Auton Robot (2006) 20:261–276
DOI 10.1007/s10514-006-7414-3

A systematic approach to the problem of odour source localisation

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Received: 10 February 2005 / Accepted: 17 January 2006 / Published online: 8 June 2006

Abstract Although chemical sensing is far simpler than vision or hearing, navigation in a chemical diffusion field is still not well understood. Biological studies have already demonstrated the use of various search methods (e.g., chemotaxis and biased random walk), but robotics research could provide new ways to investigate principles of olfactory-based search skills (Webb, 2000; Grasso, 2001). In previous studies on odour source localisation, we have tested three biologically inspired search strategies: chemotaxis, biased random walk, and a combination of these methods (Kadar and Virk, 1998; Lytridis et al., 2001). The main objective of the present paper is to demonstrate how simulation and robot experiments could be used conjointly to systematically study these search strategies. Specifically, simulation studies are used to calibrate and test our three strategies in concentric diffusion fields with various noise levels. An experiment with a mobile robot was also conducted to assess these strategies in a real diffusion field. The results of this experiment are similar to those of simulation studies showing that chemotaxis is a more efficient but less robust strategy than biased random walk. Overall, the combined strategy seems to be superior to chemotaxis and biased random walk in both simulation and robot experiment.

Keywords Odour localisation · Chemical diffusion fields · Biological search strategies · Chemotaxis · Biased random walk

1. Introduction

Despite decades of research on animal behaviour and numerous recent studies with robots, the principles of navigational strategies in chemical fields are still not well understood. Part of the reasons is that, in the literature, there is no clear and widely accepted terminology. For instance, based on early behaviourist experiments, Fraenkel and Gunn (1961) emphasized that chemoreceptors are not direction receptors and they cannot be used to orientate the animal to a gradient in a chemical field. Bearing in mind this important fact, they postulated that various distinct olfactory reaction patterns such as klino-kinesis, klino-taxis, and even perhaps tropo-taxis can play a role in chemical search performance of various species. Later, these different animal reactions to chemicals seem to have been forgotten and all search strategies in chemical fields were, in an overly simplistic way, called chemotaxis (Berg and Brown, 1972; Beer, 1990) [NB. Fraenkel and Gunn (1961) used the term tropo-taxis for this type of bisensory reaction]. These examples clearly demonstrate why it is important to have a clear and consistent terminology for experimental tests.

To clarify differences in terminology and achieve a better understanding of the principles of navigation in a chemical diffusion field we began our research on olfactory navigation in 1998. First we investigated the principles of biological strategies in simulation studies. Inspired by Berg

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and Brown's (1972) study, we introduced biased random walk strategies at a macroscopic scale for mobile robots and showed that BRW is a robust and yet more efficient strategy than chemotaxis in unstable and noisy chemical fields (Kadar and Virk, 1998a). In addition to locating the static point odour source in unstable chemical fields, BRW has also been assessed for moving targets (Kadar and Virk, 1998c), odour trails (Virk and Kadar, 2000) and turbulent plumes (Lytridis et al., 2001). In Virk et al.'s (1998) study, a fuzzy logic-based sensor fusion approach demonstrated that the BRW algorithm could be combined with obstacle avoidance based on other traditional distal sensors (acoustic, infrared, etc.).

Most of our previous work has focused on testing navigational strategies in simulation studies. In agreement with Webb (2000), we believe that robotics research provides new ways to investigate biological strategies. In particular, the principles of olfactory navigational strategies can be systematically studied on robotic platform to overcome the limitations of simulation studies (e.g., difficulties in modelling odour diffusion and dispersion processes when a moving agent introduces additional noise in the chemical field).

Although the poor quality of artificial sensors does constraint research, some of the commercially available sensors are good enough for testing basic navigational strategies including biologically inspired methods such as ant-like trail-following (Russell, 1995; Russell et al., 2000), search patterns of the mate-seeking silkworm moth (Ishida et al., 1995), and crustacean chemotaxis and rheotaxis (Grasso et al., 2000). Artificial sensors have also been used in novel artificial methods (Hayes et al., 2003). Moreover, successful localisation of an odour source based on a field model has been demonstrated (Lilienthal and Duckett, 2003; Marques et al., 2002) and approximate localisation of an odour source based on chemical information processing has also been described with a 3D "odour compass" (Ishida et al., 1996, 1999).

In an effort to overcome limitations of simulation studies, we have recently implemented some of the search methods on robot platforms (BIRAW) and tested them in natural settings (Lytridis et al., 2003; Kadar et al., 2005). The current paper presents the results of a systematic approach to designing and testing search strategies for robots. Specifically, three navigational strategies are calibrated to a concentric diffusion field and they are assessed by simulation studies and robot-based experiments.

2. Navigational strategies

Having a clear terminology is vital to investigate principles of navigational strategies. Since chemotaxis is considered the fundamental strategy in chemical search, we begin with a critical evaluation of this assumption. According to the Dictionary of Biology (1964), "taxis is a locomotory movement of an organism or cell, e.g., gamete, in response to a *directional stimulus,* the direction of movement being orientated in relation to the stimulus, e.g., to gradient of temperature, or to direction of illumination. Chemotaxis, geotaxis, phototaxis, according to nature of stimulus." p. 231.

Accepting this generic definition of taxis, it becomes clear that chemotaxis should only be used for search strategies that rely on directional information to orientate the agent towards the direction of a chemical gradient. Given the fact that chemosensors are not direction sensitive (Fraenkel and Gunn, 1961) and can only use local information (in contrast to visual and auditory sensors) a single sensory reading cannot provide sufficient information on the direction of a gradient. That was the primary reason why we decided to use the name "chemotaxis" in our research for a bisensory strategy, which is based on two spatially separated sensory readings to help the agent to orientate itself towards the gradient of the chemical field (Lytridis et al., 2001). For an agent to align itself with the gradient would require several measurements because it is implausible to assume that the animal relies on a rigid algorithm that directly links the difference between the two sensory readings and the turning angle needed to align itself with the local gradient. Accordingly, we consider Berg and Brown's (1972) use of chemotaxis for a unisensory strategy (biased random walk [BRW]) as inappropriate, and perhaps that was the reason why Berg (1983) avoided the term chemotaxis describing unisensory baised random walk search patterns in his later work.

In previous simulation studies, we have investigated navigational principles in chemical diffusion fields and identified BRW as an alternative search strategy to chemotaxis (Kadar and Virk, 1998a, b). We have also introduced a combined chemo-BRW strategy and tested this and the other two strategies under various conditions (Lytridis et al., 2001). The present study completes these preliminary studies by systematically comparing these strategies in a radially symmetric (concentric) diffusion field around a point source. First, we present the outline of the three strategies developed earlier and used in the present study.

2.1. Chemotaxis

Since most animals (insects, sharks, dogs, cats, etc.) possess two chemosensors, chemotaxis is usually believed to be the fundamental search strategy in odour source localisation (Beer, 1990). This strategy is based on the detection of a concentration difference between two chemical sensors and a steering mechanism toward the direction of higher intensity while moving forward at a constant speed. Chemotaxis-based navigation yields smooth movement trajectories in smooth chemical fields without major environmental perturbations.

Although chemotaxis is a simple mechanism, its implementation on mobile robots is not straightforward due to differences between biological and artificial sensors. In bisensory search, animals can rely on sensitive sensors with fast response time and they keep on moving while steering based on differences in sensory readings. In contrast, in robotic applications, the implementation of chemotactic search requires significant waiting times for sensory readings because of the long response time of artificial sensors. Thus, the continuous search pattern in biological chemotaxis has to be replaced by search steps with intermittent stops to measure local field intensity. Consequently, the chemotaxis algorithm consists of the repeated application of the following 4 steps:

(1) Waiting for a short period to allow settling time for the sensory measurement,
(2) Comparison of the field strengths at the left and right sensors,
(3) Turn towards the higher reading by a constant angle,
(4) Move forward by a constant step length.

