

Bi-modal search using complementary sensing (olfaction/vision) for odour source localisation.

Gideon Kowadlo, David Rawlinson, R.Andy Russell and Ray Jarvis

Intelligent Robotics Research Centre

Monash University, Clayton, Victoria, Australia

Email: {gideon.kowadlo, david.rawlinson, andy.russell, ray.jarvis}@eng.monash.edu.au

Abstract—Odour localisation in an enclosed area is difficult due to the formation of sectors of circulating airflow. Well-defined plumes do not exist, and reactive plume following may not be possible. Odour localisation has been partially achieved in this environment by using knowledge of airflow, and a search that relies on chemical sensing and reasoning. However the results are not specific, with the odour source only restricted to a broad area. This paper presents a solution to the problem by introducing a second search stage using visual sensing. It therefore comprises a bi-modal, two-stage search, with each stage exploiting complementary sensing modalities. This paper presents details of the method and experimental results.

I. INTRODUCTION

Over the past 15 years, odour localisation has become recognised as a valuable area of robotics with humanitarian and practical applications, as well as for gaining a deeper understanding of the behaviour of organisms that display odour localising behaviour. Some of the animals that have inspired research are *e-coli* bacteria that locate nutrients, silk worm moths that find a mate through tracking pheromones carried in the air, and lobsters that seek out food under water. Applications of odour localising robots include detection of drugs, gas leaks, fires in their initial stages, fuel leakage from underground tanks and injured people in search and rescue missions. These applications and scenarios have been tackled by researchers in a variety of ways.

The bulk of work on the problem has focused on small robots at a scale of the order of tens of centimetres, operating in open areas free of obstacles with a background fluid flow. Fluid flow in this environment is dominated by turbulence. The odour is carried downwind from the source forming a plume. Due to turbulence, the plume meanders, and the chemical concentration within the plume is patchy.

Under these conditions, researchers have developed methods that employ combinations and variations of plume acquisition and plume upwind following using reactive control algorithms. This has been accomplished with passive sensors in air [1] [2] and underwater [3], as well as using more advanced sensors that give directional information regarding the chemical plume [4]. In these implementations, the robot must travel from its current position, the entire length of the plume to the source, which is time consuming, and not always possible.

Recently, there has been a move away from local sensing; and away from purely reactive control systems. Ishida et al. [5] and Loutfi et al. [6] added an ability for long range sensing

using vision. Loutfi employed vision to identify candidates, and then used odour measurements and data processing to ascertain whether or not the candidate was an odour source.

Ishida used a Subsumption architecture to combine random, visual and olfactory search behaviours. The olfactory search consisted of reactive plume tracing, and under visual search, the robot moved towards a visible bottle placed on the floor. The priority from highest to lowest was: olfactory search, visual search, and random search. The visual search became activated when a bottle entered the field of view, and the olfactory search when an odour was detected. The robot is able to avoid moving all the way to a bottle that is not the source, through activation of the olfactory search due to odour from the real source. In addition, it will continue to move towards an odour source that is in view, despite momentarily losing the plume, which often occurs due to its patchy and meandering nature. The method was very efficacious, enabling the robot to locate odour sources more effectively than with either of the behaviours alone, and would not have been successful with vision alone.

Kowadlo and Russell [7], [8] have addressed enclosed areas by exploiting long range information, and adopting a sense-map-plan-act style control strategy. Enclosed areas may occur in such places as mines, caves, industry, under tree canopies, and in emergency situations. For example, in pockets that form in buildings damaged by earthquakes or explosives, it is necessary to locate injured people as well as gas leaks that may be toxic and/or create a dangerous fire hazard. In these environments, sectors of circulating air form, and the chemical will mix throughout the sector in which it is released, remaining predominantly constrained to that sector. In this case, a well defined plume does not exist, and it is not possible to use conventional plume tracking.

