New Insights into Bio-inspired Intelligence: Safety-Aware Navigation and Mapping of an Autonomous Vehicle

A Dissertation

Submitted to the Graduate Faculty of University of Detroit Mercy
in Partial Fulfillment of the Requirement for the Degree of
DOCTOR OF ENGINEERING

Department of Electrical and Computer Engineering
College of Engineering and Science
University of Detroit Mercy

By

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March 2016

DOCTORAL DISSERTATION

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF **DOCTOR OF ENGINEERING**

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Acknowledgement

First of all, I would like to express my gratitude to my academic advisor, Professor Chaomin Luo. His contributions to my dissertation are invaluable, as his wise guidance, encouragement, assistance, instruction and friendly attitude. His suggestions and discussions with me for this dissertation are highly appreciated.

Many thanks also go to Professor Mark Paulik, Professor Mohan Krishnan, Professor Lazaros Kikas and Professor Nizar Al-Holou. Their directions and contributions are greatly appreciated. Their instructions and suggestions are very valuable to this thesis. I would like to take this opportunity to extend thanks to the external examiner, Professor Wenbing Zhao, for his valuable comments and assistance.

A special thanks is extended to my company, Denso, for its Tuition Reimbursement Program (TRP). This support has significantly reduced my financial burden for my doctoral research.

Abstract

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Real-time navigation and mapping of an autonomous robot is one of the major challenges in autonomous robot systems. In this dissertation, a novel sensor-based biologically inspired neural network algorithm to real-time collision-free navigation and mapping of an autonomous mobile robot in a completely unknown environment is proposed. The topologically organized neural network with nonlinear analog neurons is efficient for trajectory planning with obstacle avoidance, in which each neuron in the neural network is described by a Glasius and Komoda equation. The proposed biologically-inspired neural network model for motion planning with *safety* consideration is studied in known and unknown map of environments. A virtual obstacle methodology is developed to enlarge the obstacle to have safer distance from the mobile robot to the obstacles.

A two-level LIDAR-driven hybrid real-time mapping and navigation system is proposed by using the biologically inspired neural network algorithm of an autonomous robot. A local map composed of cells is built up through the proposed neural dynamics for robot navigation with restricted incoming sensory information. According to the measured sensory information, an accurate map with grid representation of the robot with local environment is dynamically built for the robot navigation. The proposed model for autonomous robot navigation and mapping is capable of planning a real-time reasonable and safe trajectory of an autonomous robot.

A distance matrix scheme associated with the biologically inspired neural network model is developed to achieve safe navigation in an indoor environment. A safe navigation scheme is developed to reduce collision risk considering distance from the robot to obstacles.

Simulation and comparison studies are carried out to demonstrate the effectiveness and efficiency of the proposed methodologies that concurrently performs collision-free navigation and mapping of an autonomous robot.

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1 Introduction

Real-time collision-free navigation of an autonomous robot in an unknown environment is a crucial issue in robotics. Robotic path planning and map building is one of the issues in the field of robotics that attempts to find and optimize the path from the initial configuration to the final location while the local map is dynamically constructed as the robot traverses in an unknown environment. Real-time navigation and map building is a challenging task for autonomous mobile robots, especially in unknown and dynamical environments. For real-time autonomous navigation, the autonomous mobile robot is able to sense its environment, interpret the sensed information to gather the knowledge of its position and the environment, plan a real-time collision-free trajectory from an initial position to goal, and send effective control commands for the robot direction and velocity to reach the goal. An autonomous mobile robot acquires sensor information about itself and its environment through a great variety of sensor modalities. In this dissertation, biologically inspired models with heuristic search method for navigation and mapping of a mobile robot are proposed.

This chapter will begin with a problem statement, which involves an introduction to motion planning, navigation and mapping. Then, the objectives of this dissertation will be addressed. Finally, the contributions of this thesis will be summarized, and the organization of this thesis will be outlined.

1.1 Problem Statement

Navigation and mapping for autonomous vehicles such as Unmanned Ground Vehicles (UGVs) has received a great deal of attention in recent years. Path planning of an autonomous robot aims to compute a continuous sequence of collision-free robot configurations connecting the initial and goal configurations. In this dissertation, global path planning, local navigation and mapping for a mobile robot with obstacle avoidance in non-stationary and unknown environments with safety consideration are developed. In light of knowledge of the environment, path planning is classified as two types, global path planning and local path planning (navigation): global path planning is in the sense that a robot has *prior* environmental information represented as a map, in which the robot trajectory is able to be planned *offline* by means of the available map. The second sort of path planning of a robot has no a *prior* knowledge of its environment. The workspace needs to be sensed by the robot to construct an estimated map in real time while the robot moves in the workspace, which is the *local* navigation or reactive navigation. The environment of path planning is divided into two classes: static and dynamic environments. A static environment remains unchanging, in which locations of the initial, target, and obstacles are not changed over time. However, the autonomous mobile robot is exposed to unexpected cases, where the locations of obstacles and goal may vary over time. The developed method should be suitable for both a single robot and multiple robots. The aim of the thesis is to investigate and develop a possible strategy for an autonomous robot to be navigated in the most efficient manner while the robot is able to build a local map in light of environmental information.

1.2 Objective of this Dissertation

The proposed biologically inspired neural network model in this thesis is motivated by Glasius and Komoda (1996) [1] neural map model for a biological neural system to real-time motion planning, navigation and mapping with obstacle avoidance in unknown environments. The topologically organized neural network with nonlinear analog neurons is efficient for trajectory planning with obstacle avoidance, in which each neuron in the neural network is described by a Glasius and Komoda equation. The target globally attracts a mobile robot in the entire robot workspace through neural activity propagation, while the obstacles only locally repel the robot away in a small region to avoid the possible collisions. The term "real-time" is in the sense that the robot navigator responds immediately to the robot workspace, including the robots, targets, and obstacles. Each neuron has only local lateral connections to its adjacent neurons. The computational complexity of the proposed algorithms linearly depends on the neural network size. The present model is not very sensitive to model parameter variations. The real-time collision-free robot trajectory is generated through the neural activity without any prior knowledge of dynamic workspace, without any learning procedures, without any explicitly searching over the global environments, and without any templates.

Secondly, the proposed biologically-inspired neural networks for motion planning with safety consideration will be studied in known map of environments. Neither prior knowledge of the dynamic environment, nor any template will be needed. A virtual obstacle methodology is presented to enlarge the obstacle to have safer distance from the mobile robot to the obstacles. A virtual robot algorithm is developed to acquire safer and more reasonable trajectory planned by the robot. The simulation and comparison studies

are performed to validate the effectiveness and efficiency of the proposed real-time, safety-aware, autonomous robot trajectory-planning model based on the bio-inspired neural network model integrated with an obstacle enlargement algorithm.

Thirdly, when robots work in unknown environments, map building is required for the robots to effectively complete navigation missions. Real-time concurrent map building and robot navigation are desirable for efficient performance in a number of real-time applications. A real-time concurrent map building and navigation model under unknown environments based on the proposed biologically inspired neural network methodology will be developed with sensor configuration. It is desirable that a mobile robot is capable of fulfilling navigation missions under *completely unknown* environments. A novel neural-dynamics-based approach is proposed for real-time map building and navigation of autonomous mobile robots in a completely unknown environment. The proposed method does not need any templates, even in unknown environments. A local map composed of square or rectangular cells is created through the neural dynamics during the navigation with limited sensory information. From the measured sensory information, a map of the robot's immediate limited surroundings is dynamically built for the robot navigation. In addition, square and rectangular cell map representations are proposed for real-time concurrent map building and navigation. Simulation and comparison studies of the proposed approach demonstrate that the proposed method is capable of planning more reasonable and shorter collision-free trajectories under unknown environments.

Fourthly, a two-level LIDAR-driven hybrid real-time mapping and navigation system is proposed of an autonomous robot. Top level is designed biologically inspired neural

network model to plan a global trajectory for an autonomous robot. Vector Field Histogram (VFH) algorithm based on the LIDAR sensor information is utilized in the bottom level to locally navigate the robot under complicated and unknown environments workspace with obstacle avoidance. To find the least-cost path within the biologically inspired neural network planner, novel distance and angle based search heuristic algorithms are developed. Its effectiveness and efficiency of real-time navigation and map building for the mobile robot have been successfully validated by comparison studies and experiments. The vehicle appears to follow a very stable path while navigating through various obstacles.

Fifthly, a distance matrix scheme associated with a biologically inspired neural network model is developed to achieve safe navigation in an indoor environment. A safe navigation scheme to reduce collision risk considering distance from the robot to obstacles is proposed. The simulation studies have demonstrated that the proposed approach is capable of performing collision-free and safe navigation of an autonomous mobile robot. The robot can navigate to reach the specified target with a safe distance away from obstacles. It is verified that a robot safely navigates in indoor environment by adopting the proposed distance matrix scheme. While the robot moves in the vicinity of obstacles, the distance matrix scheme is trigged to create a safer trajectory. The biologically inspired neural network methodology with safety consideration to real-time collision-free navigation of an intelligent vehicle with safety consideration in a non-stationary environment is proposed. The real-time vehicle trajectory is planned through the varying neural activity landscape, which represents the dynamic environment, in conjunction of a safety aware distance matrix algorithm.

1.3 Contributions of this Dissertation

The proposed biologically inspire neural network strategy for real-time navigation and mapping of an autonomous mobile robot can contribute to real world applications such as Unmanned Ground Vehicles (UGVs) [2][3], maze simulator [4], automotive navigation system [5][6], robotic surgery [7], driver-less car [8], computer-aided drug design [9][10], industrial robotics [11][12], service robots [13][14], and rescue robots [15][16], etc. The principal contributions of this dissertation are summarized as follows.

A novel neural network strategy, based on a biologically inspired model, for real-time collision-free path planning of an autonomous robot is developed. Each neuron in the topologically organized neural network is described by a Glasius equation. The robot trajectory formulation with obstacle avoidance is generated by the biologically inspired neural network strategy. Through the neural connections, neural activity propagation directs the movement of the mobile robot along the planned path from the current location to the goal location. The stability and convergence of the neural network system is guaranteed by both qualitative analysis and Lyapunov stability theory. The proposed algorithms are not sensitive to model parameter variations. The real-time collision-free path planning is planned through the dynamic activity landscape of the neural network without any templates, without any supervisors, without any prior knowledge of the dynamic environment, and without any learning procedures. Therefore, the model algorithms are computationally efficient. There are only local connections among neurons. The computational complexity of the present algorithms depends linearly on the neural network size.

Real-time navigation and mapping of an autonomous robot is one of the major challenges in intelligent robot systems. When robots traverse in unknown environments, map building is required for the robots to effectively fulfill perform navigation in the workspace. Real-time concurrent map building and robot navigation are desirable for efficient performance in many applications. In this thesis, a novel neural-dynamics-based approach is proposed for real-time map building and CCN of autonomous mobile robots in a completely *unknown* environment. The proposed method does not need any templates, even in unknown environments. A local map composed of square grids is created through the neural dynamics during the navigation with restricted sensory information. In light of the measured sensory information, a map of the limited surroundings of a mobile robot is dynamically constructed for the robot navigation. In addition, square grid map representations are proposed for real-time map building and robot navigation based on the biologically inspired neurodynamics model. Comparison studies of the proposed approach with the existing path planning approach demonstrate that the proposed method is capable of planning more reasonable and shorter collision-free trajectories in unknown environments.

A virtual obstacle scheme and virtual robot method are developed to generate safer trajectory of an autonomous mobile robot with obstacle avoidance. By utilizing virtual obstacle models, it is possible to produce a safer trajectory in obstacle-cluttered environments. By using virtual robot scheme, an autonomous mobile robot is able to avoid costly distance calculations and thus speed up the planning process. A bubble band method was initially proposed by Khatib *et al* 1997 [17]. In this thesis, the contribution in this section is in terms of the integration of the proposed biologically inspired neural

networks and the virtual obstacle scheme and virtual robot method to perform a safer and more reasonable robot trajectory. A novel biologically inspired neural network methodology to real-time collision-free navigation of an autonomous mobile robot with safety consideration in a non-stationary environment is developed by employing the virtual obstacle scheme and virtual robot model. The proposed model for robot path planning with safety consideration is capable of planning a real-time safe path. The term of safety navigation is in the sense that a trajectory is planned of a mobile robot with certain distance from the robot to obstacles. Compared with Khatib *et al.'* s bubble band algorithms, the proposed BNN model in this thesis associated with the virtual obstacle scheme and virtual robot method is computationally efficient. Unlike the method in Khatib *et al.* 1997, BNN model effectively avoids complicated calculations.

1) With a global path planner only, a navigation system is incomplete. In this thesis, a goal-oriented, biologically inspired neural network model, is applied to a concurrent, sensor-based navigation and mapping formation integrated with a histogram-based local navigator for an autonomous robot. Sensor-based path planning is problematic, as the trajectory has to be continually and dynamically recalculated as new configuration information. A biologically inspired neurodynamics approach is developed that provides concurrent navigation and sensor-based map for concurrent path computation and execution. A fusion method based on biologically inspired neurodynamics as the global path planner with an integration of local robot navigation fulfills the concurrent mapping and navigation mission of a mobile robot. The developed, biologically inspired neurodynamics model algorithms and real-time map building approach with histogram-based obstacle avoidance are capable of autonomously planning collision-free

trajectories for an autonomous mobile robot in completely unknown environments. The best result of real-time robot trajectory planning in an unknown environment is in the sense of a continuous, smooth and collision-free trajectory sustainable towards the goal.

2) There have been various developed collision-free algorithms and path planning schemes a robot only avoids obstacles. In this thesis, the proposed distance matrix-based safe navigation approach method is able to not only avoid obstacles but also generate safe trajectory with safety consideration. An innovative distance matrix method is developed in vicinity of obstacles to assist in generating a safer trajectory of an autonomous mobile robot. The solution to vicinity problem of obstacles in path planning is achieved by using a distance matrix. The smoother and safer trajectory is the result of the intrinsic dynamics of the biologically inspired neural networks and construction of the distance matrix. The planned trajectory is the more reasonable and smoothed path in terms of the metric of the representation. In this thesis, a distance matrix is introduced to represent the dynamic neighboring neuron information and the neighboring neuron distance to the obstacles. The proposed distance matrix enabled model is capable of planning a real-time path to reasonably produce a safe distance away from obstacles in the vicinity of obstacles. The neural activity is able to autonomously propagate by detecting the distance matrix and identifying the strength of neural activities among neighboring inter-neurons.

1.4 Organization of this thesis

The rest of this thesis is organized as follows. The literature review and background on navigation and mapping is presented in Chapter 2. The proposed fundamental biologically inspired neural networks model is introduced in Chapter 3, in which the

virtual obstacle neural network model for robot navigation is discussed. Chapter 4 presents a neural network model based path planning under unknown environments with limited sensor capability. A two-layer concurrent navigation and mapping through the BNN with sensor configuration in unknown environment is described in Chapter 5. An innovative distance matrix based on the BNN model is addressed in Chapter 6. A number of necessary and important points are summarized and recommendations for future work are discussed in Chapter 7.

2 Literature Review and Background

Intelligent path planning has been an interesting area and the subject of studies for many years. To autonomous vehicles in a stationary or dynamic environment, real-time, collision-free motion and trajectory planning is a very realistic and challenging issue. The basic navigation problem for an autonomous vehicle is concerned with finding a safe and highly functional collision-free path from an initial point to a destination. This navigation capability becomes more critical for robots operating in the dynamic environment or for moving obstacles where sudden changes can occur. The intelligent robot system should adapt and modify its path accordingly if the robot sensory system detects a dynamic change affecting the planning. Usually, the robot path should prevent the robot from collision with obstacles. The robot should remain right distance: not "too far" or "too close" from obstacles. On the other hand, the robot must not get lost or fail to reach the destination during the navigation path.

There are a great number of studies that have employed various approaches to path planning for robots. The earliest research on the path-planning problem is from Lozano-Perez and Wesley [18][19]. In 1979 and 1983, they proposed a solution to the path-planning problem using the configuration space approach (C-Space). In their study, a single point represents the robot. Thus, the mobile robot path planning in the C-Space is reduced to a two-dimensional problem. As one of the fundamental concepts, the C-Space approach has been used in a number of studies. One example is that Latombe [20] in 1991, who proposed a roadmap approach using C-Space for solving the path-planning problem. In the roadmap approach, the network is constructed in a 2D space by

connecting start and target points. The collision-free path planning is conducted under the constructed network. Other example based on C-Space is the cell decomposition approach [19]. It computes the configuration space of the robot, decomposes the resulting space into cells, and then searches for the path in the free space cell graph. The results of all of these studies are found to be effective in the static or complete known environment. However, sometimes these approaches can be time consuming in the computation. Such drawbacks have made them not effective in the complex environment.

A new intelligent motion planning approach to mobile robot navigation is addressed in 2015 by Monhanty *et al.* [21]. Adaptive neuro-fuzzy inference system (ANFIS) is a well-known hybrid neuro-fuzzy structure for modeling the engineering system. It has also taken the advantages of both learning ability of neural network and the reasoning ability of the fuzzy inference system. In this navigational model, different sensor-extracted information, such as front obstacle distance, right obstacle distance, left obstacle distance, heading angle, left wheel velocity and right wheel velocity, are given input to the ANFIS controller and output from the controller is steering angle for the robot. Based on the output information, the robot moves safely in an unstructured environment populated by variety of static obstacles. Using ANFIS tool box, the obtained mean of squared error for the training dataset in the current paper is 0.0021. Finally, the simulation results are verified with real-time experimental results using Khepra-III mobile robot to show the feasibility and effectiveness of the proposed navigational algorithm.

In order to apply robot path planning in the dynamic environment, which means the obstacles can change or move, and the target or destination could move, the Genetic

Algorithm (GA) approach is proposed. Based on the genetic selection theory of Darwin and the biological evolution process of natural selection, the genetic algorithm approach is an effective computation model used in path planning. One of the early studies of genetic algorithms was conducted by Zhou. *et al.* [22] in 1994. By using the GA to address the path-planning problem for a mobile manipulator system, the proper sequence of base positions and manipulator configurations for performing a sequence of tasks can be solved. The computer simulations are carried out on a 3-degree-of-freedom manipulator, mounted on a 2-degree-of-freedom mobile base to seek the nearest proper path planning solution. Han *et al.* [23] in 1997 published their study using the GA in dynamic path planning with obstacle avoidance of mobile robots. Their coding technique can speed up the GA process. In 2000, Xiao *et al.* [24] used a CoEvolutinary GA to solve the path planning problem for two articulated robot's arms. Hu and Yang [25] in 2004 combined a local search technique and knowledge-based GA method for robot path planning. In their study, the domain knowledge is embedded into the specialized operators to achieve improved search efficiency in both static and dynamic environments. The simulation results demonstrated their improved model's effectiveness and efficiency. Elshamli *et al.* [26] in 2004 also used the domain-based knowledge GA to carry out a path planning study, in which they applied different evolutionary operators to improve effectiveness. In 2005, Castillo *et al.* [27] published their GA study analyzing the problem of Offline Point-to-Point autonomous mobile robot path planning. Their proposal extended the conventional GA to implement the ideas of Pareto optimality, creating a Multi Objective Genetic Algorithm model MOGA. Their simulation results demonstrated that both conventional and MOGA can solve the point-to-point path-

planning problem when applied to grid representations of binary code and continuous simulation of terrains, respectively. Sedighi *et al.* [28] in 2004, Zhao *et al.* [29] in 2007, and Al-Taharwa *et al*. [30] in 2008 all have published their studies using GA and Improved GA on path planning in static and dynamic environments. Their study results have been able to reduce the length of the path and the number of turns for robot motion. In 2012, Zou *et al*. [31] published a new study using an improved GA for dynamic path planning. They divided the entire path planning into three steps: unknown environmental modeling, path search, and the proper path. Through comparing other models, their improved GA model can effectively find the proper path.

Even though there are many studies with effective demonstration of the GA model, some studies [28] found that sometimes the invalid path with the target had not been reached and interference with obstacles appeared in some incidences by GA computation. Additionally, the algorithm can result in very high computation time.

At the same time, a sensor-based approach was introduced in many studies to overcome some of the GA models drawbacks. In 1990, Lumelsky *et al.* [32] introduced the sensor-based approach. In an unknown environment, a mobile robot uses the incoming sensor data to search for a proper path. Sensors were included in the study to provide the detection for all parts. In 1995, Choset *et al.* [33] introduced a 1-dimensional network of curves, termed the generalized Vornoi graph (GVG), and the hierarchical generalized Voronoi graph (HGVG). Both GVG and HGVG provided the basis for sensor-based path planning in an unknown environment. Laubach *et al.* [34] in 1999 proposed a new algorithm to use sensor-based path planning on planetary rover navigation. The algorithm uses only the on-board sensors, and it can guide the robot

efficiently by only using the sensor data needed for the path planning. In 2000, Noborio *et al.* [35] proposed a sensor-based path-planning algorithm and applied it to a mobile robot. By using the algorithm and the sensors, the robot can navigate the path from starting point to the target point with position and orientation. Later on in 2001, Acar *et al.* [36] proposed a study to deal with path planning in unstructured environments using a sensor-based algorithm. The algorithm relies on exact cell decomposition in terms of critical points of Morse functions and has the capability to overcome sensor noise. Acar *et al.* conducted the experiments using a mobile robot with 16 ultrasonic sensors and confirmed that the features of the algorithm can be used to avoid failures under bad sensor signals. Philippsen *et al.* [37] in 2007 conducted a study using sensor-based path planning in highly dynamic environments. A smooth navigation function is combined with motion detection and probabilistic motion modeling, and then re-planning is applied in a cluttered dynamic environment. The motion detection from a mobile platform is combined with position estimation. This information is processed using a probabilistic motion prediction to yield a co-occurrence risk that unifies both dynamic and static elements. Finally, this algorithm produced smooth paths.

With sensor's incoming data, a robot uses many different algorithms, such as Vornoi graph, hierarchical generalized Voronoi graph and probabilistic motion modeling for the robot's motion. However, in the real world of robot path planning, the problem of uncertainty in logic exists naturally. The fuzzy logic approach is introduced to path planning to deal with uncertainty problems. The position and orientation of a robot, the existence of an object, and unknown environment or obstacles are possible uncertainties in the navigation. Yen and Puger [38] introduced a fuzzy logic-based robot navigation

system. The controller they developed takes a path based on known information, which may or may not be complete or contain uncertainty. The navigation systems fuzzy and de-fuzzy the sensor data, then adapt it to the given environment. The robot can adjust for plans made with incomplete or inaccurate maps. With the fuzzy logic implementation, the mobile robot can effectively cope with unforeseen obstacles and other problems which impact the path in the dynamic environment, resulting in improved adaptability. Later on, in 1996, Chee *et al.* [39] proposed a path planning method using comprehensive fuzzy logic theory. Path planning is a crucial function for autonomous mobile robots to navigate along a desired path. This task includes tracking of previously computed paths using a path planner, a defined path by a human operator, and tracking of walls, road edges, and other natural features in the robot workspace. It involves real-time perception of the environment to determine the position and orientation of the robot with respect to the desired path. Their study demonstrated the effectiveness of using fuzzy logic in path planning. Wang *et al*. [40] in 2008 proposed a fuzzy logic study on robot navigation in an unknown environment. A new grid-based environment map model, called "memory grid", was introduced. Based on the map, they proposed a new navigation method to address the local minimum problem during the myopic goal-oriented robot navigation. Their method consists of designing a novel regional Path-Searching (PS) behavior that complements the local Obstacle-Avoidance (OA) and global Goal-Seeking (GS) behaviors. By coordinating these three behaviors, PS, OA and GS, the final command output can be obtained. Fuzzy logic provided the behavior control and coordination. Their design can effectively handle errors due to sensor noise and self-localization. Fu *et al.* [41] in 2009 presented a double-layer fuzzy logic approach to control robot path

navigation using both speed and the turn angle of the mobile robot. They also introduced a novel method to solve the local minimal issue, which often occurs in local path planning. The simulation results from this double layer approach demonstrated its effectiveness.

