Complete Coverage Path Planning of Cleaning Robot

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Abstract : In this paper, a novel neural network approach is proposed for cleaning robot to complete coverage path planning with obstacle avoidance in stationary and dynamic environments. The dynamics of each neuron in the topologically organized neural network is characterized by a shunting equation derived from Hodgkin and Huxley's membrane equation. There are only local lateral connections among neurons. The robot path is autonomously generated from the dynamic activity landscape of the neural network and the previous robot location without any prior knowledge of the dynamic environment.

Keywords : stationary and dynamic environments, workspace, neural network, shunting equation

1. Introduction

Complete coverage path planning (CCPP) of a mobile robot is a special type of trajectory generation in 2-dimensional (2D) environment, which requires the robot path to pass through the whole areas in the workspace. In addition to cleaning robots, many other robotic applications also require complete coverage path planning, e.g., painter robots and window cleaners [1,2]. Autonomous cleaning robots are particularly useful in hazardous environments. There have been many studies on CCPP using various approaches, e.g., approximate cellular decomposition, exact cellular decomposition, artificial potential field, neural networks, and fuzzy logic.

In this paper, a novel network approach to complete coverage path planning is proposed. The state space of the topologically organized neural network is the 2-D workspace. The dynamics of each neuron is characterized by a shunting equation derived from Hodgkin and Huxley's membrane [3,4] model for a biological neural system. There are only local lateral connections among neurons. The robot path is autonomously planned without any prior knowledge of the time-varying environment, and without any learning procedures. Therefore the model algorithm is computationally simple. The proposed model is capable of planning real-time complete coverage paths with obstacle avoidance in an unstructured indoor environment.

2. The Proposed Model

In order to present the model algorithm of the proposed approach, first, we briefly introduce the origin of the proposed neural approach to CCPP.

2.1 Biological Inspiration

In 1952 Hodgkin and Huxley proposed a computational model for a patch of membrane in a biological neural system using electrical circuit elements. In this model, the dynamics of the voltage across the membrane V_m is described using a state equation as

$$C_m \frac{dV_m}{dt} = -(E_p + V_m)g_p + (E_{Na} - V_m)g_{Na} - (E_K + K_m)g_K \tag{1}$$

where C_m is the membrane capacitance, and E_k, E_{Na}, and E_p are Nernst potentials (saturation potentials) for potassium ions, sodium ions, and passive leak current in the membrane, respectively. Parameters g_K, g_{Na} and g_p represent the conductance of potassium, sodium, and passive channels, respectively. This model provided the foundation of the shunting model and led to many model variations and applications [5-7].

By setting $C_m=1$, and substituting $x_i=E_p+V_m$, $A=g_p$, $B=E_{Na}+E_p$, $D=E_k-E_p$, $S_i^e=g_{Na}$, and $S_i^i=g_K$ in (1), a shunting equation is obtained as

$$\frac{dx_i}{dt} = -Ax_i + (B - x_i)S_i^e(t) - (D + x_i)S_i^i(t) \tag{2}$$

where x_i is the neural activity (membrane potential) of the ith neuron. A, B and D are non−negative constants representing the passive decay rate and the upper and lower bounds of the neural activity, respectively. Variables S_i^e and S_i^i are the excitatory and inhibitory inputs to the neuron. This shunting model was first proposed by Grossberg to understand the real−time adaptive behavior of individuals to complex dynamic environmental contingencies and has many applications such as visual perception and sensory motor control.

