DOI: http://dx.doi.org/10.7551/978-0-262-31709-2-ch150

A Situated and Embodied Model of Ant Route Navigation

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Abstract

This abstract summarises a model of route navigation inspired by the behaviour of ants presented fully in Baddeley et al. (2012). The ant's embodiment coupled with an innate scanning behaviour means that robust route navigation can be achieved by a parsimonious biologically plausible algorithm.

The ability of social insects to learn long foraging routes guided by visual information (Wehner, 2009) shows that robust spatial behaviour can be produced with limited neural resources (Chittka and Skorupski, 2011). As such, social insects have become an important model system for understanding the minimal cognitive requirements for navigation and, more generally those studying animal cognition using a bottom-up approach to the understanding of natural intelligence (Wehner, 2009, Shettleworth, 2010) while also providing inspiration for biomimetic engineers. Models of visual navigation that have been successful in replicating place homing are dominated by snapshot-type models where a single view of the world as memorized from the goal location is compared to the current view in order to drive a search for the goal (Cartwright and Collet, 1983; for review, see Möller and Vardy, 2006). Snapshot approaches only allow for navigation in the immediate vicinity of the goal however, and do not achieve robust route navigation over longer distances (Smith et al., 2007). Here we present an embodied parsimonious model of visually guided route learning that addresses these issues (Baddeley et al., 2012). By utilising the interaction of sensori-motor constraints and observed innate behaviours we show that it is possible to produce robust behaviour using a learnt holistic representation of a route. Furthermore, we show that the model captures the known properties of route navigation in desert ants.

Our navigation algorithm consists of two phases (see Baddeley et al., 2012, for details). The agent first traverses the route in 4cm steps with direction determined by a combination of noisy path integration (PI; true heading plus Gaussian noise, mean 0, s.d. 5^o) and obstacle avoidance, during which the training views used to learn the route are experienced (a view is used after every 4cm step). In some experiments, a predefined learning walk is added to the start of the training path with training views taken every 2cm. To navigate, the agent visually scans the world by rotating on the spot through $\pm 90^o$ of the current heading in 1^o steps, behaviour similar to that observed in ants (P. Graham, *Personal Observation*). The most familiar direction during the scan is identified by inputting each view into an artificial neural network (ANN) trained to perform familiarity discrimination using the training views. Views are panoramic in azimuth and cover 68^o of elevation above the horizon. Acuity is 4^o meaning views are 90x17. The ANN is fully connected with 90x17 (one per pixel) inputs and outputs and no hidden layer. Weights are adjusted once per training view using an Infomax learning rule, with training views then discarded. The algorithm thus 'learns' routes after a single journey and memory load does not scale with route length. After training, the ANN outputs a familiarity score for each view input during a scan. Gaussian noise (mean 0, s.d. 15^o) is added to the direction associated with the most familiar view, a 10cm step is made in this directoin, and the scanning routine repeats, until within 4cm of the goal or timed out.

We test our route navigation by learning a series of routes through visually cluttered environments consisting of objects distinguishable only as silhouettes against the sky. The model's performance is shown in figure 1. The model is able to learn idiosyncratic routes after a single training run (fig. 1A). As with ants, the routes show clear polarity and can only be traversed from start to goal. While successful for route navigation, if the agent misses the goal, it will typically continue in a direction similar to the last steps of the training route (fig. 1B) rather than search for it. To learn how to return to a specific goal location from nearby local surrounding regions, some ants perform a learning walk consisting of several loops out and back towards the goal when they first leave it. Adding such a walk to the training path means that when the agents nears or passes the goal, familiar directions are set by views experienced during the learning walk and draw the agent to the goal (fig. 1C). The model thus exhibits both place-search and route navigation with one mechanism. The model also learns multiple idiosyncratic routes to a goal (Fig. 1D-E). Here, three different routes are used but encoded within the same network which does not separate routes into distinct paths but stores all the information holistically. Given this performance, we believe our model represents the only detailed and complete model of insect route guidance to date.

Our approach is differentiated from previous attempts to understand route navigation in insects in several ways. 1) Navigation is independent of odometric or compass information. Unlike most snapshot-type models, training views are used as they are experienced, and are not rotated into common orientation before use. 2) The algorithm does not specify when or what to learn, but uses all views experienced during training. 3) Training views are not discrete waypoints. Previous route navigation algorithms navigate from one waypoint to another in a sequence, meaning one needs to know which waypoint is being used. Here, we do not navigate to each training view. Rather training views recall familiar directions not discrete places and are used to learn a holistic representation of the route; this representation says "What should I do?" not "Where am I?". This means that 4) navigation proceeds through a simple embodied strategy of rotating on the spot – a behaviour observed in navigating ants – and moving in the most familiar direction.

