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A DYNAMIC RISK LEVEL BASED BIOINSPIRED NEURAL NETWORK APPROACH FOR ROBOT PATH PLANNING

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ABSTRACT—Path planning problem is one of the most important and challenging issue in robot control field. In this paper, an improved bioinspired neural network approach is proposed for real-time path planning of robots. In the proposed approach, a new function is used to calculate the connection weight of the bioinspired neural network, to reduce the fluctuation of the path produced by the general bioinspired neural network. Furthermore, a dynamic risk level is introduced into the proposed approach, to improve the performance of the proposed approach in dynamic obstacle avoidance task. In comparison to the general bioinspired neural network based method, experimental results show that the trajectories of robot produced by the proposed approach is optimized, and the proposed approach can deal with the path planning task in dynamic environment efficiently.

Key Words: Path planning; Bioinspired neural network; Dynamic risk level; Mobile robot control

1. INTRODUCTION

The intelligent mobile robot is an integrated system with various functions, such as environmental perception, dynamic decision-making and planning, and behavior control and execution. Intelligent mobile robots are widely used in industrial production, aerospace, military reconnaissance, family services, and so on [1–3]. Path planning is a very important and challenging issue in these applications of intelligent mobile robots. The main task of path planning is to find an appropriate trajectory from the starting point to the destination for robot. Path planning is the basis of a lot of tasks by robot, which is a reflection of the robotic interactive ability with the environment in the movement process of intelligent robot [4–7].

Various approaches have been proposed to deal with the path planning problem of mobile robot, such as artificial potential field method, neural network method, genetic algorithm method, and so on [8–10]. However, these methods have some limitations. For example, the path planning methods based on artificial potential field method often get into the local optimum problems, because they lack global information. The computation of the traditional neural network methods are very complex, which isn't suit for path planning in dynamic environment. To deal with these problems above, some bioinspired intelligent methods have been proposed for robot path planning recently. For example, Chang [11] applied a computational model of habituation to real robots and discussed the problem of the oscillatory movements using a biologically inspired neurocontroller. Yang, et al [12] proposed a bioinspired neural network based on a shunting model for the robot navigation in unknown environment. Most of these bioinspired methods can deal with path planning problem efficiently without any prior knowledge of the dynamic environment, without any learning procedures, and without explicitly optimizing any global cost functions. The bioinspired method is a hot topic in the field of robotic path planning.

In this paper, a biologically inspired neural network method is proposed to achieve the task of path planning in dynamic environment. Although many applications of this biologically inspired neural network have been achieved [12][13], there are some limitations of the models used in those papers. For example, the trajectory produced by those models is not smoother enough. In addition, although those models consider the problem of dynamic environment, few models consider the effects of different velocity of dynamic obstacles on the safety of robots. In this paper, an improved biologically inspired neural network method is proposed, which is based on our previous improvement on the bioinspired neural network model [14]. In the proposed approach, a new function is used to calculate the connection weight of the bioinspired neural network, to reduce the fluctuation of the produced path. Furthermore, a dynamic risk level is introduced into the proposed approach, to improve the performance of the proposed approach in dynamic obstacle avoidance task. Some simulation experiments were conducted in various situations. The results of the simulation experiments show the efficiency of the proposed approach.

This paper is organized as follows. In Section 2, the proposed bioinspired neural network based path planning method is given out. Section 3 presents the simulation experiments for various situations. Finally, the conclusion is given in Section 4.

2. THE PROPOSED BIOINSPIRED NEURAL NETWORK APPROACH

2.1 The General Bioinspired Neural Network Based on Shunting Model

The architecture of the bioinspired neural network used in this paper is a discrete topologically organized map, which is expressed in a 2-D Cartesian workspace W of mobile robots [12, 14]. The position of the i-th neuron in the state space S of the neural network, denoted by a vector $q_i \in R^2$, uniquely represents a position in W. In the proposed model, the excitatory input results from the target and its neighboring neurons, while the inhibitory input results from the obstacles only. Each neuron has local lateral connections to its neighboring neurons that constitute a subset R_i in S. The subset R_i is called the receptive field of the i-th neuron in neurophysiology. The neuron responds only to the stimulus within its receptive field. Thus, the dynamics of the i-th neuron in the neuron network is characterized by a shunting equation as

$$\frac{dx_i}{dt} = -Ax_i + (B - x_i)([I_i]^+ + \sum_{j=1}^{k} \omega_{ij}[x_j]^+) - (D + x_i)[I_i]^- \tag{1}$$

