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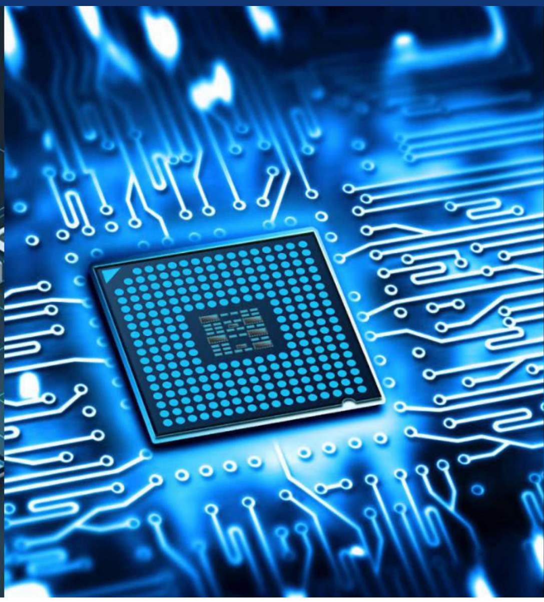


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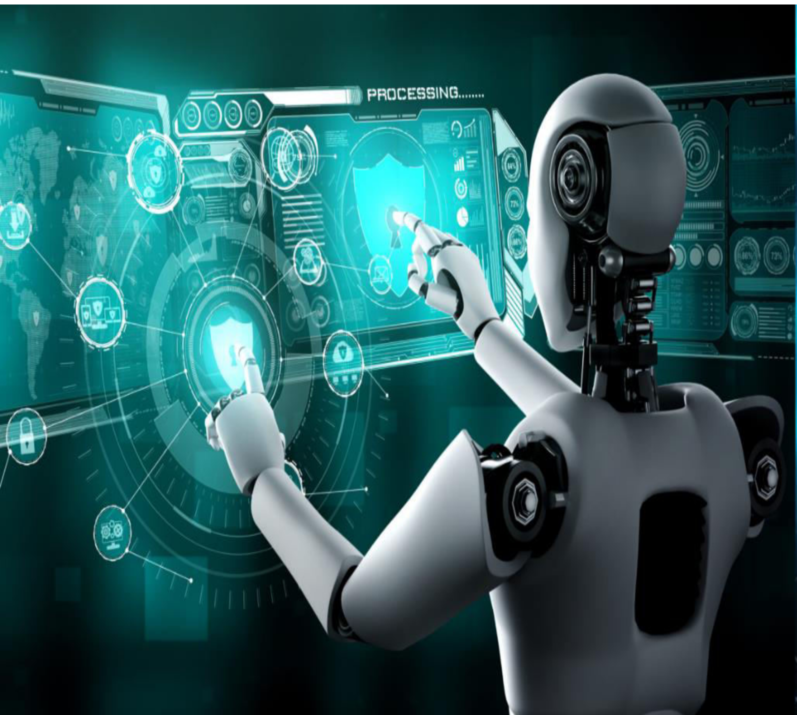