The parameters (i.e., step length and turning angle) of this search algorithm should be calibrated to the specific test conditions (i.e., field intensities, sensor characteristics, etc.). Chemotaxis is expected to produce a relatively smooth trajectory from any initial position to the source of a chemical concentration field, but animal search patterns in odour source localisation are usually meandering (Hangartner, 1967). This discrepancy between the traditional view on olfactory navigation and empirical data led us to consider alternative strategies (Kadar and Virk, 1998a, b, c).

Although most higher-order species possess a pair of chemical sensors, experimental findings suggest that chemotaxis is not the only search strategy animals use. For instance, bi-sensory animals can perform odour source localisation even if one of their sensors is impaired (Hangartner, 1967). Moreover, very small organisms, such as bacteria, do not possess such bi-sensory system due to their physical size, and yet, they are still able to successfully search for nutritious chemicals. These facts strongly suggest that unisensory search strategies are also used by most species even if they can normally rely on their bisensory system.

2.2. Biased random walk

In principle, unisensory search could be based on chemotactic principles because unisensory temporal sampling of the chemical concentration field could be interpreted as a method of compensation for the absence of spatially separated sensors in a uni-sensory organism. But this ‘chemotaxis mimicking’ strategy would require a memory for registering spatial locations with associated intensity values of the chemical field to calculate a new movement direction. The use of this complicated computational mechanism is unlikely in primitive organisms and it may not be necessary in higher-order species either.

And indeed, studies suggest that bacteria use a much simpler unisensory strategy. Berg and Brown (1972), for instance, have observed that in a flat dish the 2D motion of the Escherichia coli bacterium consists of straight runs with occasional directional changes (tumbling). Alternating these two modes of motion, the bacterium generates polygon shaped trajectories. It has been shown that both the run lengths and directional changes can be described by Poisson distributions (see Appendix for details). The characteristics of movement patterns depend on the concentration distribution in the search environment. In a homogeneous field, there is no gradient information and the resulting motion is a purely random walk. In an inhomogeneous environment, the distribution function of the run lengths is continuously changing since the mean of the distribution depends on the detected concentration gradient (e.g., intensity difference between two different locations). When the concentration level increases, the frequency of directional changes decreases, and therefore the forward runs tend to be longer. The result of this strategy is an overall drift toward the source of the diffusion field. To put it differently, the random walk becomes a biased random walk process. This is a simple but efficient strategy using a fast adaptation process to the local field conditions instead of relying on memory of previously measured intensities at various locations in the search process. During the search process, the moving organism can adjust its sensory organs to the local concentration level and can detect relative increases or decreases in field intensities when it drifts into another region.

A similar approach has been used to develop the BRW algorithm at a macroscopic scale. Its use in artificial agents was first demonstrated in noisy Gaussian fields (Kadar and Virk, 1998a, b) and this work was extended to dynamic fields (Lytridis et al., 2002). The basic BRW strategy is a repeated application of the following sequence of steps:

(1) The stationary robot samples the field and makes a random turn based on a Poisson distribution (see Section A.1 in Appendix).
(2) The robot makes a step forward in the new direction, samples the field again and calculates the concentration difference between the initial and the current positions.
(3) Using the detected intensity difference (for convenience this will be referred to as gradient information here), the length of the next move forward is chosen randomly from another Poisson distribution (see Section A.2 in Appendix).

The BRW strategy in odour source localisation has been shown to be a robust method under a variety of conditions, but its efficiency can be improved (Kadar and Virk, 1998a; Lytridis et al., 2001). The first modification to the basic BRW algorithm was to introduce a 180 degrees turn when the robot detects a negative gradient in the new direction after a random turn. After the 180° turn, the robot moves forward and calculates the gradient (i.e., intensity difference between the current and previous positions). If the gradient is positive, the new step length is calculated as described previously, but if the gradient is negative, the mean step length (λ_{STEP} in Section A.2 of Appendix) is set to its minimum, thus the probability of generating a very small step length is higher. This modification is also biologically inspired, since a similar pattern has been observed on the *Spirochaeta aurantia* (Fosnaugh and Greenberg, 1988).

The physical characteristics of the BIRAW robot (see Section 3.1) allowed a second modification to the basic BRW algorithm. Chemical sensors were added on the front and back of the robot, so that the gradient in the direction of movement can be directly calculated by a simple comparison between the readings of these sensors. The forward movements for the calculation of the gradient (temporal field sampling) were therefore replaced by comparisons between the front and back sensor readings (spatial field sampling). This modification reduces the search duration since the time consuming forward steps are replaced by the calculation of the concentration gradient in the direction of motion. The BRW algorithm with these two modifications was used in both the simulation and experimental studies of the present paper. Thus, the modified BRW algorithm consists of the following steps:

(1) The robot makes a random turn based on a Poisson distribution with its mean, λ_{DIR}, defined in advance by a calibration process. The predefined parameter, λ_{DIR}, is the mean random turning angle which defines the change in orientation of the agent at the beginning of each run. (See for more details on the Poisson distribution for turning angle generation and calibration of λ_{DIR} in Section A.1 of Appendix and in Section 4.2.1.)
(2) After the random turn, the BIRAW robot makes use of their front and back sensors to calculate the field intensity difference in this new direction.
(3) If the robot detects a negative gradient in the new direction, the robot turns again by 180 degrees, samples the field and calculates the gradient (field intensity difference). In this case, if the gradient is found to be positive, the new step length is calculated as described in Step 4, but if the gradient is negative again, it is set to zero, thus increasing the probability of a very small step length being generated in Step 4.
(4) Using the gradient information the length of the next move forward is generated. The length of the next move forward is chosen randomly from another Poisson distribution whose mean, λ_{STEP}, is calculated on-line based on the concentration difference detected. The parameter λ_{STEP} increases linearly with the value of the gradient, thus, large concentration difference result in a higher probability of large step length generation. By biasing the step length in the random walk, longer steps are taken in those directions where large positive field intensity differences are detected. The steepness α of the linear function that governs the variation of λ_{STEP} is predefined and subject to calibration (see for more details in Sections 4 and A.2 of Appendix).

After these modifications, the BRW became a complex computational algorithm. One could argue that a 'chemotaxis mimicking' strategy might be simpler than the BRW proposed here. This paradoxical situation is due to the fact that the elements of BRW are based on chemical "lawful responses" in simple biological processes, but their robotic implementation becomes a complex algorithm in the artificial language of computer hardware. Besides these 'virtual' theoretical concerns, there is a real empirical problem with BRW. Although BRW is successful in driving the searching agent close to the target from regions of low concentration level, BRW is less efficient in the neighbourhood of the target because it tends to generate longer runs which may lead to 'mistakes' such as overshooting or passing by the target. We have tried to remedy this shortcoming based on the observation that search patterns in animals get less meandering as they get closer to the target.

2.3. The combined chemo-BRW strategy

Previous simulation studies have revealed the relative merits of the BRW and chemotaxis (Kadar and Virk, 1998a; Lytridis et al., 2002). By combining the two strategies one would expect better performance with less meandering paths while maintaining the robustness of BRW. It is obvious that BRW should be dominant on the outskirts of the chemical field where the chemical field is weaker and noisier, and chemotaxis should become increasingly dominant as the robot gets closer to the odour source where the chemical field is stronger and less affected by noise.

The two strategies can be combined easily as there is no directional bias in the BRW method other than the reversal (the turns are randomly generated based on a Poisson distribution). For the proposed combined strategy, a smooth merging strategy is adopted which does not require switching between the two strategies. If such a switching strategy were adopted, a switching threshold would have to be determined and this would depend on the type of chemical, range of concentrations, etc. Thus, the combined algorithm is a repeated application of the following two steps:

(1) The robot turns towards the sensor where the field is stronger by a specified amount after a comparison of the left and right sensors (chemotaxis step).

