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Dynamic Obstacle Avoidance Technique for Mobile Robot Navigation Using Deep Reinforcement Learning

Ravi Raj[1], Andrzej Kos[2]
[1,2]Faculty of Computer Science, Electronics, and Telecommunications,
AGH University of Science and Technology,
Al. Adama Mickiewicza 30, 30-059 Kraków, Poland
raj@agh.edu.pl , kos@agh.edu.pl
ORCID: [1](0000-0001-8073-1812); [2](0000-0003-3089-241X)

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ABSTRACT

In the realm of mobile robotics, navigating around obstacles is a fundamental task, particularly in constantly changing situations. Although deep reinforcement learning (DRL) techniques exist that utilize the positional information of robot's, environmental states, and input dataset for neural networks. Although, the positional information alone does not provide sufficient insights into the motion trends of obstacles. To solve this issue, this paper presents a dynamic obstacle mobility pattern approach for mobile robots (MRs) that rely on DRL. This method employs the positional details of dynamic obstacles dependent upon time for establishing a movement trend vector. This vector, in conjunction with another mobility state attribute, forms the MR mobility guidance matrix, that essentially conveys the pattern variation of dynamic obstacles trend over a specified interval. Using this matrix, the robot can choose its avoidance action. Also, this methodology uses the DRL-based dynamic policy algorithm for the testing and validation of the proposed technique through Python programming. The experimental outcomes demonstrate that this technique substantially improves the safety of avoiding dynamic obstacles.

Key words: artificial intelligence (AI), dynamic obstacles, deep reinforcement learning (DRL), dynamic policy, mobile robot (MR), navigation.

1. INTRODUCTION

MRs are advancing and developing more effectively at doing activities that were formerly too complicated and challenging as AI technology quickly improves. Robots can become autonomous by combining robotics and AI technologies, allowing them to do duties without human assistance [1]. Currently, there are several uses for MRs including medical treatment, pattern recognition, freight, inspection and development of infrastructure, security, passenger travel, defense, and many more [2]. Also, MRs are broadly used nowadays by various industries in multiple ways including warehouse logistics, automated production lines, and versatile materials loading/unloading operations.

Generally, the mobility and navigation capabilities of any MRs are subject to stricter constraints. Sensors such as Lidars are required for monitoring the variations in the environment and enable them to navigate freely without collision with obstacles [3], [4]. The dynamic obstacle avoidance technique for navigation is used to estimate operational stability in variable scenarios, which brings the technique dependent upon this issue has better influence [5]. Currently, there are two major existing techniques to handle obstacles, the first one is the traditional approach is to make a novel path for the MR during the avoidance of real-time obstacles including vector field histogram, RRT-based and artificial potential field (APF) based techniques [6], [7], [8]. These techniques are very useful to achieve an optimal collision-free path for static obstacle avoidance. While, for the problems related to dynamic obstacles, it is necessary to make a novel path in each step of robot movements. These techniques might be categorized precisely as a very higher frequency of path replans from a macro viewpoint. It requires adequate computational requirements, which results in poor performance for highly dynamic applications.

The second method is for the avoidance of dynamic obstacles in real-time operations by selecting an optimal action plan including potential field and cost function-based methods based on an intelligent algorithm. The cost function-based techniques estimate each action plan, and later select the minimum criteria [9]. In the case of the potential field technique, firstly the resultant force is created for dynamic obstacle avoidance and encouraged the robot to obstacle-free movement [10]. An intelligent algorithm-based technique is the best choice to tackle dynamic obstacles because it requires less computing power and environmental information.

