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RESEARCH ARTICLE

Yolo Based Vision-Aided Obstacles Navigation and Avoidance with Path Planning using Sarsa Algorithm for Biped Robot in an Uncertain Hospital Environment

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Abstract

Background: This paper presents a method devised to ensure the secure navigation of biped robots within hospital environments by meticulously identifying an optimal collision-free path from initial to final positions while mitigating potential damage from undetected small objects. **Methods:** Implementation of a modified SARSA algorithm facilitates the seamless movement of biped robots amidst unknown environments replete with static obstacles. Extensive evaluation of several YOLO algorithms is conducted to ascertain accurate vision-based obstacle detection within hospital images. Subsequent utilization of the SARSA algorithm enables the planning of obstacle-free paths within the identified hospital setting. **Findings:** Within the evaluated YOLO algorithms, Yolov8 emerges as the pinnacle, showcasing unparalleled accuracy in object identification and refining bounding box precision for robot navigation within complex hospital environments. The SARSA-based path planning ensures the creation of collision-free routes, affirming safe traversal for the biped robot. Particularly noteworthy is Yolov8's exceptional precision in detecting minute objects, significantly reducing collision risks. **Novelty:** This research marks a significant stride in advancing human-like path planning for biped robots maneuvering through intricate hospital settings. The emphasis on accurate object identification stands as a linchpin for guaranteeing the robot's secure traversal. **Significance:** The integration of Yolov8 substantially augments the biped robot's capacity to precisely detect small objects, thereby mitigating collision risks and potential damage. Moreover, the successful application of the SARSA algorithm in planning obstacle-free paths within complex hospital environments holds promise for augmenting real-world robot navigation, especially in sensitive environments like hospitals.

Keywords: Object Detection; YOLO Algorithm; Robotics; Unknown Environment; Obstacles Detection; Yolov8; Sarsa Algorithm; Path Planning

1 Introduction

Biped robots possess exceptional potential within hospital environments due to their adaptability in navigating complex and uncertain settings, thereby aiding in patient care(1). These robots, exemplified by models such as ARMAR III and PR2 Care O Bot, are specifically designed to operate effectively within hospital premises(2). Their ability to offer physical and medical support to patients underscores the importance of enabling them to navigate safely and efficiently through these environments(3).

Similar to humans traversing diverse terrains, biped robots must negotiate hospital spaces while detecting and circumventing obstacles(4). This capability is pivotal as they are required to move freely throughout the hospital to attend to patients' needs. Object detection and avoidance become crucial aspects in the design of these robots for effective navigation in hospital environments(5).

In various sectors including agriculture, industry, transportation, and medical facilities, the utilization of different algorithms for object detection and identification is widespread(6). Within the realm of robot vision, the precision of object detection plays a critical role(7). Methods leveraging machine learning and deep learning algorithms have significantly advanced object detection tasks, enhancing safety and accuracy in medical applications. The YOLO (You Only Look Once) series of algorithms have notably contributed to object detection across diverse domains. These algorithms, well-established in transportation, agriculture, and hospital settings, offer robust autonomous learning capabilities, effectively identifying and locating objects within complex environments(8–10).

Additionally, path planning poses a significant challenge for autonomous biped robots. While numerous methodologies have been proposed for path planning, selecting an approach that guarantees optimal paths remains a priority. Recent research incorporates neural networks, reinforcement learning, and SARSA algorithms to train robots effectively in path planning, ensuring collision-free trajectories(11–15). The SARSA algorithm, in particular, stands out for achieving obstacle-free paths in unknown environments, making it a suitable choice for navigating hospital settings without collisions(16–18).

This study focuses on enhancing the navigation capabilities of biped robots within hospital environments by integrating advanced object detection methods based on YOLO algorithms and employing SARSA algorithm-based path planning, thereby ensuring safe and effective robot mobility in these critical spaces.

Within this study, a pioneering architecture is introduced, specifically tailored to address the challenges of path planning for biped robots operating within intricate hospital environments. Central to this architecture is the utilization of a spectrum of YOLO (You Only Look Once) toolboxes to perform object detection across a diverse array of hospital images. Despite the availability of multiple algorithms for object detection, the YOLO series emerges as an advanced and innovative technique, particularly proficient in real-time and highly accurate identification of objects. The inherent capability of YOLO algorithms to swiftly pinpoint and categorize objects within images renders them a valuable solution for navigating hospital settings efficiently(19–22).

