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DESIGN AND DEVELOPMENT OF A HYBRID ARTIFICIAL IMMUNE SYSTEM NAVIGATION SYSTEM FOR A MOBILE ROBOT IN AN UNKNOWN ENVIRONMENT

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ABSTRACT

Due to their better mobility, autonomous mobile robots have potential uses in a variety of situations, including indoor, outdoor, industrial, undersea exploration, and many more. Mobile robot navigation relies heavily on obstacle avoidance and path planning. In this paper, a hybridized

Introduction

Over time, various algorithms for mobile robot navigation have arisen, some of which are heuristic and others classical (Mohanty and Parhi2016). Heuristic algorithms are nature-inspired algorithms such as artificial neural networks, fuzzy logic, genetic algorithms, particle swarm optimization, and AIS. ANN, for example, is inspired by the neurological system's functioning, whereas GA is based on the body's cellular mutations. Classical algorithms, on the other hand, rely solely on

variation of AIS has been used to navigate a mobile robot, which switches between idiotypic network theory and clonal selection theory depending on the situation. This is a good countermeasure for getting out of concave-shaped obstacles like U traps and other local minima scenarios. Any robot navigational system's goal is to get the mobile robot to its destination in the most efficient way possible, without colliding with any impediments. This article proposes an algorithm that leverages both the idiotypic network theory and the clonal selection theory of the artificial immune system to solve the problem of obstacle avoidance for mobile robots in an unknown environment. While the former is utilized for general navigation, the latter is used when there is a local minimum. In addition, the antibody concentrations were calculated using a modified version of Farmer's equation for Jerne's idiotypic network model. The proposed algorithm's navigation simulation results are shown. The results shown that our method may successfully escape a variety of barriers, including local minima traps. A comparison of the suggested algorithm to a number of different algorithms is also provided. Finally, a physical robot is used to do experimental validation of the simulation results for the proposed approach.

Keywords: *Mobility: Autonomous Mobile Robots: Artificial immune system, robot Navigation, Clonal selection theory: Obstacle avoidance, Path planning*

mathematical models, such as the artificial potential field theory (Andrews and Hogan 2020), the roadmap (Bacaa et al. 2019), cell decomposition (Lingelbach2018), and the Voronoi diagram (Shojaeipour et al. 2016). These algorithms are effective, however they have flaws such as becoming stuck in local minima conditions and other issues. This has prompted the researchers to improve the algorithms' robustness and efficiency.

Kurz (2017) created a layout of free space in the environment for the robot to travel using data from ultrasonic sensors. Gueaieb and Miah (2016) employed RFID (radiofrequency identification) tags strategically placed across the arena to help mobile robots navigate in an unfamiliar area. In circumstances where an impediment is present near the goal, Ge and Cui (2018) created a novel repulsive potential function that takes into account the relative distance between the robot and the goal. Rashid et al. (2014) took images of the environment with a camera attached on the robot and then utilized image processing to extract obstacle elements for robot navigation. Wang et al. (2018) proposed a neuro-fuzzy network theory for regulating the obstacle using sensory input provided by the obstacle.

Mohanty and Parhi (2014) used an adaptive neuro-fuzzy inference system to design a navigational control system for a mobile robot (ANFIS). For robot navigation, Xiao et al. (2018) used an ANN based on a multi-layer feed forward network with nonlinear functional approximation. Tuncer and Yildirim (2015) defined a new mutation operator that selects the best mutation node from the nearby nodes for navigation. Using the particle swarm optimization (PSO) technique and adaptive neural networks, Li and Chen (2019) devised a low-cost approach to avoid obstacles. For 'ball pursuing' and 'position locating,' Gu et al. (2017) used a mix of GA and fuzzy logic controllers (FLCs). Mohanty and Parhi (2014) used an adaptive neuro-fuzzy inference system to design a navigational control system for a mobile robot (ANFIS). Through nonlinear functional approximation, Xiao et al. (2018) used an ANN based on a multi-layer feed forward network. Wahab (2017) employed two ANNs, one to create a map of open space and the other to locate a navigation target. For navigation, Rusu et al. (2017) employed a neuro-fuzzy algorithm on a sensory input-based mobile robot. Mohanty and Parhi developed an adaptive cuckoo search (CS) algorithm for robot path planning (2016).