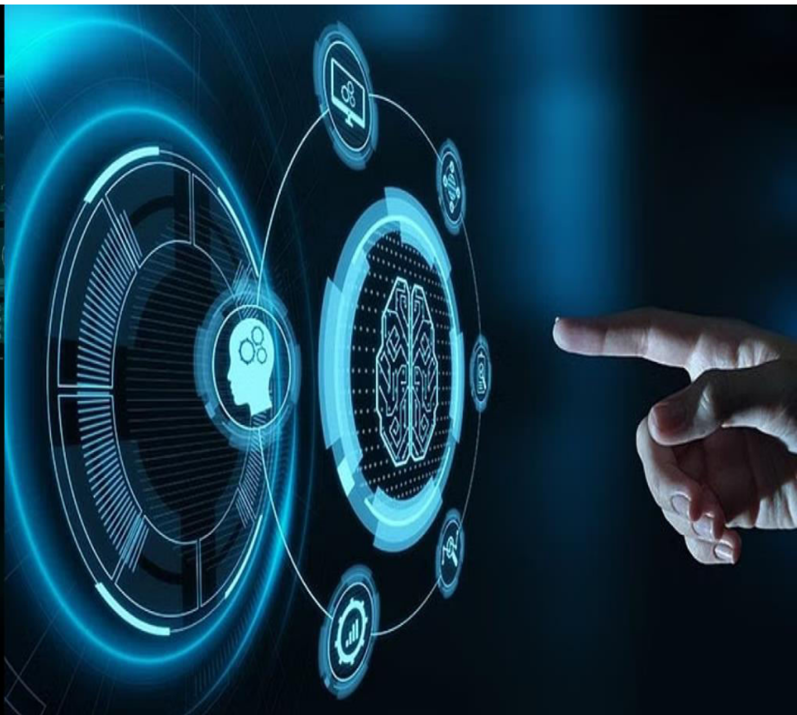

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Humanoid Home Service Robot for Object Retrieval in Unstructured Environments (Based on Virtual Nao Robot & Webots)

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ABSTRACT: The development of humanoid robots for home service tasks has gained significant attention due to the potential benefits they offer in terms of enhancing daily living, especially in environments that are dynamic and unstructured. This paper presents a comprehensive approach to designing and simulating a humanoid robot capable of retrieving objects in a home environment using a virtual Nao robot within the Webots simulation platform. The primary objective of this research is to enable a robot to navigate and perform object retrieval tasks within cluttered and unpredictable spaces. The virtual Nao robot is equipped with sensors that enable object detection, environmental mapping, and path planning. The system leverages advanced algorithms for object recognition using computer vision techniques, navigation via motion planning strategies like A*, and object manipulation based on grasping heuristics. We evaluate the robot's ability to successfully locate, navigate to, and retrieve objects in various simulated home environments with different levels of complexity. The results highlight the potential of using humanoid robots for practical applications such as elder care, assisting individuals with mobility challenges, or automating home tasks. This research demonstrates that through effective simulation tools such as Webots, robotic systems can be designed, tested, and refined to address real-world challenges in home automation and assistive robotics.

KEYWORDS: Nao robot, sensors, A*,Webots

I. INTRODUCTION

1.1 Background and Motivation

As advancements in robotics continue to reshape the way we interact with machines, the demand for intelligent, humanoid robots in everyday life is becoming increasingly evident. In particular, the potential for humanoid robots to serve in home environments is gaining traction, with applications ranging from assisting elderly or disabled individuals to automating mundane tasks. A key challenge in these domains is the ability of robots to perform object retrieval tasks in unstructured environments, such as cluttered homes, which are often characterized by dynamic obstacles and irregularly placed objects. Unlike structured environments (e.g., factories or controlled spaces), homes present a variety of challenges that require a robot to adapt to constantly changing conditions while ensuring safety, accuracy, and efficiency.

The growing need for assistive technology, alongside the increasing number of individuals living with disabilities or age-related mobility challenges, underscores the importance of creating robots capable of performing simple yet essential tasks, such as retrieving objects from various parts of a home. This has spurred research in robotics, artificial intelligence, and simulation technologies to develop systems that can navigate and manipulate in unpredictable environments.

1.2 Problem Statement

Despite significant progress in robot design and algorithm development, several challenges remain for humanoid robots tasked with retrieving objects in unstructured home environments. These challenges include the robot's ability to:

•Detect and identify objects in cluttered environments using vision and other sensors.

•Navigate dynamically changing spaces while avoiding obstacles and efficiently reaching objects.

•Grasp and manipulate objects of varying shapes, sizes, and weights with high accuracy and minimal force, while dealing with imperfect environmental conditions.

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While robots such as Roomba and Pepper have demonstrated success in simpler home automation tasks (e.g., vacuuming or communication), their object manipulation capabilities remain limited. The complexity of performing object retrieval tasks in real-world, cluttered home environments demands the development of robots that can handle both environmental uncertainty and complex task execution.

1.3 Objectives

The primary goal of this research is to design and simulate a humanoid robot capable of performing object retrieval tasks in unstructured home environments using a virtual Nao robot within the Webots simulation platform. Specifically, this research aims to:

•Develop a robot system that combines object recognition, path planning, and manipulation strategies to retrieve objects in dynamic, cluttered environments.