In recent years, researchers have found a novel method to avoid dynamic obstacles by exploring DRL. By using this technique MR is allowed to understand through its past actions [11]. For reliable use of a system like this, the robot commonly referred to as an agent, recognizes the environment and makes a decision, then receives either an incentive or a penalty based on the environment and modifies its approach until that ultimately receives a greater reward. The agent can acquire diverse behavioral techniques by creating a variety of rules. It must be noted that researchers trained the robot in static situations before deploying it for dynamic scenarios. It performs effectively in simpler environments. Following that, by examining the environment and gathering frames of images, Lidar data or raw images are utilized as input to fully connected layers and input data in the deep convolutional neural network and to support decision-making, leading to an improvement in the adaptation [12]. By following several training sessions in a virtual scenario, the robotic system can take optimal action when confronted with obstacles [13]. Although there are two major drawbacks. Firstly, the characteristics of the input data are particularly important to these algorithms and secondly, sometimes, its effectiveness could be inadequate because of the extensive variety of activities. Therefore, the fully connected layers in making decisions must not over-rely on the initial convolutional neural network (CNN) output to improve the network's adaptability. Additionally, the environment's reward rule requires being revised to train the MR to establish a plan containing a lesser action range.

Lack of knowledge about the exact direction of obstacle mobility is the primary cause of this problem, making it difficult for MRs to determine their patterns of motion and avoid collisions. To overcome this issue, this article provides a real-time mobility pattern-based avoidance of dynamic obstacles technique for the taken MR, that attains higher efficiency and better adaptability. This work contributes in the following ways:

- A trajectory trend vector has been generated using the most recent variations in the dynamic obstacles mobility for precisely predicting their motion pattern.
- The MR mobility guidance matrix can generated to represent the current position of motion for the MR and the environmental parameters when combined with the mobility state of dynamic obstacles in real-time scenarios.

Despite using neural networks as input, MRs safety and DRL training can be enhanced along with avoiding collisions with dynamic obstacles. The remaining part of the article is structured in the following ways: Section II contains the background details of problems associated with dynamic obstacle avoidance, Section III illustrates the most important related available literature, Section IV describes the proposed methodology, Section V discusses the experimental result and analysis, Section VI provides the future research directions, and lastly, Section VII provides the conclusion of this work.

2. RESEARCH BACKGROUND

Humans can shift their actions to prevent collisions that depend on the quick consideration of perceptions and prior knowledge. However, an MR needs a complex procedure that includes data gathering, path planning, prediction of motion, online trajectory correction, and automation to prevent collisions. For the MR to avoid collisions, it is vital to forecast the motion pattern of dynamical obstacles. Most research focuses on the estimation of a single, volatile probability distribution that is insufficient in scope. It has been proven that while addressing the obstacle avoidance problem as presented in Figure 1, the dynamic environment perception will have a direct impact on the accuracy and efficiency of decision-making.

The MR has to track and analyze the environment before taking appropriate collision-free operations utilizing a DRL-based avoidance of obstacles technique. The main issue with these kinds of approaches is that they often base their decisions entirely on the location of obstacles. Although, the obstacle's location does not always reflect its trajectory of movement, making it difficult to estimate the obstacle's approximate location or direction in the following phase. Generally, raw sensor data or just after normal processing that raw data is utilized for the training of neural networks, which means the input dataset only contains information about the spatial location of obstacles. This approach performs well when addressing stationary obstacles and static environments when the locations of the obstacles cannot fluctuate.

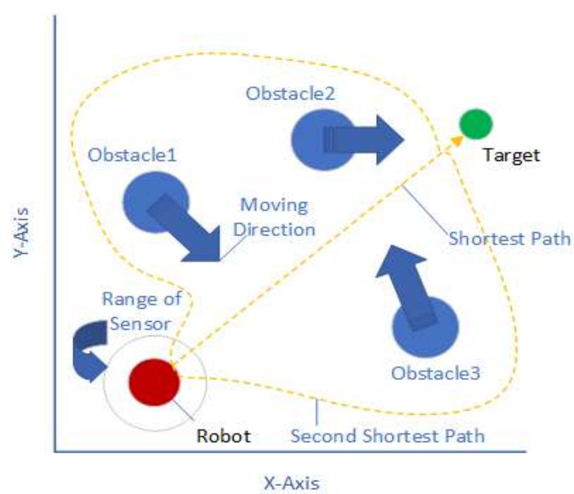

Figure 1: Dynamic obstacles with different directions of motion.

