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A Robocentric Paradigm for Enhanced Social Navigation in Autonomous Robotic: a use case for an autonomous Wheelchair

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***Abstract*—The rise of autonomous technologies with unparalleled accuracy is revolutionizing computing and robotics by integrating machine learning techniques. This study focuses on advancing social navigation in autonomous robotics by improving object detection methods. We have refined the classification of objects within social environments into four distinct categories: living dynamic objects, non-living dynamic objects, living non-dynamic objects, and non-living non-dynamic objects. This differentiation in social navigation enables robots to process and respond to social cues, fostering a harmonious coexistence between humans and machines in shared spaces. Furthermore, we have introduced an adaptive proxemic zone surrounding these objects to define the boundaries for interaction. This concept, borrowed from human sociology, is instrumental in developing socially aware robots that respect personal space and societal norms. The proxemic zone is a buffer that helps mitigate potential conflicts or uncomfortable situations during human-robot interactions. The efficacy of our approach is validated through results presented herein, which lay the groundwork for the development of socially intelligent robots that can seamlessly integrate into human environments and interact with people in a more natural and empathetic manner.**

***Index Terms*—Object Detect, Proxemic Zone, Social Navigation, Robot-Human Interaction**

I. Introduction

In our rapidly globalizing world, technological evolution has been shaped by human needs and advancements in knowledge and materials since the first industrial revolution. This progression is exemplified by theories like Moore's Law, proposed by Gordon E. Moore, highlighting the exponential growth of microchip and processor capacities, typically doubling every two years [1]. This trend reflects the increasing computational power for complex activities and influences the integration of Machine Learning techniques in everyday human tasks [2], [3]. The emergence of intelligent systems capable of learning and adapting offers a revolutionary perspective in our interaction with technology, marking a significant shift in how we comprehend and engage with the world.

The challenge to robotics, extends beyond mere task execution; developers must consider the more social aspects of human-robot interaction and navigation, focusing on adaptive responses to context [4]. In line with these approaches, pioneering work introduces a robocentric perspective, aiming to bring assertive practicality to the field [5]. Building on this foundation, our work presents an architecture designed to enhance the interaction between robots and humans in shared environments. This architecture employs an objective classification system that categorizes objects into four distinct classes based on their dynamic and non-dynamic properties. Such classification ensures that the robot's movements are harmonious with those of the people in its vicinity, thus avoiding any restriction or interference in human mobility. This approach optimizes the robot's navigational capabilities and aligns with the ethos of creating machines that are adaptive to human presence and behaviour.

Continuing from the established framework, our classification system within the proposed architecture delineates objects into four distinct categories, each with specific characteristics and implications for the robot's navigation and interaction strategies. These categories are as follows: dynamic non-living objects (*e.g.*, vehicles), dynamic living objects (*e.g.*, people), non-dynamic non-living objects (*e.g.*, chairs), and non-dynamic living objects (*e.g.*, flowers). This categorization guides the robot's movement and interaction within its environment and in recognizing and responding appropriately to different elements in its surroundings. To do this, our work delves into an aspect critical to social robotics: the navigation concerning proxemic zones. The concept of proxemic zones, initially studied by anthropologist Edward Hall [6], plays an important role in the interaction dynamics between robots and humans. These zones delineate the spatial boundaries of human comfort levels in social interactions, which are crucial for robots to navigate and operate effectively in human-centric environments. Our architectural design incorporates these proxemic principles into each one of the objects detected in the scene, ensuring that robots respect these invisible yet significant boundaries.

Incorporating proxemic zones into the robot navigation process, as highlighted in recent research [7], enhances the social acceptability and integration of intelligent machines into daily life. By recognizing and adhering to these spatial norms, robots can interact more naturally and respectfully with humans, facilitating a seamless integration into various environments. This approach advances the technical prowess of robotics and addresses the socio-cultural dimensions of human-robot interaction. The emphasis on proxemic zones within our architecture marks a significant advancement in social robotics, aligning technological innovation with the nuanced complexities of human social behaviour.

