MOBILE ROBOT NAVIGATION SYSTEMS IN AN UNKNOWN ENVIRONMENT

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ABSTRACT

Mobile robots on wheels have the unique challenge of navigating their way through obstacles whether in the open or in confined spaces. This challenge is amplified when mobile robots have to navigate their way in unknown environments. Researchers approach this problem from different perspectives. Most robot rely on sensors to avoid collision with static and dynamic objectives on their path. Encoded signals from the sensors are analysed in real-time for decision-making purposes by special algorithms designed for that purpose. Others rely on the combination of sensors and images. Images are captured and usually analysed in real time by algorithms for the decision-making process. The choice of algorithm depends on the type of function that the mobile robot was designed to perform. Same goes for image captured through the use of camera. The choice of camera depends on the purpose and function of the mobile robot. In this seminar paper, the most common scenarios were reviewed and analysed. The work is presented in sections. Three popular algorithms namely, the QAPF, the Grasshopper algorithm (GOA) and the artificial neural network (ANN) were extensively reviewed for an in-depth understanding of how mobile robot algorithms accomplish navigation in unknown environments. According to available literature, image based navigation systems are classified into monocular and stereo based systems. Monocular rely on a single camera as image-source. In stereo, several camera angles supply the mobile robot with several images from different angles for navigation decisions in real-time.

KEYWORDS: Algorithm, fuzzy-logic, mobile robot, monocular, navigation, stereo

1. INTRODUCTION

Robots are nothing new. They have been used in various capacities in industries such as automobile, cargo movement, heavy duty lifting, and in the transportation of goods and services in recent times. Depending on the purpose, robots are sometimes designed with wheels or artificial limbs for movement. Movements however, creates a challenge – the challenge of navigating around obstacles. There are two general categories of obstacles for most robots to navigate through. One is recognizable obstacle. The other are unrecognizable obstacles. Robots must be designed with the capacity and aptitude to navigate through known and unknown obstacles under varying environmental conditions. For instance Orozco-Rosas *et al.* (2022) in their study proposed a novel path planning approach using a grasshopper algorithm for mobile robot navigation in dynamic and unknown environments. The approach uses a sensory system to detect obstacles and a new method to predict and avoid static and dynamic obstacles while the velocity of obstacles is unknown. The robot uses this information to find a collision-free, optimal, and safe path. The proposed controller is tested in crowded and complex environments, and simulation results show its success in all test environments. The controller is also compared with several heuristic methods, showing promising results in terms of running time, optimality, stability, and failure rate. The proposed controller is promising in terms of running time, optimality, stability, and failure rate.

The path planning problem is a crucial aspect of mobile robot navigation, as it requires algorithms to convert high-level task specifications from humans into low-level descriptions of how to move. This problem has been successfully used in various industries and academic disciplines, such as robotics, manufacturing, and aerospace applications. The path planning problem involves the mobile robot (MR) determining to move in an environment to its predicted goal point without colliding with obstacles. Path planning can be static or dynamic, depending on the nature of the obstacles. Reinforcement learning is one approach that can be employed for MR path planning for known and unknown environments (Orozco-Rosas *et al.*, 2022). The major aim of the current study is to study and understand the various mechanisms of mobile robot navigation under varying conditions.

2. ROBOT NAVIGATION PATH PLANNING

Reinoso and Paya (2020) proposed that robot navigation involves two main tasks: recognizing the environment and extracting relevant information (mapping problem) and solving the localization problem (control). This information is then used to plan a trajectory towards the target points, guided by the vehicle in a reactive manner. Onboard sensors can be used to perceive the environment, resulting in a model or map. The localization task is designed considering available sensors, map structure, and robot movement constraints. Integrated exploration systems jointly consider these issues, developing trajectory planning and control while obtaining a model of the environment and estimating the robot's position and orientation. Path planning methods are categorized into static, dynamic, local, global, and complete. Global path planning is used for known environments, while local path planning uses sensors to explore the environment and find the local path. Both conventional and heuristic navigation methods are used for robot navigation. Significant approaches in this category include graph search algorithms, sampling-based algorithms, probabilistic roadmaps, rapidly-exploring random trees, artificial neural networks, genetic algorithms, ant colony optimization, artificial particle swarm optimization, simulated annealing, bee algorithms, bacteria forging algorithms, cuckoo search algorithms, and fuzzy logic.

2.1 USE OF SPECIAL ALGORITHMS FOR ROBOTIC NAVIGATION

Several machine learning algorithms have been designed and developed to solve the problems of robotic navigation in unknown environments and terrains and how to avoid both static and dynamic obstacles in the immediate environment. Robot perception involves the extraction of raw sensor data and interpretation of it to capture the environment or internal robot attributes. Researchers have investigated various sensor modalities to improve perception, including cameras, LiDAR, radar, sonar, GNSS, IMU, and odometry sensors. Sensor modalities input specific forms of energy and process the signal using similar methods. They include input types like sound, pressure, light, and magnetic fields. The modular or end-to-end robot navigation approach relies heavily on sensors for accurate perception.

