Experimental comparison of random search strategies for multi-robot based odour finding without wind information

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Abstract

In this paper, three random search strategies are implemented and compared in odour finding using multiple robots. The first strategy is Brownian walk (BW). As a typical uncorrelated random search strategy, BW combines a Gaussian distribution of move length with a uniform distribution of turning angles. Another two strategies are correlated random search strategies, namely correlated random walk (CRW) and Levy walk (LW). CRW and LW are obtained by replacing the distribution of move lengths and turning angles in BW with wrapped Cauchy distribution and Levy distribution, respectively. Experiments with the three random search strategies were conducted using four MrCollie robots in our laboratory. Results show that the two correlated random search strategies (i.e., CRW and LW) are more time-efficient than BW, and that LW obtains higher time-efficiency than CRW with respect to our experimental setup.

1. Introduction

Recent advances in microelectronics have accelerated the investigation on artificial olfactory systems, which can be divided into passive olfaction and active olfaction (Meng and Li, 2006). The former concerns mainly about the discrimination of different odours by processing olfaction-related signals (Jing et al., 2014), while the latter investigates the problem of controlling mobile olfactory mechatronic devices to locate the source of odour plume. In active olfaction, which is considered in this paper, autonomous mobile robots equipped with olfactory sensors are commonly utilized. Potential applications of active olfaction cover locating toxic or harmful gas/odour leakage source, humanitarian demining, and fighting against terrorist attacks, etc. Compared with skilled professionals and trained animals, robots are immune from chemical injuries, and thus, are more robust and more flexible.

The process of robot-based odour source localization comprises three alternating sub-processes (Lilienthal et al., 2006): odour finding (OF), odour source tracing, and odour source declaration. OF is conducted at the initial stage of odour source localization and ended when the robot detects the odour for the first time. After the first odour detection event, the robot searches for the odour source based on collected odour information. Then, if a certain condition is satisfied, the robot starts to declare whether the odour source lies at a nearby region or not. Obviously, OF serves as the basis of the other two sub-processes. Compared with the vigorous studies on odour source tracing and declaration, investigations concerning OF are really rare. Moreover, part of these investigations focused on the case of utilizing only a single robot, which means even fewer published works have concerned about OF based on multiple robots.

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To the author's knowledge, two representative systematic search strategies (Bartumeus et al., 2005) were proposed for multi-robot based OF. Li et al (Li, 2009) proposed a scattering strategy which makes the robots scatter with equal angel spans from the start and bounce back when any robot hits the edge of valid search region (VSR). Marjovi et al (Marjovi and Marques, 2013) proposed to move a line formation of robots along the upwind direction, which forms a sweeping search strategy. Both the scattering and sweeping strategies utilize deterministic algorithms, and thus are systematic strategies. Another important class of search strategies are random search strategies (Bartumeus et al., 2005), which rely on stochastic processes. Pasternak et al (Pasternak et al., 2009) simulated four random search strategies: Brownian walk (BW), correlated random walk (CRW), Levy walk (LW), and Levy taxis, in the context of finding the filamentous odour plume using a single robot in a ventilated environment. However, Pasternak's work lacks of real experimental results and results with respect to multiple robots. In environments with weak airflow, the less-dispersed odour distribution increases the difficulty of OF. The performance of these random search strategies on multi-robot based OF in real weak airflow environments needs further evaluation and comparison.

In this paper, we implement the BW, CRW, and LW strategies on multi-robot based OF in a closed indoor environment, where the wind information cannot be acquired using normal anemometers. Levy taxis is not considered since it needs real-time wind information. It is common to define random search strategies by the probabilistic distribution of the move lengths (MLs) and turning angles (TAs) at different steps. In each step, a new position is calculated based on ML, TA, and the old position. Being an uncorrelated random search strategy, which do not account for directional persistence (DP) (Bartumeus et al., 2005), BW utilizes a Gaussian distribution of MLs and a uniform distribution of TAs. Based on BW, DP is incorporated in CRW and LW by replacing the distribution of TAs and MLs with wrapped Cauchy distribution (WCD) and Levy distribution, respectively. Real multi-robot odour finding experiments were conducted to test whether DP increases the search efficiency or not and which of the BW, CRW, and LW strategies is the most time-efficient.