2.2 Model Algorithm

The proposed discretely and topologically organized model is expressed in 2D Cartesian workspace W of the cleaning robots. By properly defining the external inputs from the varying environment and the internal neural connections, the neural activities of the unclean areas and obstacles are guaranteed to stay at the peak and the valley of the activity landscape of the neural network, respectively. The unclean areas globally attract the robot in the entire state space through neural activity propagation, whereas the obstacles have only local effect to avoid collisions. The location of the ith neuron in the state space S of the neural network, which is denoted by a vector $q_i \in R^2$, uniquely represents an area (a robot location) in W. In the proposed model, the excitatory input results from the unclean areas and the lateral neural connections, whereas 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 ith neurophysiology. The neuron responds only to the stimulus within its receptive field. Thus, the dynamics of the ith neuron in the neural network can be characterized by a shunting equation as

$$\frac{dx_i}{dt} = -Ax_i + (B - x_i)([I_i]^+ + \sum_{j=1}^{k} w_{ij}[x_j]^+) - (D + x_i)[I_i]^- \quad (3)$$

where k is the number of neural connections of the ith neuron to its neighboring neurons within the receptive field R_i. The external input I_i to the ith neuron is defined as I_i = E, (if it is an unclean area) $I_i = -$ E, (if it is an obstacle area) I_i=0, (otherwise) where E >> B is a very large positive constant. The terms $[I_i]^+ + \sum_{j=1}^{k} w_{ij}[x_j]^+$ and $[I_i]$ are the excitatory and inhibitory inputs S_i^e and S_i^i, respectively. Function $[a]^+$ is a linear−above−threshold function defined as $[a]^+ = \max\{a,0\}$. And the nonlinear function $[a]^-$ is defined as $[a]^- = \max\{-a,0\}$. The connection weight w_{ij} between the ith and jth neurons can be defined as

$$w_{ij} = f(|q_i - q_j|) \quad (4)$$

where $|q_i - q_j|$ represent the Euclidean distance between vectors q_i and q_j in the state space, and $f(a)$ can be any monotonically decreasing function, such as a function defined as $f(a) = \frac{\mu}{a}$, (if $0 < a < r_0$) $f(a) = 0$, (if $a \geq r_0$)

where μ and r_0 are positive constants. Therefore each neuron has only local lateral connections in a small region $(0, r_0)$. It is obvious that the weight w_{ij} is symmetric. Note that the neural connection weights that satisfy the fundamental concept of the proposed approach are predefined at the neural network design stage. A schematic diagram of the neural network is shown in Fig.1

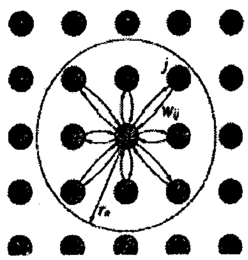

Figure1: Schematic diagram of the proposed neural network for CCPP

In the proposed CCPP model, the robot path is generated from both the dynamic activity landscape and the previous robot location to achieve fewer changes in navigation direction. For a given current robot location in the state space S denoted by p_c, the next robot location p_n (also called "command location") is obtained by.

$$p_n \Leftarrow x_{p_n} = max\{x_j + cy_j, j = 1, 2..., k\} \quad (5)$$

where c is a positive constant, and k is the number of neighboring neurons of the p_cth neuron, i.e., all the possible next locations of the current location p_c.

Variable x_j is the neural activity of the jth neuron, and y_j is a monotonically increasing function of the difference between the current and next robot moving directions. Variable y_j can be defined as a function of the previous location p_p , the current location p_c , and the possible next location p_j , e.g., a function defined as $y_j = 1 - \frac{\Delta\theta_j}{\pi}$ where $\Delta\theta_j \in [0,\pi]$ is the absolute angle change between the current and next moving directions. After the robot reaches its next location, the next location becomes a new current location. The current robot location adaptively changes according to the varying environment.

The dynamic activity landscape of the topologically organized neural network is used to determine the next robot location. Whenever the neural activity at the current robot location is smaller than the largest neural activity of its neighboring locations, the robot starts to move to its next location. Thus, the robot movement is determined by both the robot speed and the neural activity landscape. The moving speed of a cleaning robot can be assumed to be slow because of its cleaning task. In a fast changing environment, where obstacles suddenly appear in front of the robot, the neural activities at those locations will immediately reduce to a very large negative value due to their very large inhibitory input.