It is possible that the fuzzy logic algorithm can be locked into the local minimal issue [41]. Sometimes, the computation time of fuzzy logic is relatively long as well. A large number of studies have searched for different approaches. One important development is to apply neural network theory to robot path planning. Neural network methodology plays an important role in autonomous robot navigation and mapping. Many studies have been conducted in recent years. Chang *et al.* [42] utilized a neural network technique to implement a local navigator that drives a robot to traverse from an initial point to the target with obstacle avoidance. Wang *et al.* [43] suggested a hybrid system with fuzzy logic and neural networks for robot navigation of an autonomous robot in unknown environments. The fuzzy system is automatically designed to train the neural network weights. Fuji *et al.* [44] suggested a multi-layered methodology for collision-free navigation via reinforcement learning. However, the planned robot motions using learning-based approaches are not appropriate, particularly at the initial learning stage. Yang and Meng [45] proposed a biologically-inspired neural network approach for real-time path planning with obstacle avoidance of a mobile robot and a multi-joint robot manipulator in a non-stationary environment. Luo and Yang [46] extended the neural dynamics model to coverage-type motion planning of an autonomous robot, and this approach is applied to solve vicinity problems of obstacles in complete coverage navigation; however, the neural network models described previously are only suitable

for navigation in non-stationary environments without map building. Luo and Yang [47] recently developed heuristic algorithms, based on a biologically-inspired neural network model (BNN), which concurrently perform motion planning and map building in unknown environments; however, this model lacks safety considerations when planning the shortest trajectory of an autonomous robot. One significant BNN study was proposed by Glasius *et al.* [48]. They introduce a discrete-time Hopfield type of neural network. This network is a large collection of locally and symmetrically connected elementary processors. A network dynamic function and a piecewise linear transfer function were also defined. The algorithm to compute proper feasible path is an activity of wave propagation. Through the simulations, they demonstrated the new algorithm's effectiveness and feasibility. In 2014, Luo and Gao [49][50] conducted studies to use the BNN network for robot path planning. These studies introduce the concept of virtual obstacles to the BNN study. With regular obstacles, the virtual enlarged obstacles are considered in the simulation. The robot-planned path can then be made safer. In the other study, the dynamic unknown environment was considered. A robot with limited sensing range successfully navigated from starting point to target point with the proper path. In both studies, many simulation results have demonstrated the effectiveness of the BNN model.

Even though there are many different approaches to the path planning problem, A* is widely considered to be one of the best-established algorithms for general searching of a feasible path. In general, A* algorithm uses a best-first search algorithm, which explores a graph by expanding the most promising node chosen according to a specified rule. A* algorithm will find a least-cost path from a given initial node to the target node. A*

combines a heuristic estimate of the cost to reach a goal and the distance traveled from the initial node. Since first proposed by Hart *et al.* [51]. there are many studies using this algorithm in path planning successfully and effectively. Based on the A*, Lu *et al.* [52] in 2011 published a study of an incremental multi-scale search algorithm for dynamic path planning. They proposed a dynamic shortest-path planning algorithm using a graph with a single endpoint pair potentially changing edge weights over time. The study concluded that their modified A* algorithm leads to an improvement, both in terms of robustness and computational complexity. In 2012, Neuman *et al*. [53] introduced an algorithm AO*, a modified version of A*, to study path planning in large dynamic environments with interactive uncertainty. The framework of this study is to break the graph up into AND nodes and OR nodes. Each OR node has a single edge for each action connecting to an AND node. Each AND node has a directed edge connecting to each possible successor. The study demonstrate its AO* feasibility in the thousands of uncertain dynamic obstacle environments. El-Halawany *et al.* [54] in 2013 conducted a study to modify the original A* to include the consideration of robot size parameters in path planning. The original A* did not take the size of robot into account, which could produce unsafe paths with possible collisions. Their study can generate a safer path for a robot and avoid the robot making sharp turns. One of the latest studies of using the A* algorithm is from Persson *et al.* [55] in 2014. They presented a generalization of the classic A* algorithm to the domain of sampling-based motion planning. Behind the generation of new samples in a motion graph, the A* algorithm is examined and reformulated to enable it as direct use of the search strategy's driving force. Their study claims reliability and quality in the proposed methods.

The following chapters will present different BNN model simulation studies and their effectiveness. Additionally, comparisons are made to validate simulation results and demonstrate the performance of BNN models.

3 A Computationally Efficient Neural Dynamics Approach to Trajectory Planning of An Intelligent Vehicle

Real-time safety-aware navigation of an intelligent vehicle is one of the major challenges in intelligent vehicle systems. Many studies have been focused on obstacle avoidance to prevent an intelligent vehicle from approaching obstacles “too close" or “too far," but in situations which it is difficult to obtain a feasible trajectory. In this chapter, a novel, biologically-inspired neural network methodology for a real-time, collision-free navigation of an intelligent vehicle with safety considerations in a non-stationary environment is proposed. The real-time vehicle trajectory is planned through the varying neural activity landscape, which represents the dynamic environment, in conjunction with a safety-aware navigation algorithm. The proposed model for intelligent vehicle trajectory planning with safety considerations is capable of planning a real-time feasible trajectory by overcoming the either “too close” or “too far” shortcoming. Simulation results are presented to demonstrate the effectiveness and efficiency of the proposed methodology that performs safer collision-free navigation of an intelligent vehicle.

3.1 Introduction

Real-time trajectory planning of an autonomous vehicle with obstacle avoidance is one of the issues in the field of robotics that attempts to find and optimize the path from the initial position to a destination, required for autonomous vehicles and many other robotic applications. The basic navigation problem for autonomous vehicles is finding a safe and good-quality collision-free path from an initial point to a destination. In the

sense of safety navigation, the robot's movement should have no collision with obstacles, even sometimes maintaining a reasonable gap between robot and obstacles, with consideration of the dynamic environment during navigation from starting point to specified target.

There have been plenty of approaches proposed in terms of autonomous vehicle navigation with obstacle avoidance, such as the potential field method, fuzzy logic, the sampling-based method, the wave front approach, sensor-based techniques, graph-based methods, and neural network models, etc.

Pathak and Agrawal [56] proposed a kinematic model based on a potential field method for the motion planning of an autonomous mobile unicycle robot. A string of variable-sized bubbles connecting the start point to the goal point is used for the global planner.

Li and Choi [57] proposed path planning with the obstacle avoidance methodology of an autonomous mobile robot in unknown environments by utilizing a fuzzy logic system. The distances from a robot to obstacles and their positions are detected by ultrasonic sensors. Rule-table technique and a fuzzy logic-based angular velocity control algorithm are developed to find a more reasonable trajectory. Plaku *et al.* [58] developed a sampling-based path planning method of an autonomous robot by a multilayered framework in combination of a search strategy.

Luo *et al*. [59] proposed a real-time, simultaneous, trace-guided navigation and map building (STNM) methodology for an intelligent vehicle by integrating a wavefront-based global path planner that generates a global trajectory for an intelligent vehicle, and

a Modified Vector Field Histogram (MVFH) local navigator based on the LIDAR sensor information to guide the vehicle locally autonomously. A local map composed of square grids is built up through the local navigator while the vehicle traverses with limited LIDAR sensory information.

Yazici *et al.* [60] developed a sensor-based approach for multi-robot coverage navigation. A sensor-based coverage path planning performed in narrow spaces is implemented by a generalized Voronoi diagram (GVD)-based graph that models the environmental information. The graph-based approach is an efficient approach to vehicle navigation as well. Luo *et al.* [61] developed a two-level LIDAR-driven hybrid system for real-time unmanned ground vehicle navigation and map building. The top level features a newly-designed, enhanced Voronoi Diagram (EVD) graph method to plan a global trajectory for an unmanned vehicle. The bottom level employs a Vector Field Histogram (VFH) algorithm based on the LIDAR sensor information to locally guide the vehicle in a complicated workspace, in which it autonomously traverses from one node to another within the planned EDV with obstacle avoidance.

Some research models integrate two methodologies to take advantage of the various properties. For instance, complete sensor-based coverage path planning for the multi-robot is achieved by taking advantage of sensor capability and a generalized Voronoi diagram graph solution. Wang *et al.* [62] successfully combined fuzzy logic and neural networks methodologies for vehicle path planning.

Neural network methodology plays an important role in intelligent vehicle trajectory planning. Chang *et al.* [63] utilized neural network techniques to implement a local

navigator that drives a vehicle to traverse from an initial point to the target with obstacle avoidance. Wang *et al.* [62] suggested a hybrid system with fuzzy logic and neural networks for navigation of an autonomous vehicle in unknown environments. The fuzzy system is automatically designed to train the neural network weights. Fujii *et al.* [64] suggested a multi-layered methodology for collision-free navigation via reinforcement learning. However, the planned vehicle motions using learning-based approaches do not work well, particularly at the initial learning stage. Yang and Meng [65] proposed a biologically-inspired neural network approach for real-time path planning with obstacle avoidance of a mobile vehicle and a multi-joint robot manipulator in a non-stationary environment. Luo and Yang [66] extended the neural dynamics model to coverage-type motion planning of an autonomous vehicle, and this approach is applied to solve vicinity problems of obstacles in complete coverage navigation. However, the neural network models described previously are only suitable for navigation in non-stationary environments without map building. Luo and Yang [67] [68] recently developed heuristic algorithms based on a biologically-inspired neural network model which concurrently perform motion planning and map building in unknown environments. However, this model lacks safety considerations while planning the shortest trajectory of an autonomous robot.

In this chapter, a biologically-inspired neural network model, in conjunction with the developed virtual obstacle algorithm (VOA) and the safety-aware navigation algorithm, is utilized for an intelligent vehicle navigation. The biologically-inspired neural network model is applied to intelligent vehicle trajectory planning.

Through this biologically-inspired neural network model, the vehicle motion in a static environment is globally generated although there is no explicit optimization of any global cost functions. The property of the real-time vehicle trajectory is planned through the dynamic activity landscape of the neural network without any prior knowledge of the dynamic environment, without explicitly searching over the free workspace or the collision paths, and without utilizing any learning procedures. Therefore, it is computationally efficient. The proposed model for vehicle trajectory planning with safety consideration is capable of planning a real-time feasible trajectory with suitable distance from obstacles.

The rest of this chapter is organized as follows: Section 3.2 derives a biologically-inspired neural network model. Section 3.3 conducts a compare between A*/D* with BNN. Section 3.4 addresses the safety-aware navigation technique and its properties, the performances of which are simulated with results are presented in section 3.5. Finally, Section 3.6 concludes the chapter.

3.2 The Neural Network Model

In this chapter, a biologically-inspired neural network model is derived for trajectory planning of an intelligent robot. The topologically-organized neural network, with nonlinear analog neurons, is efficient for trajectory planning with obstacle avoidance. This model resembles Dijkstra's algorithm in the sense of searching the lengths of the shortest trajectories from the goal. The computational complexity of this biologically-inspired neural network model on a graph with N neurons is $O(N^2)$ in comparison with Dijkstra's algorithm of $O(N^2)$ [69].

The real-time, sensor-based, collision-free robot motion is planned, through the dynamic activity landscape of the neural network and the previous robot position, to guarantee that the goal is reached and the robot travels along a smooth and continuous path.

The proposed topologically-organized model is expressed in a 2D Cartesian workspace $\mathbf{W}$ of the intelligent robots. The position of the ith neuron in the state space $\mathbf{S}$ of the neural network, denoted by a vector $q_i \in R^2$, uniquely represents a position in $\mathbf{W}$. In the proposed model, the excitatory input results from the goal and the lateral neural connections, while the inhibitory input results from the obstacles only. Each neuron has local lateral connections to its neighboring neurons that constitute a subset $\mathbf{R}_i$ in $\mathbf{S}$. The subset $\mathbf{R}_i$ is called the receptive field of the ith neuron in neurophysiology. The neuron responds only to the stimulus within its receptive field. In the proposed model, collision-free robot motion is planned in real time based on the dynamic activity landscape of the neural network. The dynamics of this discrete-time neural network is described as the following equations,

$$x_i(t+1) = g\left(\sum_{j \in S_i} W_{ij} x_j(t) + I_i\right) \tag{1}$$

$$W_{ij} = \begin{cases} e^{-\gamma|i-j|^2}, & \text{if } |i-j| \le \gamma \\ 0, & \text{if } |i-j| > \gamma \end{cases} \tag{2}$$

where W_{ij} are symmetric connection weights between the ith neuron and the jth neuron; |i-j| is the Euclidian distance from the ith neuron to the jth neuron; g is the transfer function; γ and r>0 are constants. The external input I_i to the ith neuron is defined as $\mathbf{I}_i = \mathbf{E}$, if it is a target; $\mathbf{I}_i = -\mathbf{E}$, if it is an obstacle position; $\mathbf{I}_i = 0$, otherwise, where $\mathbf{E} \gg 1 \in \mathbf{R}$, is a positive constant.

$$\mathrm{I}_i = \begin{cases} E, & \text{i is the target} \\ -E, & \text{i is an obstacle}, \quad E \in \mathrm{R}, E >> 1 \\ 0, & \text{else} \end{cases}$$

Transfer function **g** may be any monotonically-increasing function. A piecewise linear function is selected as the transfer function as follows,

$$\mathrm{g(x)} = \begin{cases} 0, & \mathrm{x} \le 0 \\ \beta x, & \mathrm{x} \in [0,1], \text{and } \beta > 0 \\ 1, & \mathrm{x} \ge 1 \end{cases}$$

Where, β is a positive constant.

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, i.e., $W_{ij} = W_{ji}$. Usually, r_0 is selected as r_0=2. The receptive field of the ith neuron is represented by a circle with a radius of r_0. The ith neuron has only eight lateral connections to its neighboring neurons that are within its receptive field.

The proposed network characterized by equation (1) guarantees that the positive neural activity is able to be propagated to all the state space, but the negative activity only

stays locally. Therefore, the goal globally attracts the robot through the neural activity propagation, while the obstacles only locally avoid the collision by local connection to the local adjacent neurons.

The activity landscape of the neural network dynamically changes due to the varying external inputs from the goal and obstacles and the internal activity propagation among neurons. The proper robot path is planned from the dynamic activity landscape, and the previous robot location. The robot will move to the neuron with maximal neural activity, which is addressed in the following sections of Navigation and Autonomous Navigation (AN) Algorithms. After the current location reaches its next location, the next location becomes a new central location.

The current robot location *adaptively* changes according to the varying environment. The locations of the obstacles may vary with time, as in the case of moving obstacles. The activity landscape of the neural network dynamically changes due to the varying external inputs from the target and obstacles, and from the internal activity propagation among neurons. For energy and time efficiency, the robot should travel the shortest path and make the least possible turns and changes of directions. For a given current robot location in $\mathbf{S}$, i.e., a location in $\mathbf{W}$, denoted by L_c, the next robot location L_n (also called "command location") is obtained by

$$L_n = \underset{\mathrm{m,n}}{\operatorname{argmax}}(x\,(m,n)) \in \{N_k\,|(m,n)\}$$

where k is the number of *neighboring neurons* of the L_cth neuron (k=8), i.e., all the possible next locations of the current location L_c. Variable x(m,n) is the neural activity of

the jth neuron. After a robot reaches its next location from its current location, the next location becomes a new current location (if the found next location is the same as the current location, the robot stays there without any movement). The current robot location *adaptively* changes according to the varying environment. The computational complexity depends linearly on the state space size of the neural network, which is proportional to the workspace size. The number of neurons required is equal to $N = N_x \times N_y$, where N_x and N_y are the discretized size of the Cartesian workspace. Each neuron has at most eight local connections. Thus the total neural connections are 8N. For the proposed biologically-inspired neural network model, the computational complexity of the proposed algorithm is $\mathbf{O}(N^2)$. Workspace size and rules to be used will mainly affect the computational complexity.

3.3 Compare A*/D* with BNN algorithm

A* and D* algorithms are widely considered as one of the best approaches to path planning. This thesis focuses on the new alternative in both the known and unknown environments to search for a feasible robot path. A* is based on the graph theory, and BNN is based on the neural propagation theory. In order to prove that the BNN model is a very effective approach as well, A comparison study between A*/D* algorithm and BNN is conducted here. The same maps in A* study [70] and D* study [71] are re-drawn in this thesis to conduct BNN study and then the results are compared between them.

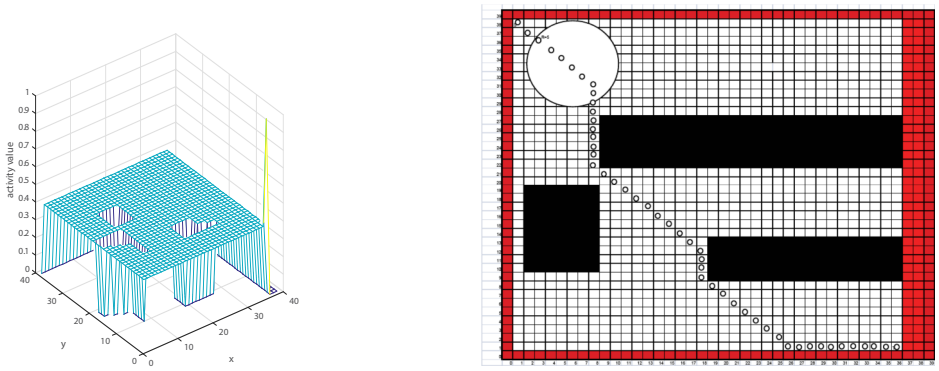


Figure 3-1 BNN robot path and its neural activity landscape on redrawn map from [70]'s Fig. 5

Model	Length	Steps	Turns
A*	159	134	11
EA*	159	134	5
This Study	149	94	4

Table 3-1 Compare BNN, A* and EA*

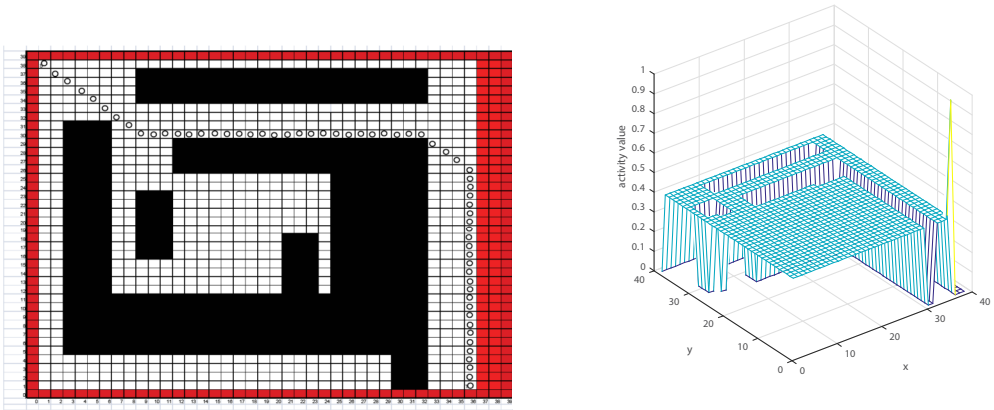


Figure 3-2 robot path and its neural activity landscape on redrawn map from [70]'s Fig.6

Model	Length	Steps	Turns
A*	175.8	162	8
EA*	175.8	162	4
This Study	174	122	3

Table 3-2 Compare between BNN, A* and EA*

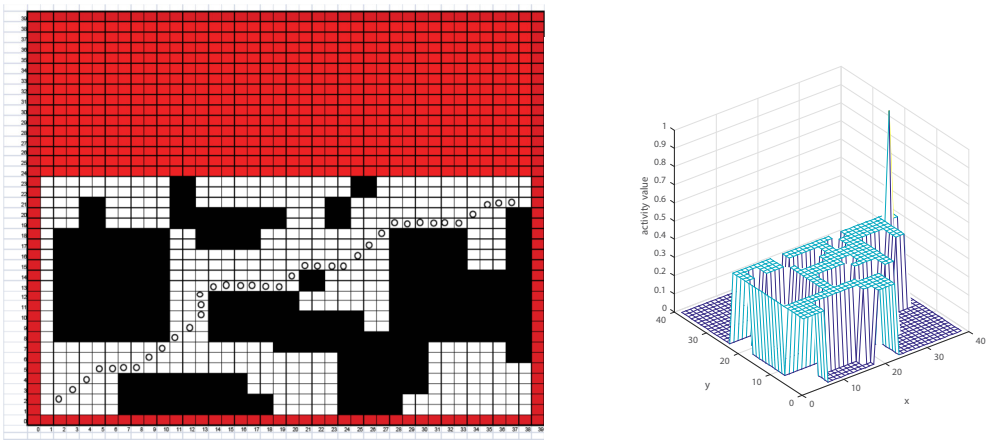


Figure 3-3 Robot path and its neural activity landscape on redrawn map of [70]'s Fig 8.

Model	Length	Steps	Turns
D*	126	74	4
This Study	120	76	9

Table 3-3 Compare BNN and D*

Figure 3-1 shows that BNN robot path and its neural activity landscape on the redrawn map from [70]. Table 3-1 compares the results of BNN, A* and EA*. In this particular map study, BNN has some improvement over the A* and EA*.

Figure 3-2 is the similar study on another redrawn map from [70].

Table 3-2 shows that BNN also improve both from robot steps and turns over A* and EA*.

Figure 3-3 shows robot path and its neural activity landscape on redrawn map of [70] 's Fig 8. Table 3-3 summarizes the BNN and D* results. BNN method has few more steps and turns than D* on this particular map.

In summary, it is demonstrated that the path planning effectiveness using BNN can be very close performance to A* or D* through the compare.

3.4 The Safety-Aware Navigation Algorithm

This section addresses the obstacle enlargement (OE) algorithm associated with the proposed bio-inspired neural network model in *known* environments. The contribution of this section is to effectively integrate the OE algorithm with the proposed BNN model. The algorithm contains three portions: *Initialization* portion, *Obstacle Enlargement* portion and *Navigation* portion.

A workspace populated with unstructured obstacles is shown in Figure 3-4A, in which there are six sets of obstacles. Assume that the workspace is decomposed of cells and the map shows cell representation for the autonomous vehicle navigation. In order to obtain virtual obstacles, the obstacles are enlarged by enclosing them with virtual obstacles illustrated in Figure 3-4B. After the enlargement of obstacles, the autonomous vehicle navigation is performed to plan a safer trajectory for an autonomous vehicle.

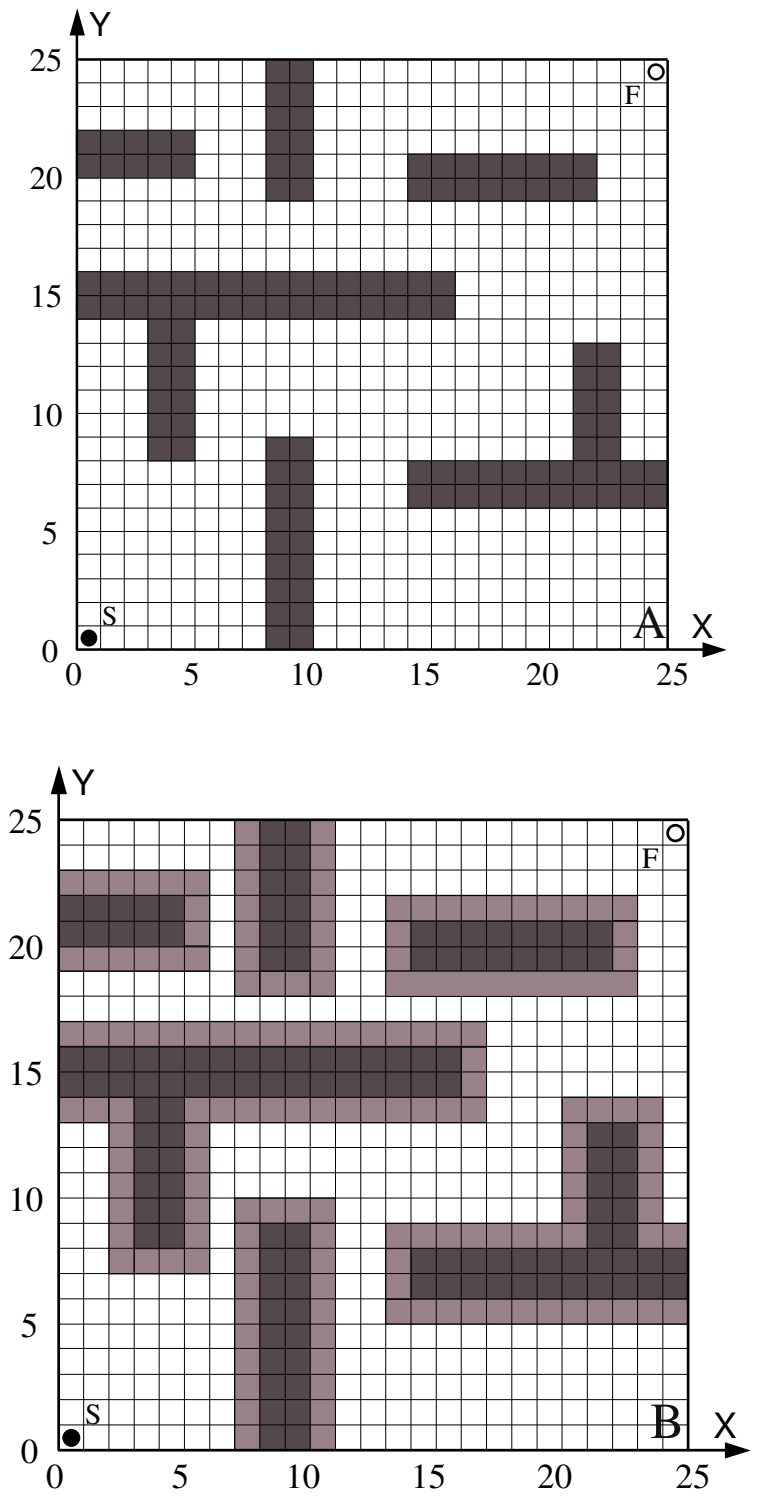


Figure 3-4 Illustration of obstacle enlargement for virtual obstacles. A: The original workspace with obstacles; B: The workspace with virtual obstacles

The **Initialization Algorithm** portion: The initialization algorithm is shown in Figure 3-5.

