

Available online at www.sciencedirect.com



Neural Networks 18 (2005) 267-285

Neural Networks

www.elsevier.com/locate/neunet

The dynamic wave expansion neural network model for robot motion planning in time-varying environments[☆]

Dmitry V. Lebedev*, Jochen J. Steil, Helge J. Ritter

Neuroinformatics Group, Faculty of Technology, University of Bielefeld, P.O. Box 10 01 31, 33501 Bielefeld, Germany

Received 2 July 2004; accepted 4 January 2005

Abstract

We introduce a new type of neural network—the dynamic *wave expansion neural network* (DWENN)—for path generation in a dynamic environment for both mobile robots and robotic manipulators. Our model is parameter-free, computationally efficient, and its complexity does not explicitly depend on the dimensionality of the configuration space. We give a review of existing neural networks for trajectory generation in a time-varying domain, which are compared to the presented model. We demonstrate several representative simulative comparisons as well as the results of long-run comparisons in a number of randomly-generated scenes, which reveal that the proposed model yields dominantly shorter paths, especially in highly-dynamic environments.

© 2005 Elsevier Ltd. All rights reserved.

Keywords: Path planning; Neural networks; Wave expansion; Activity waves; Inhibitory waves; Potential field; Dynamic environment; Benchmarks

1. Introduction

One of the major challenges in the development of intelligent robotic systems is endowing them with an ability to plan motions and to navigate autonomously. This ability becomes critical particularly for robots which operate in dynamic environments, where unpredictable and sudden changes may occur. Whenever the robot's sensory system detects a dynamic change, its planning system has to adapt the path accordingly. Prominent examples are real world environments that involve interaction with people, like museums, shops, or households. Usually, it is required that the path of a robot is *safe* (i.e. collision-free), *optimal* or close to optimal, and *natural*, i.e. in a complex situation the robot does not get lost and goes far away from its destination.

Different types (and complexity levels) of the path planning problem can be distinguished (Fig. 1). The simplest problem is, given the exact description of the environment, to find a continuous path from a starting location to a target location. There exists a number of global approaches, such as decomposition, road-map, and retraction methods (Latombe, 1991; Hwang & Ahuja, 1992; Henrich, 1997), randomised approaches (Kavraki, Svestka, Latombe, & Overmars, 1996; Barraquand et al., 1997; Song, Thomas, & Amato, 2003), genetic algorithms (Paredis & Westra, 1997; Mazer, Ahuactzin, & Bessière, 1998; Eldershaw & Cameron, 2000), as well as several local approaches, e.g., potential field methods (Khatib, 1986; Barraquand & Latombe, 1991) to solve this problem. Usually, global approaches require a preprocessing stage, during which a graph structure containing the information about the connectivity of the robot's free space is formed, before the path search can be performed. Local methods need some heuristics, as, e.g. the estimation of local gradients in a potential field to provide an effective path search.

If the environment is *dynamic* (i.e. if obstacles and/or the target are moving), then two cases are possible. If trajectories of obstacles are *known* in advance and the robot dynamics is not considered (like for free-flying objects), the problem is reduced to the stationary case by adding the time axis to the planning space (moving obstacles

 $[\]star$ The work of the first author (D.V.L.) is supported by the DFG (German Research Council), grant GRK256-2.

^{*} Corresponding author. Tel.: +49 521 106 2944; fax: +49 521 106 6011.

E-mail addresses: dlebedev@techfak.uni-bielefeld.de (D.V. Lebedev), jsteil@techfak.uni-bielefeld.de (J.J. Steil), helge@techfak.uni-bielefeld.de (H.J. Ritter).