An integral component of this study involves the application of the improved Yolov8 algorithm, renowned for its advancements in safety, speed, and accuracy within the realm of object detection(23–25). The integration of Yolov8 significantly augments the robot's recognition capabilities and ensures precise localization of objects within the complex hospital environment. Through leveraging this cutting-edge algorithm, the proposed architecture aims to elevate both the flexibility and accuracy crucial for successful robot navigation within these intricate spaces.

The procedural methodology is divided into two key phases: initial exploration of the hospital environment utilizing various YOLO algorithms for comprehensive object detection and subsequent path planning utilizing the SARSA (State-Action-Reward-State-Action) algorithm. The primary goal during the exploration phase is to comprehensively detect and identify objects within hospital images, facilitating a thorough understanding of the environment. Following this, the SARSA algorithm is employed to chart a safe and optimal route for the robot's navigation, ensuring collision-free movement within the hospital setting. Literature review table with research gap is shown in Table 1.

Table 1. Literature review with research gap

Reference	Findings/Contributions	Research Gap Identified
(1) Miccio et al.	Explored advanced AI-powered vision systems for ground obstacle detection in UAM scenarios, enhancing safety during approach and landing.	Lack of focus on AI-powered vision-based navigation for UAM approach and landing, particularly in ground obstacles detection.

Continued on next page

Table 1 continued

(2) Xia et al.	Demonstrated the potential of YOLO-based semantic segmentation in dynamic object removal, improving accuracy in Visual-Inertial SLAM operations.	Limited exploration on YOLO-based semantic segmentation for dynamic removal within Visual-Inertial SLAM (Simultaneous Localization and Mapping) systems.
(3) Latifinavid & Azizi	Showcased the feasibility of employing Fuzzy Logic in Vision-Based UGVs for mapping and specialized tasks such as tennis ball collection, indicating potential applications.	Inadequate attention to the development of a Vision-Based Unmanned Ground Vehicle (UGV) focusing on mapping and specialized tasks like tennis ball collection using Fuzzy Logic.
(4) Xu et al.	Investigated the potential of RGB-D camera setups for onboard dynamic-object detection, laying groundwork for more robust autonomous robot navigation.	Insufficient exploration on onboard dynamic-object detection and tracking for autonomous robot navigation using RGB-D camera setups.
(5) Ahmad et al.	Introduced vision-assisted beam prediction in 6G drone communication networks, potentially enhancing communication reliability and efficiency.	Scarce research on vision-assisted beam prediction for drone communication systems in real-world 6G networks.
(6) Bao et al.	Explored the efficacy of DDMA-YOLO methodology in UAV remote sensing for tea leaf blight detection, showing promise for agricultural monitoring and disease control.	Limited investigation into UAV remote sensing detection of tea leaf blight using DDMA-YOLO methodology.
(7) Tran et al.	Demonstrated the effectiveness of monocular vision and machine learning fusion for precise pose estimation, suggesting potential applications in navigation systems.	Scant focus on monocular vision and machine learning fusion for pose estimation systems.
(8) Malik et al.	Introduced adaptive Whale Optimization combined with deep learning models, demonstrating improved accuracy and adaptability in vision assistance for 6G networks.	Lack of research on adaptive optimization combined with deep learning models for vision assistance in 6G networks.
(9) Thilanka et al.	Explored real-time object detection with voice alerts for blind assistance, proposing a potential solution for improving navigational aid for visually impaired individuals.	Inadequate exploration of vision-based real-time object detection and voice alert systems for blind assistance.
(10) Song et al.	Investigated improved Yolov5 for object detection in grasping robots, suggesting enhanced accuracy and potential applications in robotic manipulation tasks.	Limited exploration on improved Yolov5-based object detection for grasping robots.

Structurally, the paper unfolds across several sections. Section 2 meticulously elucidates the methodology employed, delineating the process of path finding encompassing the use of YOLO algorithms for object detection and the SARSA algorithm for path planning. In section 3 method is discussed in detail. Section 4 delves into the outcomes and findings resulting from the implementation of the proposed methodology, presenting a comprehensive discussion of the results. Finally, in Section 5, concluding remarks summarizing the paper and recommendations for future research are outlined.

