Ant-Inspired Navigation In Unknown Environments

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In contrast to most other ant species, desert ants (*Cataglyphis fortis*) do *not* use pheromones to mark their path. When returning from a foraging trip to their nest they navigate both by path integration and by visual landmarks. An egocentric navigation system based on path integration alone suffers from two major pitfalls: 1. It must run uninterrupted as long as the animal moves and 2. It is inherently susceptible to cumulative navigation errors. Hence, if the animal visited an area repeatedly, it is advantageous to take an occasional positional fix by acquiring landmark-based geocentered (alocentric) information. Indeed desert ants and honeybees use such information in addition to path integration. On a familiar route, when ants can steer by visual landmarks, they adopt a fixed and often circuitous path consisting of several separate segments that point in different directions. Such multi-segment journeys are composed partly of stored local movement vectors, which are associated with landmarks and are recalled at the appropriate place.

During the experiments reported in [4] and [1], ants collected right before entering their nest after a foraging trip are deprived of their **global vector**[1]. When these ants were placed at points along their familiar route, they were able to use previously seen visual features in order to return to their nest. It is believed [1], that two dimensional visual snapshots of landmarks along the homing path are stored in the memory of the ants and upon recognition they trigger a **local vector** that describes the transition to the next landmark on the way to the nest. These local vectors are also calculated based on odometry. They are links that point towards the direction of the next landmark along the path and are proportional to the distance between consecutive locations. Due to their limited length compared to the global vector the local transitions are more precisely learned and reproduced during foraging trips.

The vision-based (local) navigation in ants works in parallel with global navigation. In order to ensure that an alternative navigation mechanism is available, desert ants use landmark-based navigation as the main method along familiar paths. They resort to global navigation only if the former fails, that is if in a dynamic environment landmarks are missing or are being occluded by new ones. If one of

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[1]This is the vector that is calculated through path integration. It originates at the ant's position and points towards the nest.

the anticipated landmarks does not appear at the expected location, the ant steers towards the next one along its path. The position of the new target location is determined by the combination of two consecutive local vectors. In cases where most of the expected landmarks along the path cannot be found, the landmark-based navigation becomes untrustworthy and the ant switches to global navigation. That is, it continues on a straight line that connects its current position to the nest (Figure 1).

On the other hand, if the global vector calculation is interrupted, e.g., due to sudden relocation of the ant, a search strategy is introduced in order to discover some of the stored landmarks and recover from the loss of the global positioning information. After the first known landmark is found, the ant continues along its familiar trip to its nest. The combination of the two navigation mechanism, namely local (visual landmark-based) and global (odometry-based) navigation results in increased reliability even along paths thousands of times larger relative to the length of an ant.

During path integration two types of information are continuously being measured by the ant: angles steered and distances covered. Skylight information provides **absolute orientation** information. To estimate **distances traveled**, desert ants use self-induced retinal image flow [3]. The orientation information along with the distances covered are combined to synthesize the local or global transitional vectors. The exact mechanism that ants use for learning **landmarks** is yet to be discovered. It is believed that retinotopically fixed snapshots of the visual cues are stored in the memory of an ant and then compared and matched to the current retinal image. A match indicates a learned landmark location and allows the ant to steer towards the next feature along its path. The contribution of the visual information to the navigation task is that landmarks can be learned and distinguished and therefore used in a chain formation linking the nest to a foraging area.

Instead of trying to replicate the sensing mechanisms of an ant, we intend to model their functionality within the navigation task. In order to calculate the angles steered by a robot in an outdoors scenario, a magnetic compass can provide **absolute orientation** with respect to the magnetic field of the earth instead of the polarization vectors of the light of the sun. In a similar fashion, a robot equipped with exteroceptive sensors such as a laser scanner can detect straight line segments inside a building and thus consider their orientation (at least within a small area) as an absolute orientation measurement. Wheel encoder signals can be used for continuously calculating **distances traveled**. The resulting vector can either be the global vector pointing towards the initial location or a local vector determining the direction and distance of the previously visited known location. The remaining navigational functionality is the detection and recognition of **landmarks**. In principle it should not make any difference if the landmarks detected and memorized are visual or not. Any type of sensor that can detect a gradient of any identity of the area could be
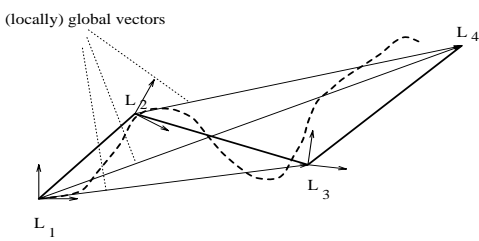
Figure 1: Integration of consecutive local maps to a global representation.

Figure 2: The local vector that connects landmark L_n to L_{n+1} is calculated as $L_n L_{n+1} = \vec{s}_1 + \vec{s}_1 + \vec{s}_3$ where $\vec{s}_2$ is calculated by the odometry and $\vec{s}_1$ and $\vec{s}_3$ are determined by the exteroceptive sensors.

