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ROS-based Multi-Robot System for Efficient Indoor Exploration Using a Combined Path Planning Technique

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***Abstract*—This study introduces an innovative combined system utilizing the Robot Operating System (ROS) to enhance multi-robot systems for comprehensive coverage in indoor settings. The research emphasizes integrating diverse robotics technologies, such as map partitioning, path planning, and adaptive task allocation, to boost deployment and coordination for localization and navigation. The system uses occupancy grid maps for effective map partitioning and employs a market-based algorithm for adaptive task distribution. A hybrid path planning approach, merging Boustrophedon Traversing Coverage (BTC) and Spiral Traversing Coverage (STC), ensures complete area coverage while reducing redundancy. During thorough testing, our system showed coverage efficiencies between 94% and 98% in different layouts and conditions, with task completion rates as high as 19.6% per minute, highlighting its ability to effectively handle and adjust to various indoor environments. Additionally, dynamic robot deployment in response to environmental changes has led to enhanced operational efficiency and flexibility. The initial results are promising, though future research will focus on incorporating dynamic obstacle management and path planning to boost the system's robustness and adaptability. This study paves the way for further exploration and development of advanced path-planning algorithms to enhance the performance and usability of multi-robot systems in dynamic environment applications.**

***Keywords*—ROS, Multi-Robot Systems; Path Planning; Map Partitioning; Task Allocation; Indoor Navigation; Area Coverage.**

I. INTRODUCTION

The increasing need for autonomous robotic devices capable of fully covering a given area with minimal human intervention prompted this study. These systems are particularly useful in applications such as material transport, cleaning, and surveillance. Traditional methods often fall short in delivering optimal coverage and efficiency, highlighting the necessity for novel approaches. This study aims to enhance the deployment and coordination of multi-robot systems to boost their operational efficiency and ensure thorough coverage in various indoor environments.

The primary objective of this research was to develop an integrated system that enhances the performance and operational efficiency of multi-robot systems in indoor environments. This involves tackling several key challenges, including path planning, map partitioning, effective task allocation, localization, and navigation. Past research has mainly concentrated on path planning or task allocation separately. This study combines these components to create a unified system, with the goal of enhancing the performance of multi-robot systems. We aim to show how this comprehensive approach can result in improved resource use and coverage completeness when compared to conventional methods. The ultimate objective is to build an organized structure in which robots are able to adjust on their own to changes in their surroundings, guaranteeing effective and through coverage. In this study, the research problem focuses on the inefficiency and ineffectiveness of current autonomous robotic systems in achieving full and optimal area coverage in indoor settings. Conventional path planning and task allocation techniques frequently struggle to adjust to intricate indoor environments, leading to less-than-ideal operational efficiency and resource utilization.

This research stands out for its innovative approach, combining a market-based task allocation algorithm with path planning techniques like Boustrophedon Traversing Coverage (BTC) and Spiral Traversing Coverage (STC). The creation of a novel hybrid path planning algorithm that combines Spiral Traversing Coverage (STC) and Boustrophedon Traversing Coverage (BTC) along with a novel market-based task allocation mechanism that optimizes based on the static layout and complexity of indoor environments are the main contributions of this research. The operational efficiency and coverage capabilities of multi-robot systems are greatly improved by these contributions, which also improve the systems' performance in controlled indoor environments. The inclusion of a unique strategy for dynamically modifying the number of deployed robots based on the size and complexity of the indoor map is an important addition to this research. By adapting the deployment to the particular requirements of the environment, this adaptive technique enhances operational efficiency while also optimizing resource use. This approach offers a full solution to the area coverage problem by integrating with algorithms to generate path planning, map partitioning, task allocation, localization, and navigation in a seamless manner. The path-planning component ensures that each robot follows the most efficient route to cover its assigned area. Map partitioning divides the environment into manageable segments, reducing the overall time required for complete coverage. Effective task allocation assigns specific roles to each robot based on its capabilities, ensuring a balanced distribution of tasks. Localization techniques enable robots to navigate the given environment.

To address these challenges, the study employs specific strategies and techniques to optimize multi-robot systems. Key elements of this approach include a market-based mechanism for adaptive task allocation, Boustrophedon Traversing Coverage (BTC) and Spiral Traversing Coverage (STC) for path planning, and occupancy grid maps for efficient map partitioning. These techniques were selected for their proven ability to minimize duplication and maximize resource utilization. By integrating these advanced algorithms, the study presents a comprehensive solution that significantly improves the coverage and operational efficiency of multi-robot systems in indoor environments. And research contributes greatly to robotics by offering a fresh approach to combining adaptive path planning and dynamic task allocation, ultimately boosting the flexibility and effectiveness of multi-robot systems. Additionally, it presents a technique for adapting robot deployment dynamically by establishing a new benchmark for operational adaptability.

The study uses a combination of simulation, test results, and algorithm development to show how effective the suggested strategy is. Each element of the integrated system is methodically addressed by the research by utilizing modern robotics and technological approaches. Robot deployment is dynamically adjusted, and effective assigning tasks and navigation algorithms work together to make sure that every robot fully covers its assigned area without unnecessary overlap or redundancy.

The findings of this research have the potential to increase the reliability of operation and coverage efficiency in indoor scenarios. The integrated approach holds an opportunity for moving indoor robots forward by navigating the limitations of current techniques and providing useful solutions for a wide range of applications. Setting a new standard for autonomous indoor operations, the full integration of path planning, map partitioning, task allocation, localization, and navigation approaches makes up a comprehensive strategy for optimizing multi-robot area coverage.

In conclusion, this offers fresh and comprehensive methods for enhancing indoor robots' area coverage algorithms, with an emphasis on multi-robot systems. Despite the promising advancements, this study faces challenges in managing computational complexity and ensuring scalability. Coordinating and controlling a larger number of robots over an expanded area can be difficult. Additionally, while the focus is on optimizing static indoor environments, handling dynamic changes such as moving obstacles remains an area for future research. Overcoming these limitations is crucial for enhancing the resilience and practical applicability of multi-robot systems. Through a combination of innovative methods and rigorous validation, the research significantly enhance the autonomy and efficiency of these systems, paving the way for advanced applications in various indoor settings. The developed system not only addresses the challenges of the environments but also sets a new benchmark for operational efficiency in the field of robotics. The literature review explores previous research and recent advancements impacting the efficiency and capabilities of multi-robot systems. The Methodology section details the specific processes and algorithms used for task allocation, path planning, map division, localization, and navigation key elements for optimizing indoor robotic operations. The Results and Discussion section evaluates the effectiveness of various techniques through simulation testing, focusing on improvements in area coverage. The Conclusion and Future Work section provides a comprehensive summary of the research findings and offers recommendations for future exploration. It underscores the importance of integrating emerging technologies to enhance the usability and functionality of multi-robot systems.

II. Literature Review

The evolution of autonomous robotic systems, especially in the realm of Multi-Robot Systems (MRS), marks a significant stride towards achieving comprehensive space coverage, task allocation, and efficient navigation and localization. The integration of advanced path planning, map partitioning, and task distribution methodologies is imperative for enhancing the operational efficiency and adaptability of MRS in various indoor environments.

Path planning algorithms have become much more developed for autonomous mobile robots in the past few years. These types of algorithms help boost operational efficiency in many fields. Path planning techniques, together with the help of the Robot Operating System (ROS), provide a concrete platform to develop an integrated complex multi-robot system, especially for an indoor environment. In this regard, the current literature review will pertain to implementing a hybrid strategy that covers Spiral and Boustrophedon algorithms in this system toward the development of full-coverage path planning.

Area coverage without overlap, while ensuring duplication of effort is minimized, is a very big problem for autonomous navigation in indoor environments. To overcome these challenges, one can choose from among the classical approaches to path planning, for instance, the Boustrophedon cellular decomposition proposed in [1]. These methods decompose the environment in cells of the desired shape where back-and-forth action can effectively cover the space. However, a noticeable gap in the research is the lack of consideration for dynamic environments where obstacles and conditions change in real-time. This process can very well be used in a well-structured environment but may sometimes be ineffective all the time in complex or irregularly shaped places.

The Spiral algorithm is often suggested to these issues, most known for its systematic coverage pattern. The algorithm offers smooth mobility that saves energy and time during the start and stop, which is very important in places with lots of obstructions [2]. It is not that every region can be well covered by the Spiral algorithm per se, in particular the ones that require precise motion inside limited bounds or around obstacles. To further optimize the coverage and efficiency, a hybrid approach that capitalizes on the strength of both the Boustrophedon and Spiral is suggested. This scheme combines the strength of the continuous coverage by the Spiral pattern and the completeness of Boustrophedon moves that overcame the limitations in an individual approach in case a single algorithm was utilized. Some research works have established the superiority of path planning using such hybrid schemes and obtained better performance under complex conditions than in an individual algorithm-based approach [3], [9]. The main issues in the hybrid path planning approaches discussed focus on difficulties in adjusting to changing environments and improving the allocation of computational resources. These mixed approaches, despite being successful in merging the advantages of Spiral and Boustrophedon techniques, could face challenges in adjusting in real-time and being computationally efficient in dynamic and highly variable environments.

This is yet another research area where heuristic techniques, known for obtaining solutions on dynamic path planning, have been recently added, such as the D* and A* algorithms. Algorithms like these are relevant for indoor applications, where obstacles may be unexpected. With such algorithms, the robot can keep track in real time and alter its path accordingly to respond to unpredictable changes in its environment [6], [15]. Gaps of these researches on heuristic algorithms such as D* and A* [6], [15] is lacking in terms of their ability to adapt and scale in fluctuating or uncertain environments, especially when handling real-time data from multiple sensors. In static or slightly dynamic situations, these algorithms work well, but they may not work as efficiently in highly dynamic or cluttered environments with unpredictable changes in obstacles and conditions. Moreover, route planning uses metaheuristic algorithms, such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA), which are specialized in finding optimized solutions toward a number of objectives, such as the length of the path and obstacle avoidance [7], [14]. For research using metaheuristic algorithms such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA), the gap lies in their computational efficiency and effectiveness in real-time applications.

These new techniques, such as Artificial Neural Networks (ANN) and Fuzzy Logic Controllers (FLC), have adaptive capabilities for learning and decision-making in unpredictable settings and can be used to further improve path planning [10]. In some way, modern techniques can let robotic systems learn from the surroundings and allow brilliant judgments to be made, hence increasing the operational efficiency of robots. These techniques can be incorporated in the ROS framework to enhance simulation, visualization, and real-time changes in multi robot systems. Libraries and tools can be provided for the implementation and development of complex path planning algorithms in practical application using the ROS framework [4], [11]. Utilization of ROS also simplifies standardization and modularity, thereby reducing development cycles, and even aids in the easy addition of new algorithms or their updates. The hybrid approach of Spiral and Boustrophedon algorithms, supported by heuristic and metaheuristic methods, presents a comprehensive solution for enhancing full coverage path planning in ROS-integrated multi-robot systems for indoor environments. This approach not only addresses the geometric and operational challenges but also enhances the adaptability and efficiency of robotic operations in complex indoor settings [12], [5], [8], [13].