The rest of this paper is organized as follows: the real robots and odour source used in the experiments, as well as the test scenario, are introduced in section 2; the implementation of BW, CRW, and LW are described in section 3; experimental results are proposed and discussed in section 4; conclusions are given in section 5.

2. Materials and methods

2.1 MrCollie robots

Four isomorphic MrCollie (i.e., Mobile Robots for Cooperative Odour-source LocaLization in Indoor Environments) robots (Cao et al., 2015) were used in our experiments. One of the MrCollie robots is shown in Fig. 1. A metal-oxide-semiconductor sensor (MICS-5521, SGX sensor technology) is sustained by a pillar on the front side of the robot. Eight ultrasonic sensors and eight infrared sensors are mounted around the robot to detect the remote (0.8 m~3 m) and nearby (0 m~0.8 m) obstacles, respectively. An anemometer (WindSonic, Gill instruments) is mounted on the top of the robot. Although the anemometers were not used in our experiments, they were not removed so as to keep the integrity of the robots. On top of the anemometer, there is an identification label, which records orientation, index, and global position of

the robot. Through ultra-high-frequency radio waves, the robots periodically sent their concentration measurements to and received movement commands from a workstation. By processing the image acquired by a hard-wired CCD camera (DFx 31BG03, Imaging source technology) mounted on the ceiling, the workstation can recognize the information recorded by the identification labels, thereby the pose of each robot could be obtained.

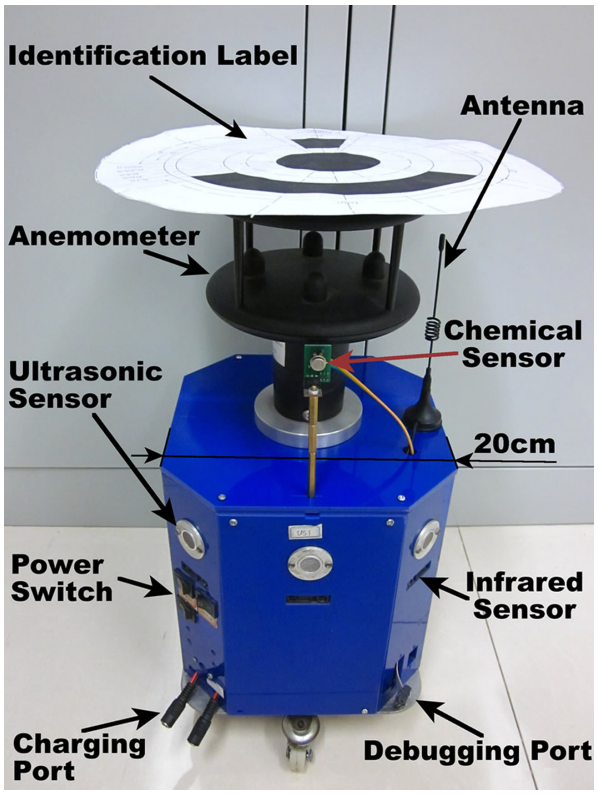

Figure 1: One of the MrCollie robots.

To determine odour detection events, only binary odour measurements are needed. As a typical MOS senor, the MICS-5521 sensor suffers from the problem of slow recovery time. To solve this problem, the odour detection event was determined by comparing the raw concentration measurement of MICS-5521, i.e., c_k, with an adaptive threshold, i.e., $\overline{c_k}$, which is defined as (Li et al., 2011):

$$\overline{c}_k = \begin{cases} \lambda \overline{c}_{k-1} + (1-\lambda) c_k, & k \geq 0 \\ c_k, & k = 0 \end{cases} \quad (1)$$

where λ is a predefined constant parameter. The value of λ was set to 0.5 in (Li et al., 2011). It was verified in (Cao et al., 2015) and (Neumann et al., 2013) that setting λ to 0.5 can effectively reflect realistic chemical contact. Based on equation (1), the case of $c_k > \overline{c_{k-1}}$ indicates an odour detection event at the k-th time step. Otherwise, a non-detection event is considered.