The proposed neural network model shares some common ideas with the standard artificial potential field and standard distance transform path planning techniques : a topologically organized discrete map is used to represent the workspace; each location uses a number to represent its environmental information; the target locations have the largest value; and robot moves from a location with a smaller value to that with a larger value. However, there are important differences between the proposed model and artificial potential field or distance transform based model. The activity landscape of the neural network is automatically changing due to the neural activity propagation. Thus, it can deal with arbitrarily changing environments, and will not be trapped in any deadlock situations if a solution exists.

When the robot arrives in a deadlock situation, (all the neighboring locations are either obstacles or cleaned locations, all the neural activities of its neighboring locations are not larger than activity at the current location, because its neighboring locations receive either negative external input (obstacles) or no external input (cleaned locations), and all the cleaned neighboring locations passed a longer decay time as they were cleaned earlier than Location P. Thus, for a pure artificial potential field-based approach, the robot is unable to move away from such a deadlock situation. In the proposed model, the neural activity at the deadlock location P will quickly decay to zero due to the passive decay term $-Ax_i$ in (3). Meanwhile, due to the lateral excitatory connections among neurons, the positive neural activity from the unclean locations in the workspace will propagate toward the current robot location through neural activity propagation. Thus, the robot is able to find a smooth path from the current deadlock location directly to an unclean location, just in the same way as the conventional path planning from a start point to a target point. The robot continues its cleaning task until all the areas in the workspace become cleaned. Thus, the proposed model is capable of achieving complete coverage path planning.

3.ASolutiontoCCPP

3.1 Stationary Environment

There are a lot of stationary obstacles in stationary environment, such as the corners in the room or some obstacles which are stationary. One case is shown in Fig. 2A

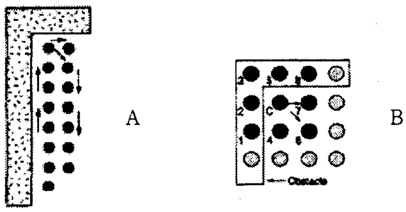

Figure 2

Fig.2B shows the neighboring neurons structure of the Fig2A. Variable 1, 2, ..., 8 denote neuron 1, ..., neuron 8, which are lateral connections to the central neuron C. The dynamic activity landscape of the neural network is used to determine where the next location is in the vicinity of the obstacles. The central neuron C compares its neural activity with those of the other lateral neurons. Simulation result shows that x_1, x_2, x_3, x_5, x_8 are negative neural activities, while x_4, x_6, x_7 are positive neural activities. The next location will be neuron 7, because it has the maximum neural activity.

3.2 Dynamic Environment

The proposed neural network approach is also capable of generating complete coverage paths for cleaning robots in a dynamic environment. As shown in Fig.3.

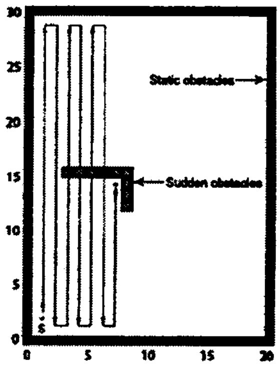

Figure 3

First we set all initial neural activities to zeroes. The robot starts from the location (1,1). When the robot arrives at the location (6, 13), a set of L-shaped obstacles suddenly appear in front of the robot. Then, the neural activities at the place on the obstacles immediately become very large negative values. The robot can not move forward due to the suddenly added obstacles. Later the robot will solve the problem just like it did in the stationary environment. We can also use this method to the multi-robots that will clean the place cooperatively.

4. Conclusion

The proposed neural network approach enable the cleaning robot to avoid the obstacles and cover every area autonomously in a stationary or dynamic environment. The workspace is discreted into many neurons, but there are only local connections among neurons and each neuron has at most eight local connections. The robot path is generated through dynamic neural activity landscape and the previous robot location without any prior knowledge of the dynamic environment, so the model algorithm is computationally simple.

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