

Innate immune based path planner of an Autonomous Mobile Robot

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Abstract

Path planning of mobile robot is related to generating safest trajectories within its work space by avoiding obstacles, escaping traps and finally reaches its destination within optimal period. While an autonomous mobile robot is motion, each robot task needs a different form of learning because of its environmental changes. To select suitable robotic action at different environmental situations, a new motion planner is described in the current research work. The proposed motion planner is motivated from the biological innate immune system. To actuate a suitable robotic action, one new parameter named as learning rate has been introduced, which correlates the robot sensory information and the pre-engineered robot actions. The further movement of the robot is then decided by selecting of a suitable robot predefined task, there by the robot will move in sequence until it reaches to its destination. Finally, the developed path planner is executed in various simulated robotic environments.

Key words: autonomous mobile robot; artificial immune system; mobile robot navigation; behaviour learning.

1. Introduction

Mobile robots are widely using in various fields such as domestic fields, industries, security environments and hospitals etc. because of their mobility nature. So motion planning is one of the vital issues in the field of mobile robots. In which, the robot should adapt the behavior learning from the sensory information without continuous human intervention. The main goal of a navigational controller of an autonomous mobile robot is to generate collision free trajectories within its workspace.

To solve mobile robot navigation problem various approaches have been developed form the last few decades. Although artificial potential fields [13] are widely used because of its easy implementation and simple in structure, but the robot may face local minima situation in certain conditions. Chris [3] has implemented genetic algorithm based motion controller for an autonomous mobile robot. Ellips and Davoud [6] have presented a new path planner based on particle swarm optimization. Beside these many algorithms were proposed for solving motion planning problem as described in [5]. Most of these algorithms have been implemented by adjusting the controlling parameters to optimized values in order to obtain efficient results. Local minima is one of the well-known drawback in mobile robot navigation; in this situation the robot may get trapped in its maze environment or it wanders indefinitely in a region. As explained by Luh and Liu [9], most of the past approaches didn't consider local minima problem solving.

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AIS is a computational methodology, which was inspired by biological immune system [2], [4]. Computer scientists and engineers have been used AIS for solving engineering problems because of its properties like uniqueness, anomaly detection, reinforcement learning and memory etc. Previous researchers have been applied AIS for real world problems such as recognitions of promoters in DNA sequence [7], travelling salesman problem [18], and reduce the dimensionality of image space and generates network structure [11] for navigation and localization etc.

In recent years, researchers have applied artificial immune system algorithms to autonomous mobile robot for generating collision free trajectories [1], [10], [11], [14], [17]. While developing immunological system architectures, they have been investigated the interactions among the various immune components. Mamady et al. [11] have developed a new immunized computational method for mobile robot navigation, if the robot environment having uniform mass and general shape objects. To get better results from the methodology as described in [12], it is necessary to evolve the immune network by the presence of much more connections, but this will increase the network complexity. An adaptive AIS mechanism has been introduced in [16], for arbitration of an autonomous mobile robot. An adaptive learning mechanism based on immune system has been developed for Lego robots by Singh and Nair [15]. Later they applied their mechanism for two moving robots on their pre-defined near concentric tracks. An AIS based robot navigation has described in [8], but their implementation is in early state and requires a lot of work to apply this mechanism to a real robot.

In the present research work, a new efficient immunological path planner has been modeled for an intelligent mobile robot. This motion planner is inspired from the innate immune system and is focused on the special feature anomaly detection. From the previous work, it is observed that the analysis of interactions among the immune components (antigen-antibody stimulation; antibody- antibody suppression and antibody- antibody stimulation) give the numerical complexity due to consideration of more number of controlling parameters. The proposed methodology is simple and less numerical complexity because of very few controlling parameters in its structure. Moreover this approach is useful for solving local minima problems (avoiding obstacles & escaping traps in maze environments) and mobile robot navigation task in unknown complex environments by generating optimal collision free trajectories.

This paper is organized into five chapters; chapter 2 describes about the basic biological innate immune system and chapter 3 explains the inspiration and implementation of the biological immune system for autonomous mobile robot navigation. Finally simulation results are presented in chapter 4 to verify the effectiveness of the proposed methodology in various maze environments and chapter 5 concludes the paper with results obtained from the developed methodology.

