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Autonomous Differential Drive Mobile Robot Navigation with SLAM, AMCL using ROS

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Abstract: Today world is marching towards high degree of industry automation along with intelligence integration. Many industries uplifting their traditional machine work to smart robotic operating system (ROS-1) based mobile robotic automation. This paper discuss the autonomous robotic navigation which is the most important part of robotic automation, it includes simultaneous-localization-and-mapping (SLAM) implemented through robotic operating system to understand the necessary workspace along with exploration of shortest low coast path within workspace. Multiple algorithms now a day available which explores collision free navigation path to reach the goal position without disturbing in-path obstacles. This paper elaborate the method combining ROS based SLAM along with vision sensory based AMCL and the DWA path planning technique which continuously capture the workspace and localize all moving and static obstacles along with robot. The experimented result shows the explored path is safe and collision free which is feed to a controller program to continuously govern autonomous mobile robots by utilizing prior knowledge of workspace and robots mechanism.

Keywords: ROS, ROS based Mobile Robot Navigation; Optimal Path Planning Algorithm; Adaptive Monte Carlo Localization (AMCL) algorithm and the Dynamic Window Approach (DWA) planner.

1. Introduction

The high degree intelligence based industrial automation enhancing the industries processes by improving the traditional machine work in to smart automation. This paper discusses the autonomous robotic navigation which is the most important part of industrial robotic atomization. The robot autonomous navigation is a crucial aspect of robotics, enabling robots to operate in dynamic environments with or without human intervention [1].. Many researchers experimenting variety of SLAM methods for indoor autonomous mobile robot navigation which continuously updates the information of the workspace and localize all moving and static obstacles along with robot [2].Mobile robots moreover shares a similar mechanism and overall architecture e.g. in industrial robotic arm has multiple joints with specific degree of freedom, turn tables and measurement tables for accurately measuring each dimension of auto parts, moving autonomous indoor mobile robot or cart transporting material between different stations[3,4]. The autonomous mobile robot navigation field is continuously upgrading, as many mature algorithm are develop and deployed in mobile robot assisting human application [5, 6].

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There are three major parts in mobile robot navigation:

1. Robot self-localization and workspace mapping.
2. Exploring realistic and true optimal path.
3. Navigating mobile robot on planned path.

Robot Simultaneous localization and Workspace Mapping

Localization of static as well as moving objects is major and important task in robotic navigation. From last few decades various SLAM algorithms introduces great number of robot and obstacle localization methods e.g Hector SLAM-based Navigation[7, 8]. Thus the localization information of the current workspace helps mobile robot for effective safe navigation [9]. There are different methods used to acquire surrounding environmental information such as mobile robots are equipped with distance laser (LiDAR), ultrasonic or Infrared light (IR) based distance sensors, image processing based or some contactive type of sensor for exploring and understanding the current workspace[10]. Workspace exploring with distance sensor is an exhaustive process, mobile robot has to move and explore every corner of the workspace [11]. This method become prolongs as working space dimensions of mobile robot increases. The major hurdle in such navigation system is need of calibrated sensor with appropriate fixing on the autonomous mobile robot; moreover these robots might be trapped in local loop this leads to keep self-track of mobile robot. The contact type based sensor robot continuously touches obstacle to localize them thus these both methods are unsuitable for real-world applications [12].