where k is the number of neural connections of the i-th neuron to its neighboring neurons within the receptive field; x_i is the activity of the i-th neuron. The terms $[I_i]^+ + \sum_{j=1}^{k} \omega_{ij}[x_j]^+$ and $[I_i]^-$ are the excitatory and inhibitory inputs. Function $[a]^+$ is a linear-above-threshold function defined as $[a]^+ = \max\{a, 0\}$, and the nonlinear function $[a]^-$ is defined as $[a]^- = \max\{-a, 0\}$. I_i is the external input to the i-th neuron. The lateral connection weight w_{ij}, from the i-th neuron to the j-th neuron, is defined as $\omega_{ij} = f(d_{ij})$, where function $f(d_{ij})$ is a monotonically decreasing function. e.g., a function defined as

$$f(d) = \begin{cases} \mu / d_{ij}, & \text{If } 0 \le d_{ij} \le R_n \\ 0, & \text{If } d_{ij} \ge R_n \end{cases} \tag{2}$$

where μ and R_n are positive constants; d_{ij} is the distance between the i-th neuron and the j-th neuron. It is obvious that the weight $w_{ij} = w_{ji}$.

The positions of target and obstacles may vary with time. The activity landscape of the neural network dynamically changes according to the varying external inputs and the lateral excitatory connections. From (1), each neuron responds to only the real-time inputs from target and obstacles. The real-time trajectory is generated from the dynamic activity landscape by a steepest gradient ascent rule. For a given current robot location in W, denoted by p_r, the robot motion direction for next time $(\theta_r)_{t+1}$ is obtained by

$$(\theta_r)_{t+1} = \text{angle}(p_r, p_n) \tag{3}$$

$$p_n \Leftarrow x_{p_n} = \max\{x_j, j = 1, 2, \cdots, k\} \tag{4}$$

where $x_j, j = 1, 2, ..., k$, is the activity of all the neurons in the robot detection region; p_n is the location of the neuron, with the maximum activity in these neurons; Function $\text{angle}(\cdot)$ is used to calculate the angle between two locations in a 2-D environment. Then the next location of the robot is

$$\begin{aligned} (x_r)_{t+1} &= (x_r)_t + v_r \Delta t \cos(\theta_r)_t \\ (y_r)_{t+1} &= (y_r)_t + v_r \Delta t \sin(\theta_r)_t \end{aligned} \tag{5}$$

where (x_r, y_r), v_r and θ_r are the location, the velocity, and the moving direction of the robot, respectively; Δt is the simulation step size. Due to this bioinspired neural network, the target and the obstacles keep staying at the peak and the valley of the activity landscape of the neural network, respectively. The robot keeps moving toward the target with obstacle avoidance till the designated objective is achieved.

2.2 The Dynamic Risk Level Based Bioinspired Neural Network for Robot Path Planning

To deal with the shortcomings of the general bioinspired neural network in path planning task, an improved bioinspired neural network model is proposed based on our previous work [14]. At first, a new connection weight function based on a cubic function is used to replace the inverse function in the general bioinspired neural network (see (2)), which is defined as follows:

$$\omega_{ij} = \begin{cases} -\left|q_i - q_j\right|^3 + \delta & \left|q_i - q_j\right| \le R_n \\ 0 & \left|q_i - q_j\right| > R_n \end{cases} \tag{6}$$

where q_i and q_j are the positions of the i-th and the j-th neurons; and δ is a positive constant. It is easy to prove that the change rate of the proposed weight function based on the cubic function is higher than those based on the general inverse function and the negative exponential function, when the value of the argument is bigger than 1. Also, the cubic function has a better stability than other higher power function, which is very important in the robot navigation based on the bioinspired neural network.

To improve the sensitivity of the path planning approach to the speed of dynamic obstacles, a concept of dynamic risk level *CR* is introduced into the bioinspired neural network based approach, which is defined as follows:

$$CR = \omega_d CR_d + \omega_\theta CR_\theta + \omega_v CR_v \tag{7}$$

where CR_d, CR_θ and CR_v are used to denote the risk of relative distance, the risk of relative direction and the risk of relative speed respectively; ω_d, ω_θ and ω_v are the weights of CR_d, CR_θ and CR_v respectively. In this paper, the risk of relative distance CR_d is defined as

$$CR_d = \frac{R_c}{d}, \qquad d \geq R_c \tag{8}$$

where $d = \sqrt{(x_r - x_o)^2 + (y_r - y_o)^2}$ is the distance between the center of robot (x_r, y_r) and the center of the obstacle (x_o, y_o); R_c is a constant to denote the safe range of the robot, which is bigger than the radius of the robot. The risk of relative direction CR_θ is defined as

$$CR_\theta = \sin(\frac{d\theta}{2}) \tag{9}$$

where $d\theta = |\theta_r - \theta_o|$ is the difference between the direction of robot θ_r and the direction of obstacle θ_o. Because there are various conditions in the robot movement, to introduce clearly, the calculation of the risk of relative speed CR_v is listed in Table 1.