The method begins with the construction of a map of the airflow (to be confirmed with anemometry), which is carried out using a physical map that has been provided *a priori*. The airflow map is used to compute the most useful locations for measuring the chemical concentration. The robot moves to these locations, gathering data which is processed to predict odour source locations with associated confidence levels. It is assumed that odour sources can only be stand-alone objects within the enclosing walls, and their locations are identified from the physical map before gathering data - which reduces the search space considerably. There are two major limitations:

- 1) The odour may originate from locations other than from the objects within the surroundings. Especially in an industrial setting, where the source could be a crack in the wall or pipes that run along the wall.
- 2) If the odour does originate from an object within the area, there remains a large surface from which chemical could be leaking. The final prediction is non-specific.

This study builds on, extends, and combines the work by Ishida et al. and Kowadlo et al. It improves the method of [8] for enclosed environments, with the addition of visual sensing, a complementary sensing modality. Within an enclosed area, the robot uses the method employed in [8] to predict a set of potential odour source locations. This is sufficiently restricted, that a second search mode becomes effective. It is used to identify a specific location of the target and move towards it for verification. With this method, the aforementioned limitations can be overcome. Odour sources can be along walls as well as objects, and the robot is able to disambiguate the many potential source positions previously identified with the method of [8]. The strategy depends upon both odour/airflow sensing, and visual sensing, and would be unsuccessful with either of these modes used alone.

The method comprises a bi-modal search using complementary sensing. It resembles the way humans perform many types of searches. An analogical example was given by Ishida et al. [5]. If a person smells gas, they may follow their nose to an extent, but will then look around for a salient feature (such as a stove) with a specific location. Likewise, if a person is looking for their ringing phone, they will move towards the sound searching aurally, before switching to a visual search when they arrive within the proximity of the phone. We have a poor ability to localise aurally, and cannot complete the task. However, after the initial ‘coarse’ localisation, a specific visual search can take place effectively. These examples illustrate that physical realities mandate variable search modalities within some localisation problems. At different stages of a search some sensing modalities may be more effective than others, and or rely on the information garnered from preceding stages. An appropriate sequential combination is likely to be more efficient than any individual used in isolation, indeed, it may be essential for a successful outcome at all, as in our odour localisation task. This is distinct from sensor fusion, the simultaneous combination of more than one sensing modality to provide enhanced sensing of an aspect of the environment. However, sensor fusion may also be incorporated into a multi-stage scheme. In this paper we explain the method, experimental work, and present conclusions with suggestions for future work.

II. METHOD

We have devised a complementary sensing, odour source localisation scheme for enclosed spaces where odour has spread throughout, and been confined to airflow sectors. The behaviour of many chemicals in enclosed volumes of arbitrary size fits this description. In order to characterise the likely source of odour, we have concentrated on a hypothetical

industrial scenario in which an accidental discharge from a gas transport system has occurred, either due to corrosion (cracked or burst pipes) or misdirection to atmosphere (venting). This allows us to limit the visual features associated with potential odour sources. The method could be extended to a variety of source types for other contexts.

A. Overview

The system is comprised of three sections summarised below, and explained in detail in following sections.

1) Pre-processing

- Map airflow in the environment, predicting the topology of boundaries that define separate cells.

2) Stage 1 - general search - Sense: olfaction

This comprises an efficient, fast sparse sampling of a large volume to reduce the initially large search space.

- *Compile a list of targets for chemical search:* Using the airflow map, compile a list of locations for which a chemical concentration measurement provides the highest utility. These are targets for the ‘chemical sensing’ search. In most cases these locations fall at the centre of a sector.
- *Move to targets:* Move to these locations recording the chemical concentration.
- *Prediction:* Use the results to predict sections of the surroundings where an odour source may exist, sort and rank these in terms of confidence levels. The list is referred to as the ‘Odour Source Prediction List’ (OSPL). In most cases, these sections consist of surfaces exposed to or falling within a sector where a high concentration was measured.

