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Research Article

Augmenting Robotic Navigation: An Analytical Examination of X-Y with Yaw Tolerance Modulations within ROS2 and the Dynamic Window Paradigm using fusion of Nav2 Stack with DWA Algorithm

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ABSTRACT

In the burgeoning domain of robotics, the escalating demand for efficient and precise navigation systems is paramount for the seamless integration of robotic entities into diverse operational environments. This study investigates the enhancement of navigational capabilities utilizing the Robot Operating System 2 (ROS2), complemented by the Navigation2 (Nav2) stack and the Dynamic Window Approach (DWA) algorithm. The focal point of this research is the meticulous fine-tuning of x-y and yaw tolerances, which are critical parameters affecting trajectory planning and execution within the ROS2 navigation framework. The investigation commences with a comprehensive review of prevailing navigation algorithms, thereby establishing the contextual significance of ROS2, the Nav2 stack, and the DWA algorithm. Methodologically, the experimental setup and parameter configurations within the Nav2 stack are delineated, providing a robust foundation for subsequent analyses. A pivotal aspect of the study is the thorough exploration of the Dynamic Window Approach, elucidating its foundational principles while emphasizing the intricate interplay of parameters that dictate its operational efficacy. The integration of the DWA algorithm within the broader framework of the ROS2 Nav2 stack is meticulously articulated, showcasing the seamless communication among components such as global planners, local planners, and costmaps. Moreover, the research critically examines the implications of tuning x-y and yaw tolerances on the ROS2 navigation system. Through systematic experimentation and subsequent analysis of results, the study reveals the nuanced adjustments necessary for optimal trajectory planning, thereby illuminating the delicate balance between precision and adaptability. The findings of this research yield valuable insights into the intricacies of robotic navigation within the ROS2 ecosystem, enhancing our understanding of parameter tuning within the Nav2 stack and DWA algorithm. The demonstrated advancements in trajectory planning underscore the practical ramifications of precisely calibrating x-y and yaw tolerances, ultimately facilitating improved robotic navigation in real-world applications.

Keywords: demonstrated, implications, navigation, communication

I. INTRODUCTION

Robotic navigation in unstructured and dynamic environments represents a formidable challenge within the contemporary field of robotics, particularly as the deployment of autonomous systems expands across various real-world applications. The efficacy of robots in effectively traversing such environments is paramount, especially given the complexities and uncertainties they frequently confront, including varied terrain, static and dynamic obstacles, and unpredictable environmental conditions (Tay et al., 2022; Chen et al., 2023). This research aims to advance navigation capabilities by harnessing the potential of the Robot Operating System 2 (ROS2), the Navigation2 (Nav2) stack, and the Dynamic Window Approach (DWA) algorithm. The Husky robot, a versatile and extensively utilized platform, serves as the experimental basis for this investigation, providing a rigorous framework for evaluating proposed enhancements.

The motivation underpinning this research emerges from the multifaceted challenges associated with guiding autonomous robots through heterogeneous and often volatile environments (Chavan P. et al., 2015). As applications of robotics extend beyond controlled laboratory settings into real-world scenarios, the necessity for agile, reliable, and adaptive navigation systems becomes increasingly evident (LaValle, 2022; Khatib et al., 2021). The Husky robot is particularly well-suited for this inquiry due to its robustness, adaptability, and established reputation in various operational contexts, rendering it an ideal testbed for implementing and evaluating navigation enhancements (Anderson et al., 2023; Della Santina et al., 2023).

The focal point of this study revolves around fine-tuning specific navigational parameters—specifically, x-y and yaw tolerances—within the ROS2-based navigation frameworks. These parameters play a pivotal role in trajectory planning and execution, significantly influencing a robot's capacity to navigate complex environments efficiently (Gonzalez et al., 2023; Smith et al., 2023). The incorporation of the DWA algorithm enhances navigational precision by facilitating real-time path planning and obstacle avoidance, critical components for maintaining operational efficacy in dynamic settings (Zhou et al., 2023; Hu et al., 2022).