Set starting point to a central neuron

Set external input of the goal as $I_i = E$

Set all neural activities as zero

Figure 3-5 The Initialization Algorithm

The **Obstacle Enlargement (OE) Algorithm** portion: This algorithm relies primarily on the vehicle's on-board range sensors. The obstacles populated in the workspace in the proposed model are assumed to be known. Cell representation is utilized in this chapter for environmental information. Once a cell (grid) representing obstacles is detected by the vehicle onboard sensors as a neuron its neurons are to be marked as $I_i = -E$ in Figure 3-6.

Loop

Find obstacle areas with $I_i = -E$ by vehicle onboard sensors,

if (the current central neuron is an obstacle cell) **then**

Flag as obstacle cell and $I_i = -E$

if (adjacent neuron is either an unvisited point with $I_i = E$) then

Flag its adjacent neurons as virtual

obstacles $I_i = -E$

end if

end if

Set the current neuron to neighboring neuron

Set external input to covered neuron as zero

End loop

Figure 3-6 The Obstacle Enlargement Algorithm

The **Autonomous Navigation (AN) Algorithm** portion: The goal globally attracts the vehicle in the entire state space through neural activity propagation, while the obstacles have only local effect in a small region to avoid collisions. The Autonomous Navigation (AN) algorithm is shown in Figure 3-7. Based on the previously addressed OE algorithm, the vehicle applying the AN algorithm generates a safer trajectory with a safe distance from obstacles.

Loop

Find unvisited neighboring neuron with largest activity

if (neighboring neural activity <= current neural activity)

then

Flag as *visited* and external input as zero

if neighboring neuron is either visited or with smaller activity)

then

```
        Flag it as deadlock
    end if
    end if
    if (neighboring neurons are all visited) then
        Flag it as visited
    end if
        Set the central neuron to neighboring neuron
        Set external input to covered neuron as zero
                                End loop
```

Figure 3-7 Autonomous Navigation Algorithm

3.5 Simulation studies

Simulation studies are performed in this section to validate the effectiveness and efficiency of a proposed real-time, safety-aware, autonomous vehicle trajectory planning model based on a bio-inspired neural network model in conjunction with an obstacle enlargement algorithm under known environments. In this section, the proposed approach is first applied to a typical double U-shaped case. Then, the bio-inspired neural network model in a room-like environment with multiple *doors* is studied. Finally, this model is applied to a mobile robot in an unstructured environment.

A. Trajectory Planning in a Double U-shaped Environment

To illustrate safety-aware trajectory planning, the proposed model is first applied to a double U-shaped test scenario. In most situations, a small and maneuverable autonomous vehicle may be considered as a point vehicle compared with vehicle's size and its maneuvering possibilities to the size of the free workspace. Practically, a vehicle in traffic planning in large cities or a tank in field military operations may be regarded as point vehicles.

The proposed bio-inspired neural network model navigates an autonomous vehicle in the double U-shaped environment, shown in Figure 3-8A. The workspace has a size of 40 x 40, which is topologically organized as a grid-based map.

The parameters are selected as follows: $\gamma = 3$; $E = 200$ and $\beta = 0.01$. Initially, the starting point is located at S(15,6) and the vehicle moves toward the designated goal at G(15,27). The double U-shaped workspace is shown in Figure 3-8A.

All the neural activities are initialized to zero. In Figure 3-8A, the vehicle starts moving from S(15,6), and it is able to move to the goal G(15,27). By means of the incoming sensory knowledge, the vehicle is smoothly capable of planning a reasonable trajectory, illustrated in Figure 3-8A.

The dynamic activity landscape of the neural network when the vehicle reaches the goal G(15,27) is shown in Figure 3-8B. The neural activity of the goal has very large value, represented by a peak, whereas the neural activities of obstacles are represented by a valley with negative values.

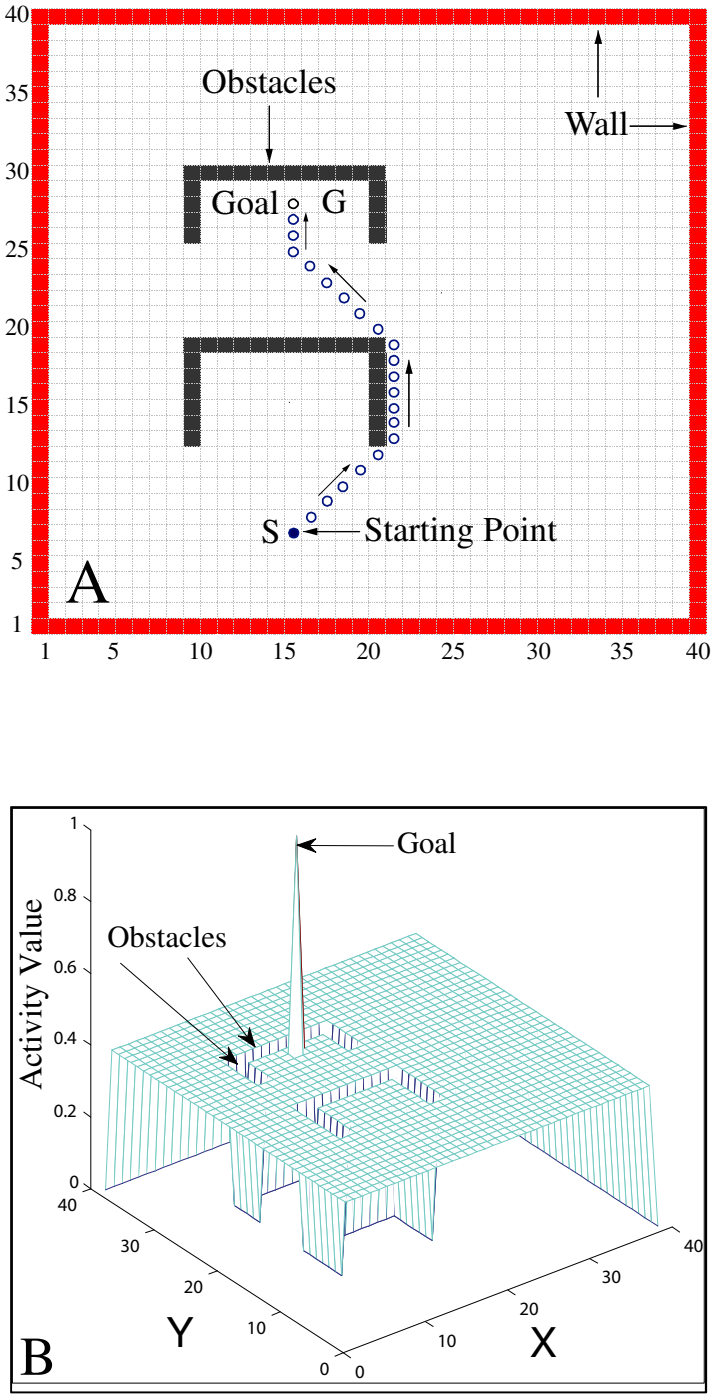


Figure 3-8 Illustration of trajectory planning in a double U-shaped workspace A: The workspace with obstacles; B: The neural activity landscape of the neural network

To plan a *safer,* collision-free trajectory in the same double U-shaped case, the obstacles represented by squares are enlarged. The obstacles in Figure 3-9A are enlarged by the proposed Obstacle Enlargement algorithm, described previously. The double U-shaped test scenario, with enlarged obstacles to construct virtual obstacles, is illustrated in Figure 3-9A, in which the obstacles are indicated by black squares, and virtual obstacles are represented by light-colored squares.

The workspace has the same size of 40 x 40, which is topologically organized as a grid-based map with the same parameters as above. Initially, the starting point is located at S(15,6), and the vehicle moves toward the designated goal located at G(15,27), as shown in Figure 3-9A. The dynamic activity landscape of the neural network when the vehicle reaches the goal G(15,27) is shown in Figure 3-9B.

In comparison to the regular trajectory planning results in Figure 3-8, the trajectory generated in Figure 3-9A with virtual obstacles is safer and more "appropriate" than the one generated in Figure 3-8A without virtual obstacles. The dynamic activity landscape of the neural network when the vehicle reaches the goal G(15,27) is shown in Figure 3-9B. The neural activity of the goal has a very large value represented by a peak, and the neural activities of obstacles are represented by a valley with negative values.

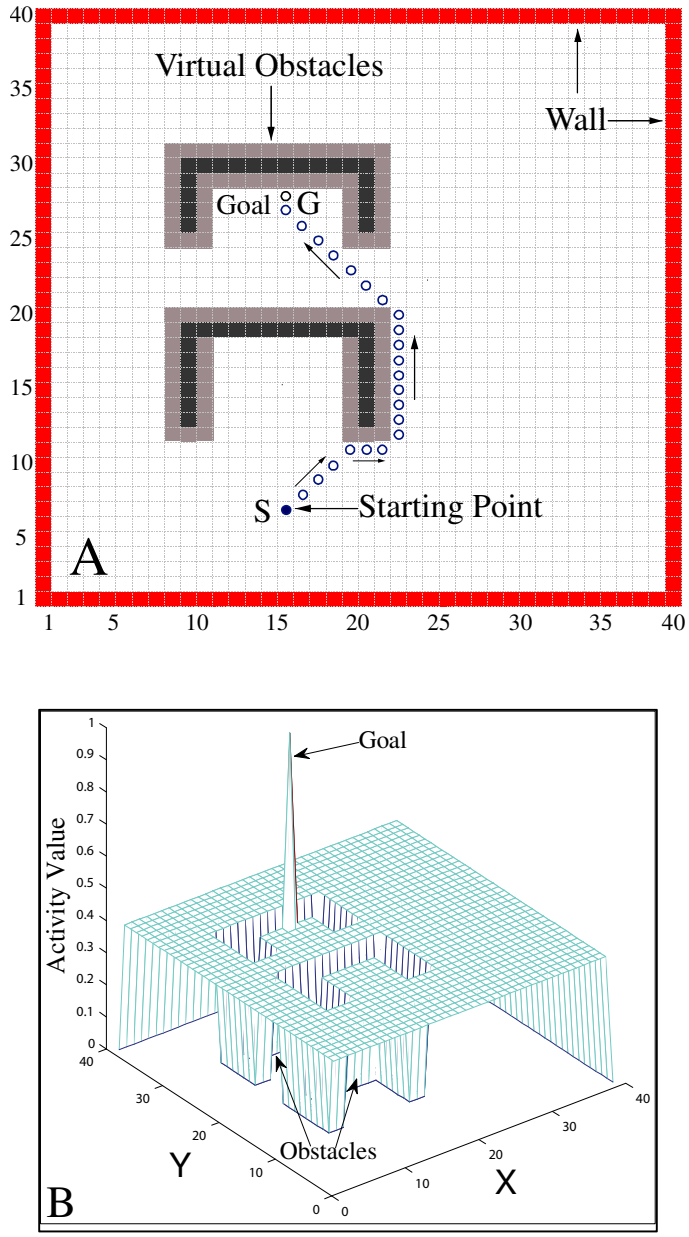


Figure 3-9 Illustration of trajectory planning in a double U-shaped workspace with safety consideration. A: The workspace with virtual obstacles; B: The neural activity landscape of the neural networks.

B. Trajectory Planning in a Room-Like Environment

To validate the effectiveness of the proposed model, it was applied to a room-like test scenario, where there were some obstacles, especially doors, placed in the known workspace. The workspace is shown in Figure 3-10A, where S(2,3) indicates the starting point, and the squares represent the obstacles.

The neural network consists of 40 x 40 topologically organized neurons, where all the neural activities are initialized to zero. The room-like workspace populated with obstacles is topologically organized as a grid-based map with the following parameters: $\gamma = 3$; $E = 200$ and $\beta = 0.01$. Initially, the starting point is located at S(2,3), and the vehicle moves toward the designated goal located at G(37,37) in Figure 3-10A. There are several doors in the workspace. The vehicle traverses in the workspace guided by the proposed bio-inspired neural network model. The planned trajectory is close to the wall and doors. The vehicle traverses in order to pass through four doors, indicated by *D-1, D-2, D-3* and *D-4* in Figure 3-10A. There is no negative neural activity that propagates to the other neurons. The planned vehicle trajectory in Figure 3-10A has the shortest path from the starting position to the goal.

The dynamic activity landscape of the neural network when the vehicle reaches the goal G(37,37) is shown in Figure 3-10B. The neural activity of the goal has a very large value represented by the peak, while the neural activities of the obstacles are represented by a valley with negative values.

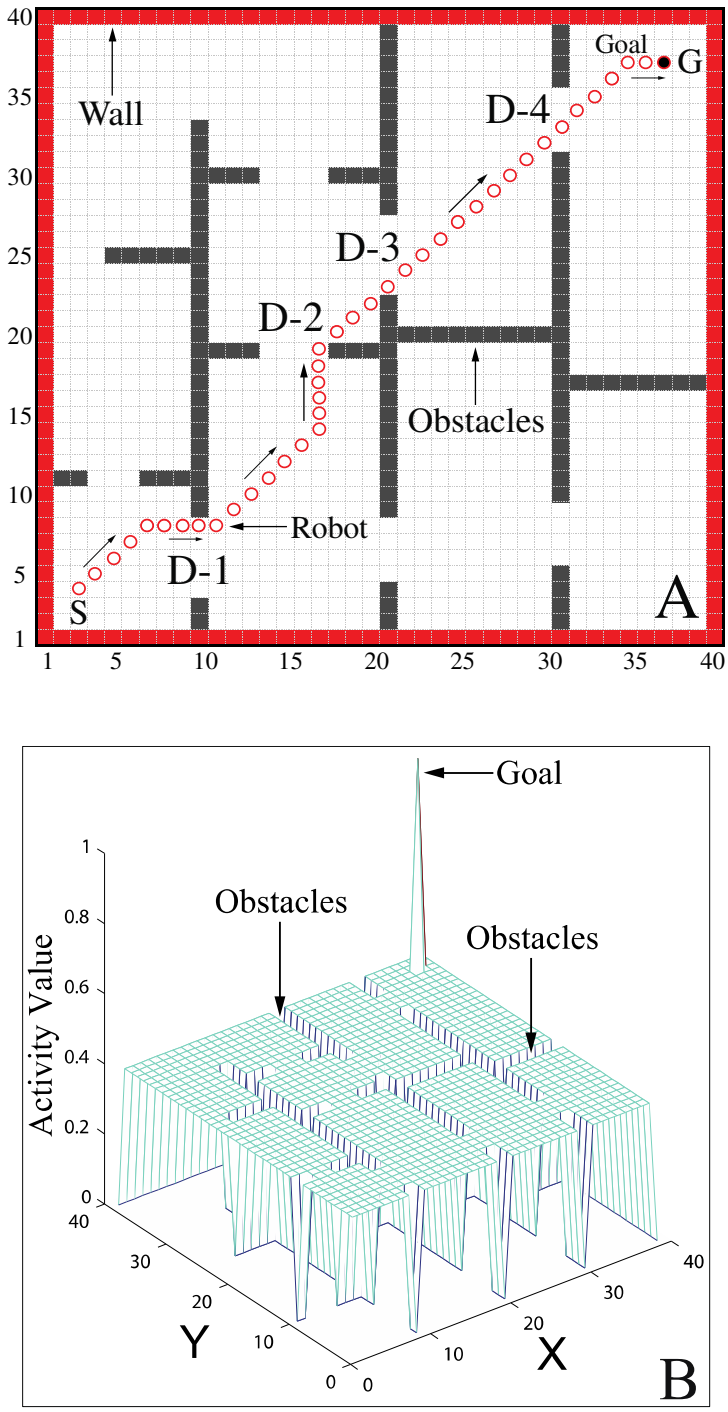


Figure 3-10 Illustration of trajectory planning in a room-like workspace. A: The workspace populated with virtual obstacles; B: the neural activity landscape of the neural networks.

The safety-aware navigation is taken into consideration by virtual enlarged obstacles in the environment. The obstacles are enlarged using the previously-modeled *Obstacle Enlargement* algorithm, illustrated in Figure 3-6, in which the virtual obstacles are depicted as grey-colored cells. The vehicle, driven by the proposed bio-inspired neural network model with the following parameters: $\gamma = 3$; $E = 200$ and $\beta = 0.01$ and virtual obstacle algorithm, is navigated along a smooth trajectory, which constantly retains safer and more "appropriate" distances from four doors, indicated by *D-1, D-2, D-3* and *D-4* in Figure 3-11A. The dynamic activity landscape of the neural network when the vehicle reaches the goal G(37,37) is shown in Figure 3-11B, in which there are more valley areas due to the virtual obstacles. The neural activity of the goal has a very large value, represented by the peak, and the neural activities of obstacles are represented by a valley with negative values.

Compared with the regular trajectory planning results in Figure 3-10, the trajectory generated in Figure 3-11A with virtual obstacles is safer and more "appropriate" than the one generated in Figure 3-10A without virtual obstacles. Particularly, when the vehicle passes through, there is a safer distance as buffered space to plan a smooth trajectory with safety considerations.

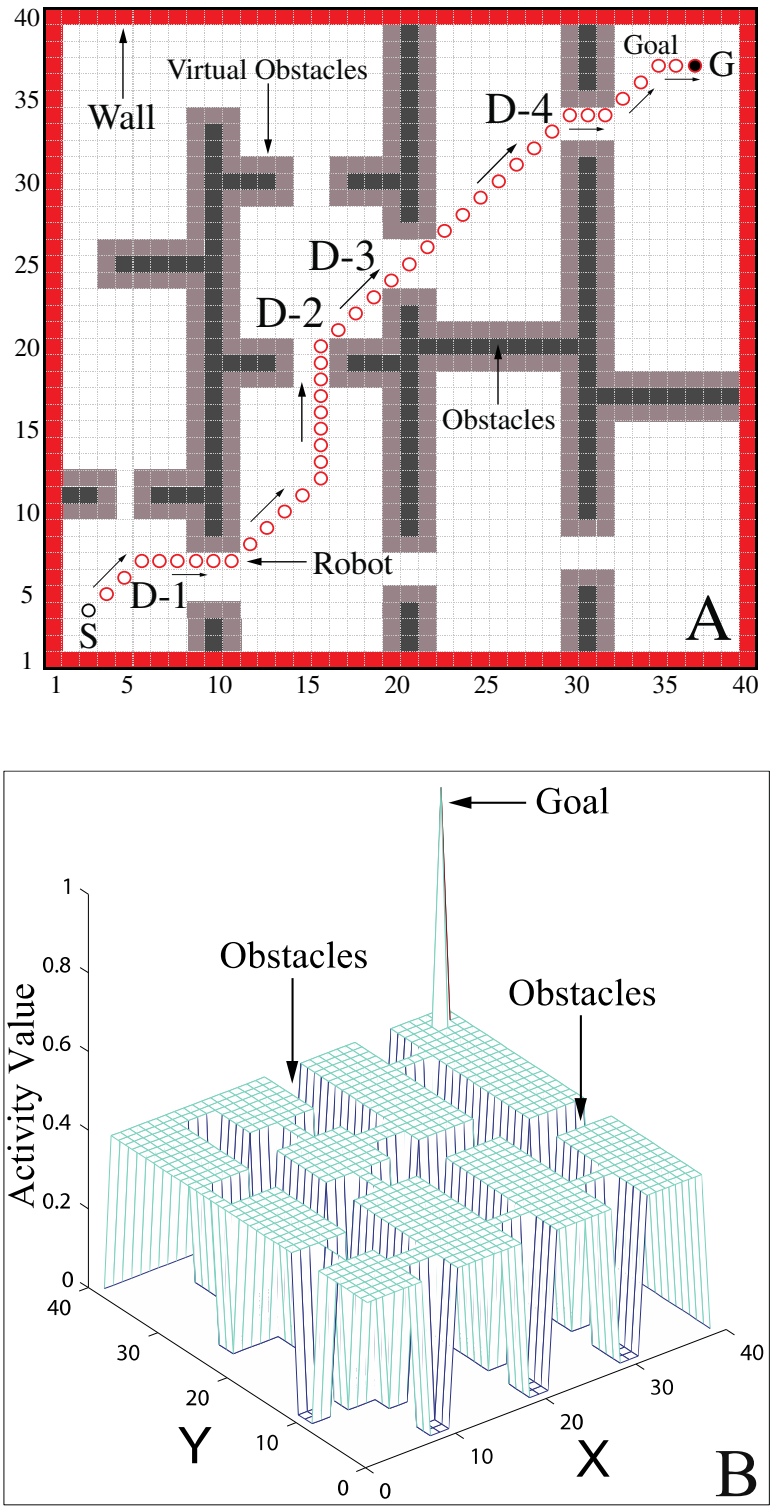


Figure 3-11 Illustration of trajectory planning in a room-like workspace with virtual obstacles. A: The workspace populated with obstacles; B: The neural activity landscape of the neural networks.

3.6 The Conclusion

In this chapter, a novel, biologically-inspired neural network model is proposed that includes safety considerations for real-time vehicle trajectory planning which allows for avoidance of obstacles. The optimality of the real-time vehicle trajectory planning in a stationary environment is in the sense of a continuous, smooth and safe, collision-free trajectory toward the goal. The real-time safe-aware vehicle trajectory is planned through the varying neural activity landscape. The proposed model is capable of planning a real-time feasible trajectory with suitable distance from obstacles. The term “real-time” is in the sense that the BNN path planer responds immediately to the dynamic environment including the robot, goal and obstacles [70]. Effectiveness and efficiency have been demonstrated through simulation studies that also show the proposed model is capable of performing collision-free and safe navigation of an intelligent vehicle. However, in real-world applications, the environments are most likely unknown and dynamically varying. Therefore, the proposed BNN model will be extended to motion planning, navigation, and mapping in *unknown* environments in the next Chapter.

4 Sensor-based Autonomous Robot Navigation In Unknown Environments with Grid Map Representation

Real-time navigation and mapping of an autonomous robot is one of the major challenges in intelligent robot systems. Many studies have focused on path planning, navigation, and obstacle avoidance in known environments, but it is difficult to obtain a proper trajectory in unknown environments.

In this chapter, a novel, sensor-based biologically-inspired neural network algorithm is proposed that will allow for real-time collision-free navigation and mapping of an autonomous mobile robot in a completely *unknown* environment. A local map composed of square grids is built up through the proposed neural dynamics for robot navigation with restricted incoming information. Equipped with sensors, the robot still can only sense a limited reading range of surroundings with grid map representation. Using measured sensory information an accurate map with grid representation of the robot in a local environment is dynamically built for robot navigation. Real-time robot motion is planned through the varying neural activity landscape, which represents the dynamic environment. The proposed model of autonomous robot navigation and mapping is capable of planning a real-time reasonable trajectory of an autonomous robot, in which the local mapping is for navigation purpose. Simulation and comparison studies are presented to demonstrate the effectiveness and efficiency of the proposed methodology that concurrently performs collision-free navigation and mapping of an intelligent robot.

4.1 Introduction

In the previous chapter, robot navigation was conducted in a static environment. The current knowledge of the environment is assumed to be completely known. However, in most of real-world applications, the robot motion needs to navigate autonomously in the dynamically-varying and unknown environments. These environments can be completely unknown, so that robot has to adapt to the incoming environment information. In this chapter, a novel, biologically-inspired neural network approach as described in Chapter 3 is proposed for path planning of a mobile robot in a dynamic environment, where that environment is assumed to be completely unknown and can change arbitrarily.

The rest of this chapter is organized as follows: Section 4.2 addresses the algorithm of concurrent navigation and mapping and its properties. Simulation and comparison studies are presented in Sections 4.3 and 4.4 to show the algorithm's performance. Finally, Section 4.5 concludes this chapter.

4.2 The Navigation Algorithm

This section addresses the navigation and mapping algorithms, which contain three portions*: Initialization portion, Map Building portion, and Navigation portion*.

The **Initialization Algorithm** portion: The initialization algorithm is shown in Figure 4-1. It aims to initialize the starting position of the robot, to set all the neural activities as zeros, etc.

Set starting point to a central neuron

Set external input of the goal as $\mathbf{I}_i = E$

Set all neural activities as zero

Figure 4-1. Initialization Algorithm

The **Map Building Algorithm** portion: This phase mainly relies on the robot's on-board range sensors, limited by distance. The around range of sensors will be discussed in this section. The environment in the proposed model is assumed to be completely unknown. The external input $\mathbf{I}_i$, provided by the robot's on-board sensors that sense a limited range, reflects the knowledge of both the robot itself and its surroundings. The robot thus may have only a limited range of knowledge about its environment to save to its limited memory. A map of the surrounding environment can be dynamically built in an unknown environment. The robot moves toward the area that has maximal neural activity and dynamically updates the map as it moves, until the robot reaches the target.