Advanced route planning algorithms in developing multi-robot systems for indoor situations help in attaining effective and full coverage. Improvements made recently in this field, using various methods, highly contributed to the optimization of these systems. Here, we present findings aggregated from numerous research to outline advances and challenges that exist in improving full-coverage path planning using a hybrid strategy of Spiral and Boustrophedon algorithms, coupled with a multi-robot system based on ROS. The systematic area coverage approach is based on Boustrophedon and Spiral algorithms. Boustrophedon uses an up-and-down approach to handle settings with regular geometrical characteristics fast [16], while the Spiral algorithm is capable of spanning complicated regions with ease [17]. By combining the benefits of both the techniques to handle the range of spatial layouts, path planning may be optimized. Several researchers have worked on the optimization of these algorithms to guarantee reliable navigation and task distribution in contexts. For instance, in warehouse operations, combining odometry with heuristic algorithms, including Dijkstra's, significantly improves the performance of the navigation algorithms [16]. Moreover, using the potential force algorithm together with kinematic control allows disinfection robots the flexibility to adjust the pathways to the instant environmental changes surrounding them [19].

Multi-robot path planning optimization has further progressed by incorporating intelligent search algorithms and obstacle avoidance mechanisms. These methods enhance computational effectiveness as the robots are executing tasks and moving about in crowded environments in real time [20, 28]. Another application in which smart search techniques have been integrated is in path planning through dynamic node allocation systems for productivity improvements with real-time changes in robot allocation [29]. However the optimization of multi-robot path planning still faces challenges in effectively managing dynamic environments, avoiding obstacles in crowded areas, and efficiently reallocating robots in real-time to enhance productivity.

ROS is very critical in multi-robot systems. ROS acts as a middleware allowing the integration of complex algorithms needed to carry out advanced path planning techniques, such as the hybrid use of Spiral and Boustrophedon [21]. Besides, a strong motion planning is necessary for applications in real-world environments, especially for places with a high level of population density. Topological guidance can be applied for proper scaling of multi-robot systems, and the coordination can be improved without degrading the quality of the planning, which can be found in research studies, for example [30]. Furthermore, new advances in planned directed motion have enabled new and varied methods for handling the complexity of multi-robot operations. Hybrid strategy improvement approaches in combining the Spiral and Boustrophedon algorithms have been studied in the improvement process of planning with respect to several robotic applications via hypergraphs and other multi agent pathfinding heuristics [22], [23], [24], [25]. The main focus of these studies is on the difficulties of maintaining scalability and immediate responsiveness while managing intricate task assignments in ever-changing and varied settings. This involves dealing with matters like the effectiveness of algorithms in real-time scenarios and the reliability of path planning in dynamic environments with common unpredictability and obstacles.

Another multi-robot research area that could be relevant to coverage path planning is the use of cleaning distribution techniques in large-scale environments; in this case, the division of space into smaller units with minimal overlapping and, if possible, minimal conflicts would result in more efficiency in coverage. The research gap lies in the division of space for cleaning distribution in large-scale environments. While it improves efficiency and reduces overlap, it fails to account for adapting to environmental changes and robot movement patterns, impacting overall cleaning efficiency and performance [26]. Social awareness of robotic navigation is achieved through the implantation of side preference in path planning to help in the maximization of traffic flow of robots and prevent conflicts for the use in constrained environments. Robotic navigation with social awareness allows the usage of more sophisticated movement patterns that are human-like, and these are indeed desirable for systems using the hybrid route planning technique. The challenge in researching robotic navigation with social awareness is implementing navigation strategies that are similar to those used by humans. While the goal is to incorporate human-like side preferences in robot path planning, the effectiveness of these strategies in busy or fast-changing environments is not thoroughly examined, potentially hindering their practical use in a range of real-life situations [27].

Autonomous robotic systems need to be equipped with enhanced path planning algorithms for better operation in complex indoor environments. Recent enhancements to multi-robot system efficiency and flexibility were improved by advancements in route planning with bio-inspired algorithms, such as the real-time navigation through 3D environment using the dragonfly algorithm. the gap is that while the Dragonfly Algorithm facilitates efficient 3D path planning for heterogeneous multi-robot systems, it may not handle highly dynamic environments where obstacles and robot objectives change rapidly [31]. Autonomous work allocation algorithms should, therefore, be developed to minimize the inter-robot communication that has been found to be a constraint during multi-robot operations. Such algorithms have to be developed, therefore, to allow the effective working of the robots in situations where there is limited or even no communication, because it facilitates decentralized decision-making. Here gap is that while the algorithms minimize inter-robot communication effectively, they may not address issues of coordination and decision-making latency in environments with high robot density or complex interaction scenarios [32].

Likewise, Boustrophedon and Spiral patterns are included in the coverage path design for more balanced results and lower redundancy, as well as turning reduction in regions. The method works extremely well, in particular, for cases where random and regular forms are combined [33]. The dynamism of adaptive multi-agent coverage control algorithms increases safety in navigation and operational efficiency by responding to barriers and changing environmental conditions in the execution of flexibility of path planning [34]. The variability and risk profiles of the robot teams influence job allocation tactics. Therefore, the ability to select jobs according to the skills and risk aversion of each robot could be optimized in performance and resilience in such challenging settings [35].

These algorithms support coordination efficiency and allow robots to autonomously generate a sequence of tasks with predefined spatial and temporal divisions. This is a critical capability for task allocation in low communication scenarios, whereby the network is compromised [36]. In fact, these findings also present that the DEPSO is adaptable to bring dynamic task allocation among robots, which will consequently improve the performance of robots in responsive environments [37]. The attachment model based on those findings is considering the willingness of robots. It can be incorporated with full coverage path planning for management of the task's preference, thus an achievement of an improvement in real-time decision-making [38]. Gaps of this studies lies on include challenges in scaling task allocation algorithms for real-time operations in low communication environments, and integrating social awareness effectively in complex scenarios.

The research on the integration of location and navigation technology with the combination of Simultaneous Localization and Mapping (SLAM) with Visible Light Positioning (VLP) is crucial to understanding indoor precision navigation. It has been demonstrated that the algorithms offer very good levels of localization accuracy for the robots, which are the key for the good use of the coverage algorithms [39]. Moreover, the use of the Ant Colony System and Consensus-Based Bundle Algorithm depicts superior scalability and efficiency in the multi-robot job allocation, which is crucial for the performance of large-scale robot operations inside constrained spaces [40].

This task is further complicated by met reasoning. Through the application of multi agent systems, one can set up robots to assess and modify their strategies of decision in respect to the communication dynamics and with a goal to further enhance effective coverage and resource utilization [41]. The last paper in this line is a development that considers multi agent met reasoning that is aware of the communication and decentralizes the administration of teams of robots, while at the same time ensuring reliable job allocations under varied communication conditions [42]. Coordinated research techniques used here with optimization based on swarms reduce the computation burden and maximize the route efficiency within dense-obstacle space and, thereby, enhance the efficiency of the multi-robot exploration [43].

More studies have shown that the decomposition of maps can apply to cleaning distribution in big indoor spaces with numerous robots in warehouses. Cleaning distribution based on map decomposition is much better for large areas, in turn better cooperativity among robots and lower cleaning time [44]. Another study explored a natural multi robot navigation approach in which the robot responsibilities were prioritized based on environmental changes. An efficient means of general Voronoi-based path planning for robots, the technique allows for alteration of pathways according to job priorities and environmental constraints, ensuring effective robot navigation [45].

The combination of online task assignment and coordination systems makes the effectiveness of the path planning even higher in multi-robot systems. These frameworks are designed to manage task assignments in a dynamic manner by reacting to changes in job demand and robot availability without losing the efficiency of the fleet operations [46]. Specifically developed for the smart warehouse scenario, the adaptive task planning methods use real-time information to update job allocation and path planning strategies based on robot status and real-world environmental conditions. This thus enables robots to respond dynamically to changes within the warehouse, which results in better coverage efficiency and optimization of task executions [47]. When applied within complex indoor environments, multi-agent action graphs will allow strategies to be built in for changes in environment prediction and further adaptation of robot path and job changes to be more proactive in execution and to maximize path efficiency [48].

The fields of indoor mapping and navigation have immensely benefited from the swift growth of robotics and automation. A significant body of research work was based on geometric features-based mapping to enhance the multi-robot systems' collaboration in indoor mapping. Use of geometric information in map creation has been observed to have benefit in terms of more accurate and faster mapping procedure [49]. This becomes critical for highly accurate activities like object avoidance where high population densities or structurally challenging environments are encountered. Visual SLAM has experienced a revolution, thanks to significant advancements that deep learning algorithms have over traditional methods. These techniques have been very successful in boosting the accuracy and robustness of SLAM systems, making them more capable of adapting to a greater variety of indoor environmental conditions. Convolutional neural networks have proved very effective in both improving feature extraction and depth estimation, two processes of utmost importance for the development of fully autonomous SLAM systems [50].

Advanced coordination requires the deployment of complex mechanisms for dealing with the unpredictable nature of the agricultural conditions in the deployment of UAVs and ground robots in such applications. The issue lies in the fact that even though advancements are tackling intricate agricultural situations for the coordination of UAVs and ground robots, the uncertain and ever-changing nature of these environments continues to present major obstacles for maintaining steady operational efficiency [51]. In multi-robot systems, performance task efficiency can be significantly enhanced by task job prioritization and effective path planning. Using the Generalized Voronoi Diagram for planning paths based on a sequence of priorities in a common region showed promise in maximizing the robots' movement in the region, thus reducing job completion times and increasing system throughput. The gap lies in ensuring that the priority-based path planning via the Generalized Voronoi Diagram remains efficient in extremely dynamic environments where priorities and environmental conditions may rapidly change [52].

In this respect, the application of active SLAM techniques in shared indoor environments presents a rich avenue for conducting participatory mapping. Environments of interest, such as retail or hospitality environments where the layout changes at a fast pace, can be mapped successfully by robots with high success through updating the exploration paths based on a fixed interval [53]. Along similar lines, for the development of disease-fighting robots that use UV light in indoor scenarios, path planning optimization is carried out to ensure full coverage of all the areas that are supposed to be covered. This is done through the UV* approach in which path length is optimized in order to reduce time and energy spent on operations while achieving full coverage through the incorporation of the Boustrophedon pattern with an optimization approach [54].

New developments in multi-robot systems place an emphasis on effective path planning using creative mapping and communication techniques. Scalability and flexibility are improved by combining decentralized planning [56] with Gaussian Mixture Models [55]. Real-time operations are made easier by enhancements in ROS 2.0 [57], and robustness is enhanced by hybrid methods that combine ROS 1 and 2 [58]. By reducing turns, algorithms such as TMSTC* minimize complexity [59], while ideas from underwater robot systems provide tactics for adaptive behavior and task distribution [60]. All of these improvements improve full coverage path planning in indoor contexts with ROS integration. Significant progress has been made in the autonomous robotics field regarding the development of systems that efficiently navigate and map indoor spaces using ROS and SLAM technologies. Research conducted in [61] and [65] has shown that these technologies can effectively be used in robotic path planning and obstacle avoidance, showcasing their abilities in challenging settings. Nevertheless, despite the progress made in enhancing specific robotic capabilities, there is still a need for developing more cohesive and effective systems for coordinating and navigating multiple robots.

Recent studies have delved deeper into improved SLAM path planning and creative algorithmic answers to global and local navigation difficulties. An example is when [62] and [66] talk about incorporating algorithms such as A* and DWA to enhance effectiveness in robotic navigation and logistics systems. Moreover, [63] and [64] build upon these concepts by implementing ROS in humanoid and walking robots, demonstrating wider uses and experimentation in more active environments. Even with these advancements, a large portion of current literature continues to concentrate mainly on scenarios involving a single robot, neglecting the challenges of multi-robot systems and their coordination.

The advancement of self-contained robotics has been more and more centered on incorporating sophisticated navigation and obstacle avoidance features to improve efficiency in changing surroundings. These studies showcase how ROS is combined with advanced path planning algorithms such as A*, Dijkstra, and SLAM to improve robot navigation in service-oriented environments. Significantly, the study on disinfection robots [67] highlights the importance of enhancing path planning with Particle Swarm Optimization and Dynamic Window Approach to tackle the difficulties presented by high-risk environments in pandemics.

