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REGULAR PAPER

Evaluation of ROS Navigation Stack for Social Navigation in Simulated Environments

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Abstract
Accuracy and safety are necessary characteristics in social navigation. These characteristics still constitute a challenge in this area. Yet, human comfort is the main goal in interactions involving human beings. The ROS Navigation Stack (RNS) allows the variation of local path planning methods. This paper consists in a comparative study of methods related to social navigation. This study promotes better social navigation on Home Environment Robot Assistant (HERA). This is a robot platform developed by FEI University Center. This work evaluated various parameter combinations: type of environments, types of obstacles, local and global planning algorithms and costmaps. The work also evaluated people in static, dynamic and interacting ways. This study observed aspects of safety, accuracy of estimated time and space. Other aspects observed are the smooth trajectory realized and respect for personal space. The experiments performed 1000 attempts for 37 combinations of methods, environments and sensors. In total, the experiments counted 37000 attempts. With these experiments, was possible to select a configuration for the navigation system. The point to the Timed Elastic Band (TEB) as a local planner and a proxemic costmap as a good combination. The results reach 97.6% of success in a more complex environment with this combination.

Keywords ROS · Path planning · Performance evaluation · Social evaluation · Social navigation

1 Introduction

A mobile robot should be able to navigate freely in its environment. It should address common issues regarding autonomous navigation such as mapping, localization, motion planning, and motion control. However, the coexistence of robots and humans in the same environment adds some news dimensions to mobility, like comfort and sociability. People should not be treated as simple obstacles, because there is a set of social and cultural rules that dictate how people should move. Naturalness is related to similarities between robots and humans in the low-level behavior pattern; comfort refers to suppression of annoyance or stress to the humans in interactions with the robot, while sociability deals with the robot's suitability to high-level socio-cultural patterns.

This paper focuses on the social navigation challenges presented in [12]. The motivation for this work lies in the difficulties encountered to treat the navigation of an autonomous service robot in a safe, natural, social and comfortable way for humans that interact in the same context of use. Exhaustive experiments were carried out with various environments, types of obstacles, simulated people in a static and dynamic way, interacting with other people and objects, also varying local and global planning algorithms and costmaps.

This work aims to increase human receptivity while maintaining safe navigation in an environment with different types of objects. An optimal configuration for the navigation process is selected to make the robot navigation safer, natural, social and comfortable for humans while providing sociability in the robot's behavior. Some methods of global and local planning were tested, with a variety of sensors, navigation costmaps and environments. This study was completely evaluated in simulated environments. Real environment experiments will be conducted in a future work.

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This study contributes on the following:

- Methodology presented for the development of a social navigation that takes into account different types of objects present in the environment as well as the comfort of people who interact with the robot.
- Evaluation and selection of a set of methods and sensors that best suit the robotic platform for social navigation.
- Introduction of new evaluation metrics that assess spatial and temporal coefficients in addition to the level of naturalness and sociability necessary to carry out social navigation.

After this introduction, the next sections are organized as follows: Section 2 presents concepts and a review on mobile robot navigation and social navigation. Section 3 presents the materials, methods and metrics used in this study, such as testing environment, robot, software tools and applied methodology. In Section 4 the results and discussion are presented. Finally, Section 5 presents conclusions and future works.

2 Background

Social robot systems capable of assisting human beings must address not only traditional robotics research topics (movement planning, navigation and manipulation), but also must have human interaction skills. In particular interest to this project are the social robots designed to share the living space and have degrees of interaction with one or more human users, like social gatherings and conversations. The next subsection presents definitions of a series of key concepts used throughout this study and some related works.

2.1 Concepts

2.1.1 Navigation

According to [8], collision prediction approaches for mobile robots can be divided into two categories: global and local. Global techniques, such as roadmaps, cell decomposition and potential field methods generally assume that a complete model of the environment and of the robot is available. The advantage of global approaches lies in the fact that a complete trajectory from the starting point to the target point can be calculated. However, these approaches are not adequate to avoid obstacles quickly, and in this case local approaches [8] are more appropriate.

The most common local planners found in the literature are the Base Local Planner (Base) or Trajectory Rollout [9] and the Dynamic Window Approach (DWA) [8]. They are planners that provide control for a mobile base on a 2D space. Using a map, the planner creates kinematic trajectories for a robot to move from a start point to an end point. The DWA planner differs from the Base planner in the way it controls discretized space. While the Base local planner checks all future simulation states [9], the DWA local planner checks only the spaces immediately after the current state.