The **Autonomous Navigation (AN) Algorithm** portion: The goal globally attracts the robot in the entire state space through neural activity propagation, while the obstacles have only local effect in a small region to avoid collisions. The Autonomous Navigation (AN) algorithm is shown in Figure 4-2. Based on the previously addressed OE algorithm, the robot applying the AN algorithm generates safer trajectory with safe distance from obstacles.

```
Loop
    Find unvisited neighboring neuron with largest activity
    if (neighboring neural activity <= current neural activity)  then
            Flag as visited and external input as zero
    if (neighboring neuron is either visited or with smaller activity)  then
            Flag it as deadlock.
    end if
    end if
    if (neighboring neurons are all visited)  then
            Flag it as visited
    end if
            Set the central neuron to neighboring neuron
End loop
```

Figure 4-2 The Autonomous Navigation Algorithm

4.3 Simulation studies

Simulation studies are performed in this section to validate the effectiveness and efficiency of proposed real-time autonomous robot navigation and mapping algorithm in an unknown environment based on a bio-inspired neural dynamics model. In this section, the proposed approach is first applied to a typical U-shaped case. Then, the bio-inspired neural network model of the autonomous robot in a complicated U-shaped environment is studied. The simulations were programmed in C language.

A. Navigation and Mapping in a U-shaped Unknown Environment

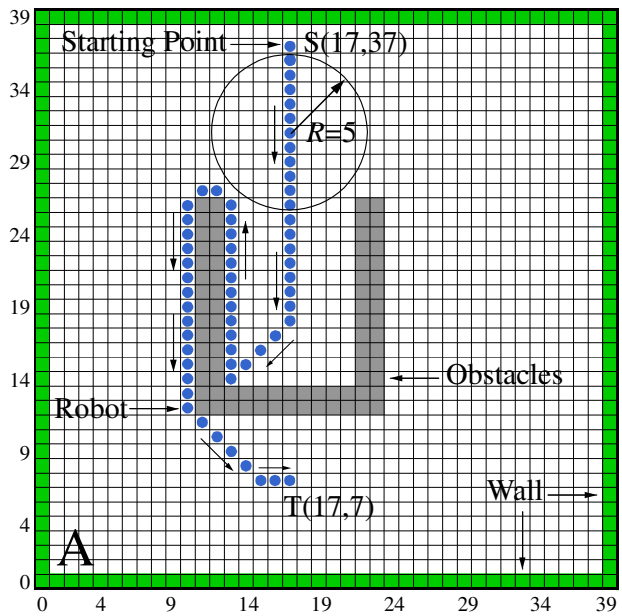
To illustrate concurrent mapping and navigation of an autonomous mobile robot, the proposed model is first applied to a U-shaped test scenario. In most situations, a small and maneuverable autonomous robot may be considered as a point robot based on a comparison of the size of the robot and its maneuvering possibilities to the size of the free workspace. Mobile robots such as iRobot (Roomba) are round in shape. Practically, a robot involved in traffic planning in large cities or a tank in field military operations may be regarded as point robots. In real world applications, most mobile robots have arbitrary that might be simplified. The robot may be regarded as a point-object by a technique, Minkowski-Sum [72].

The proposed bio-inspired neural network model navigates an autonomous robot in the U-shaped test scenario in an unknown environment, shown in Figure 4-3. The workspace has a size of 40 x 40, which is topologically organized as a grid-based map. The parameters are selected as follows: $\gamma = 3$; $\mathbf{E} = 200$ and $\beta = 0.01$.

The entire environment is assumed to be completely unknown except that the entire workspace is set initially as free areas. The robot can only sense a limited range, with a radius of R = 5, from its on-board robot sensors.

Initially, the starting point is located at (17,37), and the robot moves toward the designated target at T(17,7). The U-shaped workspace is shown in Figure 4-3A. Initially, the environmental information is unknown. Only the initial point and target are assigned to the robot in terms of GPS sensor coordinates. The placements of obstacles are assumed to be unknown, initially.

All the neural activities are initialized to zero. In Figure 4-3A, the robot starts moving from (17,37), and it is able to move to the target T(17,7). By virtue of the incoming sensory knowledge, the robot is capable of planning a smooth, reasonable trajectory while the local map is built up, as illustrated in Figure 4-3A. The dynamic activity landscape of the neural network when the robot reaches the target T(17,7) is shown in Figure 4-3B. The neural activity of the goal has a very large value, represented by the peak, whereas the neural activities of the obstacles are represented by a valley with negative values.



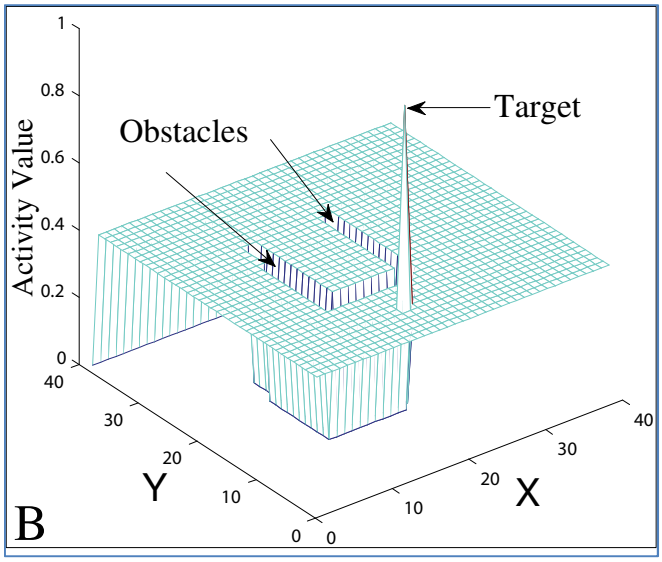


Figure 4-3 Illustration of navigation and mapping in a U-shaped workspace in an unknown environment. A: The workspace with U-shaped obstacles; B: The neural activity landscape of the neural networks.

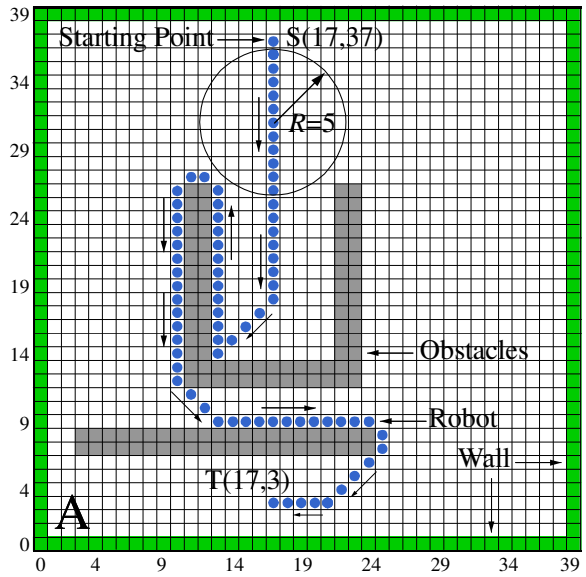
B. Navigation and Mapping in a Complicated, U-shaped, Unknown Environment

To illustrate the effectiveness and efficiency of the proposed real-time autonomous robot navigation and mapping algorithm in an unknown environment, the algorithm is applied to a more complicated U-shaped test scenario in Figure 4-4.

A map is simultaneously built during the navigation of the autonomous robot. The robot has already built a global map of the entire environment once it has completely explored the entire workspace when reaching T(17,3). Initially, the starting point is located at S(17,37), and the robot moves toward the designated target at T(17,3). The U-shaped and rectangular-shaped obstacles in the unknown environment are shown in Figure 4-4A. The entire environment is assumed to be completely unknown except that

the entire workspace is set initially as free areas. With its on-board robot sensors, the robot can only sense a limited range, a radius of R = 5.

All the neural activities are initialized to zero. In Figure 4-4A, the robot starts moving from S(17,37), and it is able to move to the target T(17,3). According to the incoming sensory knowledge, the robot is capable of planning a smooth, reasonable trajectory while the local map is built up, as illustrated in Figure 4-4A. The dynamic activity landscape of the neural network when the robot reaches the target T(17,3) is shown in Figure 4-4B. The neural activity of the goal has a very large value, represented by the peak, and the neural activities of obstacles are represented by a valley with negative values.



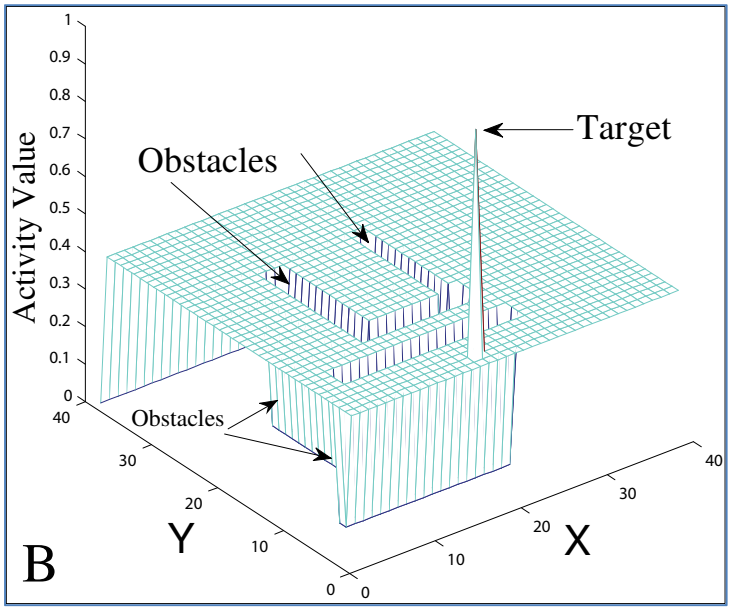


Figure 4-4 Illustration of navigation and mapping in a complicated U-shaped workspace. A: Workspace with a rectangular obstacle; B: Neural activity landscape of the neural networks

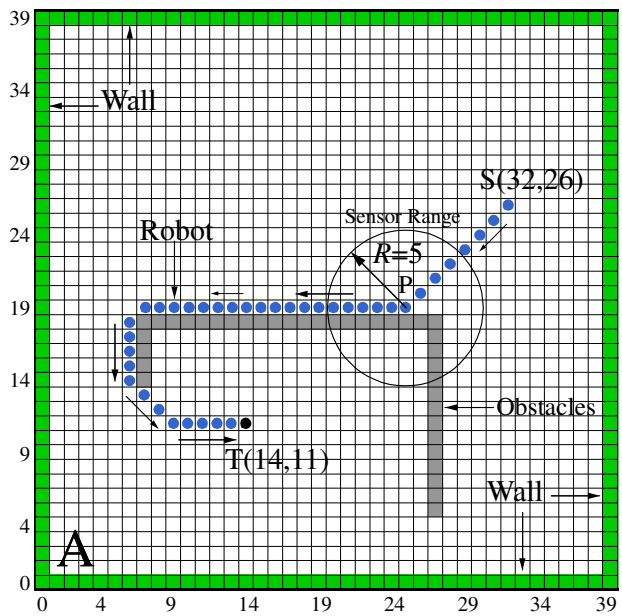
C. Navigation and Mapping in an Unstructured, U-shaped, Unknown Environment

To validate the effectiveness of the proposed model, the proposed model is applied to an unstructured U-shaped test scenario, where the lengths of two sides of a U-shaped obstacle are not identical. The workspace is shown in Figure 4-5A, where S(32,26) indicates the starting point, and the squares represent the obstacles. The neural network consists of 40 x 40 topologically-organized neurons, where all the neural activities are initialized to zero. The room-like workspace populated with obstacles is topologically organized as a grid-based map with the following parameters: $\gamma = 3$; $\mathbf{E} = 200$ and $\beta = 0.01$.

Initially, the starting point is located at S(32,26), and the robot moves toward the designated goal located at T(14,11) in Figure 4-5A. The entire environment is assumed to

be completely unknown except that the entire workspace is set initially as free areas. The robot can only sense a limited range, with a radius of R = 5 with its on-board robot sensors.

The dynamic activity landscape of the neural network when the robot reaches the target T(14,11) is shown in Figure 4-5B. The neural activity of the goal has a very large value represented by the peak, while the neural activities of the obstacles are represented by a valley with negative values. When the robot reaches point P(25,19), as illustrated in Figure 4-5A, the robot can only sense in a limited range, a radius of R = 5. Therefore, in Figure 4-5B, there are only five grids on the right hand side of obstacles, shown by Q point, that can be sensed by the robot. Beyond point Q, the neural activity of the U-shaped obstacles representing obstacles does not illustrate a valley with negative values, which is different from the last case (B).



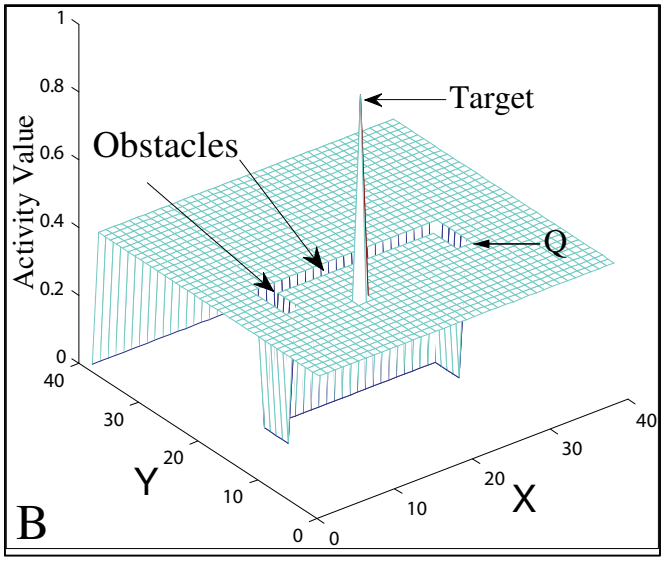


Figure 4-5 Illustration of trajectory planning in an unstructured U-shaped unknown environment. A: The workspace; B: The neural activity landscape of the neural networks.

When the robot reaches point P1(25,19), the robot can only sense part of the map in a limited range, where the is radius R = 5. The built map with some partial obstacles is illustrated in Figure 4-6A. The built map with some partial obstacles is illustrated in Figure 4-6B where the robot reaches point P2(12,19). When the robot reaches point P1(6,14), the robot can sense more obstacles, in which case the built map is illustrated in Figure 4-6C.

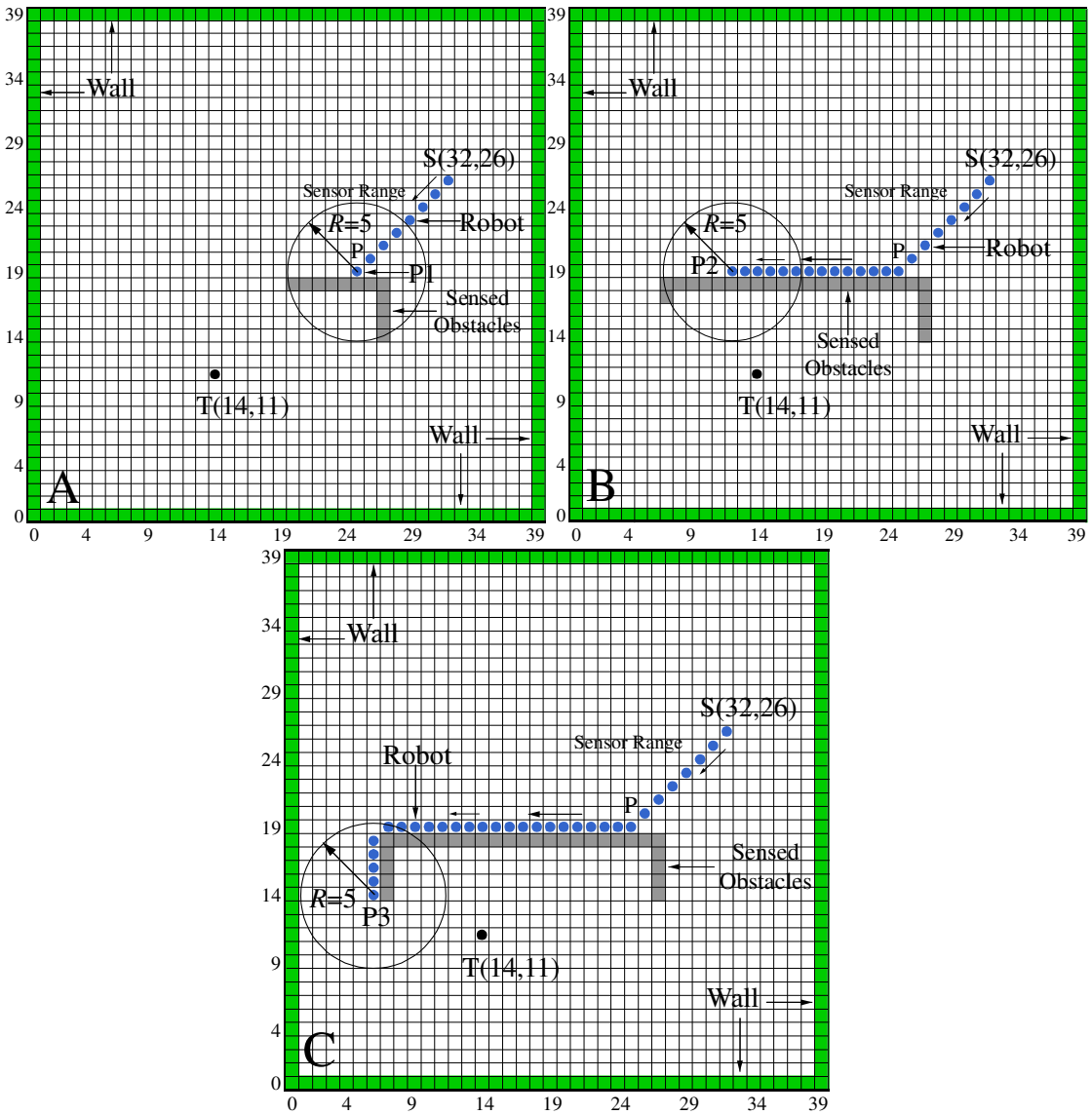
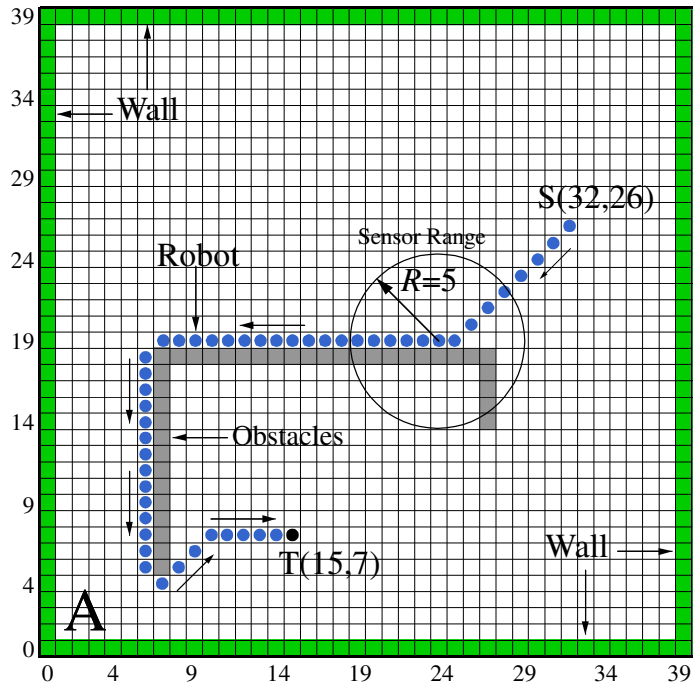


Figure 4-6 Illustration of the built map in an unstructured, U-shaped, unknown environment. A: The built map when the robot reaches P1(25,19); B: The built map when the robot reaches P2(12,19); C: The built map when the robot reaches P3(6,14).

Furthermore, for comparison purposes, the proposed model is applied to an unstructured, U-shaped test scenario, where the left side is longer than right side of the U-shaped obstacle. The workspace is shown in Figure 4-7A, where S(32,26) indicates the starting point, and the squares represent the obstacles.

The neural network consists of 40 x 40 topologically organized neurons, where all the neural activities are initialized to zero. The parameters are selected the same as above. Initially, the starting point is located at S(32,26), and the robot moves toward the designated target located at T(15,7) seen in Figure 4-5A. With its on-board robot sensors, robot can only sense a limited range radius of R = 5. The dynamic activity landscape of the neural network when the robot reaches the target T(15,7) is shown in Figure 4-7B. The neural activity of the goal has a very large value represented by the peak, while the neural activities of obstacles are represented by a valley with negative values.



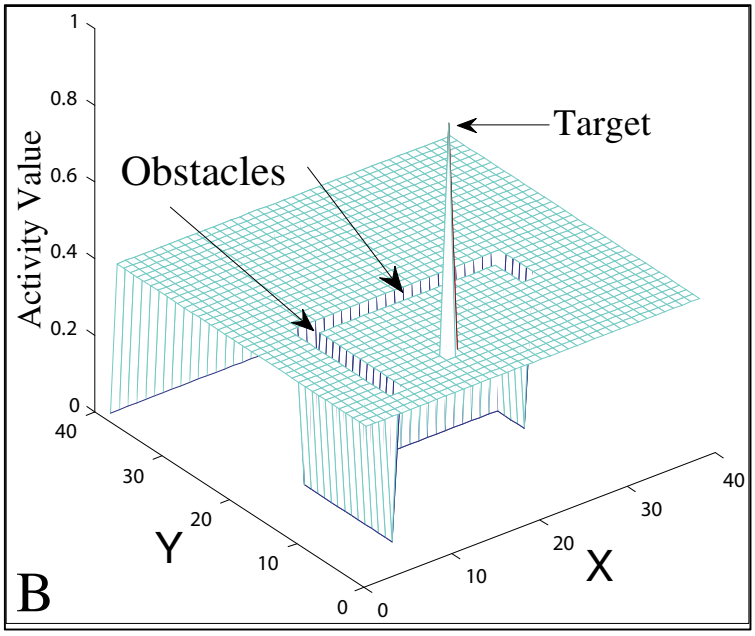


Figure 4-7 Illustration of real-time mapping and navigation in an unstructured, U-shaped, unknown environment. A: The workspace; B: The neural activity landscape of the neural networks.

4.4 Comparison studies

Comparison studies are presented in this section to validate that the proposed navigation and mapping model is more efficient than other models. Various scenarios with different positions of obstacles were simulated to compare other approaches. To verify the validity of the proposed algorithm, an intelligent robot mounted with sensors was simulated to navigate in unknown environments from a given starting position to a desired target with different scenarios.

A. Navigation and Mapping in an Office-Like Environment

The proposed model is applied to an office-like map filled with obstacles in an unknown environment. Bin and Xiong [71] modified a neural network model for path planning application. In comparison with their model, the workspace is shown in Figure 4-8, where the starting position is located in S (2,2), and the square cells represent the obstacles. Figure 4-8 illustrates the unreasonable path of the robot generated by their model. The neural network contains 30 x 30 discretely and topologically-organized neurons, where all the neural activities are initialized to zero. The model parameters are the same as before. There are five sets of wall-like obstacles populated in the workspace. The mobile robot starts from S(2,2). The generated robot path driven by the proposed sensor-based BNN model is shown in Figure 4-9A, where the robot is autonomously capable of traversing the entire workspace with obstacle avoidance along a more reasonable path. Finally, the robot reaches the target at T(27,27). The varying environment is represented by the dynamic activity landscape of the neural network. The real-time robot trajectory is planned from the dynamic neural activity landscape, and the previous robot location. Figure 4-9B illustrates the neural activity landscape of the BNN in this office-like environment. The peak point indicates the goal at T(27,27), while the valley areas illustrate the obstacles. The trajectory length and number of turns by the proposed model and the model of Bin and Xiong were calculated (Table 4-1). It shows that the trajectory length of our proposed model is shorter than their model. The length of the trajectory by the proposed model is 26.5% shorter than theirs. The number of turns of the proposed model is only 1/3 of that of their model. Furthermore, the number of steps to navigate the robot from the starting position to the target by the proposed model is 35.8% less than that of their model.