Mohanty and Parhi (2014) used an adaptive neuro-fuzzy inference system to design a navigational control system for a mobile robot (ANFIS). According to the above-mentioned methodologies, heuristic methods inspired by nature are more suitable for tackling uncertain real-life issues currently. Xiao et al. (2018) used ANN based on multi-layer feed forward network through nonlinear functional approximation. Due of its simplicity and dynamic nature, AIS is one such algorithm that has recently caught the attention of researchers. Jerne (1974) proposed the concept of an idiotypic network based on the biological immune system's functioning. Farmer et al. (2019) expanded on this concept and created a differential equation that reflected the immune system's idiotypic network model. Challo et al. (2016) studied mixed inter-antibody interactions. In a congested environment, Das et al. (2015) compared GA and AIS for online path planning and found AIS to be more effective and efficient. Yuan et al. (2016) improved the simple immunity network technique using artificial potential field theory (APF) (INA). As a 'vaccine,' new antibodies were generated using APF and injected into INA. The researchers discovered that their modified INA was more effective than the traditional INA and ant colony method. Bhaduri (2017) proposed the GAIN (genetic artificial immune network), which is a hybrid of a genetic algorithm and an artificial immune network. GAIN outperformed the general GA in terms of preventing early convergence.

For mobile robot navigation, Shrivastava et al. (2016) combined both AIS models, clonal selection and idiotypic network theory. They also added a 'pain' mechanism to penalize the robot when it faces unfavorable circumstances. Henery et al. (2018) created an immunity-based control framework that can self-organize in response to changing environmental conditions. Mathur (2019)

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used AGV for garbage collection by developing a map of the surroundings and utilizing an immune-based approach to identify the shortest path. For navigation, Luh and Liu (2019) combined an adaptive virtual target technique with a reactive immune network inspired by the biological immune system. They were able to get out of local minima problems thanks to the virtual target strategy.
Whitbrook et al. (2018) offered three idiotypic network theory ideas. They compared reinforcement learning (RL), partial AIS and RL, and complete AIS and RL in a study. Some academics have concentrated on robot systems that use the AIS algorithm, demonstrating its robustness and flexibility in an unstructured environment (Raza et al. 2019; Deepak and Parhi 2016; Cho et al. 2019; Huang and Fei 2019; Deng et al. 2016). The unique hybrid AIS is implemented for mobile robot navigation system due to promising outcomes in terms of efficacy and accuracy. The following are the sections of the current article: introduction to AIS, robot navigation mapping using AIS, hybrid AIS, robot kinematics, hybrid AIS stages, simulation results and comparison research, experimental validation, and conclusion.

System of Artificial Immunity (AIS)

The immune system is a self-replicating machine that produces antibodies to defend the body against invading diseases or antigens as they are recognized. Antibodies are produced by B-lymphocytes, which are unique cells. Millions of antibodies are attached to the surface of these cells, which are produced when an antigen is identified by the immune system. A single B-lymphocyte produces antibodies that are all of the same type and structure. These antibodies use a paratope, which is a chain of amino acids arranged in a certain pattern, as a special detecting system. These paratopes are responsible for recognizing the antigen via an epitope, which is a detectable structure on antigens or antibodies. When the epitope of an antigen matches the paratope of an antibody, the concentration of that antigen is reduced while the concentration of the defending antibody is increased. Because the number of antibodies that match the epitope of every antigen that enters the

body is too great, the body does not have a collection of antibodies whose paratope matches the epitope of every antigen that enters the body. Instead, the immune system has some building blocks that join in various ways to generate a pool of antibodies that can mimic any antigenic epitope and so reduce antigen concentration.
Antibodies can also be identified by other antibodies due to the presence of epitopes (or Iditopes, in the case of unique epitopes) on antibodies. This creates a situation in which the immune system's healthy antibodies are eliminated. And, rather than attempting to prevent the production of self-attacking antibodies in the first place, this is how a pool of antibodies is kept under control. Multiple antibodies can detect an epitope of a particular antigen, and the antibodies with the highest paratope match with the antigen's epitope proliferate the most, while the concentration of the other antibodies remains proportional to their degree of match with the antigen's epitope.
Clonal selection is a form of defense that involves selecting antibodies with the highest affinity. Another line of defense is Jerne's (1974) idiotypic network theory, which involves the suppression and activation of antibodies as well as the suppression of the antigen, as shown in Figure 1.