The shortcoming of above method overcomes by image processing method where either camera is placed over the robot head or attached to a fixed position inside the workspace. In the former case camera moves according to robot motion, this will help mobile robot to avoid local obstacle, but cannot have knowledge of hidden area and obstacles behind the visible objects. The fixed position placement of camera covers most of the part of workspace at the same time all the obstacles can be localization globally. Thus image processing (Vision based) systems have more beneficial than the other system such as lighter in weight as it require very few components, the new generation sensor and communication module make the system compact along with more power saving and durability. These systems are also ubiquitous, thus making the cameras ideal for capturing devices to be implanted inside mobile robots. Vision based workspace exploration used in variety of important functions in robotics application such as specific obstacle detection, colour object or people detection and tracking object following through visual servoing [13].Many algorithms are designed for computer games are equally used in mobile robots path planning such as A*, D*, D* lite, Basic Theta, Theta* and Phi*, Sub Goal Graph, ANYA, JPS and JPS plus goal bounding are the few most famous path planning algorithm [14]. The fundamental task in path planning is to search and finds the best suitable path by avoiding obstacles and robot collision. The process of dividing the continuous path into optimal sub-path edges which makes navigation safer and faster. The path planning algorithms are categories under two broad categories namely Indoor application and Outdoor application, in former case the dimensions and workspace complexity of arena or workspace is priory known whereas in later case the dimensions and complexity is uncertain. The environmental exploring sensors are the important components inside the mobile robot, as they represent the complete environment correctively and efficiently [15]. This paper elaborate differential drive robot equipped with a LiDAR sensor that utilizes the Adaptive Monte Carlo Localization (AMCL) algorithm and the Dynamic Window Approach (DWA) planner to achieve robust and efficient navigation [16]. It also investigates the performance of AMCL and the DWA planner in real-world scenarios, particularly in the presence of dynamic obstacles. The integration of AMCL and the DWA planner within the Robot Operating System (ROS) Noetic provides a comprehensive framework for localization and path planning [17]. AMCL is a probabilistic algorithm that utilizes particle filtering to estimate the robot's position and orientation relative to a known map. It allows the robot to adapt to environmental changes and effectively localize itself even in the presence of uncertainty. The DWA planner, on the other hand, is a real-time path planning algorithm that takes into account the robot's kinematics and dynamically computes a feasible trajectory by considering its dynamic constraints and the environment. This approach ensures that the robot can navigate smoothly while avoiding obstacles and achieving its desired goal.Experimentation and its result of the evaluation of the performance of AMCL and the DWA planner. It also provides a detailed analysis of the robot's path planning capabilities by initially plotting its trajectory without any obstacles and subsequently introducing a new obstacle to observe how the robot recalculates its path in response. The comparison between the initial and recalculated paths will provide insights into the effectiveness of AMCL and the DWA planner in adapting to dynamic environments.The findings of this study have significant implications for the field of autonomous navigation. By understanding the strengths and limitations of AMCL and the DWA planner, thus one can enhance the development of navigation systems for robots operating in real-world scenarios. The ability to accurately localize and plan paths in dynamic environments is crucial for the successful deployment of autonomous robots in various domains, including exploration, surveillance, and transportation. In the subsequent sections, this paper explains a comprehensive overview of AMCL and the DWA planner, describe the experimental setup, present the results of experimentation, and discuss the implications and potential areas for further research [18].

1.1. Adaptive Monte Carlo Localization (AMCL)

The Adaptive Monte Carlo Localization (AMCL) algorithm is a powerful technique used for probabilistic localization in robotics. It allows a robot to estimate its position and orientation within a known map by utilizing a particle filter-based approach. AMCL is particularly well-suited for robots operating in dynamic environments where the surroundings may change over time. In this experimentation integration of AMCL algorithm into the ROS framework to enable accurate localization of the differential drive robot. The AMCL algorithm maintains a set of particles, each representing a possible pose of the robot. These particles are updated and resampled based on sensor measurements and motion data, allowing the algorithm to converge towards the most likely robot pose [19].The key advantage of AMCL lies in its adaptability to environmental changes. As the robot navigates through the environment, the particles are adjusted to reflect the changes in sensor readings and robot motion. This adaptability ensures that the robot's estimate of its pose remains accurate even in the presence of uncertainty and dynamic obstacles.To evaluate the performance of AMCL, a real-world environment experimentation conducted. Initially, user goal position provided to the robot and observed how AMCL converged towards the true pose estimate. By comparing the estimated pose with ground truth data, then the accuracy and reliability of AMCL is assessed under normal operating conditions. Furthermore, a new obstacle along the robot's path to simulate a dynamic environment. This allowed evaluating AMCL's ability to adapt and recalibrate its pose estimate in the presence of a changing environment. Thus the analysis of the impact of the obstacle on the estimated poses and assessed the convergence speed and accuracy of the algorithm in dynamically evolving scenarios. The subsequent section will discuss the implementation details of the DWA planner, which complements AMCL by providing real-time path planning capabilities based on the robot's estimated pose and the environment map.