Table 4-1 Comparison of trajectory length and number of turns and steps of Bin and Xiong's model and the proposed model

Model	Length	Turns	Steps
Bin and Xiong's Model	72.62	27	67
Proposed Model	53.36	9	43

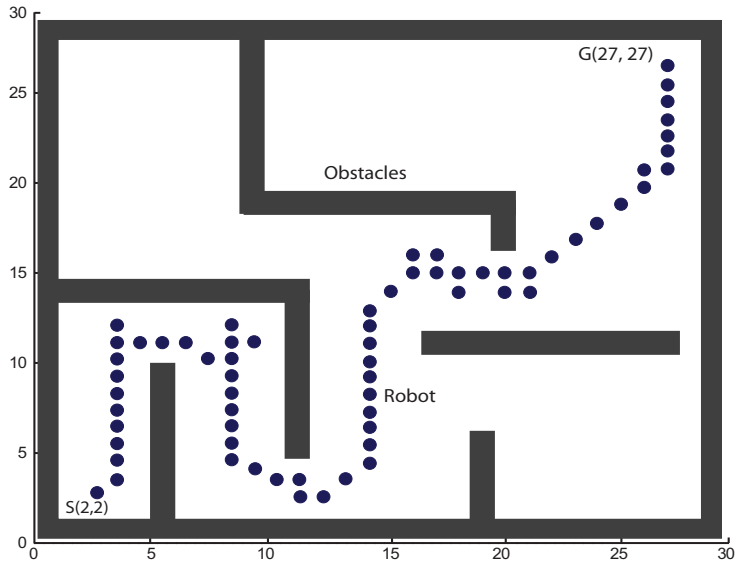


Figure 4-8 The generated path by Bin and Xiong's model (redrawn from Bin and Xiong 2004).

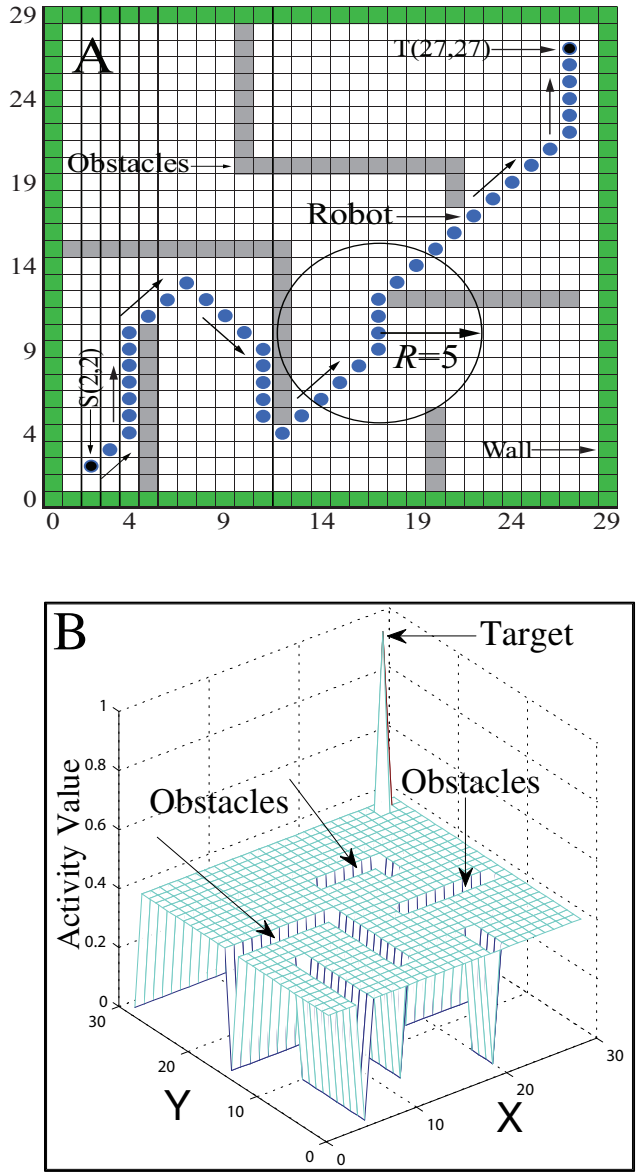


Figure 4-9 Simulation results by the proposed model in the unknown office-like environment. A: The generated trajectory; B: The neural activity landscape of the bio-inspired neural networks.

B. Navigation and Mapping in a U-shaped Workspace

Hu *et al.* [73] suggested an artificial immune network (AIN) for robot motion planning for an autonomous robot. The proposed model is compared with a U-shaped

workspace in Hu *et al's.* model. The workspace is illustrated in Figure 4-10, where the starting position is located at S (12,9), and the square cells represent the obstacles.

In order to validate the efficiency and effectiveness of the proposed model, a simulation was performed to navigate the robot in a U-shaped environment, as shown in Figure 4-11A, which demonstrates that the trajectory generated in a square cell map environment representation is reasonable, without local minima. The robot position at starting point S(12,9) is indicated by a blue dot, whereas the path in grid map representation is denoted by blue solid circles, with the final target at T(18,18). Figure 4-11B illustrates the neural activity landscape of the bio-inspired neural networks in the *unknown* U-shaped environment. The peak point denotes the target at T(18,18), while the valley areas indicate the U-shaped obstacles.

The robot trajectory length and number of robot's body turns and steps using both the proposed model and the model of Hu *et al.* were calculated according to Figure 4-10 and Figure 4-11A. The results in Table 4-2 indicate that our trajectory length and number of turns are competitive with their model. In this case, the length of the trajectory by the proposed model is 12.3 shorter than that of their model. The number of turns of the proposed model is 13.3 less than that of their model.

Table 4-2 Comparison of trajectory length and number of turns and steps of Hu *et al's.* model and the proposed model

Model	Length	Turns	Steps
Hu *et al's.* Model	30.87	5	30
Our Proposed Model	27.07	5	26

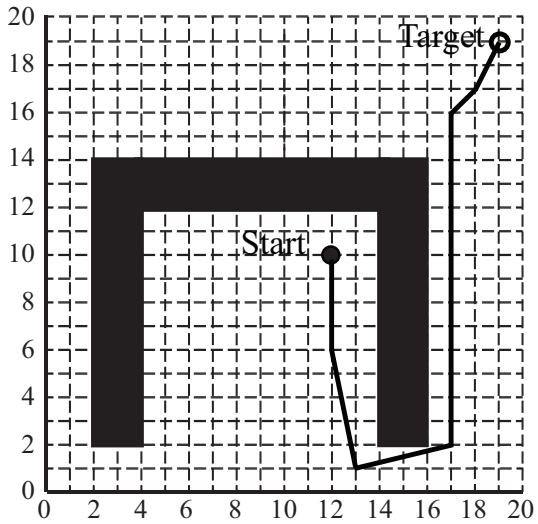
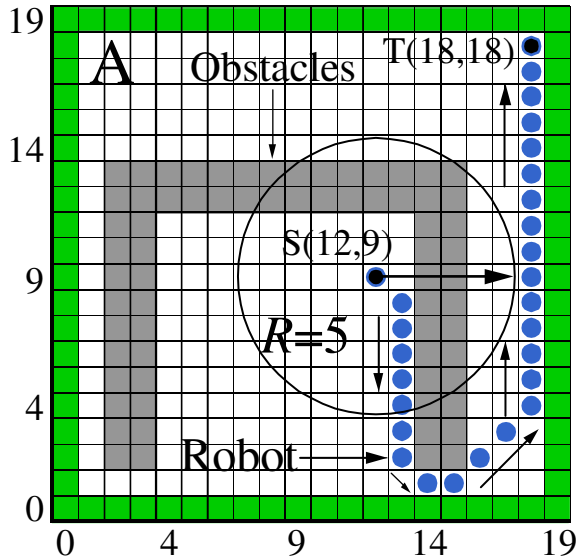


Figure 4-10 The robot trajectory generated by Hu *et al's.* AIN model (redrawn from Hu *et al's.* 2007).



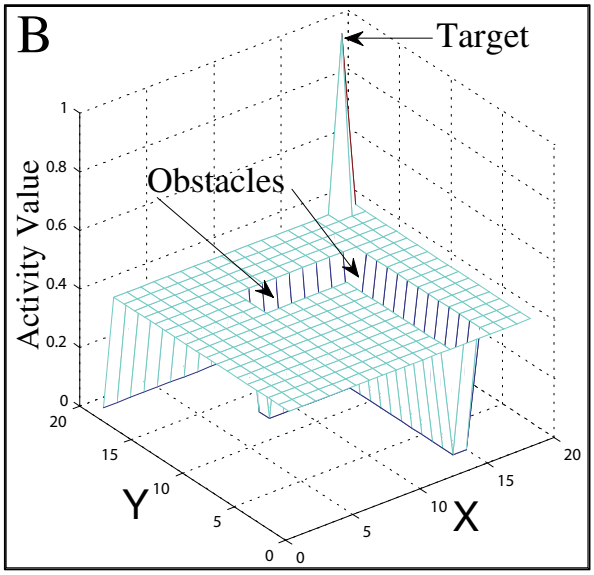


Figure 4-11 Simulation results by the proposed model in the U-shaped unknown environment. A: The generated trajectory; B: The neural activity landscape of the bio-inspired neural networks.

In the proposed model, the neural networks in workspace are organized topologically and discretely. The positive neural activity always propagates to the neuron location with the maximal neural activity until the robot reaches the target. Using the proposed algorithm, no local minima are encountered in this simulation with the U-shaped obstacles. Only the positive neural activity can propagate to the entire state space. The negative neural activity remains *only* local. Since the target grid in the workspace is set as $\mathbf{I}_i = E$, the positive neural activity propagates to the entire workspace until it reaches the target at T(18,18).

4.5 Conclusions

A novel, neural dynamics-based algorithm for real-time concurrent map building of grid map representation and navigation in unknown environments is proposed. The developed biologically-inspired neural network model algorithms and real-time map

building approach are capable of autonomously planning a collision-free path for an autonomous mobile robot in completely *unknown* environments, with grid map representation. The desired result of the real-time robot trajectory planning in an unknown environment is in the sense of a continuous, smooth and collision-free trajectory toward the target.

The model algorithm is computationally efficient in the sense that the computational complexity is proven to be $O(N^2)$. The map is built during the robot's navigation. The robot's path is planned through the dynamic neural activity landscape with limited sensory information in unknown environments *without* any template, *without* explicitly optimizing any global cost functions, *without* any prior knowledge of the dynamic environment, and *without* any learning procedures.

The feasibility and efficiency of the proposed algorithms are discussed and illustrated through simulation studies and further comparison studies in unknown environments. However, in the robot navigation, sensors are necessary to be integrated with the robot. The next chapter will focus on sensor configuration in combination with BNN to guide a robot as it moves autonomously to a specified destination.

5 Goal-Oriented Autonomous Robot Navigation and Mapping with Sensor Configurations

An efficient, goal-oriented, sensor-based, biologically-inspired neural network (BNN) path planner, integrated with a histogram-based local navigator to generate a real-time, collision-free navigation and mapping of an autonomous mobile robot in a completely *unknown* environment is proposed. With the goal-oriented BNN path planner and local navigator model, an autonomous robot is guided towards the goal with obstacle avoidance while a local map is dynamically and continuously built up. According to the sampled sensory data, an accurate map, including a grid representation of the robot and the local environment, is dynamically built for the robot navigation. The proposed navigation and mapping model, associated with an efficient histogram-based local navigator, is capable of planning a real-time, reasonable trajectory for an autonomous robot. Simulation and comparison studies are addressed to demonstrate the effectiveness and efficiency of this proposed methodology that concurrently performs collision-free navigation and mapping of an autonomous robot.

5.1 Introduction

Chapter 4 discussed mobile robot navigation in the completely unknown environment. By applying the biologically-inspired neural network (BNN) model, the mobile robot can navigate itself from the starting position to the target destination. However, in real-world applications, a robot has to be equipped sensors in order to be provided with the real-time data for its navigation system. A local navigator providing

sensory data to guide the robot with local obstacle avoidance towards the goal is needed for autonomous navigation.

In this chapter, a goal-oriented, biologically inspired neural network (BNN) model, as well as a concurrent, sensor-based navigation and mapping algorithm associated with a histogram-based local navigator, are developed for an autonomous robot. The biologically-inspired neural network model [74][75] is applied to autonomous robot motion planning and mapping in the completely unknown environment. In terms of navigation with restricted sensory data in *unknown* environments by configuring LIDAR, a local map composed of cells is built through the proposed neural dynamics. The robot is capable of dynamically building an accurate map of its momentary location for its navigation. The robot can only scan a limited reading range by gaining measurable sensory data from LIDAR and GPS as used for navigation. A global trajectory for an autonomous robot is generated by the proposed BNN algorithm, while histogram-based VFH algorithm based on the LIDAR and GPS sensor data locally guides the robot to move constantly towards the goal.

A BNN network model is derived for trajectory planning of an intelligent robot. The topologically-organized neural network with nonlinear analog neurons is efficient for trajectory planning with obstacle avoidance. The proposed topologically-organized model is expressed in a 2D Cartesian workspace **W** of the intelligent robots Figure 5-1.

The rest of this chapter is organized as follows: Section 5.2 presents the sensor configurations. The navigation algorithm with the local LIDAR-based navigator for concurrent navigation and mapping is addressed in Section 5.3. Simulation and

comparison studies are implemented in Sections 5.4 to show BNN model's performance. Finally, this chapter concludes in Section 5.5.

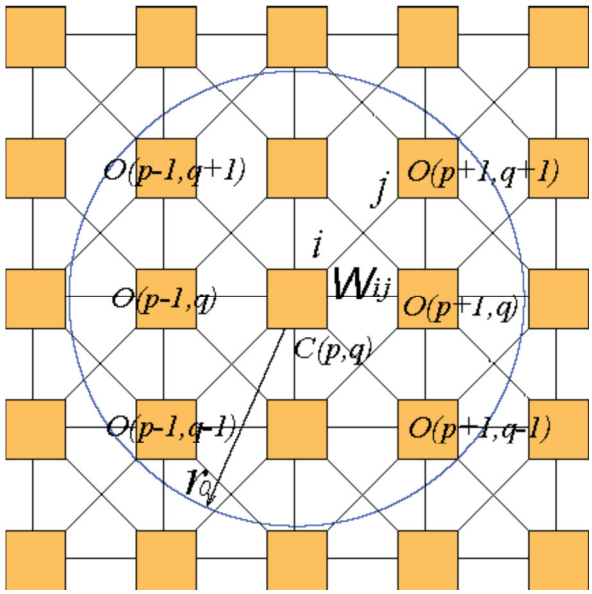


Figure 5-1 Architecture of a 2D neural network with adjacent neurons with regard to the central neuron C.

5.2 The Sensor Configuration

The goal-oriented navigation works in the sense that the real-time global robot trajectory is planned, based on the dynamic activity landscape of the neural network and the previous robot position, to guarantee that the *goal* be reached and the robot travel along a smooth and continuous path while a sensor-based local navigator guides the robot to move towards the goal, with obstacle avoidance. The developed, intelligent vehicle incorporates two sensors into its compact design: a LIDAR and a DGPS. Each sensor is enclosed in a waterproof case and firmly mounted to the vehicle which, at the same time, permits relatively facile removal for servicing, as shown in Figure 5-2. A 270^0 SICK

LMS111 LIDAR unit was employed for the purposes of obstacle detection described in the previous section. DGPS is used to obtain positioning data in the navigation system, selected as Novatels ProPak-LB Plus DGPS system. The DGPS antenna is mounted to the top of the vehicle's mast, while the receiver is securely positioned inside the chassis. Using Omnistar HPs DGPS system, the signal is corrected to the extent of +0.1m accuracy. In this section, the BNN driven motion planning and navigation model with sensor configuration is simulated in the Player/Stage simulator.

Figure 5-2 Sensor configuration for the goal-oriented autonomous robot navigation and mapping.

5.3 The Navigation Algorithm

This section addresses the navigation and mapping algorithms, which contain three portions: *Initialization* portion, *Navigation* portion, and *Local Navigator and Map Building* portion, as follows.

5.3.1 The Navigation Algorithm

In these algorithms, it is necessary to define a flag, denoted by *f(p,q),* for a neuron at Point *(p,q)* to indicate its status as visited, unknown (unvisited), obstacle, or goal (Figure 5-1.)

$$f(x,l) = \begin{cases} 0 & if\ it\ is\ unknown/unvisited \\ 1 & if\ it\ is\ visited \\ 2 & if\ is\ obstacle \end{cases} \qquad (1)$$

Initially, the autonomous robot has no *priori* knowledge of any obstacles in the environment, except the entire workspace dimension. The model algorithm is composed of following the three phases: initialization phase, navigation phase, and local navigator and map building phase.

The Initialization Phase: The initialization algorithm aims to initialize the starting point of the robot, to set all the neural activities as zeros, etc., which is given in Algorithm 1. The Navigation Phase: The goal globally attracts the robot in the whole state space through neural activity propagation, while the obstacles only exercise a local influence on a small region to prevent collisions. The navigation algorithm for the autonomous robot is given in Algorithm 2. In this algorithm, for a robot, once it traverses from the current point to its next point, the next point becomes a new current point, and the previous point is marked as visited (see Algorithm 2). The definition of "next point" is in the sense that the next point is selected based on the neural activity (see Equation (1) and Algorithm 2).

The following notations will be utilized to describe the proposed three algorithms. N_x *and* N_y are the discrete size of the Cartesian workspace.

Ø(p,q)	The set of the discretized workspace
	$\{(p,q),\ 1 \le p \le N_x,\ 1 \le q \le N_y\}$.
***O*(p,q)**	The unknown point (p,q)
	$1 \le p \le N_x,\ 1 \le q \le N_y$
Ȯ(p,q)	The visited point (p,q).
	$1 \le p \le N_x,\ 1 \le q \le N_y$
Ö***(p,q)***	The point (p,q) with the second largest neural activity.
	$1 \le p \le N_x,\ 1 \le q \le N_y$
X(p,q)	Neural activity at the unknown point (p,q)
(p_c, q_c)	The current point (p_c, q_c)
(p_n,q_n)	The next point (p_n,q_n) with the maximal neural activity.
$X_m(p_n,q_n)$	The maximal neural activity at the Point of (p_n,q_n)
I(p,q)	External input to neuron O(p,q).

The neighborhood of a central neuron C(p,q) is composed of some neighboring neurons that enclose the central neuron C(p,q), shown in Figure 5-1. The neighborhood of a central neuron C(p,q) in the Grossberg neural network is defined by $O_r(p,q) = \{N(m,n) | \max\{|m-p|,|n-q|\} \le r, 1 \le m \le N_x, 1 \le n \le N_y\}$ where r is the number of circles enclosing the central neuron (see Figure 5-1). The position of an adjacent neuron O(m,n) near to the central neuron C(p,q) has the following property: m Є {p-1,p,p+1} and n Є

{q-1,q,q+1} illustrated in Figure 5-1, in which the architecture of a 2D neural network with adjacent neurons with regard to the central neuron C(p,q) is shown. The central neuron C(p,q) illustrated by a dark shaded square, has eight neighboring neurons if **r** =1. In this model, the central neuron locally connects with the closest neurons, i.e., **r**=1.

Algorithm 1 Initialization Algorithm

1) set pc := p0; set qc := q0, where (p0,q0) is a starting point

// Set starting point to a current neuron

2) set f(p,q) := 0; set I(p,q) := 0, $\forall\ 1 \leq p \leq Nx, 1 \leq q \leq Ny$

// Set all areas as unvisited except obstacles

3) set x(p,q) := 0, $\forall\ 1 \leq p \leq Nx, 1 \leq q \leq Ny$

// Set all neural activities as zero

Algorithm 2 Motion Planning Algorithm

1) Compute neural activity by Equation (1)

2) $O_r(p,q) = \{N(m,n)|, m \in (p-1,p,p+1) \text{ and } n \in (q-1,q,q+1)\}$

// scan unknown adjacent neurons (p_n,q_n) =

$$\underset{m,n}{\operatorname{argmax}}\, x(m,n) \in \{\Theta r \mid m \in (p-1,p,p+1) and\ n \in (q-1,q,q+1)$$

// find the next adjacent neuron with the maximal neural activity

3) set pc := p_n; set qc := q_n

// Set current neuron to neighboring neuron

$if\ \exists\ (p,q) \in Or(m,n), s.t\ .x(p,q) \leq x(pc,qc)$

// if adjacent neural activity ≤ current neural activity then

set I(p,q):=0

set Ȯ(p,q):= O(p,q)

flag f(p,q) := 1

// Mark it as visited and external input as zero

end if

$if\ \exists\ (p,q) \in Or(m,n), s.t\ .x(p,q) \leq x(pn,qn)$

// if adjacent neural activity ≤ maximal neural activity then

set I(p,q):=0

set Ö(p,q):= O(p,q)

flag f(p,q) := 3

// Mark it as the second largest neural activity

end if

$if\ \exists\ (p,h) \in Or(m,n), \forall\ g \in \{p-1, p, p+1\}$ and h Є {q-1,q,q+1}, s.t. f(g,h)=1

// if adjacent neurons are all visited then

set I(g,h):=0

set Ȯ(g,h):= O(p,q)

// Mark them as visited and external input as zero

end if

go to 1).

The computational complexity depends linearly on the state space size of the neural network, which is proportional to the workspace size. The number of neurons required is equal to $M = N_x \times N_y$ The workspace is discretized with dimension of width N_x and height $N_{y.}$.

If the workspace is an N× N square in shape, there are N^2 neurons, and each neuron has at most eight local neural connections. The computational complexity of the proposed algorithm is $O(N^2)$. Therefore, it is computationally efficient.

5.3.2 The Local Navigator and Mapping Algorithm

Although a trajectory by the proposed BNN model is planned for an autonomous robot, as the environmental data is completely unknown, a local navigator is necessary for obstacle avoidance. Polar histogram, a sort of intermediate data-representation, was proposed by Borenstein and Koren illustrated, as in Figure 5-3, in their Vector Field

Histogram (VFH) model. A 2D Cartesian Histogram Grid is utilized for representation of a workspace by VFH method, in which the real-time data sampled by LIDAR scans dynamically and updates the entire workspace information. With the environmental data represented by the 2D Cartesian Histogram Grid, an one-dimensional Polar Histogram is formed to guide the robot to avoid obstacles while it continuously constructs maps. The VFH algorithm outputs a preferred goal sector for the robot to move towards to reach the *goal* based on local environmental information. The recommended direction is derived from an analysis of a polar obstacle density histogram sampled from LIDAR scans of the obstacle field in front of the robot, as illustrated in Figure 5-3. This decision is made from current sensor data, as there is no prior data in the sensor memory. Unknown obstacles are detected, and thus collisions are avoided, by the VFH algorithm while simultaneously driving the mobile robot toward the goal and building up maps. Once a trajectory is globally planned by the BNN path planner, it is automatically marked by points, namely, markers. These markers are converted into GPS coordinates and presented to VFH as consecutive goals to make the robot constantly move towards the *goal*. VFH then generates motion commands, which are passed on to the drive controllers to move the robot towards these intermediate *goals*. Once the robot approaches an intermediate goal, it is considered that it achieves and substitutes the next intermediate goal along the desired trajectory.

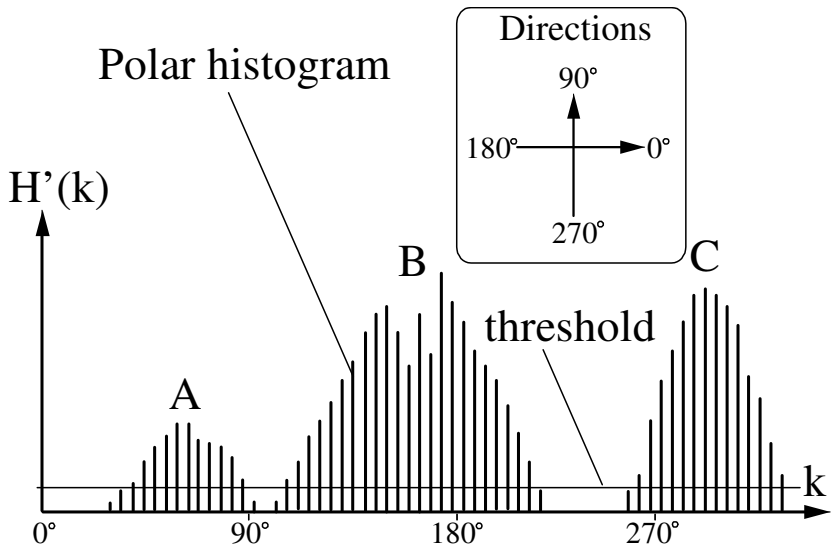


Figure 5-3 Polar histogram of obstacles in workspace with VFH method

5.4 Simulation and Comparison Studies

Simulation and comparison studies are fulfilled in this section to validate the effectiveness and efficiency of the proposed real-time autonomous robot navigation and mapping algorithm in unknown environments on the Player/Stage platform. In this section, the proposed approach is first applied to a typical U-shaped case. Then, the BNN model of the autonomous robot is studied in both a complicated U-shaped environment and an office-like environment. Comparison studies are presented to demonstrate that the proposed navigation and mapping model is more efficient than other models.