2.2 THE Q-LEARNING ALGORITHM

Q-learning is a reinforcement learning algorithm that uses a reward to interact with complex environments, mapping situations to actions and maximizing numerical rewards. It involves a trade-off between exploration and exploitation, with rewards for collision-free actions and penalties for collisions. Q-learning is used in mobile robot path planning due to its self-learning capability, but it has slow convergence to the optimal solution. To address this, partially guided Q-learning through the Artificial Potential Field (APF) weighting is employed. The proposed QAPF learning algorithm can enhance learning speed and final performance, overcoming the disadvantages of conventional methods in mobile robot navigation.

2.3 OFFLINE PATH PLANNING MODE WITH THE QAPF ALGORITHM

The study focuses on the use of the QAPF learning algorithm in offline path planning to find a feasible, collision-free path between start point q0 and goal point QF in a static environment. The QAPF learning algorithm was tested in various environments, with the best path obtained being QG in each test environment. A quantitative comparison was conducted between the proposed QAPF learning algorithm and the CQL algorithm in offline path planning mode. For each test environment, twenty different path planning problems were generated by modifying the start point at random. The results showed that the QAPF learning algorithm outperformed the CQL algorithm in all test environments, particularly in terms of path length, path smoothness, and computation time. The mean and standard deviation were slightly lower for the QAPF learning algorithm in all test environments. In terms of path length, the QAPF learning algorithm achieved an average of 8.5599 meters, a 7.51% improvement from the CQL algorithm. In terms of path smoothness, the QAPF learning algorithm achieved an average of 15.9806 units, a 169.75% improvement from the CQL algorithm. Finally, in terms of path planning computation time, the CQL algorithm achieved an average of 6.56 ms, while the QAPF learning algorithm achieved an average of 6.28 ms, a 4.46% improvement. See Figure 1.

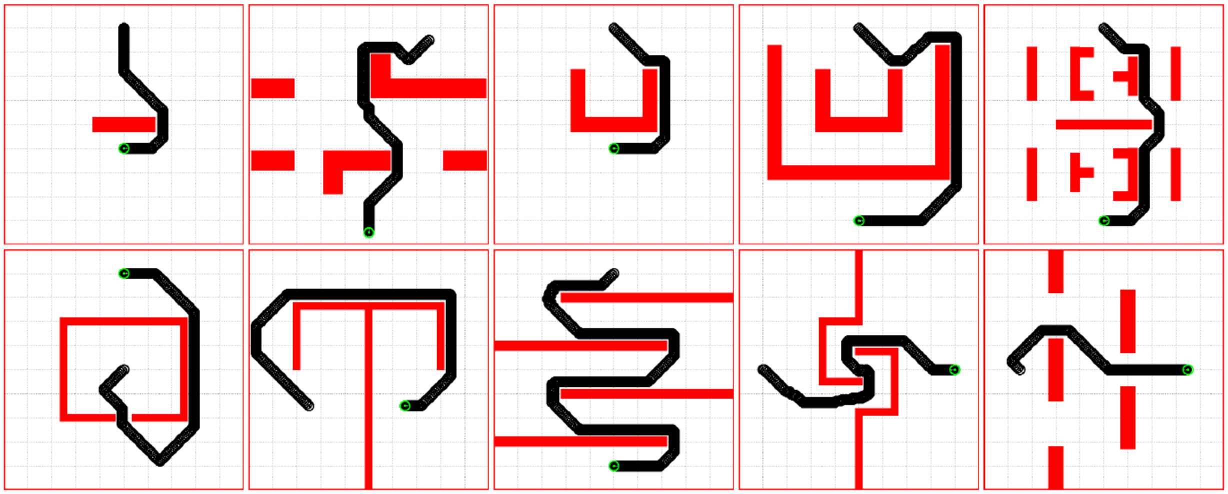

Figure 1. Path planning results for the different test environments. Each map shows the best path QG obtained by the QAPF learning algorithm in offline path planning mode (source: Orozco-Rosas *et al.*, 2022).

2.4 ONLINE PATH PLANNING MODE WITH THE QAPF ALGORITHM

In real-world missions, the MR often faces unknown or partially known environments, requiring the MR to respond and make decisions through online path planning. In this experiment, three new static obstacles are added to the test environment Map01, affecting the path length. The minimum path length is 7.0418 meters, and the MR path planning algorithm based on the QAPF learning algorithm now has a different environment layout. A second static obstacle is added at position (6.8000, 4.9800), and the MR senses the second obstacle and calculates the obstacle position to update the environment layout. The third new obstacle is added at position (5.9800, 4.0000), and the MR senses the third obstacle and calculates the obstacle position to update the environment layout. The MR follows the new path to reach the goal point, with a total path length of 9.8159 meters from the original start point to the goal point. The MR path planning algorithm now needs to update the path and continue with the movement to reach the goal point. See Figure 2.