Moreover, improvements in all-directional movement, such as the incorporation of Mecanum wheels in mobile robots [68], and the impact of different ROS motion planning settings [69], demonstrate continuous endeavors to boost robots' accuracy and flexibility in service settings. These findings show notable advancements in the field; yet, they frequently focus on particular types of settings or activities, restricting their applicability. For instance, the simulation-focused method in reference [69] offers understanding on how parameters affect navigation systems, but it might not completely grasp the intricacies of real-life interactions and varying obstacles faced in less predictable environments.

The latest studies, like [70], aim to fill these gaps by suggesting inclusive models that emphasize not only mobility but also the importance of high code reuse and openness in navigation systems for quick deployment on various platforms and environments. This study utilizes URDF modeling and kinematics analysis with a Mecanum wheel chassis, integrated with MOVE_BASE framework and SLAM technology, to develop a navigation system that is more adaptable and expandable. These attempts focus on improving the ability of autonomous systems to adapt to different dynamic environments, making the robot more efficient and independent in carrying out complex navigation tasks.

Recent research in autonomous robot systems has focused on improving navigation, scheduling, and cooperative strategies with the use of ROS (Robot Operating System). Some important contributions are the development of smart indoor service robots that use deep learning for complex environment interaction [71], and the enhancement of path planning with modified Dijkstra algorithms, showcasing improvements in computational efficiency and robot navigation accuracy [72]. Additionally, the study of dynamic surroundings such as simulation soccer delves deeper into the obstacles of collision prevention and path optimization, underscoring the ongoing necessity for improved route mapping methods in critical situations [73].

Nevertheless, even though these studies focus on important elements of autonomous robotics, they frequently fail to consider the collaboration between multiple robot systems and the effectiveness of large-scale operations. For example, while autonomous navigation and SLAM implementations have achieved significant success in single robot operations [74], the collaborative aspects and scalability in multi-robot systems are not as thoroughly examined. Advancements in multi-robot cooperative scheduling are helping to partially fill this gap, with advanced ROS-based systems showing enhanced task allocation and operational efficiency in warehouse settings [75]. These research findings indicate a potential path for combining separate robotic improvements within a unified multi-robot setup. Our research suggests a comprehensive method that combines the strengths of advanced path planning and navigation techniques while improving the cooperation among multi-robot systems. By using the groundwork in self-guided navigation and merging it with the efficiencies of scheduling multiple robots, our method is focused on creating a scalable, effective, and strong structure for multi-robot tasks. This combined system will be created to enhance both the performance of each robot and the management of joint tasks, guaranteeing that improvements in robot navigation actively improve the overall effectiveness of multi-robot collaborations.

Current developments in robotics highlight the utilization of ROS (Robot Operating System) to enhance performance and versatility in various applications, as evidenced in multiple researches. Specifically, there has been notable improvement in the advancement of smart home service robots, which can now control household devices, offer security functions, and enable extensive environmental communication thanks to advanced sensor integration [76]. Likewise, utilizing laser SLAM in intricate settings like exhibition halls is crucial for improving service robots' navigation and mapping abilities, showcasing the importance of these technologies [80].

Nevertheless, despite advancements in single robot functions and navigation systems, there is still a significant deficiency in coordinating multiple robots and managing tasks in interactive work environments. Research like [77] and [78] tackle this issue by using cooperative navigation and control systems that combine ROS and laser SLAM for multi-robot settings, improving operational effectiveness and expanding possible uses. Although there have been improvements, the exploration of real-time adaptive response systems in environments with unpredictable elements is still limited, which is crucial for applications like industrial maintenance and public space service.

A crucial need exists for research that concentrates on creating advanced integration methods for multi-robot systems which can efficiently navigate, map, and react flexibly to changes and obstacles in their environment. The studies in [79] and [81] are starting to tackle these difficulties by fine-tuning control algorithms for stability and maneuverability in obstacle-filled environments, utilizing PID controllers and artificial potential functions. Expanding on these fundamentals, our study introduces a unified method merging improved SLAM methods with sophisticated multi-robot coordination algorithms, with the goal of developing a smooth and effective multi-robot system with autonomous decision-making and interactive problem-solving abilities in intricate, unorganized surroundings. This all-encompassing method will greatly enhance the practical application and effectiveness of robots in different sectors, spanning from industrial to residential settings and beyond.

III. METHODOLOGY

The development and implementation of an integrated system for improving the functionality and performance of multi-robot systems in indoor environments is at the core of our methodology. This involves developing algorithms and techniques for path planning, map partitioning, task allocation, localization and navigation. Fig. 1 represents the overview of the comprehensive methodology.

A. Map partitioning

The multi-robot approach to complete area coverage involves a sophisticated method of partitioning an area so that each robot in a system can cover different parts efficiently, minimizing overlap and ensuring thorough coverage. This process begins with the acquisition of an occupancy grid map, which in our study was manually created through scanning. This map represents the environment, where 0 indicates free space and 1 indicates occupied space, with the occupied spaces being those areas that are not traversable by the robots.

The next step involves accounting for the number of robots available for the task and the radius of the tool each robot employs for coverage (e.g., a cleaning brush or a sensor range). These parameters are critical in determining how the Environment is partitioned and assigned to each robot.

Get navigable area:

This equation provides the total area available for the robots to navigate.

$$NavigableArea = OriginalArea \times (Resolution)2 \quad (1)$$

Compute number of agents:

To calculate agents count this equation used where cardinality gain CARDINALITY_G, time gain TIME_G.

$$N_{agents} \leftarrow \left\lceil \sqrt{\frac{TIME\_G \times Navigation\ Area}{CARDINALITY\_G}} \right\rceil \quad (2)$$

The partitioning process itself uses a cell-decomposing approach, breaking down the environment into smaller, manageable polygons or cells. This is an essential step because it simplifies the complex environment into more straightforward units that can be individually assigned robots. The outer regions of the map that are marked as free or undefined are trimmed away, leaving a more concise area for the robots to cover. This trimming process helps in focusing the robots' efforts on the essential areas and avoids wasting time on regions that do not require coverage. In algorithm 1 represent how to determine whether a cell is occupied or free, a threshold is set (e.g., if more than 65% of a cell has a value of 100 in the occupancy grid map, it is considered occupied). 65% threshold for determining whether a cell is occupied or free in an occupancy grid map is a strategic decision grounded in balancing sensitivity and specificity, improving resilience to sensor noise and measurement uncertainty, and optimizing efficiency in coverage and navigation. This threshold simplifies decision-making and has been extensively validated through research and practical applications, making it a reliable choice for effective robot navigation and coverage planning this step is crucial for planning as it ensures that robots are assigned to areas that genuinely need coverage, improving the system's overall Efficiency.

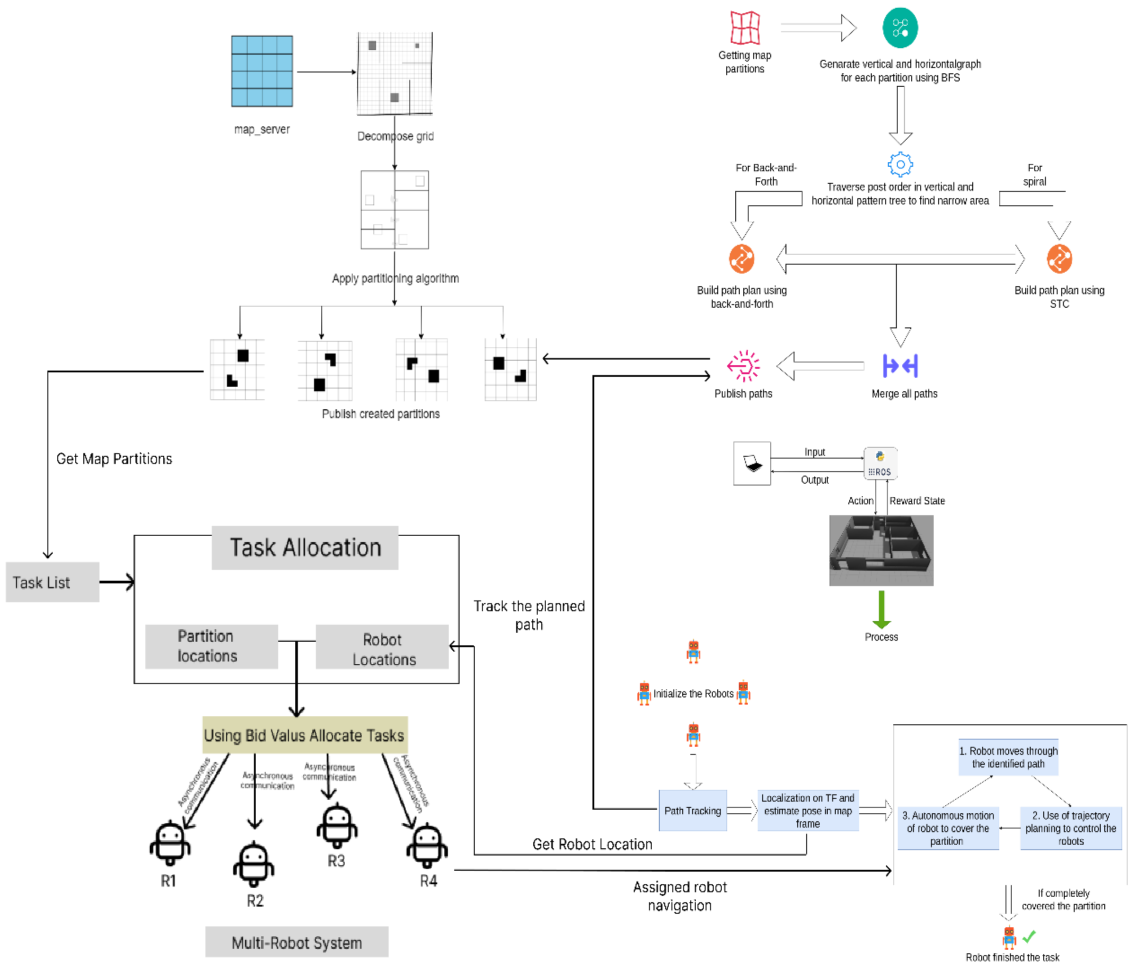


Fig. 1. Overall system architecture

Algorithm 1 Grid Parse

```
Input: cpp_grid, robot_radius, tool_radius, start
Output: grid, scaled_start
Initialize node_size and robot_node_size based on tool_radius and robot_radius
if grid dimensions are invalid then
    return false
end if
Compute tile_size and save grid origin coordinates
Convert start to grid coordinates to scaled_start
for each row with step node_size do
    for each column with step node_size do
        Set nodeOccupied to false
        for each cell in node do
            if cell.value > 65 then
                nodeOccupied ← true
                break
            end if
        end for
        Append occupancy status to grid_row
    end for
    Append grid_row to grid
end for
```

After the environment has been decomposed and the occupied cells identified, the area partitioning strategy is applied. In systems where robots are homogeneous, meaning each robot has the same capabilities, the area is divided equally based on the number of robots. This division ensures that each robot is assigned a fair portion of the area to cover, making the process efficient and systematic. The algorithm calculates the total free area to be covered and divides it by the number of robots to determine the amount of space each robot should cover.

Finally, once the areas have been partitioned as in Fig. 2, it's crucial to merge these partitions back into the main decomposed map. This merging process is necessary to prevent overlapping coverage areas, ensuring that each robot operates within its assigned region without encroaching on Another robot's territory, the map, with the partitions correctly combined, is then published, guiding the robots in their coverage tasks. This multi-robot approach for complete area coverage exemplifies how complex tasks can be efficiently managed through intelligent partitioning and assignment, leveraging the capabilities of multiple robots to achieve thorough and efficient coverage of any given area.