Dynamic obstacles might have an identical positioning but a varied velocity and direction of movement. Whereas dynamic obstacles frequently travel unpredictably, their most recent mobility can be used to predict their future short-term mobility trends, enabling MRs to take safety avoidance measures. Thus, it is essential for training neural networks using data related to the patterns of motion to enhance the security of MRs while dynamic obstacles avoidance. Particularly, the pattern in which dynamic obstacles are moving at the precise moment is essential for this objective. The neural network for DRL training can use the state of movement and pattern data for input to help the agent to develop a strategy for selecting avoidance actions [14]. This strategy considers the mobility pattern and current position of dynamic obstacles, resulting in more accurate and safer avoidance actions.

3. LITERATURE SURVEY

In recent decades, many researchers have focused on developing efficient pattern prediction-based dynamic obstacle avoidance algorithms for the collision-free navigation of MR.

Kurtz *et al.* [15] proposed an effective technique of predicting motion-based obstacles dependent upon recent considerations, through training of Long short-term memory (LSTM) neural network at an online platform. An NPVO (Nonlinear Probabilistic Velocity Obstacle) has been defined for selecting an appropriate velocity to avoid the collision. In unconditional avoidance of collisions and multi-agent situations, this paper demonstrates higher constraints for the probabilities of a collision. This study shows in simulation that this approach prevents collisions where cutting-edge approaches fall short.

Garnett *et al.* [16] presented a technique of obstacle detection through real-time categorical-based recognition for autonomous driving. A unified DCNN (deep convolutional neural networks) is integrating multiple complementary functions as a single computationally effective framework to perform this work. Lidar is used to generate the annotations to train the network manually and automatically. This paper demonstrates various enhancements to the current column-based obstacle detection method, including a fresh set of data, an enhanced network design, and a significant increase in the automated baseline technique.

Seder *et al.* [17] presented a strategy for the motion control of mobile robots by using dynamic window-based techniques in partially unknown environments containing dynamic obstacles. This proposed strategy depends upon the combination of the dynamic window local obstacle avoidance algorithm and the focused D* search algorithm with certain modifications that effectively avoid dynamic obstacles. The mobile obstacles are modeled as movable cells within the occupancy grid map, and a method related to the dynamic window technique is used to forecast their mobility. Employing an Innovative 3DX mobile robot containing a laser ranging finder, the algorithms are used and tested.

Liu *et al.* [18] described the method of obstacle avoidance by using the mobility trend of dynamic obstacles. In this study, it is recommended that movement patterns of obstacles be taken into consideration to enhance the traditional techniques of obstacle avoidance. Obstacle patterns of motion are categorized into three categories: reaching the robot, relocating away from the robot, and adjusting with the robot in this paper. These Simulation findings demonstrate that the suggested technique can assist the robot to avoid obstacles without deviating from its original path.

Zhang *et al.* [19] explained an excellent technique for the avoidance of dynamic obstacles based on motion prediction for MRs on multiple features. This study combines a data-driven mobility forecasting technique into a model-based control approach to evaluate its consistency in terms of several future projections. This paper demonstrates through simulation that the chosen model offers reliable movement estimations for a dynamic environment. The outcome of this study allows a controller to anticipate and avoid moving obstacles.

Ding *et al.* [20] presented a brand-new monocular camera-based paradigm for the complicated avoidance of obstacles. For effective DRL, this work creatively converts the acquired RGB pictures to pseudo-laser data. The proposed pseudo-laser assessment combines the semantic and depth data from the recorded RGB image, making the approach efficient in complicated obstacles. Compare this to the conventional laser assessment recorded at a specific height, which just includes one-dimensional (1-D) distance data absent towards surrounding obstacles.

Singla *et al.* [21] estimated a technique for allowing an unmanned aerial vehicle (UAV) quadrotor using a monocular camera to avoid obstacles automatically on itself in unknown and unstructured indoor environments. As UAV movement has greater difficulties than avoiding obstacles in ground vehicular robots as UAV mobility is not as restricted to an explicitly designed street or indoor environment. Recurrent neural networks (RNN) that operate with temporal attention are used in this obstacle avoidance method, which yields superior outcomes in terms of the distance travelled without interacting with previous attempts.