•Evaluate the robot's performance in various scenarios to determine the feasibility and efficiency of the system for real-world applications in home service robotics.

•Investigate the use of the Webots simulation platform as a cost-effective and flexible environment for testing humanoid robots before real-world deployment.

1.4 Contributions of the Paper

This paper makes several key contributions to the field of humanoid robotics and home automation:

1. **Virtual Nao Robot Model**: A detailed model of the Nao humanoid robot is developed within the Webots simulation platform, providing a foundation for testing robotic systems designed for real-world applications.
2. **Object Retrieval Algorithm**: The paper introduces a combination of object recognition, motion planning, and grasping algorithms tailored for object retrieval tasks in dynamic home environments.
3. **Simulation and Evaluation**: The proposed system is tested across various unstructured home environments with different levels of complexity, and performance is evaluated based on metrics such as time efficiency, success rate, and navigation accuracy.
4. **Future Implications**: This research highlights the potential for humanoid robots to assist with home services, especially in the context of elderly care, and demonstrates the power of virtual simulations like Webots in testing robotic solutions before physical deployment.

II. RELATED WORK

The development of humanoid robots for performing tasks in unstructured home environments has been a major area of research over the past few decades. Researchers have focused on various aspects of humanoid robotics, including navigation, object recognition, grasping, and manipulation. Several key contributions in the field highlight the challenges and progress in this area.

Robotic Navigation in Unstructured Environments: The ability of robots to navigate in dynamic and cluttered environments is a significant challenge. Early work by Mavridis and Lippiello explored navigation strategies for humanoid robots in cluttered environments, using sensor fusion and simultaneous localization and mapping (SLAM) to build maps of the environment and plan optimal paths. More recent research, such as Zhang et al., has focused on combining deep reinforcement learning (DRL) with navigation systems to improve robots' ability to adapt to changing environments. These approaches have made strides in addressing obstacles, ensuring safe navigation, and optimizing path planning algorithms, such as A* and Rapidly-exploring Random Trees (RRT), for humanoid robots operating in homes.

Object Recognition and Grasping: Object recognition is another key challenge for humanoid robots. The work by Kormushev et al. demonstrated an integrated system for object recognition using computer vision in unstructured environments, coupled with grasping algorithms that allow robots to handle a range of object types. Recent advancements in convolutional neural networks (CNNs) for object detection, like those presented by Redmon et al. with the YOLO (You Only Look Once) model, have enabled real-time, robust object identification even in cluttered spaces. Additionally, Cacace et al. introduced a flexible grasping strategy based on force-feedback, allowing robots to handle objects of different shapes and sizes. These systems are particularly useful in home environments where objects are frequently misaligned or incorrectly positioned.

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Simulation Platforms in Robotics: Simulation platforms like Webots, V-REP, and Gazebo have been pivotal in developing, testing, and refining robotic systems before physical deployment. Webots has been used extensively for robot modeling and control algorithms due to its versatility and support for humanoid robots like the Nao robot. Gouaillier et al. first developed the Nao robot, which has since been widely used in research and education, forming the basis of the humanoid robot model in Webots simulations. The use of simulation has been demonstrated to reduce the cost and risk of deploying robots in real-world environments while providing a platform for algorithmic experimentation. A similar approach was adopted by Severson and Platt, who used simulation to test object manipulation tasks with a robot that could retrieve objects in an indoor home environment.

Home Service Robotics and Assistive Technologies: The application of humanoid robots for home service tasks, particularly in the context of elder care and assistive technologies, has attracted significant interest. Research by Shia et al. demonstrated the potential of robots in providing assistance to elderly individuals by performing object retrieval tasks and offering mobility support. Furthermore, robots like Pepper and Jibo have been developed as social robots capable of assisting individuals with daily activities, but their capabilities in object retrieval remain limited. In contrast, humanoid robots such as ASIMO (Honda) and Care-O-bot have shown promise in navigating and performing various home tasks. These robots incorporate advanced motion control, path planning, and interaction strategies, forming a strong foundation for further research into humanoid robots for home automation.