1.2. Dynamic Window Approach (DWA) Planner

The Dynamic Window Approach (DWA) planner is a key component of autonomous mobile robot navigation system, designed to provide real-time path planning for differential drive robot. The DWA planner operates based on the estimated pose of the robot obtained from the AMCL algorithm and the environment map. At its core, the DWA planner uses a local window of robot velocities, incorporating both translational and rotational velocities. By sampling different velocity combinations within this window, the planner evaluates their feasibility and selects the best velocity that optimizes the robot's motion towards the goal while considering dynamic constraints and avoiding obstacles [20].The DWA planner relies on a cost function that takes into account various factors such as proximity to obstacles, distance to the goal, and robot dynamics. This cost function allows the planner to evaluate different trajectories and prioritize those that lead to collision-free paths while minimizing deviation from the desired trajectory. Intergradation of DWA planner into the ROS framework, leveraging its flexibility and compatibility with the said robot's differential drive system. By coupling the DWA planner with the AMCL algorithm, a result shows good achievement with comprehensive and robust navigation system capable of adaptive localization and dynamic path planning. Thus the experimentation in control environment is conducted to evaluate the performance of the DWA planner. Therefore the robot with goal positions are provided to observed how the planner generated smooth and obstacle-free trajectories to reach the desired destinations[21]. In this way one can measured the planner's ability to navigate complex environments efficiently, considering factors such as path length, execution time, and proximity to obstacles. In addition to above experimentation addition case are introduced with new obstacle in the robot's path to analysed how the DWA planner reacted to this dynamic change, recalculating the path to avoid the obstacle while maintaining the desired trajectory. This highlighted the planner's adaptability and its capability to dynamically adjust the robot's motion plan based on real-time sensor feedback. In summary, the DWA planner plays a crucial role in autonomous mobile robot navigation system by enabling real-time path planning based on the robot's estimated pose and environment map. Its dynamic nature and ability to consider various constraints and obstacles make it a valuable tool for navigating complex and changing environments. Next section discusses the integration of the LiDAR sensor and the SLAM (Simultaneous Localization and Mapping) toolbox, which enables the mobile robot to build a map of its surroundings while simultaneously localizing itself using the AMCL algorithm and executing path plans generated by the DWA planner.

1.3. The ROS Ecosystem

Robot Operating System (ROS) is a popular open-source framework widely used in robotics research and development. It provides a collection of tools, libraries, and conventions that facilitate the development of robot software. ROS offers a flexible and modular architecture, making it ideal for building complex robotic systems with various sensors and actuators.

1.3.1. SLAM Toolbox

One of the key functionalities provided by ROS is Simultaneous Localization and Mapping (SLAM), which allows a robot to construct a map of its environment while simultaneously estimating its own pose within that map. SLAM is essential for autonomous navigation as it enables the robot to understand and navigate unknown or dynamic environments. SLAM Toolbox in ROS package specifically designed for SLAM applications. The SLAM Toolbox offers a range of SLAM algorithms and tools, providing a comprehensive solution for building and updating maps in real-time. It offers flexibility in choosing different SLAM approaches based on the specific requirements of the robot and the environment. The implementation of the online async SLAM approach using the SLAM Toolbox, which combines mapping and localization in an asynchronous manner. This approach enables the robot to continuously update the map while performing localization, allowing for real-time adjustments to the map as the robot explores its surroundings. Thus the online async SLAM algorithm utilizes sensor measurements, such as the laser scan data from the LiDAR sensor, to estimate the robot's pose and incrementally build the map [22]. It leverages advanced techniques like scan matching, loop closure detection, and pose graph optimization to improve map accuracy and robustness. Utilizing the SLAM Toolbox's online async SLAM approach, the robot was able to generate accurate maps of its environment while autonomously navigating through it. The robot's ability to simultaneously update its map and estimate its pose in real-time provided a reliable foundation for path planning and obstacle avoidance. To evaluate and validate the performance of the autonomous mobile robot navigation system, two powerful simulation tools, Rviz and Gazebo are utilized, which provided a realistic and dynamic virtual environment for testing and visualization.