5.4.1 Navigation and Mapping in a U-shaped Unknown Environment

The proposed model is first applied to a U-shaped test scenario. In most situations, a small and maneuverable autonomous robot may be considered as a point robot when the

size of the robot and its maneuvering possibilities are compared to the size of the free workspace. Practically, a robot in traffic planning in large cities or a tank in field military operations may be regarded as a point robot. The proposed BNN model, associated with a histogram-based local navigator, navigates an autonomous robot in the U-shaped test scenario in unknown environment, shown in Figure 5-4. The workspace has a size of 40 x 40, which is topologically organized as a cell-based map. The parameters are selected as follows: $\gamma = 3$; $E = 200$ and $\beta = 0.01$.

The entire environment is assumed to be completely unknown except that the entire workspace is set as free areas initially. The robot can only sense a limited range, a radius of $R = 5$ with its on-board robot sensors. The starting point is located at S(17,37), and the robot moves toward the designated goal at T(17,7). The U-shaped workspace is shown in Figure 5-4A. Initially, the environmental information is unknown. Only the starting point and goal are assigned to the robot in terms of GPS sensor coordinates. The placement of obstacles is assumed to be unknown.

All the neural activities are initialized to zero. In Figure 5-4A, the robot starts moving from S(17,37), and it is able to move to the target T(17,7). By virtue of the incoming sensory knowledge, the robot is capable of planning a smooth, reasonable trajectory while the local map is built up, as illustrated in Figure 5-4A. The dynamic activity landscape of the neural network when the robot reaches the target T(17,7) is shown in Figure 5-4B. The neural activity of the goal has a very large value represented by the peak whereas the neural activities of obstacles are represented by a valley with negative values.

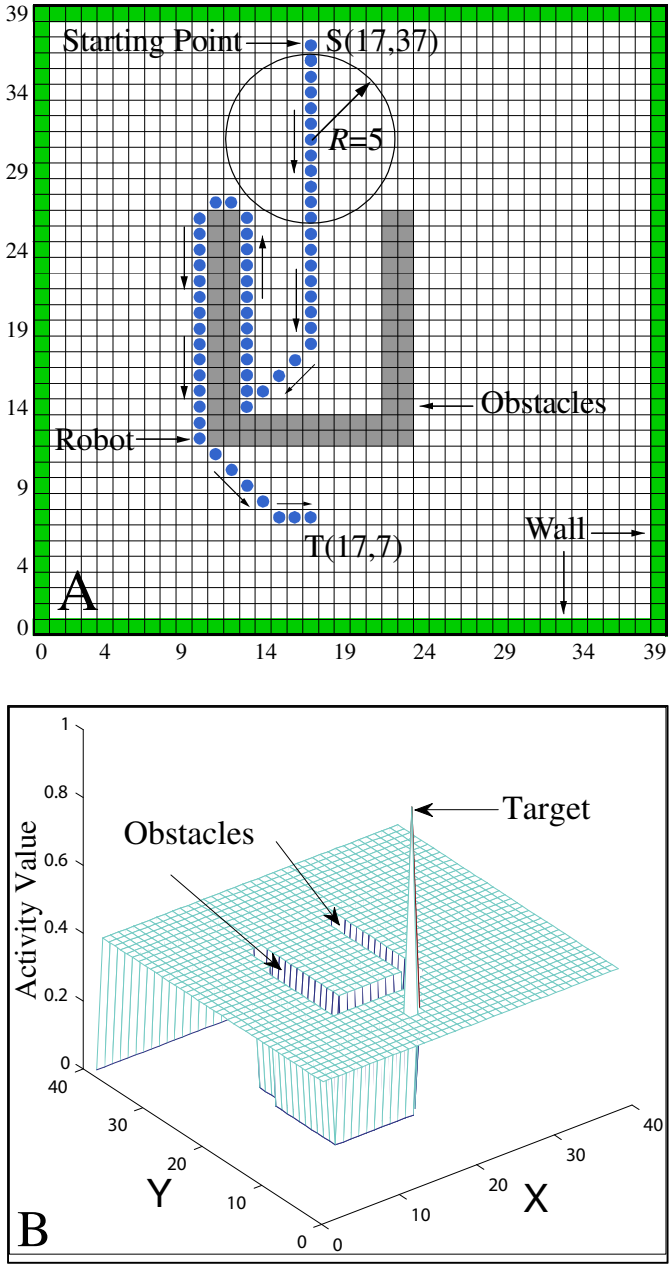


Figure 5-4 Illustration of navigation and mapping in a U-shaped workspace in an unknown environment. A: The workspace with U-shaped obstacles; B: The neural activity landscape of the neural networks.

The trajectories planned and maps built while the robot traverses in various phases towards the goal, with the BNN model as the global path planner, and the VFH as the local navigator, are simulated on the Player/Stage platform, as illustrated in Figure 5-5.

The final trajectory planned and final map built when the robot reaches the final goal is illustrated in Figure 5-6. The yellow fields indicate detected obstacles whereas the blue areas represent that the 270^0 SICK LMS111 LIDAR scanned.

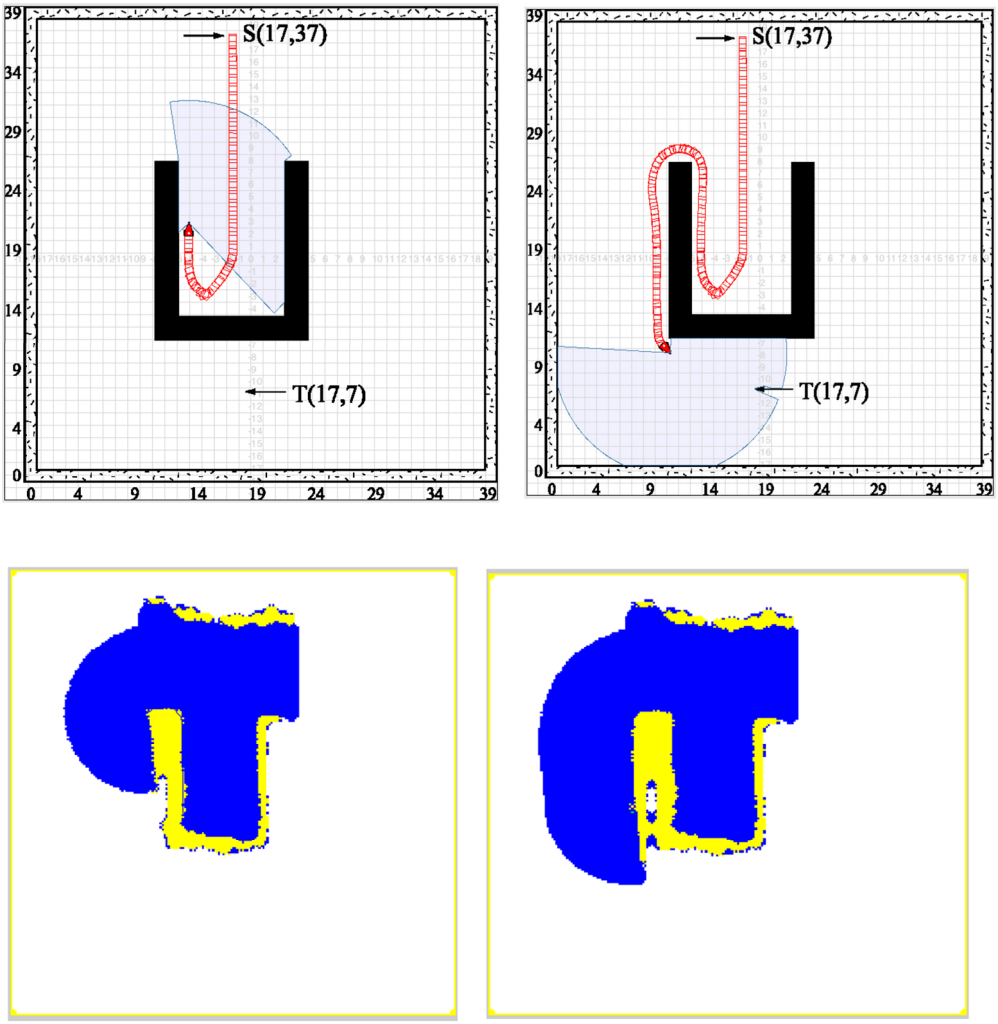


Figure 5-5 Illustration of planned trajectory and built map of a robot in a U-shaped workspace under unknown environment in various stages

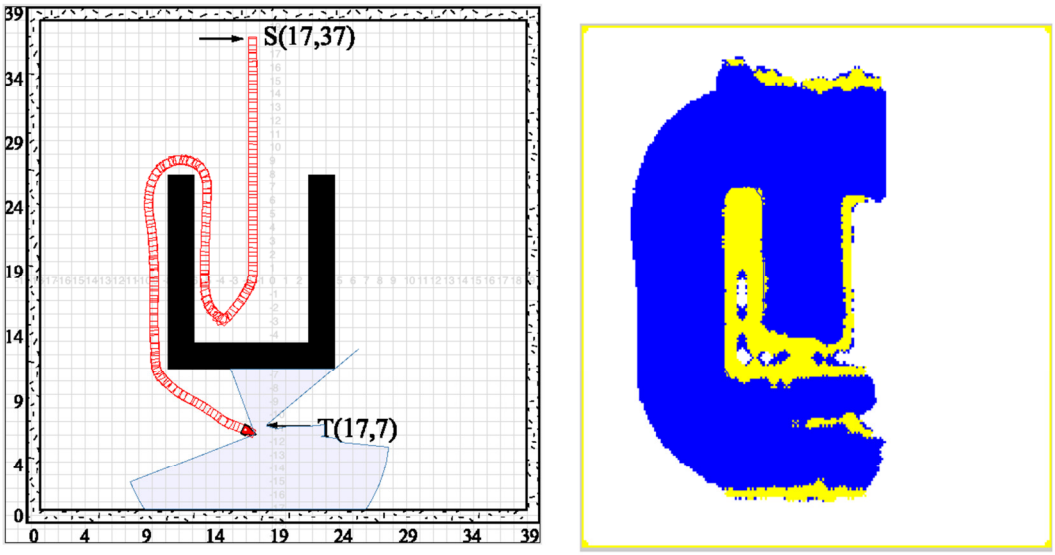


Figure 5-6 Illustration of mapping and navigation in a U-shaped, unknown environment when the robot reaches the goal. Left: the final trajectory planned; right: the final map built.

5.4.2 Navigation and Mapping in an Unstructured, U-shaped, Unknown Environment

To validate the effectiveness of the proposed model under *unknown* environments, this model is applied to an unstructured U-shaped test scenario, where the lengths of two sides of a U-shaped obstacle are not identical. The workspace is shown in Figure 5-7A, where S(32,26) indicates the starting point, and the squares represent the obstacles. The left side is longer than right side of the U-shape obstacle. The neural network consists of 40 × 40 topologically organized neurons, where all the neural activities are initialized to zero. The parameters are selected the same as above. Initially, the starting point is located at S(32,26), whereas the robot moves toward the designated goal, located at T(15,7) in Figure 5-7A. The robot can only scan a limited range having a radius of R = 5 with its on-board 270^0 SICK LMS111 LIDAR. The dynamic activity landscape of the neural

network when the robot reaches the target T(15,7) is shown in Figure 5-7A and Figure 5-7B. The neural activity of the goal has a very large value represented by the peak, while the neural activities of obstacles are represented by a valley with negative values.

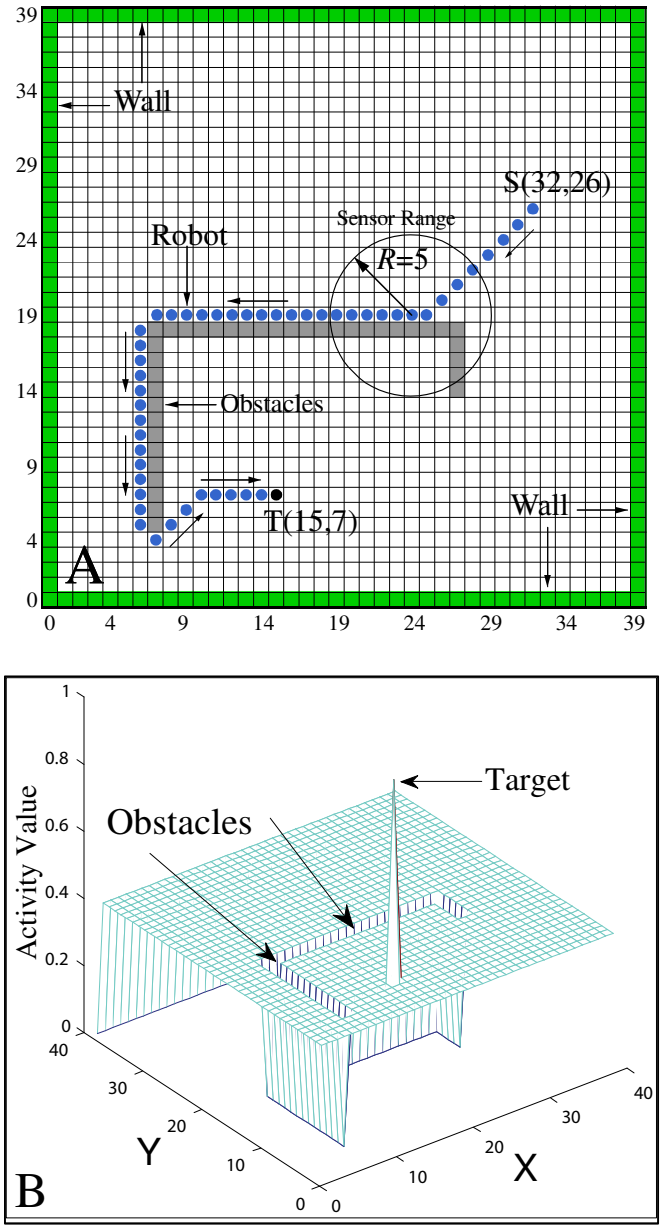


Figure 5-7 Illustration of real-time mapping and navigation in an unstructured, U-shaped, unknown environment. A: The workspace; B: The neural activity landscape of the neural networks.

The trajectories planned and maps built while the robot traverses in various phases towards the goal, with the bio-inspired neural networks as the global path planner and VFH as the local navigator, are illustrated in Figure 5-8. The final trajectory planned and final map constructed when the robot reaches the final goal are illustrated in Figure 5-9. The detected obstacles are represented by yellow images, and the explored regions are indicated by blue images.

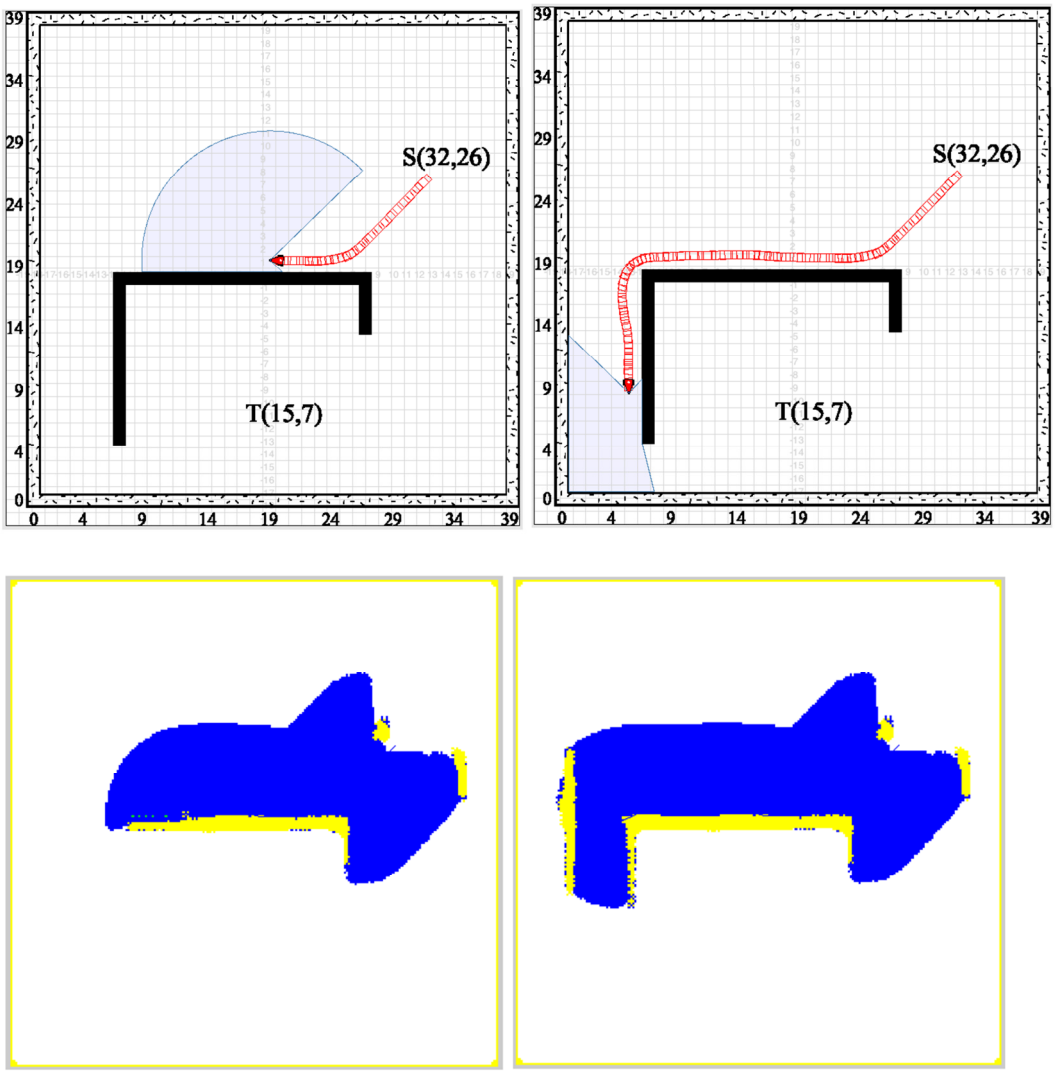


Figure 5-8 Illustration of the planned trajectory and the built map of a robot in an unstructured, U-shaped, unknown environment at various stages.

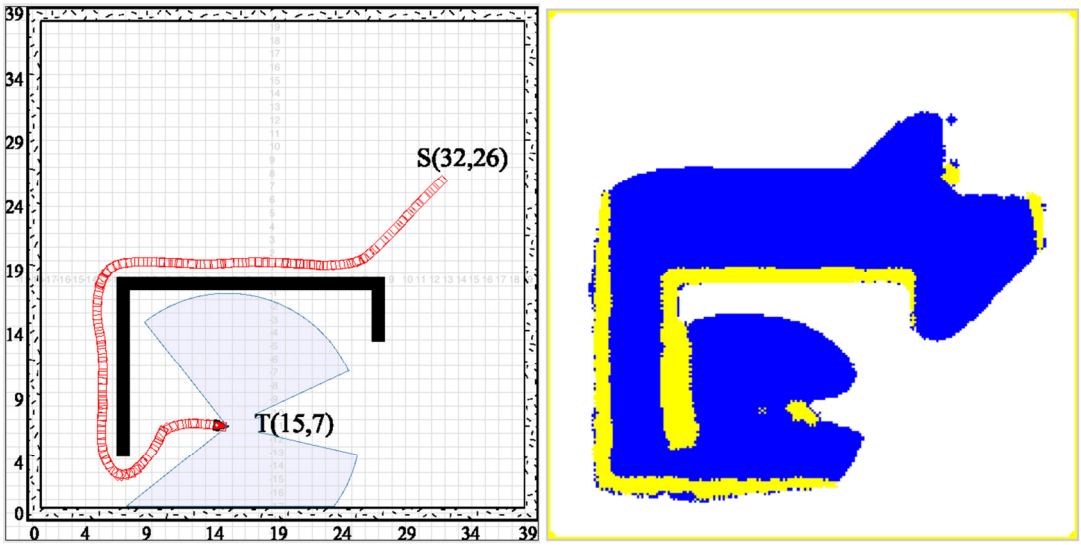


Figure 5-9 Illustration of mapping and navigation in an unstructured, U-shaped, unknown environment when the robot reaches the goal. Left: The final trajectory planned; right: The final map built.

5.4.3 Navigation and Mapping in an Office-Like Environment

The proposed model is applied to an office-like map filled with obstacles in an unknown environment. In real-world applications, a rescue robot is required to access a building to explore and find organisms in an office-like environment. Bin and Xiong [71] modified a neural network model for a path-planning application. In comparison with their model, the workspace is shown in Figure 5-10, where the starting position is located at S (2,2), and the square cells represent the obstacles. Figure 5-10 illustrates the generated, unreasonable path of the robot by their model.

The neural network contains 30 × 30 of discretely and topologically-organized neurons, where all the neural activities are initialized to zero. The model parameters are the same as previous simulations. There are five sets of wall-like obstacles populated in the workspace. The mobile robot starts from S(2,2). The generated robot path driven by

the proposed, sensor-based BNN model is shown in Figure 5-11A, where the robot is autonomously capable of traversing the entire workspace with obstacle avoidance along a more *reasonable* path. Finally, the robot reaches the goal at T(27,27). The varying environment is represented by the dynamic activity landscape of the neural network. The real-time robot trajectory is planned based on the dynamic neural activity landscape, and the previous robot location is driven by vector-based methodology. Figure 5-11B illustrates the neural activity landscape of the BNN in this office-like environment. The peak point indicates the goal at T(27,27), while the valley areas illustrate the obstacles.

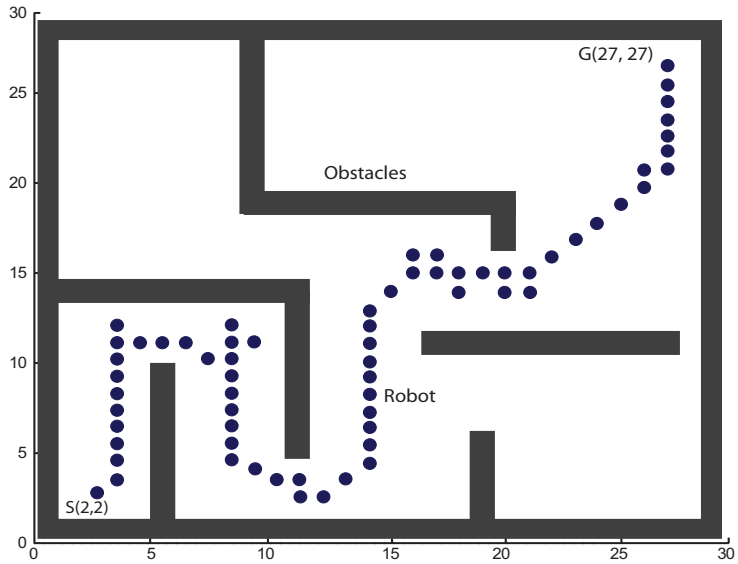


Figure 5-10 The generated path by Bin and Xiong's model (redrawn from Bin and Xiong 2004).

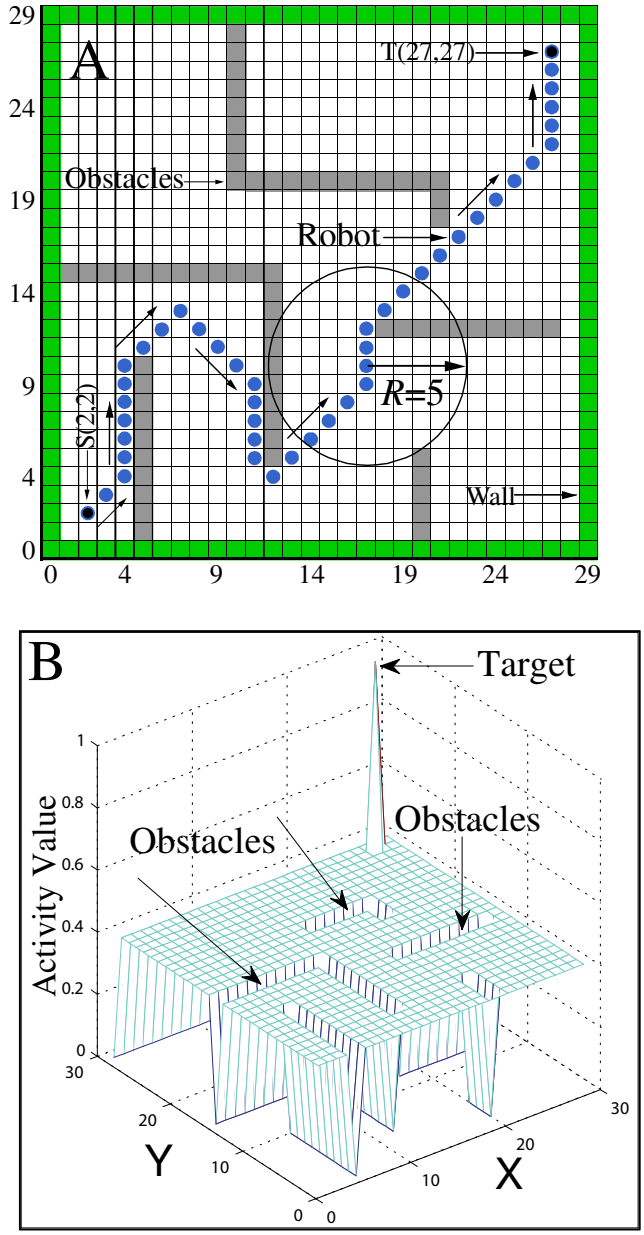


Figure 5-11 Simulation result from the proposed model in an unknown, office-like environment. A: The generated trajectory; B: The neural activity landscape of the bio-inspired neural networks.

