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

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*Abstract*— **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 the obstacle avoidance to prevent an intelligent vehicle from approaching obstacles "too close" or "too far", but difficult to obtain an optimal trajectory. In this paper, a novel 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 navigation algorithm. The proposed model for intelligent vehicle trajectory planning with safety consideration is capable of planning a real-time "comfortable" 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.**

## I. 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 concerned with finding a safe and good-quality collision-free path from an initial point to a destination.

There have been plenty of approaches proposed in terms of autonomous vehicle navigation with obstacle avoidance such as potential field method [1], fuzzy logic [2], [8], sampling-based method [3],wavefront approach [4], sensor-based techniques [5], graph-based methods [5], [6], and neural network models [7], [8], [9], [10], [11], [12] , [13], etc.

Pathak and Agrawal [1] proposed a kinematic model based on potential field method for 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 [2] proposed a path planning with obstacle avoidance methodology of an autonomous mobile robot under unknown environments by utilizing a fuzzy logic system. The distance from a robot to obstacles and their positions are detected by ultrasonic sensors. Rule-table technique and fuzzy logic based angular velocity control algorithm are developed to find more reasonable trajectory. Plaku *et al.* [3] developed a sampling-based path planning method of an autonomous robot by a multilayered framework in combination of a search strategy.

Luo *et al.* [4] proposed a real-time simultaneous trace-guided navigation and map building (STNM) methodology of an intelligent vehicle by integrating 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.* [5] developed a sensor-based approach for multi-robot coverage navigation. Sensor-based coverage path planning performed in narrow spaces is implemented by a generalized Voronoi diagram (GVD)-based graph that models the environmental information.

Graph-based approach is an efficient approach to vehicle navigation as well [5], [6]. Luo *et al.* [6] developed a two-level LIDAR-driven hybrid system for real-time unmanned ground vehicle navigation and map building. Top level is newly designed enhanced Voronoi Diagram (EVD) graph method to plan a global trajectory for an unmanned vehicle. Bottom level employs Vector Field Histogram (VFH) algorithm based on the LIDAR sensor information to locally guide the vehicle under 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, a complete sensor-based coverage path planning for the multi-robot is achieved by taking advantage of sensor capability and generalized Voronoi diagram graph solution [5], [6]. Wang *et al.* [8] successfully combined fuzzy logic and neural networks methodologies for vehicle path planning.

Neural network methodology plays an important role on intelligent vehicle trajectory planning. Chang *et al.* [7] utilized neural network technique to implement local navigator that drives a vehicle to traverse from initial point to the target with obstacle avoidance. Wang *et al.* [8] suggested a hybrid system with fuzzy logic and neural networks for vehicle navigation of autonomous vehicle under unknown environments. The fuzzy system is automatically designed to train the neural network weights. Fujii *et al.* [9] suggested a multi-layered methodology for collision-free navigation via reinforcement learning. However, the planned vehicle

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motions using learning based approaches are not optimal, particularly at the initial learning stage. Yang and Meng [10] 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 [12] 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 ( [11], [12]). However, the neural network models described previously are only suitable for navigation in non-stationary environments without map building. Luo and Yang [13] recently developed heuristic algorithms based on a biologically inspired neural network model, which concurrently perform motion planning and map building under unknown environments. However, this model lacks of safety consideration while planning shortest trajectory of an autonomous robot.

In this papers, a biologically inspired neural network model in conjunction with the developed virtual obstacle algorithm (VOA) and safety aware navigation algorithm is utilized for an intelligent vehicle. The biologically inspired neural network model [14], [15] is applied to intelligent vehicle trajectory planning. Through this biologically inspired neural network model, the planned vehicle motion in a static environment is globally optimal although there is no explicit optimization of any global cost functions. The optimality 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 thus it is computationally efficient. The primary contribution of this paper is its virtual obstacle algorithm integrated into robot navigation system based on previous biologically inspired neural network model. The proposed model for vehicle trajectory planning with safety consideration is capable of planning a real-time "comfortable" trajectory by overcoming the either "too close" or "too far" shortcoming.