Table 1. The calculation of the risk of relative speed CR_v in different conditions

Conditions	CR_v	$d\theta$	dv	**The position of the robot**
1	1	180^o	Random	Before the obstacle
2	0	180^o	Random	Behind the obstacle
3	1	0^o	≤ 0	Before the obstacle
4	0	0^o	> 0	Before the obstacle
5	1	0^o	≤ 0	Behind the obstacle
6	0	0^o	> 0	Behind the obstacle
7	$\frac{\lvert dv \rvert}{\lvert dv \rvert + 1}$	Otherwise	Random	Random

Remark: The dv in Table I is the difference between the absolute value of the robotic velocity and the obstacle's velocity, which is calculated by

$$dv = |v_r| - |v_0| \tag{10}$$

The function (4) in the general bioinspired neural network can be changed by this dynamic risk level parameter CR:

$$p_n \Leftarrow x_{pn} = \max\left\{x_j + \Delta x_j, j = 1, 2, 3.....k\right\} \tag{11}$$

$$\Delta x_j = \frac{CR_j}{\sum_{j=1}^{k} CR_j} \tag{12}$$

where CR_j is the dynamic risk level of the j-th neuron if the robot moves to this neuron at next time.

3. SIMULATION EXPERIMENTAL STUDIES

In order to verify the feasibility and effectiveness of the proposed approach, some simulation experiments are conducted. In these experiments, the position of the target is known. The robot can sense its location information, and the movement of other moving obstacles, such as the distance, the moving direction and the value of the speed of moving obstacles. In these experiments, the robot and the target are expressed by circle and triangle.

3.1 Path Planning in a Dynamic Environment with Moving Obstacles

To test the performance of the proposed approach, these experiments are conducted. In these experiments, there are some dynamic obstacles and some obstacles at rest in the environment. The initial positions of the target, the robot and obstacles are shown in Figure 1. There are four different shape obstacles denoted as O_1, O_2, O_3 and O_4 respectively. The obstacle O_1, O_2, and O_3 will stay at their initial positions, while the obstacle O_4 will move from the right side to the left side of the environment. To test the effects of different velocities of the robot and obstacles on the proposed approach, three experiments are conducted, where the velocity of the robot is 0.8(m/s), 1.0(m/s) and 1.2(m/s). The velocity of the dynamic obstacle is set as 1.0(m/s) and unchanged. To show the advantages of the proposed bioinspired neural approach (PBNN), it is compared with the general bioinspired neural network based path planning method (GBNN) used in our previous work (see [14]), and the parameters of the general bioinspired neural are the same as the proposed approach. The experimental results of the three experiments are listed in Table 2 and the path planning results of two methods are shown in Figure 2 (here just the results under the condition that the robot and the obstacle have the same velocity are given out.)

The results in Table 2 show that the proposed approach can deal with the path planning problem in dynamic environment more efficiently than the general bioinspired neural network based method. The steps to the target of the robot based on the proposed approach are less than the general bioinspired neural network. The times to change the directions of the robot based on the proposed approach are also less than the general bioinspired neural network (see Table 2), namely the robot navigated by the proposed approach needs less energy and the stability of the robotic movement is improved. This performance is very important in the real world applications by robot, such as the robotic search and rescue service under mine without power supply.

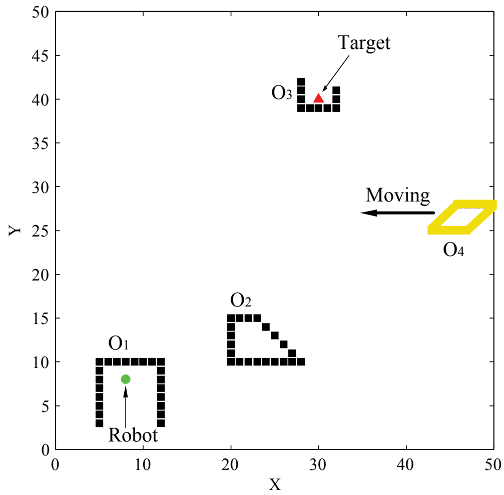

Figure 1. The initial positions of target, robot and obstacles in the first experiment.