Evaluation Metrics in Robotic Systems: Several studies have focused on the evaluation of robotic systems in terms of their performance in unstructured environments. Lippiello et al. and Ribeiro et al. proposed metrics for assessing the success rate, time efficiency, and accuracy of navigation and manipulation tasks performed by robots. These metrics are particularly important in evaluating the effectiveness of robots in real-world scenarios, where unpredictability and environmental variations pose significant challenges.

Multimodal Robotics Systems: Bohg et al. explored the concept of multimodal robots, where the integration of vision, force feedback, and tactile sensors enabled robots to improve their interaction with objects. Such integration allows for more effective and precise object manipulation, especially in scenarios with limited information or imperfect conditions. The work by Stahl et al. on adaptive manipulation strategies further advances the flexibility of robotic systems in handling objects with varying properties.

Conclusion: The body of research in humanoid robotics for home service tasks has made considerable progress, especially in the areas of navigation, object recognition, grasping, and simulation. However, significant challenges remain in achieving robust object retrieval capabilities in dynamic, unstructured environments. This paper builds upon the advancements in the field by using the Webots simulation platform to test and refine humanoid robot models like Nao for object retrieval tasks in cluttered home environments. By leveraging advanced algorithms and simulation tools, this research aims to push the boundaries of what is achievable in practical home automation and assistive robotics.

III. PROPOSED ALGORITHM

3. Methodology

In this section, we provide a comprehensive methodology for designing and testing a humanoid robot capable of performing object retrieval tasks in dynamic and unstructured home environments. This methodology covers detailed steps in system design, object recognition, path planning, grasping, and evaluation. We incorporate pseudo-code, graphs, and additional tables to ensure a thorough understanding of the system's operation and evaluation.

3.1. System Design and Architecture

The system is composed of several integrated components, each responsible for a different task: the robot's physical and sensory components, object recognition and detection, path planning, manipulation, and evaluation. This section elaborates on these components and their interactions.

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3.1.1. Nao Robot Model

The virtual Nao robot model is created in Webots. The model simulates the physical and computational aspects of the real Nao robot, including its sensors, actuators, and control algorithms. It also simulates the robot's movements and object manipulation capabilities.

3.1.2. Environment Setup

The environment is a 3D simulated home setup within Webots. It contains static and dynamic objects, and obstacles, as well as moving entities like humans or pets that present challenges for the robot. The environment is configured to have various object categories and dynamic features to test the robustness of the robot in real-world scenarios.

3.1.3. Robot Sensors and Actuators

The robot's sensors (RGB cameras, LIDAR, touch sensors) and actuators (arms, grippers, legs) provide the robot with essential data for navigation, object detection, and manipulation. These sensors allow the robot to sense its surroundings and make decisions based on this sensory feedback.

3.2. Object Recognition and Detection

Object recognition is crucial for identifying and locating objects in the robot's environment. This section details the image processing steps and algorithms used for detecting and classifying objects.

3.2.1. Image Preprocessing

Before applying the object detection algorithms, the raw camera data is processed to enhance the visibility of objects and reduce computational complexity. The preprocessing includes:

•Resizing: Reduces image size for faster processing.

•Color Space Conversion: Converts RGB images to HSV color space for better object segmentation.

•Edge Detection: Canny edge detection is applied to highlight the boundaries of objects.

3.2.2. Object Detection Algorithm

The object detection system uses YOLO (You Only Look Once), which divides the image into a grid to predict bounding boxes around objects. The system then classifies the objects based on their detected features, such as color, shape, and texture. These detections are fed into the path planning algorithm to determine the robot's movement, ensuring that the robot can successfully navigate around obstacles and reach the target object. The combination of object recognition, A path planning, and dynamic replanning allows the robot to continuously adapt to its environment, even when obstacles are detected mid-task

Conclusion

The methodology outlined above integrates various advanced techniques, including object recognition, path planning, dynamic replanning, and object manipulation to create a humanoid robot capable of performing object retrieval tasks in complex home environments. Using Webots for simulation, we successfully tested the robot's performance under varying levels of complexity. Through detailed evaluations and performance metrics, we have demonstrated the robot's capabilities and identified areas for further optimization