B. Path Planning

Path planning is a fundamental aspect of multi-robot systems aimed at achieving complete coverage of an environment. Complete coverage path planning (CCPP) involves the systematic exploration of an environment to ensure that the robots visit all areas. In this process provide path planning techniques, including grid-based methods, graph-based methods for generating effective coverage plan. In grid-based method proposed to divide main map into partitions in decomposed binary grid matrix. Then again identifying narrow areas for effectiveness of spiral traversal coverage method (STC) and combination of Boustrophedon Traversal Coverage approach (BTC) also known as Back-and-Forth approach.

The reason of making combination of path planning approaches is resolving the one unique issue of Spiral Traversal Coverage. Spiral coverage causes path repeating issues in some points of the environment Fig. 3. By considering the repeating issue in STC this study proposes the solution of using hybrid approaches.

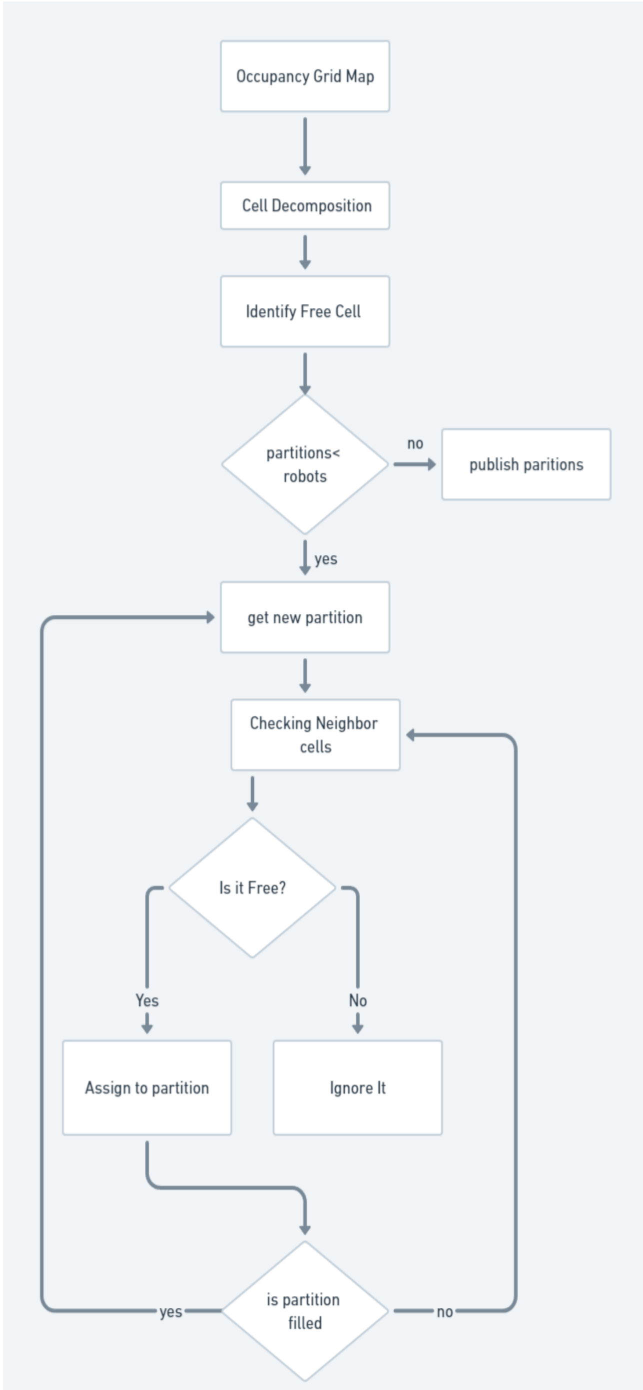


Fig. 2. Occupancy grid map processing

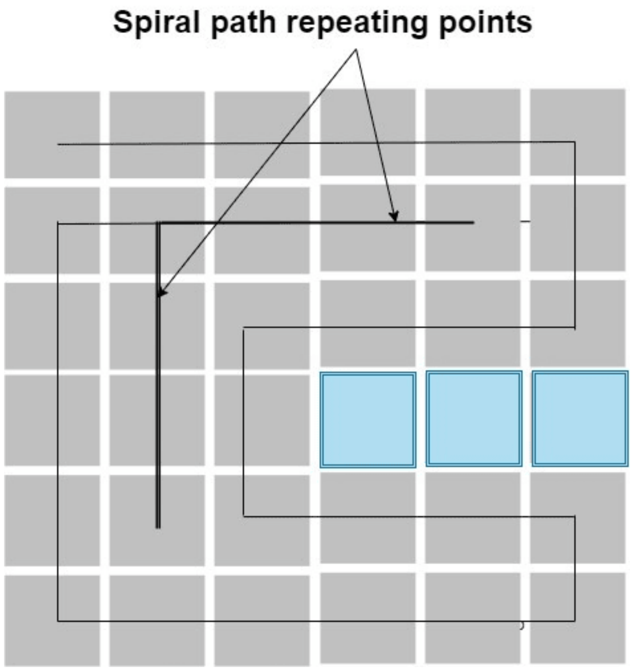


Fig. 3. Spiral path repeating points

When considering Boustrophedon Traversal Coverage approach (BTC) it's navigation back and forth technique. It's starting to navigate defined direction until reaching boundary area or obstacle point. Then it's turning in the opposite direction 180 deg in map North, West, East or South (N, W, E, S) then again repeating same process. In this study we discovered that Boustrophedon Traversal Coverage approach (BTC) is more effective than Spiral Traversal Coverage (STC) in narrow areas. It's the solution for path repeating issue in Spiral Traversal Coverage (STC) Fig. 4.

Path repeating issue of Spiral Traversal Coverage (STC) approach happens if narrow area height or width size is odd. As example if narrow area size is 3 its first and last rows are filling in first spiral round.

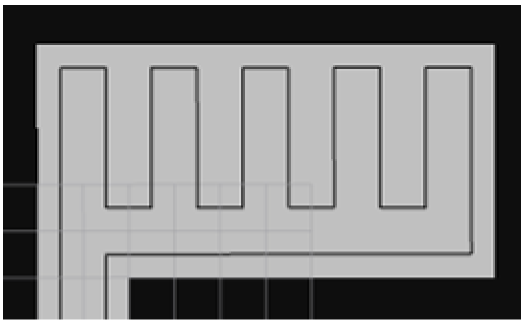


Fig. 4. Boustrophedon traversal coverage in narrow areas

Normally spiral pattern generating counter clock vise therefore the middle row is remaining for next spiral round. In the next spiral its coming middle row and again return through the middle row that's the point of path repeating issue occurred Fig. 3.

In this study the proposed solution is to find narrow areas in each partition and implement switching mechanism to those areas to generate path plan using Boustrophedon Traversal Coverage (BTC) instead of Spiral Traversal Coverage (STC). As the first step to identify narrow areas in each partition we employ graph methodologies. To generate a graph for free area in Boolean matrix we implemented Breath First Search (BFS) algorithm. To identify narrow areas in both vertical and horizontal manner we decided to generate two graphs represent vertical and horizontal Fig. 5. After that root node of both graphs saved in global variables.

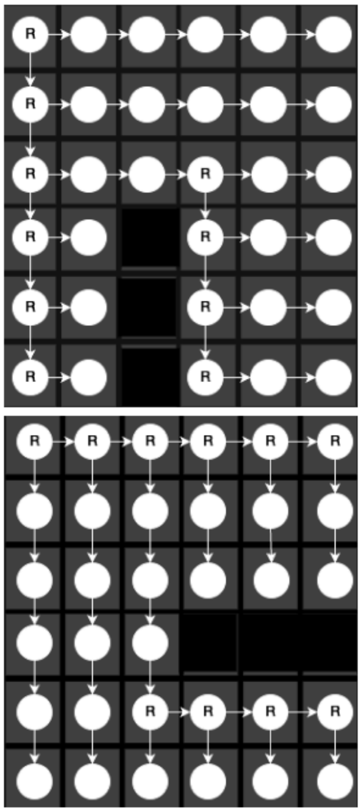


Fig. 5. Graph overview horizontal and vertical. (r) represent the root nodes

To find narrow areas using graph we implemented post order traversal methodology. The basic logic is while on post order traversal process its identifying root nodes which are having odd size depth of child nodes including root node. Then all the sub nodes under the root including root node add to narrow area list. It's continuously adding until found different depth size node or different region. Flow chart of post-order-traversal explain how it works Fig. 6. If new root node depth or region is different last added root's sub tree list added main narrow area vector as well as marking narrow area Boolean matrix sub-tree positions as zero '0' it helps to identify on path planning algorithm if current point is belonging to narrow area or not Fig. 7.

After the post-order-traversal it's moving to generate a path plan process of implemented hybrid algorithm of Spiral Traversal Coverage (STC) and Boustrophedon Traversal Coverage (BTC) Fig. 8. In hybrid approach each point is checking if the point is belonging to narrow area or not if next point is belonging to narrow area, it's switching the Boustrophedon Traversal Coverage (BTC) and continue the process until no narrow area point is visible in current point or deadlock situation. After that again switching the Spiral Traversal Coverage (STC) and continue the process until found and narrow area point of Boolean matrix.

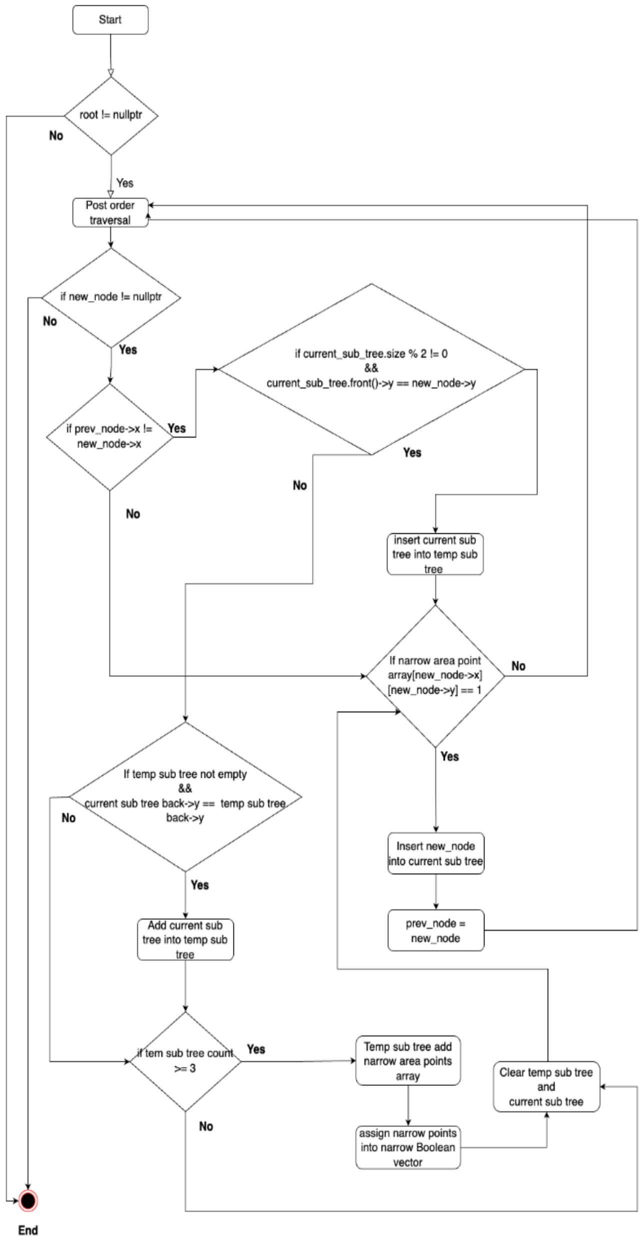


Fig. 6. Path planning post-order-traversal

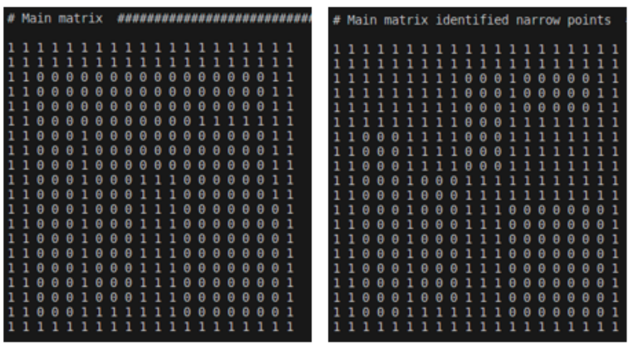


Fig. 7. Main matrix and identified narrow area

Finally, publish the generated path plan using unique topic name. And after all the partitions are done with process then merge all the paths together and publish as single plan. This hybrid strategy, which combines the Boustrophedon Traversal Coverage and Spiral Traversal Coverage approaches, successfully reduces the problems caused by path redundancy in spiral patterns, especially in small areas. This innovative approach increases area coverage as well as efficiency and would thus possibly be a very good option for robotic applications where complete area coverage is the most crucial issue. Fig. 9.