Other known planners are the Elastic Band (EBand) [20] and the Timed Elastic Band (TEB) [22]. These types of planners use the bubble concept which is defined as a subset of maximum location for a free area in a given configuration and which allows the robot to move in all directions without causing a collision [24]. The bubble is generated using the simplified model of the robot in conjunction with information available on the map. The Bubble band takes into account forces from objects and internal forces trying to minimize the energy between adjacent bubbles.

The EBand is a planner that generates a deformable and collision-free path. It deforms the generated path in real-time, keeping it away from obstacles, and continues to deform as changes in obstacles are detected. This allows the robot to adapt to an obstacle that moves unexpectedly. TEB uses the same principle as EBand, however, it focuses on time optimization. TEB also works with minimizing the cost function instead of applying forces [22].

Another important concept is the costmap or occupation grid [7]. It is a weight matrix used by a navigation system to store probabilistic information about obstacles [9]. In an occupancy grid, the environment is represented by a discrete grid where each cell is filled (part of the object) or kept empty (part of free space) [24]. It is commonly used to store information locally for short-term obstacle avoidance and globally for long-term route planning.

2.1.2 Social navigation

If only the collision avoidance is taken into account while deciding on an optimal location and trajectory, it is possible to create behavior in the robot that is considered uncomfortable, rude or inappropriate [2]. According to [21], social navigation is the strategy displayed by a social robot that identifies and follows social conventions in terms of space management, in order to preserve a safe and comfortable interaction with human beings. The resulting behavior is predictable, adaptable and easily understood by humans.

In addition to the idea of social navigation, trajectory planning must be carried out so that the robot also does not cause any kind of discomfort for humans [12]. People should not be regarded as simple obstacles, as there is a set of social and cultural rules that govern how people move, such as, for example, always approaching a person in front of them.

In [12], the authors split the main factors of social navigation into comfort, naturalness and sociability. Comfort reflects the state of mind regarding safety and well-being.

It is a complex measure to be evaluated, as it involves the perception of context, social signals, micro expressions and temporal analysis of human behavior. At the same time, this measure is very important as a response to a social robot. Naturalness reflects the behavior of a robot, seeking behavior as close as possible to the human being. Finally, sociability reflects the way the robot should behave in social environments.

People in a social environment are expected to follow a certain social rule, including distance rules. The proxemics theory, proposed by in [11], is the study of manipulation and dynamics interpretation of human social behavior that are controlled by socio-cultural rules in social gatherings. This study defines cultural rules and intimacy zone, personal zone, social zone and public zone. To allow socially accepted human-robot interaction, a robot must have the ability to understand and respect this concept.

2.2 Related Works

This review aims to investigate the state of the art on navigation systems of mobile social robots. The search words used were " *robots or robotics*", "*human aware or socially aware*", "*navigation*" and "*model or framework*". In this review, the aim was to verify if the works in the literature develop or use valid models for social navigation; which aspects of human receptivity are addressed, among comfort, naturalness and sociability; what solutions were proposed; and what problems are still open. The papers present the themes of general social navigation framework [6, 17, 23], crowd navigation [1, 18] and proxemics [3, 14].

On social navigation frameworks, [27] proposes an efficient framework divided into 3 parts: (1) fusion of a 3D camera and laser sensors for detection and tracking of human beings; (2) motion modeling and positioning and (3) integration of modeling with trajectory planning. In [23] was presented a modification of the ROS nav_core package to use social navigation. Tests were performed in simulated environments. Finally, it also presents an architecture for the social navigation system. In [17] presents a framework for social navigation by developing a fuzzy controller to perform multi-tasks in a crowd environment, as a challenge. They plan in future work to build a more realistic model and implement it in a real robot.

Concerning navigation in crowded environments, [18] presents a plan based on the intentions of the human being. It deals with the classification of human intentions and prediction of future movements in a dynamic environment shared between robot and human being. It has an offline training phase, with tests carried out in simulated and real environments, but no tests were carried out with real robots navigating. In [1] was presented the formulation of a Bayesian approach to global online learning of a crowd model.

In [14] was presented an approach to social navigation using learning. This work compares its method with those of proxemics. It uses data from surveillance cameras noted with movement of people to carry out the training. In [3], a real-time algorithm for social navigation was featured. The tests are carried out in simulated environments with dozens of pedestrians. The work uses the concept of proxemics and interpersonal distances.

The research entitled "The office marathon: Robust navigation in an indoor office environment" [16], presents a study of robust navigation for mobile robots in office environments. It presents a problem in which robots are able to avoid obstacles and walls with laser sensors, but have difficulty to avoid obstacles beyond the laser reach. The article explores how to treat 3D obstacles and small obstacles in the path of the robot. The challenge was to avoid obstacles with a non-trivial 3D structure, as well as navigate through tight environments such as corridors and doors. The author uses the autonomy time in the autonomous navigation task as a proof of the robustness of the navigation system. To evaluate the competence of navigation, the robot was faced with some tests, both in simulated and real environments. The robot completed the navigation tasks in both simulated and real environments, avoiding small obstacles up to 6 cm high.

