probability mass functions. Unlike the Bayesian Inference, the D–S theory allows each source to contribute information in different levels of detail. Furthermore, D–S theory does not assign a priori probabilities to unknown propositions; instead probabilities are assigned only when the supporting information is available. In fact, it allows for explicit representation of total ignorance by assigning the entire mass to the frame of discernment at any time, whereas using probability theory one has to assume a uniform distribution to deal with this situation.

Consider Θ to represent all possible states of the frame of discernment and the power set 2^{Θ} to represent the set of all possible subsets of Θ. In contrast to probability theory that assigns a probability mass to each element of Θ, D–S theory assigns belief mass m to each element e of 2^{Θ}, which represent possible propositions regarding the system state. Function m has two properties: $m(\phi) = 0$ and $\sum_{e \in 2^{\Theta}} m(e) = 1$.

2.2 MOSL using D-S Inference

In most OSL applications, the odour sources are immovable, thus the distribution of the odour sources can be conveniently represented by a grid map $\{C_i, i = 1,2,\cdots M\}$, where the constant M is the number of the cells in the grid map. For each cell C_i in the grid map, it has two states, named S (occupied by an odour source), $\bar{S}$ (not occupied by odour source), respectively, composing a frame of discernment $\Theta = \{S, \bar{S}\}$.

Intuitively for any proposition e, $m(e)$ represents the proportion of available evidence that supports the claim that the actual cell state belongs to e. When the robot takes a measurement, there will be a piece of evidence. Given two pieces of evidence with corresponding belief mass functions $m_1(e_1)$ and $m_2(e_2)$, $e_1, e_2 \in 2^{\Theta}$ (to be detailed in section 3), using the Dempster's rule of combination, the two pieces of evidence can be fused and produce a joint belief mass function $m_{1,2}(e)$ as (Shafer, 1976)

$$m_{1,2}(e) = (m_1 \oplus m_2)(e) = \sum_{e_1 \cap e_2 = e \neq \phi} m_1(e_1) m_2(e_2) / (1 - K), \tag{1}$$

where K represents the amount of conflict between the two evidences and is given by

$$K = \sum_{e_1 \cap e_2 = \phi} m_1(e_1) m_2(e_2). \tag{2}$$

It is not hard to find that the power set 2^{Θ} only has four elements, ϕ, $\{S\}$, $\{\bar{S}\}$, and $\{S, \bar{S}\}$ (i.e., Θ). In order to understand easily, here we denote the subset $\{S, \bar{S}\}$ as U (unknown). Thus, there is

$$m(S) + m(\bar{S}) + m(U) = 1 \quad . \tag{3}$$

Since the frame of discernment $\Theta = \{S, \bar{S}\}$ only has two states, the proposed D-S inference for MOSL itself is simple and will not suffer the exponential complexity of computations. In addition, because the Dempster's rule of combination satisfies the associative law, i.e., $m_1 \oplus m_2 \oplus m_3 = (m_1 \oplus m_2) \oplus m_3 = m_1 \oplus (m_2 \oplus m_3)$, thus there is $m_1 \oplus m_2 \oplus \cdots \oplus m_n = (m_1 \oplus m_2 \oplus \cdots \oplus m_{n-1}) \oplus m_n$, and we can easily perform a recursively inference using new coming evidence from the successive measurements by the robot.

3. Belief Mass Function for MOSL

In our earlier work, we use item "odor-patch path" to represent the trajectory that the concerned odour patch passed by. In fact, odour patches are imaged air mass which contains enough odour molecules. Not only are there air masses containing enough odour molecules, but also air masses without enough odour molecules or even having no odour molecule. When robot encounters the former, an odour detection event would be happen, the latter a non-detection event. Because both the detection and non-detection events will be helpful to localize the odour source, so we might as well use a new item "air-mass path" which is defined as the trajectory most likely taken by an air mass encountered with the mobile robot.

Same as the estimation of odor-patch path in our earlier work, we can get an estimation of air-mass path. Intuitively, if we get a detection event, there will likely be one or some odour sources in the area covered by the estimated air-mass path. Otherwise, the possibility there are some odour sources in the covered region will decrease.