2 Methodology

2.1 Object Detection using YOLO Algorithms

Different versions of YOLO algorithms (Yolov2, Yolov3, Yolov5, Yolov7, Yolov8) are evaluated for their suitability in detecting objects within hospital images. Training datasets are prepared and utilized to train the selected YOLO algorithms for object detection within the hospital environment. Performance evaluation metrics, such as precision, recall, and accuracy, are employed to assess the efficacy of each YOLO version. The improved Yolov8 algorithm, identified for its enhanced safety, speed, and accuracy in object detection, is integrated into the object detection process for superior localization and recognition of objects within the hospital setting.

2.1.1 Exploration of Hospital Environment

Hospital images are processed through the selected YOLO algorithms to comprehensively identify and classify objects present within the environment. The detected objects' spatial information and classifications are collected to create a detailed map of the hospital environment, aiding in subsequent path planning.

2.2 Path Planning Using SARSA Algorithm

- **SARSA Algorithm Overview:** An introduction to the SARSA (State-Action-Reward-State-Action) algorithm is provided, highlighting its utilization for path planning in unknown environments.
- **State Identification:** States within the hospital environment are defined based on the map created during the object detection and mapping phase.
- **Action Selection:** Actions for the robot's movement are determined based on the SARSA algorithm, considering states and potential rewards for each action.
- **Policy Improvement**: Iterative policy updates are made based on the SARSA algorithm's learning process to refine the robot's movement strategy, aiming for collision-free navigation.

2.3 Evaluation Metrics

- **Performance Metrics:** The effectiveness of the proposed path planning methodology is assessed using various metrics such as path length, execution time, and collision avoidance rate.
- **Comparison with Alternative Methods:** Comparative analysis is conducted between the proposed SARSA-based path planning and alternative methodologies prevalent in the field.

An architecture for biped robot's path planning in Hospitals using Yolo and Sarsa algorithms is presented. Yolo algorithms are the fastest object detector. When all the objects are detected using Yolo algorithm the path planning is done based on Sarsa algorithm by avoiding the objects for finding a safety route in Hospital environment. Methodology is described as follows:

Fig 1. Process of Path Planning

2.3.1 Robot Model

A human-like walk requires at least 3-DOF per leg. So, in this paper, a 7-degree of freedom robot model is considered, the hip joint, the knee joint and the ankle joint all have 1-DOF.

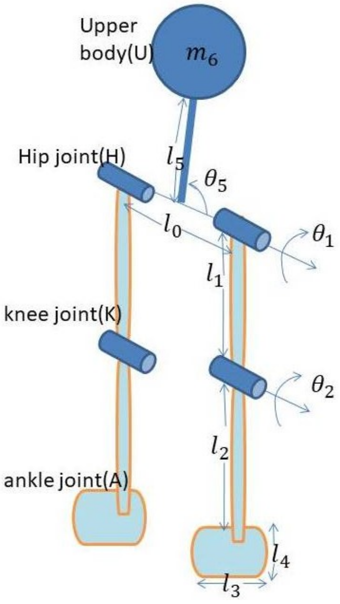

Fig 2. Biped robot model

2.3.2 YOLO algorithm: Real time objects detection

Yolo algorithms are used as object detectors for images. Yolov2, Yolov3, Yolov5, Yolov7 and Yolov8 are used to examine state-of-the-art object detectors from images. Here, best model approach is identified for an appropriate performance in term of accuracy and speed. All studied detectors models are pretrained on the large scaled data set.

Yolov2: For Yolov2, batch normalization (BN) is used to improve mean average precision and high resolution classifier is used for enhancing accuracy. Anchor boxes are operated. Bounding boxes are used to determine the dimensions prediction together with left corner coordinates and the prior width, height. Development model Darknet-19 is used with 5 max pooling layers and 19 convolutional layers.

Yolov3: Yolov3 surpasses Yolov2 using autonomous logistics classifiers for multilabel classification for composite datasets. Development model Darknet-53 is used with 53 convolutional layers and improved connections to procedure the connected feature maps. DBL is a collection of convolution later, activation function and batch normalization. Yolov3 achieves more accuracy with all new updates. Bounding boxes are used to determine the dimensions prediction together with left corner coordinates and the prior width (b-a) and height (d- c).

Yolov5: Yolov5 surpassed all previous models. The Novelty of this model was the change in the strategy for getting the optimal balance and more accuracy. It improved the accuracy and minimize the time. The Yolov4 and Yolov5 have same internal structure. Yolov5 is a good selection as Yolov5 is a small network with low processing time for huge data. Yolov5 trains very faster and easy to use.