2.2 Odour source

As shown in Fig. 2, a self-made odour source that can generate atomized ethyl alcohol was used in our experiments. The main body of the odour source is a plastic bucket.

Absolute ethyl alcohol is placed inside of the bucket and atomized by the eight ultrasonic transducers. Eight ultrasonic transducers are placed at the bottom of the bucket to atomize the ethyl alcohol. Then, atomized ethyl alcohol odour is drown out from the bucket by the electronic fan. The odour source (i.e., the fan and ultrasonic transducers) was powered on for only about ten seconds before each experiment. If the odour source was powered on through the whole process of experiments, ethanol odour would be dispersed all over the lab. In that case, it is quite easy for the robots to encounter the ethanol odour, while it is not conducive to test the efficiency of OF methods.

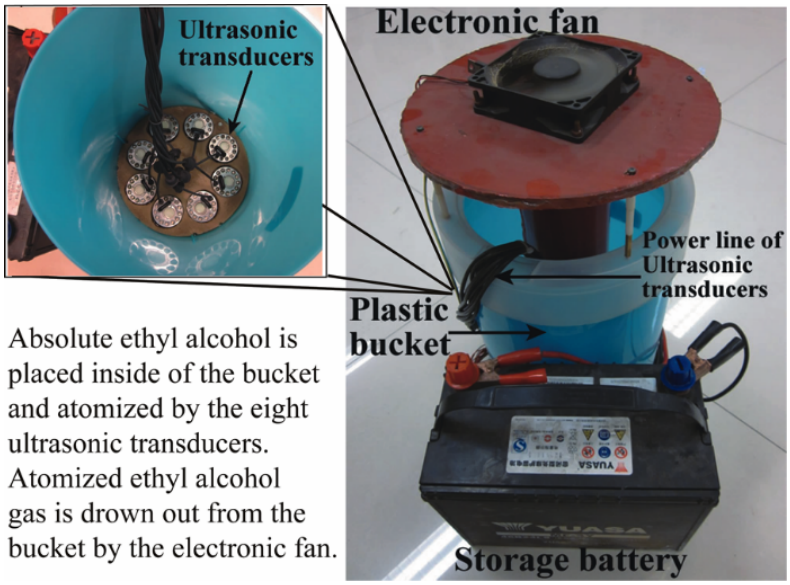

Figure 2: The schematic of the electronic nose

2.3 Test-bed scenario

All experiments were conducted in our lab, which is shaped like an irregular polygon as shown in Fig. 3. The VSR is a 5 m-by-7 m rectangular area. The odour source was placed at the north-east corner of the VSR. To maximize the difficulty of finding the odour plume, the robots started from the diagonal corner of the VSR. Correspondingly, the initial heading of the robots were equally distributed in the right angle covering the VSR.

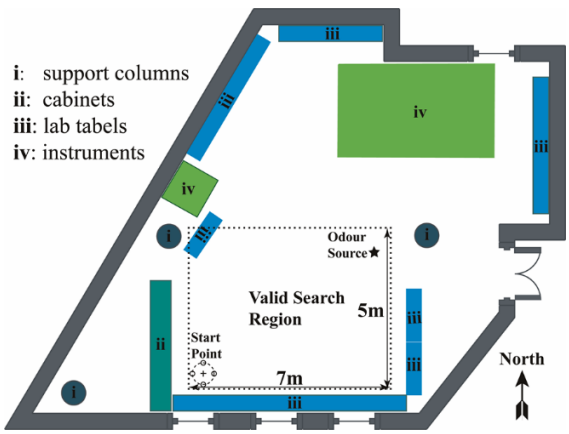

Figure 3: The experimental scenario.