Recently, the work entitled "The Marathon 2: A Navigation System" [15] was published, in which current trends in robotics are studied to create a new navigation system based on the experiences of researchers working with the ROS framework. Among the novelties is the Spatio-Temporal Voxel Layer (STVL), the Timed Elastic Band (TEB) controller and a framework for fusing sensors. In this work, the robot traveled approximately 60 km during the experiments, using the new ROS2 framework with the new navigation stack called navigation2.

In [13], the authors develops and implements a costmap of semantic layers (Fig. 1). The authors state that it is not enough for the robot to avoid obstacles just to stop collisions. It is necessary to treat obstacles differently, depending on the nature of each obstacle. There are several scenarios that take human personal space into account, where the shortest path is not always the best. The work divides the layers of the costmap into classes, the main of which are: Standard and human-robot interactions. The standard is derived from common costmaps used in literature and consists of a static map layer, representing the static map of the environment; obstacle layers, representing the obstacles identified by the sensors; voxel layer, also related to the sensed obstacles, however in 3D representation; and inflation layer, responsible for inflating obstacles, creating a collision-free region. The human-robot interaction layers composed of a proxemic layer representing the proxemic around each person; the

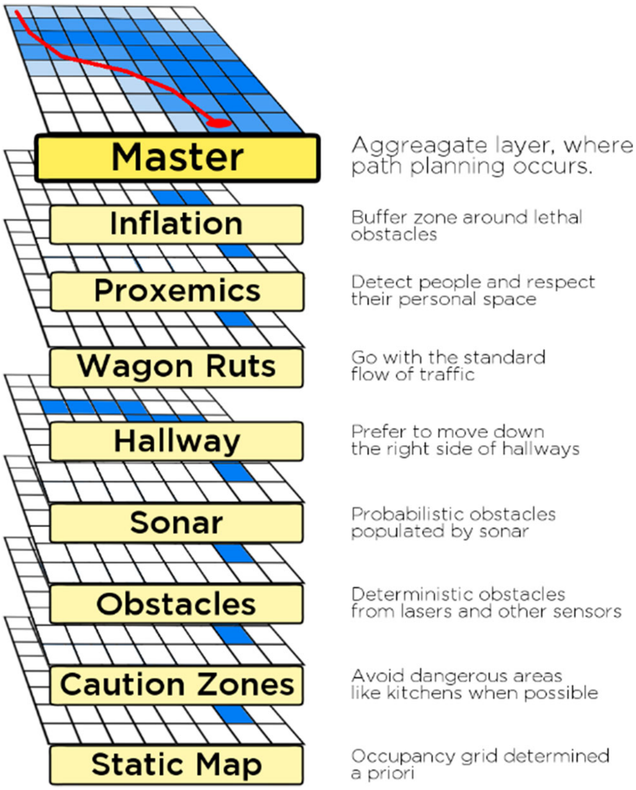


Fig. 1 Navigation layers proposed in [13]. Source: [13]

hallway layer is responsible for making the robot prefer tracing routes to the right of a human being, this is a social rule present in some cultures; and wagon ruts layer, responsible for reducing the cost in cells where a person has just passed, makes it easier for the robot to follow navigation flows. This layered costmap approach allows a wide variety of robotic behavior representation related to social rules.

In [26], the authors propose a generic and unified model for treating social navigation with a person or group of people standing or moving in different situations. The article starts by presenting some problems of social navigation observed in other studies. For example, most works deal with only one person in the environment, standing human beings or specific cases with the human being sitting or moving in a linear way and the lack of a model of generic situations. The work improves the concepts of safety, sociability and comfort. Physical and psychological security measures are used in addition to socially accepted behaviors of robots with human beings. The tests are carried out in simulated and real environments. The unified framework presented is built on top of conventional navigation and can be divided into two parts: (1) common navigation and (2) extension for social navigation. The tests were performed based on ROS costmap functions, simulating the robot available in the laboratory using DWA as the local planning technique. The robot used in the tests has 2 differential wheels. Three indices of comfort and human security based on proxemics and validation of the robot's behavior were presented. Finally, the tests were carried out with 10 different types of social situations (Fig. 2), where the robot has to navigate sequentially to approach static, dynamic individuals, and groups of humans in various social situations. The simulated environment presents 3 types of tests: simulation 1, only using human portrayed with static objects (conventional navigation); simulation 2, using dynamic social zone; and simulation 3, using the human approach framework proposed by the authors. The real environment also has 3 types of test: test 1, where the robot must approach a human or group of humans all standing; test 2, where the robot approaches the human or group of humans in motion; and test 3, where there is a human or group of humans interacting with an object of interest.