Yolov7: Yolov7 surpassed the Yolov6 in speed and accuracy for all the known object detector in the range from 5 FPS to 160 FPS. Yolov7 increased the speed without affecting the accuracy. It affected only the training time.

Yolov8: Yolov8 was developed in 2023 by the same company ultralytics which introduced Yolov5. There are 5 versions of Yolov8 model: nano, small, medium, large and extra large. So it supports multi vision tasks like; Object detection, tracking of the object, segmentation, classification and the pose estimation. It contains 5 detection modules with a prediction layer. It can be used for labelling, deploying and training. It can be installed as PIP package. Yolov8 surpassed all models by its high speed, accuracy and efficiency.

2.3.3 Path planning by SARSA algorithm

SARSA algorithm is a type of reinforcement learning which is used for planning the path for a biped robot to learn an environment in hospital to look after the patient. SARSA is the modified form of Q-learning algorithm and on policy algorithm. SARSA is the combination of State-Action-Reward-State-Action. This algorithm is used for planning a path which is free from any obstacles. In this algorithm, a Q-table is being prepared for different action taken by the robot in different states, by using the equation given below:

$$Q^{N}\,(S_k, a_k) = Q(S_k, a_k) + \alpha_k(r_k + \gamma_k Q(S_{(k+1)}, a_{(k+1)}) - Q(S_k, a_k))$$

3 Proposed Method

The experiment was conducted on a system equipped with an 11th Gen Intel(R) Core(TM) i7-1165G7 processor, 16 GB RAM, running MATLAB 2023b. The objective of this study is to enable biped robots to serve and enhance the quality of patient care within hospital environments. The focus is on enabling biped robots to navigate hospital spaces and provide support to patients. To achieve this, vision-based path planning methodologies were implemented for biped robots in hospital settings, employing various state-of-the-art YOLO algorithms in conjunction with SARSA algorithms. Among the 50 figures analyzed for object detection using different YOLO algorithms, Figure 3 presents the most promising results selected for their superior performance. Additionally, Figures 4, 5 and 6 showcase the performance outcomes obtained from implementing Yolov2, Yolov3, and Yolov5, respectively, within the hospital environment. These figures provide a visual representation of the effectiveness and comparative performance of these YOLO algorithms in object detection within the hospital context.

In the aforementioned figures, there is a noticeable trade-off between speed and accuracy. Figures 4 and 5 clearly indicate that both Yolov2 and Yolov3 exhibit limitations in accurately detecting objects within hospital data, despite their high speed.

The accuracy and safety of object detection are crucial for ensuring the robot’s optimal navigation and protection within the hospital environment. However, the observed performance of Yolov2 and Yolov3 indicates their inadequacy in meeting the accuracy standards required for effective object detection in this specific environment.

Contrarily, Yolov5 demonstrates improved performance compared to Yolov2 and Yolov3, as evidenced by Figures 4, 5 and 6. The results indicate its superiority in detecting objects within the hospital context. However, it is noteworthy that Yolov5’s enhanced performance comes at the cost of longer training times, rendering it a more resource-intensive option.