The application of our research is exemplified through the use case of an autonomous wheelchair, a context where the subtleties of social navigation are paramount [8]. Our paper presents the results validating the efficacy of the approach, laying a foundation for developing new algorithms for socially aware robot navigation. These robots are envisioned to integrate into human environments, interacting with people naturally and seamlessly. The research presented herein contributes to the technological advancements in autonomous robotics. It addresses the sociological aspects of human-robot interaction, marking a significant step towards achieving harmonious coexistence.

Our research distinguishes itself in social robotics by integrating an AI-based object classification system with the concept of proxemic zones, a synthesis not commonly observed in existing literature. Unlike studies focusing on specific scenarios or theoretical aspects, our work emphasizes practical application across diverse settings, ensuring effective navigation and interaction in predictable and dynamic environments. This approach goes beyond technical navigation strategies by prioritizing user comfort and social norms, thus balancing technological advancement with user-centric design. Our contribution lies in creating a comprehensive framework that respects the physical space and is also attuned to the social context of human-robot interactions, marking a significant advancement in the practical deployment of socially aware robotic systems.

II. RELATED WORK

The development of social robots [9], [10] contributes to the process of integrating new technologies, mainly linked to artificial intelligence, in social environments where there may be interactions between Human and Machine, promoting efficiency and agility to yours activities. Neural networks, trained to recognize and categorize objects, play a crucial role in this landscape. A notable example is the YOLO (You Only Look Once) framework [11], which has become a staple in augmenting robotic navigation systems. Our paper uses this classifier as a starting point for navigation that adapts to the typology of objects in the robot's surroundings.

In a similar research line, the authors in [12] emphasize the importance of accurate object classification in natural settings, which is crucial for mobile robots navigating outdoors. The ability to discern between natural and artificial objects helps in path planning and obstacle avoidance, ensuring the robot's smooth operation in varied terrains. Similarly, the research [13] focuses on the significance of object recognition in indoor settings. This is vital for robots to identify and navigate around everyday indoor objects like furniture and doors, aiding in tasks ranging from domestic chores to assistive care in healthcare settings.

Omrani's work [14], also brings relevance to the development of detection of static and dynamic objects to promote good robotic navigation, considering that such objects that can enter the robot's locomotion space and their recognition bring new information for the robot in terms of a more complete system about predictability and suitability.

Focusing on robot social navigation, the concept of proxemics [6], which refers to the use of space in human-robot interaction, has garnered significant attention. Proxemics is crucial for ensuring that robots can navigate and interact with humans in a manner perceived as natural and comfortable. The study [15] delves into the subtleties of proxemics in the context of casual human-robot encounters in indoor environment. Their research highlights the importance of understanding and respecting personal space in various social contexts, emphasizing that appropriate proxemic behaviour by robots is essential for their acceptance and effectiveness in social settings. This work is going on the research line of similar studies in the current literature.

In [16], the authors use proxemic theory to define personal spaces and human-human and human-object interaction spaces and associate these regions to areas where the robots' navigation is forbidden or penalized. In other recent works, such as the one presented in [17], the authors analyse the state of works on human-robot proxemics. This review synthesizes the current state of knowledge in the field and sheds light on the diverse methodologies and approaches used to study proxemic interactions. It underscores the multidisciplinary nature of proxemics research, involving aspects of psychology, sociology, robotics, and computer science. The review also points out the varying cultural and individual differences in proxemic preferences, suggesting a need for adaptive and context-aware proxemic behaviours in robots.

These last studies indicate that effective social navigation for robots transcends mere physical movement through space [17]. It involves a deeper understanding of the social dimensions of the environment and human space utilisation. Therefore, incorporating proxemics into robot navigation systems requires careful consideration of human comfort levels, cultural norms, and situational appropriateness. Leveraging advanced machine learning techniques, our research enhances social navigation in autonomous robotics by introducing an object classification system to define the adaptive proxemic zone concept.

In this respect, in the work presented in [18], the authors describe an innovative approach to integrating autonomous wheelchairs within hospital settings. Their work is a testament to the potential of robotic aids in enhancing mobility and independence for individuals in healthcare environments. Incorporating autonomous navigation systems in wheelchairs necessitates a deep understanding of proxemics, particularly in crowded and dynamic hospital spaces, to ensure the safety and comfort of patients and healthcare staff.