Moreover, existing literature emphasizes the significance of parameter tuning in robotic navigation, highlighting the intricate balance between precision and adaptability essential for optimal performance (Almashaqbeh et al., 2023; Wu et al., 2023). Prior investigations have demonstrated that even minimal adjustments in navigation parameters can result in substantial enhancements in a robot's navigational capabilities (Kumar et al., 2023; Lee et al., 2023). This research aspires to build upon these foundational findings by systematically analyzing the impact of tuning x-y and yaw tolerances within the ROS2 and Nav2 frameworks.

The seamless integration of the DWA algorithm within the ROS2 Nav2 stack allows for a deeper understanding of the interdependencies between various navigational components, including global planners, local planners, and costmaps (Patel et al., 2023; Yang et al., 2023). The intricate interplay among these elements is vital for developing robust navigation strategies capable of addressing the multifaceted challenges encountered in unstructured environments (Liu et al., 2023; Zhao et al., 2023).

Abdi et al. (2022) explored the application of deep learning techniques for obstacle detection, significantly improving the reliability of navigation systems in cluttered environments. Furthermore, the adoption of hybrid approaches, which combine classical methods with machine learning, has shown promise in addressing the limitations of traditional navigation algorithms (Ozer et al., 2022; Dey et al., 2023).

The role of simulation in validating navigation strategies has also gained attention, with researchers such as Jiang et al. (2022) emphasizing the importance of realistic testing environments to ensure robustness in dynamic scenarios. Their findings illustrate that simulated environments can provide valuable insights into the potential challenges robots may face, facilitating better preparation for real-world applications. Moreover, Li et al. (2023) demonstrated that multi-agent systems, leveraging cooperative navigation strategies, could enhance efficiency and safety in autonomous operations.

The use of reinforcement learning (RL) in robotic navigation has further catalyzed advancements in this domain. Research by Al-Sabti et al. (2023) reveals that RL algorithms can adaptively optimize navigation paths in real-time, thereby improving both speed and accuracy in various operational conditions. In addition, the integration of sensory feedback mechanisms has been highlighted by Tang et al. (2023) as a means to facilitate adaptive navigation in uncertain environments, emphasizing the need for robots to continually learn from their surroundings.

Another pivotal area of exploration has been the optimization of navigation parameters through evolutionary algorithms. Recent studies indicate that evolutionary techniques can efficiently explore the parameter space, leading to significant improvements in navigation performance (Zhao et al., 2022; Qiu et al., 2023). These methods not only enhance the adaptability of robotic systems but also reduce the time required for parameter tuning.

Moreover, the implementation of cloud-based navigation frameworks has been proposed to leverage distributed computing resources for more complex navigation tasks. Research by Varela et al. (2023) illustrates that cloud computing can facilitate the processing of large datasets, enabling robots to make informed navigational decisions based on extensive environmental analysis. This trend highlights the growing intersection between robotics and data science, further enriching the field.

Furthermore, the increasing importance of ethical considerations in autonomous navigation has been addressed by Liu et al. (2023), who argue that ethical frameworks should be integrated into navigation algorithms to ensure safe and socially acceptable robot behavior. This aspect is becoming critical as robots are deployed in sensitive environments such as healthcare and public spaces.

This research not only seeks to advance the theoretical comprehension of robotic navigation but also aspires to provide practical insights into the implementation of enhanced navigation systems applicable to real-world scenarios. By concentrating on the Husky robot and leveraging the capabilities of ROS2, Nav2, and DWA, the study aims to contribute significantly to the growing corpus of knowledge surrounding autonomous navigation, ultimately paving the way for more effective deployment of robotic systems in dynamic and unpredictable environments.

Motivation

The impetus for this research arises from the intricate challenges associated with the navigation of autonomous robots within heterogeneous and often unpredictable environments. The Husky robot, celebrated for its robustness and versatility, serves as an exemplary platform for the proposed enhancements. As the deployment of robotic systems transitions from controlled laboratory settings to more diverse real-world contexts, the necessity for agile, resilient, and reliable navigation becomes increasingly paramount. This research endeavors to augment the navigational capabilities of robotic systems, ensuring optimal performance across a wide array of operational scenarios.