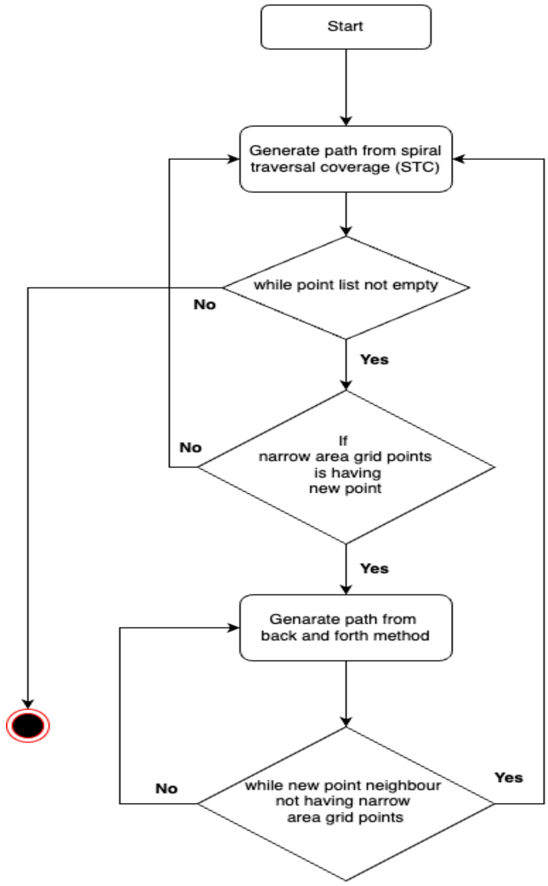


Fig. 8. Hybrid approach flow chart

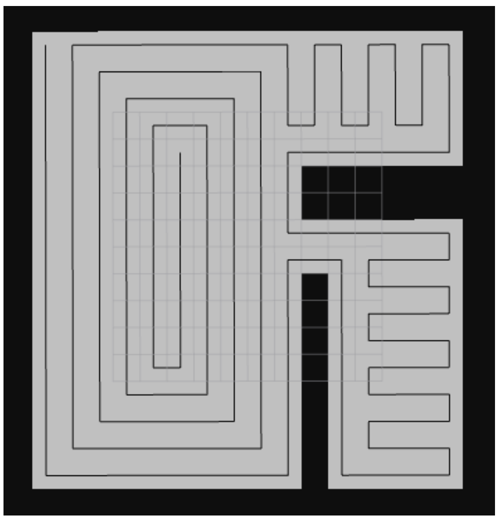


Fig. 9. Merged plan with hybrid approach

C. Task Allocation

The task allocation procedure entails coordinating the effective completion of a group of tasks (T1, T2, ... Tn). These are the task missions used here. The requirements and objects of a problem are defined in order to determine the task's priorities. This calls for a clear definition of the task at concern. It is essential for recognizing the type and scope of the tasks as shown in Fig. 10. The main problem is to assign these tasks to robots R1, R2, ... R4 while sticking to important limitations and objectives. Each robot has capabilities, and some activities may be completed by numerous robots.

This allocation mechanism is overseen by a central entity known as Queen Bot. Queen Bot allocates tasks based on complexity, robot capabilities, calculating bid values, and progress via asynchronous communication. In this system, each robot 'bids' for the task. And then calculating bid values using task priority, complexity, and distance of the robot, assigning tasks to the most suitable robots using calculated bid values, and passing messages using asynchronous communication.

A market-based algorithm is used here for the task allocation process as in Fig. 11. This is a popular method for allocating tasks in MRS. It works on the basis of an auction system in which robots bid on tasks, and a queen bot chooses the winning bid for every task.

Asynchronous communication works well with the negotiating process, allowing robots to make bids and receive task assignments. The market-based algorithm operates similarly to an auction. Auction-based mechanisms, bidding processes, and the queen bot as an auctioneer are the core concepts of this algorithm. Tasks are effectively put up for auction under this system, with robots acting as bidders. Based on their capabilities, task difficulty, and task priority, robots "bid" on tasks. Like an auctioneer, the queen bot is in charge of the bidding process. It is in charge of sending out tasks to bids and finally choosing which bids to accept for each task.

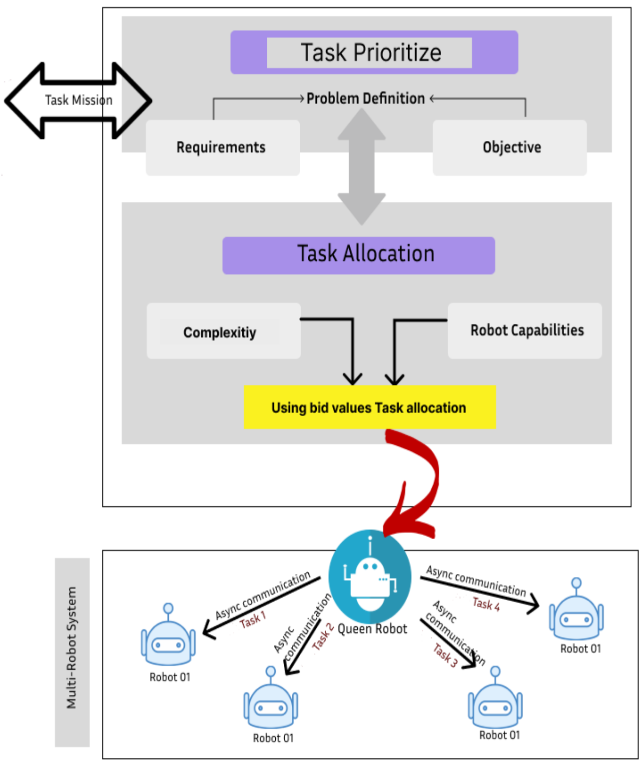


Fig. 10. Task allocation system

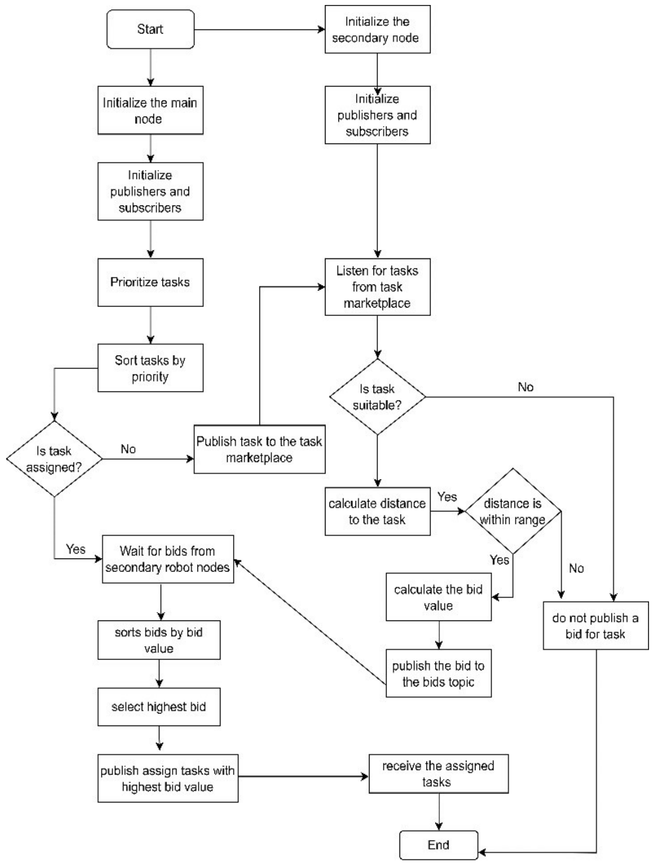


Fig. 11. Task allocation algorithm workflow

It is controlled by the main robot node and carried out by secondary robot nodes. At first, the system starts and initializes the main robot node, which sets the necessary publishers and subscribers to handle the communication for tasks and bids. Secondary robot nodes are also initialized. They are responsible for listening to tasks from the task marketplace to see if they can bid on these tasks based on suitability, such as distance, and then publishing their bids. The task marketplace is where tasks are stored. Map partitions are got as the tasks for the task marketplace and assigned the partitions as tasks to the robots.

The main robot sorts the tasks by priority, ensuring that high-priority tasks are attempted first. The main robot publishes all unassigned tasks to the task marketplace; it waits for bids from secondary robots. Secondary robots, after receiving the tasks, then calculate if the tasks are suitable by checking if the distance to the task is within their operational range.

The bid value BV is calculated as a function of task priority p, task complexity c, and the normalized distance $d_{\{norm\}}$with their respective weights ω_p, ω_c, $\omega_d$as follows (3):

$$BV = \frac{(\omega_p * p + \omega_c * c)}{(\omega_d * d_{\{norm\}})} \quad (3)$$

This formula is used to calculate the straight-line distance between the location of a task and the location of a robot. It is derived from the Pythagorean Theorem and is commonly used in robotics and navigation to find the shortest path between two points. If a task is considered acceptable for a robot, a bid value is computed once the distance has been calculated. This bid encapsulates several factors such as the urgency of the task, represented by its priority, the complexity of the task, and the computed distance to the task. To make sure that high priority activities are attempted first, the system prioritizes tasks. Prioritize tasks according to the distance to the robots. Every task that isn't allocated is published to the task list by the system. It awaits robot bids.

Following the distance calculation, the robots calculate a bid value based on task priority, task complexity and distance if the task seems suitable. Subsequently, they publish this bid values for the system to select the highest bid for assign the tasks to the robots. The robot then 'publishes' this bid within a system where task assignments are determined, often using an auction-based approach. This method makes sure that tasks are assigned not only by location but also by the robot's capacity to do the task successfully and efficiently while taking the robotic system's overall goals into consideration.