Similarly, the authors in [19] delve into the challenges of navigating wheelchairs in environments fraught with obstacles. This study underscores the importance of advanced object detection and classification in enabling autonomous wheelchairs to manoeuvre safely and effectively, especially in environments not traditionally structured for robotic navigation. While these studies in assistive robotics focus primarily on enhancing the autonomous navigation of wheelchairs in complex environments, our research distinguishes itself by integrating a comprehensive understanding of social dynamics through proxemic awareness and object classification. Our approach addresses the physical manoeuvring challenges and sensitively adapts to the social contexts of human-robot interactions, ensuring a more empathetic and social navigation experience in shared spaces.

Traditional methodologies that use YOLO for computer vision processing focus their use around the literal determination of objects through trained classes, like chair, computer and others [20]. However, our focus with this work is on building an intelligent system that can encompass reduced classification into just four classes based in dynamic or static, that will help the robot to take decisions during your navegation in dynamic cases, and determine proxemic zones to make the best trajectory for the robot. We apply these concepts to a specific use case involving assistive robotics, particularly focusing on autonomous wheelchairs. This application is a prime example of how sophisticated object classification systems and proxemic awareness can significantly improve robots functionality and social adaptability in sensitive environments.

III. METHODS

In today's world, the ubiquity of semi-autonomous machines in everyday life is increasingly noticeable. These devices are adept at adapting to and interacting within dynamic environments, with a critical requirement being their ability to navigate these settings safely. To address this need, our research has developed a robotic system that integrates computer vision for object detection and innovative navigation techniques suitable for social contexts, specifically focusing on implementing proxemic zones. Moreover, we have introduced a classification approach within our robocentric perception system, wherein objects are categorized into specific classes that significantly influence the formulation of proxemic zones. Figure 1 overviews our proposed approach, illustrating its various sensing and data processing capabilities. The system encompasses several key components:

- Robot Camera: This is the initial phase of capturing visual information from the environment.
- Obstacle Detection: Using YOLOv5, this stage processes data from the camera to identify objects in the visual field.
- Finder: This algorithm is responsible for locating objects on the map
- Generation of the Proxemic Zone: The final step in the flowchart, where both the distance measurement and the detected object class are used to generate a proxemic zone—a term that usually refers to the region surrounding each object.
- Navigation: Responsible for moving the robot from one position to another

The legend in Fig. 1 lists the components involved in the process.

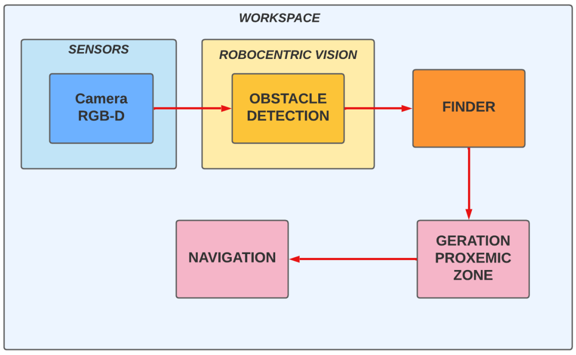

Fig. 1. Process flow diagram illustrating the generation of proxemic zones corresponding to classified objects.

A. Workspace

To carry out this work, we relied on the use of a motorized wheelchair adapted by GIPAR (Innovation and Research Group in Automation and Robotics) to carry out navigation autonomously, [21], as illustrated in Figure 2. To acquire visual data, we used the RGB-D stereo camera (ZED 2i), that is, a color camera with depth function. Odometry, responsible for guiding autonomous navigation, has two location systems, IMU and encoders. For data processing, we used a laptop equipped with an Intel Core i7-10750H processor, NVIDIA GeForce GTX 1650 4GB graphics card, 8GB of RAM and 512GB SSD. The operating system used was Linux Ubuntu 20.04, and ROS Noetic, version compatible with Ubuntu.

B. Virtual Environment

For the implementation of this study, the Robot Operating System (ROS) and robotic simulation software (GAZEBO). A virtual environment with 3D objects was created to enhance the simulation's realism and mirror the diverse array of objects in actual settings. This allowed for testing the robot's ability to detect and classify objects and the definition of specific proxemic regions.

