# Insect-Inspired Visual Navigation On-Board Autonomous Robots 

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Fig 1 Autonomous visual route navigation. A: Training (red) and test (grey) paths through a simulation of desert ant habitats. Images from one training route, down-sampled to ant-resolution, are shown in the right panel. Adapted from [3]. B: Test environment for the autonomous robot C: Training (blue) and navigated paths (other colours) of autonomous robot in the environment shown in B. B-C adapted from [7].

Small-brained insects are expert at many tasks that are currently difficult for robots especially in dealing with real-world, dynamic environments. In particular, the speed and robustness of insect learning is in stark contrast to many AI methods which take long times to train and require large amounts of labelled data. For example, the desert ant, Melophoros bagoti, is a champion navigator, able to visually navigate routes of up to 100 m through complex habitats [1] with a performance far above current map-based methods such as SLAM (simultaneous localization and mapping). Remarkably, these ants are able to learn the information needed to visually navigate 10 's of metres after only a single exposure to the route information [2]. They achieve this feat despite brains of only $\sim 500,000$ neurons and a kilo-pixel visual system (see Fig 1A for examples of low-resolution images), and this makes them ideal inspiration for engineers seeking to design resource-light control algorithms for small robots whose size makes power efficiency paramount [1]. In this spirit, we have developed a visual route navigation algorithm which replicates many aspects of ant navigation with biologically plausible computation and memory requirements (Fig 1A and [3-4]). These resource constraints mean first, that our algorithms can be used on-board fully autonomous small robots, and second, that they are amenable to swarm robotic approaches.

To understand how ants visually navigate so successfully, we have combined behavioural experiments with modelling and robotics to show how ants directly acquire and use task-specific information through specialised sensors, brains and behaviours, enabling complex behaviour to emerge without complex processing. This has lead us to an algorithm in which visual information specifies actions not locations in which route navigation is recast as a search for familiar views allowing routes through visually complex worlds to be encoded by a single layer artificial neural network (ANN) after a single training run with only low resolution vision [3]. Importantly, using views to specify actions rather than locations means that the agent - insect or robot - navigates without recognizing places (as would be needed in a map-based approach) and thus without ever knowing where it is. In addition, removing localization means that the agent does not need to specify when or what it should learn but can acquire training views continuously and without processing images to recognise specific objects.

The algorithm proceeds as follows: the agent equipped with a low-resolution $360^{\circ}$ panoramic visual sensor first travels a route. The views experienced along this route - crucially specified by both the agent's positions and headings (poses) -
are used to sequentially train ANN which learns a holistic representation of the views encountered. Subsequently, the network is used to estimate whether a given view - and thus a pose - has been experienced before (with a confidence measure). When trying to repeat the route, the agent derives a direction of movement at a position by visually scanning the environment (either by physically rotating - a behaviour seen in ants [5] - or rotating the view in silica). Each rotated current view is input to the ANN which outputs an estimate of the familiarity of each view and, thus, each heading. The agent then moves in the direction most similar to the views encountered during learning, according to the confidence measure.

Typical routes through a simulation of the ant's natural habitat driven by visual information only can be seen in Fig 1A. Notice that the images input to the network are low resolution but wide-field (Fig 1A, right side). While the reduction of resolution is beneficial in terms of reducing memory and computational requirements, we have also previously shown that these properties, which are produced by the constraints of the ant's visual system, are actually beneficial for visual navigation [6]. We next demonstrate that this algorithm, with all computation performed on a small low-power robot, is capable of delivering reliable direction information along outdoor routes, even when scenes contain few local landmarks and have high-levels of noise (from variable lighting and terrain) (Fig 1B-C and [7]). Indeed, routes can be precisely recapitulated and the use of an ANN encoding means that the required computation does not increase with the number of training views. Thus the ANN provides a compact representation of the knowledge needed to traverse a route. In fact, rather than the compact representation losing information, there are instances where the use of an ANN ameliorates the problems of sub optimal paths caused by tortuous training routes. Our results suggest the feasibility of familiarity-based navigation for long-range autonomous visual homing.

Finally, we believe that a vital component of future robotics development is to leverage the power of swarms of heterogeneous robot teams. However, how information can be usefully shared and combined between robots remains an open question. As the route knowledge in our algorithms is encoded in the weights of an ANN, it can be easily transmitted between robots making swarm robotic applications eminently possible. However, to be useful, the information needs to be encoded in such a way that it is independent of that particular robot's morphology and movements (i.e. its embodiment and situatedness) and knowledge also needs to be carefully combined from multiple robots. We are thus developing both visual processing and route encoding parts of our algorithms for heterogeneous robot teams, allowing them to efficiently explore and visually navigate large areas by sharing knowledge, despite differing perspectives, and thus take advantage of their different capabilities. For instance, a flying robot can rapidly survey an area, identify a target and pass the knowledge needed to reach that target to slower-moving, but higher payload, wheeled robots. While animals encode route knowledge efficiently they are limited in their ability to communicate it. We therefore aim to go beyond animal capabilities by developing perspective independent route encodings, route communication, and collective exploration and navigation algorithms.

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