Let the set $\{\pi_i, i = 1,2,\cdots M\}$ denote the probability map of the air-mass path that has been estimated in (Li and Yang et al., 2013), where π_i indicates the probability that the air mass arrived at the robot comes from the cell C_i, and the constant M is the number of the cells in the grid map. Therefore, the belief mass function can be given for both detection event D and non-detection event $\overline{D}$ respectively as follows:

$$m(e)\,|_i^D = \begin{cases} \mu_D \zeta \pi_i & e = S \\ 0 & e = \overline{S} \\ 1 - \mu_D \zeta \pi_i & e = U \end{cases}, \tag{4-a}$$

$$m(e)\,|_i^{\overline{D}} = \begin{cases} 0 & e = S \\ \mu_{\overline{D}} \zeta \rho \pi_i & e = \overline{S} \\ 1 - \mu_{\overline{D}} \zeta \rho \pi_i & e = U \end{cases}, \tag{4-b}$$

where μ_D is the probability of detection event D arising given that there is detectable odour at the position of the robot; $\mu_{\overline{D}}$ is the probability of non-detection event $\overline{D}$ happening given that there is no detectable odour at the position of the robot; ζ represents the reliability of the model of the air mass transportation (detailed in section 4.1); ρ indicates the reliability decreasing because of the intermittency of the odour plume or the lack of enough odour molecules (easily cause the false non-detection event).

According to our test data of the gas sensor, $\mu_D \approx 0.9$, $\mu_{\overline{D}} \approx 1.0$; ζ and ρ vary with the distance from a location to the robot, and we conservatively choose $\zeta \approx 0.6$ and $\rho = 0.5$ in this research.

4. Simulations

4.1 Simulation Platform Setup

In our research, in order to have a repeatable and controllable flow-field and plume, and also to reduce the computational load, a flow-field file with frame structure, just like a movie, is generated from the simulation platform released by Jay A. Farrell and his colleagues (Farrell and Murlis et al., 2002). The file has a constant time interval 0.5s between consecutive frames, and each frame contains the flow information with 15×15 grids as well as the positions and concentrations of all odour puffs. All data in a frame was intercepted and saved during the running of the Farrell's simulation platform without any modification. In this research, the code of the simulation platform (Farrell and Murlis et al., 2002) was modified to have several odour sources.

On our simulation experiment platform, the flow-field file is replayed just as same as the play on the Farrell's simulation platform, but almost without any calculation because the calculation has been done on the Farrell's platform when the file was being generated.

4.2 Simulations and Results

In this study, the robot simply follows a predefined path shaped like rectangular wave to cover the given search region, performing an exploratory behavior. At each time step, the robot collects the odour concentration, airflow speed and direction by the equipped gas sensor and the anemometer, respectively.

Fig. 1 illustrates four scenes of the estimated distribution of the two odour source, in which the virtual robot can achieve a maximum speed of 0.5 m/s, the mean flow velocity is about 1.0 m/s and the mean flow direction is about 0°. The two odour sources locate at (20.0m, 50.0m) and (24.0m, 55.0m), with same area 0.3m×0.3m. The robot starts at the location (33.0m, 40.0m) to search a given rectangular region with left-top corner (18.7m, 60.3m) and right-bottom corner (32.7m, 40.3m). It firstly goes vertically up to the top bound of the given region, and then goes vertically down to the bottom bound with an fixed offset 2m in left direction (called 1 return, see Fig. 1(a)), and so on. When the robot arrives at the left-top corner (called 1 round, see Fig. 1(c)), the robot comes back to the right-bottom corner, and starts a new round of the exploration, and so on.

It can be found from Fig. 1 that, the distribution map of the two odour sources is updated recursively via the proposed D-S inference using new coming evidence from the successive measurements by the robot when the robot is cruising in the given search area. Apparently, the estimated locations of the two odour sources approach to the true sites as the evidence accumulates.

It also can be found that in Fig. 1(d), near the right bound of the search region, there are still some cells with false information of being occupied by an odour source. This is because that, the mean airflow direction is about 0° in this simulation, and the robot often has detection events near the right bound, resulting some cells with confusing information. This result suggests that more exploration should be performed to the region near these cells.