The Euclidean distance D between the task location T with coordinates (x_t,y_t) and the robot location R with coordinates (x_r,y_r) is computed as (4):

$$D = \sqrt{\{(x_t - x_r)^2 + (y_t - y_r)^2\}} \tag{4}$$

The sum of these weighted factors gives the final bid value, which the robot uses to bid for the chance to execute the task. (The main robot node then assigns the task to the secondary robot with the highest bid value.) The main robot collects all the bids for each task and filters out bids from robots that have already been assigned a task to avoid overloading any single robot. The main robot selects the highest bid for each task and assigns the task to the corresponding robot by publishing the assigned task data. Then the secondary robots listen for assigned tasks, and upon receiving information that a task has been assigned to them, they will execute the tasks. To make sure that new tasks are processed and assigned on time, the main robot node repeats the task posting and assignment procedure at an ongoing rate. Additionally, a dynamic reconsideration mechanism is incorporated into the system to further improve work allocation efficiency. Through this method, robots can re-bid for tasks if they finish them if there are still tasks left. The robot nodes stay in a state of alertness where they are waiting for tasks to become available and are prepared to bid on tasks when they are received.

D. *Localization and Navigation*

Localization and navigation become key functionality when optimizing area coverage for multi-robot approaches. One of the primary prerequisites for a mobile robot's autonomy is localization. In terms of setting up the robots, using the Turtlebot3 robot models is suitable for our research area. The Turtlebot3 robot will include all the relevant parameters that describe the robot's physical properties, such as size, shape, and the configuration of sensors and actuators. This description enables ROS to understand how the robot is structured and how it should move in response to commands. Based on the implementation, robots are spawned in the gazebo simulation with a unique robot ID.

Mobile robots must be able to localize both indoors and outdoors in order to navigate their workspace on their own. Mobile robots must be aware of their precise location and orientation (pose) in order to carry out the duties that are expected of them [82]. In this context, we used the robot_localization package. We found that it is the most suitable choice for handling multi-robot scenarios. There are no limitations on the quantity of sensor sources. Even redundant sensor data, such as that from numerous IMUs and various odometer information, is supported by it [83]. It is a useful package that uses the Unscented Kalman Filter (UKF) or the Extended Kalman Filter (EKF) to fuse data from an arbitrary number of sensors.

There are some steps that developers want to follow, such as setting up odometry, simulating an odometry system in gazebo, and fusion using robot_localization [84]. In order to publish a static transformation between the "map" and "odom" frames for localization purposes using the robot_localization package, we used the static transform publisher node named "map_to_odom_tf_broadcaster" in our implementation. Then we conducted tests with a single robot to make sure the localization system was operating well before moving on to a multi-robot setup. After analyzing the test results, we implemented the localization process for the multi-robot scenario.

In the context of multi-robot navigation, as in Fig. 12, the system must be configured to enable all robots to independently cover an entire area as defined in the map based on the task allocation. To move a goal over a path while achieving complete area coverage, each robot needs to subscribe to the 'path' topic, which includes complete area coverage. While iterating through the number of agents, the robot's start position and pose are retrieved from the 'path' topic, and Fig. 13 shows the flow of this whole process.

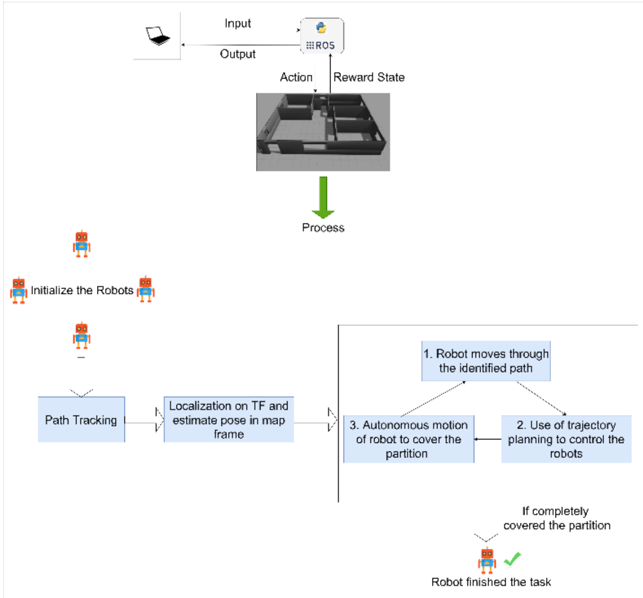


Fig. 12. Localization and navigation process

The next step is to accurately follow the path plan to efficiently cover the given area of the partition. To do that path tracking and navigation process, we used an open-source project named "tracking_pid" which provides a tunable PID control loop for precise trajectory tracking. Within that package, a goal is moved with a tunable velocity along a 'nav_msgs/Path' by an interpolator, while a separate node tracks the provided location. That package was improved and adapted for our use case. An "interpolator" node from the "tracking_pid" package is responsible for interpolating trajectories or pathways for the robot to follow. It provides target velocities for the yaw and x motions of the robot. An additional ``controller`` node from that package appears to track the robot's trajectory using a PID controller. It publishes velocity commands to control the robot's movement and subscribes to a topic for trajectory updates. The published topic named visualization_marker in the controller node is used to visualize the current goal the robot is controlled towards.

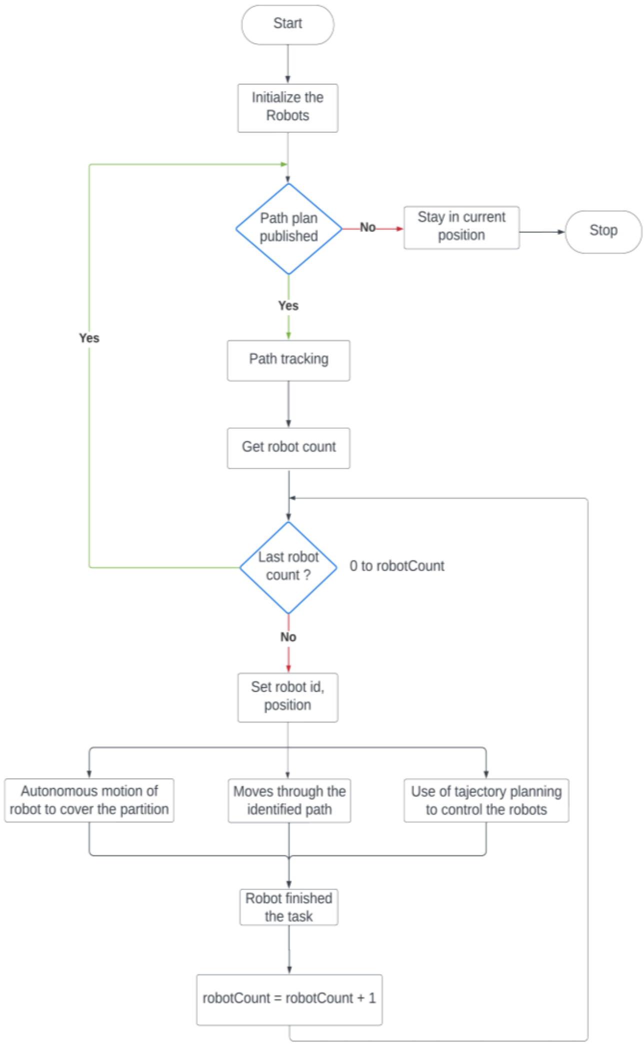


Fig. 13. Localization and navigation algorithm workflow

IV. Results and Discussion

This study presented an enhancing effectiveness of complete coverage path planning using autonomous intelligent technology. Area coverage mechanism effectiveness depend on the resources and time. In that case here point out the three main enhancement point as area partitioning, finding narrow areas and minimize the path repeating issue in Spiral Traversal Coverage (STC) and task allocation using market-based algorithm.

Map partitioning in our integrated approach for area coverage algorithms in multi-robot systems, particularly in indoor environments. This process involves dividing the overall area into smaller, more manageable segments, enabling a systematic and efficient allocation of tasks among the robots. The cell-decomposing method used for map partitioning effectively simplified the environment and ensured an even distribution of tasks among robots. This resulted in a more organized coverage process and reduced the overall time required for complete coverage.

Fig. 14 illustrates an occupancy grid map resulting from a cell decomposition algorithm applied in an indoor setting. In this binary representation, '0' indicates free space areas that are navigable by robots, and '1' represents occupied space areas that are obstructed or non-traversable.

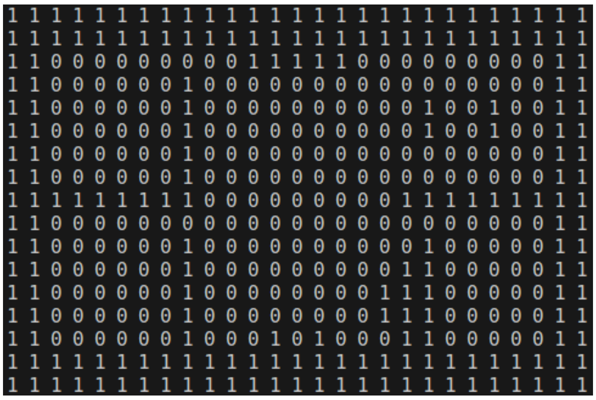


Fig. 14. Decomposed grid map

This multi-robot system was tested under various indoor scenarios with larger and more complex environments. Our system dynamically increased the partitions, resulting in a more efficient coverage process. In the subsequent image, we observe the initial partitioning phase. This step involves dividing the larger map into smaller sections. Each robot can be assigned to these sections to prevent overlap in coverage. Fig. 15.

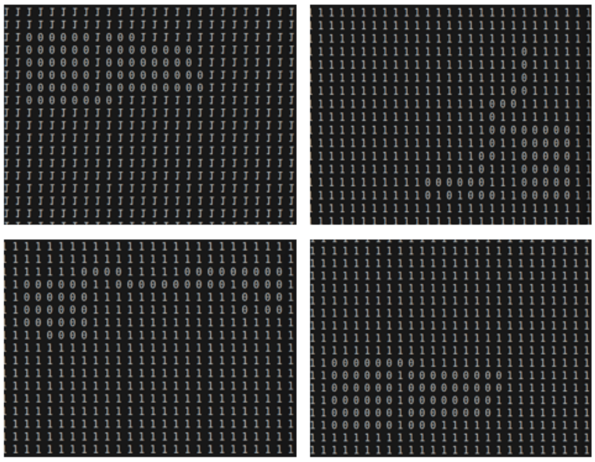


Fig. 15. Partitions grids

To start the process of generate path planning as initial step iterating partition array and taking each partition Boolean matrix. To represent each Boolean matrix partitions, create binary tree with connecting all the free positions into binary tree using breath first search (BFS).That binary tree is created by two patterns in horizontal and vertical connectivity Fig. 5.

After that generated binary tree of vertical and horizontal connectivity used to perform post order tree traversal method Fig. 6 to find narrow areas of both vertical angle and horizontal connections. After that predefined matrices (same scaled as main matrix size) were adding the identified narrow points as ‘0’ and other area is ‘1’ as in Fig. 7.

In the final step of path planning process main sub partition is passing to Spiral Traversal Coverage (STC) algorithm and performing the spiral for single partition. While performing the STC it’s checking each point is in the narrow area matrix value is zero. If position having the narrow matrix zero value. Path planning methodology switch into back-and-forth pattern until no narrow area point is not in neighbor as current point narrow point. Then it’s again continuing the normal STC method to generate path plan. After that merged path and individual paths publish as a ROS topic (Fig. 16, Fig. 17, Fig. 18, Fig. 19, Fig. 20).