1.3.2. Rviz: Visualization and Analysis Tool

Rviz, an essential component of the ROS ecosystem, served as the primary visualization and analysis tool. With its intuitive interface and comprehensive set of features, Rviz allowed to visualize and monitor critical components of the autonomous mobile robot system in real-time. By subscribing to relevant ROS topics able to display sensor data such as laser scans, odometry information, and transformed coordinate frames. This enabled to gain insights into the robot's perception of its surroundings, evaluate the accuracy of the localization algorithm, and assess the effectiveness of the DWA planner in generating feasible paths. Rviz also provided visualization of the robot's pose estimate, the costmap representation of the environment, and the execution of planned trajectories. Through Rviz's interactive interface, one can analyse the robot's behaviour, identify potential issues, and fine-tune the mobile robot system parameters accordingly. Its visualization capabilities played a crucial role in comprehending the robot's decision-making process and understanding the impact of various factors on its navigation performance.

1.3.3. Gazebo: Dynamic Simulation Environment

Gazebo, a powerful physics-based robot simulator, provided a dynamic virtual environment to simulate and test the autonomous navigation system. Gazebo's capabilities can leverage to create a realistic 3D representation of mobile robot and its surroundings, including the presence of static and dynamic obstacles. By defining the physical properties of the underline robot and incorporating accurate models of LiDAR sensor and odometry system, Gazebo simulated the robot's motion and the sensor data it would perceive in real-world scenarios. This enabled to evaluate and fine-tune the robotic navigation stack in a controlled environment before deploying it on the physical robot. One of the significant advantages of Gazebo was its ability to introduce dynamic obstacles, mimicking real-world scenarios where the robot must adapt and navigate around moving objects. Thus user can observed the robot's response to these dynamic obstacles within the simulated environment, along with valuable insights into the system's robustness, obstacle avoidance capabilities, and path planning efficiency.

1.3.4. Integration of Rviz and Gazebo

The integration of Rviz and Gazebo played a pivotal role in robotic system development and evaluation process. The seamlessly connection of Rviz to Gazebo, allows to visualize using simulated environment while monitoring the robot's perception, planning, and control in real-time. This integration facilitated quick iterations to validate the system's behaviour and performance within the simulated environment, identify potential issues or discrepancies, and make necessary adjustments to the navigation stack or system parameters. The ability to analyse and visualize the robot's behaviour in tandem with its simulated environment enhanced understanding of the system's strengths and limitations. The next section elaborate the integration of the LiDAR sensor and it contribution to the SLAM process, enabling robot to perceive its surroundings and generate laser scans for mapping and localization.

2. Experimental Set-up and Procedure

This section, describe the experimental setup and procedure employed to evaluate the performance of autonomous mobile robot navigation system utilizing AMCL and the DWA planner. The goal of the experiment was to assess the system's ability to adapt to dynamic environments by recalculating the path when encountering new obstacles.

2.1. Robot Hardware and Software Configuration

The autonomous mobile robot platform consisted of a differential drive robot equipped with a LiDAR sensor for perception and mapping. The robot's hardware included motor controllers, encoders for wheel odometry, and a computing unit running ROS Noetic. The software configuration involved integrating ROS packages such as the slam toolbox, AMCL, and the DWA planner into the ROS workspace. The robot LiDAR sensor must be configured for the parameters, such as range limits and angular resolution, to ensure accurate perception of the environment.

2.2. Experimental Environment and Goal Definition

The experimentation environment over the gazebo with a controlled indoor environment includes known landmarks and predefined pathways. Fig. 1 represents the environment included static obstacles and open spaces to facilitate robot navigation and path planning derived in Gazebo whereas in Fig. 2 represents the same environment is mapped through SLAM technique. The experiment involved defining a goal position within the environment for the robot to navigate towards the goal position was specified using coordinates in the map frame. Thus it allows the robot to autonomously plan and follow a path to reach the desired location.