2. Biological Immune System

The immune system protects human body from the foreign invaders known as antigens (bacteria and virus). The protection of immune system is classified into two categories namely 1) innate immune system and 2) adaptive immune system. The current work focuses on the innate immune system due to its special feature anomaly detection. When antigens are entered into the body, immune system produces large amount antibodies in order to neutralize them. These antibodies are released from the immune component known as B-cells. Then the produced antibodies are interacted with the recognized foreign invaders and reduce their effect on the human body. In this way, the immune system protects human body from the wide variety of harmful foreign agents.

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3. Immune system - Robotics

In the Distributed Autonomous Robotic Systems [2], the robots have to get knowledge from the objective of the system, environment, the behaviors of other robots etc., and decide their own action autonomously.

3.1. Inspiration

As explained in previous section the special feature of the innate immune system is the recognition of antigens and produces suitable antibodies in order to vanish them. The same can be implemented in the case of autonomous mobile robot navigation within its unknown environments. When a mobile robot is moving from one position to another position within its search space, it may sense different environmental criteria. According to the environmental situation robot should perform its task. Fig.1 shows the similarities of human immune system and a behavior based robot navigation system.

Procedure: Detail comparison between innate immune system and behaviour based mobile robot navigation is described as follows:

1. The first step of the Immune System Mechanism (ISM) for protecting human body is to recognize the entered antigens, where as the primary condition for autonomous mobile robot navigation is to sense its unknown work space.
2. The second step includes in ISM is to release suitable antibodies from B-cells in order to neutralize them, whereas the secondary aspect for autonomous mobile robot navigation is to learn the environmental situation in order to perform the suitable action from the pre-engineered tasks.
3. The last step of ISM concerns with the protection of the human body from foreign invaders by vanishing them, whereas the last step for autonomous mobile robot navigation is to perform its suitable action determined from the second step, to obtain feasible collision free path within its search space.

3.2. Implementation

By observing figs. 1a&1b, the basic immune components can be considered as follows:

- i. *B-cell* → Autonomous Mobile Robot
- ii. *Antibodies* → Robot Actions (antibodies are produced from B-cell)
- iii. *Antigens* → Environmental situation (B-cell has to be produced suitable antibodies according antigen structure)

Antibody consideration: The possible robot actions as represented in Fig.1b and are illustrated in Table.1.

Antigen consideration: the possible environmental situations are considered as represented in Table.2.

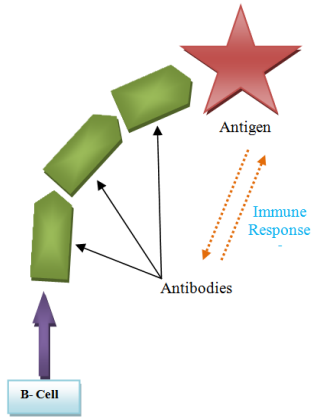


Fig. 1 (a) Basic immune structure;

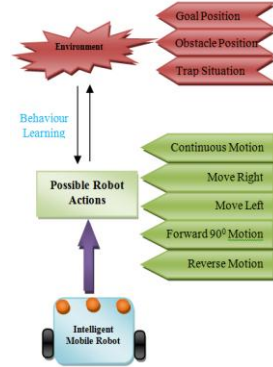


Fig. 1 (b) Mobile robot navigation system

Table 1. Possible robot actions

<i>Continuous Motion</i>	Towards Goal Arbitrary
<i>Left Motion</i>	Left 45° Left 0°
<i>Right Motion</i>	Right 45° Right 0°
<i>Forward 90° Motion</i>	90° robot motion
<i>Reverse Motion</i>	Reverse 0° (Left/Right) Reverse by +90°/-90°

Table 2. Possible robotic static environmental situations

<i>Goal Position</i>	Goal Known Goal Unknown
<i>Obstacle Position</i>	Front Left Right
<i>Stall Situation</i>	In front Behind In front & Behind

3.3. Behavior Learning

In order to select suitable robot action for specific environment, a new parameter named as learning rate is introduced and can be defined as the product of allowance parameter and antigenic weight as indicated by Eq.1.

$$Learning\ rate(\Gamma_r) = a_{\varphi} * \omega_{ag} \quad (1)$$

Where a_{φ} = Allowance parameter

and ω_{ag} = Antigenic weight

Allowance parameter (a_{φ}): a_{φ} indicates the affinity strength between one antibody and one antigen.

The value of a_{φ} is ranging from '0' to '1'.