In [5] a specification of metrics for evaluating robot navigation performance is presented. In this work, the authors uses the concept of trajectory as a continuous sequence of states following a specific plan and the concept of path as a geometric curve that the robot describes in a configuration space. Only the shape of the curve is considered and the metrics are applied over these two concepts. The work shows the problem of a robot movement system that must consider the execution time evaluation of a robot navigation task, the model of the robot used, which implies dynamic and kinematic restrictions, the model of the environment and how the information on the environment is provided. As critical factors, the trajectory characteristics and problems related to physics and the choice of the movement system that affects the state of the world, such as the speed of the robot and its final position, must be evaluated.

In [5] the authors also divide the navigation problem into two subproblems. The first is related to the destination of the robot, where the challenge is to go to a specific position or to a position near an object or a person. The second problem is related to physics, in which the robot needs to maintain a safe and comfortable navigation and generate smooth and more natural trajectory. According to [5], if the trajectory is not smooth, it becomes more difficult to apply the control in real world, it can damage the robot with sudden movements and is result in a less socially accepted behavior.

The experiments in [5] were carried out in different environments, path planning algorithms and types of mapping, concluding that there still is a lack of tools to evaluate robot movement systems. It presents steps towards a standardization of the evaluation of navigation systems in tasks of pure movement. For the authors, mapping and locating are tasks that can be assessed separately.

Throughout the works presented in this literature review, several points of interest that serve to compose the

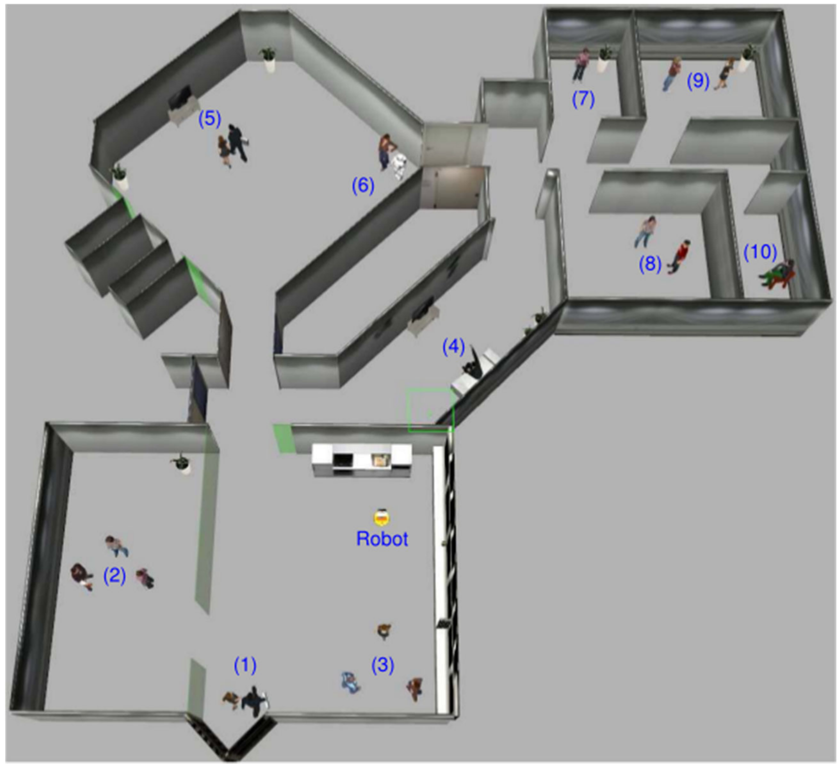


Fig. 2 Simulated scenario similar to an office with rooms, doors, corridors, walls, objects and human beings. Three people on the move, two people sitting and 13 people standing are distributed on the stage. Source: [26]

development of this work were studied. Initially, works that explore the robustness of a common navigation taking into account objects of difficult perception in everyday environments such as an office, as seen in [16] and [15]. The development of social navigation models was also observed, taking proxemics into account [3, 14], in an environment with one or more people. It was found that the trajectory planning methods using DWA were quite used, although more recent works, such as [15] suggest the use of TEB as a planning method. The basis for the development of a social costmap layer for this work was inspired by [13], while integration in common and social navigation was inspired by [26, 27]. To evaluate the experiments presented in this work, [5] inspired the development of the metrics used here. All of these works contributed to develop the methodology presented in this study and compose a scenario of tests and evaluation with metrics that explore both aspects of completeness of common navigation and comfort for social navigation that were never used before in others works.