3) Stage 2 - specific search - Sense: vision

- *Compile a list of target positions for visual search:* For each item on the OSPL (Stage 1), move to a vantage point from which to view the corresponding surfaces that have been predicted to be likely locations for the odour source.
- *Look around:* At each vantage point, rotate 360° looking for the salient visual features that may be odour sources.
 - *Validate visual targets:* Use knowledge of airflow combined with the position of the visually detected odour sources, to determine if this could be the odour source. If so, then this is an ‘Odour Source Suspect’ (OSS).
- *Home in:* Use visual servoing to move towards the OSS.

B. Pre-processing

The airflow in the environment is modelled. Using a conventional finite element analysis is impractical as it requires boundary conditions which are unavailable, is time consuming, and provides low level results that are not readily useable for high level processing. For this reason, an algorithm using Naïve Physics (a ‘Naïve Reasoning Machine’ or NaReM [7],

[8] is used. A background to Naïve Physics is given below, followed by relevant details of the NaReM. For a more in depth review of Naïve Physics, see [7], [9].

1) *Naïve Physics and NaReM's (background)*: Despite great advances in artificial intelligence, “the AI community has been unable to create successful, autonomous robots able to operate in complex, unconstrained environments” [10]. This is partly due to a lack of artificial ‘commonsense reasoning’, one aspect of which is termed Naïve Physics - the use of intuitive rules to understand and reason about the environment. For example to crack an egg, it’s necessary to understand that the shell is hard but brittle, must be broken in a controlled manner, and that the viscous fluid within the cracked shell will flow downwards, filling a vessel beneath it. There are many subtleties involved that we take for granted. We have a naïve understanding, enabling us to carry this out effectively, without recourse to complex mathematical relations. The challenge is to endow robots with similar ‘Naïve Physics’ knowledge.

Whilst some researchers have tackled this and other problems using formal logic [11], others have created systems to learn and reason about spatial relations with higher level rules [10], [12]. Whereas these approaches are used to “learn and reason about the physical behaviour of objects” [10], NaReM’s are used to model an aspect of the environment, in this case airflow. A set of intuitive rules are developed through observation. These rules are encapsulated into an algorithm. The algorithm is tested, and where necessary the rules and implementation are modified in order to achieve the desired results. The rules are defined at a high level of abstraction, and the data structures likewise, with analogical representations [13]. The result should be an algorithm that does not involve complicated mathematics, is fast, robust, provides results that are intuitive, at a high level of abstraction, and are only precise enough to carry out the task effectively.

2) *Airflow mapping*: Air flows are represented as lists of flow points. New flows are generated to simulate the air flows spreading out. The leading flow points of all flows are propagated throughout the area, which becomes filled.

When a flow merges with another, it is considered to be one of its parents. It becomes a ‘source’ to its child. If the parent was carrying a chemical, it is passed to the child. One parent can source several sectors. Flows are stored in a graph data structure, which is used to capture these relationships (ancestry) between flows. When a flow is added to the graph, its ancestry is recorded using its parent’s ancestry. This is used to detect the formation of cycles, which are labelled as air flow sectors. Through this process, the NaReM provides the following data structures (see Fig. 1).

- a list of flows, each with a list of sectors to which it leads (its ancestry).
- a list of sectors

C. Stage 1 - general search (olfaction)

The aim of the Stage 1, is to reduce the search space of the entire area to a small subset that can be visually searched. Stage 1 is almost identical to that used in [8], albeit with a

significant modification to how it is applied. A brief summary is given here, with information relevant to Stage 2.

1) *Identify candidates*: The first stage of the process is to identify all the potential odour source sites, used for further processing. Previously, it was assumed that the odour source was restricted to objects within the perimeter of the space (rather than walls). Here, every surface (except for the ceiling and floor) is a potential site, comprising a large search space. This is tackled by discretising the entire search space, and considering every point a potential source. This is the aforementioned modification and its implications are explained in ‘Further Comments’ below.

Each candidate is analysed for associated flows. An associated flow is a flow that will pick up chemical in the case that this candidate is an odour source. Each flow has a set of associated sectors (sector to which chemical would be carried) provided by the NaReM. A list of candidates with associated sectors is compiled, see Fig. 1.