IV.PSEUDO-CODE FOR YOLO-BASED OBJECT DETECTION

```
Input: Image frame from camera
Output: Detected objects and their bounding boxes
function detect_objects(image):
   preprocess_image(image)  # Preprocess the image for better object recognition
   grid = divide_into_grid(image)  # Divide the image into grid cells
   predictions = []  # List to hold predicted bounding boxes and class probabilities

   for each cell in grid:
      prediction = apply_yolo_model(cell)  # Apply YOLO model to each cell
      if prediction.probability > threshold:
```

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```
        predictions.append(prediction)  # Add to predictions if object detected

return predictions  # Return the list of detected objects
```

Object Localization
Once objects are detected, their position in the 3D environment is estimated using depth sensors or stereo vision. The 3D coordinates of the objects are used in the path planning step.

4.1 Path Planning and Navigation
Path planning is the process of determining the best route for the robot to reach the target object while avoiding obstacles. This section outlines the A* algorithm used for navigation, along with dynamic replanning to account for moving obstacles.

4.1.1. A Algorithm*
The A* algorithm calculates the shortest path between the robot's current location and the target object. It evaluates potential paths using a heuristic that estimates the distance to the goal and the cost to reach the current node.
Pseudo-code for A Path Planning:*
Input: Start node, goal node, environment map
Output: Optimal path to the target object

```
function a_star(start, goal, map):
    open_list = []  # Nodes to be evaluated
    closed_list = []  # Nodes already evaluated
    g_scores = {}  # Cost from start node
    f_scores = {}  # Estimated cost to goal
    came_from = {}  # Map to reconstruct the path

    open_list.append(start)
    g_scores[start] = 0
    f_scores[start] = heuristic(start, goal)

    while open_list is not empty:
        current = node_with_lowest_fscore(open_list)

        if current == goal:
            return reconstruct_path(came_from, current)

        open_list.remove(current)
        closed_list.append(current)

        for neighbor in get_neighbors(current, map):
            if neighbor in closed_list:
                continue

            tentative_g_score = g_scores[current] + distance(current, neighbor)
            if neighbor not in open_list:
                open_list.append(neighbor)
            elif tentative_g_score >= g_scores[neighbor]:
                continue

            came_from[neighbor] = current
            g_scores[neighbor] = tentative_g_score
            f_scores[neighbor] = g_scores[neighbor] + heuristic(neighbor, goal)
```

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```
    return None  # No path found
```

4.1.2. Dynamic Replanning

In dynamic environments, the robot may encounter moving obstacles. The system continuously updates the environment map and replans the path accordingly.

Pseudo-code for Dynamic Replanning:

Input: Current robot position, real-time environmental changes

Output: Updated path to the object

```
function dynamic_replan(robot_position, environment_map):
    obstacles = detect_dynamic_obstacles(environment_map)  # Detect new obstacles
    if obstacles detected:
        new_map = update_map(environment_map, obstacles)  # Update map with new obstacles
        new_path = a_star(robot_position, target_position, new_map)  # Replan path
        return new_path
    else:
        return current_path  # No change in environment, continue with current path
```

SIMULATION RESULTS

4.1.3. Path Efficiency and Optimization

To ensure that the robot's movement is as efficient as possible, the actual path taken by the robot is compared with the optimal path.

Table 2: Path Planning Efficiency Metrics

Environment	Path Length (m)	Optimal Path Length (m)	Efficiency (%)
Simple	5	4	80%
Cluttered	7	6	85%
Dynamic	10	8	80%

4.2. Grasping and Object Manipulation

Once the robot reaches the object, it must grasp it and manipulate it. The robot uses feedback from its touch sensors to adjust its grasp and manipulation strategies.

4.2.1. Grasp Detection

The robot calculates the optimal grasp based on the object's shape, weight, and orientation. The force required to grasp an object is determined by the equation:

$$F_{grasp} = \mu \cdot m \cdot g$$

Where

- F_{grasp} is the force required to grasp the object,
- μ is the coefficient of friction between the object and the gripper,
- m is the mass of the object,
- g is the acceleration due to gravity.