3. Methods

Three search strategies were tested in this paper. To implement these search strategies for robot-based OF, the robot control architecture shown in Fig. 4 was utilized. As shown in Fig. 4, the search strategies output goal positions for the robots. If the robots move towards their goal positions along straight routes, they would collide with each other. Thus, the artificial potential field (APF) based motion planning method, which generates mutual repulsive force between nearby robots, is used for obstacle avoidance among the robots. Moreover, as long as the robot does not arrive at its goal position, the APF-based motion planning continuously generates attractive force for the robot from its goal position. Once the robot arrives at its goal position, a new goal position is generated according to the search strategies.

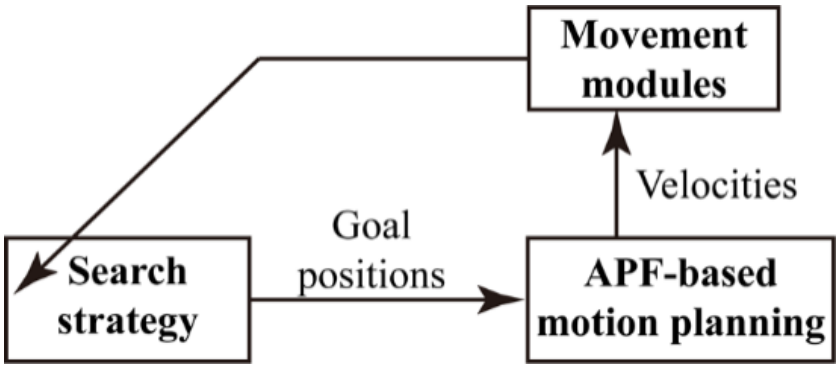

Figure 4: Control architecture for robot-based OF.

In the context of robot-based OF using random search strategies, new goal position of the robots are calculated as follows:

$$\begin{cases} x_{new} = x_{old} + l \cdot \cos(\theta + \Delta\theta) \\ y_{new} = y_{old} + l \cdot \sin(\theta + \Delta\theta) \end{cases} \quad (2)$$

where x_{new} (y_{new}) and x_{old} (y_{old}) are the coordinates of the new and old goal positions, respectively; θ is the current heading angle of the robot; l and $\Delta\theta$ are the ML and TA, respectively.

3.1 Brownian walk

As a typical uncorrelated random search strategy, BW does not account for DP in the movement. Thus, BW was used as a benchmark strategy to reveal the impact of DP on the OF efficiency without wind information. BW involves a Gaussian distribution for the MLs and a uniform distribution for the TAs. In our experiments, the MLs and TAs of BW were sampled from $N(1\ m,1)$ and $U(0,2\pi)$, respectively.

3.2 Correlated random walk

CRW utilizes a WCD of TAs, which is a non-uniform distribution, combining with a Gaussian distribution of MLs. In other words, DP is realized by controlling the probability distribution of TAs. The probability density function of the WCD is as follows (Pasternak et al., 2009):

$$p(\Delta\theta) = \frac{1-\rho^2}{2\pi\left(1+\rho^2-2\rho\cos\left(\Delta\theta\right)\right)}, \rho \in [0,1] \quad (3)$$

where $\rho, 0 \leq \rho \leq 1$ is the shape parameter. Based on equation (3), the TAs in CRW are calculated as follows (Pasternak et al., 2009):

$$\Delta\theta = 2\arctan\left(\frac{\left(1-\rho\right)\cdot\tan\left(\pi\cdot\left(r-0.5\right)\right)}{1+\rho}\right) \quad (4)$$

where r is a uniformly distributed random variable within the range of [0,1]. According to equation (4), the TAs in CRW are distributed around zero. Thus, new position is most likely generated at the same direction as in the previous step, which brings about DP. In our experiments, ρ was set to a medium value in its range: $\rho = 0.5$.