The rest of this paper is organized as follows: Section II derives a biologically inspired neural network model. Section III addresses the safety aware navigation technique and its properties. Some simulation results are presented in Section IV to show its performance. Finally, Section V concludes the paper.

## II. The Neural Network Model

In this paper, a biologically inspired neural network model is derived for trajectory planning of an intelligent vehicle [14], [15]. The topologically organized neural network with nonlinear analog neurons is efficient for trajectory planning with obstacle avoidance. This model resembles Dijkstra's algortihm in the sense of searching the lengths of the shortest trajectories from the goal. The computational efficiency of this biologically inspired neural network model on a graph with $N$ neurons is $O(N)$ in comparison of the Dijkstra's algorithm of $O(N^2)$ ( [14] [15]).

The real-time collision-free vehicle motion is planned based the dynamic activity landscape of the neural network and the previous vehicle position, to guarantee the goal to be reached and the vehicle to travel along a smooth and continuous path.

The proposed topologically organized model is expressed in a $2D$ Cartesian workspace $\mathcal{W}$ of the intelligent vehicles. The position of the $i$th neuron in the state space $\mathcal{S}$ of the neural network, denoted by a vector $q_i \in R^2$, *uniquely* represents a position in $\mathcal{W}$. 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 $\mathcal{R}_i$ in $\mathcal{S}$. The subset $\mathcal{R}_i$ is called the receptive field of the $i$th neuron in neurophysiology. The neuron responds only to the stimulus within its receptive field.

In the proposed model, the collision-free vehicle 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.

$$x_i(t+1) = g\Big(\sum_{j\in s_i} w_{ij}x_j(t) + I_i\Big), \tag{1}$$

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

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

$$I_i = \begin{cases} E & \text{if } i \text{ is the target} \\ -E & \text{if } i \text{ is an obstacle} \\ 0 & \text{otherwise} \end{cases}, \tag{3}$$

Transfer function $g$ may be any monotonically increasing function ( [14] [15]). A piecewise linear function is selected as the transfer function as follows.

$$g(x) = \begin{cases} 0 & x \le 0 \\ \beta x & x \in [0,1] \\ 1 & x \ge 1 \end{cases}, \tag{4}$$

where, $\beta > 0$ 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 $i$th neuron is represented by a circle with a radius of $r_0$. The $i$th 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 vehicle, while the obstacles only locally avoid the collision.

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 optimal vehicle path is planned from the dynamic activity landscape, and the previous vehicle location. The vehicle will move to the neuron with maximal neural activity, which is addressed in the following sections of Navigation and Vector-driven Algorithms (Algorithm 2 and Algorithm 3 in the next sections).

After the current location reaches its next location, the next location becomes a new current location. The current vehicle location *adaptively* changes according to the varying environment.

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

$$L_n = \underset{m,n}{\operatorname{argmax}}\,(x(m,n)) \in \{\mathcal{N}_k|(m,n)\}, \tag{5}$$

where $k$ is the number of *neighboring neurons* of the $L_c$th 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 $j$th neuron. After a vehicle reaches its next location from current location, the next location becomes a new current location (if the found next location is the same as the current location, the vehicle stays there without any movement). The current vehicle 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 bio-logically inspired neural network model, the computational complexity of the proposed algorithm is $O(N)$. Workspace size and rules to be used will mainly affect the computational complexity.

## III. The Safety Aware Navigation Algorithm

This section addresses the obstacle enlargement algorithm associated with the proposed bio-inspired neural network model. The algorithm contains three portions: *Initialization* portion, *Obstacle Enlargement* portion and *Navigation* portion.

A workspace populated with unstructured obstacles is shown in Fig. 1A, in which there are six set of obstacles. Assume that the workspace is decomposed of cells and the map is cell representation for the autonomous vehicle navigation. In order to obtain virtual obstacles, the obstacles are enlarged by enclosing with virtual obstacles illustrated in Fig. 1B. After enlargement of obstacles, the the autonomous vehicle navigation is performed to plan safer trajectory by an autonomous vehicle.