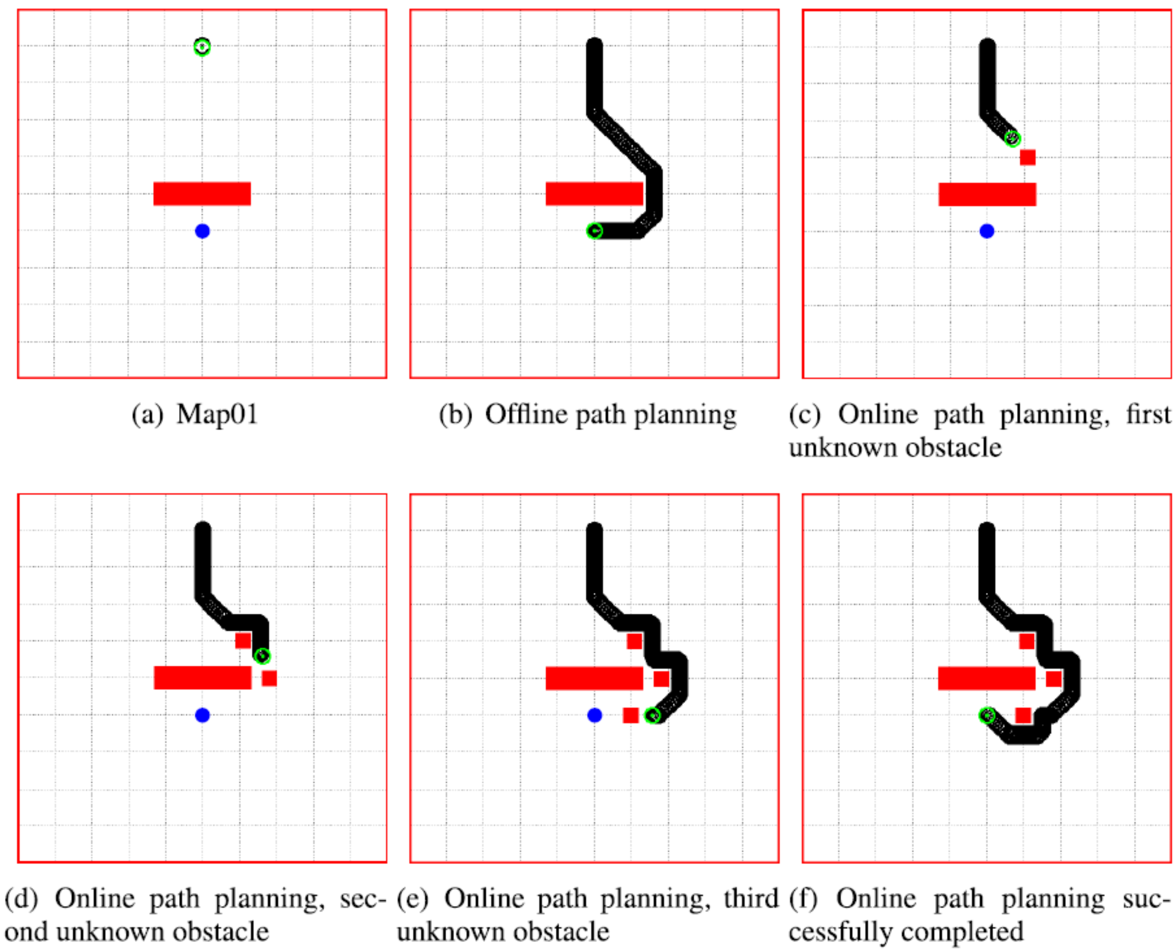

Figure 2. Online path planning with the QAPF algorithm (Source: Orozco-Rosas *et al.*, 2022)

2.5 THE GRASSHOPPER OPTMISATION ALGORITHM (GOA)

The Grasshopper Optimisation Algorithm (GOA) is an optimization algorithm that simulates the food-seeking behavior of grasshoppers, one of nature's largest swarms. The larval phase involves slow and small movements, while the adulthood phase involves larger and unexpected movements. A mathematical model is given to simulate the swarming behaviour, including the position of each grasshopper, social interaction, force of gravity, and wind advection. The simulation results discussed in this review discuss the robot's navigational strategies in different scenarios. In the first scenario, the robot moves from the start position to the target position, encountering 30 static obstacles randomly. The robot navigates according to the optimal path, constantly checking the environment for path safety. If no obstacle is detected, the robot continues its path and records 0 in the sensor matrix. If an obstacle is detected, it attempts to avoid collision by recording 1 in the sensor matrix and running GOA.

In the second scenario, there are 45 dynamic obstacles scattered randomly to different positions. The robot navigates towards the target and moves on its optimal path. The robot moves in (+x) and (+y) directions when reaches the rectangular obstacle, faces the second rectangle obstacle, waits for the second rectangle, and passes from the circular obstacle using GOA. The robot then faces another obstacle and navigates in (+x) and (+y) directions. In the fourth scenario, the robot follows a dynamic target and 30 static obstacles. The robot initially navigates towards the dynamic target, passes from the obstacle, and continues its path on the optimal path. The arrival time for the dynamic target is 20.1 seconds, with a path length of 95.13 cm. See Figure 3.