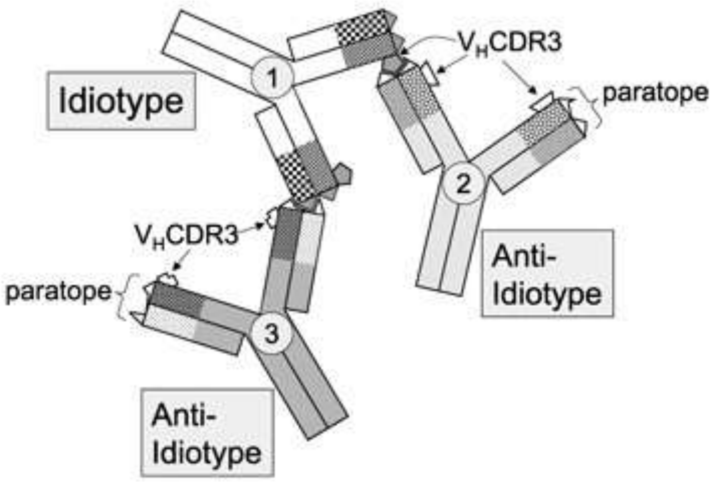

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Figure. 1 Idiotypic network theory

According to Farmer et al. (2019), the concentration of antibodies can be represented as a differential equation that is a function of

two different affinities, namely antigen–antibody affinity and antibody–antibody affinity, in accordance with the idiotypic network theory.
The number of antibodies and antigens are represented by n and l, respectively. The stimulation of antibodies xi in response to all antigens yj is shown by the first term within the brackets. Uij denotes the affinity between antibodies and antigens, while C(xi) denotes the number of antigens. C(yj) denotes the likelihood of them colliding. The suppression of antibody xi in response to all other antibodies xm is the second term. C(xi) is the suppressive affinity, and Vim is the suppressive affinity. C(xm) denotes the likelihood of them colliding. The stimulation of antibody xi in response to other antibodies xp is represented by the third term. Wip denotes the stimulative affinity, while C(xi) denotes the inhibitory affinity. The probability of them colliding is given by C(xp). 2 k2 In the absence of collisions, C(xi) represents the rate of decay of antibodies xi. b is a constant that replicates both the collision rate and the rate at which antibodies are produced when they collide.

MATERIALS AND METHOD

To apply AIS theories to a robot navigation challenge, each system involved in the problem must be properly identified. In any navigation problem, there are three basic systems involved: the robot, the robot's actions, and the environment. The robot, like the biological immune system, must take retaliatory action against the environmental conditions it is exposed to, such as when an external body attacks the body and specialized antibodies are created by the B-lymphocyte to oppose this attack. As a result, the antigen is the external stimulation or environment, the robot is the B-lymphocyte, and the robot's motions are the antibody. All conceivable antigens in this navigation system are linked to environmental conditions

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such as barrier movement, and antigens will be identified by antibodies on the mobile robot. The immune system and robot navigation have a similar relationship, as seen in Figure 2.

Hybrid AIS

When the impediments in the robot's path do not lead to any trap-like scenarios, the idiotypic network theory effectively leads the robot to its goal by avoiding the obstacles. To describe the network theory, a variation of Farmer et al(2019) .'s Equation (2) is utilized, and the antibodies employed for this purpose are listed in Table 1 with their descriptions.

$$C_i^{'}(t) = (U_i + V_i - k_i).c_i(t) \qquad (2)$$

Where ***i* = 1, 2, 3,...,2(*n*$_s$ 1)**

$C_i^{'}(t)$= Rate of change in concentration of the ith antibody, ***U****i* = Affinity/simulative effect of the antigen on the antibody, ***V****i* = Affinity between individual antibody or degree of stimulation, ***k****i* = Decay rate of antibodies (death coefficient), ***c****i*(***t***)= Sigmoid function used to regulate the concentration of each antibody; ***U****i* and ***V****i* are described as in Eqs. 3 and 4.

$$U_i = \cos\left(\theta_{c_k} - \theta_i\right) \qquad (3)$$

θ_{c_k} = Calculated angle for antibodies, θ_i = steering angle between moving route and robot head direction.