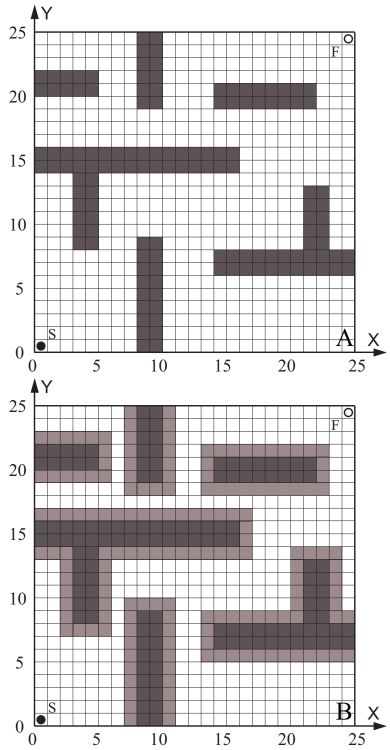


Fig. 1. The illustration of obstacle enlargement for virtual obstacles. A: The original workspace with obstacles; B: The workspace with virtual obstacles.

The **Initialization Algorithm** portion: The initialization algorithm is shown in Fig. 2.

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**Set** starting point to a central neuron
**Set** external input of the goal as $I_i = E$
**Set** all neural activities as zero

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Fig. 2. The Initialization Algorithm.

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

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**Loop**
  Find obstacle areas with $I_i = -E$
  by onboard sensors of the vehicle
  **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
**End loop**

Fig. 3. 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 Fig. 4. Based on the previously addressed OE algorithm, the vehicle 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**

Fig. 4. The Autonomous Navigation Algorithm.

## IV. SIMULATION STUDIES

Simulation studies are performed in this section to validate the effectiveness and efficiency of 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. In this section, the proposed approach is first applied to a typical double U-shaped case. Then, the bio-inspired neural network model of the autonomous vehicle in a room-like with multiple *doors* environment is studied.

### *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 manoeuverable autonomous vehicle may be considered as a point vehicle in comparison with the size of the vehicle 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 Fig. 5. The workspace has a size of 40 $\times$ 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 Fig. 5A.

All the neural activities are initialized to zero. In Fig. 5A, 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 Fig. 5A. The dynamic activity landscape of the neural network when the vehicle reaches the goal G(15,27) is shown in Fig. 5B. The neural activity of the goal has very large value represented by peak whereas the neural activities of obstacles are represented by valley with negative values.

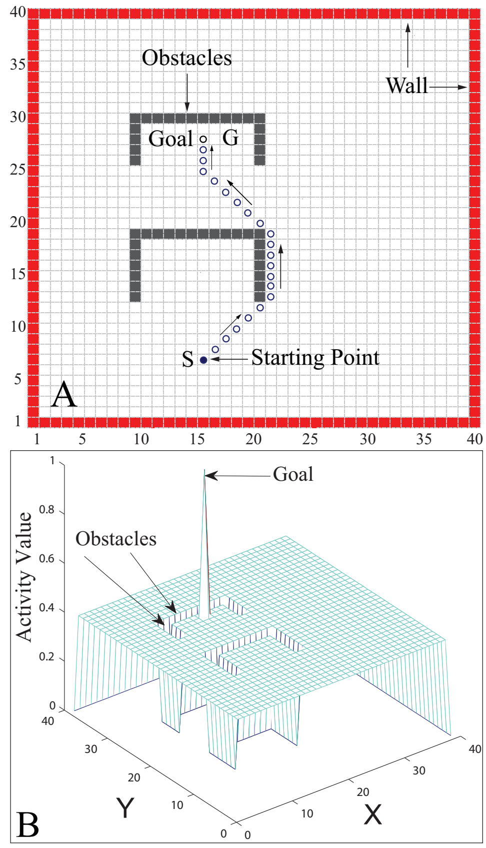


Fig. 5. The illustration of trajectory planning in a double U-shaped workspace . A: The workspace with obstacles; B: The neural activity landscape of the neural networks.