The following procedure is to be applied for calculating the affinity strength.

i. Assign antibody scores (1 to 9) arbitrarily for considering nine antibodies as illustrated in Table1.

ab-1.	Towards Goal	→ 1	ab-6.	Right 0°	→ 6
ab-2.	Arbitrary	→ 2	ab-7.	Forward 90° Motion	→ 7
ab-3.	Left 45°	→ 3	ab-8.	Reverse 0° (Left/Right)	→ 8
ab-4.	Left 0°	→ 4	ab-9.	Reverse 90° Motion	→ 9
ab-5.	Right45°	→ 5			

ii. Assign antigen score for each antigen according to antibody score. For example consider the first antibody robot motion towards the goal, it will occur when the robot is not sensing any obstacles and a criterion is goal known. So the scores for goal known (ag-1) is '1' and no object (ag-6) is '1'.

ag-1.	Goal Known	→ 1	ag-6.	No Object	→ 1
ag-2.	Goal Unknown	→ 2	ag-7.	Stalled In front	→ 9
ag-3.	Obstacle Front	→ 7	ag-8.	Stalled Behind	→ 9
ag-4.	Obstacle Left	→ 4	ag-9.	Stalled In front & Behind	→ 8
ag-5.	Obstacle Right	→ 6			

iii. Allowance factor of i^{th} antibody with respect to j^{th} antigen can be defined by Eq.(2)

$$a_{\varphi} = \frac{\min\{\text{score}(ab_j), \text{score}(ag_j)\}}{\max\{\text{score}(ab_j), \text{score}(ag_j)\}} \quad (2)$$

The allowance factor of 3rd antibody with respect to 8th antigen can be obtained as follows:

$$\text{score}(ab_3) = 3 \text{ and } \text{score}(ag_8) = 9$$

$$(a_{\varphi})_{3,8} = \frac{\min\{\text{score}(ab_3), \text{score}(ag_8)\}}{\max\{\text{score}(ab_3), \text{score}(ag_8)\}} = \frac{3}{9}$$

Antigenic weight (ω_{ag}): When the robot is in motion within its work space, there is a possibility of antigen criteria as follows:

- Sensed antigens
- Non-sensed antigens

Form the sensed antigens, robot has to perform according dominant environmental situation and other sensed environmental situation. For this purpose three antigenic strengths are defined as follows:

- i. Strength for sensed antigens → 0.5
- ii. Strength for non-sensed antigens → 0
- iii. Strength for high scored sensed antigens → 5

Once the robot gets the knowledge from its environment, it will score the antigen weights for each antigen according to Eq.(3)

$$\omega_{ag} = score(ag) * strength(antigentype) \quad (3)$$

For suppose robot got the knowledge from the environment “Goal Known & Object front (ag-1 & ag-3)”.Therefore $strength(ag_1) = 0.5$, $strength(ag_3) = 5$ and strength of all other antigens are ‘0’.

$$Weight \ of \ first \ antigen(\omega_{ag_1}) = score(ag_1) * strength(ag_1) = 1 * 0.5 = 0.5$$

Similarly weight of all antigens for the current situation can be calculated as follows:

$$\begin{aligned} \omega_{ag_2} &= 2 * 0 = 0 & \omega_{ag_6} &= 1 * 0 = 0 \\ \omega_{ag_3} &= 7 * 5 = 35 & \omega_{ag_7} &= 9 * 0 = 0 \\ \omega_{ag_4} &= 4 * 0 = 0 & \omega_{ag_8} &= 9 * 0 = 0 \\ \omega_{ag_5} &= 6 * 0 = 0 & \omega_{ag_9} &= 8 * 0 = 0 \end{aligned}$$

From the above analysis the learning rate of i^{th} antibody with respect to j^{th} antigen can be found out from Eq.(4).

$$(\Gamma_r)_{i,j} = (a_{\phi})_{i,j} * \omega_{ag_j} \quad (4)$$

$$\Rightarrow (\Gamma_r)_{i,j} = \frac{\min\{score(ab_3), score(ag_8)\}}{\max\{score(ab_3), score(ag_8)\}} * score(ag_j) * strength(ag_j) \quad (5)$$

Therefore the learning rate of i^{th} antibody with respect to all nine antigens is as follows:

$$\begin{aligned} \overline{(\Gamma_r)_i} &= (\Gamma_r)_{i,1} + (\Gamma_r)_{i,2} + \dots + (\Gamma_r)_{i,q} & (6) \\ &= (a_{\phi})_{i,1} * (\omega_{ag})_1 + (a_{\phi})_{i,2} * (\omega_{ag})_2 + \dots + (a_{\phi})_{i,q} * (\omega_{ag})_{q=9} \end{aligned}$$

$$\Rightarrow \overline{(\Gamma_r)_i} = \sum_{j=1}^9 (a_{\phi})_{i,j} * (\omega_{ag})_j \quad (7)$$

The suitable robot action for a specific environmental condition is selected from the overall learning rate value of each antibody. The antibody which is having the highest $\overline{(\Gamma_r)_i}$ can be selected as the suitable robot action.