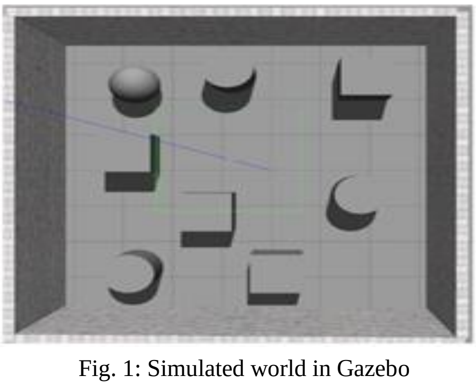

Fig. 1: Simulated world in Gazebo

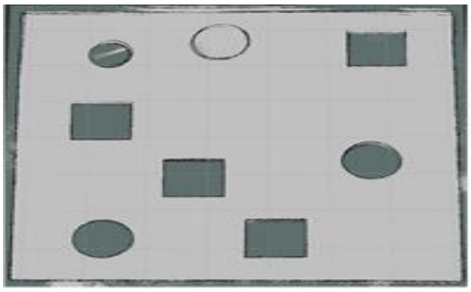

Fig. 2 Mapped by SLAM_toolbox

2.3. Path Planning and Navigation Procedure

To initiate the experiment, the robot provided with the goal position, triggering the navigation stack to generate a path using the DWA planner. The DWA planner utilizes the robot's odometry information and the costmap, which represents the environment's static and dynamic obstacles, to compute a collision-free trajectory. As the robot started navigating towards the goal position, the trajectory is monitored and traced over the map and logged relevant data, such as the robot's pose, sensor readings, and path trajectory. This data used to analyze further robot's behavior and evaluate the performance of the navigation stack. During the experiment, the robot are instructed to navigate within user given start and goal position as shown in Fig. 3 static environment for goal position 1 and Fig. 7 static environment for goal position 2. Once they successfully reached to those static points through autonomous navigation as show in Fig. 5 for goal position 1 and Fig. 9 for goal position 2, dynamic obstacles are introduced into its new path so as to observe the navigation in dynamic environment as show in Fig. 4 dynamic environment for goal position 1 and Fig. 8 dynamic environment for goal position 2. The dynamic obstacle could be a human or pet animal or an object moving across the robot's planned trajectory. Upon encountering the dynamic obstacle, the robot's perception system detected it using the LiDAR sensor and fed the information to the costmap. The AMCL module, which performs localization based on sensor data, was then triggered to estimate the robot's updated pose as shown in Fig. 4 dynamic environment for goal position 1 and Fig. 8 dynamic environment for goal position 2. Based on the updated pose estimate and the presence of the dynamic obstacle in the costmap, the DWA planner recalculated the path, ensuring that the robot could navigate around the obstacle to reach the goal position through autonomous navigation to goal position 1 as shown in Fig. 6 and goal position 2 as shown in Fig. 10 while avoiding collision with the newly added obstacle.