(2) The robot moves forward after evaluating the field gradient in the forward direction. The step length is generated randomly based on the field gradient in the longitudinal direction and associated Poisson distribution (BRW step).

Turning at the beginning of the navigational cycle (Step 1) is identical to chemotactic steering. Thus, additional field information from the left and right sensors can be used and random turns typical of BRW method are replaced with "informed turns". On the other hand, the random component in the magnitude of the step length (Step 2) is preserved and shown to be beneficial in noisy chemical fields (Lytridis et al., 2001). The generation of the step length is the same as in the BRW algorithm; after the random turn toward the direction of the sensor with the higher reading, the field is sampled again and larger steps are more likely to occur when the longitudinal field gradient is larger. In contrast, when the gradient is negative the agent turns by 180° and continues its search as described in the BRW algorithm.

3. Experimental setup to test search strategies

The experimental setup presented in this Section is similar to the simulation studies described in earlier studies by the authors Kadar and Virk (1998a, b), and Lytridis et al. (2002). The experimental settings of these studies consist of two basic components: (a) the BIRAW robot, and (b) the chemical gradient field.

3.1. Description of the robot

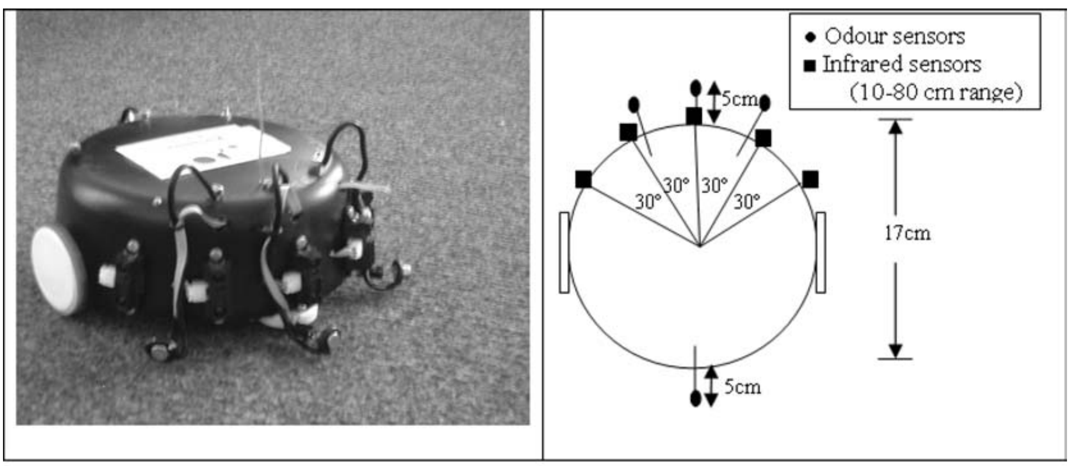
The BIRAW robot used in the present experiment was originally designed by Paul Fisher and further developed by Chris Lytridis at the University of Portsmouth (Fig. 1). The robot is cylindrical-shaped with a diameter of 15 cm and equipped with five infrared sensors for obstacle avoidance, evenly spaced, covering an angle of 120° in front of the robot. These sensors are designed for search strategies in cluttered environments but they were not needed in the current study. The robot is also equipped with four Figaro TGS2620 olfactory sensors for the implementation of the navigational strategies described in Section 2. In a previous study, we have investigated the performance of these odour sensors (Lytridis et al., 2002).

The main processing unit of the robot is a Pentium-based DIMM-PC running at 133 MHz with a 32 MB of solid-state hard disk and 32 MB of RAM. There are two add-in modules that contain PIC microcontrollers, which provide direct motor control, and are responsible for the RF communications and sensor sampling. The software running on the DIMM-PC sends high-level commands to the PIC microcontrollers depending on the action the robot is to take (i.e. move, sample odour sensors, detect obstacles, etc.). The software/hardware architecture implemented on the robot and the RF card also allow the robot to communicate with a supervisory PC.

There are two fundamental behaviours implemented on the robot: (a) the target searching behaviour, which is the default robot behaviour and (b) the obstacle avoidance behaviour, which is not used in the present study. The target searching behaviour is based on one of the three odour localisation strategies.

3.2. Experimental diffusion field

Many different types of chemical diffusion fields exist (e.g., simple point source fields, complex multiple source fields, fields with laminar and turbulent flows, continuous and

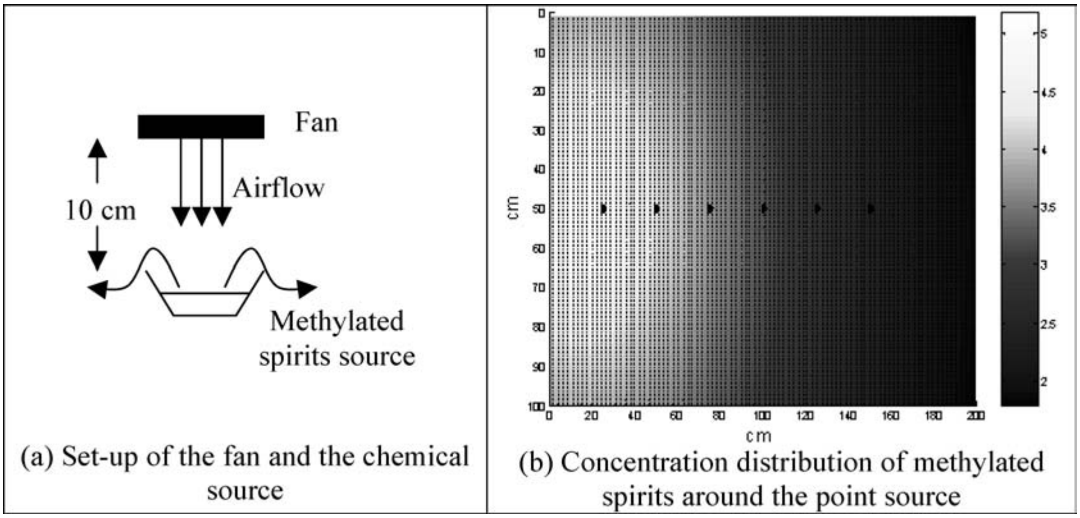


(a) (b)

Fig. 1 Two depictions of the BIRAW robot: (a) side view as it was used in experiment and a (b) top view to show the geometric representation in simulation

Table 1 A set of values to indicate the relationship between Voltage readings and concentration levels

Voltage	4.75	4.5	4.25	4	3.75	3.5	3.25	3	2.75	2.5	2.25
ppm	7574	1708	694	354	212	130	84	55	38	26	17



(a) Set-up of the fan and the chemical source

(b) Concentration distribution of methylated spirits around the point source

Fig. 2 Field creation and measurement of the concentric field in voltages in one direction from the source at point (0, 50)

discrete trails, diffuse particles of different molecular weight, etc.) and all of them need to be investigated for a complete understanding of olfactory-based navigational strategies. It is well known that certain animals often exploit the special properties of specific fields (e.g., direction of the flow of the medium can be used to orientate the animal upstream) (Papi, 1992). Various types of fields have been explored for specific tasks under specific conditions (e.g., Lilienthal and Duckett, 2003). Arguably, the most fundamental form of chemical fields is diffusion around a point source without airflow. If a heavy alcohol is used, this is a concentric, slowly developing field (taking up to 25 min to diffuse to a detectable level at a distance of 1 m from the point source). Although this type of field should be investigated first (Kadar and Virk, 1998b), this field is difficult to use in robot implementations, because it is highly unstable (i.e., can easily be affected by the motion of the robot and other disturbances). This fact combined with the lack of sensitivity and slow responsiveness of the TGS2620 odour sensors would result in unsuccessful searches. For this reason, the odorant was forced to spread by means of introducing a weak airflow with the help of a small Philips HD3500 low-velocity ($\sim$ 1.5 m/s) fan of 30 cm diameter set 10 cm above the source (see Fig. 2(a)). Using this method, detectable differences in field intensities appeared to be present at a distance of about 2 m away from the odour source, based on the relevant measurements presented later in this section. In addition, the "forced diffusion" developed faster, yielded more stable fields and the noise (perturbation) created by the robot's motion was reduced.