Figure 3: The dual navigation strategy using local and locally global representations.

used to mark an area as different from at least its immediate surroundings [2]

In the proposed navigation mechanism, a robot has to construct, update, and augment a topological map of the traveled regions of the environment containing the local transition vectors between detected landmarks. More precisely, this map would be a collection of many consecutive 1-to-1 relative maps, each of them containing two neighboring landmarks along the robot's path. The information related to each of these 1-to-1 maps is the type of the two features contained and their relative position $(\Delta x, \Delta y)$ and orientation $\Delta \phi$ vector $\vec{\Delta \mathbf{x}} = [\Delta x, \Delta y, \Delta \phi]^T$. The types of the landmarks are determined by the exteroceptive sensors that the robot is using and the vector $\vec{\Delta \mathbf{x}}$ is calculated primarily by integrating the motion information provided by the proprioceptive sensors (Figure 2). No previous knowledge of the spatial layout of the environment is required. As depicted in Figure 1, a compiled global map of the environment can be derived by "stitching" together all these relative maps using the common landmarks as the connecting points and requiring that each has the same orientation when it is being incorporated in each of the maps that contain it.

As the robot moves in unexplored areas, the topological description is augmented to include new links (1-to-1 maps) to newly discovered landmarks (Figure 1). As the total distance from the initial position of the robot increases, the precision of the global vector calculated by summing the local vectors decreases. For example, in the case of a simple global map that contains 3 consecutive positions A, B, C, the overall uncertainty related to the direct transition between A and C: $\vec{AC} = \vec{AB} + \vec{AC}$ would be: $P_{\vec{AC}} = P_{\vec{AB}} + P_{\vec{BC}}$ where $P_{\vec{AC}}, P_{\vec{AB}}, P_{\vec{BC}}$ are the covariance matrices of each of these vectors that describe the corresponding uncertainty ellipsoids associated with each of these transitions. Covariance matrices are positive definite and thus the covariance of the total transition, i.e., the size of the overall uncertainty ellipsoid, is monotonically increasing with the number of nodes added to the path. Therefore the quality of the global vector decreases as the robot moves towards the outskirts of the explored area. The dimensions of the overall ellipsoid determine the size of the area that the robot will have to search in order to find C, having started from A.

Ants also suffer from error accumulation during the calculation of their homing (global) vector when landmark information is not available and they have to servo on their global vector. The result is that at the end of their trip they have to employ search patterns in order to determine the exact location of the nest. If landmarks are found along the path, ants depend predominantly on local transitions between those landmarks in order to find their way towards the nest. They resort to **locally-global vector** (the vector from landmark A to C if landmark B cannot be found) navigation if some or all of the anticipated landmarks are missing (see Figure 3). We apply the same methodology to the case of a mobile robot constructing and navigating in an ant-inspired map of its environment. As in the previous example the robot is commanded to move from A to C. Initially it has to navigate
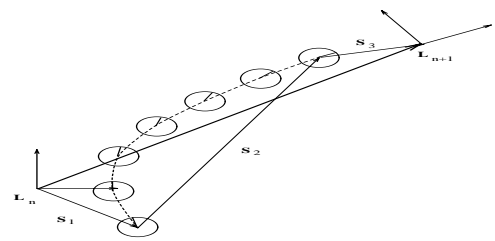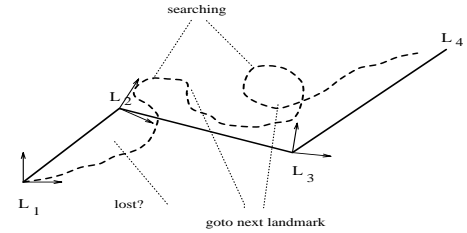
using the local representation (transition $A \to B$ and then $B \to C$) and if it cannot find landmark B it steers towards the direction of C. Let us assume that $\vec{AB} = \vec{BC}$ and thus the probability that the robot will successfully make each of these transitions is equal: $Pr(A \to B) = Pr(B \to C) = p_1$ while the direct transition from A to C has probability of success $Pr(A \to C) = p_2 < p_1$ due to the increased uncertainty. Then the overall probability for successfully moving from A to C using the ant-inspired navigation algorithm is: $Pr(A \to C) = Pr(A \to B)Pr(B \to C) + (1 - Pr(A \to B))Pr(A \to C) > Pr(A \to B)Pr(B \to C)$ where $Pr(A \to B)Pr(B \to C)$ is the probability of success if only local navigation is involved, and $Pr(A \to C) = Pr(A \to C) + Pr(A \to B)(Pr(A \to B) - Pr(A \to C)) > Pr(A \to C)$ where $Pr(A \to C)$ is the probability of success if only global navigation is involved. Results similar to the ones given by the previous two equations can be derived for trajectories that combine more than one via point between an initial and a final location that the robot has to navigate. Since the dual navigation algorithm increases the probability of a successful multisegment transition, the overall reliability of the navigation algorithm is increased. We are in the process of implementing and evaluating this algorithm on a mobile robot.

1. REFERENCES

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