A Polar Neural Map for Mobile Robot Navigation

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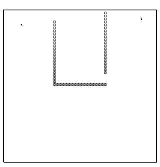
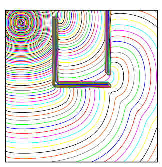
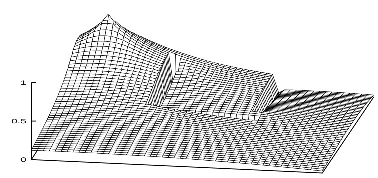
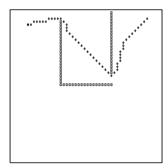
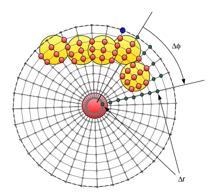
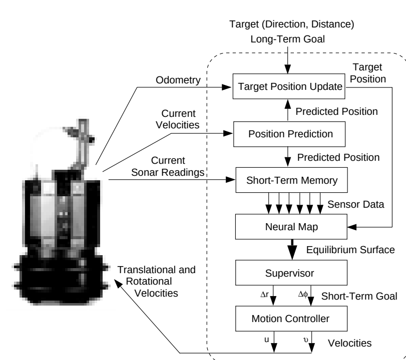
Potential fields methods resemble a large class of methods for mobile robot navigation. Within this class, navigation is defined as the process of following the maximum gradient of some quantity in the environment. Such methods are in use by both animals and humans; e.g. a planarian reaches a food source by testing the water and moving toward the direction where chemical stimulation increases. For robots, this is accomplished by building a model of the environment, simulating the diffusion of the stimulus from the target position, determining the maximum gradient direction at the present position, and finally moving the robot.

Traditional models for potential fileds include electrostatic fields, harmonic functions, distance transform and wavefront propagation. Neural maps have been recently proposed as an alternative solution[1]. Information about the environment is mapped on a topologically ordered neural population. The diffusion dynamics force the system into a unique equilibrium state. The stable pattern formed by the neuronal activations defines the navigation landscape for the given target. A path from any initial position to the target (corresponding to the peak of the activation surface) is derived by a simple hill-climbing (steepest ascent) procedure. The four figures below show an example on a 50×50 rectangular map.

We attempted to implement the approach on a Nomad 200 mobile robot for sonar-based navigation. However, we found that the neural map requires reorganization in a polar topology that reflects the distribution of the sonar data points, the only source of information about the environment. The polar map covers the local egocentric circular area around the robot. At each step, the map is used to derive the angular and radial displacement required to reach the target from the current configuration (see last figure above). Sensor uncertainty and noise is handled by a sonar short-term memory and appropriate mapping. Motion control is based on an optimization procedure that accounts for the kinematic and dynamic constraints of the robot. One can think of the polar map as the working memory of the robot, whereby local (spatially and temporally) information is recorded and processed. The complete architecture of the resulting local (sensor-based) navigation system is shown below.



Our implementation was able to successfully navigate the robot in indoor environments with several obstacles and walking people. Our conclusion is that neural maps for navigation perform better when optimized for the situation at hand. Allowing also for self-organization might make the system dynamically adaptive.

Further, motivation for future work results from some analogies with the human vision system. The polar neural map would be the retina-fovea of some "eye" looking at some image (environment). Environment learning could probably be accomplished by a process similar to image memorization; by storing chains of sensor-motor associations (in analog to eye saccades). Localization would be analog to image recognition and way finding might be similar to the way people solve visually maze problems.

[1] R. Glasius et al. "Neural Network Dynamics for Path Planning and Obstacle Avoidance," *Neural Networks*, **8**, 1, 1995, pp. 549-563.