Hu *et al.* [22] described a novel motion prediction-based technique for avoiding obstacles for MRs. The movement of MR guidance matrix might create using the positional data of moving obstacles in the time field to create a movement trend vector and then combined with different mobility state attributes to represent the movement variation pattern of dynamic obstacles within a time range and present additional useful data in the robot in selecting avoiding action. The study's results demonstrate that avoidance of dynamic obstacles is significantly enhanced.

4. PROPOSED METHODOLOGY

In this study, an improved motion pattern prediction-based obstacle-avoiding technique for MR navigation using DRL is presented. This technique primarily includes two advancements. Firstly, A trajectory trend vector is generated by considering the latest position-changing activity of dynamic obstacles to demonstrate the trajectory transition of dynamic obstacles and, to some extent, anticipate their next possible move [23]. And secondly, a mobility guidance matrix is developed by integrating four features including the mobility trend vector for dynamic obstacles, the velocity vector for dynamic obstacles, the positional vectors of MR and target, and the positional vectors of MR and obstacles. This matrix is further considered for the input data in the DNN (deep neural network) for DRL. By comparing this method with traditional techniques those are utilizing only positional information as input data for neural networks, it can enhance the safety of MR from obstacle avoidance.

For the avoidance of collisions with dynamic obstacles, it's important to estimate their motion characteristics accurately.

One way to achieve this is by analysing the state variations of an obstacle in current times to evaluate its speed and angle of motion. These values are then used to calculate the changes in the obstacle's speed and angle over time. To incorporate the variations in angle and speed of dynamic obstacles over time, a weighting system based on the time domain is used. This system assigns weights to the values of variations in angle and speed of dynamic obstacles in every interval, and an average weight can be calculated to present the trend of speed variations and angular variable pattern of dynamic obstacles. As well as these trends estimate the movement trend vectors for time-variant obstacles. The trend vectors, velocity vectors of the time-variant obstacle, positional vectors of the MR, obstacle, and target can be utilized to estimate the MR mobility guidance matrix. This matrix serves as the structure of input layer for DRL training for the neural networks. By using the MR mobility guidance matrix for the architecture of input layer in the DNN, the MR can effectively learn how to navigate around dynamic obstacles in real time. The neural network takes in the input dataset and outputs the appropriate MR avoidance actions based on the current environment. The remaining parts of the proposed methodology are characterized by the following steps:

4.1 The Mobility Trends Vector of Dynamic Obstacles

Contemporary MR can effortlessly gather information about obstacle positions with the aid of sensors including Lidars and RGB-D cameras. As a result, a popular approach is to employ DRL dependent upon real-time positions of obstacle for training. The robot can then avoid obstacles by taking the necessary actions according to its current location. This approach has been shown to perform well in managing the issue of avoiding stationary obstacles. However, when it comes to dynamic obstacle avoidance, the robot might still choose an incorrect course of action due to the inability to predict the movement of the obstacles. While incorporating speed as an input to DRL algorithms has been found to improve action selection, it is still insufficient, especially when prioritizing action safety during travel.

The primary cause for the challenge in predicting dynamic obstacle movement is that it involves a continuous process, where the current position and speed data can not fully reflect the obstacle's movement status. Relying solely on position data at a single moment to determine the next step of a dynamic obstacle is insufficient. Even if the obstacle is in the same location as the previous time, it might have changed direction, leading to the robot's inability to handle the situation accurately. While the movement changes of dynamic obstacles might be irregular over extended periods, short-term trends in movement changes can still be observed. By analyzing an obstacle's recent behavior, it is possible to estimate its next movement change. Figure 2 indicates different direction of motion of dynamic obstacle.