4. Simulation Results

From the developed algorithm, further movement of the robot is decided by finding the maximum $\overline{(\Gamma_r)_i}$ from all considered antibodies. The autonomous mobile robot will perform its further action according to the selection of best robot action. Figs. 2-3 represent the activation of suitable robot actions by different colours for various environmental situations. The algorithm of the proposed methodology is as follows:

- Step.1: Initialise various robotic static environmental situations and corresponding robotic actions as antigens and antibodies respectively.
- Step.2: Allocate scores for each environmental criterion according to predefined robot action.
- Step.3: For each iteration calculate $\overline{(\Gamma_r)_i}$ of each antibody by using Eq.(7)
- Step.4: Determine the suitable robot action for each cycle, corresponds to the robot sensory environment.
- Step.5: Perform the selected robotic action in order to generate collision free trajectories within robotic search space.
- Step.6: Repeat Steps. 3, 4 and 5; until robot completes its task.
- Step.7: Stop, when robot reaches its destination.

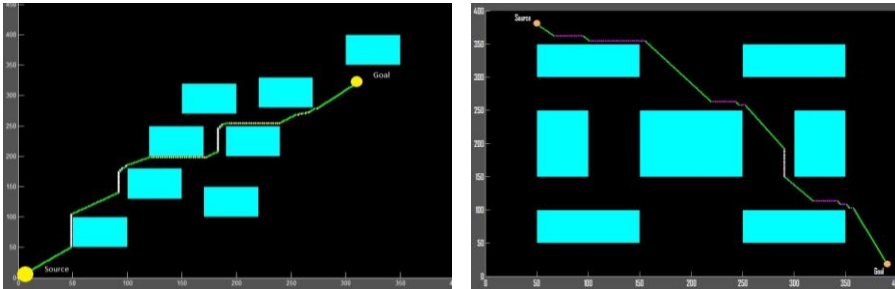


Fig. 2 Mobile robot navigation in arbitrarily arranged obstacles environment

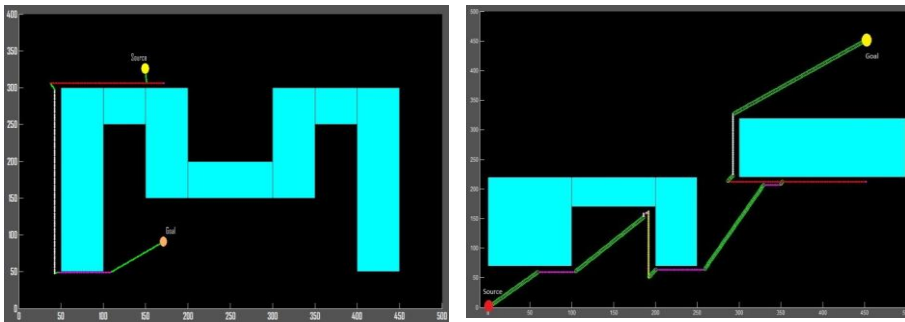


Fig. 3 Mobile robot navigation in trap environment

5. Conclusion & Future Work

Efficient immune based path planner has been implemented to an autonomous mobile robot. The proposed methodology works on the special feature of innate immune system, anomaly detection. When the robot acquires knowledge from its search space in each iteration, an appropriate pre-engineered robot action is selected and performed for the specific environmental situation. A new parameter named learning rate has been introduced in order to perform the suitable robot task for further robot movement within its work space. The proposed intelligent mobile robot motion planner is simple in its mathematical structure because of less number of adjusting parameters usage and can be implemented easily in unknown maze environments. Simulation results showed to verify the effectiveness and validate the feasibility of the current mobile robot motion planner in various robotic environments.

Further, the proposed algorithm can be implemented to noisy environments by considering some dynamic behaviors of environment as well as corresponding robotic actions. As a future work, the modeled motion planner is to be applied in real robotic platforms.

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