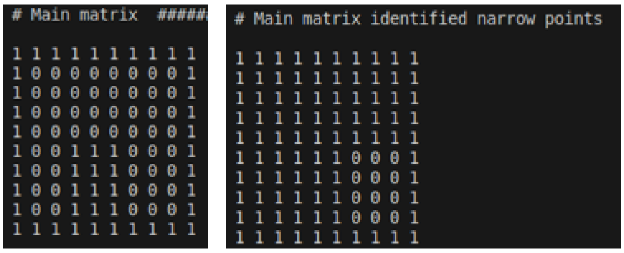


Fig. 16. Horizontal narrow main matrix and horizontal narrow identified matrix

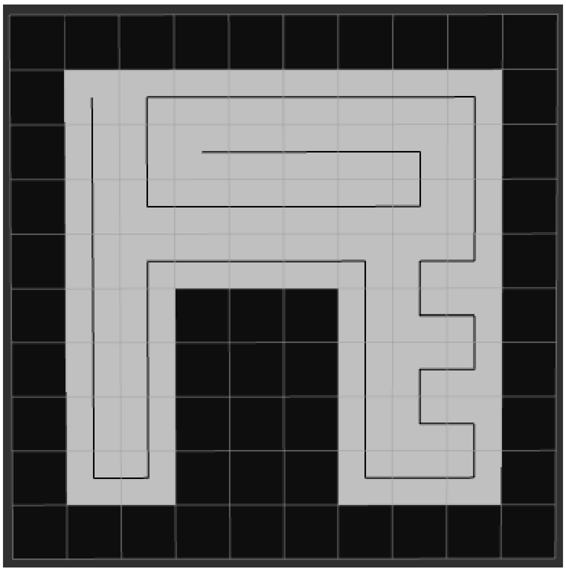


Fig. 17. Horizontal narrow result path plan

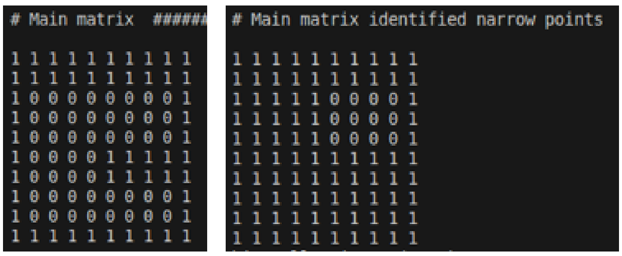


Fig. 18. Vertical narrow main matrix and vertical narrow identified matrix

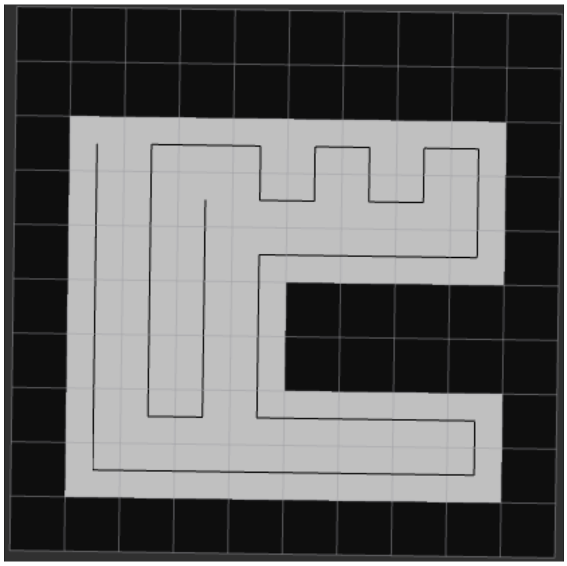


Fig. 19. Vertical narrow result path plan

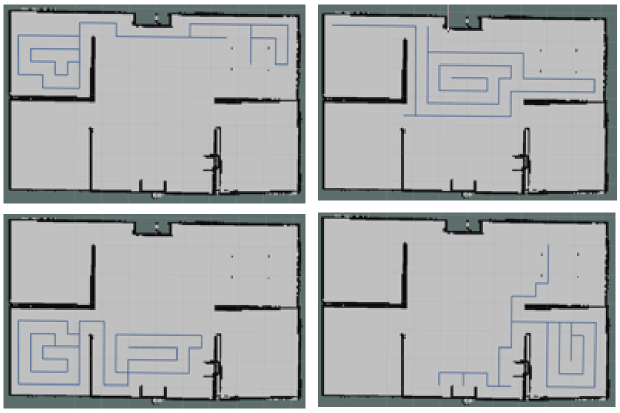


Fig. 20. Path planning visualizations for different partitions of a map

The other, however, was the market-based algorithm is an algorithm controlled by the system for the distribution of tasks (map partitions are the tasks) among the robots, showing noticeable efficiency according to the distribution of tasks to be performed by robots considering their capabilities and priority. Some of the operational metrics were significantly high. This approach improved the task completion rate overall. Every robot has to analyze the tasks and make bids for the given task based on a priority mix, complexity of the task, and distance to be covered using a procedure for bidding. This ensured that the tasks of topmost priority should be done first and maximized the total output of the system. In this sense, it was correct to use the Euclidean distance formula as the algorithm, since it accurately calculated the priority each potential task for the robot had in totality. After calculating bids highest bid receive the task and according to that order robots are allocated to the tasks. After that each robot will display in the suitable partition on the map as in Fig. 22.

For localization, using the robot_localization package was a good approach when handling multi-robot scenarios. There are no limitations to sensor counts and could handle the multiple odometry information to get the robot positions data accurately. So that we were able to get the benefit of that approach properly (Fig. 21).

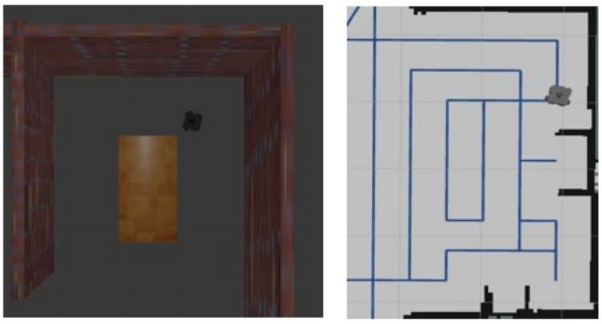


Fig. 21. Positioned robot gazebo and rviz view

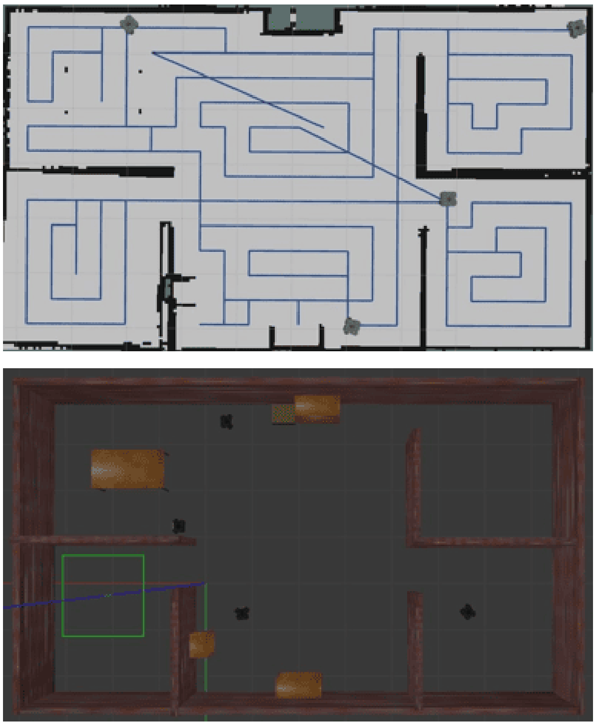


Fig. 22. After task allocating robots loading on the map rviz behavior view and gazebo simulation view

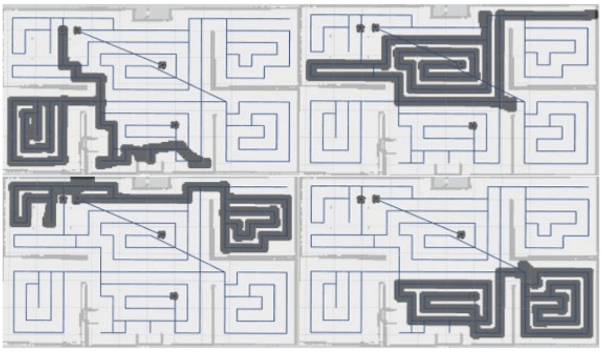


Fig. 23. Navigating robots in each partition

When navigating the robots on the given test map, each robots accurately follows a trajectory planning to complete the given task in the area. A one important thing is when robots move very close to each other those robots move properly without colliding with each other. The correctness of the path plan also affects it. Otherwise those robots will collide when navigating over a given path. After covering the given area, the robot will stay at the end of the path until it gets another new task (Fig. 23, Fig. 24). According to the test results, we want to improve how navigation happens currently when there are obstacles. Also, there is a limitation on how to handle the navigation in places where the depth of the ground varies. The primary focus of this study was to enhance the coverage efficiency using a combined path planning technique. The results demonstrate significant improvements in coverage efficiency. It is important to note that this study does not provide a comprehensive analysis of navigation performance under conditions involving dynamic obstacles or uneven terrain. These aspects were beyond the scope of the current research and will be addressed in future work.

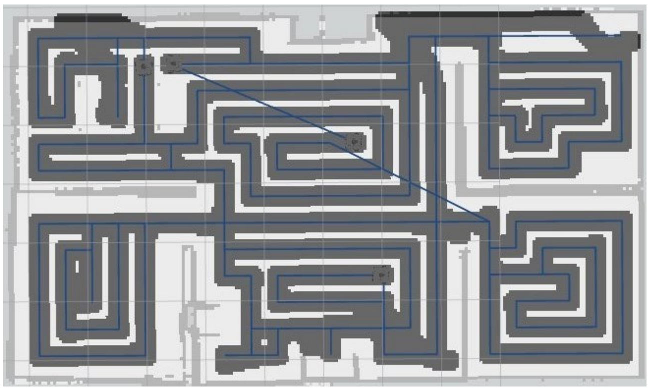


Fig. 24. All robots after covering their partition

To expose how successful this narrow area finding mechanism is in the Boolean matrix using the Post Order Traversal (POT) method, we experimented with four types of sample matrixes such as horizontally directed and vertically directed both top and bottom direction narrow area points. Experiment table (Table I) Original matrix column representing functioning original Boolean matrix in Post Order Traversal (POT). The narrow area best case column shows the best case of finding the narrow area of the original matrix. After POT it generates another matrix with narrow area points marked as ‘0’, it’s compared with the predefined best-case matrix using an assert equation. System output of assert result shown in Fig. 25.

Fig. 26 demonstrates the coverage efficiency of the robots in three different simulated environments with the settings of obstacles and layouts differing. The first map, with four robots, 96% of the coverage is completed after six minutes. Map 2 with a simpler layout had a 98% coverage efficiency with three robots. Map 3 shows a slightly different coverage efficiency of 94% in about 9 minutes with three robots. Considering these different scenarios, the coverage efficiency can vary on map layout and robot count.