2) *Compile list of targets for ‘chemical’ search*: The candidates (with their associated sectors) are processed to add information to the sector data structures. The result is that for every sector, multiple associated candidates are assigned (see Fig. 1). An associated candidate is a candidate that, if emitting a chemical, will result in that chemical being found in significant concentrations within that sector.

The list of sectors is then pruned to produce a subset that have a unique set of candidates. Each one of these sectors is then considered a target location for information gathering (the centre of the sector is the specific target location). The initial pruning is important. It is possible that all the candidates in a sector would result in high concentrations in another sector. Therefore it is only necessary to investigate the latter. The pruning avoids redundant information gathering.

3) *Prediction*: After the robot has visited all relevant targets, the target list is sorted by descending chemical concentration and segmented into groups of similar concentration; it is referred to as the ‘Odour Source Prediction List’ (OSPL). The confidence levels for each segment are determined by the disparity between segments.

4) *Further comments*: Making every point a candidate (section II-C.1) is initially unintuitive. It seems more obvious to use the information in an upwind sense i.e. detect an odour, and trace it back to the potential source location. However, this would require searching a cyclic graph which is difficult. Using our method, a list of sectors with associated candidates is already available. It encapsulates ‘upwind’ information - derived from an inversion of the ‘one candidate to many sectors’, created by tracing ‘downwind’ from every candidate.

D. Stage 2 - specific search (vision)

In several of the following sections, image processing is used to identify visual features that characterise odour sources such as grilles and cracks. This is described first, followed by the other sections that rely on it.

1) *Image Processing*: The robot is equipped with a colour video camera; a 2.4GHz video sender transmits the picture

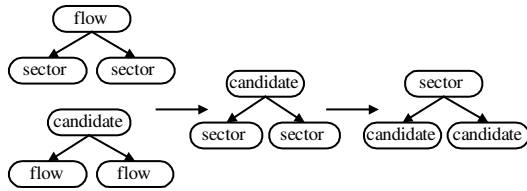


Fig. 1. Data structures produced by the NaReM and Stage 1 data processing. They show one to many relationships.

to the base computer. Images are captured at 320x240 pixel resolution. Frames are captured only on demand.

The basis of the visual candidate detection is an assumption that the target stimuli incorporate high-contrast corners and edges in predominantly plain arena. Such features are well suited to local feature detectors such as [14], [15]. We have chosen to use the SUSAN edge and corner detector [16], as the initial kernel response highlights both edges and corners, with greater output for the latter. Since both edges and corners are detected, the kernel response is hereafter known generically as ‘interest’. Interest is calculated from greyscale images.

Video transmission introduces significant high-frequency noise that may be mistaken for interesting features, so each frame is heavily smoothed by Gaussian convolution with a kernel whose σ is equal to 1.5.

The robot moves only within the ground plane; the floor and roof are assumed for the purposes of this experiment not to contain odour sources. For this reason pixels from rows above 120 and below 170 are considered to have zero interest. The remaining visible window retains features within the walls at all distances encountered within the arena, but strong specular reflections on the floor from overhead lighting are eliminated.

In the experimental scenario, prospective visual candidates are characterised by clusters of high-contrast corners; moreover the targets must be identified regardless of distance (in the arena the grilles are between 0.05m and 4m from the robot). Both issues are handled by creation of an image pyramid [17]: The base of the pyramid is the interest image; each subsequent layer is built by aggregating pixels from the layer below. Each pixel in the i^{th} layer of the pyramid is the sum of a 7x7 pixel swatch from the preceding layer. The swatches do not overlap, so that each layer is reduced in size by a factor of $\frac{1}{49}$. Three layers are constructed.

The maximum pixel in the top layer is likely to represent a cluster of highly interesting pixels in all previous layers. Therefore, to determine the focus of interest in any given view the maximum pixel is selected in the top view, and traced back to the base image by selecting the maximum of all contributing pixels in each subsequent layer.