The downward airflow helped the chemical disperse evenly in all directions creating a close to uniform distribution similar to that of the simulated diffusion field in previous studies. In order to assess the properties of this chemical field, the distribution of concentrations was measured by six sensors positioned in a straight line with a spacing of 25 cm between adjacent sensors in 4 different directions. The instantaneous readings (after the sensors have settled) were recorded in each direction. Figure 2(b) shows a smoothed Gaussian function of the field intensities as well as the sensor positions at the time of the field measurement indicated by the black dots for one direction. The grey-scale shows the range of sensor voltages measured in the concentric field.

Since the chemical spreads evenly, it is assumed that similar measurements would be obtained if sensors were positioned symmetrically around the source of the diffusion field. Practically, only a semicircular area was used in our experiments. Separate measurements in different radial directions and repeated measures in a specific direction (connecting the target with the position of initial condition) before each experimental session supported the assumption of concentric field. A Gaussian function was fitted to the data ($R^2 = 0.96$):

$$f(x) = 4.663e^{-\left(\frac{x+1.397e-015}{139.8}\right)^2} \quad (1)$$

The field measurements showed that the range of concentrations in the search area were detectable by the sensors (0.7 to 5 V). In Fig. 2(b) the sensor output voltages in this chemical field range from 1.8 to 4.8 V. Table 1 shows a set of Voltage values with their corresponding concentration level (ppm).

4. Simulation to calibrate and assess strategies

In general, simulation work is helpful to speed up the overall development and testing process. The fact that simulations are much faster than the real experiments, combined with the advantage of having a to better control on the environmental conditions, allows the replication of the same experiment several times for statistical evaluation. It is then possible to assess the search behaviour across a number of conditions. Specifically, in investigating the problem of odour source localisation, simulation studies could help us calibrate navigation parameters for the three strategies. Also, simulation studies could be used to test the robustness of search strategies in diffusion fields with controlled noise.

4.1. Simulation environment

To implement and test the three search strategies, a simulation environment has been developed in MATLAB based on the stationary simulated environment originally developed by Virk and Kadar (1998) and Kadar and Virk (1998a, b, c). The field strength at any point in the search area (with the sensors at a constant height) can be calculated via a Gaussian function. More specifically, the field strength at a position (x, y) was $Field(x, y)$:

$$Field(x, y) = \frac{G}{\sqrt{2\pi} \times \sigma \times e^{d^2/2\sigma^2}} \tag{2}$$

where G and σ are parameters that determine the shape of the field (height and width) and d is the distance of the position (x, y) from the odour source.

The searching agent used in the simulations is based on the BIRAW mobile machine (Lytridis et al., 2003). The physical and dynamic characteristics of the BIRAW machine, such as shape, size, sensor's positions, speed etc, have been incorporated in the model. The simulated agent possesses five infrared sensors for obstacle avoidance (not used in this study), and four odour sensors arranged as shown in Fig. 1(b).

The response characteristics of odour sensors provided by the manufacturer cannot be used under the variable environmental conditions of our experiment. We realized that the sensors are influenced by so many variables (e.g., temperature, other chemical compounds, air flow, humidity, hysteresis, etc.) that it is impossible to rely on the theoretical values (based on stable ideal conditions). Some of these factors have been investigated in one of our preliminary studies and it has been shown that these electronic sensors have significant delays and their readings are very noisy (Lytridis et al., 2002). Nevertheless, in our simulation we used a simple model of the sensor response with a 4 s settling time for sensory reading.

4.2. Selection of navigation parameters for the search strategies

The purpose of this part of the simulation is to select the navigational parameters (e.g. the step length, duration of field sampling, etc.) according to the robot's physical characteristics and the search environment in order to optimise the performance for each strategy. There are three performance measures commonly used in robotic research: (1) the average duration of searches, (2) the average distance travelled and the (3) success rate. These performance metrics are generally accepted as sufficient for assessing the efficiency of a search strategy and have been used in a variety of related studies (Ishida et al., 1996; Grasso et al., 2000; Hayes et al., 2003; Russell et al., 2003).

The simulation used a Gaussian field model; the initial distance from the target was 1.25 m and the initial orientation was chosen randomly in each trial. A target search is considered successful when the robot entered a circle of 25 cm radius around the odour source. By using randomly generated sets of navigation parameters (within the operational range) for each of the navigational strategies, we simulated 100 search trials for each parameter pair. Since the success rate was 100% for all experimental conditions for the idealised, smooth (noise-free) diffusion field, we could exclude this measure at this stage. The other two performance measures (average distance and average search duration for 100 trials) were plotted as surfaces. These two surfaces are used to identify (calibrate) parameters for a specific search strategy by selecting a pair of (optimal) parameters from the lowest regions of these surfaces.

4.2.1. Biased random walk

The BRW strategy consists of a sequence of straight runs and turns. The angle of each turn is chosen randomly from a Poisson distribution and the length of each random step is chosen randomly from another Poisson distribution (see Appendix). During a search trial, the Poisson distribution for the angles remained the same but the Poisson distribution for run lengths was changing as a function of the local intensity values of the diffusion field.

Specifically, the mean of the run length distribution increased linearly with the concentration gradient measured by the front and back sensors after each random turn. Therefore, the parameters that need to be calibrated (i.e., selected

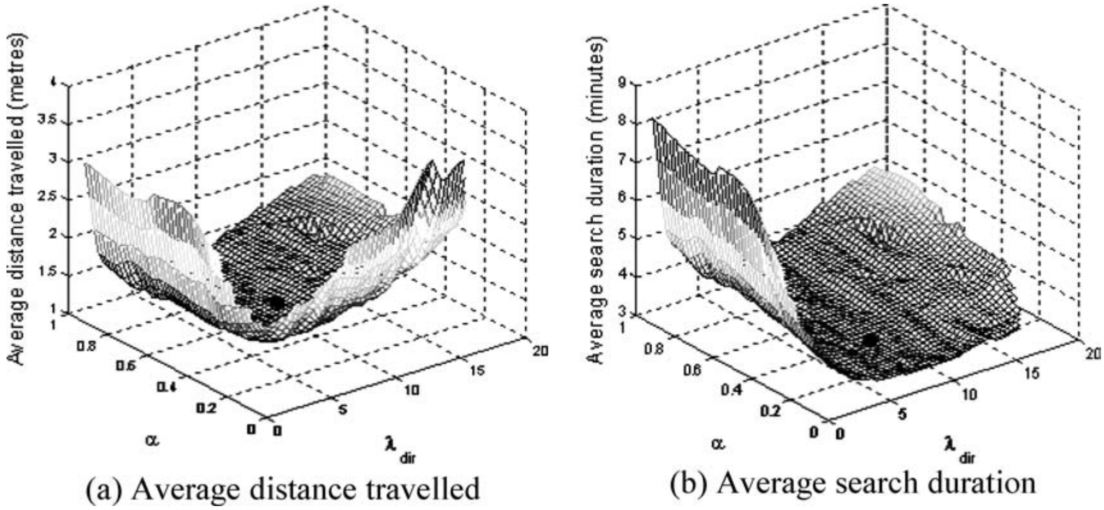


Fig. 3 Simulation results to assess BRW performance for a range of parameters. The small region of parameter pairs that produced the best performance is marked on the surfaces as a black circle

by simulation) for this strategy are λ_{DIR} (the mean of the Poisson distribution used for the turning angle generation) and the slope α of the linear function that maps the gradient to the mean of the Poisson distribution used for the step length generation (see A.2 in Appendix). The results of this simulation are shown in Fig. 3. Small values of α and λ_{DIR} result in smaller average distance travelled, whereas very small values for the λ_{DIR} parameter result in increasing average search duration. The parameter pairs which produced the best performance were located at the minimum of both surfaces at approximately $\alpha = 0.2$ and $\lambda_{DIR} = 5$ corresponding to 50°.