3 Materials and Methods

In this section, a development method to evaluate and select a social navigation system is presented. The next subsections will list the materials used to carry out experiments (Section 3.1), what procedures were performed (Section 3.2) and finally, which metrics were used in order to evaluate the results (Section 3.3).

3.1 Materials

This subsection is divided into two parts. The first part describes the hardware configuration, including the machine where the simulations were carried out and the Home Environment Robot Assistant (HERA), used as a case study in this project. The second part contains the software settings used in this project.

3.1.1 Hardware

To perform the simulated experiments, a DELL XPS 8500 desktop computer was used, with intel® Core^{TM} i7-3770 CPU @ 3.40GHz processors with 8 cores, 12GB RAM and NVIDIA GeForce GT640 graphics card, and Ubuntu 18.04 LTS (Bionic Beaver) 64bits operation system.

The HERA [25] (Fig. 3) is used for the development of this project. The HERA robot was developed by the RoboFEI@home team[1] at FEI University Center.[2] It has 4 omni-directional wheels capable of moving the robot in any direction on a 2D plane and sensors used for 2D and 3D

[1] https://robofei.aquinno.com/athome/

[2] https://portal.fei.edu.br/

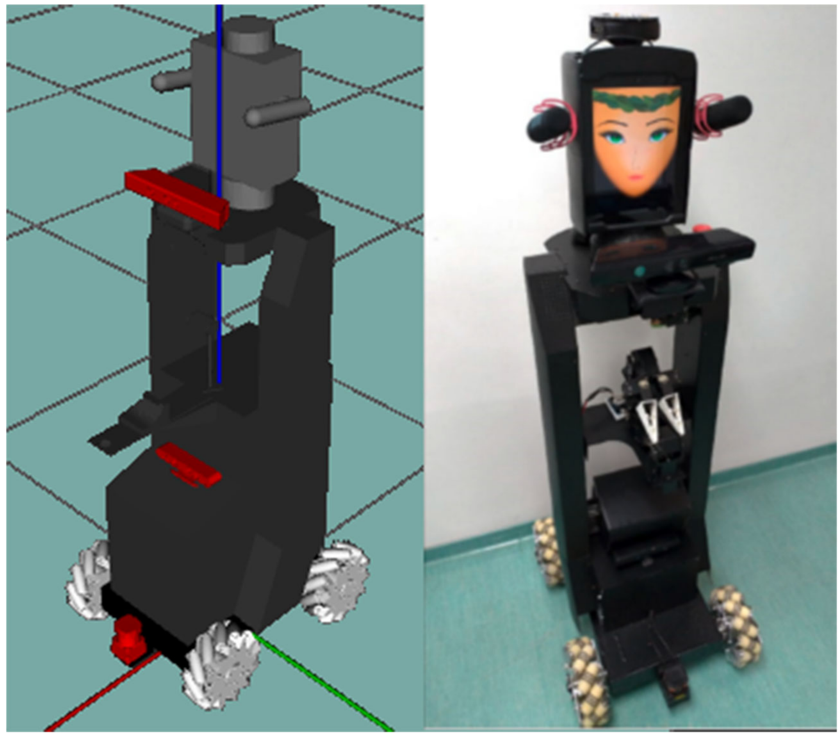


Fig. 3 Real and simulated HERA. In the simulated version (left side) you can see the sensors of the robot (red) used in this study

mapping. The component parts of the robot can be seen in the Table 1:

3.1.2 Software

The main tools used throughout this work were the Gazebo (version 9.0.0), used in the simulated experiments, and the Robot Operating System (ROS) Melodic Morenia for the development of the robot modules and the communication system for these modules.

3.2 Methods

The development methodology of this work aims to evaluate social, safety and accuracy criteria in navigation planning methods using different combinations of sensors, planners, map layers, and different environments. The job here is to select a navigation to be as natural, social and comfortable as possible for the human being. With this, it is possible to approach a more efficient, effective and safe navigation for the social context.