Finally a swatch of radius 10 pixels is taken from the interest image around the selected pixel. The normalised sum of all pixels in the swatch is taken as an overall measure of interest in the image.

2) *Compile list of target positions for ‘visual search’*: Stage 1 produced the OSPL. The candidates associated with the top ranking targets are the most likely to be odour sources.

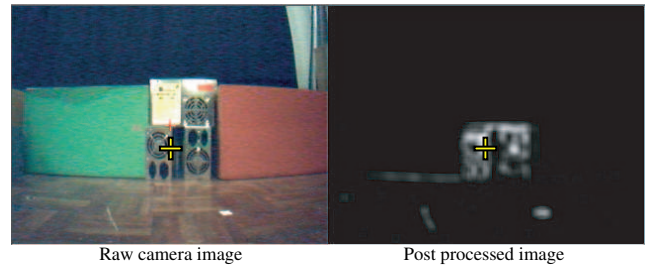


Fig. 2. Robot’s view. The cross shows the point of maximum interest.

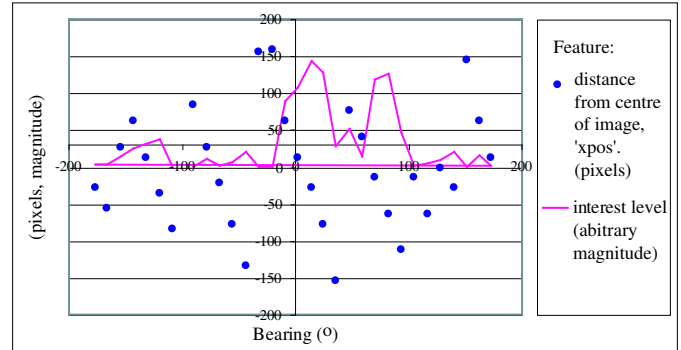


Fig. 3. Data regarding visual features recorded during ‘Look Around’.

The areas where they occur is visually searched. While none has been found, the process is repeated for each target with medium to high confidence levels, in order of highest to lowest measured chemical concentration.

In order to visually search the candidates for a target, the robot moves to the centre of the sector. This is considered to be the best vantage point from which to see the candidates that sourced the sector. However, this is not always the case. There can be a source that is remote from, but near a flow that carries it to, a sector. The source will therefore not be visible from the robot’s position. However, we predict that in every case, odour will also fill other sectors that will then be visited. Another caveat is that the odour source may be occluded if located on the far side of an obstacle. These issues could be overcome with more advanced path planning. We designed the behaviour to work on our test conditions to demonstrate the approach. A more complex path around the sector based on visibility (e.g [18]) could ensure that all possible source locations are visually examined.

3) *Look Around*: The robot rotates 360° in 12° increments, looking for an odour source. At each bearing, the image is analysed, looking for the most interesting feature. The position of the feature in the image (with respect to the centre of the image) as well as the interest level are recorded. They are plotted against bearing in Fig. 3. As the robot rotates, visual features enter the field of view and progressively move across the image with each rotational increment. Due to the clockwise rotation, this results in lines with a negative gradient and an x intercept equal to the bearing at which the robot is directly facing the feature.

In order to isolate potential odour sources from other features, only those with an interest level above 35 are considered (the threshold is shown in Fig. 3). The points are clustered into segments, where each segment corresponds to one visual feature, using a simple type of ‘distance’ classifier/clusterer.

The classifier exploits the inherent ordering of the points. It cycles through them sequentially, testing against the distance conditions given in equations (1) and (2). If they are satisfied, then the point is added to the current cluster, otherwise a new cluster is formed. Distance is calculated in a circular sense, avoiding problems that arise from the artificial discontinuity in θ . The clusters are ignored if they consist of less than 3 points, which accounts for the minimum expectation given the lens angle and arena size, and adequately tolerates inclusion/exclusion of spurious points due to noise. Then, for each cluster, linear regression is used to identify straight line segments. In reality, the data fit a \tan graph, however in the range of bearings where the feature is in the field of view, the data is approximated well by a line.

$$|xpos_j - xpos_i| \geq xpos_{thresh} \quad (1)$$

$$|\theta_j - \theta_i| \geq \theta_{thresh} \quad (2)$$

Where the current point is denoted by i , and the previous point that was assigned to this cluster is j .