To plan a *safer* collision-free trajectory in the same double U-shaped case, the obstacles represented by squares are enlarged. The obstacles in Fig. 6A 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 Fig. 6A, 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 $\times$ 40, which is topologically organized as a grid-based map with 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) in Fig. 6A. The dynamic activity landscape of the neural network when the vehicle reaches the goal G(15,27) is shown in Fig. 6B.

In comparison of the regular trajectory planning results in Fig. 5 , the trajectory generated in Fig. 6A with virtual obstacles is safer and more "comfortable" than the one generated in Fig. 5A without virtual obstacles. The dynamic activity landscape of the neural network when the vehicle reaches the goal G(15,27) is shown in Fig. 6B. The neural activity of the goal has very large value represented by peak, and the neural activities of obstacles are represented by valley with negative values.

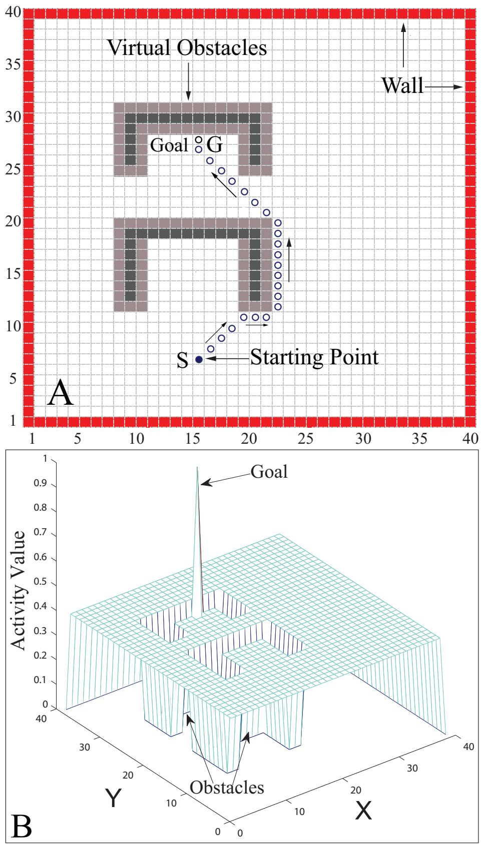


Fig. 6. The illustration of trajectory planning in a double U-shaped workspace with safety consideration. A: The workspace with virtual obstacles; B: The neural activity landscape of the neural networks.

### B. Trajectory Planning in a Room-like Environment

To validate the effectiveness of the proposed model, the proposed model is applied to a room-like test scenario, where there were some obstacles, especially, doors, placed in the known workspace. The workspace is shown in Fig. 7A, where S(2,3) indicates the starting point and the squares represent the obstacles.

The neural network consists of 40 $\times$ 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 Fig. 7A. 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 to pass through four doors indicated by *D-1*, *D-2*, *D-3* and *D-4* in Fig. 7A. There is no negative neural activity that propagates to the other neurons. The planned vehicle trajectory in Fig. 7A has the shortest path from the starting position to the goal. This bio-inspired model is able to deal with moving obstacles as well [12], [13].

The dynamic activity landscape of the neural network when the vehicle reaches the goal G(37,37) is shown in Fig. 7B. The neural activity of the goal has very large value represented by peak, while the neural activities of obstacles are represented by valley with negative values.