4.2.2. Chemotaxis

For chemotaxis, both the turning angle and the step length are assumed to be constant during navigation. Thus these two parameters had to be calibrated to optimise performance. Figure 4 shows the surfaces of the two performance measures in the parameter space of Step length vs. Turning angle. Small turning angles result in shorter total distance travelled and the average search duration is reduced with larger steps. Inspection of the surfaces in Fig. 4 suggests that there is no common optimal parameter pair for the two performance measures. Thus, we needed a compromise between the two performance measures for the calibration of real robot's navigation. We have chosen 40° for the constant turning angle and 10 cm for the constant step length.

4.2.3. Combined chemo-BRW method

As described in Section 2, the combined method consists of a turn (constant angle as in chemotaxis) towards the sensor that detects a stronger field and a forward step (generated in the same way as in BRW). Thus, the two parameters to be calibrated are the constant turning angle, and the slope α involved in the step length generation for BRW. The performance was assessed in the same way as in chemotaxis and BRW. The average distance travelled and the average search duration for various parameter combinations are shown in Fig. 5.

According to Fig. 5, small turning angles and small α parameter values result in reduced search duration. On the other hand, small turning angles and mid-range α parameter values are better in terms of average distance travelled. Again, based on these results a compromise was needed between the two performance measures and 30° was chosen for the constant turning angle while α was set to 0.2.

4.3. Evaluation of navigational strategies

To test the robustness of the search strategies, noise was added to the field value based on the following equation:

$$noise(x, y, t) = random(x, y, t) \times Field(x, y) \times noise\_level \quad (3)$$

where $random(x, y, t)$ is a random number generated between -1 and $+1$, $field(x, y, t)$ is the noise-free field strength, and $noise\_level$ is the level of noise present in the field. This noise level was expressed as a percentage of the noise-free field strength at a particular location. The calculated noise is then added to the noise-free field strength value and the result is a "noisy" field value measured by the agent. Since random noise could lead to unsuccessful search in this analysis we have to include success rate in addition

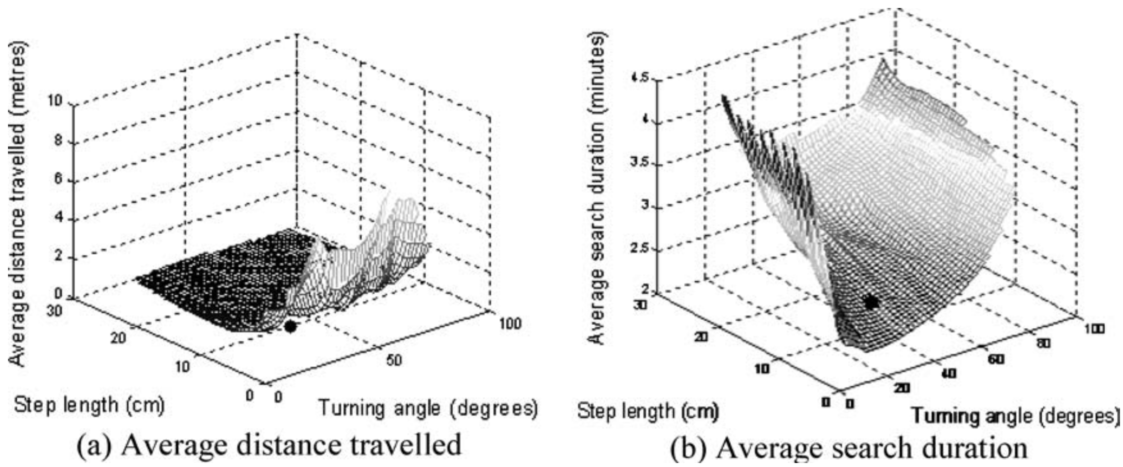


Fig. 4 Simulation results to assess chemotaxis for a range of parameters

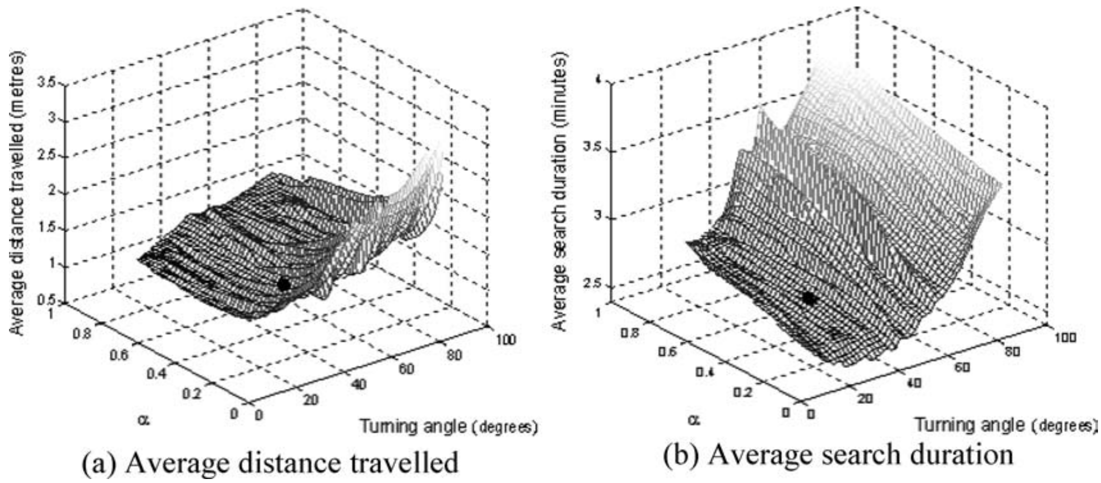


Fig. 5 Simulation results to assess combined strategy for a range of parameters

to the other performance measures (average search length and search duration). Each search path was unique and the overall performance of each strategy was assessed based on the average of 100 trials.

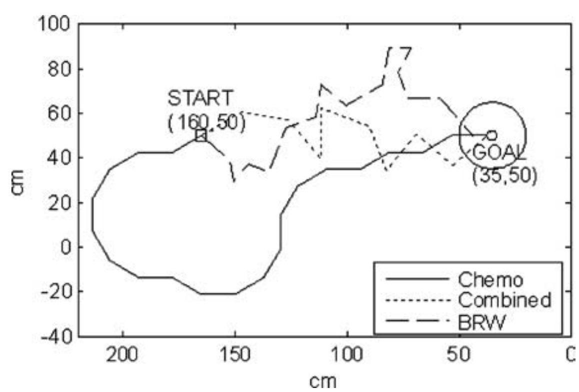


Fig. 6 Typical trials for the three strategies with 50% field noise

4.3.1. Chemotaxis

The chemotactic strategy was tested in the simulated stationary chemical field for a range of noise conditions. In all trials, the artificial agent is positioned within the field with a random initial orientation, at an initial distance of 1.25 m from the source. This initial distance was selected based on the field size and the concentration levels at various distances from the odour source. Figure 6 shows a typical successful search trial with the noise level of 50%. The movement trajectory is only locally smooth and slightly meandering due to the presence of noise.