4) *Validate visual features - identify OSS*: The bearings to visually identified odour sources have been extracted from the ‘visual search’. In order to work out if they could have given rise to the chemical concentrations measured, thereby making them Odour Source Suspects (OSS), they are matched with the candidates extracted from the ‘chemical search’ using the procedure shown in pseudocode in Fig. 4.

5) *Home In*: Visual servoing to the target location is carried out using a procedure shown in the pseudocode in Fig. 4.

<pre>repeat { - cycle through candidates associated with the current target location. if (looking in direction of candidate) - this is OSS, home in on it else - disregard } until (no more candidates)</pre> <p style="text-align: center;">(a) Identify OSS</p>	<pre>repeat { - move forward by 20cm if (visual interest is left of centre) - turn 10° ACW else if (visual interest is right of centre) - turn 10° CW } until (bump into target)</pre> <p style="text-align: center;">(b) Home In</p>
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Fig. 4. Pseudocode for ‘Identify OSS’ and ‘Home In’

III. EXPERIMENTAL SETUP

A. Robot and Environment

The wheeled mobile robot measured approximately 260mm in diameter and 150mm in height. It was equipped with a Figaro TGS2600 tin oxide chemical sensor and visual sensing hardware described in II-D.1. The robot was controlled by an on-board microprocessor (motor control and data acquisition) and a program running on a PC, communicating via radio modem. Robot behaviour was controlled using a Subsumption architecture implemented with the SubsuMeLib library (<http://sourceforge.net/>

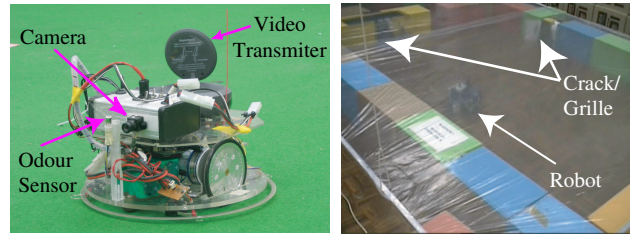


Fig. 5. The robot and arena.

projects/subsumelib). The enclosed environment was constructed with reconfigurable boxes and a ceiling consisting of an aluminium frame, plastic sheeting, and which was suspended from the exterior ceiling (of the larger room that contained the experimental setup). It was rectangular and measured 2100mm x 2900mm and with a height of 280mm. Objects were created with boxes of the same height as the ceiling. An airflow was introduced with an array of DC fans. The odour source was created by injecting ethanol vapour into the environment at 0.5 ml/min from a crack/grille. The robot and environment are shown in Fig. 5.

IV. RESULTS AND DISCUSSION

The system was tested experimentally twice for each of three diverse scenarios. The following parameters were varied: The airflow pattern, number of airflow sectors, robot origin, odour source location and potential odour source (crack/grille) location (variable position on both walls and objects).

The results are illustrated in Fig. 6. The robot’s trajectory is shown with a solid black line for the first trial, and a grey dashed line for the second (the latter is not visible if superimposed directly over the former). Time labels, t_n , show the order of events along the trajectory. Start positions are indicated with an open circle and termination positions with a smaller solid circle. The sectors of airflow computed by the NaReM are shown with grey dotted lines. The odour source is labelled.

The locations compiled for Stage 1 are labelled with Target n . In every case, the robot moved to each of these positions before returning to the position in which it measured the highest chemical concentration. At that point it rotated 360° and homed in on the visual target that would result in odour filling the sector where it was measured. In every case, the robot successfully homed in on the actual odour source.