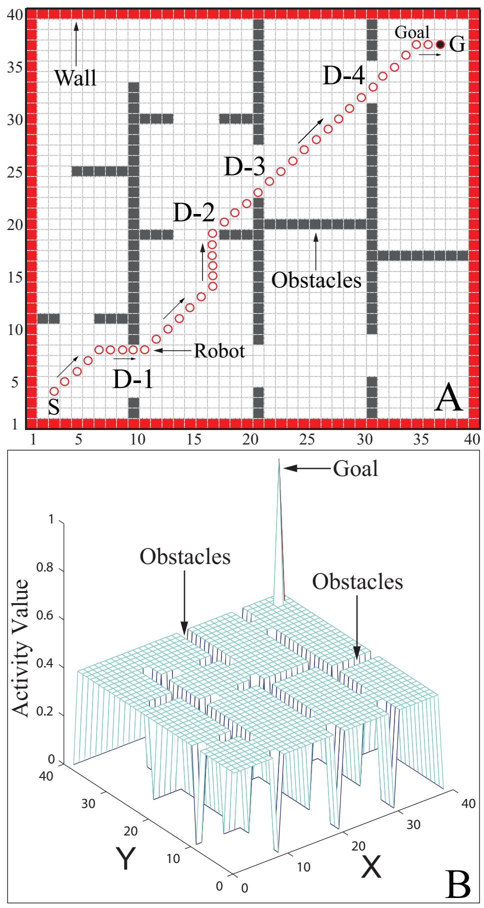


Fig. 7. The illustration of trajectory planning in a room-like workspace . A: The workspace populated with virtual obstacles; B: The neural activity landscape of the neural networks.

The safety aware navigation is taken into consideration by virtual enlarged obstacles in the environment. The obstacles are enlarged by the previously modeled Obstacle Enlargement algorithm illustrated in Fig. 8A, in which the virtual obstacles are depicted in 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 "comfortable" distance from four doors indicated by *D-1*, *D-2*, *D-3* and *D-4* in Fig. 8A. The dynamic activity landscape of the neural network when the vehicle reaches the goal G(37,37) is shown in Fig. 8B, in which there are more valley areas due to the virtual obstacles. The neural activity of the goal has very large value represented by peak, and the neural activities of obstacles are represented by valley with negative values.

Compared with the regular trajectory planning results in Fig. 7 , the trajectory generated in Fig. 8A with virtual obstacles is safer and more "comfortable" than the one generated in Fig. 7A without virtual obstacles. particularly, when the vehicle passes through, there are safer distance as buffered space to plan a smooth trajectory with safety consideration.

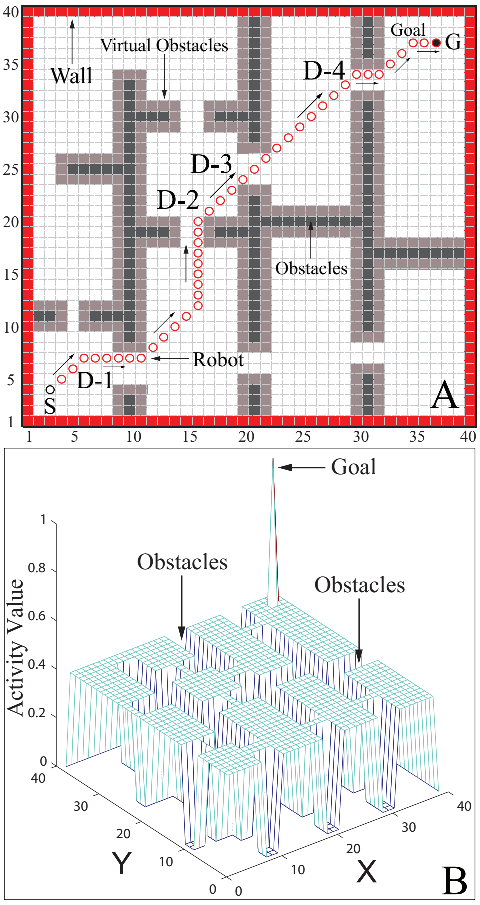


Fig. 8. The illustration of trajectory planning in a room-like workspace with virtual obstacles. A: The workspace populated with obstacles; B: The neural activity landscape of the neural networks.

## V. Conclusions

In this paper, a novel biologically inspired neural network model with safety consideration for the real-time vehicle trajectory planning with clearance from obstacles is proposed. The optimality of the real-time vehicle trajectory planning in a non-stationary environment is in the sense of a continuous, smooth and safe collision-free trajectory toward the goal. The real-time vehicle safe aware trajectory is planned through the varying neural activity landscape. The proposed model is capable of planning a real-time "comfortable" trajectory away from obstacles. The effectiveness and efficiency have been demonstrated through simulation studies that the proposed model is capable of performing collision-free and safe navigation of an intelligent vehicle.

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