To further illustrate the relationship between the noise and performance, various noise levels were applied. The success rate is an indication of the strategy's robustness in noisy conditions; where the success rate is less than 100%, the performance is derived from the successful trials only so that success rate and directness of the strategy can be viewed

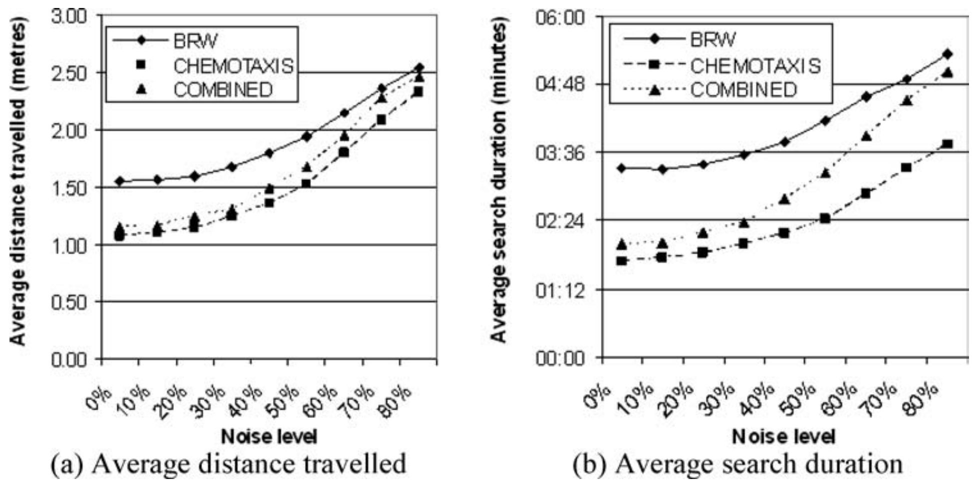


Fig. 7 Comparison of strategies for different noise levels in a stationary field

separately. Chemotaxis is not always successful (success rate is 99%) for 60% noise level and the performance deteriorates rapidly as the noise level further increases (i.e., success rate is 92% for 70% noise level and drops to 88% for 80% noise level).

4.3.2. Biased random walk

The conditions for the simulated BRW searches were the same as for chemotaxis except the movement control was different. A typical BRW-based search in a stationary chemical field and with a 50% noise level is illustrated in Fig. 6. BRW-based searches are more robust than chemotactic searches (no unsuccessful searches at any noise levels), and they even appear to be slightly more efficient for higher noise levels. Although this navigational strategy is robust, it is less efficient than chemotaxis. The search performance is expected to improve when BRW and chemotaxis are combined.

4.3.3. Combined chemo-BRW method

Using the movement parameters from calibration, the performance of the combined method was also assessed. Figure 6 shows a typical example of a successful trial at a 50% noise level. The abrupt changes in orientation are significantly reduced in comparison to the BRW strategy and a less meandering path is obtained. The combined method performs better than BRW especially when the noise levels are low. In addition, even though it is less efficient than chemotaxis at low noise levels, the combined method is actually as robust as BRW. Therefore, these findings suggest that the combined method is superior to both chemotaxis and BRW.

4.4. Comparative analysis of navigational strategies

The three navigational strategies have been assessed and compared under various field conditions. Figure 7 shows (a) the average distance travelled and (b) the average search duration for searches in the point source stationary field at different noise levels.

According to Fig. 7, chemotaxis appears to be more efficient than BRW and the combined method. The difference in efficiency is more pronounced if performance is assessed by average search duration. However, chemotaxis cannot be considered superior to BRW or the combined method because it is not robust as evidenced by the failed trials at noise levels higher than 60%. In particular, Fig. 7(a) shows that the average distance travelled in chemotaxis-based searches is slightly lower than when using the combined method for noise levels above 55%, but only if the successful trials are

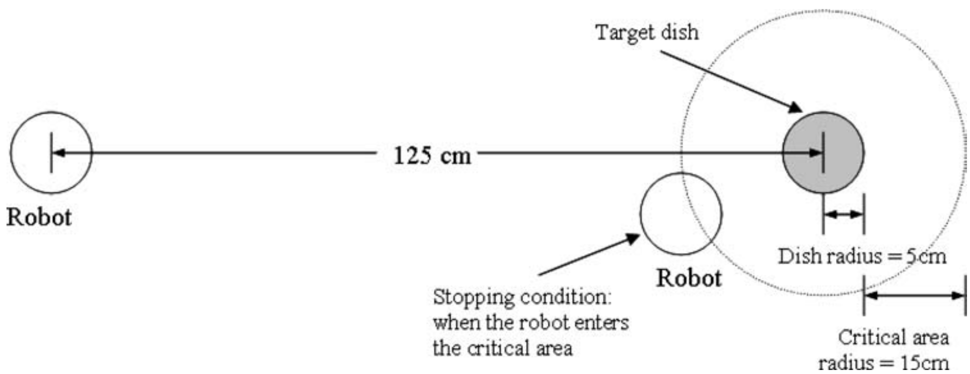


Fig. 8 Experimental set-up for the robotic trials

taken into account. On the other hand, the robustness of BRW and the combined method has been demonstrated even though chemotaxis is better at low noise levels. Overall, the combined method appears to be the best strategy of the three tested methods because it combines the advantages of chemotaxis and BRW: it is more robust than chemotaxis and more efficient than BRW in the relatively stable field of the present experiment.

5. Robot experiment for testing strategies

The primary aims of the following experiment on odour source localisation with the BIRAW robot are (1) to demonstrate that the biologically inspired strategies could be implemented in natural settings, (2) assess the performance of the three strategies in natural settings, and (3) compare these robotic results with those of simulation studies.

5.1. Experiment

The experimental conditions are similar to those of simulation studies but they are not identical due to limited control on the noise (e.g., unstable and noisy diffusion field, further perturbations caused by the moving robot itself, and instabilities in the sensory readings). Because of these uncertainties, the outcome of this experimental test, in principle, could be different than those of simulation studies. Nevertheless, our preliminary findings suggest that similar results can be expected (Lytridis et al., 2003; Kadar et al., 2005).

5.1.1. Experimental setup

In all the experimental conditions, we used the same type of diffusion field (see Fig. 2) and the experimental set-up presented in Fig. 8. The odour source was a small dish containing approximately 150 ml of methylated spirits. The robot started the searches at an initial distance of 1.25 m from the odour source and with various representative initial orientations chosen from a range [0° 360°] relative to the odour source. Due to restrictions imposed by the robot's size, a search was considered successful when the robot enters an area of 15 cm distance from the source (a dish of 5 cm radius). Twenty-five trials were carried out for each strategy and the duration of the search and the total distance travelled were averaged.

The robot performance was monitored on-line by means of a data capture board connected to a PC. The board's design is similar to the radio board used in the robot. The board allows two-way radio communication between the PC and the robot, and it serves two basic functions; firstly, the remote selection of the search strategy at the beginning of each trial, and secondly, the on-line monitoring of the search progress and the recording the search data for subsequent analysis.

5.1.2. Biased random walk

Figure 9 shows four typical search trajectories of the 25 trials. The performance measures for BRW are as follows: Average search duration: 3 min 10 s (ranging from 1 min 19 s to 6 min 13 s) and Average distance: 156 cm (ranging from 118 cm to 256 cm).

5.1.3. Chemotaxis

Again, twenty-five trials were carried out and four of the successful search paths are shown in Fig. 10. Two of the 25 trials were unsuccessful. Both occurred when the robot was facing away from the source at the beginning of the search. Thus, this strategy cannot be considered a sufficiently robust method. If only the successful trials are considered, the performance measures show that chemotaxis is superior to BRW (average search duration was 2 min 5 s [min = 1:38, max = 2:50] and average distance was 116 cm [min = 100 cm, max = 130 cm). These results are in agreement with findings in the corresponding simulation study.