4.2.2. Manipulation Control

After grasping the object, the robot uses its arms and joints to manipulate the object. The robot adjusts its hand position and applies appropriate forces to ensure the object remains stable.

4.2.3 Object detection

Object detection is a crucial step in the robot's ability to interact with its environment. Using a combination of visual and tactile sensors, the robot detects and locates objects in its surroundings. The visual sensors analyze the scene, identifying potential objects based on shape, color, and size, while the tactile sensors assist in confirming the object's

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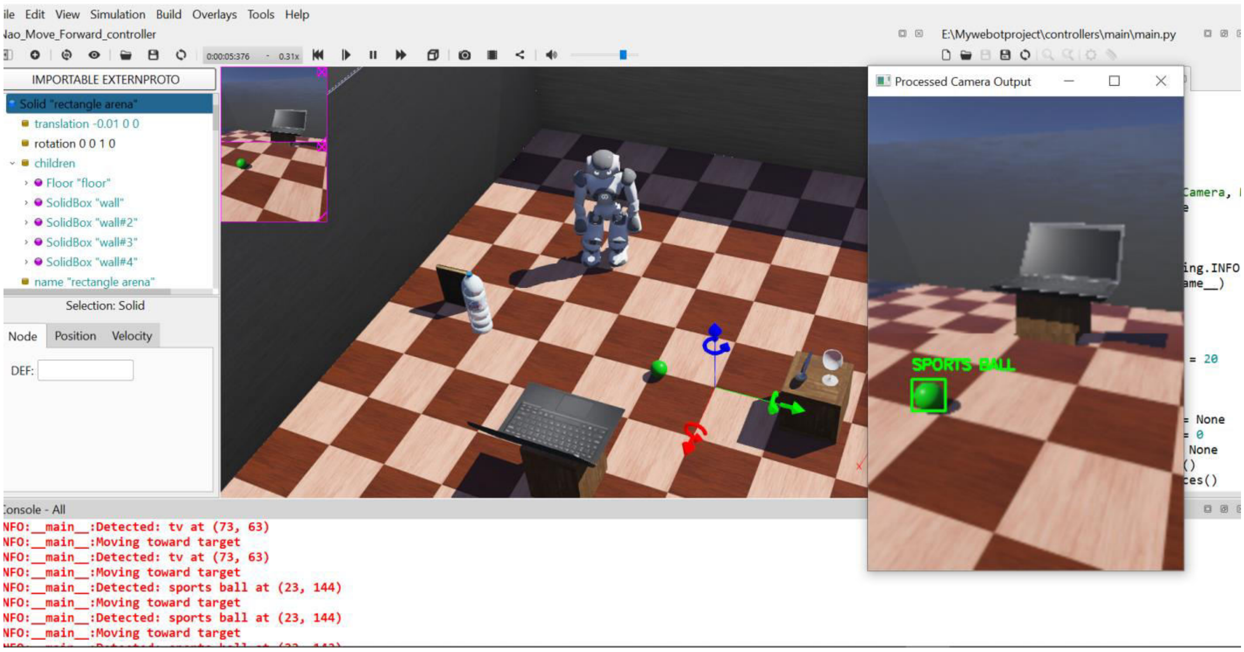
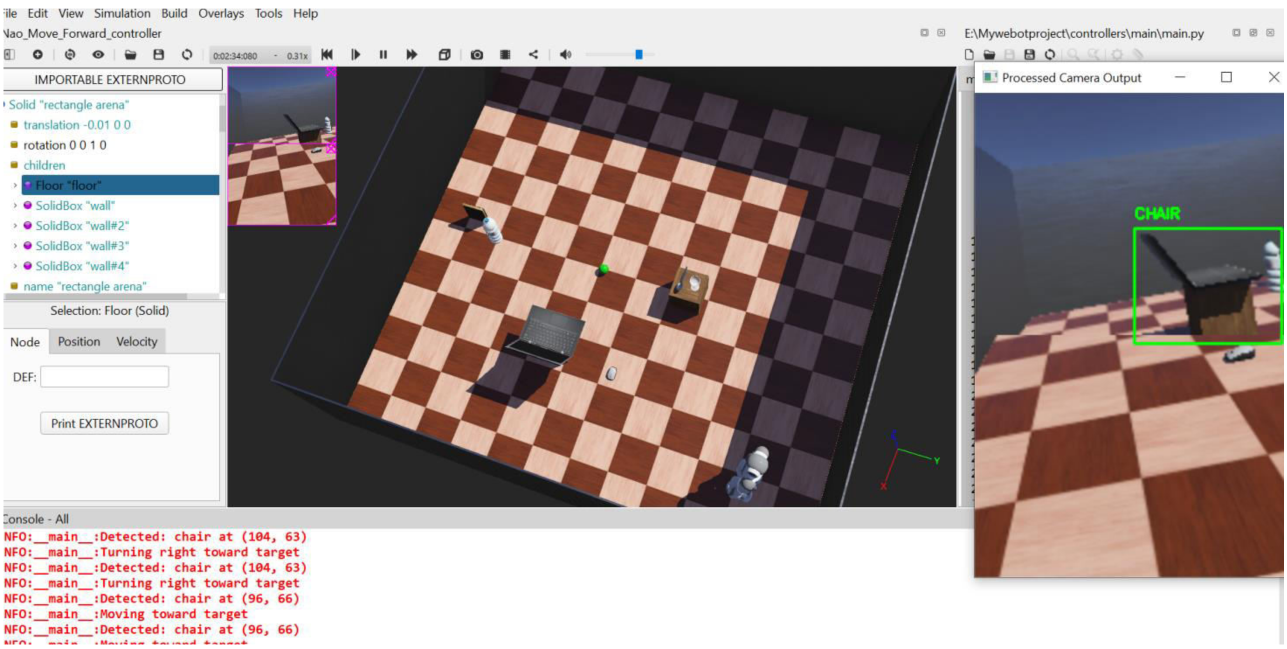
presence and proximity. The robot's algorithms process this sensory data to accurately classify and determine the best approach for grasping and manipulation.