We integrated the ROS navigation stack into our framework, augmenting it with the capability to incorporate proxemic

Fig. 2. Modified motorized chair for autonomous navigation.

zones into the mapping process. This addition enabled the system to navigate efficiently and respect the spatial boundaries defined by proxemic principles. As a result, the robot could generate proxemic regions for each object within the virtual environment, simulating realistic human-robot interaction scenarios.

C. Object Detection and classification

In artificial intelligence, computer vision is a subarea that empowers machines to derive meaningful information from the real world. This field spans a wide spectrum, from processing images to applications in diverse sectors such as industrial automation, medical diagnostics, and surveillance. A fundamental aspect of computer vision is object detection in robotics for autonomous vehicles working in human environments. Accurate identification of entities such as pedestrians, vehicles, and road signs is critical for social-awareness navigation for these systems. This capability is quantified by metrics like accuracy, precision, and recall, which evaluate the effectiveness of object detection algorithms in varied environments.

In our research, we utilize an RGB camera with a resolution of 640×480 pixels for environmental image capture. The images are processed using the YOLO, Object Detection Algorithm, formulated as:

$$P(\text{object}) \times \sum_{i=1}^{n} P(C_i|\text{object})$$

where $P(\text{object})$ estimates the probability of an object's presence in the image, and $P(C_i|\text{object})$ calculates the conditional probability of the object belonging to class C_i out of n classes. We propose a new classification system, tabulated in Table I, consisting of four obstacle categories. This system groups objects by living/non-living (L/NL) and static/dynamic (S/D) attributes with a binary classification approach:

$$\text{Class} = \begin{cases} 1 & \text{if L and S} \\ 2 & \text{if NL and S} \\ 3 & \text{if L and D} \\ 4 & \text{if NL and D} \end{cases}$$

For example, dynamic non-living obstacles such as cars are classified under Class $= 4$. This streamlined classification enables object categorization, enhancing the robot's navigation and interaction capabilities in human environments.

TABLE I
RELATIONSHIP BETWEEN SECURITY ZONE REGION AND DETECTED OBJECT CLASS

Class Group	*Example of Objects*
Dynamic Object - Living Being	Human, animals
Dynamic Object - Inanimate Being	Vehicles, other robots...
Static Object - Living Being	Plants
Static Object - Inanimate Being	Table, chair

D. Finder

This section focuses on the Finder algorithm, which was developed to improve robotic navigation by detecting obstacles and generating appropriate safety zones for each. Unlike traditional approaches that use uniform safety zones across the navigation map, Finder dynamically adjusts these zones to suit each detected obstacle. This functionality allows for more context-aware navigation, adapting the robot's path according to the specific obstacles it encounters.

Finder uses computer vision techniques to identify obstacles and a depth camera to gauge their distance from the robot accurately. This dual approach ensures the robot recognises the obstacles and their spatial relationship within its environment. Fig. 3 provides a comprehensive overview of how Finder operates, illustrating the process from data input to the final output. This depiction offers insights into the algorithm's operational flow, highlighting how it processes environmental data to make informed navigation decisions.

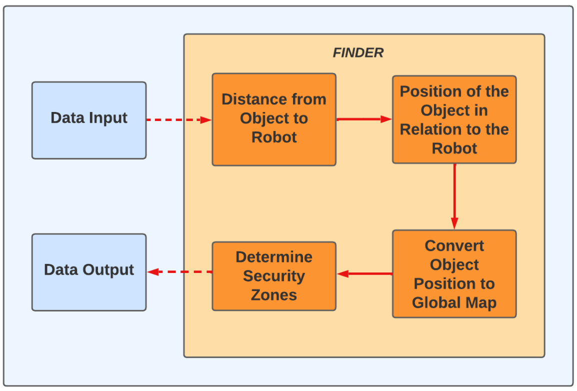

Fig. 3. Flowchart illustrating the operational process of the Finder algorithm.

1) Data Acquisition for the Finder algorithm: The Finder algorithm's effectiveness depends on acquiring 3D data from the environment using a depth camera, the YOLOv5 model, and the robot's positional data on the map.

This depth data is then published on a ROS topic, facilitating the communication between the different services in the proposed system.