2.6 ARTIFICIAL NEURAL NETWORK BASED ALGORITHMS

Artificial Neural Networks (ANN) are widely used for mobile robot navigation in unknown environments due to their high approximation capabilities. The neural network-based path planning method is a common approach, considering sensor information, previous position, or movement direction. However, ANN methods can fail in highly chaotic environments. Backward ANN is applied for movement control in dynamically changing environments with moving obstacles, allowing the robot to adaptively predict next coordinates. Two deep neural networks are used for pedestrian collision avoidance and path following tasks, with computer vision-based labeling technology and a monocular RGB camera-based one used for comparison. An ultrasonic sensor is used for static obstacle avoidance, with a deep learning method using a RGB camera being more robust than a computer vision-based method.

Guan *et al.* designed an interval type-2 fuzzy neural network for wheeled mobile robots to achieve smoother obstacle avoidance and position stabilization. A neural network-based Q-learning architecture was developed for autonomous mobile robots, while a modified pulse-coupled neural network method was proposed for collision-free paths in dynamic environments. Wang *et al.* designed a distance-based spiking neural network behavior controller for wheeled mobile robots using ultrasonic sensory information, achieving collision avoidance motion planning with less neurons compared to traditional NNs. Numerous other algorithms have been developed for nonlinear control of single mobile robots, multi-robot systems with moving obstacles, leader-follower-based formation control problems, feed-forward neural networks, and formation control solutions for multi-agent systems in the presence of heterogeneous communication delays.

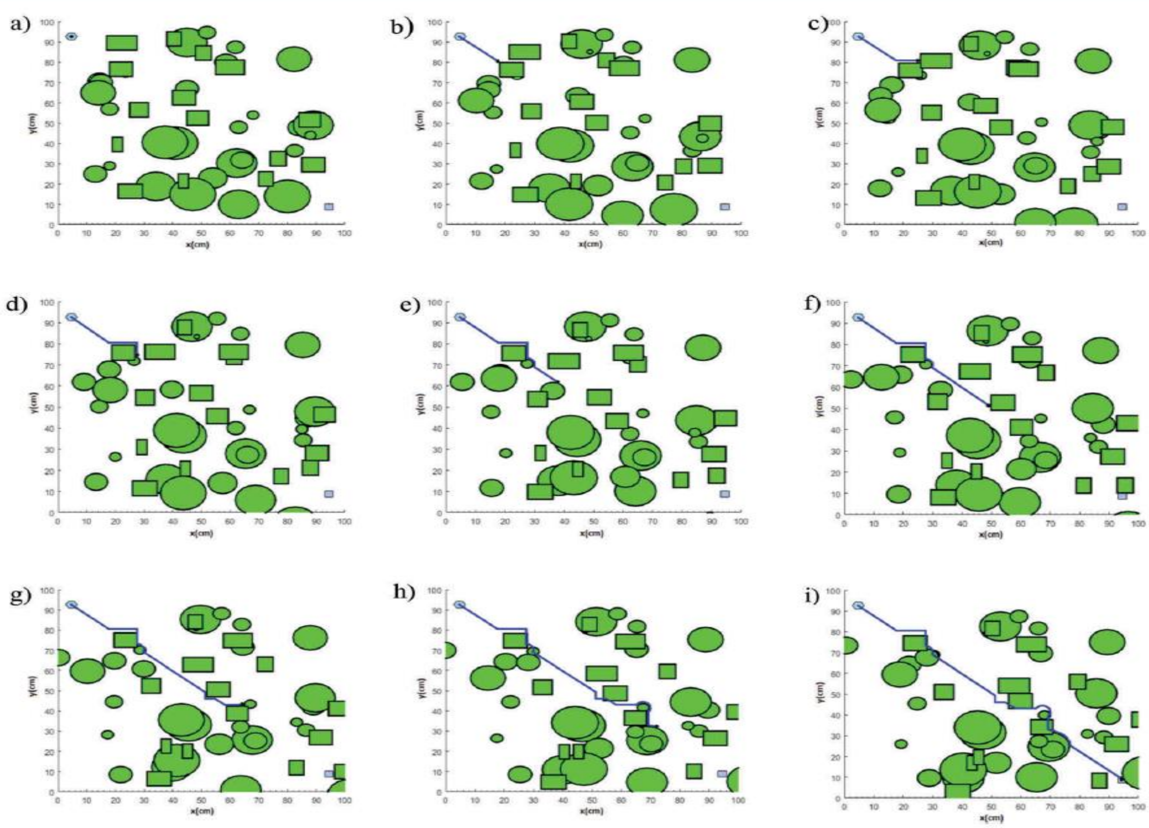

Figure 3. Simulation results of the proposed algorithm in the environment with dynamic obstacles (source: Elmi and Efe, 2020).