3.3 Levy walk

LW utilizes Levy distribution as the distribution of the MLs while still retaining the uniform distribution of the TAs as in BW. The probability of generating long MLs in LW is higher than that in BW. Obviously, long ML brings about DP with respect to the current moving direction, which is different from the DP realized by controlling the probabilistic distribution of TAs in the CRW. The ML in LW is calculated as follows (Pasternak et al., 2009):

$$l = l_0 \cdot r^{\frac{1}{1-\mu}} \quad (5)$$

where l_0 is the minimal value of MLs, $\mu(1 \leq \mu \leq 3)$ is the Levy index, and $r(r \in [0,1]$ is a uniformly distributed random variable. According to equation (5), smaller value of μ yields lower probability of long MLs and degree of DP. Conversely, the bigger the value of μ, the higher the probability of long MLs and the degree of DP. In our experiments, l_0 and μ were set to 1 m and 2, respectively.

4. Results and Discussion

Each of the BW, CRW, and LW strategies was tested for several times. Then, two criteria were used to summarize the experimental results. The first is success rate. If the robots detected the odour in four minutes after the start, the correlated trial is considered successful. The success rate was calculated as the ratio of successful trials in the corresponding group of experiments for each random search strategy. The second is the average time spent in each group of successful trials, which means the time spent in failed trials were not summarized in the average time.

Table 1: Ratios of the standard deviations of the three wind components (σ_u, σ_v and σ_w) *to the horizontal wind velocity u depending on the stability of the atmosphere (Robins, 1979).*

	BW	CRW	LW
Success rate	2/13	12/14	**13/14**
Average time (s)	227	156	**104**

The success rates and average time spent in successful trials are shown in Tab. 1. BW succeeded in only 2 out of 13 trials, and the average time spent by BW is close to the

time limit, i.e., 240 seconds (four minutes). CRW and LW succeeded in most of the corresponding trials and yielded much higher success rates than BW. Moreover, LW spent less average time than CRW.