5.1.4. Combined chemo-BRW method

The combined strategy produced paths similar to chemotaxis but without unsuccessful trials (see Fig. 11). This strategy was slightly superior to chemotaxis in terms of efficiency (average search duration: 2 min 5 s [min = 1:01 and max = 3:42] and average distance: 111 cm [min = 101 cm and max = 155 cm]).

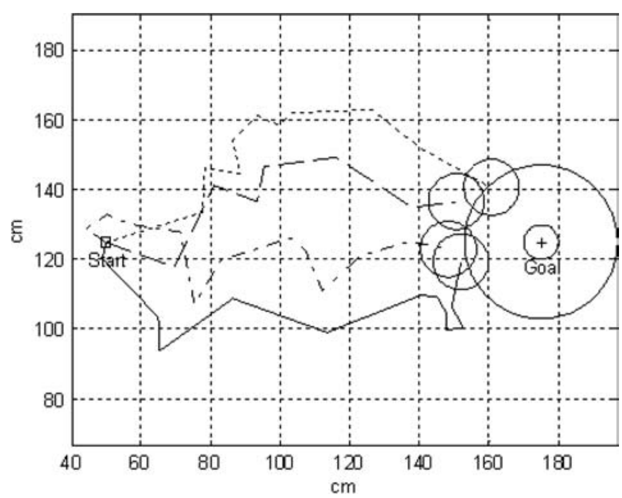


Fig. 9 Typical paths for successful BRW search trials

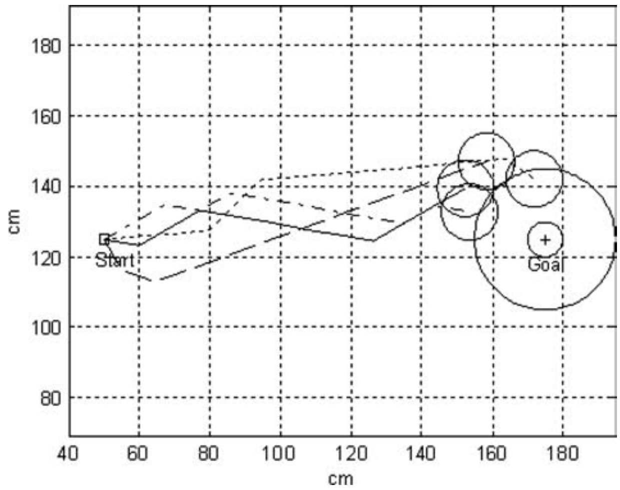


Fig. 10 A sample of trials for successful chemotaxis search

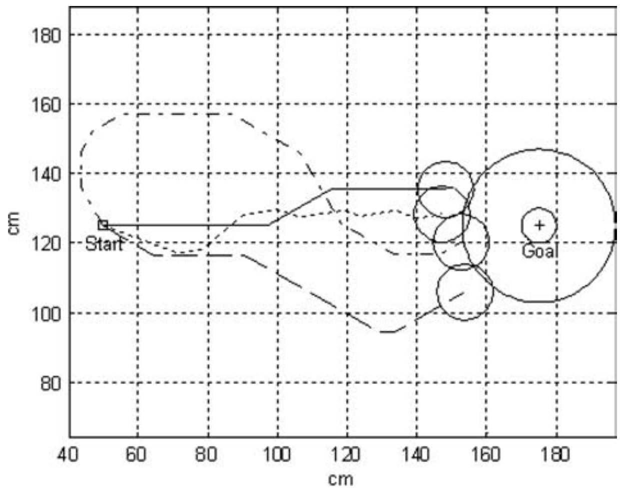


Fig. 11 A sample of search trials with the combined method

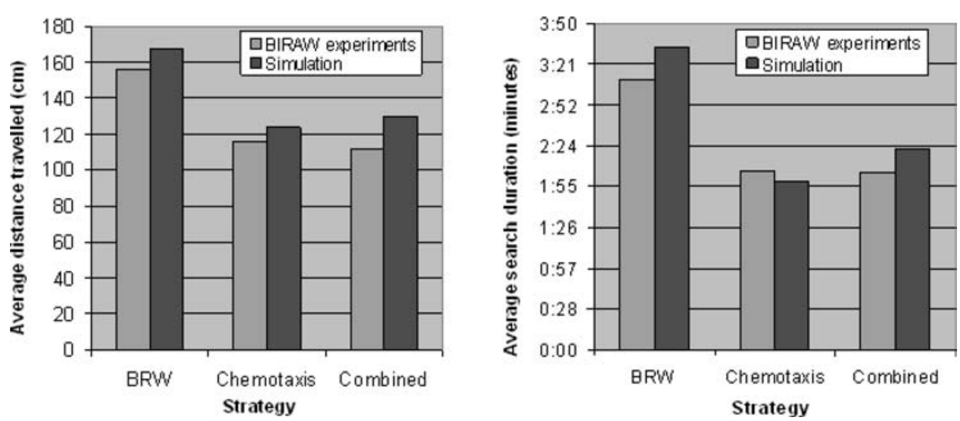
5.2. Comparative analysis of search strategies

To compare the search efficiency of the three strategies in simulation and robotic experiment, the average distances and search durations are given in Fig. 12. Chemotaxis was much more efficient than BRW both in terms of distance travelled and search duration. The robustness of BRW was demonstrated by the fact that there were no unsuccessful BRW trials. The variable step length in BRW searches prevents the robot moving too far away from the region where the field is strong, while helps the robot drift away from regions where the field is weak.

As expected from the simulation studies, the combined strategy proved to be the most effective of the three strategies tested. Its effectiveness was evidenced by the smooth paths (smaller angular changes similar to chemotaxis) and variable random step lengths (runs), which depended on the difference between the front and back sensor readings. The forward steps toward a higher concentration tended to be longer, whereas shorter steps were typically produced when the robot moved away from the source of the diffusion field. The search is also speeded up by the 180° turns when the gradient is negative. In this case, the robot does not make small successive turns (which, considering the field sampling duration, would incur large time overheads) to find its direction towards the source. Instead, the robot makes a fast 180° turn effectively orienting itself towards higher concentrations. The main advantage of the combined method is its robustness (i.e., lack of unsuccessful searches).

Since the noise level was difficult to measure in robotic experiment, it is plausible to compare experimental results with findings of various noise levels in our simulation. Figure 12 suggests that the experimental results are generally in agreement with the corresponding simulation condition with 30% noise. The differences between the robot experiment and the simulation (especially in BRW searches) are mainly due to the approximations made in the simulations regarding the chemical field parameters and the odour sensor response. More specifically, the shape of the field created during the experimental work varies over time. The magnitude of the detectable gradient decreases as the ambient concentration increases in the experimental room. Although clear air was frequently introduced into the room in order to restore the ambient concentration levels between

Fig. 12 Comparison of the results of simulation and robot experiment



experimental trials (the overall chemical concentration level in the closed environment increases over time and reduces field gradients), the field characteristics were difficult to control.

6. Conclusions and future work

In previous studies, we have successfully tested three biologically inspired search strategies: chemotaxis, BRW, and a specific combination of these two basic methods (Kadar and Virk, 1998a, b; Lytridis et al., 2001). Preliminary findings from simulation studies and robot experiments were encouraging (Lytridis et al., 2003; Kadar et al., 2005). The present study has attempted to use both simulation and robot-based experiments in a complementary fashion to assess search strategies in a concentric point source field. Specifically, we have conducted simulation studies (1) to calibrate search strategies in a diffusion field, and (2) to assess search strategies in diffusion fields with various noise levels.