2.7 FUZZY LOGIC BASED NAVIGATION SYSTEMS

Fuzzy logic control (FL) is a concept introduced by Zadeh, inspired by human reasoning. FL-based methods are widely used for mobile robot navigation due to their ability to handle uncertainty and imprecise information using linguistic rules. In Li and Yang, a vision-based landmark recognition system is developed for mobile robot navigation, while Faisal *et al.* investigate an FL-based online robot navigation method for mobile robots under unknown dynamic environments. Neuro-fuzzy controllers integrate the advantages of neural networks and fuzzy logic control. Behavior-based control approaches for mobile robots navigation decompose complex navigation tasks into several easy-to-design and perform behaviors. Song and Lin propose a neural network architecture for determining the fuzzy weight of every behavior, while Wen proposes an Elman neural network and fuzzy logic integrated control algorithm to enhance robot performance in obstacle avoidance. Yang *et al.* (2018) further apply the method proposed in Wen, while Zhu and Yang propose a neuro-fuzzy-based method for WMR under unknown environments. They design a fuzzy logic system with both target tracking and obstacle avoidance performances, using two neural network-based learning algorithms to tune membership functions and suppress redundant fuzzy rules. Ye *et al.* (2020) propose a neuro-fuzzy system with mixed supervised learning and reinforcement learning usage, which improves learning ability by improving Sutton and Barto's model.

Pandey (2016) investigated the safe-navigation problem of multiple WMRs under unknown cluttered environments, developing an adaptive neuro-fuzzy control system that integrates ANN and fuzzy logic technology. The proposed control system achieves collision-free during motion planning by combining a repelling influence between WMRs and nearby obstacles with an attracting influence between WMRs and targets. A hybrid rule-based-neuro-fuzzy controller with rules incorporating desired motion and direction, distances between WMRs and obstacles/targets, and appropriate heading angle as control variables improves navigation performance of multiple WMRs in complex and unknown environments. In Pradhan *et al.*'s FL-based navigation performance, it is concluded that controllers with Gaussian membership function are most efficient for WMRs navigation. However, the considered environmental obstacle is static in Pandey, and every robot independently moves along the generated traveling path without considering communication between robots. For online interaction, the connectivity problem of multiple WMRs networks should be addressed. See Table 1.

3. IMAGE-BASED NAVIGATION SYSTEMS FOR MOBILE ROBOTS IN UNKNOWN ENVIRONMENTS

Robots often use a combination of sensors and cameras for navigation in unknown environments. Vision is crucial for robot navigation, and cameras are used to understand environmental information (Wijayathunga *et al.*, 2023). Cameras are generally cheaper than LiDAR sensors and are passive, with monocular configurations being highly used in standard RGB cameras. Stereo cameras, inspired by human eyes, use two lenses and separate passive image sensors to obtain two perspectives of the same scene. RGB-D camera sensors consist of monocular or stereo cameras coupled to infrared transmitters and receivers. The Kinect camera from Microsoft is a relatively inexpensive RGB-D sensor used for indoor robot applications due to the saturation of infrared receivers in outdoor scenarios. RGB-D sensors use three depth measurement principles: structured light, TOF, and active infrared stereo techniques. Event cameras have advantages like high temporal resolution, high dynamic range, low latency, and lower power consumption but are not suitable for static object detection. Omnidirectional cameras provide a wider-angle view but have distortions due to lens configuration, requiring different mathematical models to correct image distortions.

3.1 DEEP REINFORCEMENT LEARNING

Lee and Yusuf (2022) proposed an end-to-end approach using deep reinforcement learning for autonomous mobile robot navigation in an unknown environment. They proposed two types of deep Q-learning agents, deep Q-network and double deep Q-network agents, to enable the mobile robot to learn about collision avoidance and navigation capabilities. Simulation results showed that the DDQN agent outperforms the DQN agent in reaching the target object location by 5.06%. SLAM (Static-Location Algorithm) is used to create a coherent map of an unknown environment while localizing itself on it. However, large-scale problems remain, such as computational complexity and conflicts when updating the map through data association. Path planning algorithms are used to generate a collision-free path with the least cost, but offline path planning is easier to find the optimal path. To reduce overestimations, the authors decoupled the selection from the evaluation in the max operator, allowing for double Q-learning. This method evaluates the greedy policy as per the critic network but uses the target critic network to estimate its value. The proposed framework consists of a mobile robot, an agent, and an environment, with the mobile robot containing two sensors: a laser rangefinder sensor and an RGB-D camera.

3.2 VISUAL STUDIO 2015 OPERATING SYSTEM BASED NAVIGATION SYSTEM

Khairudin et al (2020) developed a mobile robot navigation system for detecting suspicious objects in unknown environments. The system combines camera vision, wireless communication, metal sensor, and gas detection systems. The robot can operate on various tracks and detect various movements, such as forward, backward, right turn, left turn, and oblique 45 and 135 degrees. The XBee receiver and transmitter can be removed within a maximum distance of 150 meters. The camera's performance in detecting objects horizontally and vertically ranges from 10 to 200 degrees and 0 to 100 degrees, respectively.