Concurrently, the YOLOv5 object detection model identifies objects in the camera's field of view, providing data like each object's class and bounding box. When an object is detected, YOLOv5 generates bounding box coordinates $(x_{\text{min}}, y_{\text{min}}, x_{\text{max}}, y_{\text{max}})$, which are used to determine the object's location and size. This information is also communicated via a ROS topic.

2) Distance from Obstacle to Robot: In our proposal, implementing proxemic zones depends on the robot's ability to measure distances between itself and detected objects. We use a method that calculates the midpoint of a bounding box generated by the object detection algorithm.

3) Determining the Object's Position Relative to the Robot: Upon calculating x_{mid} and y_{mid}, the central points of the bounding box, the algorithm then focuses on determining the object's distance from the robot's camera. This value is obtained from the depth camera data, specifically from the previously calculated D_{pixel} array.

4) Convert Object Position to Global Map: In our paper, we address the need to contextualize the robot's perception within its environment. Although the previously determined coordinates are relative to the robot, understanding the robot's position on the map is crucial. This knowledge allows us to combine the position and orientation data of the robot with geometric calculations to pinpoint the location of obstacles on the map. The position of the obstacle in the map coordinates is determined using the following equations:

$$X_{o.m} = \left\{ \sin\left[\gamma + \sin^{-1}\left(\frac{Y_{o.r}}{\text{dist}}\right)\right] \times \text{dist} \right\} + X_r \quad (1)$$

$$Y_{o.m} = \left\{ \cos\left[\gamma + \sin^{-1}\left(\frac{X_{o.r}}{\text{dist}}\right)\right] \times \text{dist} \right\} + Y_r \quad (2)$$

In these equations, $X_{o.m}$ and $Y_{o.m}$ represent the obstacle's coordinates on the map. The variables X_r and Y_r are the robot's coordinates on the map, while $X_{o.r}$ and $Y_{o.r}$ are the obstacle's coordinates relative to the robot. The term dist is the distance from the robot to the obstacle, and γ is the orientation angle of the robot.

E. Proxemic Zones

In our research, the concept of proxemic regions in robotics is redefined to encompass the distance social robots should maintain from humans during interactions and the robot's safety in the environment. This work introduces a novel perception of these spaces, considering human comfort and robotic safety. Since proxemic zone classifications traditionally apply to interactions with people, we present the term 'safety zone' for object-related distances. The extent of these safety zones correlates with the category into which an object is classified. In Table II, specific spaces for each class's proxemic zone are suggested, considering potential hazards to both the robot and the object.

TABLE II
RELATIONSHIP BETWEEN SAFE ZONE REGION AND DISTANCE IN METERS

Order	*Class Group*	*Safety Zone*
1	Dynamic Object - Living Being	1.5 m
2	Dynamic Object - Inanimate Being	1.0 m
3	Static Object - Living Being	0.4 m
4	Static Object - Inanimate Being	*

* Defined by the navigation system

Notably, the safety zone for the 'Dynamic Object - Living Being' class is the largest, addressing both the physical risks and potential human discomfort caused by the robot's proximity. The second largest safety zone is allocated for dynamic non-living objects, recognizing the potential dangers these moving objects pose to the robot. For the last class, specific distances are not provided, as the navigation algorithm typically pre-determined these non-dynamic objects ($e.g.$, A* algorithm), being static elements already present in the robot's mapped environment. This approach ensures a comprehensive and adaptive navigation strategy, balancing safety and social acceptability requirements.

IV. RESULTS

Our research focuses on several critical aspects of robotic perception and social-awareness navigation, including environmental perception, obstacle classification, and the generation of proxemic zones. These components are integral to enhancing the autonomous navigation capabilities of robots, particularly those that rely on environmental perception [22], [23]. Using this information, the robot is programmed to travel from one location to another, adeptly identifying and circumventing obstacles while maintaining a safe distance.

This section presents the outcomes of implementing each one of the stages of our robocentric paradigm for enhancing social robot navigation. First, the results of the proposed classification algorithm are presented, detailing its performance in a series of tests conducted in both real-world and simulated environments. Subsequently, we showcase the results of the proxemic zones generated by the algorithm, emphasizing their dual role in facilitating social interaction and ensuring safety. The section finishes with an in-depth evaluation of the complete robocentric navigation algorithm, where we rigorously test its efficacy through a series of real and simulated experiments utilizing an autonomous wheelchair. These experiments are designed to comprehensively assess the algorithm's capabilities in practical scenarios, demonstrating its applicability and effectiveness in enhancing the navigation and interaction of autonomous wheelchairs in real environments.