The trajectories planned and the maps built while the robot traverses at various phases towards the goal with the BNN-based global path planner and histogram-based local navigator are illustrated in Figure 5-12.

The final trajectory planned and the final map built exactly when the robot reaches the final goal is illustrated in Figure 5-13. The yellow fields indicate detected obstacles, but the blue image represents zones explored by the LIDAR scans.

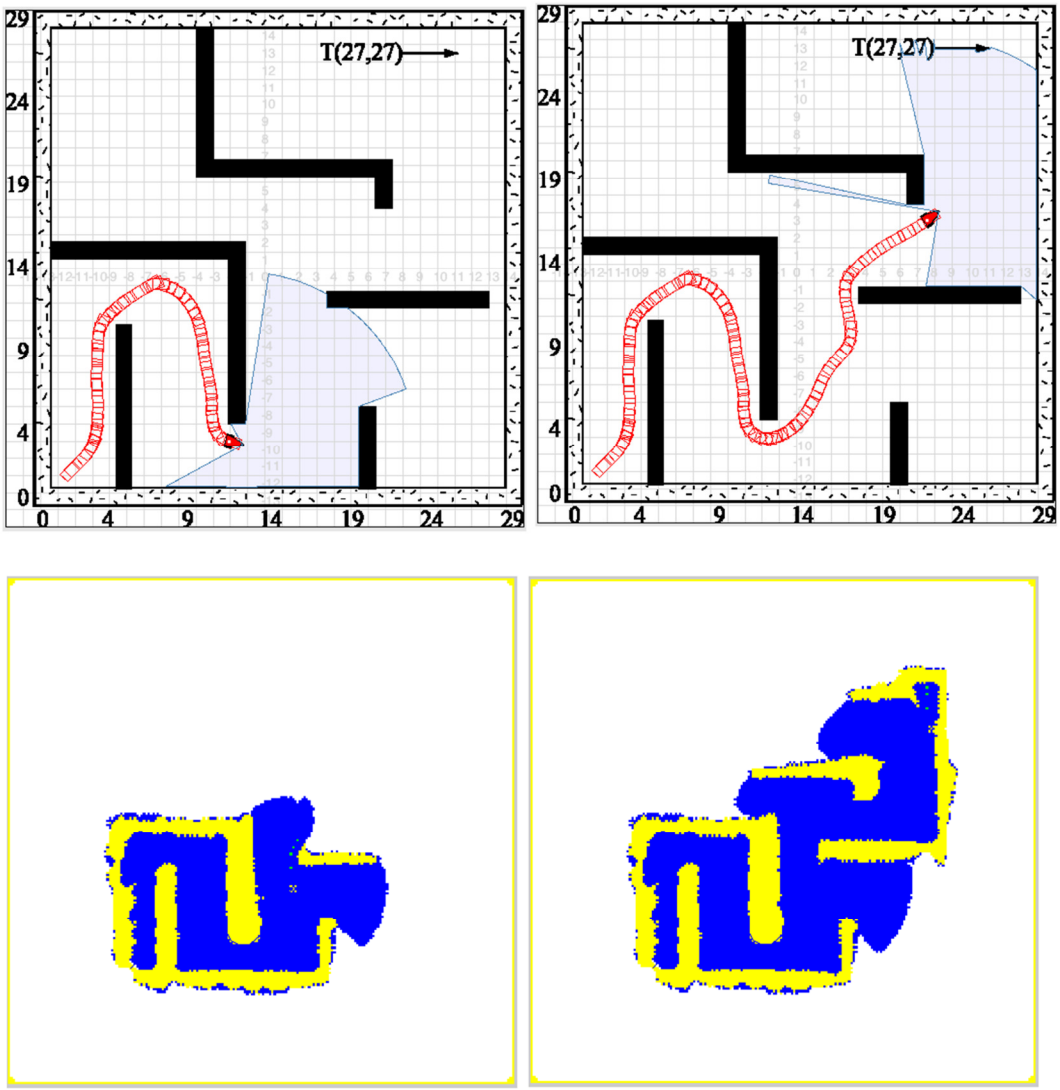


Figure 5-12 Illustration of the planned trajectory and the built map of a robot in an office-like environment in various stages.

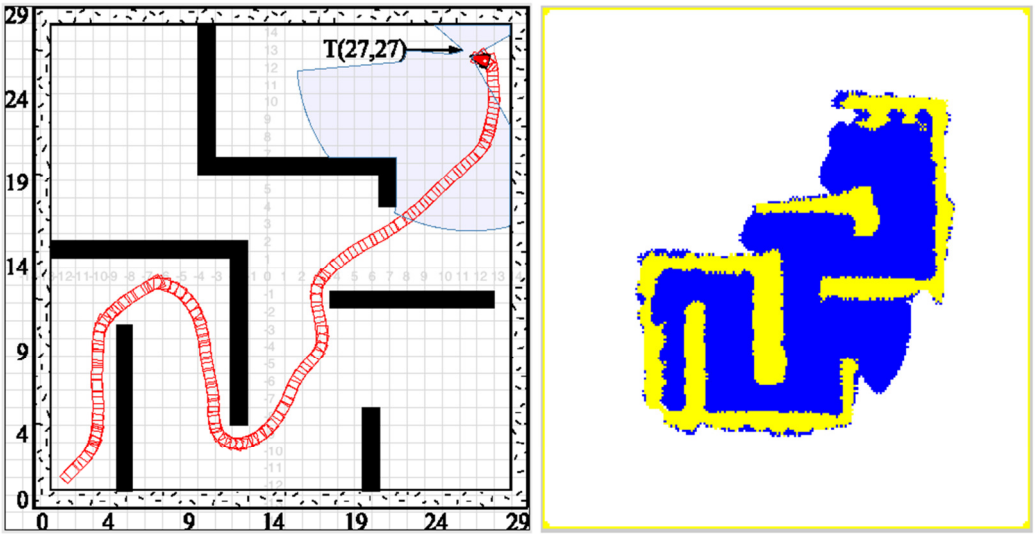


Figure 5-13 Illustration of mapping and navigation in an office-like environment when the robot reaches the goal. Left: The final trajectory planned; right: The final map built.

The trajectory length and number of turns from the proposed model and the model of Bin and Xiong were calculated (Table 5-1). Results show that the trajectory of length of our proposed model is shorter than their model. The length of the trajectory of the proposed model is 26.5% shorter than theirs. The number of turns made by the proposed model is only 1/3 that of their model. Furthermore, the number of steps from the proposed model to navigate the robot from the starting position to the target is 35.8% less than that of their model.

Model	Length	Turns	Steps
Bin and Xiong's Model	72.62	27	67
Proposed Model	53.36	9	43

Table 5-1 Comparison of trajectory length and number of turns and steps of Bin and Xiong's model and the proposed model

5.4.4 Navigation and Mapping in a U-shaped Workspace

Hu *et al.* [73] suggested an artificial immune network (AIN) for the robot motion planning of an autonomous robot. The proposed model is compared to a U-shaped workspace in Hu *et al's.* model. The workspace is illustrated in Figure 5-14, where the starting position is located at S (12,9).

In order to validate the efficiency and effectiveness of the proposed model, a simulation was performed to navigate the robot in such a U-shaped environment in Figure 5-15A. This simulation demonstrates that the trajectory generated in a square cell map representation is reasonable without local minima. The robot position at starting point S(12,9) is indicated by a blue dot, whereas the path in grid map representation is denoted by blue, solid circles with the final target at T(18,18). Figure 5-15B illustrates the neural activity landscape of the bio-inspired neural networks in the *unknown* U-shaped environment. The peak point denotes the target at T(18,18), while the valley areas indicate the U-shaped obstacles.

The robot's trajectory length and number of the robot's body turns and steps using the proposed model and the model of Hu *et al*. were calculated according to Figure 5-14 and Figure 5-15A. The results in Table 5-2 indicate that our trajectory length and number of turns are competitive with their model. In this case, the length of the trajectory by the proposed model is 12.3% shorter than that of their model. The number of turns of the proposed model is 13.3% less than that of their model.

Model	Length	Turns	Steps
Hu *et al's.* Model	30.87	5	30
Proposed Model	27.07	5	26

Table 5-2 Comparison of trajectory length and number of turns and steps of Hu *et al's.* model and the proposed model

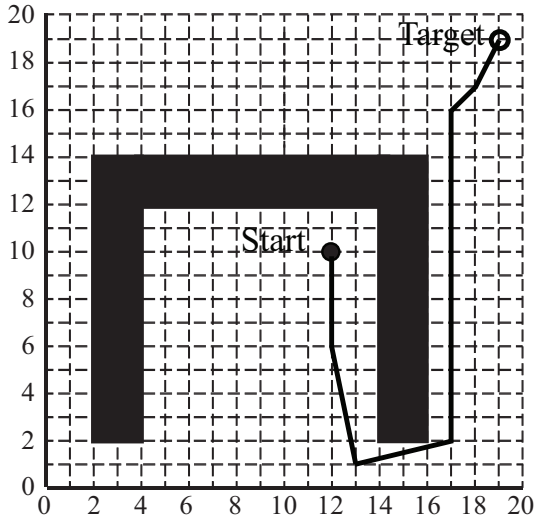


Figure 5-14 The robot trajectory generated by Hu et al's. AIN model (redrawn from Hu et al. 2007).

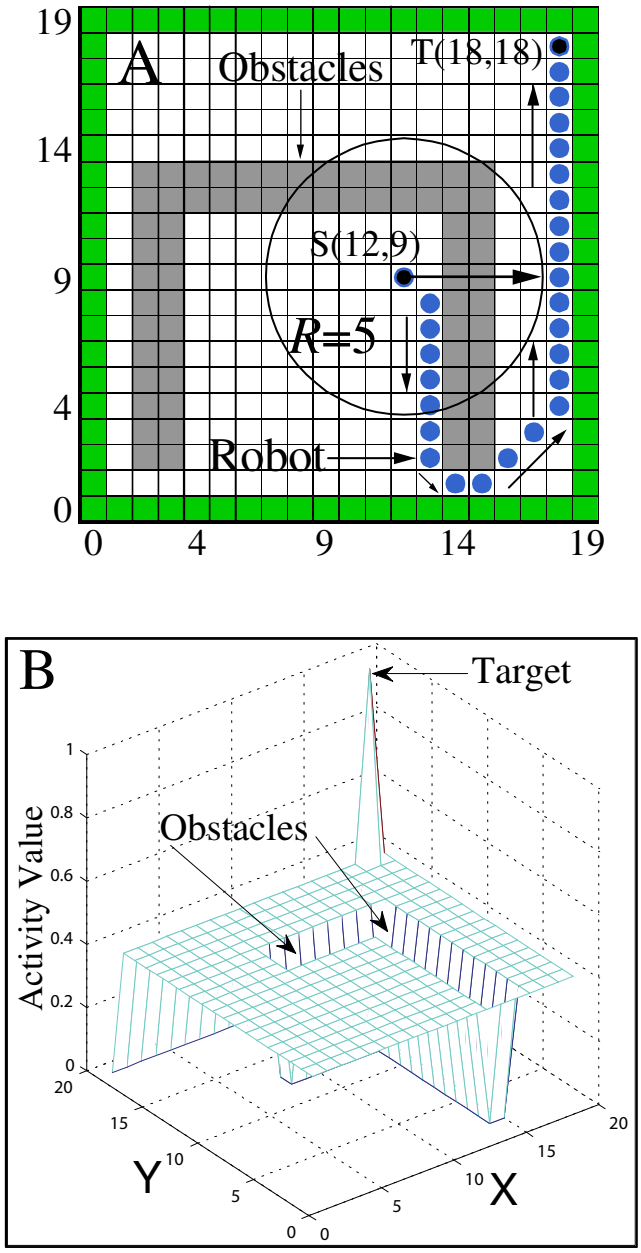


Figure 5-15 Simulation results of the proposed model in the U-shaped, unknown environment. A: The generated trajectory; B: The neural activity landscape of the bio-inspired neural networks.

The positive neural activity always propagates to the neuron location with the maximal neural activity until the robot reaches the goal. No local minima are encountered in this simulation with the U-shaped obstacles using the proposed algorithm. Only positive neural activity can propagate to the whole state space. Negative neural activity remains *only* local. Since the target grid in the workspace is set as $I_i = E$, the positive neural activity propagates to the entire workspace until it reaches the target at T(18,18).

With regard to implementing the proposed model onto an actual robot, an actual autonomous vehicle is being developed as a test-bed for real-time navigation and mapping of an autonomous robot. The robot incorporates two sensors into its compact design as follows: a LIDAR and a DGPS (Novatel's ProPak-LB Plus DGPS system), each of which is enclosed in a waterproof case and firmly mounted to the robot. It has been implemented on an actual autonomous vehicle in The Advanced Mobility Laboratory (AML), at University of Detroit Mercy, USA.

5.5 Conclusions

A novel, goal-oriented, neural dynamics-based algorithm for real-time concurrent map building of grid map representation and navigation, integrated with a histogram-based local navigator in *unknown* environments is proposed. The developed, biologically-inspired neural network model algorithms and real-time map building approach with histogram-based obstacle avoidance are capable of autonomously planning collision-free paths for an autonomous mobile robot in completely *unknown* environments. The best result of real-time robot trajectory planning in an unknown environment is in the sense of a continuous, smooth and collision-free trajectory sustainable towards the *goal*.

In real-world applications, for an autonomous mobile robot the top priority should be placed on safe navigation. However, moving obstacles in these environments may increase collision risk for the mobile robot. Consequently, the next chapter will introduce a new idea to enhance the safety of robot navigation using a model named as Distance Matrix method.

6 A Safe Navigation of an Autonomous Mobile Robot Using the Distance Matrix Model

One of the major challenges in intelligent robotic systems is safe or collision-free navigation. A novel, biologically-inspired neural network combined with a distance matrix model is proposed in this chapter for robot path planning to attain obstacle avoidance and a safe path. Using the proposed model, many computer simulations are conducted. The simulation studies have demonstrated that the proposed approach is capable of performing collision-free and safe navigation of an autonomous mobile robot. The robot can navigate to reach the specified target without getting lost, "too close," or "too far" to obstacles.

6.1 Introduction

All of the previous chapters have discussed robot navigation in the static or dynamic environment from the starting position to the target point by using virtual obstacles, in an unknown dynamic environment, and with a sensor-based goal-oriented BNN model. All of the studies have more or less attained obstacle avoidance during robot motion. However, in many applications, the real-world environment may have conditions that are more dynamic and unstable. For example, the dynamic environment may consist of many moving objects such as people and/or moving vehicles et al. A robot navigation with safer and more collision-free results is a very challenging topic for autonomous robot and intelligent navigation systems. In order to achieve safe robot navigation without "getting lost," and avoiding being too "far" or too "close" to obstacles, the distance matrix idea is

introduced to the biologically-inspired, neural network model. By applying the distance matrix model, several simulations have been conducted to demonstrate the effectiveness of this methodology with more safety considerations.

The rest of this chapter is organized as follows: the distance matrix model and algorithm are described in Section 6.2. Simulation studies are conducted in Section 6.3 to demonstrate their performance and effectiveness. Finally, Section 6.4 summarizes the study in this chapter.

6.2 Distance Matrix Model and Algorithm

6.2.1 Distance Matrix Model

During the robot's autonomous navigation process, the robot's path must be safe and collision-free, and the robot should not get lost and go far away from the target point. The neural network architecture of the proposed model is a discrete, topologically-organized map. This map is presented in a 2D Cartesian workspace and divided by evenly-spaced grids. The schematic diagram of the robot, from (i,j) neuron position to (i',j') position in 2D, is shown in Figure 6-1. The neurons located within the receptive field of the (i,j) neuron are referred to as its neighboring neurons. Therefore, there are eight neighboring neurons to (i,j) neuron.

A distance matrix is introduced to represent the dynamic neighboring neuron information and the neighboring neuron distance to the obstacles. The element numbers in the matrix represented the distance of closest obstacles to this element. Figure 6-2

shows an example of the distance matrix with a “0” element, which is a non-feasible target step, per distance matrix methodology during robot navigation.

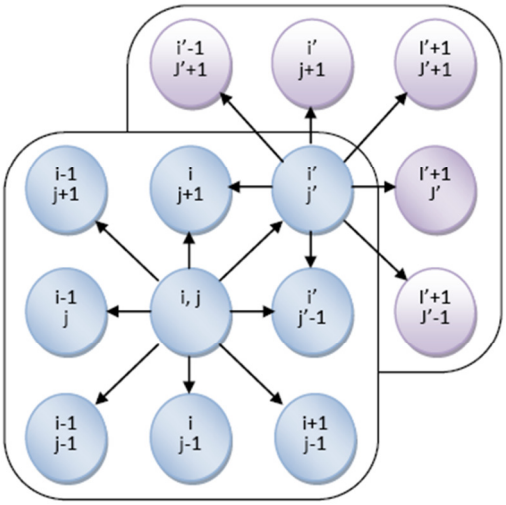


Figure 6-1 A robot position from (i,j) moving to target the next step (i’, j’).

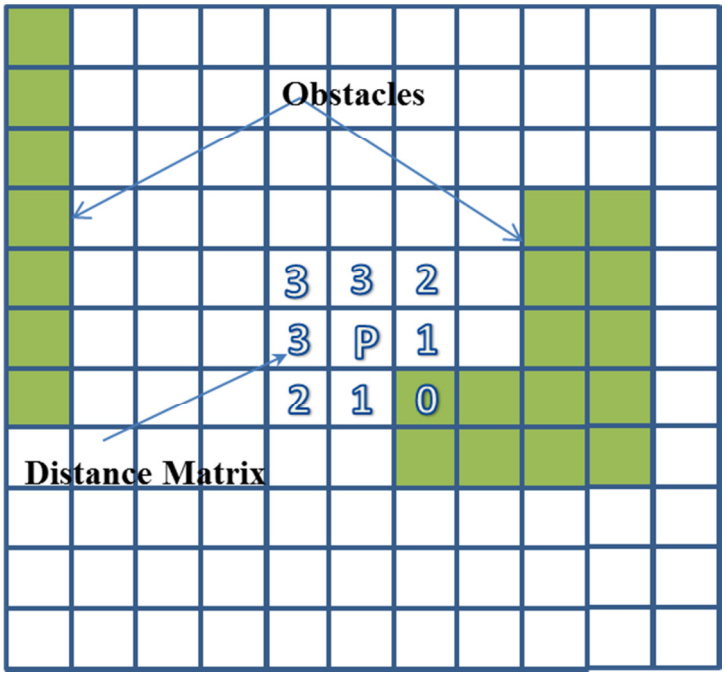


Figure 6-2 A distance matrix example with 0 element

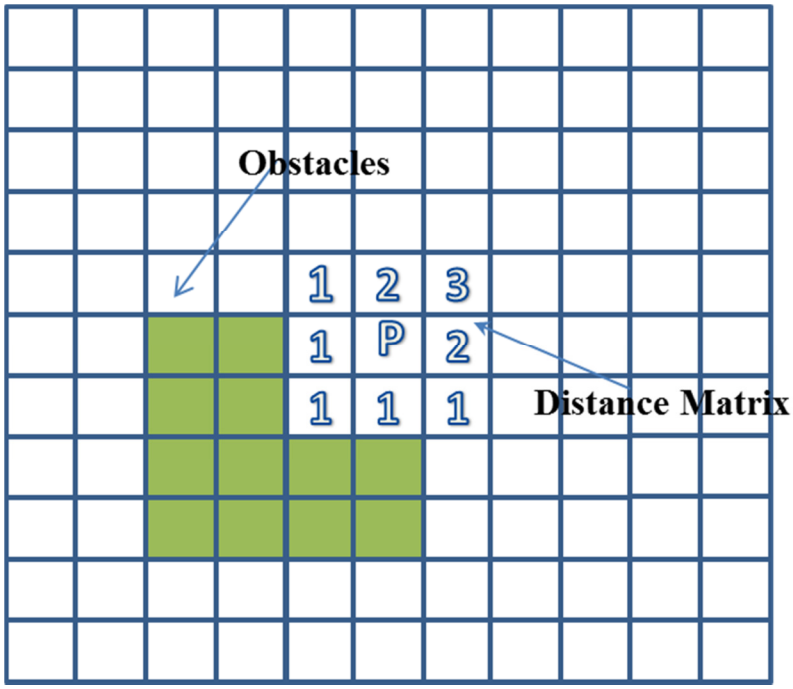


Figure 6-3 A distance matrix without 0 element

P in the distance matrix represents the new position (i',j') to which the robot is planning to move. The 3's in the matrix indicate that the closest distances between corresponding, neighboring neurons to obstacles are 3; 2 means that the upper right neuron in the matrix has the distance 2 to the closest obstacle. 1's in the matrix show that the distances of the related, neighboring neurons to the closest obstacles are 1's. "0" in the distance matrix means that the right, bottom, neighboring neuron is an obstacle. If there is a "0" in these matrix elements, the BNN integrated-distance matrix model will prevent the robot from moving from (i,j) to (i',j') because the next targeted step neuron position has the distance "0" to the closest obstacle, creating a potential safety concern. Instead, the distance matrix model will find the next largest neural activity among the neighboring neurons as the new targeting next step. By applying the distance matrix model, the robot will be

guaranteed to navigate a safe and collision-free path regarding obstacles. A distance matrix without "0" elements is shown in Figure 6-3. The robot can move to this new position because the distance matrix has represented no obstacles among the neighboring neurons.

6.2.2 Algorithm of the Distance Matrix Model

This algorithm consists of two portions: The initialization algorithm portion and navigation algorithm portion. Table 6-1 shows the initialization algorithm portion, in which, the neural network is initialized to prepare the start of the navigation algorithm portion. The initial condition is preprocessed.

Set starting point to a central neuron
Set external input of the goal as $\mathbf{I}_i = E$
Set all neural activities as zero

Table 6-1 The Initialization Algorithm

Table 6-2 describes the navigation algorithm portion. In this portion, the specified target attracts the robot through neural activity propagation. The loop will run continuously with time increments until the robot reaches the specified target.

```
Loop
    Find unvisited neighboring neuron with largest activity
    Step 1: Let current neural activity = largest neural activity
   if (neighboring neural activity <= current neural activity)
      and (neighboring neuron(i',j') not next to obstacles) then
            Flag as visited and external input as zero
    Else
     Find the next unvisited neighboring neuron with largest neural activity
     Go to step 1.
    if (neighboring neuron is either visited or with smaller activity)  then
            Flag it as deadlock.
    end if
     end if
     if (neighboring neurons are all visited)  then
            Flag it as visited
    end if
            Set the central neuron to neighboring neuron
End loop
```

Table 6-2 The Navigation Algorithm

6.3 Simulation Studies

Figure 6-4 is a U-shaped neural network map and its neural activity landscape when the robot reaches the target. The robot starts from the point of (17,37) and reaches the target point of (17,3). By using the distance matrix model, the robot navigation has an obstacle-collision-free path. A mobile robot travels total 34 steps from initial position to the destination. The mobile robot will be guaranteed a safe gap, at least one grid, with the obstacles during the motion.