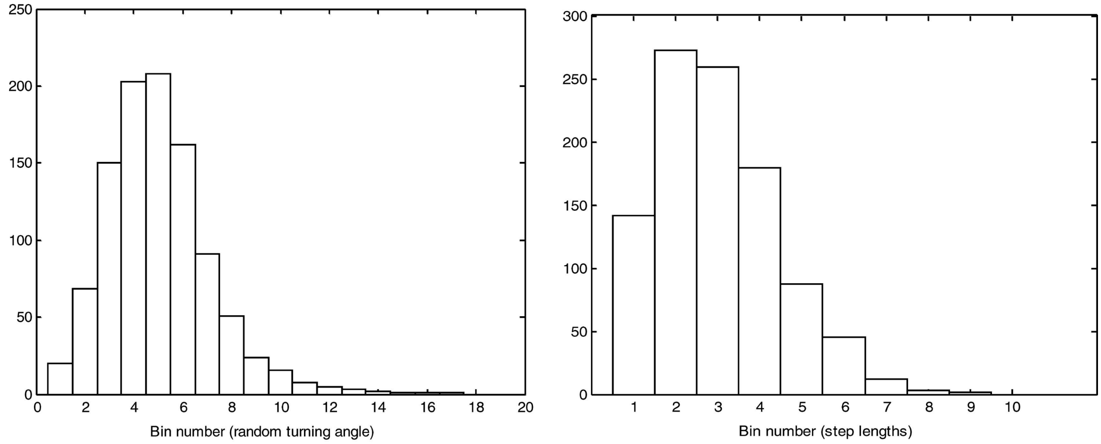
These simulation studies confirmed the validity of similar findings of our previous studies. First, all three biologically inspired strategies are shown to be mostly successful under various conditions. Second, chemotaxis is shown to be an efficient but not sufficiently robust strategy; the average distance of search was shorter than BRW but not all search trials were successful. Third, BRW is shown to be a robust but less efficient strategy (i.e., although all trials were successful, the average distance of search trials was longer). Fourth, the proposed combined method provides a good compromise between chemotaxis and BRW. In general, these results are in agreement with our previous simulation studies, even though there are some quantitative differences due to the differences in experimental conditions (Kadar and Virk, 1998a, b; Lytridis et al., 2002; Virk et al., 2001).

Based on the calibration parameters derived from our simulation study, our three biologically inspired strategies have been successfully tested on a mobile robot. These experimental findings strongly support the theoretical proposals of Virk and Kadar presented in previous studies (Kadar and Virk, 1998a, b; Lytridis et al., 2002; Virk et al., 2001). Whilst the utility of bisensory chemotaxis has been confirmed, BRW has also been shown an important search strategy in chemical diffusion fields. Thus, it seems that BRW may play a role not only at a micro-scale of bacteria but also underlie the meandering search patterns of higher species. Although the present study tried and mimicked unisensory BRW by using front and rear sensors, our findings confirm that unisensory search patterns are robust and they should be further investigated when sensory technology will produce better quality sensors. Finally, the primary reason we needed a confirmation of results from simulation studies with a test on a robotic platform was the difficulties we have to face in finding an accurate model of noise in both the diffusion field and sensory readings. Since these experimental results are fairly similar to the findings of simulation studies in concentric diffusion field with 30% noise, we can assume that the experimental set-up had an average of 30% noise (including noise in sensory readings).

With the fast developing sensor technology, we expect that biologically inspired navigational strategies will become increasingly common in various applications in the near future. In addition to developing better sensors, there is also a need for theoretical work to further study navigational principles in olfactory search. Here we mention just a few of the concerns future research should address. Perhaps, the most enigmatic issue is that biological search patterns in olfactory navigation are typically slow. Animals seem to be 'aware' of this problem and often try to find ways to enhance their performance. Some species have developed strategies to benefit from detecting the direction of wind (e.g., moth) or water-current (e.g., salmon). They keep moving upstream as long as they detect attractive chemicals carried by the current of the medium. Sucking in air is another smart strategy used by numerous species (sniffing animals such as dogs, cats, etc.) to improve olfactory search performance. Collective search behaviour is also common to enhance search performance in insects (e.g., ants, bees, etc.) and we have already started exploring this alternative in another study (Lytridis et al., 2002). We continue our research on investigating navigational principles of biological search strategies and try to address some of these concerns with the help of simulation studies and robot experiments conjointly.

Appendix: Poisson distributions

Poisson distributions can be characterised by one parameter, the statistical mean value: λ. There are discrete and continuous versions of these functions. The continuous distributions are the generalized version of the discrete ones which can be described by the following formula: $P(x = k) = (1/k!)\lambda^k e^{-\lambda}$. Poisson distributions are often used to describe various types of random events such as the number of randomly scattered points in a specific region. These distributions have also been identified in biological search patterns in a diffusion field. For instance, Berg and Brown (1972) have shown that during the locomotion of *E*-coli bacteria turning angles and run lengths can be described by Poisson distributions. Based on these findings, Poisson distributions have been used in our previous studies on testing navigational strategies in chemical fields (Kadar and Virk, 1998a, b; Lytridis et al., 2001). In the present study, Poisson distributions are also used for the generation of random turning angles and step lengths in the BRW and combined



(a) (b)

Fig. A.1 Empirical Poisson distributions of (a) turning angles for BRW with the mean value, $\lambda_{\mathrm{DIR}} = 5$ (corresponding to 50) and (b) of step lengths for $\lambda_{\mathrm{STEP}} = 2$ (corresponding to 8 cm)

strategies. The specific implementation of these distribution functions is discussed in the following two sections.

A.1. Random turning angle generation

The generation of random turning angles is based on a Poisson distribution whose mean (expected value) is a constant value, λ_{DIR}. In the present study, the BRW and combined strategies used two different λ_{DIR} values, 50° and 30° respectively.

To implement the Poisson distribution on the robots' software, the distribution was approximated by an empirical distribution function with a range of angles partitioned into segments (bins) of equal width. The range of the turning angle was [0°, 180°] and it was divided into 18 bins. Thus, the first bin represents an angle of 10°, the second bin represents 20°, etc. Each numbered bin is assigned to a range of values according to the Poisson function and the pre-defined mean λ_{DIR} of the Poisson distribution. To demonstrate the validity of the algorithm, an empirical distribution function was generated. Figure A.1(a) also shows the histogram obtained by repeating the random Poisson process for 1,000 samples with $\lambda_{\mathrm{DIR}} = 50°$. The number of values is largest for the fifth bin because the mean and the median of the Poisson distribution are the same (i.e., $\lambda_{\mathrm{DIR}} = 50°$ in this specific case).

A.2. Random step length generation

In both the BRW and combined chemo-BRW strategies, the step length is selected randomly from another Poisson distribution. Unlike random angle generation, in this case, the mean of the Poisson distribution, λ_{STEP} is a variable parameter. The mean, λ_{STEP}, increases linearly with the magnitude of the measured gradient. Specifically, when the gradient increases, the probability of generating a long step also increases. For smaller gradient values, the distribution is skewed towards smaller step lengths. For a gradient value of zero (i.e., when the gradient is negative), the minimum step length segment is always selected (bin 1), thus the probability of the shortest possible step being selected is maximised. In the algorithm, the field gradient and λ_{STEP} are linked by a linear function with steepness α.

The Poisson distribution covers a range from 5 up to 30 centimetres, which is partitioned into 10 equal bins. Again, each bin is assigned to a specific step length. After the calculation of λ_{STEP}, based on the measured gradient, the bin selection is the same as for the random-angle generation. The robot can then move forward according to the step length assigned to the selected bin. Histogram in Fig. A.1(b) shows an empirical distribution obtained by repeating the Poisson-based random step length generation for 1,000 samples with $\lambda_{\mathrm{STEP}} = 2$ (i.e., the distribution is peaked around the second bin corresponding to 8 cm).

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