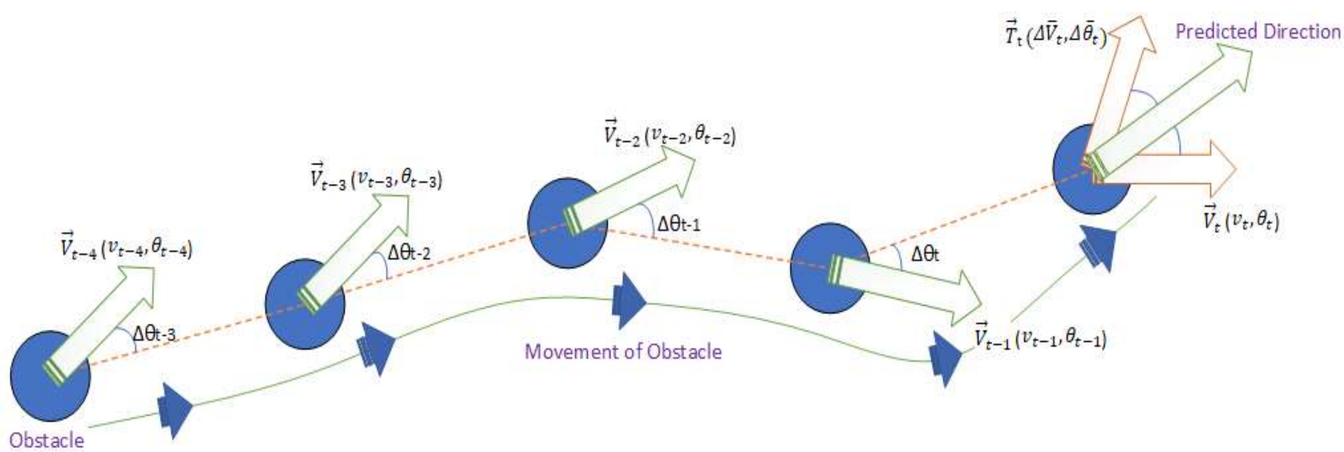

Figure 2: Dynamic obstacles mobility pattern and prediction

According to Figure 2, Let's consider the dynamic obstacle velocity vector as $\vec{V}(v_t, \theta_t)$ at time t, where the mobility velocity and direction are represented as v_t and θ_t respectively. The changed velocity vector for this proposed methodology can be in the time range between t-1 to t and is considered as $\Delta\vec{V_t}(v_t - v_{t-1}, \theta_t - \theta_{t-1})$, which shows a normal condition of the mobility variation for dynamic obstacles in the time range between t-1 to t. Similarly, from time t-2 to t-1, the velocity vector for obstacle is denoted by $\Delta\overrightarrow{V_{t-1}}(v_{t-1} - v_{t-2}, \theta_{t-1} - \theta_{t-2})$, and so on. Dynamic obstacles often experience gentle contemporary motion transitions, despite any unexpected shifts in their motion state, since they can partially represent a movement shift in dynamic obstacles. Although this information can have a lesser standard deviation regardless of how far it is from the present time. As a result of it, distinct weights need to be assigned to the variation in velocity at every instance. The dynamic obstacle's mobility variation pattern at time t can be described by equations (1), (2), and (3) [22].

$$\Delta\bar{V}_t = \frac{1}{n}\left(\sum_0^t \gamma^i \Delta v_i\right) \qquad (1)$$

$$\Delta\bar{\theta}_t = \frac{1}{n}\left(\sum_0^t \gamma^i \Delta\theta_i \right) \qquad (2)$$

$$\vec{T_t} = (\Delta\bar{V_t}, \Delta\bar{\theta}_t) \qquad (3)$$

Where the speed variation of obstacle at time t is represented by ΔV_t, obstacle direction changes at time t is denoted by $\Delta\theta_t$, n is the number of changes in speed and direction of the obstacle, and the speed change weight is denoted by γ at time T, for a constant of 0-1.

The vector follows the changes in the mobility of dynamic obstacles within a specific timeframe leading up to time t, and it expresses the trend of motion changes for dynamic obstacles at time t using an average weight technique. By incorporating the dynamic obstacle through mobility vector for at time T, it becomes feasible to predict the potential position of the time-variant obstacles at time t+1 in the environment. By supplying more relevant data to the robot's decision-making process, this approach enhances the accuracy of obstacle avoidance.

4.2 The Motion Guidance Matrix of Mobile Robot

This paper presents a technique for the avoidance of dynamic obstacles that has mainly two objectives including sending MR to their predefined target and safely avoidance of dynamic obstacles available in the environment. To full-fill these objectives, it is required to get various information including the relative distance among the target and MR, the present movement of obstacles, the movement pattern of obstacles, and the relative position between obstacles and MR. Thus, during DRL training, it is necessary to obtain these two objectives at the same moment, and for this, above discussed information must be gathered by the neural networks. For the representation of this information, four two-dimensional (2D) vectors are defined which are mentioned below [22].