The experiments execute a script that follows the steps (Fig. 4): (1) Receive input data with a set of configurations that will be used in the experiment; (2) An initial data processing is performed. A set of regions ($R = [CR_0, ..., CR_{nr}]$) that has nr regions is extracted from the environment. This represents the regions through which the robot must pass during the experiment, here called ChechRegions ($CR = [P_0, ..., P_{ncr}]$). Each CR has ncr points ($P = [x, y]$). The points of the same region are space separated

Table 1 The component parts of the HERA (2020 version [25])

Control	Mini PC Zotak ZBOX-EN-1060K, Intel® Core^{TM} i5 7500 CPU, 8GB RAM and GeForce graphics card GTX 1060	
	Sensors	Actuators
Base	1 Laser Hokuyo UTM-30LX, 1 Laser Hokuyo URG-04LX-UG01, and 1 Depth camera Asus Xtion pro.	1 Omnidirecional base (Mecanum Wheel Vectoring Robot - IG52 DB).
Torso	1 Emergency button.	1 Manipulator with 7 degrees of freedom.
Head	1 rgb and depth camera Microsoft Kinect, 1 Multi-sensor Matrix Creator, e 2 Directional Microphones RODE VideoMic GO.	1 Apple Ipad (3rd generation) serving as a virtual face display for interaction.

from each other in the simulated world by 0.5 meters and have spatial information (x, y) relative to the origin of the simulation. For each CR, a P is selected randomly. It will compose the path that the robot will take during the experiment ($CP = [P_0, ..., P_{nr}]$). Then, the global planer is used to calculate the shortest distance passing through all P in CP; (3) The environment and the robot are then reset with their initial settings; (4) The experiment is started by passing the list of CP to RNS. The experiment is finished when the robot reaches its final destination or some navigation failure occurs; (5) Finally, the experiment data is saved for future analysis.

The RNS used in this work was optimized using the ROS navigation[3] tutorials and the ROS Navigation Tuning Guide [28] in contrast to the previous work [19] that used non-optimized parameters. The optimization process was carried out observing the robot's behavior next to obstacles and taking into account the physical properties of the HERA platform. The main influence of this optimization was the safety in the trajectory planning versus the execution speed.

Aspects of success in navigation between two points, percentage of collisions are evaluated in environments with different kind of objects and simulated people. Also, an adaptation of the navigation algorithms for a social navigation is carried out. In this step, a layer of social navigation is added as a cost map and environments are tested with simulated humans. All experiments were carried out without using a graphical interface in the simulator (headless).

The testing methodology is divided into 6 stages. In each stage, a modification is made in the RNS environment or configuration, in order to promote a gradual increase in the complexity and capabilities of the HERA platform. It is a way to isolate the behavior of the robot in specific situations and configurations such as, to evaluate if these configurations lead to a complete task (navigation between two points) and to evaluate the naturalness of the robot's movements that even being an important point of social navigation as pointed by [12], and in it can be observed without (stages 1, 2, 3 and 4) the presence of people or with the presence of people (stages 5 and 6). For the stages 1, 2 and 3 the environments of Fig. 5 was used, for the stage 4 the environments of Fig. 6 was used, for the stage 5 the environments of Fig. 7 was used and for the stage 6 the environments of Fig. 8 was used.

The 6 stages are, as follows. Stage I (Simple Configuration): The simplest RNS configuration is evaluated. Stage II (Global Planners): The global planners NavFn and GlobalPlanner are variated and evaluated. Stage III (Local Planners): Local planners Base, DWA, EBand and TEB are varied and evaluated. Stage IV (Sensors): Changes are made in the environment to include objects that are difficult to perceive by the robot, as well as the addition of a new sensor to facilitate this perception. Stage V (Navigation Layer): Environments are presented with simulated people, in static positions or with dynamic behavior and interaction with other people and objects. The costmap layers used in this stage are based on [13] and can be seen in the Fig. 1. The selected layers were: Static Map layer, representing the map of the environment previously created; the Obstacle layer, representing the obstacles captured by the sensors; the Proxemics layer, representing people and their personal spaces; and finally, the inflation layer that determines a safe zone around the obstacles. All of these layers make up the master layer, where trajectory planning takes place. Stage VI (Marathon): A mix of all the previous steps is presented, where the robot must go through a series of checkpoints in a more complex environment.

After the end of the experiment, the results are evaluated based on the criteria presented in the following subsection.

3.3 Evaluation

These evaluations aim to select optimal planners in the current navigation of the robot so that it becomes safer, more natural and comfortable for the human being, since these features are the main pillars for social navigation according to [12]. With this we can improve aspects of social navigation while minimizing the compromise of basic navigation. The following variables will be analyzed in this study:

- **Success rate (SR):** Determines the percent number of experiments, where the navigation was successfully completed. It is given by:

$$SR = \frac{s}{ex\_max} * 100 \quad (1)$$

  where s is the number of experiments completed successfully and ex_max is the maximum number of experiments performed.
- **Failure rates (FR):** Determines the ppercentage of experiments in which the navigation failed. There are five types of FR and they are given by the following formulas:
  - **Space Exceeded (FR_SE):**

$$FR\_SE = \frac{f1}{ex\_max} * 100 \quad (2)$$

    where $f1$ is the number of experiments that failed by space exceeded.
  - **Time Exceeded (FR_TE):**

$$FR\_TE = \frac{f2}{ex\_max} * 100 \quad (3)$$

    where $f2$ is the number of experiments that failed by time exceeded.