Table 1. Summary of algorithm-based navigation systems for robots in unknown environments

S/N	Algorithm	Algorithm characteristics	Type of sensor	Unknown environment	Obstacle	Reference
1	Q-learning through Artificial Potential Field (QAPF)	Reinforcement algorithm uses a scalar reinforcement signal reward-based	-	Geometric shapes	Static and dynamic	Orozco-Rosas *et al.* (2022)
2	Grasshopper optmisation algorithm (GOA)	It is a mathematical model that aims to simulate the food-seeking behavior of grasshoppers. It uses a modified version of the model to calculate the next position of each grasshopper, considering the current position of each grasshopper and the exploration and exploitation of the entire swarm around the target.	four circles of range sensors	Geometric shapes	Static and dynamic	Elmi and Efe, 2020
3	Artificial immune system (AIS)	Mimics the human immune system	-	Geometric shapes	Static and dynamic	Mohanty *et al.* (2020)
4	Artificial Neural Network (ANN) based	Various ANN based models	Various types	Mostly geometric shapes		Wang *et al.* (2021)
5	Fuzzy logic-based	Various Fuzzy logic based models	Various types	Mostly geometric shapes		Wang *et al.* (2021)

The robot can also monitor objects containing metal and gas with detection distances of 0.11 meters and 480 ppm up to 805 ppm.

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The robot consists of a module with four wheels, sensor parts, and a processor. The metal and gas detection sensors are placed in the front position for easier detection. The robot uses noncable equipment like XBee S2B Pro and USB Wi-Fi TL-WN8200ND for serial communication. The algorithm for communication between the robot and a monitoring station was applied in several stages, starting with the Arduino robot connecting the XBee serial and Xbox controller to Wi-Fi. The FOSCAM FI8910W IP camera was used for faster and more consistent results. The speed and distance of the mobile robot navigation varied greatly based on location and environment. The robot performed various movements during the performance test, with a backward motion different after performing normally in the first two seconds. See Figures 4 and 5.

3.3 CLASSIFICATION OF IMAGE-BASED NAVIGATION SYSTEMS IN UNKNOWN ENVIRONMENT

Badrloo *et al.* (2022) classified image-based navigation systems in mobile robot (MR) into two broad categories with many sub-categories, and they are *monocular* and *stereo* obstacle detection methods. This review examined the development of image-based obstacle detection methods over the past two decades. Image-based obstacle detection methods can be divided into monocular and stereo methods. Monocular methods are discussed in four groups: appearance-based, motion-based, depth-based, and expansion-based, while stereo-based approaches are studied separately in IPM-based and disparity histogram-based categories.

To ensure safe and accurate navigation, an obstacle detection algorithm should have the following abilities: (a) narrow and small obstacle detection (e.g., rope, wire, tree branches), (b) moving obstacle detection (e.g., birds, mobile robots, humans), (c) obstacle detection in all directions (e.g., in complex environments), and (d) fast/real-time obstacle detection (e.g., robots' response speed depends on the algorithm's speed. For simplicity, the terms Narrow and Small Obstacle Detection (NSOD), Moving Obstacle Detection (MOD), Obstacle Detection in All Directions (ODAD), and Fast Obstacle Detection (FOD) are used. The review discusses monocular and stereo image-based obstacle detection techniques in detail, with papers published since 2015 listed to indicate current trends and interests. See Figure 6.

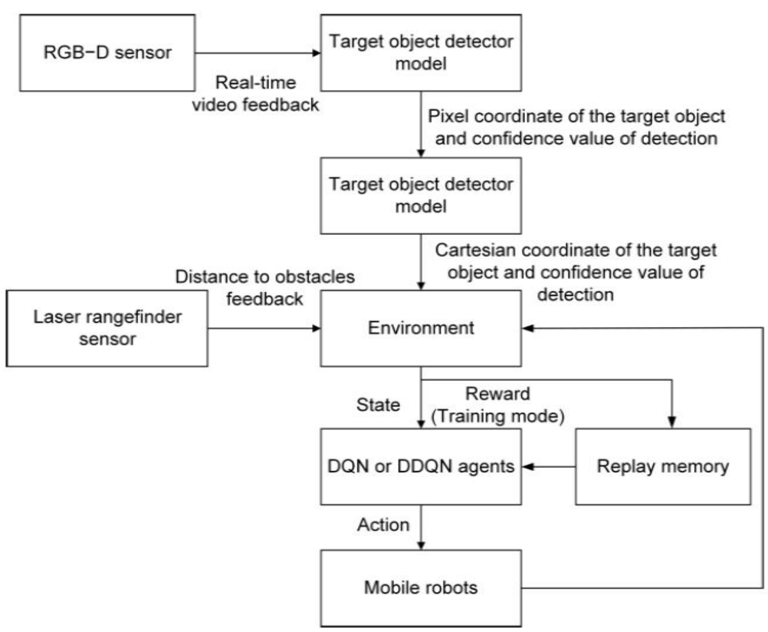

Figure 4. Proposed block diagram for the mobile robot navigation using DQN/DDQN algorithm (Source: Lee and Yusuf, 2022).