Figure: 2

$$V_i \exp\left(- \sum_{j=1}^{2(n_s=1)} \cos\left(\theta_i - \theta_j\right).c_j(t) \right) \qquad (4)$$

Where θ_j is the jth antibody, $c_j(t)$ is the concentration of jth antibody and n_s is the number of sensors. A sigmoid function is used to regulate the concentration $c_j(t)$ of the ith antibody as shown in Eq. 5.

$$c_j(t) = \frac{1}{1 + e^{(0.5 - c_i(t))}} \qquad (5)$$

Because network theory fails to take effective steps when locked in local minima scenarios, alternative methods such as reinforcement learning (Whitbrook et al. 2018) or artificial neural networks (ANN) (Wahab2017) can be used in conjunction with network theory to create a more robust system. However, a distinct hybrid system has been established here, which involves toggling between clonal selection theory and the AIS's own idiotypic network theory. Switching between the two immunity theories entails recognizing the trap scenario in real time as well as determining whether or not the trap has been averted. When the trap is recognized, the algorithm switches from idiotypic network theory to clonal selection theory, which proliferates the antibody with the highest affinity in such a circumstance. To neutralize this scenario, the wall following algorithm was utilized as the antibody. It's also crucial to recognize when the trap has been cleared successfully so that the algorithm can return to the idiotypic network theory for future hurdles.

RESULT AND DISCUSSION

On a core i7, 2.6 GHz PC running Ubuntu 16.04 with 8 GB RAM, simulations for the hybrid method in partially known settings were ran on V-REP (version 3.5.0) with Python 3 on a core i7, 2.6 GHz PC running Ubuntu 16.04 with 8 GB RAM. The simulation results for various climatic setups are shown in Figures 5, 6, and 7. Figures 5a, b demonstrate robot navigation in clear areas, whereas Figure 6 depicts robot navigation in a congested environment. Only the AIS network theory is used in these illustrations. Figure 7 depicts robot navigation in a cluttered environment with a local minimum condition, indicating the transfer from network theory to clonal selection theory.

Table 1: Path length covered by robot in simulation (Fig. 7) during various iterations

S. no	Path in meters covered by robot in simulation mode	Collision avoidance (Yes/no)
1	15.50	Yes
2	16.00	Yes
3	16.25	Yes
4	19.00	Yes
5	14.20	Yes
6	16.15	Yes
7	19.21	Yes
8	19.40	Yes
9	19.00	Yes
10	15.05	Yes

The number 6 is the optimal path followed
Simulation results from various iterations of the proposed algorithm for the environment depicted in Figure. 6 are presented in Table 1. The optimal path from the obtained results is shown in Figure. 6.

Other Navigation Systems in Comparison
The suggested hybrid algorithm's simulation results are compared to those of previous robot navigation techniques. Deepak et al. (2019), Yuan et al. (2016), Wahab (2017), and Luh and Liu (2019) show simulation results in Figures 7b, 8b, 9b, and 10b, respectively. Figures 7a, 8a, 9a, and 10a demonstrate the outcomes of the suggested hybrid algorithm.
The suggested technique is compared to various navigational algorithms in terms of the number of pixels travelled by the robot in its environment. The suggested algorithm employs a shorter and smoother path in the various offered situations, as evidenced by the comparison analysis. Table 2 summarizes the findings of the comparison investigation.