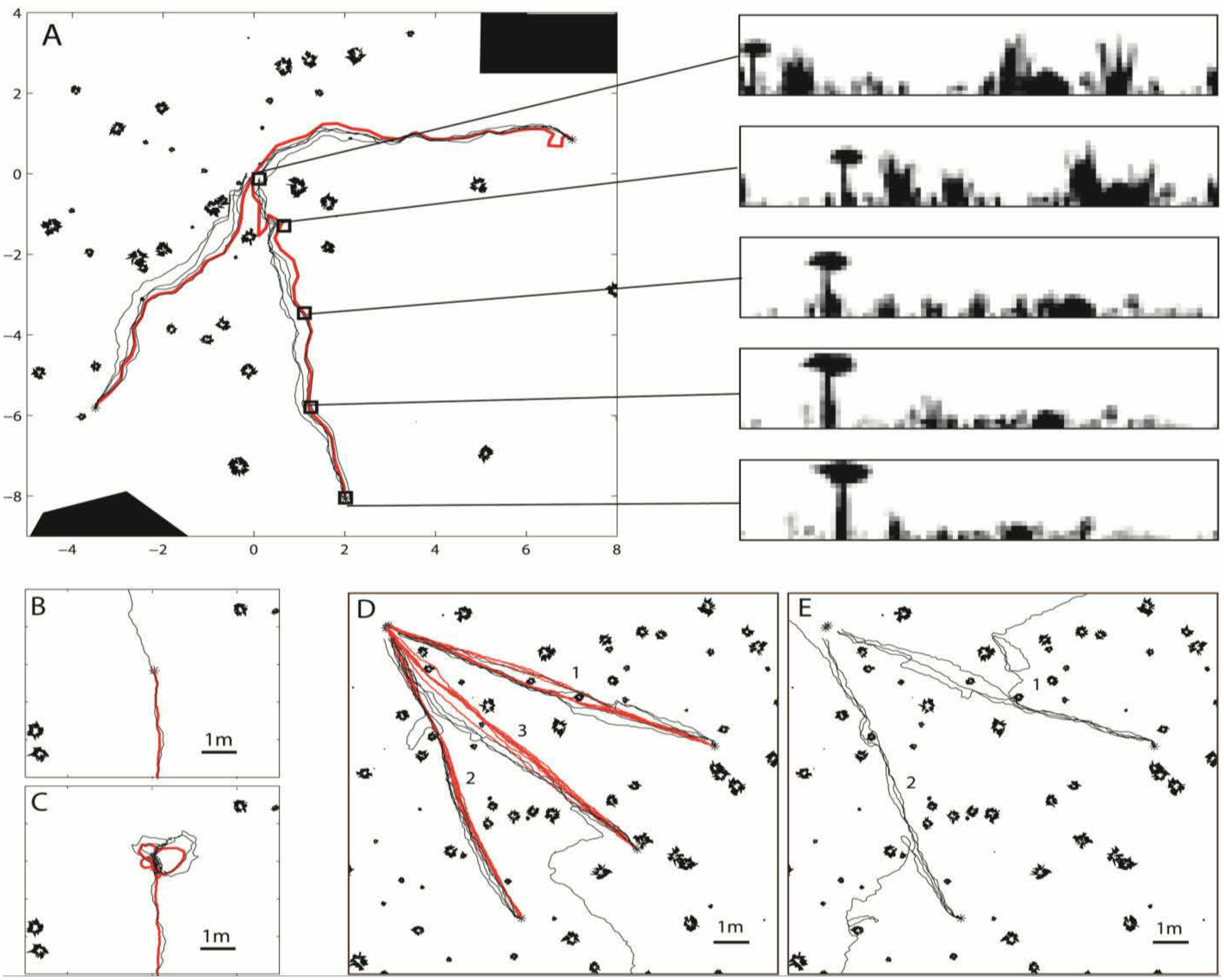

Figure 1: Route navigation with an embodied holistic model. The simulated world is viewed from above and is comprised mainly of small tussocks and a few larger more distant objects (trees and bushes). In all panels, red lines are training paths, black lines recapitulations. **A:** Successful return paths for three different routes. The panels to the right show example views covering 360^ox68^o with 4^o acuity from points along the training route (squares). **B-C:** Including learning walks prevents return paths from overshooting the goal. B) Without a learning walk the simulated ant overshoots and carries on in the direction it was heading as it approached the nest location. C) By including the views experienced during a learning walk the simulated ant, instead of overshooting, gets repeatedly drawn back to the location of the nest. **D-E:** Learning multiple routes. D) Route recapitulation performance (black lines) for each of three routes (red lines) that are learned with the same network. Testing of each of the routes is performed immediately following training on that route and prior to experience of other routes. Numbers by training routes show order in which routes were learnt. E) Performance on first two routes following learning of all routes, indicating that the route knowledge gained during the first two phases of learning is retained. Having learnt all 3 routes the network encodes 30m of route information.

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