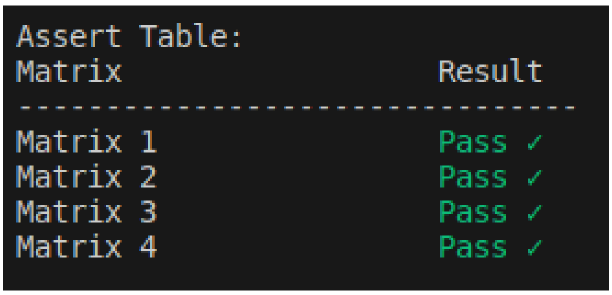


Fig. 25. System experiment result evidence

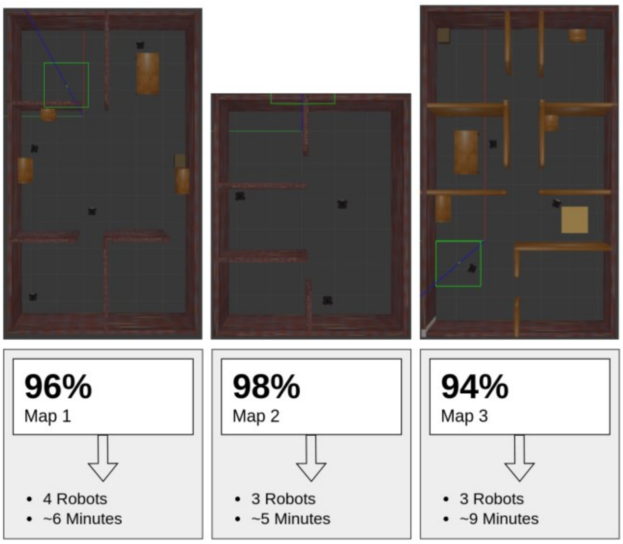
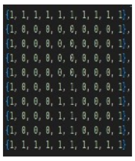
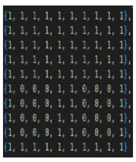


Fig. 26. Coverage values

TABLE I. TABLE EXPERIMENT CASES

No	Original matrix	Narrow area best case	Description	Result
1			Horizontal left-side directed matrix narrow area accurately identifying	Pass
2			Vertical top-directed matrix narrow area accurately identifying	Pass
3			Horizontal right-side directed matrix narrow area accurately identifying	Pass
4			Vertical bottom-directed matrix narrow area accurately identifying	Pass

Coverage Percentage:

- Map 1: 96% coverage in 6 minutes with 4 robots.
- Map 2: 98% coverage in 5 minutes with 3 robots.
- Map 3: 94% coverage in 9 minutes with 3 robots.

Task Completion Rate:

The rate of completing tasks can be described as the proportion of the space traveled by the robots during a specific period. This measurement gives an understanding of how well the robots are performing the designated coverage task during a defined timeframe.

- Map 1: 16% per minute (96% coverage / 6 minutes).
- Map 2: 19.6% per minute (98% coverage / 5 minutes).
- Map 3: 10.44% per minute (94% coverage / 9 minutes)

The overall efficacy and efficiency of our multi-robot system improve as the number of robots increases, impacting several key aspects. With more robots, task distribution becomes more effective, significantly enhancing coverage efficiency. Each robot is assigned a specific portion of the map, reducing overlap and ensuring more area is covered in less time. This systematic allocation of tasks leads to a more organized and thorough coverage of the region, while also speeding up the entire coverage process. However, the increase in the number of robots brings challenges such as communication delays and processing overhead. Our integrated approach tackles these issues by utilizing advanced path planning and task allocation algorithms that minimize computational demands and optimize resource utilization. The market-based algorithm for task allocation has proven particularly effective in this regard. By allowing dynamic task redistribution based on real-time assessments of each robot's position and performance, it ensures optimal resource use without overloading the system's capacity. Furthermore, our system incorporates efficient communication protocols that minimize latency, enabling rapid and reliable exchange of information between robots. We introduce a significant advancement in multi-robot area coverage systems, focusing on task assignment and path planning. To transition from theory to practice, we are addressing practical deployment challenges, such as ensuring compatibility with various hardware configurations and seamless integration with diverse software environments. Additionally, we are developing detailed deployment plans to aid users in the implementation process. Our goal is to enhance the usability of our system for robotics practitioners and researchers, making it not only theoretically robust but also practically feasible and easy to deploy across a range of operational scenarios.

Our study improves current methods in multi-robot and UAV coverage of fixed environments by incorporating innovative route optimization strategies that boost efficiency and decrease operational time, when compared to the techniques used in ' Hybrid Path Planning Model for Multiple Robots Considering Obstacle Avoidance ' and 'Coverage Path Planning for UAV Based on Improved Back-and-Forth Mode' [28], [33]. The "Hybrid Path Planning Model" utilizes an advanced algorithm that combines enhanced particle swarm optimization with artificial potential field methods to improve coordination among multiple robots and avoid obstacles [28]. This model is very efficient for stationary environments with intricate layouts and several obstacles. Nevertheless, our method enhances these abilities by improving efficiency and coverage time more efficiently, streamlining the implementation while still maintaining high coverage accuracy. Furthermore, through improving the process of optimizing paths, we achieve better evenness and accuracy in coverage, establishing new benchmarks for speed of deployment and efficiency of operations in unchanging settings. Comparison to the study "Coverage Path Planning for UAV using Enhanced Back-and-Forth Mode" is being made [33]. The study "Coverage Path Planning for UAV using Enhanced Back-and-Forth Mode" concentrates on enhancing UAV path planning in familiar static environments. It enhances traditional coverage techniques by adjusting the back-and-forth motion to reduce redundancy and boost area coverage productivity. Although this method decreases the duration that UAVs are allocated to areas that have already been surveyed, it does not tackle the swiftness of the initial coverage or the ability to adapt to different obstacle arrangements in static environments. On the other hand, our study presents techniques that reduce coverage path overlap and better accommodate various static environment layouts. Our methods improve the initial path planning stage, decreasing the total time needed for full coverage and boosting efficiency in environments containing various static obstacles. These comparisons demonstrate that our research not only tackles but also effectively surpasses the constraints present in existing methods, resulting in improved and streamlined robotic coverage across various operational scenarios.

Compared to other two researches we got here our research has demonstrated a significant enhancement in the operational efficiency and coverage capabilities of multi-robot systems in indoor environments. By integrating a hybrid path planning algorithm that combines Spiral Traversal Coverage (STC) and Boustrophedon Traversal Coverage (BTC) with a market-based task allocation mechanism, we achieved a more organized and thorough coverage. The results indicate that our approach not only optimizes the operational workflow but also reduces the time required for complete area coverage, evidencing a substantial leap in performance metrics when benchmarked against existing techniques.

The results of our research highlight how advanced robotic systems significantly improve efficiency in covering areas in indoor environments. By combining BTC and STC algorithms, our robots are able to efficiently maneuver their surroundings, reducing duplication and increasing the extent of coverage. This strategy improves both the speed of operations and the thoroughness of coverage tasks. Furthermore, our task allocation system based on market dynamics adjusts according to the environment's complexity, maximizing resource usage and fairly distributing tasks among robots. The improvements impact our map partitioning techniques as well as our localization and navigation methods. Through the efficient map partitioning into distinct segments, we guarantee that every robot functions within a clearly defined region, minimizing duplication and enhancing coverage effectiveness. The advanced localization and navigation allow for accurate positioning and movement of the robots, important for navigating intricate indoor environments. These abilities enable us to implement our system in various environments, such as industrial warehouses and healthcare facilities, where accurate and efficient task completion is crucial. This comprehensive method enhances the operational efficiency of multi-robot systems and also creates new opportunities for their use in different industries, offering significant enhancements in workflow and productivity.

Strengths and limitations of our research compared to the others is the fresh combination of hybrid path planning and dynamic task allocation, leading to a notable improvement in the coverage effectiveness of multi-robot systems. This method decreases operational expenses by reducing duplication and improving flexibility in different indoor settings. Nonetheless, the research is constrained by its dependence on artificial surroundings, which might not completely replicate the intricacies of actual settings. Future studies must investigate this by testing the systems in increasingly dynamic and unpredictable environments to verify the results and broaden the applicability of our methods.

In conclusion, while the scalability of our system introduces challenges in terms of computational and communication demands, the methodologies we have developed and implemented successfully address these issues. Our approach not only supports scaling up the number of robots effectively but also enhances the overall performance of the system.

V. FUTURE WORK

Our current study utilizes simulated environments, which are valuable for initial testing but do not fully capture the complexity and unpredictability of real-world settings. Future research must focus on transitioning from simulation-based trials to field testing, particularly in diverse and dynamic environments. This phase will allow us to evaluate the proposed approaches in more realistic scenarios, accounting for factors such as sensor noise, lighting variations, and physical interactions with obstacles. And future research will focus on developing and integrating advanced navigation algorithms capable of dynamic obstacle avoidance and terrain adaptation. This will ensure the reliability and safety of robot navigation in more complex and dynamic environments, addressing the current system's limitations and enhancing its applicability in real-world scenarios. Through these field tests, we can validate and enhance the effectiveness, resilience, and reliability of the multi-robot system, ensuring it is both theoretically sound and practically efficient.

While the current system performs well in controlled indoor conditions, further testing is necessary to assess its scalability to larger or more complex environments and its ability to respond to dynamic changes. Future research should focus on integrating real-time dynamic obstacle detection and handling to enhance the system's responsiveness and flexibility. Additionally, scaling the system to larger areas or more intricate scenarios will be crucial. This involves refining task allocation mechanisms and map partitioning algorithms to effectively manage an increasing number of robots and varying map complexities, ensuring the system's applicability across a broader range of situations. While our current research primarily focuses on the technical aspects and performance of our system, we acknowledge the importance of considering broader implications. To address job displacement, we will explore the impact of our multi-robot system on employment and develop strategies such as retraining and upskilling programs. Ensuring privacy, we will implement robust data protection measures and adhere to legal standards. To tackle algorithmic bias, we will thoroughly evaluate our algorithms to identify and mitigate any biases. We recognize the need for interdisciplinary collaboration to enhance our research. We plan to work with experts in human-computer interaction to improve user interfaces, ethicists to address ethical considerations, sociologists to understand social implications, and urban planners to facilitate deployment in urban environments. This interdisciplinary approach will help us address complex challenges more comprehensively. We believe it will significantly enhance the relevance and impact of our work. Additionally, we will study human-robot interaction to enhance safety and trust, and review legal and ethical frameworks, collaborating with experts to incorporate these considerations comprehensively.

VI. CONCLUSION

In this work, we have created a complex multi-robot system for full area coverage that combines a market-based job allocation mechanism with sophisticated path planning approaches, namely Boustrophedon Traversing Coverage (BTC) and Spiral Traversing Coverage (STC). To assess the effectiveness and efficiency of these approaches, we have put them through a rigorous testing process in simulated indoor situations. Through rigorous testing in simulated settings, our system has shown a significant reduction in overlap and increased coverage efficiency, proving its potential to enhance productivity and safety in industrial applications. In conclusion, our research has significantly advanced indoor operations with multi-robot systems by seamlessly integrating path planning, task allocation, and real-time adaptive approaches. In response to reviewers' constructive feedback, we have identified specific future directions to enhance the applicability and scope of our techniques. Future studies will focus on refining dynamic path planning and real-world deployment to validate the theoretical models we have presented. Furthermore, we believe these technological advancements will revolutionize indoor operations by introducing more intelligent and flexible solutions, pushing the boundaries of current robotic research, and delivering significant improvements in productivity, safety, and operational efficiency. Our research is poised to significantly enhance the efficiency and safety of indoor robotic operations, thereby improving productivity across multiple industries. These advancements are expected to lead to substantial societal impacts, including the reduction of human exposure to hazardous environments and the optimization of resource use in industrial settings. This research aims to enhance the autonomy and efficiency of multi-robot systems through innovative approaches and thorough validation, paving the way for cutting-edge applications in a variety of indoor environments. To ensure robust and effective research outcomes, we propose adopting an iterative development process, breaking our efforts into smaller cycles for regular assessment and improvement. Implementing feedback loops will incorporate insights from stakeholders, helping us adapt to evolving needs and challenges. Establishing continuous evaluation mechanisms with benchmarks and performance metrics will allow for ongoing assessment. Our flexible and adaptive research approach will enable us to respond to new developments and changing circumstances. By incorporating these iterative and agile principles, we aim to enhance the robustness and effectiveness of our future research endeavors, contributing to the continuous improvement and success of our multi-robot system.

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