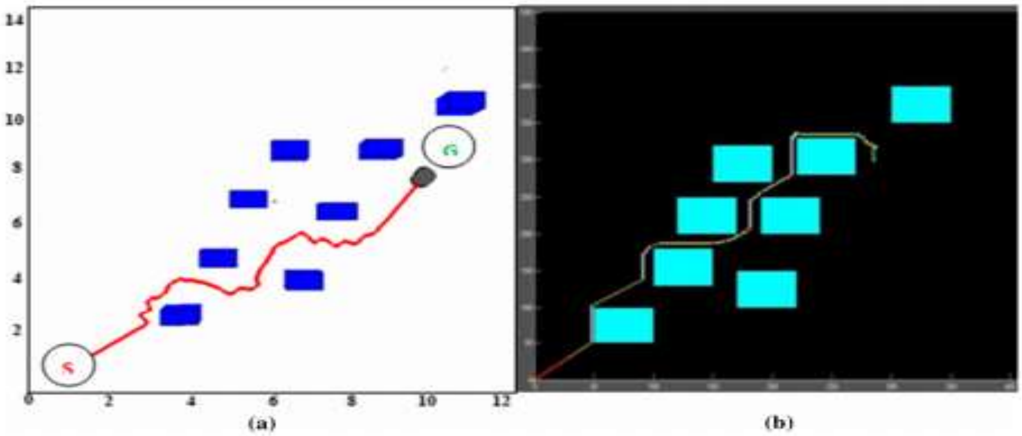

Figure 3: a, b Path obtained by the proposed algorithm (a) and by Deepak et al. (2019) (b)

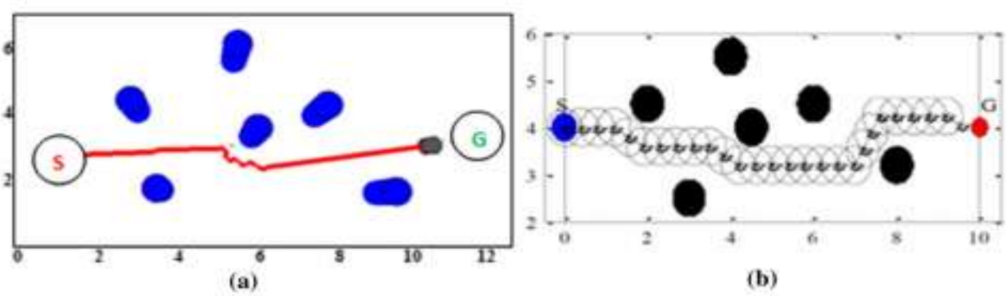

Figure 4: a, b: Path obtained by the proposed algorithm (a) and by Yuan et al. (2016) (b)

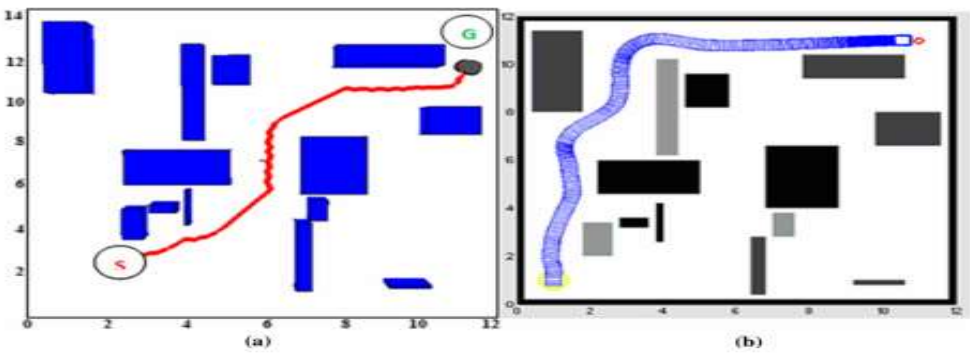

Figure 5: a, b Path obtained by the proposed algorithm (a) and by Wahab (2017) (b)