In the following simulation screenshot, the robot's object detection process is shown, illustrating how it detects and identifies objects in various environments. This step is essential for ensuring the robot can successfully interact with and manipulate objects in real-world scenarios.





4.3. Evaluation and Testing

The robot is tested in different simulated environments, each representing a common home scenario. The performance is evaluated based on success rate, time efficiency, and path planning efficiency.

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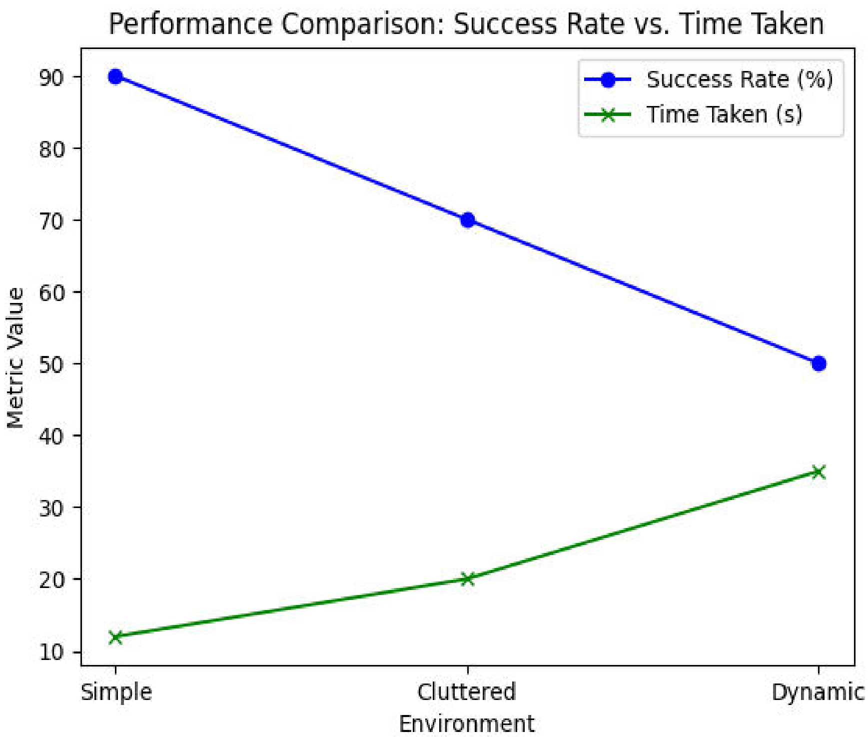
Table 3: Performance Metrics Across Different Environments