1) $\vec{D}_1$ as a positional vector of MR and target.
2) $\vec{D}_2$ as a positional vector of MR and obstacle.
3) $\vec{V}$ as a movement vector of obstacles.
4) $\vec{T}$ as a vector of trend or pattern of obstacle.

A matrix is formed with the help of these vectors as mentioned in equation 4 [22]. This matrix is known as the mobility guidance matrix for MR at time t. This matrix has all four types of information that are required by the MRs to reach their target. The motion of MR within the global environment is capable of being mapped using this matrix.

$$W_t = \begin{bmatrix} \vec{D_1}_t \\ \vec{D_2}_t \\ \vec{V_t} \\ \vec{T_t} \end{bmatrix} = \begin{bmatrix} \Delta X_{1_t} & \Delta Y_{1_t} \\ \Delta X_{2_t} & \Delta Y_{2_t} \\ V_t & \theta_t \\ \bar{v}_t & \bar{\theta}_t \end{bmatrix} \qquad (4)$$

Both major objectives of achieving the desired location and avoiding obstacles have been taken into consideration simultaneously while tackling to address the dynamic obstacle avoidance challenges for MRs. As a result, a matrix is constructed that contains the data required to reach that objective and can be a helpful resource of information for DRL training. The initial sensor data might be utilized to determine or freely get the data and parameters needed to create the MR motion guidance matrix. Its layout is unaffected by variations in the scene or the sensors. Also, the hidden and output layers are free to use for designing a DRL neural network, however, the input layer must match the structure of the network.

5. EXPERIMENTAL RESULT AND ANALYSIS

A mapping environment for simulation is created for performing DRL training and testing in an environment full of dynamic obstacles for the purpose verify the approach that has been proposed. Each action has a predetermined positive reward depending on the forward range of only one step, and that also implies a negative reward must be presented when it travels backward. Whenever MR collides with any obstacles during simulation, it will get a huge negative reward and if MR easily reached the desired position without collision, it would get a big positive reward, and the training episode will be stopped.

Table 1: Hyperparameters and Configuration of System

System Configuration	Description
Python Version	2.9.1
Numpy Version	1.21.5
Number of Episodes	200
Matplotlib Version	3.7.0
Processor	Intel(R) Core (TM) i3-4005U

Table I describes the list of hyperparameters and details of the system configuration used during experimental analysis. Figure 3 shows the mobility of dynamic obstacles and the optimal path taken by MR during the proposed experiment to reach their goal within the prescribed time limit.

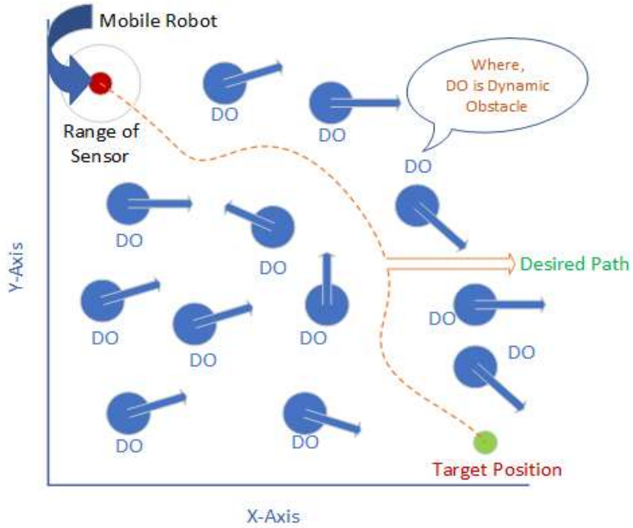

Figure 3: Movement of MR during the experiment.