Table 2. The experimental results for path planning in a dynamic environment with moving obstacle

The velocity of the robot (m/s)	The path planning method	The steps to the target	The times to change the direction
1.2	GBNN	69	19
	PBNN	65	13
1.0	GBNN	78	21
	PBNN	76	17
0.8	GBNN	98	23
	PBNN	92	13

3.2 Path Planning in a Complex Environment

To further test the efficiency of the proposed approach in some complex applications, this experiment is conducted, where the target and the obstacle are both movable. Furthermore, the obstacles will construct some difficult conditions for the robot movement. The initial positions of the target, the robot and obstacles are shown in Figure 3. There are four different shape obstacles. The obstacle O_1, O_2, and O_3 will stay at their initial positions, while the target and the obstacle O_4 will move from the left side to the right side of the environment simultaneously. At last the obstacle O_1, O_2 and O_4 will form a dead end. In this experiment, the velocities of the robot, the target and the obstacle are set as 1.0(m/s). The comparative results of this experiment are shown in Figure 4.

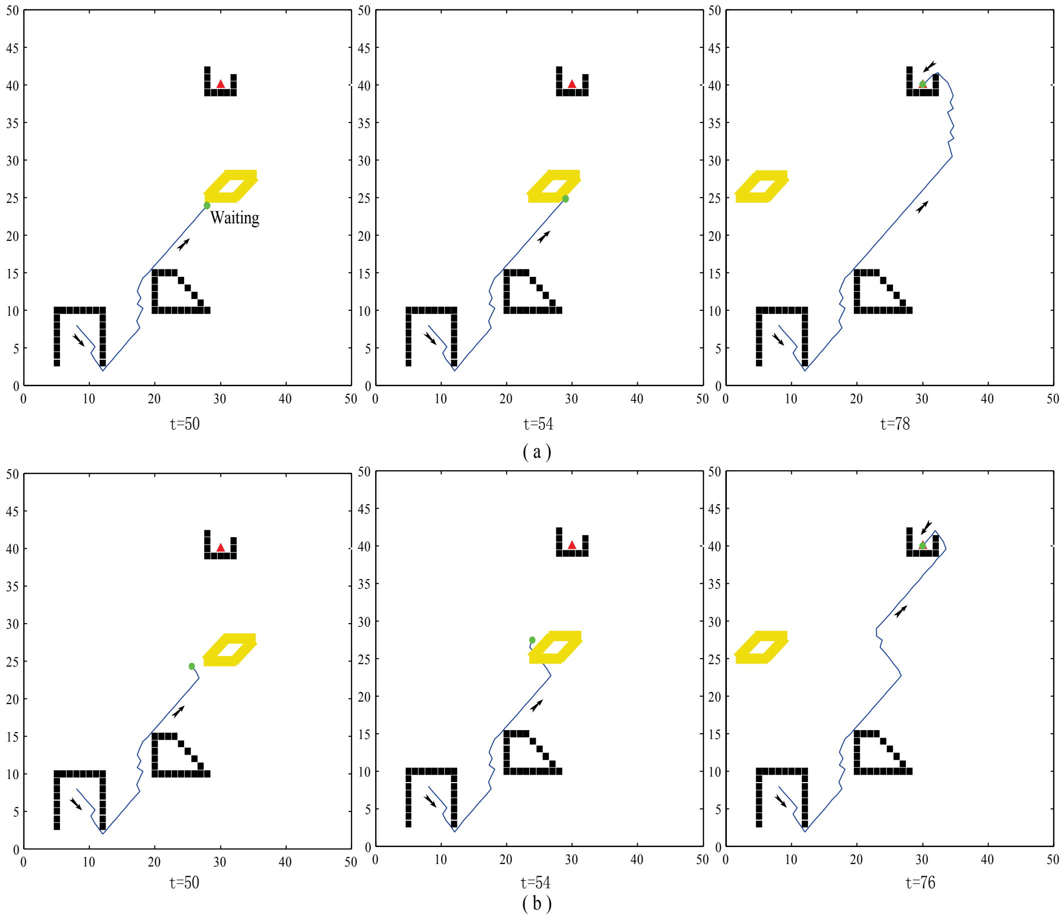

Figure 2. The experimental results of path planning where robot and obstacle have the same velocity: (a) based on the GBNN method; (b) based on the PBNN method.