A. Object classification system

Central to our methodology is implementing the object classification system, categorizing objects into four distinct classes: Dynamic Object - Living Being, Dynamic Object - Inanimate, Static Object - Living Being, and Static Object - Inanimate. This categorization encompasses many objects, each sharing common characteristics within their respective class. The aim is to streamline the information the robot processes, facilitating the efficient generation of a safety zone. In Figure 4, our algorithm demonstrates its capability to identify a person, a bench, and a moving vehicle.

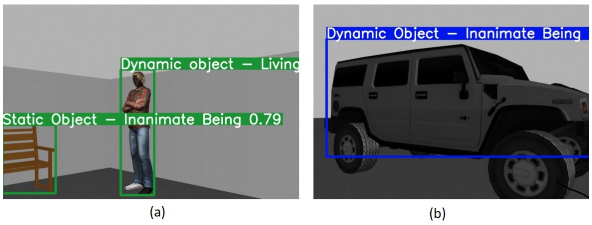

Fig. 4. (a) Classification of the person in Dynamic Object: Living Being and of a bank in Static Object: Inanimate Being, (b) Classification of the car in Dynamic Object: Being Inanimate.

B. Adaptive Proxemics for social navigation

In autonomous navigation, a critical functionality of robots is their ability to identify and safely navigate around objects. They must maintain a safe and social distance from these obstacles, a concept integral to generating safety areas [24]. These areas, particularly regarding humans, are often referred to as proxemic zones, which describe spaces where interactions are deemed socially acceptable and non-intrusive [25]. Our work brings a new perspective to this concept by assigning a safety zone to each classified object category. In our methodology, each object class is assigned a specific safety zone. We evaluated the effectiveness of these zones using the GAZEBO 9 simulator. The robot is programmed to identify an obstacle and, based on its classification, generate the appropriate safety zone. In the first set of tests, the robot successfully identifies an object from each class and creates a corresponding safety zone. Figures 5, 6, and 7 illustrate the proxemic zones generated around a person (Dynamic Object: Living Being), a vase (Static Object: Living Being), and a car (Dynamic Object: Inanimate), respectively. These figures show the robot's ability to avoid or take into account obstacles while respecting their safety zones, ensuring safe distances from living beings and inanimate objects.

In the second series of tests, the robot was placed in an environment with two objects of different classes. The objective was for the robot to traverse from one side of the room to the other, negotiating past these objects while respecting their safety zones. Figure 8 depicts the robot's starting point, with the planned shortest path (green line) and the initial object detection. As the robot approaches the objects (Figure 9), the safety zones become more accurately defined, and the robot's trajectory is adjusted accordingly.

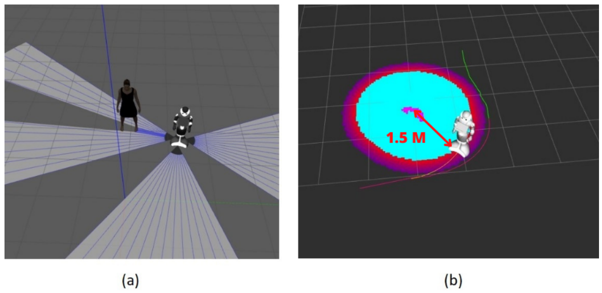

Fig. 5. Dynamic Object - Living Being: (a) simulation in the Gazebo scenario detecting a person, (b) representation of the scenario and visualization of sensors in RViz.

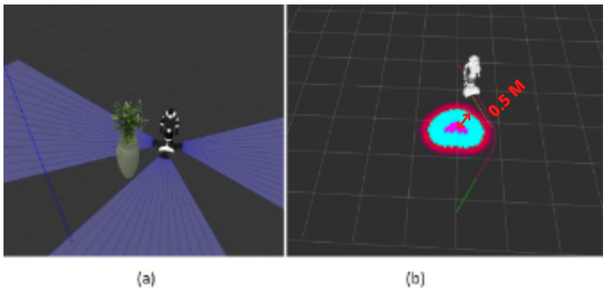

Fig. 6. Static Object - Living Being: (a) simulation in the Gazebo scenario detecting a plant, (b) representation of the scenario and visualization of sensors in RViz.