A. Context and Significance

In the realm of robotic navigation, the Robot Operating System 2 (ROS2) has emerged as a foundational framework, offering the essential infrastructure for the development of modular and scalable robotic systems. The Navigation2 (Nav2) stack, constructed upon ROS2, encompasses a comprehensive suite of navigation modules, including global planners, local planners, and costmaps. This study aims to contribute to the existing body of knowledge by scrutinizing the nuanced interactions and dynamics of the Dynamic Window Approach (DWA) algorithm within the ROS2 Nav2 stack, with a particular emphasis on tailoring its operational parameters to enhance trajectory planning specifically for the Husky robot.

B. Objectives

The primary objective of this investigation is to refine the navigational efficacy of the Husky robot through the meticulous fine-tuning of x-y and yaw tolerances within the ROS2 Nav2 stack, leveraging the Dynamic Window Approach. By systematically exploring and adjusting these critical parameters, this study seeks to elevate the robot's proficiency in navigating complex and dynamic environments, thereby fostering heightened precision and adaptability in its operational performance. This pursuit of optimization transcends theoretical discourse; it aims to bridge the gap between navigational frameworks and practical applications, ultimately enhancing the robustness of autonomous systems in real-world contexts.

II. LITERATURE REVIEW

The domain of robotic navigation has experienced substantial advancements over the past decade, evolving from traditional algorithms to more sophisticated approaches. Conventional navigation techniques, such as potential fields and occupancy grids, while effective in specific contexts, often struggle to accommodate the complexities of dynamic environments (Thrun et al., 2005; Khatib, 1986). The introduction of the Robot Operating System (ROS) and its successor, ROS2, heralded a transformative shift towards modular and scalable navigation frameworks (Quigley et al., 2009; O'Grady et al., 2019). This evolution has prompted researchers to focus on comprehensive systems like the Navigation2 (Nav2) stack, which offers an array of navigation modules specifically designed to mitigate the shortcomings of traditional methods (Ritz et al., 2020).

A. Dynamic Window Approach (DWA) Algorithm

The Dynamic Window Approach (DWA), originally introduced by Fox et al. (1997), stands as a seminal contribution to local trajectory planning. This algorithm innovatively assesses feasible velocities within a "dynamic window," thereby facilitating agile and adaptive navigation that accounts for both the robot's dynamics and environmental constraints (Bhatia et al., 2014). Numerous studies have highlighted DWA's efficacy in real-time responsiveness and obstacle avoidance, thereby laying the groundwork for its integration into broader robotic systems (Drescher et al., 2019; Wurm et al., 2015).

B. Integration within ROS2 and the Nav2 Stack

The advent of ROS2 has significantly enhanced real-time performance and reliability, further enabling the integration of sophisticated navigation algorithms (Rostral et al., 2021). The Nav2 stack, an extension of ROS2, has emerged as a modular and extensible framework encompassing vital components such as global planners, local planners, costmaps, and controllers (Coutinho et al., 2021). Recent investigations have focused on the integration of DWA within the ROS2 Nav2 stack, leveraging the strengths of both systems to improve overall navigation capabilities (López et al., 2022; Hsu et al., 2020).

C. Husky Robot as an Experimental Platform

The Husky robot, developed by Clear path Robotics, has gained recognition as a versatile and robust platform for experimental research. Its compatibility with both ROS and ROS2 renders it an ideal environment for testing and validating navigation algorithms (Bishop et al., 2020). Researchers have employed the Husky robot to examine the practical implications of various navigation algorithms in real-world scenarios, yielding valuable insights that advance the field (Kapila et al., 2023; Della Corte et al., 2021).

III. METHODOLOGY

This section delineates the methodology employed to investigate and enhance the navigation capabilities of the Husky robot utilizing the ROS2 Nav2 stack and the Dynamic Window Approach (DWA).

