

Robot Navigation with a Polar Neural Map

Michail G. Lagoudakis*

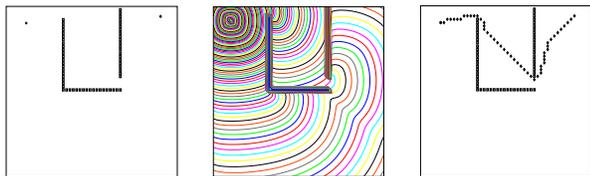
Department of Computer Science
 Duke University
 Durham, NC 27708
 mgl@cs.duke.edu

Anthony S. Maida

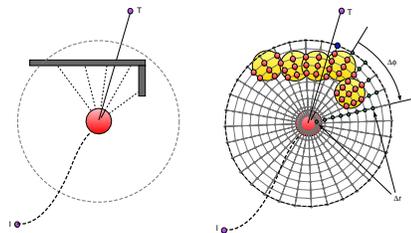
Center for Advanced Computer Studies
 University of Southwestern Louisiana
 Lafayette, LA 70504
 maida@cacs.usl.edu

Neural maps have been recently proposed as an alternative method for mobile robot path planning (Glasius, Komoda, and Gielen 1995). However, these proposals are mostly theoretical and are primarily concerned with biological plausibility. Our purpose is to investigate their applicability on real robots.

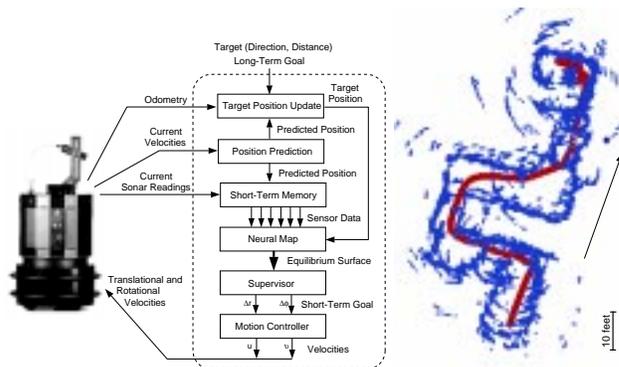
Information about the environment is mapped on a topologically ordered neural population. The diffusion dynamics force the network into a unique equilibrium state that defines the navigation landscape for the given target. A path from any initial position to the target (corresponding to the peak of the activation surface) is derived by a steepest ascent procedure. The figures below show an example on a 50 × 50 rectangular map (a. Environment, b. Contours of activation, c. Path).



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 circular area around at the robot. Sonar data points are mapped scaled to the physical robot size. At each step of the control loop, the dynamics of the map is used to derive the angular and radial displacement required to reach the target from the current configuration. A simplified example is shown below (bird's eye view). Sensor uncertainty and noise is handled by a sonar short-term memory and appropriate coordinate mapping for reuse. Motion control is based on an optimization procedure that combines ideas from Fox, Burgard, and Thrun (1997) and Hong et al (1996), and takes into account the kinematic and dynamic constraints of the robot. The complete architecture of the resulting local (sensor-based) navigation system is shown below.



The system was tested in both simulated and real world (office) environments (see figure). It was able to successfully navigate avoiding static and dynamic obstacles. Complete description of the system as well as information on how it can be used for global navigation can be found in (Lagoudakis 1998).



References

Fox, D.; Burgard, W.; and Thrun, S. 1997. The Dynamic Window Approach to Collision Avoidance. *IEEE Journal of Robotics and Automation* 4(1):23–33.

Glasius, R.; Komoda, A.; and Gielen, S. 1995. Neural Network Dynamics for Path Planning and Obstacle Avoidance. *Neural Networks* 8(1):125–133.

Hong, S.; Kim, S.; Park, K.; and Lee, J. 1996. Local Motion Planner for Nonholonomic Mobile Robots in the Presence of the Unknown Obstacles. In *Proc. IEEE Intl. Conf. on Robotics and Automation*, 1212–1217.

Lagoudakis, M. 1998. Mobile Robot Local Navigation with a Polar Neural Map. M.Sc. thesis, Center for Advanced Computer Studies, University of Southwestern Louisiana. Available online at <http://www.cs.duke.edu/~mgl/acadpage.html>.

*Partially supported by the Lilian-Boudouri Foundation in Greece. Copyright ©1999, American Association for Artificial Intelligence (www.aaai.org). All rights reserved.