5. Conclusion

In this research, the robot carries out the proposed D-S inference and iteratively updates a grid map indicating the possible locations of two odour sources, using the successive measurements from a gas sensor and an anemometer when the robot performs an exploration in the given region. Simulations are carried out and the results in a time-variant airflow environment show that the locations of the multiple odour sources can be estimated and approach to the true sites as the evidence accumulates. The simulations also indicate that the proposed method has a low computational cost which allows it to be used in online applications.

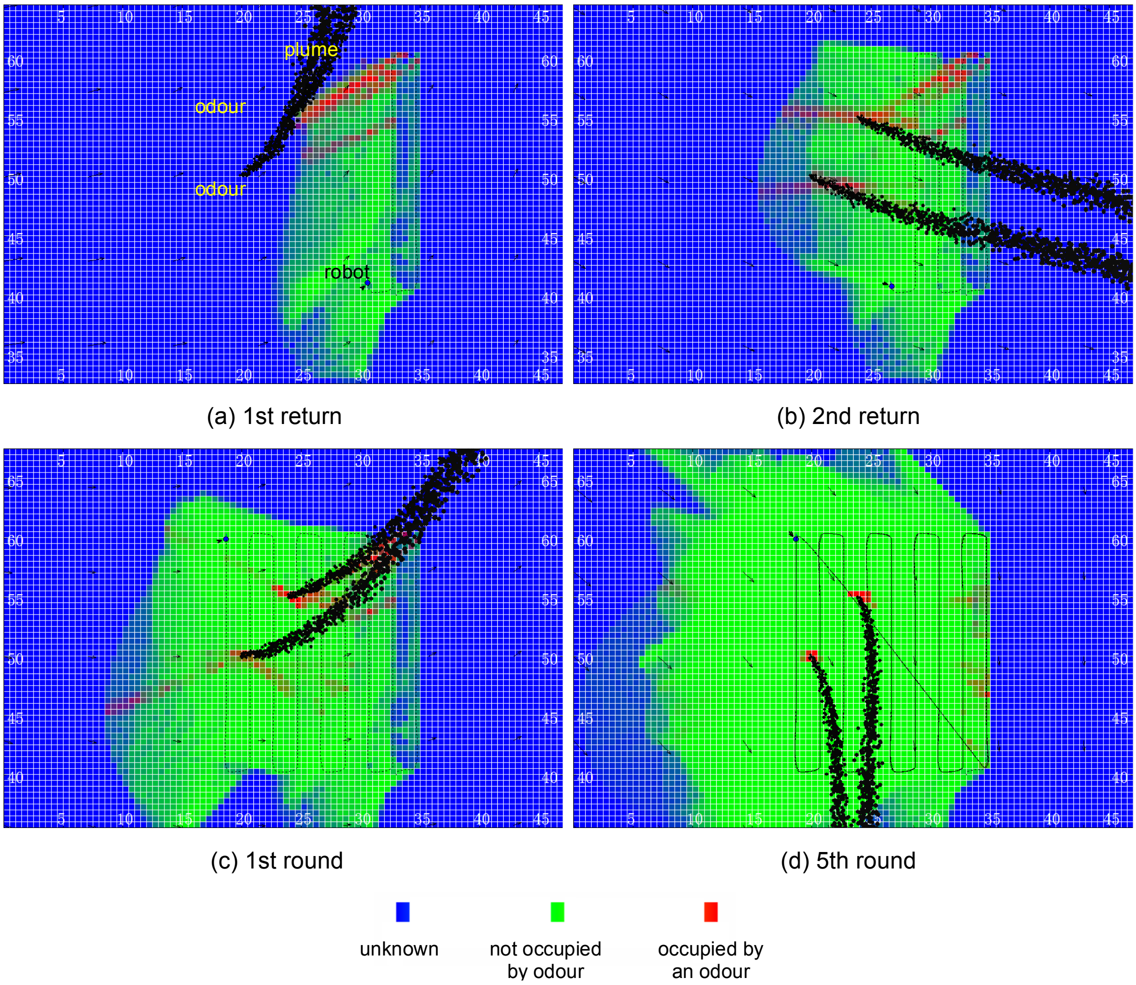

Figure 1: Estimated distribution map of two odour sources at different time via the proposed D-S inference algorithm.

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