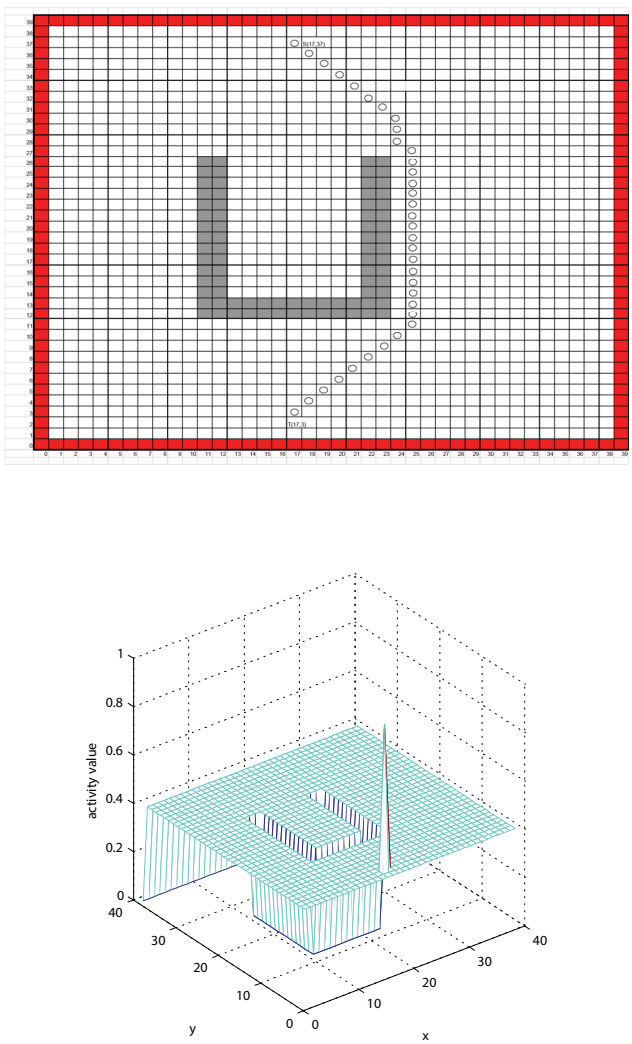
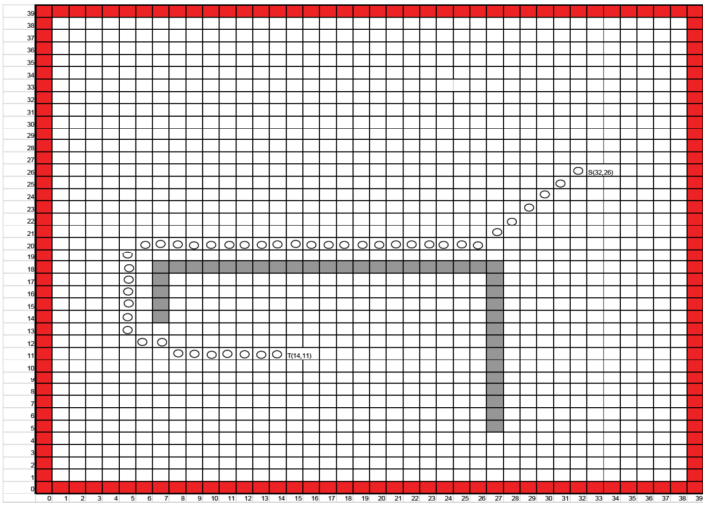


Figure 6-4 U-shaped neural network map and its neural activities landscape



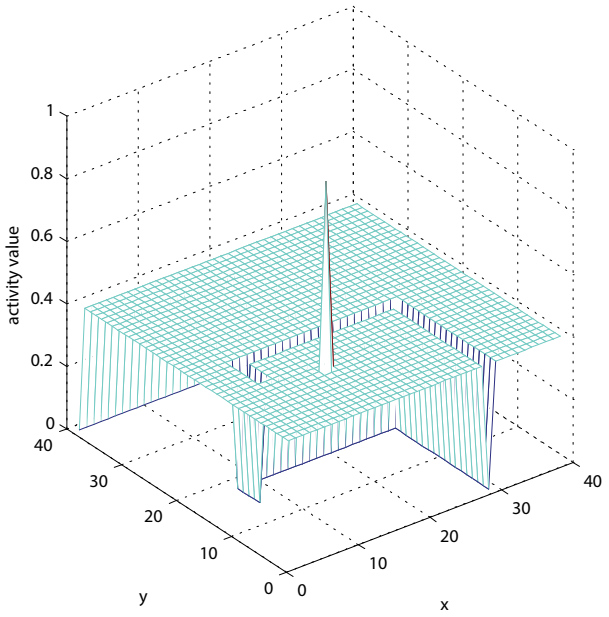


Figure 6-5 A neural network with long right side, U-shaped map, and its neural activity landscape.

Figure 6-5 is a neural network map with U-shaped open down and a long right side. The initial starting point is set at (32, 26) and the target point is set at (14, 11). The computer simulation results show that the robot reaches the target with a 42-step safe path. The target point has the highest neural activity, with a value of 1.

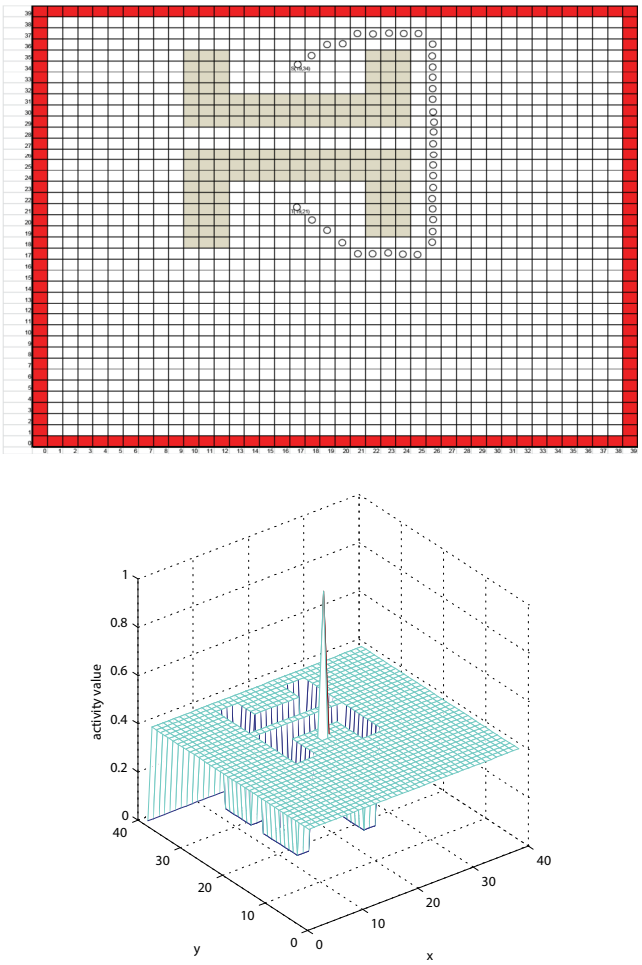
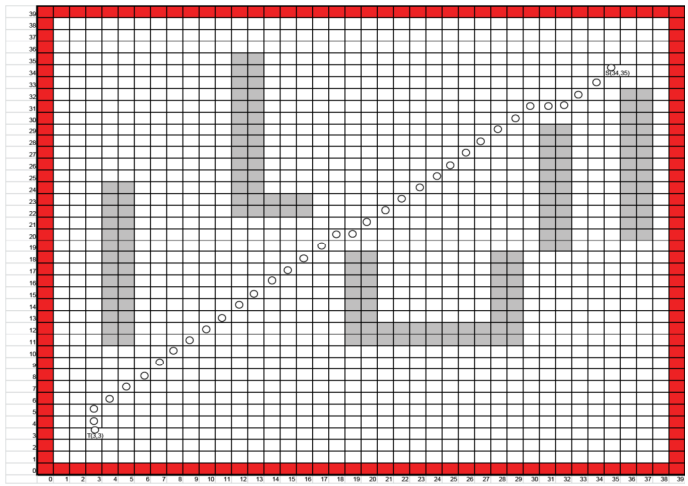


Figure 6-6 Two U-shaped maps and their neural activity landscape

Two U-shaped network map simulation results are shown in Figure 6-6. A robot starts from (19,34) and reaches the target (19,21) with a safe and collision-free path. The distance from the start to the target is 36 steps.



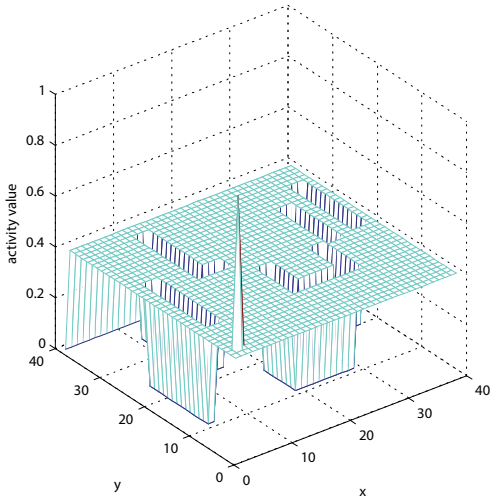


Figure 6-7 Bar-filled network map and its neural activity landscape

Figure 6-7 shows the results of a bar-filled network map simulation. A distance matrix model simulation with a safe robot path is planned. A robot starts from (34,35) and reaches the specified target (3,3) in 34 steps total.

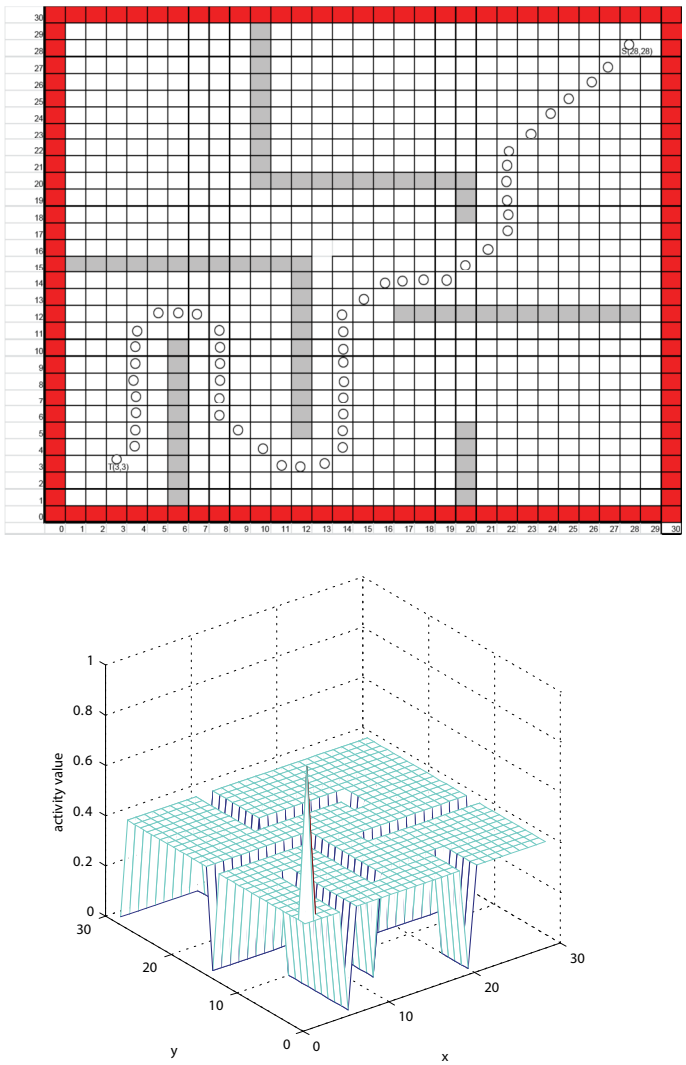


Figure 6-8 Door-shaped network map and its neural activity landscape

Figure 6-8 shows another network with a door-like map in the simulation study. From the starting position (28,28), the robot can navigate its way to reach the target (3,3). A total of 50 steps are used to reach the target.

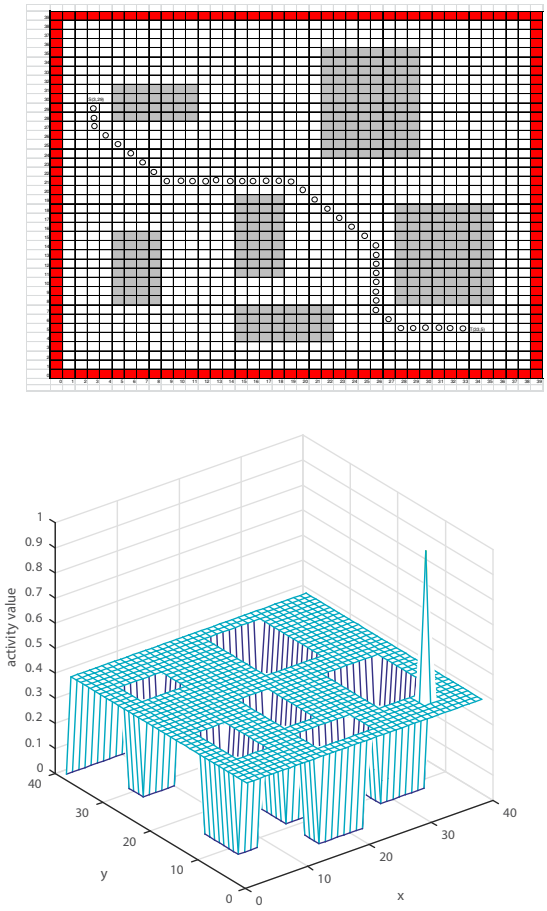
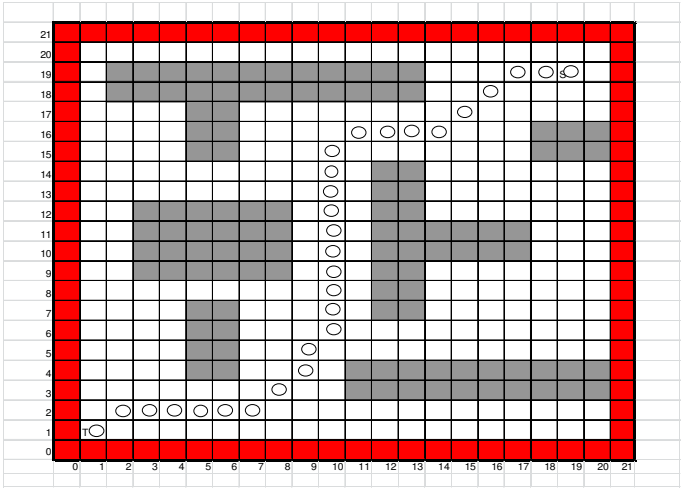


Figure 6-9 The neural network map in Gao et al's. [76] and its neural activity landscape

The sixth distance matrix simulation study is the network map redrawn from the Gao *et al.* [76]. The robot navigation path and its neural activity landscape when the robot reaches the target are shown in Figure 6-9. Using our distance matrix study, the proper path of 39 steps total is successfully planned. A robot autonomously moves from (3,29) to the destination point (33,5).



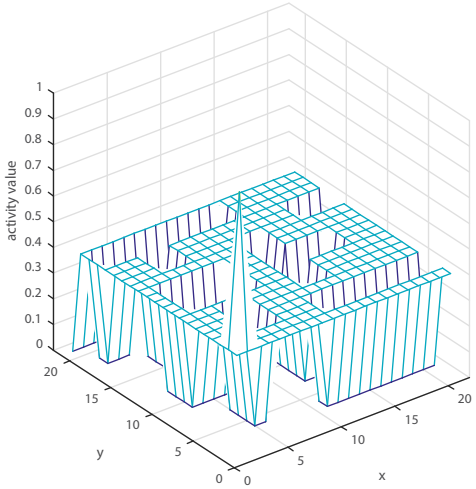


Figure 6-10 The network map in Qu et al's. [77] and its neural activity landscape.

Figure 6-10 is the application of using the distance matrix model map redrawn from Qu *et al.* [77]. A robot starts its navigation from the initial position (19,19) and reaches the target (1,1) with a total of 28 steps. It demonstrated a safe path as a result.

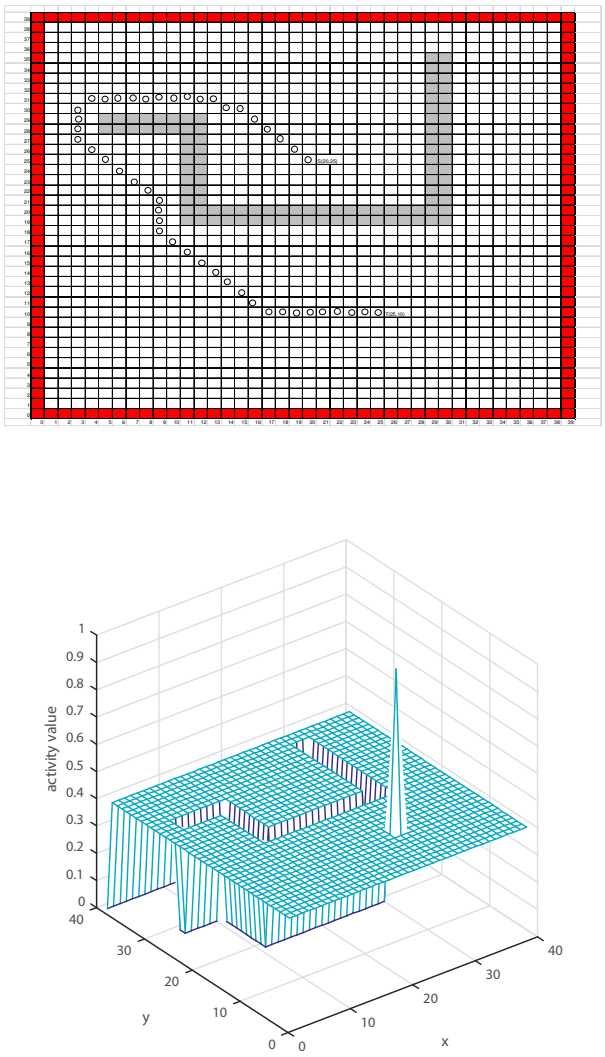


Figure 6-11 The network map in Dahm et al's. [78] and its neural activity landscape.

The last simulation study we used is the redrawn map from Dahm et al. [78]. The robot's initial starting point is [20,25], inside the U shape. The robot navigates itself and reaches the target point [25,10] maintaining a proper path as seen in Figure 6-11. The total distance used by the robot is 45 steps in this study.

From all of the above studies, we can see that a safe and collision-free path can be planned for a robot to reach its target. The planned path can make robot avoid obstacles

and being “too far” or “too close”. The reasonable and shortest path is planned effectively by using the distance matrix model.

6.4 Conclusions

In this chapter, robot navigation using a biologically-inspired neural network model combined with a distance matrix is proposed. Based on BNN network dynamic theory, eight different neural network maps are used in the simulations. This newly-introduced model can effectively help the robot achieve the safe paths of all of the studies. The conclusion can be made that this distance matrix model is capable and effective for robot path planning and navigation.

7 Conclusion and Future Work

In this thesis, a novel neural network system has been proposed and applied to robot navigation and mapping. Some of the important points are summarized as follows

7.1 Conclusion

In this thesis, a novel and efficient biologically inspired neural network systems has been proposed for robot motion planning, navigation, and mapping.

Firstly, the Virtual Obstacle Neural Network model was proposed for the shortest path of robot navigation. The obstacles are purposely enlarged to help the robot achieve the proper path and avoid becoming "too close" or "too far" in relation to nearing obstacles. Second, the biologically-inspired neural network model is applied to completely unknown dynamic environments. With the robot sensing limited distance, the safe and short path can be planned through the BNN model. Next, the study of sensor configurations with goal-oriented, autonomous robot navigation is conducted. The simulation results have demonstrated that the shortest path can be achieved using this model. Last, in order to achieve the most feasible path without the "too close" and "too far" issue, the BNN in combination with the developed distance matrix model is introduced to the neural network study. The simulation results have demonstrated that the proposed distance matrix model is effective and feasible for robot navigation of intelligent systems.

The simulations have proven that all of the proposed neural network models can be applied to robot navigation systems. The robot autonomously navigates itself from the

starting point to the target destination with a short and feasible path. Comparison to some other studies has been conducted to demonstrate the effectiveness of the proposed models. Through this study, the conclusion can be made that all of the proposed models are valuable and effective to path planning of robot navigations.

7.2 Future Work

The effectiveness and efficiency of the proposed bio-inspired neural networks were validated for robot navigation and mapping. Some challenging future work is summarized in this section.

1) In order to effectively generate short and reasonable trajectories in more complicated, cluttered, unstructured and unknown environments, it is necessary to apply a fuzzy logic approach [79]. While the cleaning path planner collects map information by sensors, an uncertainty situation exists such as uncertainty in the position and orientation of robots, uncertainty in existence of an object, and uncertainty about unknown environment. Neuron-fuzzy model is more effective than neural network or fuzzy logic only in dealing with path planner under complicated and cluttered environments.

2) Nowadays cooperation of multiple robots becomes very vital. Multiple robots collaboratively achieve a common goal efficiently, which can improve work capacity, share coverage tasks, and reduce completion time. A neural dynamics approach based on the navigation model in this dissertation is proposed for robot navigation and mapping by multiple robots [80]. A bio-inspired neural network is designed to model the workspace and guide a swarm of robots. The dynamics of each neuron in the topologically organized neural network are characterized by a neural dynamics equation. Each mobile robot regards other robots as moving obstacles. Each robot path is autonomously generated from the neural activity landscape of the neural network and the previous robot position.

3) The concurrent mapping and navigation has been accomplished in this dissertation. The localization is necessary to be studied in the future. The objective of simultaneous localization and mapping (SLAM) is to construct or update a map under unknown environments while simultaneously keeping track of a mobile robot's location within it. SLAM is one of the fundamental challenges for mapping and navigation of an autonomous mobile robot [81]. It would be advantageous to update the robot's locations through SLAM. The SLAM would be utilized to update the robot's locations in the map in addition to using them for localization [82]. The SLAM requires extensively computational effort to sense a sizable area and process the resulting data for both mapping and localization. A named OrthoSLAM that is a fast and lightweight solution developed to decompose the complexity of the environment into orthogonal planes, will be investigated for our BNN-based mapping and navigation model [83]. Structure of most environments by the OrthoSLAM algorithm may be estimated greatly accurately that makes only a single line processed at a time. Therefore, only the planes that are orthogonal to each other are mapped of the OrthoSLAM algorithm by decrementing SLAM to a linear estimation problem.

4) In this dissertation, a VFH-based local navigator was employed for obstacle avoidance. However, traditional VFH based methods suffer from some issues such as the local minimum problem and high computational complexity for in complicated, cluttered and dynamic environments. Especially, a robot attempts to avoid obstacles with narrow gaps. An improved VFH model will be investigated for real-time robot path planning and mapping under dynamically changing environments [84]. A fuzzy logic controller will be taken into account to avoid obstacles with various size and shape by adjusting the

rotation angle of the robot and integrating area ratio parameter into the traditional VFH based local navigator. In the modified VFH model, the size of the robot and obstacles are considered under dynamic environments [85]. Additionally, the field of view and the nonholonomic constraints of the robot are considered to overcome the local minimum issue that would generate safer trajectories due to its inherent properties in the histogram-based algorithms. In terms of collision-free navigation and mapping through our BNN model in environments with moving obstacles, a look-ahead tree method will be developed in light of neural activity of the bio-inspired neural dynamics model. While a mobile robot driven by our BNN model traverses, a look-ahead tress is created by the values of neural activity that reflect and represent the environmental information of the free-space and obstacles.

5) Distance matrix approach has been implemented in this dissertation. In the future, this method will be extended as an adaptive distance matrix model. A distance matrix is dynamically constructed to the distance from the robot to obstacles. The next position the robot moves to depends not only on the values of neural activities, but it is determined by the distance matrix also while the robot traverses in the workspace. An adaptive distance matrix method will be explored in order to adaptively build up a distance matrix to navigate the robot more accurately by a graph with distance matrix [86] in dynamic environments. In our BNN approach, a positive neural activity to the neural network is input to the goal in the grid, whereas obstacles are either sinks or held at a minimum neural activity value. The neural activity is dynamically propagated through the neural network by local connections while mobile robots traverse along the trajectory of steepest ascent to the goal [87]. A penalized distance will be utilized to propagate through

the network. The minimized sum of the current known distance to a target and the cumulative local penalty functions along the trajectory will be studied associated with the distance matrix in the future.

6) The computational complexity in our BNN model will be further investigated to optimize the computational performance. This may be accomplished by different map representations such as triangular-based, hexagon-based, or quadtree-based map representations. Triangular-based and hexagon-based map representations have been proposed to improve the computational efficiency. Unlike cell-based map representation, the quadtree-based map representation decomposes the workspace into different-size blocks as sub-regions, each of which is a recursive decomposition of a 2D region into kinds of blocks [88]. A graph is constructed to form a quadtree-based graph, in which a quadtree leaf node is a tip node of the tree. The entire workspace is recursively subdivided until either a sub-region free of mixtures is found or the smallest cell-size of grid is reached. The construction of a workspace through quadtree-based map representation consists of two phases. Firstly, the location and size of each homogeneous region is depicted by the tree structure. Secondly, the cell value is designated at each leaf node, or, sub-node, of the tree to represent a location as an obstacle, visited call or unvisited cell.

7) In the future research, nonholonomic car-like robots should be investigated and studied. The motion characteristics of a mobile robot play a crucial role in planning its trajectory. A car-like robot is unable to traverse freely in all three degrees of motion due to their steering constraints [89]. A robot traverses in a plane with three degrees of freedom, such as translation along the two axes in the plane, and rotation about the axis

perpendicular to the plane. Implemented on a nonholonomic car-like robot with nonholonomic motion constraints, a continuous steering control model will be developed to track the trajectory smoothly and smoother trajectory will be generated through the proposed speed modulation approximation.

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