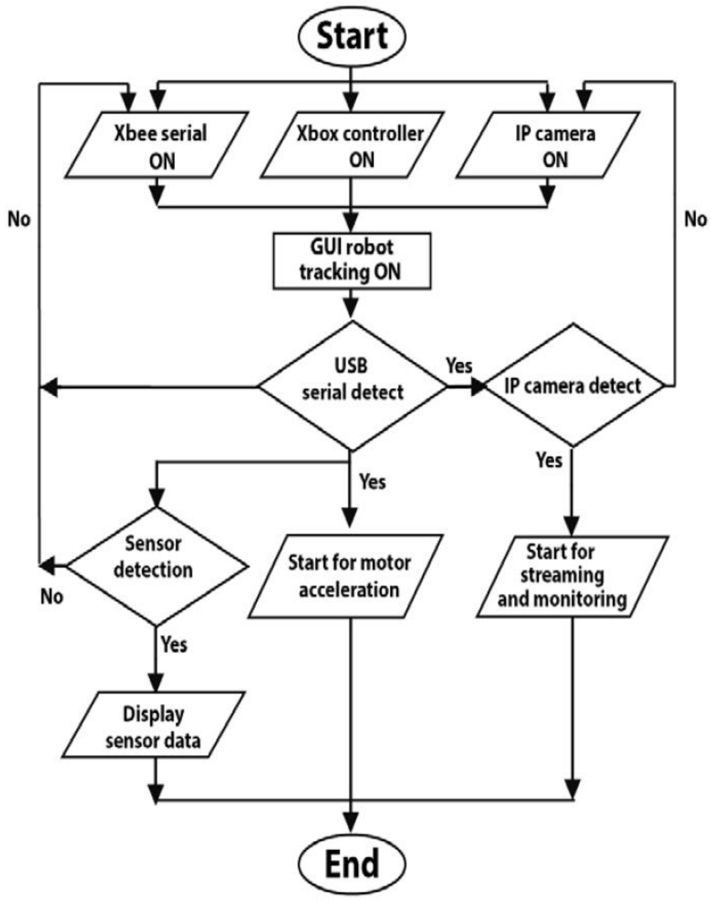

Figure 5. Algorithmic flow chart for the Visual studio 2015 OS based MR navigation system (source: Khairudin *et al.*, 2020).

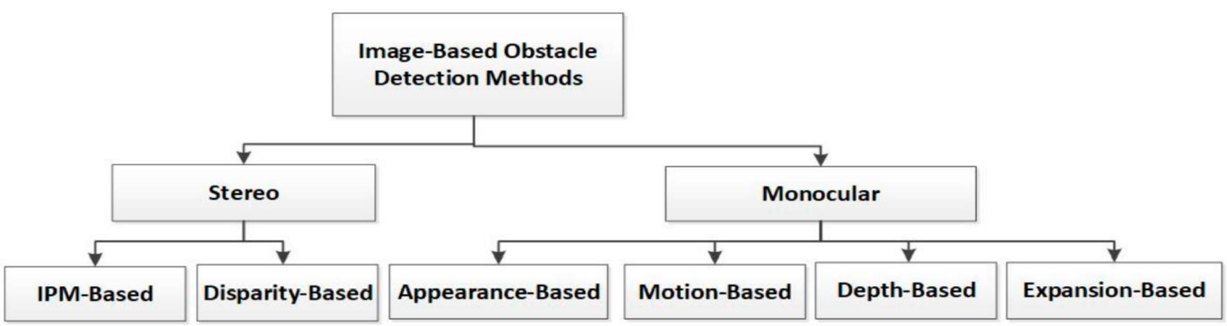

Figure 6. Classification of image-based obstacle detection methods (Source: Badrloo *et al.*, 2022).

3.3.1 MONOCULAR IMAGE-BASED OBSTACLE DETECTION METHOD

Monocular image-based obstacle detection methods use a single camera mounted in front of a robot to detect obstacles as foreground objects against a uniform background. These methods work based on prior knowledge from the relevant background, such as edge, color, texture, or shape features. Obstacle detection is performed on single images taken sequentially, examining if they conform to sky or ground features. Techniques such as Markov's Random Field (MRF) segmentation, an omnidirectional camera system, the Hue Saturation Value (HSV) colour model, object-based background subtraction, and image-based obstacle detection techniques have been proposed. However, conventional image processing techniques do not meet real-time application expectations. Recent research has focused on increasing the speed of obstacle detection using

Convolutional Neural Networks (CNNs), such as TensorFlow and OpenCV, YOLOv3, SORT, YOLOv4, fusing features, and a novel semantic segmentation algorithm for real-time obstacle detection in marine environments.