Figures 10 and 11 show the robot in the final stages of its journey, bypassing the object on its left. Despite no longer detecting objects, the robot's trajectory remains altered, respecting the established safety zones.

These tests, conducted in both simulated and controlled environments, effectively illustrate the capability of our algorithm to identify objects accurately, classify them into predetermined categories, and generate appropriate safety zones based on these classifications.

C. Use case: autonomous wheelchair

Transitioning from virtual environment tests, our research progressed to validate the Robocentric strategy for social robot navigation in real-world settings. For this practical test, we

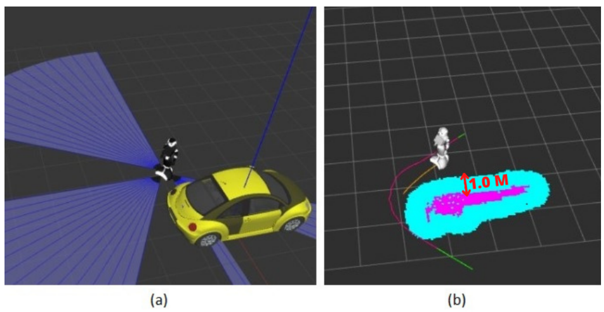

Fig. 7. Dynamic Object - Inanimate Being: (a) simulation in the Gazebo scenario detecting a car, (b) representation of the scenario and visualization of sensors in RViz.

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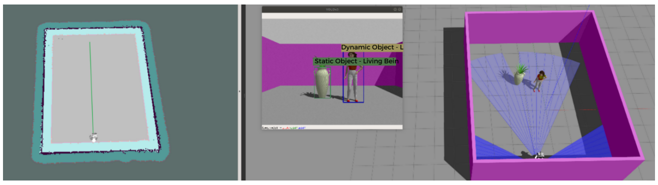

Fig. 8. Robot starting point. From left to right: visualization of the map in RVIZ, identification of objects by YOLO, and visualization of the environment in Gazebo.

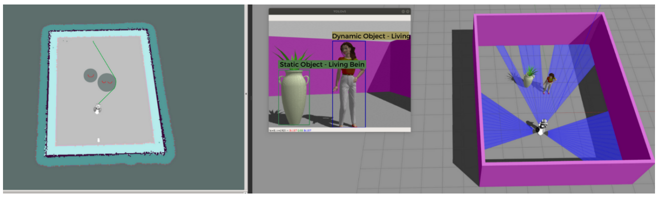

Fig. 9. Visible security zones. From left to right: visualization of the map in RVIZ, identification of objects by YOLO, and visualization of the environment in Gazebo.

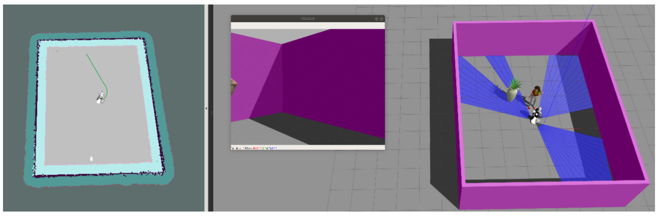

Fig. 10. Robot circumventing the object on its left. From left to right: visualization of the map in RVIZ, identification of objects by YOLO, and visualization of the environment in Gazebo.

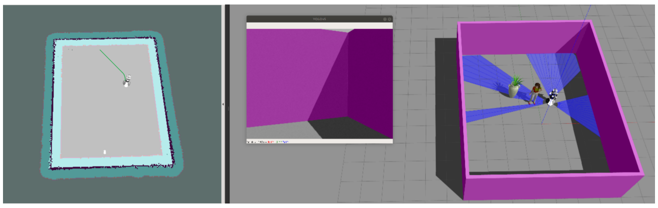

Fig. 11. Final stage of the robot's trajectory. From left to right: visualization of the map in RVIZ, identification of objects by YOLO, and visualization of the environment in Gazebo.

positioned the robot in a room interspersed with objects from various classes. The robot's task was to traverse from one side of the room to another, navigating past these objects while strictly adhering to their designated safety zones.