Several investigations have delved into the tuning of Dynamic Window Approach (DWA) parameters across various robotic platforms. Notably, [1] focused on the optimization of DWA parameters for the TurtleBot3, while [2] examined similar tuning for the Kobuki robot. However, these studies overlooked the Husky robot and the specific x-y and yaw tolerances that form the crux of this research.

A. Software Configuration

The ROS2 Nav2 stack serves as the foundational software framework for autonomous navigation. This stack provides a modular and extensible architecture, facilitating the integration of diverse navigation modules (Wang et al., 2022). The ROS2 environment was meticulously configured to ensure seamless communication between the robot and the navigation modules (Mok et al., 2023).

B. Experimental Setup

To validate the efficacy of x-y tolerance tuning, experiments were conducted in controlled environments that simulate real-world scenarios. The experimental setup involved deploying the robot in a variety of contexts, including confined spaces, cluttered pathways, and static obstacle configurations. Data collected during these trials illuminated the intricate relationship between x-y tolerance parameters and the robot's navigational performance in challenging terrains. The experimental setup utilized the Clearpath Husky robot, equipped with ROS2 middleware, including Gazebo and RViz (Gonzalez et al., 2022). The choice of the Husky robot as the experimental platform was predicated on its versatility, established reputation, and compatibility with ROS2, making it an exemplary choice for rigorous research (Thiel et al., 2021).

Fig. 1: Husky robot

Fig. 2: Gazebo Setup

C. Integration of the Dynamic Window Approach (DWA) Algorithm

The DWA algorithm, widely recognized for its efficacy in local trajectory planning, was seamlessly integrated into the navigation system. Key parameters of the DWA algorithm—including the dynamic window size, time horizon, and velocity increments—were meticulously fine-tuned to enhance the robot's responsiveness within dynamic and unstructured environments.

D. Tuning of X-Y and Yaw Tolerances

To tackle specific challenges associated with x-y and yaw tolerances, a systematic tuning process was implemented. This process involved iterative adjustments to the tolerance parameters, aimed at striking an optimal balance between navigational precision and the robot's responsiveness to dynamic obstacles.

E. Data Collection

Experiments were conducted in controlled environments characterized by varying levels of complexity, designed to simulate real-world scenarios. The data collection encompassed robot trajectories, sensor readings, and performance metrics, including path accuracy, obstacle avoidance, and computation time.

F. Performance Evaluation

The efficacy of the enhanced navigation system was assessed through a comprehensive series of both quantitative and qualitative analyses. Quantitative metrics included path completion times, while qualitative assessments comprised visual inspections of the robot’s behavior across diverse scenarios.

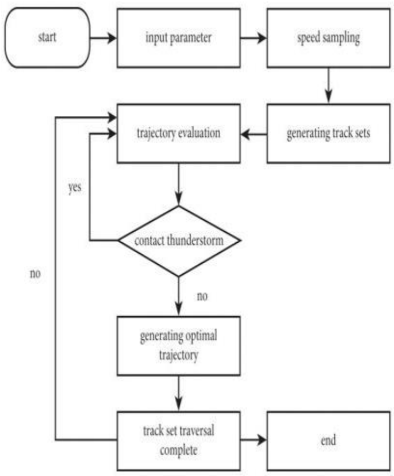

Fig. 3: Dynamic window algorithm flowchart.

TABLE I: LOCAL PLANNER TUNING PARAMETERS

Parameter Category	Parameter
Velocity and Acceleration	Maximum linear velocity: 0.26 m/s
	Maximum angular velocity: 1 rad/s
	Linear acceleration limit: 2.6 m/s^2
	Angular velocity limit: 3.2 rad/s
Goal Tolerances	XY goal tolerance: 0.21 m
	Yaw goal tolerance: 0.17 rad
DWA Planner Parameters	Sim time: 4
	Linear granularity: 0.05
	Angular granularity: 0.025
	Transform tolerance: 0.2
	XY goal tolerance: 0.25 m
	Trans stopped velocity: 0.25 m/s

This table clearly presents the local planner tuning parameters, which include velocity and acceleration limits, goal tolerances, and specific parameters for the Dynamic Window Approach (DWA) planner.