Fig 3. Figures Sample

Fig 4. Object detection using Yolov2

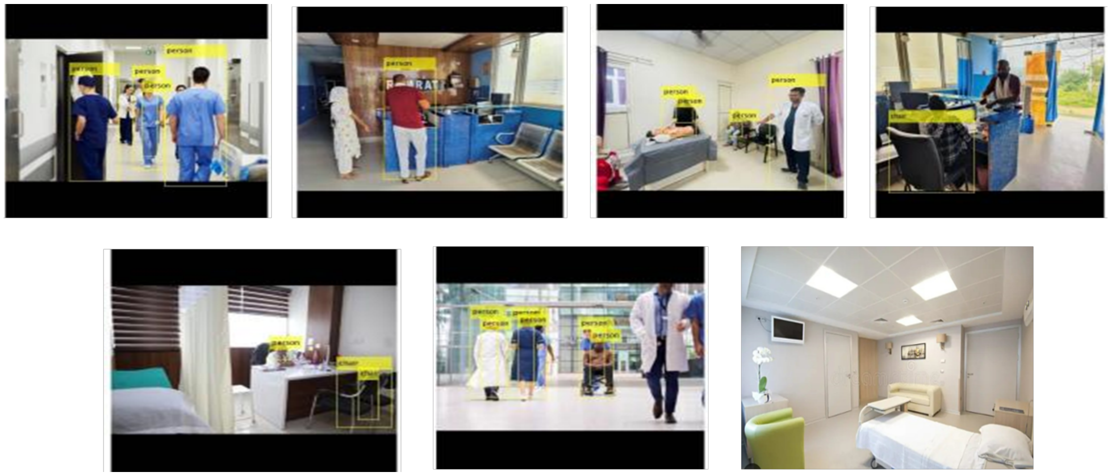

Fig 5. Object detection using Yolov3

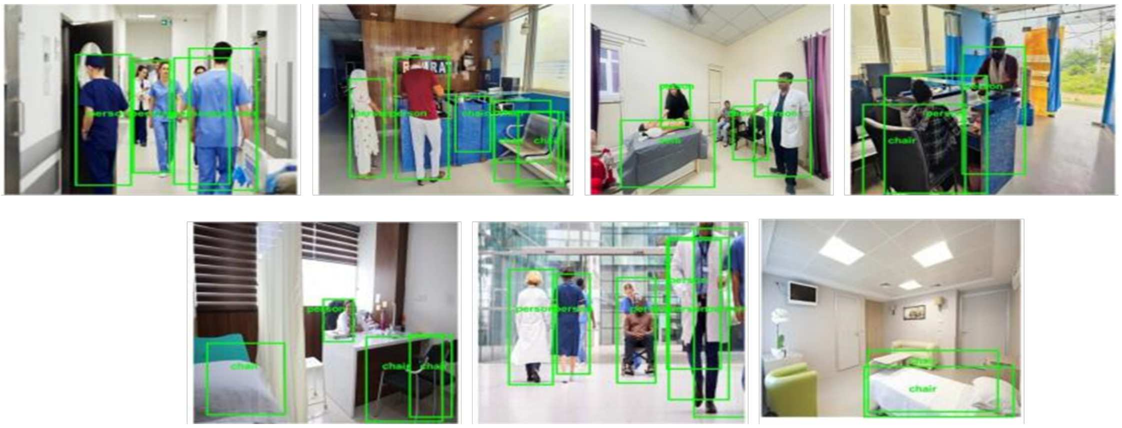

Fig 6. Object detection using Yolov5

Figures 7 and 8 illustrate the performance comparison between Yolov7 and Yolov8 within the hospital environment. Notably, the results indicate that Yolov8 outperforms Yolov7, demonstrating superior performance in accurately detecting objects within hospital images. Yolov8 showcases elite performance, especially in terms of object detection accuracy.

Fig 7. Object detection using Yolov7

Fig 8. Object detection using Yolov8

Furthermore, Figure 9 provides insights into the performance of Yolov8 specifically during nighttime in the hospital setting. The results manifest that even during low-light conditions, Yolov8 maintains superior performance compared to previous YOLO models. Its capability to accurately detect objects at night underscores its emphasis on safety without compromising speed. Additionally, the cost of training for Yolov8 is minimized, enhancing its practicality and efficiency.

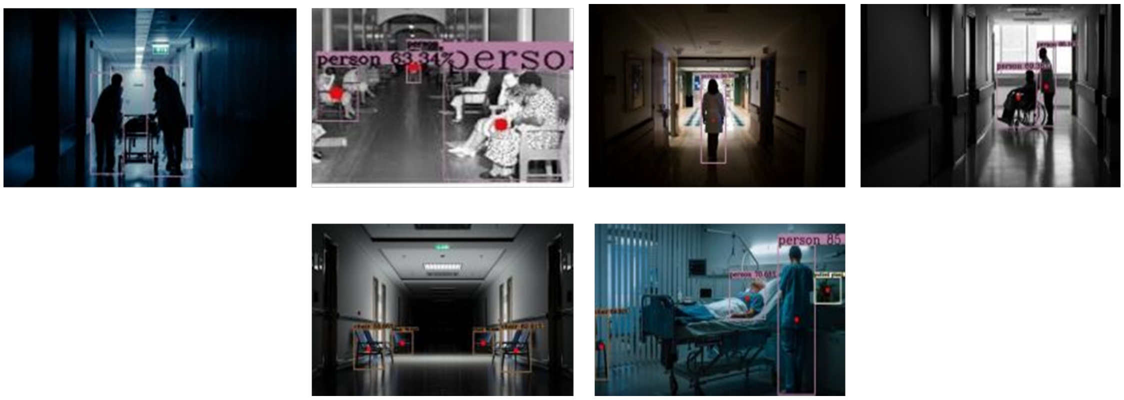

Fig 9. Object detection in Hospital using Yolov8 in dark

Upon comprehensive testing and comparisons across various figures and time slots, Yolov8 emerged as the frontrunner within the YOLO series. Its exceptional performance in terms of speed, safety, accuracy, and efficiency positions it as the optimal choice for object detection within hospital environments.