The results in Figure 4 show that the proposed approach has a good ability to follow the target and avoid the moving obstacle. In this complex environment, the robot navigated by the proposed approach can pass through the moving obstacle to the target, before the dead end formed. The step to the target by the proposed approach is just 52, which is less than that of the general bioinspired neural network based method (which is 198 in this experiment).

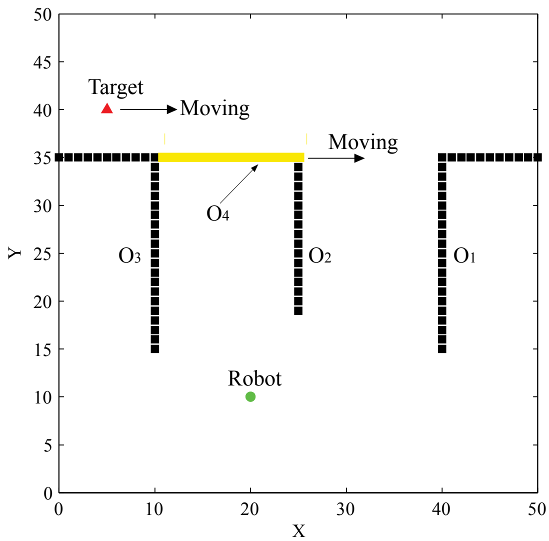

Figure 3. The initial positions of the target, the robot and obstacles for the path planning in a complex environment.

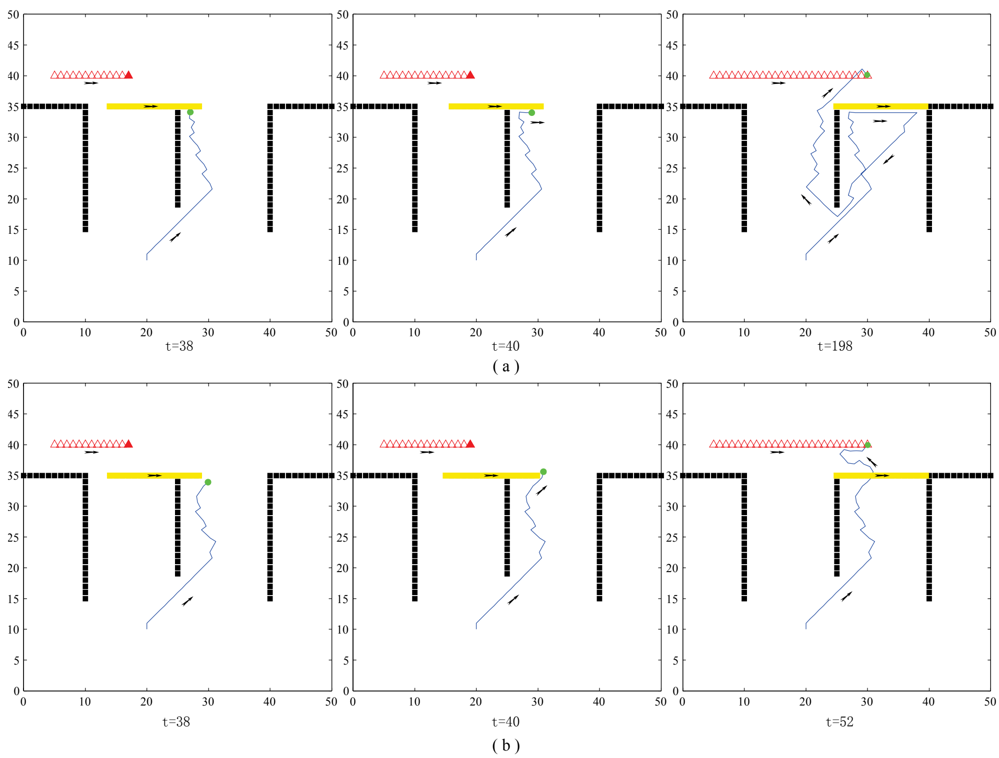

Figure 4. The experimental results of the path planning in a complex environment: (a) based on the GBNN method; (b) based on the PBNN method.

4. CONCLUSIONS

Path planning of robot in dynamic environment is investigated. An improved bioinspired neural network based method is proposed. The proposed approach can deal with the path planning efficiently under various situations. Integrated with the new weight function and the concept of dynamic risk level, the robot can reach to the target and avoid obstacles efficiently. The proposed approach is applicable of path planning in various unknown environments such as the fire disaster response and the radioactive object searching.

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