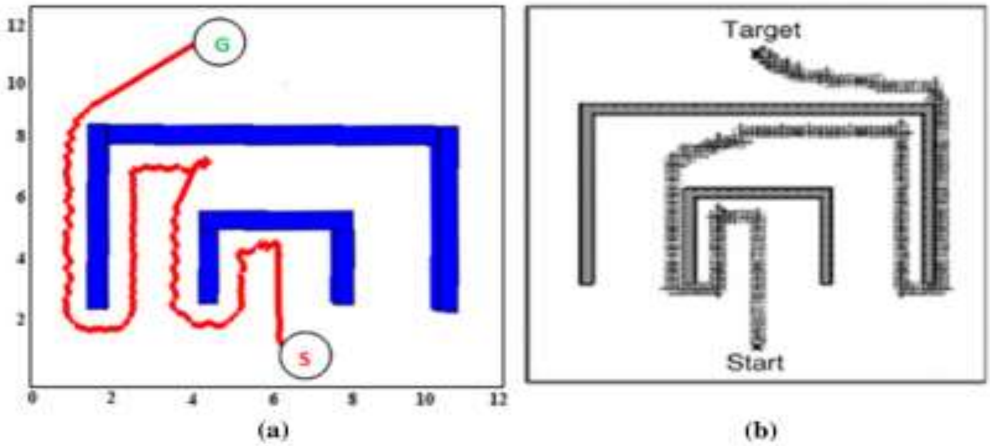

Figure 6: a, b Path obtained by the proposed algorithm (a) and by Luh and Liu (2019) (b)

Table 2: Path length comparison of the proposed hybrid AIS with other algorithms

Figure no.	Path length covered by robot in simulation (pixel)	Path length covered by robot in simulation using the proposed hybrid AIS (pixel)
Figure 7	800.	750

(Andrews, 2020)

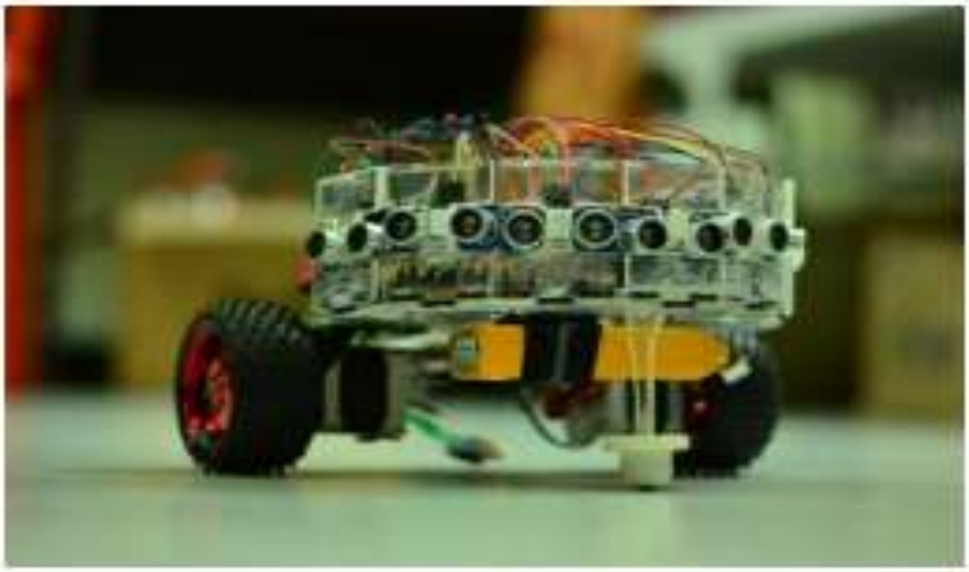

Figure 7: The Implemented mobile Robot

CONCLUSIONS

Through an unknown set of obstacles, the proposed hybridized algorithm was able to avoid barriers and attain the goal. When a trap is encountered, the algorithm might move from idiotypic network theory to clonal selection theory, and then back to idiotypic network theory when the trap is navigated. Utilizing a modified Farmer's equation and determining the priority of the next action based on various characteristics, the winning antibody was picked using the idiotypic network theory. When compared to other algorithms, the generated path was shorter, according to the simulation findings. Experiments with a physical robot revealed that the robot was capable of avoiding impediments in its path and achieving its goal in real time.

RECOMMENDATION

Although the current system is successful at avoiding unexpected obstacles and achieving the goal, it might be enhanced by incorporating some classic methods such as Roadmap and RL, as well as combining them with additional heuristic approaches such as PSO, GA, and ANN. The algorithm can also be tweaked to work with dynamic barriers and multi-robot setups. Instead of ultrasonic sensors, LASERs might be utilized to get far more accurate and dependable data on the hardware side. The use of omnidirectional wheels could help improve the robot's maneuverability.

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