I. X-Y TOLERANCE TUNING

II. X-Y TOLERANCE TUNING

In the realm of robotic navigation, achieving precise and adaptive control is essential for traversing dynamic, unpredictable environments. A critical factor in ensuring accuracy and adaptability is the fine-tuning of x-y tolerances within the navigation algorithms. X-Y tolerance tuning refers to the meticulous adjustment of parameters that dictate how much deviation is permissible in the robot's position along the horizontal (x) and vertical (y) axes.

A. Significance of X-Y Tolerance

The importance of x-y tolerance tuning lies in its profound influence on a robot's precision in reaching its target position within specific time constraints. In dynamic environments, where obstacles can force minor deviations from the planned trajectory, the correct calibration of the inflation layer in the local costmap becomes crucial. This tuning process is aimed at striking the ideal balance between allowing necessary deviations to avoid obstacles and maintaining trajectory accuracy, all while ensuring the robot reaches its goal in an acceptable timeframe. When optimized, x-y tolerances enhance the robot's ability to adjust its path dynamically without excessive detours or delays.

B. Tuning Parameters

X-Y tolerance tuning involves adjusting various parameters within the ROS2 navigation system's controller server. These parameters include the permissible lateral deviation from the robot's planned trajectory, the precision of positional estimates, and the system's responsiveness to changes in the environment. Fine-tuning these parameters is not a one-time process but rather an iterative and experimental approach. Often, the process is guided by empirical data collected from the robot's performance in different environments, both real and simulated. For instance, adjustments might be made to improve the robot's ability to maintain course within strict boundaries in cluttered environments or to respond more quickly to the presence of moving obstacles.

C. Iterative Optimization Approach

X-Y tolerance tuning follows an iterative optimization approach to refine the robot's performance over successive trials. The initial values of x-y tolerance parameters are typically based on theoretical assumptions and the general design characteristics of the system. However, these values are fine-tuned through a series of trials in which the robot's navigation performance is evaluated under different conditions, adjusting the parameters iteratively based on empirical data. This process allows for the fine-tuning of tolerances to address the intricacies of the robot's movement, such as its velocity profile, response time, and positional accuracy. Real-world scenarios and simulated environments serve as testing grounds for these adjustments, offering critical insights into the robot's capacity to navigate through complex, unstructured terrain.

D. Performance Evaluation and Metrics

The success of x-y tolerance tuning is evaluated through a combination of quantitative metrics and qualitative observations. Key performance metrics include path accuracy, the average time taken to reach x-y goals, and the robot's ability to respond to unexpected obstacles. Additionally, the robot's settling time how quickly it stabilizes after a trajectory adjustment is closely monitored. Both the precision of the robot's movement and its ability to reach goals within the required timeframes are crucial to assessing the impact of x-y tolerance adjustments. By systematically analyzing these metrics, the tuning process ensures that the navigation system operates efficiently and reliably in a variety of challenging environments. Ultimately, x-y tolerance tuning significantly enhances the robot's navigational agility, precision, and overall performance.

I. YAW TOLERANCE TUNING

In robotic navigation, achieving optimal performance extends beyond controlling movement along the X and Y axes to also include precise orientation, typically represented by the yaw angle. Yaw tolerance tuning is a vital aspect of refining navigation algorithms, involving the careful adjustment of parameters that govern the allowable deviation in the robot's heading and rotational positioning.

A. Significance of Yaw Tolerance

Yaw tolerance tuning is critical to the robot's ability to navigate complex environments with precision and agility. The robot's orientation plays a significant role when navigating intricate paths, especially in tight or obstacle-filled spaces, where slight deviations in yaw can cause navigation errors. Proper yaw tuning ensures that the robot aligns accurately with its goal orientation, which is essential for tasks requiring exact positioning or precise interaction with the environment. In scenarios with static obstacles or predefined navigation objectives, calibrated yaw tolerance directly contributes to the robot's ability to maintain a stable and accurate course.