[3]http://wiki.ros.org/navigation/Tutorials

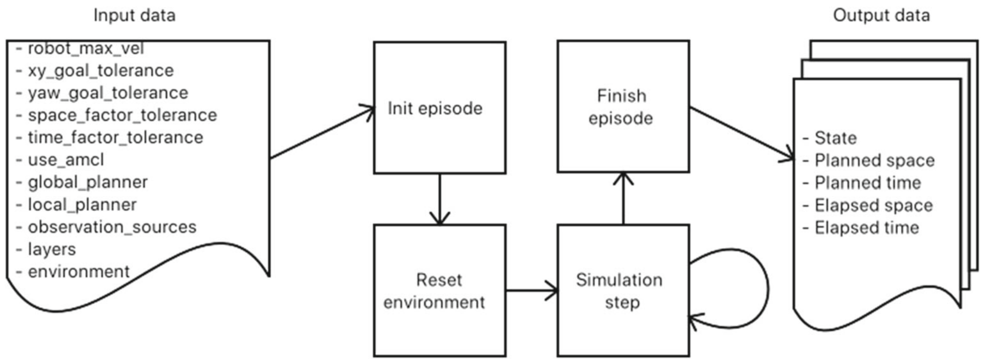
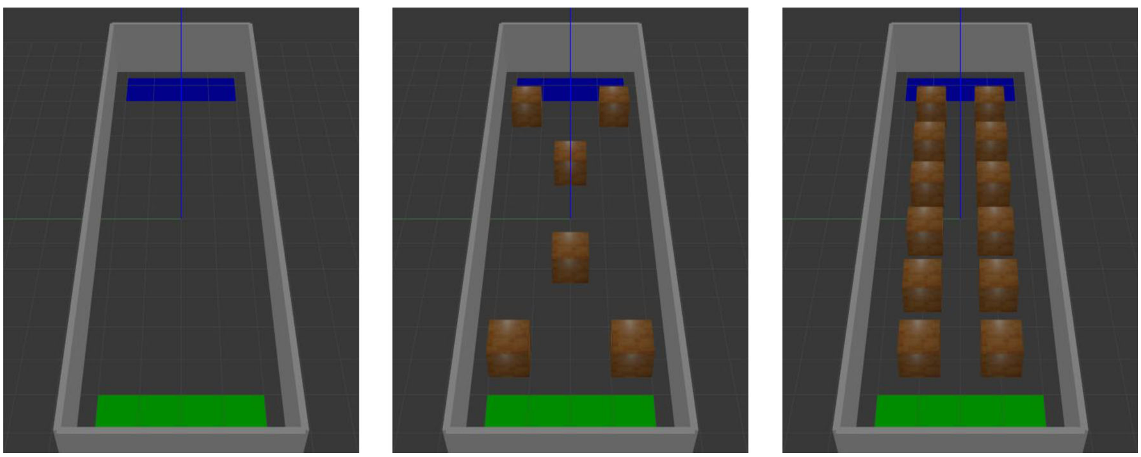
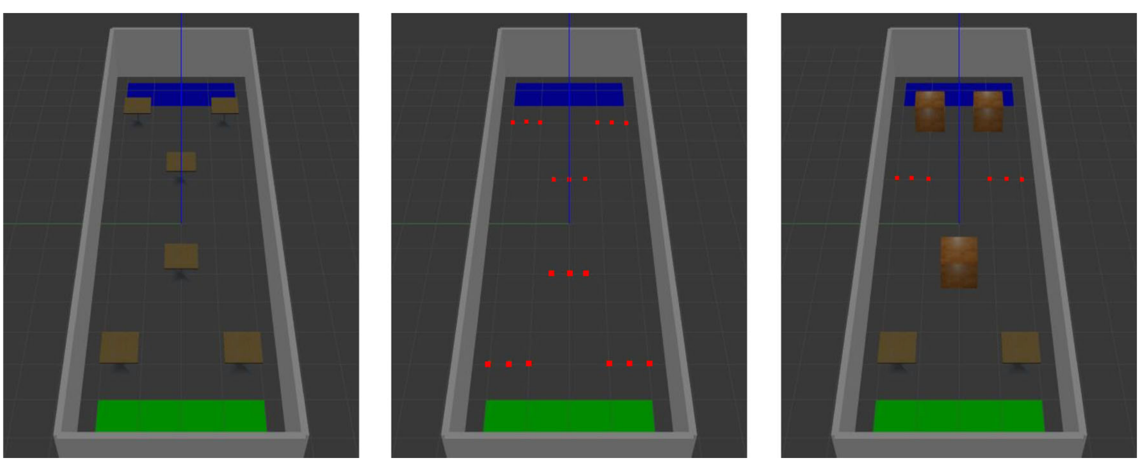