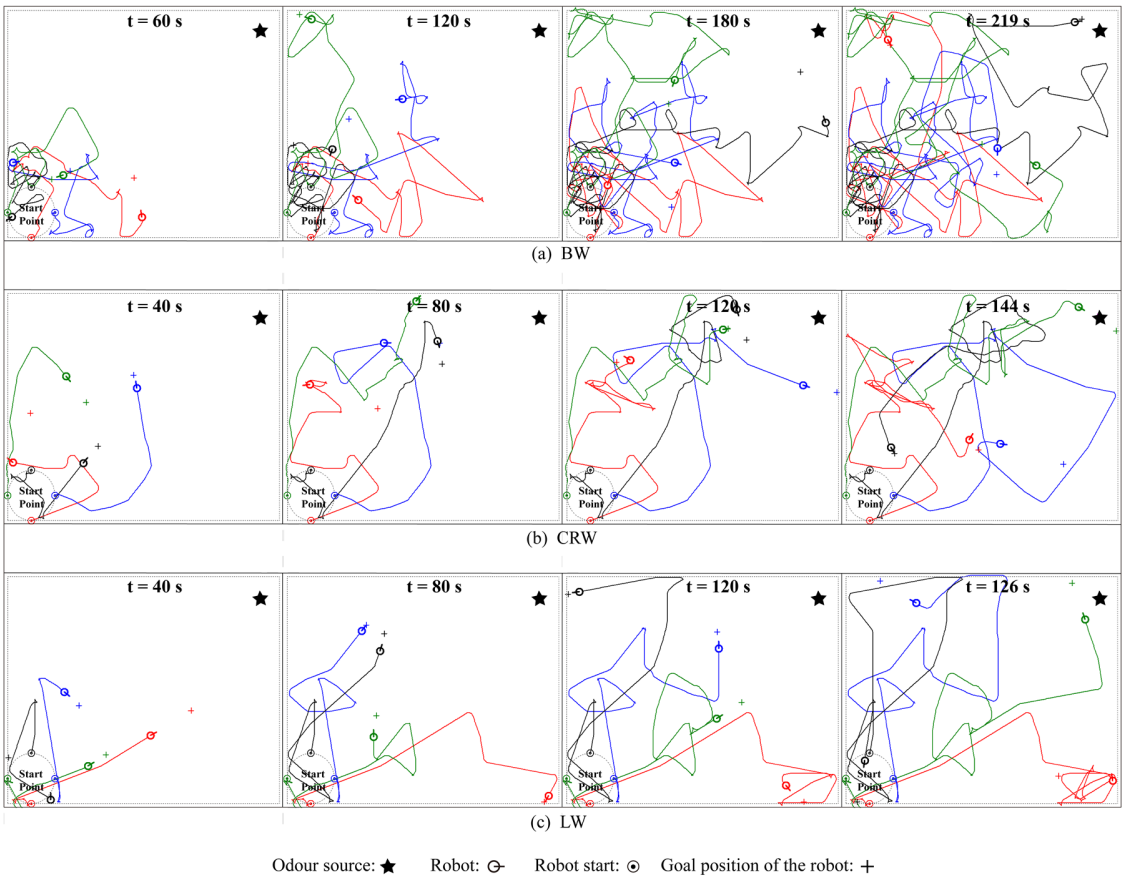

Figure 5: Robotic trajectories obtained using BW, CRW, and LW.

To further investigate the search processes, typical robotic trajectories obtained at different time points by BW, CRW, and LW are displayed in Fig. 5-a, 5-b, and 5-c, respectively. In Fig. 5-a, most MLs are about 1 m, moreover, the robots were trapped at the beginning stage in areas around the start point. This is because the robots started from the corner and most new goal positions generated using BW were repeatedly constrained by the left boundary of the VSR at the beginning. Even when the robots got into the central area of the VSR, the robots often return to the areas that have been passed by. In Fig. 5-b and 5-c, the search processes were seldom affected by the boundaries of the VSR. It is readily seen that several MLs much longer than 1 m were generated using CRW and LW in Fig. 5-b and 5-c, respectively. The robots in Fig. 5-b appear to search along more or less the same direction, while those in Fig. 5-c tend to search in individual separated areas. Therefore, the trajectories in Fig. 5-b were more overlapped than those in Fig. 5-c.

From the above experimental results, it can be deduced that DP is important for random search strategies to improve the search efficiency. Once the robot moved for a long distance along entirely or nearly the same direction, i.e., DP emerged, it usually got into a new area that is far from the visited area, and thus avoided being trapped or repeatedly searching within the visited areas. Moreover, it can be inferred that making

the robots search within different areas can improve the search efficiency. As mentioned, DP is realized in CRW and LW by controlling the distribution of TAs and MLs, respectively. In our experimental setup, the initial heading of the robots were equally distributed within an angle span of 90 degrees. Thus, the WCD in CRW, which generated TAs around 0 degree, caused the robots searching near each other. On the other hand, the uniform distribution of TAs in LW tends to make the robots leave each other. The higher time-efficiency of LW than CRW can be tentatively attributed to the higher diversity of robot positions during the search process.

5. Conclusions

We have implemented three random search strategies, i.e., BW, CRW, and LW, in a multi-robot system for finding environmental odours. BW is a typical uncorrelated random search strategy. As two correlated ransom search strategies, CRW and LW incorporate DP by controlling the probability distribution of TAs and MLs, respectively. With the help of DP, CRW and LW yielded higher time-efficiency than BW. The robotic trajectories obtained by CRW are more overlapped than those obtained by LW. Consequently, the time-efficiency of multi-robot odour finding is higher for LW than for CRW.

Acknowledgements

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