This technique used DRL algorithms to get the best result through dynamic policy application in the system. Where the main environment of 500×500 is divided into 100 of 4×4 grids for testing and training purposes. With this technique, obstacles inside a 4×4 grid might consist of arbitrary initial and final locations with floated numbers of them. It just used a single phase, and we didn't have a beginning point for any episodes. For each action carried by the MR in a new environment, if an instruction is not given for that step, a different instruction is generated for storing the prescribed instruction. The set containing regulations is extended as long as the MR goes step by step until that achieves its intended target. Figure 4 shows the step-by-step movement of MR toward the target position while avoiding dynamic obstacles over the number of episodes.

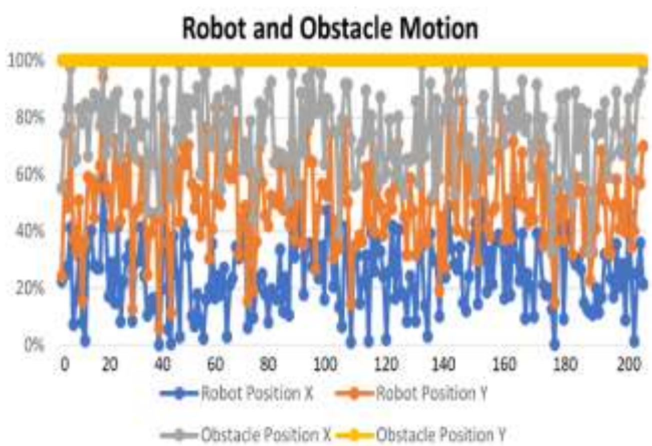

Figure 4: Movement of MR and obstacles over the number of episodes.

If the MR crosses the specified boundaries and has any collision with dynamic obstacles, then it will receive a negative reward, and the training episode will be stopped. Additionally, during the training phase, a random generator determines the MRs starting location, goal position, and environmental obstacles. The Python codes and methodology applied in this experiment are considered from [24]. Table II describes the comparative studies between different types of algorithms for dynamic obstacle avoidance.

Table 2: Comparison Between Different Techniques

Techniques	Accuracy
Bayesian [24]	75%
Static Policy [24]	65%
Proposed technique	79%

6. FUTURE RESEARCH TRENDS

Although the mobility pattern and velocity prediction-based dynamic obstacle avoidance method for MRs through DRL has shown promising results, several areas allow further research. The integration of this method with other techniques or algorithms could enhance its decision-making capabilities. For example, combining it with computer vision techniques may enable the robot to better perceive and respond to its environment. Moreover, investigating the use of different types of neural networks, such as CNNs or RNNs, can lead to even more effective and efficient dynamic obstacle avoidance strategies. It is important to validate the performance of the method in real-world scenarios and under different conditions. Conducting experiments in various environments, such as cluttered spaces or outdoor settings, can provide valuable insights into the robustness and adaptability of the method. Exploring the use of the method in conjunction with other MR navigation techniques could lead to more sophisticated and versatile systems. For example, incorporating path planning or SLAM algorithms could improve the robot's ability to navigate and avoid obstacles in complex environments [25]. Although the motion pattern prediction-based dynamic obstacle avoidance technique for MRs by DRL represents a significant advancement in the navigation of MR, several probabilities for future research can build upon this approach and further improve its effectiveness and applicability in real-world scenarios.

7. CONCLUSION

To find a solution for the issue related to the avoidance of dynamic obstacles by robots within dynamic environments. This article presents a DRL technique for dynamic obstacle avoidance using obstacles pattern prediction methodology. By considering the trajectory variations of dynamic obstacles throughout the most recent time, the subsequent mobility pattern of dynamic obstacles is anticipated by creating the mobility pattern vector for dynamic obstacles. The consideration of this factor is an integral part of the decision-making process for avoiding robots, and it is combined with other relevant factors to create the matrix of motion guidance options for the robot. This matrix then serves as input data for the neural network. The use of DRL enables the robot to access and utilize a wider range of information beyond just the position of obstacles, resulting in a more effective and accurate selection of avoidance actions. This technique used DRL algorithms to get the best result through dynamic policy application in the system. The outcomes of our experiments conducted in a simulated environment demonstrate that training an MR for dynamic obstacle avoidance using the dynamic obstacle movement pattern vector and MR mobility guidance matrix with DRL can significantly enhance the robot's safety.

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