3.3.2 APPEARANCE BASED MONOCULAR METHOD

Application-based methods have been used on various robots, with each study having its own concerns. Appearance-based methods are generally limited to environments where obstacles can easily be distinguished from the background, which can be violated in complex environments containing objects with varying shapes and colors. Some techniques are affected by the distance to the object or the noise in the images. When using deep learning approaches, the detection of obstacles is primarily affected by the change in the environment and the number and types of samples in the training data set. Therefore, it is suggested to use a semantic segmentation algorithm performed by deep learning networks, provided that sufficient training data is available.

3.3.3 MOTION-BASED MONOCULAR METHOD

Motion-based methods detect nearby objects using motion vectors in images. This process involves taking two consecutive images or frames, extracting match points, and computing displacement vectors. Any point with a displacement value exceeding a certain threshold is considered an obstacle pixel. Studies have been conducted to distinguish obstacles from shadows and road markings. Optical flow is the data used in most motion-based approaches. Ohnishi and Imiya's research prevents mobile robots from colliding with obstacles without a map of the environment. Gharani and Karimi used two consecutive frames to estimate optical flow for obstacle detection on smartphones, helping visually impaired people navigate indoor environments. Tsai *et al.* used Support Vector Machine (SVM) to validate Speeded-up Robust Features (SURF) point detector locations as obstacles. Motion-based obstacle detection relies on the quality of matching points, which can decrease if the number of mismatched features is high. An expansion-based approach is suggested to detect obstacles in the central parts of the images, ensuring the strength of the expansion-based technique in detecting frontal objects while analyzing other parts using the motion-based method.

3.3.4 STEREO-BASED OBSTACLE DETECTION METHODS

Obstacle detection based on stereo uses two synchronised cameras fixed on a robot to detect obstacles. These methods can be classified into IPM-based and disparity histogram-based. IPM-based methods are used to detect all types of road obstacles and eliminate the perspective effect of original images in lane detection problems. Currently, IPM images are mostly used in monocular methods.

3.3.5 IPM BASED ALGORITHM

The IPM algorithm produces an image representing the road seen from the top, using internal and external parameters of the cameras. The difference in grey levels of pixels in overlapping regions is computed, generating a polar histogram image. If the image textures are uniform, this histogram contains two triangles/peaks: one for the lane and one for the potential obstacle. These peaks are then used to detect the obstacle, i.e., non-lane object. Limited research on stereo IPM obstacle detection exists, with some studies using a stereo pair of cameras to create two IPM images for each camera and combine them with another IPM image created using a pair of consecutive images taken with a smaller FOV to detect obstacles. IPM-based methods have limitations, such as using uniform texture or color objects, noise generation, and needing specific acquisition conditions. They are recommended only for lane detection and obstacle detection in cars due to the limitations of this method in unknown environments, particularly when using drones.

3.3.6 DISPARITY HISTOGRAM-BASED SYSTEM

Disparity histogram-based obstacle detection techniques were initially developed for terrestrial robots, focusing on car parking assistance. However, these techniques have limitations, such as low-quality points at the edges and decreased accuracy in areas close to the image center. Ball *et al.* introduced an algorithm that adapts to changes in illumination and brightness in farm environments but cannot detect hidden obstacles. Salhi and Amiri proposed a faster algorithm implemented on Field Programmable Gate Arrays (FPGA) to simulate human visual systems. Murmu and Nandi presented a novel lane and obstacle detection algorithm using video frames captured by a low-cost stereo vision system. Sun *et al.* used 3D point cloud candidates extracted by height analysis for obstacle detection. With the development of neural networks, researchers have turned to deep learning methods, such as stereo object matching techniques, deep learning methods, and hybrid encoders. Haris and Hou improved the robustness of obstacle detection methods in complex environments.

4. CONCLUSION

Robots have become increasingly used in various industries, including automobile, cargo movement, and transportation. However, they face challenges in navigating around obstacles, which can be recognizable or unrecognizable. Robots must be designed to navigate through known and unknown obstacles under varying environmental conditions. A novel path planning approach using a grasshopper algorithm for mobile robot navigation in dynamic and unknown environments amongst other algorithms proposed by other researchers.

Path planning is a crucial aspect of mobile robot navigation, as it requires algorithms to convert high-level task specifications from humans into low-level descriptions of how to move. Reinforcement learning is one approach that can be employed for MR path planning for known and unknown environments. Path planning methods are categorized into static, dynamic, local, global, and complete. Both conventional and heuristic navigation methods are used for robot navigation, with heuristic methods often used to overcome limitations. Significant approaches in this category include graph search algorithms, sampling-based algorithms, probabilistic roadmaps, rapidly-exploring random trees, artificial neural networks, genetic algorithms, ant colony optimization, artificial particle swarm optimization, simulated annealing, bee algorithms, bacteria forging algorithms, cuckoo search algorithms, and fuzzy logic. Image based systems for mobile robot navigation in unknown environment have also been found useful in the industries, logistics, the military and even in nuclear facilities to detect harmful radiations.

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