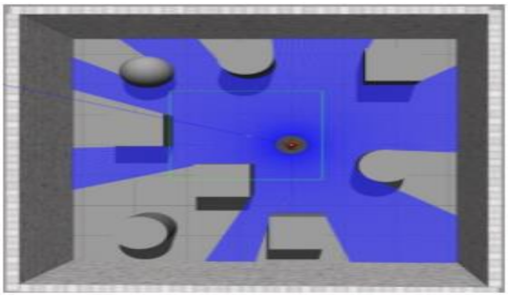

Fig. 3 Static Environment for goal position 1

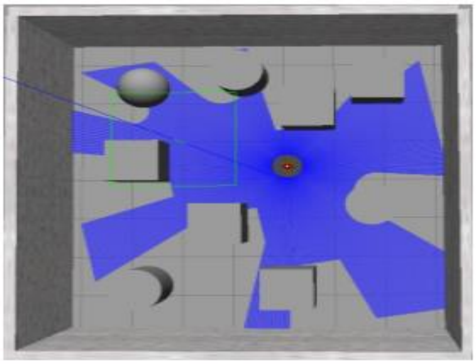

Fig. 4 Dynamic Environment for goal position 1

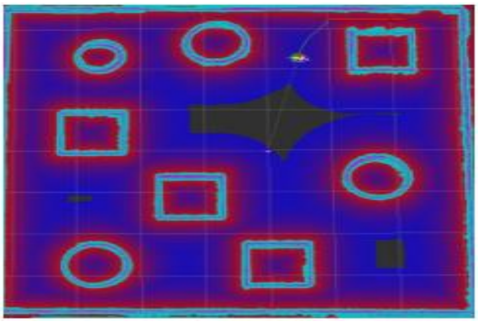

Fig. 5 Autonomous Navigation to goal 1 in static environment

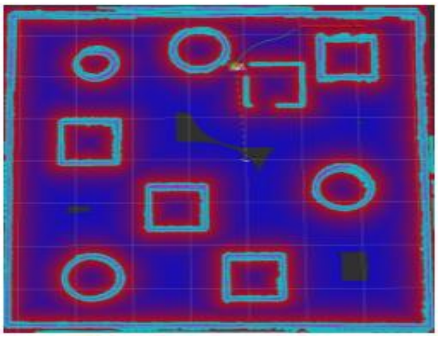

Fig. 6 Autonomous Navigation to goal 1 in dynamic environment

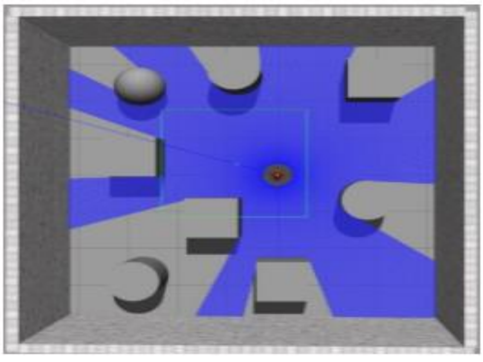

Fig. 7 Static Environment for goal position 2

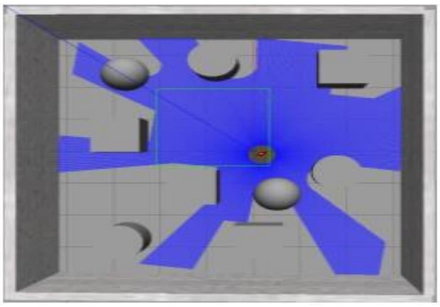

Fig. 8 Dynamic Environment for goal position 2

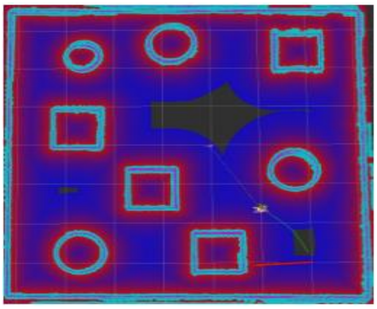

Fig. 9 Autonomous Navigation to the goal 2 in static environment

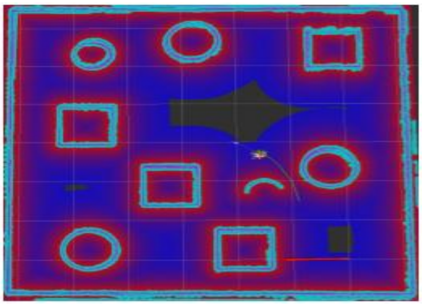

Fig. 10 Autonomous Navigation to the goal 2 in dynamic environment

2.4. Path Comparison and Evaluation

The navigation system performance is assessed by comparing the robot's original path, generated before the introduction of the dynamic obstacle, with the recalculated path after encountering the obstacle. Thus plotted the paths on a map to visualize the changes and deviations caused by the dynamic obstacle. In addition to this the analysis of the path comparison provides more insights into the system's ability to adapt and plan alternative trajectories in response to dynamic changes in the environment. This helps to improve the metrics such as path length, clearance from obstacles, and the efficiency of the robot's navigation. The results and findings obtained from experimental evaluation, discussing the effectiveness and limitations of the autonomous navigation system utilizing AMCL and the DWA planner is discussed in the subsequent section.

3. Result Analysis

This section discussed the various experiment recordings, results and analysis of the experimental evaluation conducted over autonomous navigation system utilizing AMCL and the DWA planner, focusing over the experiential deviation in the robot's path when encountering a dynamic obstacle and provides insights into the system's adaptability and response.