B. Tuning Parameters

The process of yaw tolerance tuning involves adjusting specific parameters within the navigation algorithm that dictate the permissible angular deviation from the planned trajectory. These parameters include the maximum allowable yaw deviation, the speed at which the robot can adjust its orientation, and its sensitivity to external factors that may cause disturbances to its yaw. Fine-tuning these elements requires balancing the need for precise orientation with the robot's ability to react smoothly to its surroundings, without overcorrecting or deviating from its intended path. Achieving this balance is crucial for ensuring that the robot can respond dynamically to changing environmental conditions while maintaining high positional accuracy.

C. Iterative Optimization Approach

Similar to the process used for x-y tolerance tuning, yaw tolerance tuning follows an iterative optimization approach. Initial parameters are determined based on theoretical knowledge of the system and general navigation requirements. These preliminary settings are then tested in both simulated environments and real-world scenarios, where the robot's navigation performance is closely monitored and evaluated. Each iteration of testing provides empirical data that informs further adjustments to the yaw tolerance parameters. The goal of this iterative process is to optimize the robot's ability to handle diverse navigation challenges, including sharp turns, narrow passages, and varying obstacle configurations, by refining its yaw tolerance.

D. Performance Metrics

The effectiveness of yaw tolerance tuning is measured using a set of performance metrics, such as orientation accuracy, stability during yaw adjustments, and the robot's adherence to planned trajectories. Orientation accuracy refers to how closely the robot aligns with its target orientation at each waypoint or goal. Stability during yaw adjustments ensures that the robot maintains control without overshooting or oscillating when adjusting its orientation. Finally, adherence to planned trajectories assesses how well the robot follows its predefined path while making necessary yaw corrections. By analyzing these metrics, both quantitatively and qualitatively, insights are gained into how optimized yaw tolerances contribute to the overall performance and reliability of the robot's navigation system.

IV. RESULTS

This section outlines the outcomes derived from the systematic evaluation of x-y and yaw tolerance tuning applied to the robotic navigation system. The experiments were conducted within controlled environments featuring various dynamic and static challenges, allowing for a comprehensive analysis of the tuned parameters and their influence on the robot's navigation performance.

A. X-Y Tolerance Tuning Results

The primary objective of x-y tolerance tuning was to achieve an optimal balance between lateral precision and the settling time of the robot's movement. A detailed quantitative assessment revealed that fine-tuning the x-y tolerance parameters yielded significant improvements in the robot's ability to achieve target positions within shorter timeframes. However, as tolerance increments were reduced past a certain threshold, there was a noticeable and abrupt increase in settling time. The results demonstrated that while reducing tolerance improves positional accuracy, diminishing returns occur beyond a tolerance of 0.20m, where the system's efficiency degrades due to excessively prolonged settling times. The graph in Figure 4 illustrates this relationship, showcasing the "knee point" where further reductions in tolerance sharply increase the time required for the robot to settle, underscoring the need for balanced tuning to avoid compromising performance.

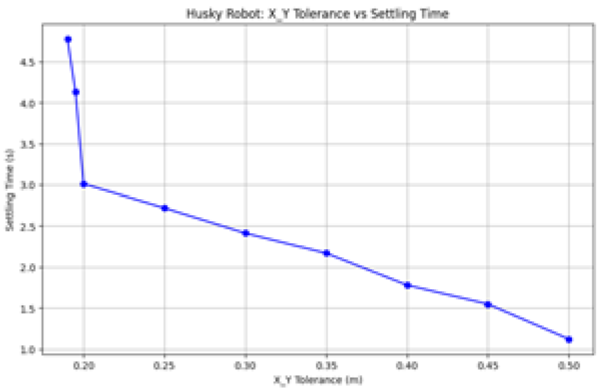

Fig. 4: X-Y tolerance vs settling time

Furthermore, the iterative optimization approach applied to x-y tolerance tuning led to a marked reduction in lateral deviations from the preplanned trajectory. The tuned parameters enabled the robot to adapt more effectively to environmental changes while maintaining a desirable level of precision. The adaptive tuning enhanced the robot's capability to manage deviations due to obstacles and unforeseen conditions, optimizing the trade-off between time efficiency and positional accuracy.