Nomenclature

$C \subset \Re^N$	robot's configuration space	x_i	activity level of neuron <i>i</i>
N	the number of robot's degrees-of-freedom	I_i	the external input of neuron <i>i</i>
S_i	the neighbourhood of the <i>i</i> th neuron in the	$g(\cdot)$	the transfer function of a neuron
	network field	δ_{ij}	the Kronecker symbol
s _i	the neighbourhood of the <i>i</i> th neuron in the	3()	the transfer function of a neuro

become stationary in the new space; Latombe, 1991). There exist also a number of methods, which account for the constraints on the robot dynamics during the planning (see, e.g. Fiorini and Shiller (1998), Fraichard and Laugier (1993), and Hsu, Kindel, Latombe, and Rock (2002)). For the most complex case, when obstacle placements/trajectories are unknown in advance, there exist much fewer approaches. Obstacles in that case are detected locally during the robot movement and are dynamically incorporated into the path generation process, which often makes global approaches with replanning computationally demanding. In Zelinsky (1992), for instance, the whole path is replanned from scratch each time the robot bumps into an obstacle. Koenig and Likhachev (2002) and Stentz (1995) proposed graph-search algorithms which utilise the information from previous searches to accelerate the replanning. The algorithms in Lumelsky and Stepanov (1986) guarantee to find a path to the target (if one exists) in an unknown stationary environment based on the local 'tactile' input. Other approaches (Bennewitz, Burgard, & Thrun, 2003; Miura, Uozumi, & Shirai, 1999; Yu & Su, 2001) try to predict and to approximate the movement of obstacles in the workspace, which reduces the problem to the previous case. Several neural network models for path generation in a non-stationary environment have been proposed, which are surveyed in Section 2 and evaluated in simulations in Section 4. Generally, the local nature of these methods allows to integrate the information about changes in the environment into the path generation process

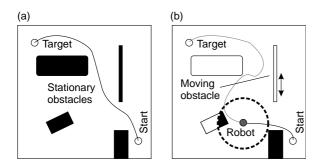


Fig. 1. The path planning problem at two extremes: (a) The simple problem: to find a path from the start to the target in a stationary environment with a given description of obstacles. (b) The complex problem: the environment is initially unknown and the information about (potentially moving) obstacles is acquired during the motion. To get a reasonable path in a time-varying environment and to escape possible local minima effects, this information has to be efficiently integrated into the path planning process.

in an efficient way, such that real-time planning is possible in many situations.

In this paper, we present a novel type of neural network-the dynamic wave expansion neural network (DWENN)-which is capable of generating dynamic distance potentials for real-time path planning in a timevarying environment. This model can be applied to all aforementioned types of the path planning problem. The underlying idea of the DWENN algorithm is to organise wave propagation in a way similar to waves in water spreading, for instance, around a dropped stone. The neurons of the network are arranged in a regularly discretised lattice. In our model a scalar potential field is formed by repetitively generated waves of neural activity, which originate from the target location. Each subsequent wave 'brings' an updated distance information from the target, and increases the potential of lattice nodes in such a way that farther (from the target) neurons accumulate larger activity values. If at some instance of time a location is not reached by the actual wave front, it is regarded as untraversable for the robot.

To prevent local minima problems, in our model the propagation of inhibitory waves (waves of zero activity) is triggered in particular situations to temporarily interrupt the planning process, and thus to avoid undesired path oscillations. The robot then waits several time steps until a new activity wave reaches its position from an appropriate direction, and then continues to move. Thus, no replanning from scratch is needed, since the potential field adapts to changes in the environment dynamically and rapidly. The DWENN's update rules are computationally very efficient, and its state equations are *parameter-free*. Preliminary versions of the model have been reported in Lebedev, Steil, and Ritter (2002, 2003a,b). In Lebedev et al. (2003b), we have shown that DWENN can be viewed (with minor simplifications) as a dynamic version of the distance transform algorithm (Zelinsky, 1992), used for path planning in stationary environments.

The paper is organised as follows. Section 2 provides a taxonomy and review of existing neural network approaches for path planning with particular attention to neural network models for trajectory generation in a time-varying domain. In Section 3 we describe the proposed DWENN model and analyse its dynamics. Comparative simulation studies and a complexity analysis are presented in Section 4, and, finally, conclusions are discussed in Section 5.

Download English Version:

https://daneshyari.com/en/article/10326006

Download Persian Version:

https://daneshyari.com/article/10326006

Daneshyari.com