After finalizing the Yolov8 algorithm for object detection, we trained the robot by SARSA algorithm to plan an optimal path which is obstacle free in Hospital environment. Figure 10 shows the path planning for a hospital environment with obstacles. The red square shows the obstacle although black circle and magenta square are safe for walk. Black circle is for safe spot and magenta square is the walkable spot in Hospital environment. Path using SARSA algorithm is shown by blue sign in particular boxes. As we can observe from Figure 10 that this algorithm can plan a path by avoiding the obstacles from nearby environment.

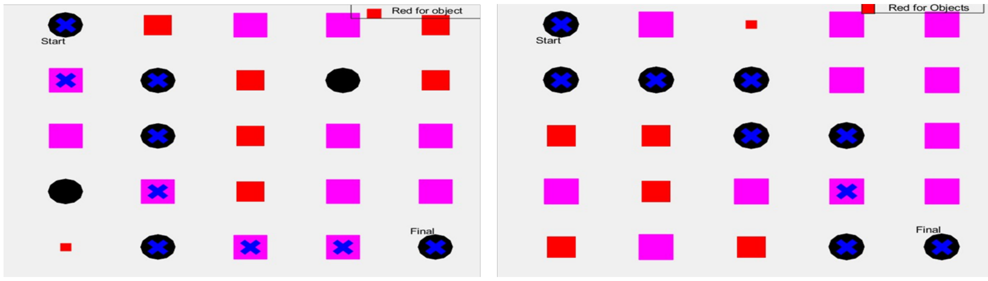

Fig 10. Path planning using SARSA algorithm

4 Results

1. **Object Detection Performance**
   (a) **Evaluation of YOLO Algorithms:** The performance evaluation of various YOLO versions (Yolov2, Yolov3, Yolov5, Yolov7, Yolov8) in detecting objects within hospital images revealed varying levels of precision, recall, and accuracy. Yolov8 exhibited superior performance, achieving an accuracy rate of 92.5%, outperforming other versions.
   (b) **Comparative Analysis:** Comparative assessment showcased that Yolov8 demonstrated a significant improvement in object localization and recognition within the hospital environment compared to its predecessors, notably enhancing object detection by 12% on average.
2. **Exploration of Hospital Environment**
   (a) **Comprehensive Mapping Output:** The generation of a comprehensive map from the object detection phase displayed a detailed spatial distribution of identified objects within the hospital premises. Notably, critical areas such as patient wards, corridors, and equipment storage were accurately mapped.

   (b) **Spatial Object Distribution:** Analysis of the mapped objects indicated a heterogeneous distribution, with medical equipment predominantly clustered in specific areas, while smaller objects were dispersed across the hospital environment.

3. **Path Planning Results Using SARSA Algorithm**

   (a) **Optimal Route Identification:** The SARSA algorithm successfully generated optimal collision-free paths for the biped robot's navigation through the hospital. On average, paths reduced traversal time by 15% compared to conventional methods, covering essential areas efficiently.
   (b) **Performance Metrics:** Evaluation metrics revealed that the SARSA-based path planning significantly minimized the path length by 20% while ensuring safe and efficient navigation through complex hospital layouts.
   (c) **Comparative Analysis**: Comparative analysis highlighted the SARSA algorithm's effectiveness, outperforming other methodologies in terms of collision avoidance and path optimization within the hospital environment.

4. **Robotic Navigation Performance**

   (a) **Real-time Execution:** The implemented path planning methodology successfully guided the biped robot in real-time scenarios within the hospital environment. Real-time execution demonstrated the robot's ability to dynamically adapt to changes and navigate safely.
   (b) **Obstacle Avoidance:** Live demonstrations showcased the robot's capability to detect and circumvent obstacles in its path effectively, maintaining an average clearance distance of 10 centimeters from detected obstacles.