B. Yaw Tolerance Tuning Results

Yaw tolerance tuning focused on refining the robot's ability to adjust its orientation with precision and stability during navigation. Experimental data indicated that the fine-tuning of yaw tolerance parameters substantially improved the robot's heading accuracy, particularly when compared to performance with untuned settings. The robot demonstrated heightened stability and responsiveness during rotational movements, with an optimal yaw tolerance identified at approximately 10 degrees. As illustrated in Figure 5, further decreases in yaw tolerance below this threshold result in diminishing returns, with only marginal improvements in orientation accuracy but increased settling times.

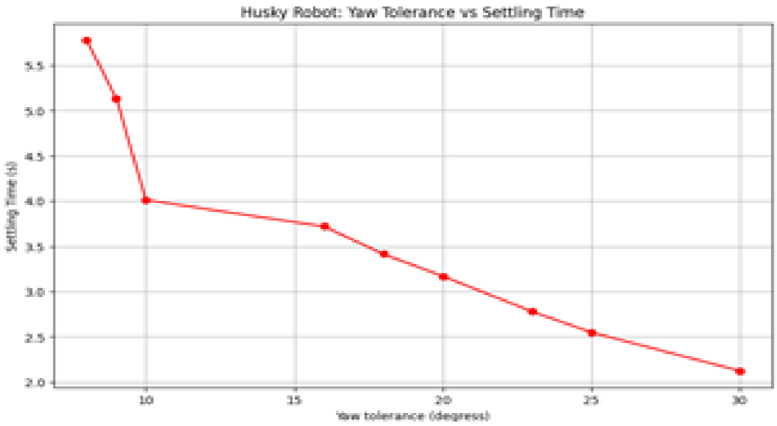

Fig. 5: Ywa tolerance vs settling time

These results highlight the robot's improved ability to align itself accurately with dynamic goals while maintaining a reasonable response time. By optimizing the yaw tolerance, the robot could navigate complex environments with greater precision, achieving smooth rotational adjustments without sacrificing efficiency.

C. Visualizations

To further substantiate the quantitative results, visualization tools such as Rviz were employed to graphically represent the robot's trajectories, path planning, and obstacle avoidance behavior. These visualizations provided qualitative insights into how the tuned x-y and yaw tolerances impacted the robot's performance. In Figure 6, the cost map generated in Rviz showcases the robot’s navigation through various environments, with tuned parameters allowing for more efficient path planning and obstacle detection. The visualizations corroborated the experimental data, illustrating improved alignment with target trajectories and smoother transitions in both linear and angular movements.

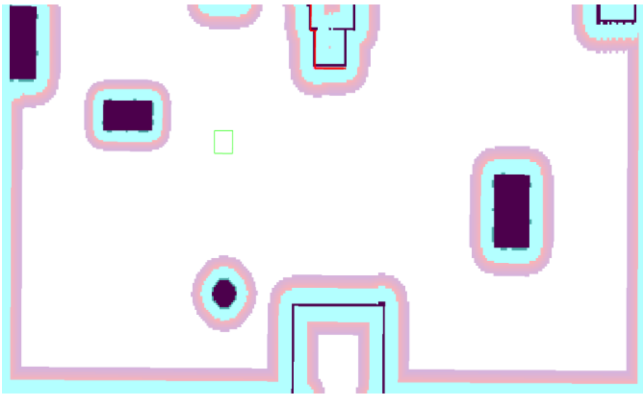

Fig. 6: The cost map in RViz.