3.1. Path Deviation Analysis

Upon analyzing the plotted paths, it can be observed a clear and significant deviation in the robot's trajectory after the introduction of the dynamic obstacle. Initially, the robot followed a relatively straight path towards the goal position, avoiding any static obstacles present in the environment as show as graph in Fig. 11 for static environment goal position 1 and Fig. 13 for static environment goal position 2. However, as the robot encountered the dynamic obstacle, It experience a notable shift in its planned path. The DWA planner, leveraging the updated pose estimate from AMCL and the information provided by the Costmap, recalculated the trajectory to navigate around the obstacle effectively.

The global plan refers to the high-level path plan that spans the entire environment. It typically represents the path from the robot's current position to the goal position in a global coordinate frame. The global plan is generated by DWA Planner Algorithm and is often pre-computed before the robot starts moving. The global plan topic provides information about this planned path as show as graph in Fig. 12 for dynamic environment goal position 1 and Fig. 14 for dynamic environment goal position 2.

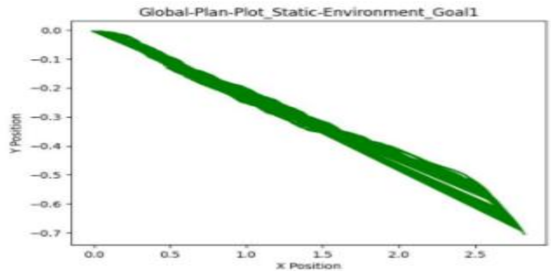

Fig. 11 Global Plan Plot with static environment for goal position 1

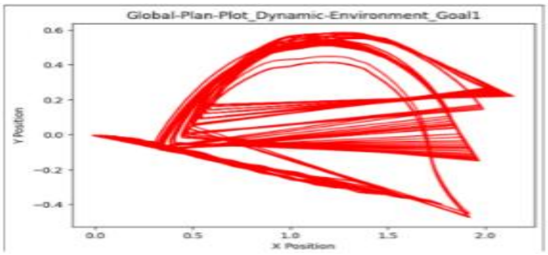

Fig. 12 Global Plan Plot with dynamic environment for goal position 1

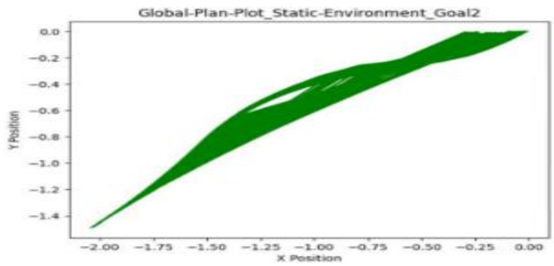

Fig. 13 Global Plan Plot with static environment for goal position 2

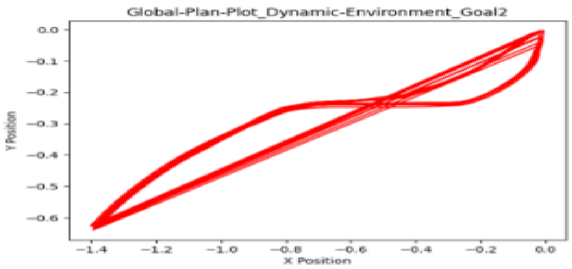

Fig. 14 Global Plan Plot with dynamic environment for goal position 2

3.2. Path Recalculation and Adaptability

Fig. 15 and Fig. 17 depicts the odometry plan plot for user instructed goal 1 and goal 2 position respectively in static environment. The recalculation of the path demonstrated shown as graph in Fig. 16 and Figure 4.2.4 is the system's ability to adapt to dynamic changes in the environment. By incorporating the dynamic obstacle's presence into the costmap, the DWA planner considered the obstacle as a constraint while generating the new trajectory.

The recalculated path exhibited a clear deviation from the original planned path. It strategically guided the robot to navigate around the obstacle, ensuring collision avoidance while still aiming to reach the goal position. This adaptive behavior showcases the effectiveness of the navigation stack in dynamically adjusting the robot's path to handle unforeseen obstacles.