In Fig. 12, showcase a scenario where the robot visually identifies 3 objects and then generates a safety zone around the nearest object, Dynamic Object - Inanimate Being (other robots), then defines the path to follow (red line), then Fig. 13 the robot encounters a chair. Upon detection, the robot generates a safety zone around the chair and accordingly adjusts its trajectory to circumvent the obstacle. The path, marked by a red line, highlights the robot's shortest planned route before the obstacle detection.

In Figure 14, the robot identifies a person and promptly generates a second safety zone. The updated robot trajectory, considering both obstacles, ensures the robot passes between them without encroaching upon their safety zones. We have documented the process in a video to provide a comprehensive view of the robot's navigation in a real environment. This video can be accessed through the following link: https://youtu.be/IwYOkD_M0IQ.

V. Conclusion

Our research has successfully demonstrated a novel approach to enhancing autonomous robotic navigation by integrating advanced object classification and proxemic zone generation. The key innovation of our work lies in developing a four-category classification system for objects, enabling robots to navigate and interact intelligently in dynamic, human-centric environments. This system classifies objects as either dynamic or static and as living beings or inanimate, thereby allowing robots to make informed decisions about their navigation strategies.

The practical application of our methodology was tested using the Robot Operating System (ROS) and GAZEBO simulation software. These tests, conducted in simulated and real-world settings, validated the robot's ability to identify, classify, and maintain appropriate safety distances from various obstacles. The results underscored the efficiency of our approach in enabling robots to safely and socially navigate spaces shared with humans, thereby addressing a critical need in the field of social robotics.

Looking ahead, several avenues for further research and development have been identified. We plan to explore ways to improve the robot's perception system, considering factors such as varying light conditions, environmental dynamics, and other real-world challenges that could affect the system's performance. Besides, further studies will focus on the social aspects of human-robot interactions. We aim to investigate how different demographic groups perceive and interact with robots, using these insights to refine the proxemic zones and improve the overall user experience. Finally, we will explore the application of our system in various fields, such as healthcare, hospitality, and urban mobility, to assess its effectiveness and utility across different sectors.

Fig. 12. Robot navigating around the object on its left. From left to right: map view in RVIZ and real-time environment view.

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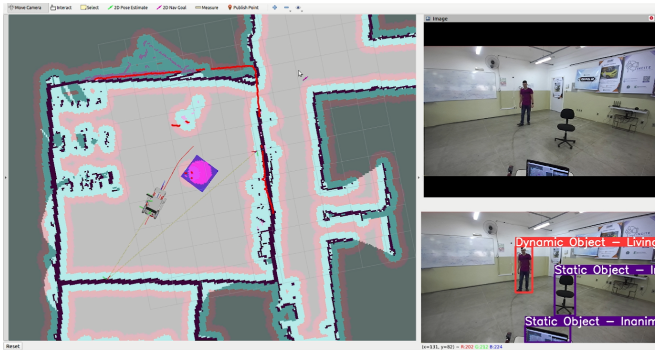

Fig. 13. Robot navigating around the object on its right. From left to right: map view in RVIZ and real-time environment view.

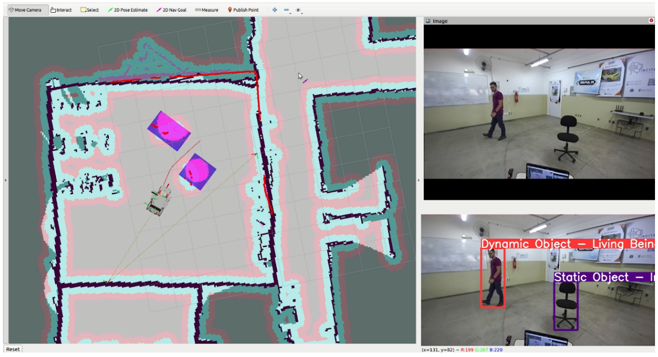

Fig. 14. Final stage of the trajectory. From left to right: map view in RVIZ and real-time environment view.

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