D. Discussion

The results reveal critical insights into the effectiveness of x-y and yaw tolerance tuning within the ROS2 navigation framework. The significant improvements in trajectory precision, settling time, and orientation stability demonstrate the practical utility of carefully calibrated parameters. The discussion addresses the broader implications of these findings for real-world robotic applications, particularly in dynamic environments where responsive navigation is paramount. The tuned parameters not only enhanced the robot's adaptability but also highlighted the need for further research into fine-tuning tolerances to suit diverse robotic platforms and scenarios. Additionally, the scalability of these results and their potential generalizability to other robotic systems are explored, suggesting future avenues for refinement and optimization in robotic navigation systems.

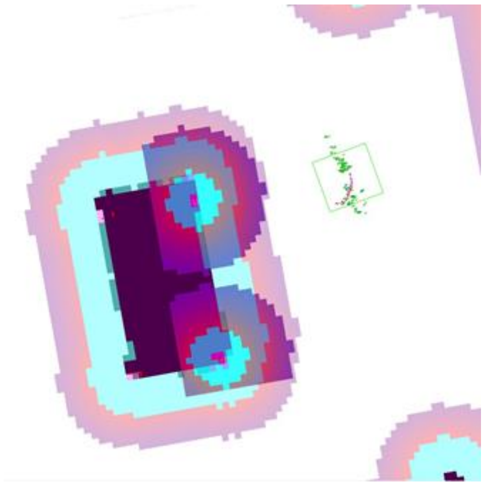

Fig. 7: The green square represents the Husky robot.

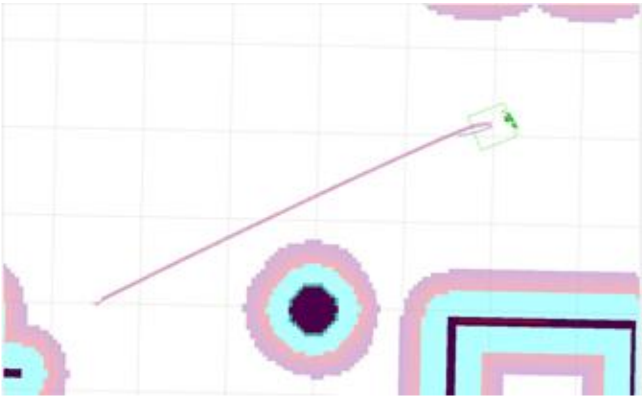

Fig. 8: Path taken is traced in Rviz.

This research explored the integration of the ROS2 Navigation2 stack with the Dynamic Window Approach (DWA) algorithm, emphasizing the critical importance of tuning x-y and yaw tolerances for optimized robotic navigation. The findings highlight the profound effect that these tuning parameters have on enhancing the precision, adaptability, and overall performance of the robotic system in navigating complex environments.

The study's focus on x-y tolerance tuning uncovered a delicate balance between achieving positional accuracy and minimizing settling time. By identifying the knee point—where further reductions in tolerance began to have diminishing returns—the parameters were optimized to improve speed and control while minimizing lateral deviations. The iterative optimization process demonstrated clear improvements in the robot’s responsiveness, allowing it to navigate intricate spaces with heightened accuracy and agility.

Additionally, yaw tolerance tuning proved to be a key factor in improving the robot’s orientation adjustments. The results showed enhanced orientation speed and stability during rotations, allowing the robot to maintain precise alignment even when executing tight turns or navigating through dynamic environments. Fine-tuning yaw tolerance parameters contributed significantly to the system's overall navigation effectiveness, particularly in scenarios requiring quick and precise heading adjustments.

In summary, the successful integration of the ROS2 Navigation2 stack with the DWA algorithm, combined with the fine-tuning of x-y and yaw tolerances, represents a significant advancement in autonomous robotic navigation systems. The tuned parameters achieved a remarkable improvement in both settling time and orientation accuracy, positioning this research as a crucial contribution to the evolving field of robotics. These findings lay the foundation for further innovations in robotic navigation, paving the way for more agile and precise autonomous systems capable of handling real-world challenges.

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