Neurocomputing 134 (2014) 230–238

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Mobile robots' modular navigation controller using spiking neural networks

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ARTICLE INFO

Article history:
Received 10 March 2013
Received in revised form
30 June 2013
Accepted 24 July 2013
Available online 24 January 2014

Keywords:
Mobile robot
Spiking neural networks
Modular navigation controller
Target-approaching
Obstacle-avoidance
Wall-following

ABSTRACT

Autonomous navigation plays an important role in mobile robots. Artificial neural networks (ANNs) have been successfully used in nonlinear systems whose models are difficult to build. However, the third generation neural networks – Spiking neural networks (SNNs) – contain features that are more attractive than those of traditional neural networks (NNs). Because SNNs convey both temporal and spatial information, they are more suitable for mobile robots' controller design. In this paper, a modular navigation controller based on promising spiking neural networks for mobile robots is presented. The proposed behavior-based target-approaching navigation controller, in which the reactive architecture is used, is composed of three sub-controllers: the obstacle-avoidance SNN controller, the wall-following SNN controller and the goal-approaching controller. The proposed modular navigation controller does not require accurate mathematical models of the environment, and is suitable to unknown and unstructured environments. Simulation results show that the proposed transition conditions for sub-controllers are feasible. The navigation controller can control the mobile robot to reach a target successfully while avoiding obstacles and following the wall to get rid of the deadlock caused by local minimum.

1. Introduction

Navigation of mobile robots refers to planning a path with obstacle avoidance to a specified goal and to execute this plan based on sensor readings and deduction in an unknown, uncertain and unstructured environment. The autonomous navigation plays an important role in mobile robots for fulfillment of given tasks [1].

Traditionally, mobile robots' navigation control requires accurate environmental models, and is effective only in structured environments. Besides, the traditional navigation controller can only fulfill some simple, repetitive tasks, and the robots are usually controlled to follow planned paths. It is very difficult to build mathematical models of unknown and unstructured environments, so the design of mobile robots' navigation controller in such circumstances is very difficult. Since neural networks (NNs) are useful tools for modeling and control of nonlinear systems, some NNs-based controllers for mobile robots have been developed successfully [2–15]. The new trend for mobile robot's controller designing is that some classical methods for controllers are usually combined with artificial neural network (ANN) methods [12–15].

Many studies have shown that the neurons in the mammalian brain use spikes, which are short electrical pulses, to communicate with other neurons. Those spike sequences can represent spatio-temporal information, and lead to a new type of neural network – spiking neural network (SNN). In SNNs, spiking neurons are employed to represent spatio-temporal information with pulse coding, like real neurons do. SNNs represent more plausible models of real biological neurons than those traditional ones. Besides that spiking neurons can be used to compute and communicate.

Some scholars believe that ANNs have developed from the first generation of artificial neural networks which consist of McCulloch–Pitts threshold neurons, the second-generation neurons which use continuous activation functions to compute their output signals, to the third generation – spiking neural networks (SNNs) [16].

SNNs, which use individual spike times to convey information, have stronger computational power than traditional neural networks (NNs). Besides that, SNNs can not only approximate arbitrary continuous functions, but also simulate any feed forward sigmoidal neural networks [17]. Because spikes are conveyed in SNNs, SNNs have better robustness to noise than other types of NNs. Moreover spikes can be modeled relatively easily by digital circuits, so SNNs are suitable to be realized by hardware. In addition, SNNs also show their good capabilities in pattern recognition and classification [18–29]. The approach used by Natschläer and Ruf [18] gives rise to a biologically plausible algorithm for finding clusters in a high-dimensional input space using SNN, even if the environment is changing constantly. In [23] new spiking neural network architecture and its corresponding

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http://dx.doi.org/10.1016/j.neucom.2013.07.055

learning procedures are presented to perform fast and adaptive multi-view visual pattern recognition.

Because of the attractive features of SNNs, many people are involved in the research of SNNs, and new results are constantly obtained. Various spiking neuron models are built, such as spike response model (SRM model), dynamic firing threshold model, leaky integrated-and-fire (LIF) neuron model, probabilistic spiking neuron model (PSNM). The LIF neuron model is the most famous and widely used model to simulate the SNNs. PSNM is a novel spiking neuron model, which has good robustness. There is a rigorous computational model, the liquid state machine (LSM), and there are some novel SNNs architecture: evolving SNNs, spike pattern association neuron (SPAN) architecture, the neurogenetic brain cube (NeuCube) architecture. SPAN is capable of learning input–output spike pattern association and output the desired spike train [26]. NeuCube is a novel evolving spiking model and it is used for modeling brain data specifically.

The training algorithms of SNNs can be categorized into the unsupervised methods and the supervised methods. The unsupervised spike-based learning methods include long-term potentiation (LTP) learning, long-term depression (LTD) learning, learning spike-based Hebbian learning and spike-timing-dependent plasticity (STDP). The supervised spike-based methods include statistical learning methods, spikeProp method [50], evolutionary methods, linear algebra methods, spike-based supervised-Hebbian learning (Remote Supervised Method ReSuMe) [21], SPAN method [26], and so on.