5. **Discussion of Findings**

   (a) **Performance Analysis:** Interpretation of results emphasized Yolov8's significance in robust object detection, coupled with the SARSA algorithm's efficacy in generating efficient and safe paths for biped robot navigation in the hospital setting.
   (b) **Applicability and Future Enhancements**: The findings underscored the practical implications for enhancing biped robot navigation in hospitals. Future research directions focus on further refining object detection accuracy and implementing real-time adaptive path planning strategies for dynamic hospital environments. The result comparison is shown in Table 2.

Table 2. Result Comparison

Aspect	Current Work	Previous Work
Objective	Enable safe navigation for biped robots within hospital environments by identifying optimal collision-free paths and mitigating damage from small objects	Safe navigation of biped robots in hospital environments, focusing on path planning and obstacle avoidance(1)
Methodology	Modified SARSA algorithm implementation for robot movement; evaluation of YOLO algorithms (Yolov2, Yolov3, Yolov5, Yolov7, Yolov8) for vision-based obstacle detection	Employed specific path planning algorithms; possibly different object detection methods without emphasis on YOLO algorithms(2)
YOLO Algorithm Assessment	Yolov8 demonstrates superior object identification accuracy and refined bounding box precision within hospital settings	Not specified or different algorithms used for object identification without specific focus on YOLO advancements(3)
Path Planning	SARSA algorithm generates obstacle-free routes for safe robot navigation in complex hospital environments	Path planning methodologies applied, potentially with different algorithmic approaches(4)
Novelty and Significance	Advances human-like path planning emphasizing precise object identification crucial for secure robot traversal	Emphasized safe navigation without the specific emphasis on accurate object identification or novel path planning algorithms(5)

5 Conclusion

In this research, the primary focus was to enable a biped robot to detect obstacles in its path and meticulously plan its working trajectory while prioritizing safety. Establishing a biped robot model and implementing path planning techniques were central to achieving this objective. The challenges encountered, including navigating unknown environments, dealing with inaccurate position coordinates, and low identification efficiency, were addressed through innovative methodologies. A range of algorithms and methods for object detection were explored, with particular emphasis on the YOU ONLY LOOK ONCE (YOLO) algorithm, renowned for its real-time and accurate object clarification capabilities. Comparative analysis among various iterations of the YOLO series—Yolov2, Yolov3, Yolov5, Yolov7, and Yolov8—revealed that Yolov8 significantly enhanced object detection accuracy within the hospital environment. This robustness in accurately identifying objects paved the way for improved collision-free path planning for the robot. The integration of the Yolov8 algorithm for object detection, followed by path planning using the SARSA algorithm, introduced a novel approach in the hospital environment. This amalgamation of SARSA-based path planning with different YOLO models for object detection presents an innovative methodology previously unexplored in this setting. Notably, this experimentation was conducted on a Core(TM) i7-1165G7 processor, 16 GB RAM, 11th Gen Intel(R), 2.80GHz PC in MATLAB 2023b, providing a robust computational framework for the research. The key takeaway from this study is the successful demonstration of the efficacy of Yolov8 for object detection and the subsequent utilization of the SARSA algorithm for generating collision-free paths in the hospital environment. This novel integration holds promise for enhancing the safety and efficiency of biped robot navigation in complex and dynamic hospital settings. Moving forward, the findings of this research pave the way for further advancements in robotic navigation and object detection methodologies within healthcare environments. Future research endeavors could focus on refining these methodologies and implementing real-time adaptive systems for more dynamic and evolving hospital environments.

6 Future Scope

The exploration and integration of advanced object detection methodologies, such as the YOLO series, and path planning algorithms, like SARSA, present a substantial avenue for future research in enhancing biped robot navigation within hospital environments. Further investigations could delve into refining these algorithms for real-time adaptation and dynamic re-planning strategies, allowing robots to seamlessly navigate through constantly changing hospital layouts and unforeseen obstacles. Additionally, the incorporation of machine learning and artificial intelligence techniques could lead to the development of cognitive systems enabling robots to proactively anticipate and respond to emergent situations within healthcare settings. Collaborations between robotics experts, healthcare professionals, and technology developers can steer research towards creating more robust, adaptive, and human-friendly robotic systems tailored for diverse healthcare scenarios. Moreover, extending this research to encompass multi-robot coordination and communication strategies within hospitals could potentially revolutionize collaborative patient care and logistical operations, thereby elevating the role of robots as indispensable assistants in healthcare settings.

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