V. CONCLUSIONS AND FUTURE WORK

This paper reports experimental results for a method that achieves odour localisation in enclosed spaces for the first time. This has been made possible by augmenting a search based on chemical sensing, airflow modelling, and reasoning, that can only be non-specific in this environment, due to the way the chemical disperses across a large area. The extension consists of a second search stage employing visual sensing. The robot is able to ‘home in’ on the odour source very specifically. The technique was successful for three varied

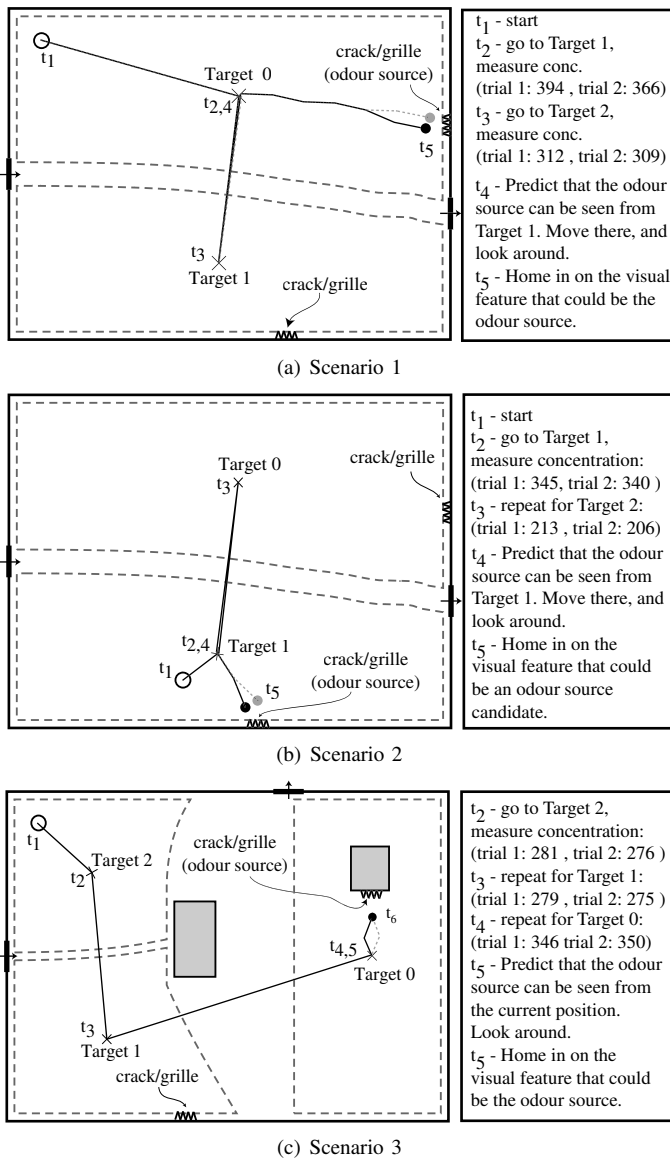


Fig. 6. Odour search illustrated.

scenarios. In these scenarios, the odour source could have been at any position in the area, and there was more than one site (crack/grille) that could be identified visually as a potential odour source.

The total solution comprises a two-stage, bi-modal search using complementary sensing. It could not be successful with either search stage alone. Chemical sensing is not adequately specific, and the search space is too large for vision alone, as it may include visual features that are not the odour source, and covers a large area with occlusions. This searching strategy represents many other situations, where a uni-modal search would be ineffective or impossible. Often it is necessary to use one or a set of sensors to perform a general search reducing the search space, followed by a specific search that takes place using another set of sensors.

Future work will involve more sophisticated path planning

to explore areas that may contain the odour source, but are occluded when traversing a straightforward path. In addition, the robot's behaviour will be extended to resolve more than one Odour Source Suspect, which is not straightforward, as the odour source itself may not be a local maximum in terms of odour concentration. The work could be further enhanced by sealing the potentially toxic leak with a surrounding wall built by a robotic swarm [19].

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