

How Active Vision Facilitates Familiarity-Based Homing

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The ability of insects to visually navigate long routes to their nest has provided inspiration to engineers seeking to emulate their robust performance with limited resources [1-2]. Many models have been developed based on the elegant snapshot idea: remember what the world looks like from your goal and subsequently move to make your current view more like your memory [3]. In the majority of these models, a single view is stored at a goal location and acts as a form of visual attractor to that position (for review see [4]). Recently however, inspired by the behaviour of ants and the difficulties in extending traditional snapshot models to routes [5], we have proposed a new navigation model [6-7]. In this model, rather than using views to recall directions to the place that they were stored, views are used to recall the direction of facing or movement (identical for a forward-facing ant) at the place the view was stored. To navigate, the agent scans the world by rotating and thus actively finds the most familiar view, a behavior observed in Australian desert ants. Rather than recognise a place, the action to take at that place is specified by a familiar view.

Such familiarity-based navigation is well-suited to navigating along a route where the ant generally travels in a small range of directions ($\sim 45^\circ$, say). It seems less well-suited, however, to locating a specific goal location (food or nest) which must be approached from any direction. In [7-8] we showed that place search could be achieved with a familiarity-based mechanism if a learning walk – an active sensing strategy composed of stereotypical movements made by ants when they first leave the goal and used to scaffold visual learning of the goal position - is added to the training route. To add more weight to this idea, we wanted to show that the combination of active vision with our familiarity mechanism could replicate ants' behaviour in a classic experiment used as evidence for an attractor-type snapshot. To this end, we replicated the experiment of Wehner et al [9] in which ants were trained to find food in the centre of three landmarks. During tests with food removed, ants' search distributions are recorded with landmarks in either their original positions at twice the distance, or at twice the distance with landmarks of twice the size (Fig. 1 A-C). This experiment has been used to support the idea that a single snapshot is used for homing as the view of the surroundings from the goal in A matches that from the goal in C, but not B, and the search distribution of ants is the same in A and C, but not B.

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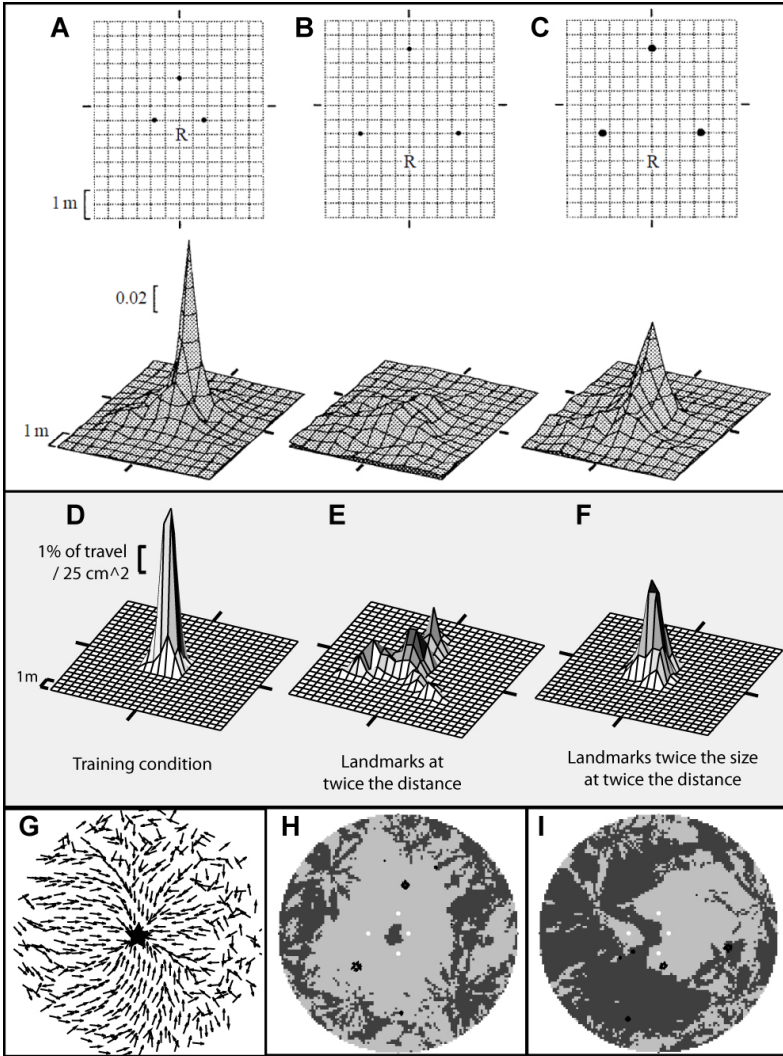


Fig. 1. (A–C): The experimental setup and search densities of homing ants from Wehner et al., [9] in training condition (A), with 20cm high cylinders at twice the distance (B) and with cylinders twice the size and at twice the distance (C). Food position in training indicated by cross-hairs. (D–F): Search density profiles from the model in training condition (D), with cylinders at twice the distance (E) and with cylinders twice the size and at twice the distance (F). Search densities are collected for 24 ‘ants’ after 10m of search starting at random positions. (G–I): Homing performance of the algorithm in two environments with four training views in the same positions (white dots in H and I) oriented toward the goal (star in G). (G) Arrows show direction of movement in environment 1. (H, I) To illustrate homing difference between environments 1 (H) and 2 (I), we coloured regions where homing error was less/greater than (an arbitrary threshold of) 45° in light/dark grey. Black objects are randomly generated grass tussocks (height in the range [20-50] cm). Each environment is 12m in diameter and there are a variety of objects outside this region. A-F adapted from [10] with permission.

However, the same search distributions can be achieved by an agent navigating with a familiarity-based model using training views oriented towards the food, but crucially, *not* at the food location itself (Fig 1. D-F and [10]). During a learning phase, the views are used to train a network so that it subsequently outputs a measure of the familiarity of any view input to it. Navigation then proceeds iteratively, by an agent scanning the world from -90° to $+90^\circ$ around the previous heading in 1° steps and moving 1cm in the direction specified by the most familiar view found across the scan. Search distributions recovered are similar to those in [9] showing that familiarity-based navigation can explain the observed behavior (Fig. 1 D-F). See [10] for full description of this and another behavioural experiment replicated with this algorithm.

In the above, the location of training views are based on a learning walk of the ant *Ocymyrmex* [11]. However, we next ask whether the learning walk, and by extension the training view locations, are adapted to the environment or whether there is a set of training view locations relative to the goal suited to all environments. To test this we examined navigation in two simulated environments using training views from the same four locations oriented towards the goal. Heading directions are derived by rotating the current view through 360° in 1° steps and finding the orientation which best matches each training view. The resultant heading is a weighted average based on closeness of match to each training view. While performance is good in both environments, the pattern of success and failure is different suggesting that training view positions and thus learning walk shape should be adapted to the environment.

Insect navigation has long been a source of elegant solutions for complex engineering tasks. Here we show how a parsimonious algorithm actively produces robust homing. The key for engineering and biology is to further understand how active processes underpinning visual learning and navigation are shaped by the environment.

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