SNNs have been employed in the robotic area successfully, such as path planning [37], environment perception [28,29], and robots' behavior controllers [30–40].

Because SNNs convey temporal and spatial information, they can be used for "real" dynamic environments. While mobile robots always work in the unstructured and dynamic environments, SNNs are more suitable for robots' controller design than the traditional ANNs. The research team led by Prof. Floreano has done a lot of work on robots' controllers and they use genetic algorithm to optimize the weights and the structure of the SNNs [33,34]. In recent years there are also many new research results for robots' controllers based on SNNs: Gamez et al. [41,42] propose iSpike – a C++ library that interfaces between spiking neural network simulators and the iCub humanoid robot. iSpike converts the robot's sensory information into input spikes for the neural network simulator, and the output spikes from the network are decoded into motor signals to control the robot. Andre et al. [43] present a novel learning rule based on spike-timing-dependent plasticity for the designed SNNs which allows the SNNs to serve as a brain-like controller for the simulated robots successfully. Luque et al. [44–46] put forward a cerebellumlike spiking neural network which stores the corrective models as well-structured weight patterns distributed among the parallel fibers to Purkinje cell connections to achieve accurate control of non-stiff-joint robot-arm. The SNNs-based robot-arm controller can accomplish the given task fluently and has better robustness against noise. Alnajjar et al. [47] have designed a novel hierarchical adaptive controller, which is based on SNNs, for a real mobile robot with the goal of optimal navigation in dynamic environments. In [48], a three-layered spiking neural network with STDP learning rules as a target approaching controller for robots is used by Paolo et al.

In this paper, a behavior based target-approaching controller using spiking neural networks is designed. The modular navigation controller has three sub-controllers, and the sub-controllers are partially based on the previously designed obstacle-avoidance controller [30] and the wall-following controller [32].

This paper is organized as follows: Section 2 presents the mobile robot Casia-I's kinematical model and its sensor system. Section 3 discusses the proposed modular navigation controller based on spiking neural networks. Section 4 presents the simulation results. The paper is concluded in Section 5.

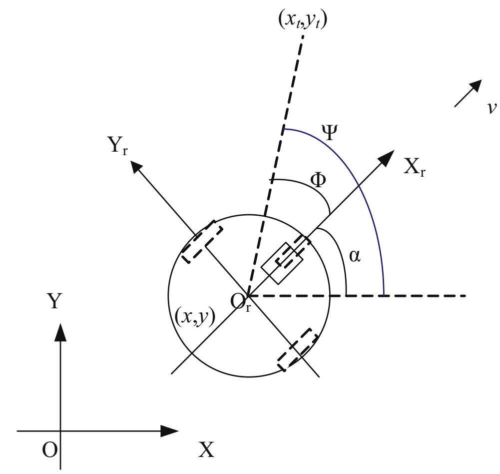

Fig. 1. Mobile robot's pose.

2. Kinematic model and sonar system of the mobile robot

2.1. The kinematic model

In this study, the mobile robot as shown in Fig. 1 is a system satisfying the nonholonomic constraints. In 2-dimensional Cartesian space, the pose of the mobile robot q is represented by

$$q=(x,y,\alpha)^T, \tag{1}$$

where $(x,y)^T$ is the position of the robot in the reference coordinate system XOY, and the heading direction α is taken counterclockwise from the positive direction of the X-axis. $X_rO_rY_r$ is the coordinate for the robot system. (x_t,y_t) is the coordination of the target for the mobile robot's navigation. The angle ϕ is taken counterclockwise from the positive direction of the X_r-axis to xx_t. The angle ψ is taken counterclockwise from the positive direction of the X-axis to xx_t. The solid line rectangle represents the camera, and the dashed line rectangles represent the robot's driving wheels and the guided wheel. If Δt is small enough, the mobile robot's trajectory can be approximated by the following equation from t to $t+m\Delta t$:

$$\begin{cases} x(m+1)=x(m)+v\cos(\alpha(m))\Delta t \\ y(m+1)=y(m)+v\sin(\alpha(m))\Delta t \\ \alpha(m+1)=\alpha(m)+\omega(m)\Delta t, \end{cases} \tag{2}$$

where m is an integer and $m=1,2,\ldots,[1/\Delta t]$.

2.2. The mobile robot's sonar sensor system

Ultrasonic sensors have been widely used in mobile robots because of its attractive properties, e.g. cheapness, reliability and so on. The mobile robot Casia-I used in our experiment has a peripheral ring of 16 evenly distributed Polaroid ultrasonic sensors, which are denoted by S1–S16. The sonar sensor system is shown in Fig. 2.

3. Modular navigation controller based on spiking neural networks

There are many different kinds of behavior-based controllers. According to the various given tasks, the entire task module can be divided into the goal task module and the sub-goal task module. By various classification standards, the behaviors of the mobile robots can not only be classified into the planned behaviors and the reactive behaviors, but also be classified into combined behaviors and basic behaviors. In this paper, the combined behaviors or the target-approaching behaviors have been divided into several sub-goal