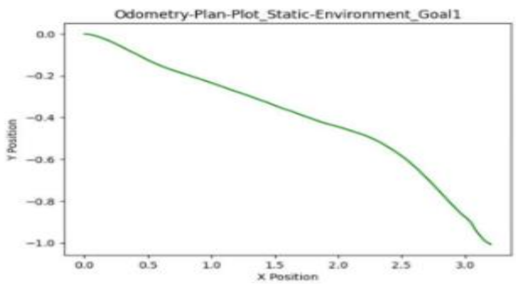

Fig. 15 Odometry Plot with static environment for goal 1

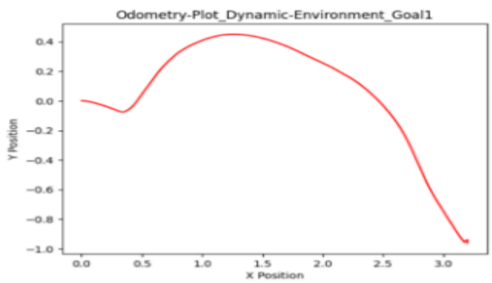

Fig. 16 Odometry Plot with dynamic environment for goal 1

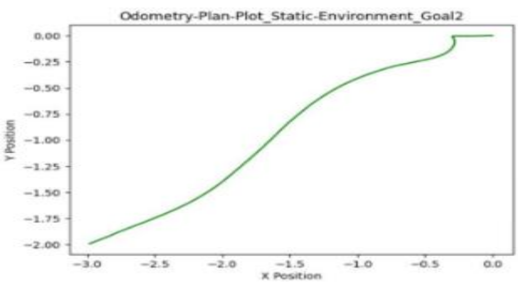

Fig. 17 Odometry Plot with static environment for goal 2

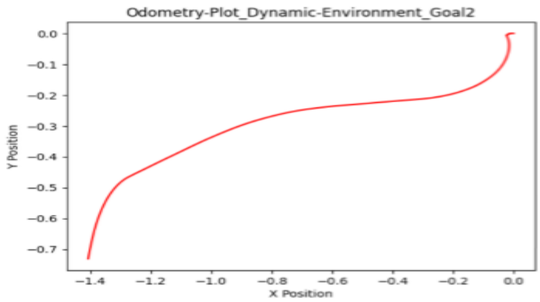

Fig. 18 Odometry Plot with dynamic environment for goal 2

3.3. Quantitative Evaluation of Deviation

To quantify the observed path deviation various metrics are analyzed such as path length, clearance from obstacles, and the efficiency of the robot's navigation. Comparing these metrics between the original path and the recalculated path provided valuable insights into the system's performance. Thus it can be clearly observed that the recalculated path exhibited a longer trajectory compared to the original path due to the detour necessary to avoid the obstacle. However, the increased path length was accompanied by a noticeable increase in the clearance between the robot and the dynamic obstacle, ensuring a safe and collision-free navigation. Table 1 shows Quantitative evaluation of deviation.

Table 1 Quantitative evaluation of deviation.

Goal	Calculated trajectory		
Position	Static Environment	Dynamic Environment	Difference
1	3.3982952	4.0076955	0.6094
2	1.7550746	3.3982952	1.643221

4. System Limitations and Future Improvements

While the system demonstrated impressive adaptability and path recalculation capabilities, It also encountered a few limitations during the experiment. In some instances, the robot exhibited slight deviations from the optimal trajectory, which could be attributed to factors such as sensor noise, localization inaccuracies, or limitations in the DWA planner's optimization algorithm. To further enhance the system's performance, future improvements could focus on refining the obstacle detection and mapping process, optimizing the path planning algorithm to consider dynamic obstacles more effectively, and fine-tuning the parameters of the navigation stack to minimize path deviations.

5. Conclusion

In conclusion, the experimental evaluation of the autonomous mobile robot navigation system utilizing AMCL and the DWA planner showcased its ability to dynamically adapt and recalculate paths upon encountering dynamic obstacles. The observed deviation in the robot's trajectory, along with the associated metrics, demonstrated the system's effectiveness in ensuring significant collision avoidance while pursuing the goal position with marginally increase of path by approximately 16% for the restricted environment. These findings highlight the potential of the navigation stack for real-world applications where robots need to operate in dynamic and changing environments. By leveraging AMCL for accurate localization and the DWA planner for adaptive path planning, autonomous mobile differential drive robot system lays the foundation for reliable and safe autonomous navigation.

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