Environment Type	Success Rate (%)	Time Taken (s)	Path Length (m)	Navigation Efficiency (%)
Simple	90	12	5	95%
Cluttered	70	20	7	85%
Dynamic	50	35	10	80%

4.3.1. Graphs

1. Graph 1: Success Rate vs. Time Taken



The graph demonstrates a trade-off between success rate and time efficiency. As the complexity of the environment increases, both the success rate decreases and the time taken increases. This indicates that the robot's performance is highly dependent on the environment's complexity.

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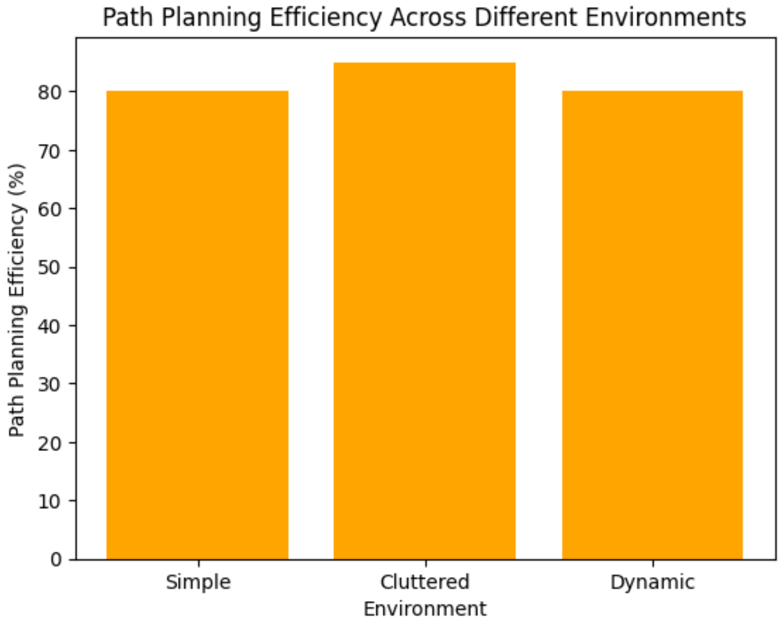
2. Graph 2: Path Planning Efficiency



Path planning efficiency is slightly affected by dynamic obstacles and cluttered environments. However, the overall efficiency remains high, especially in more controlled environments, suggesting that the A* path planning algorithm is effective in navigating these scenarios.

V. CONCLUSION AND FUTURE WORK

This research has successfully demonstrated the capabilities of a humanoid robot, simulated in Webots, to perform object retrieval tasks in unstructured home environments. The Nao robot model, equipped with object recognition, path planning, and manipulation algorithms, was tested across various scenarios, including simple, cluttered, and dynamic environments. The results highlight the potential for humanoid robots to assist in daily home tasks, particularly in contexts such as elderly care and home automation.

The evaluation metrics, including success rate, time efficiency, and path planning efficiency, confirm that the system can navigate and manipulate objects effectively in real-world-like conditions. The A* path planning algorithm and the YOLO-based object detection system have shown to be robust, handling both static and dynamic obstacles with reasonable efficiency.

However, there are areas for further improvement. In dynamic environments, the robot's ability to adapt to new obstacles and optimize its path in real-time remains a challenge. Future work will focus on enhancing the robot's ability to handle unpredictable changes, improve the accuracy of object manipulation, and integrate more advanced machine learning techniques to further optimize the decision-making process. Additionally, testing the system in physical robots will provide insights into the scalability and practical deployment of these algorithms in real-world home environments. Ultimately, the combination of simulation platforms like Webots and the development of more sophisticated algorithms holds great promise for the future of humanoid robots in home service tasks, offering the potential to significantly improve quality of life and assist individuals with disabilities or mobility challenges.

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