Fig. 4 Experiment pipeline



(a) Simple (b) Boxes (c) Narrow Corridors

Fig. 5 The simulated environments used in stage 1, 2 and 3. The green area represents the start region and the blue area represents the goal region



(a) Tables (b) Boxes Small (c) Mix 1

Fig. 6 The simulated environments used in stage 4. The green area represents the start region and the blue area represents the goal region

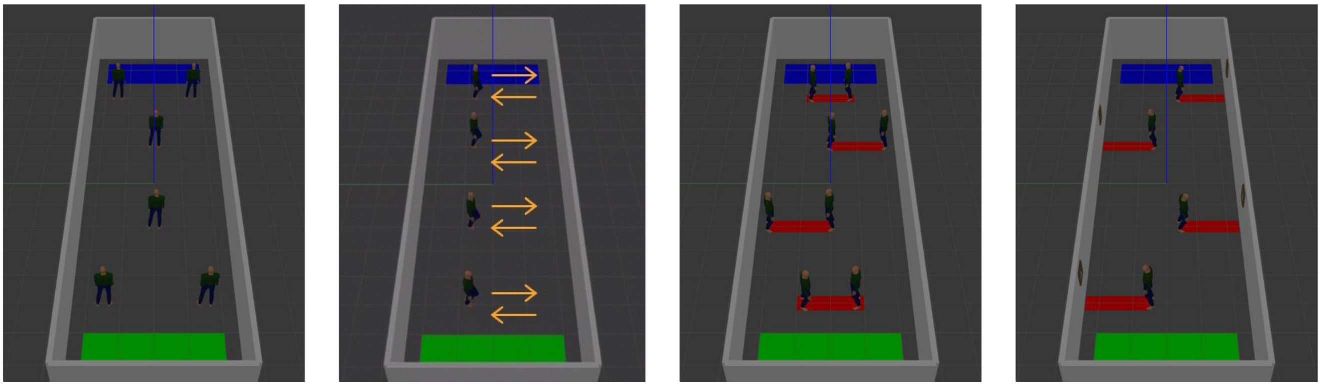


Fig. 7 The simulated environments used in stage 5. The green area represents the start region and the blue area represents the goal region. The red area represents prohibited regions where the robot will cause discomfort to the humans

– **Abortion** (FR_A)**:**

$$FR\_A = \frac{f3}{ex\_max} * 100 \tag{4}$$

where $f3$ is the number of experiments that failed by abortion.

– **Collision** (FR_C)**:**

$$FR\_C = \frac{f4}{ex\_max} * 100 \tag{5}$$

where $f4$ is the number of experiments that failed by collision.

– **Invasion** (FR_I)**:**

$$FR\_I = \frac{f5}{ex\_max} * 100 \tag{6}$$

where $f5$ is the number of experiments that failed by invasion of personal space.

- **Spatial Coefficient** (SPC)**:** determines how close the distance traveled by the robot is to the planned navigation distance, given by:

$$SPC = 1 - \frac{s_e - s_{min}}{s_{max} - s_{min}} \tag{7}$$

where s_e is the space traveled by the robot, s_{min} is the minimum space between the initial and the final position, s_{max} is the maximum space the robot can navigate in this experiment, being defined as $5 * s_{min}$. The result varies from 0 to 1, where 1 means that the path executed is equal to the path planned.

- **Temporal Coefficient** (TEC)**:** Determines how close the execution time by the robot is to the estimated time to perform the navigation, given by:

$$TEC = 1 - \frac{t_e - t_{min}}{t_{max} - t_{min}} \tag{8}$$

Fig. 8 The simulated environments used in stage VI. The green area represents the start region and the blue area represents the goal region. The red area represents prohibited region where the robot will cause discomfort to the human. The orange area represents the regions where the robot needs to go through in the experiment

where t_e is the time used by the robot in the experiment, t_{min} is the minimum time needed by the robot to travel from the starting point to the end in a straight line, given the maximum speed of the robot, t_{max} is the maximum time that the robot can navigate in this experiment, being defined as $5 * t_{min}$. The result varies from 0 to 1, where 1 means that the time elapsed is equal to the time planned.

- **Smooth Coefficient (SMC):** Determines how smooth the trajectory performed by the local planner is. It is used with a measure to evaluate the naturalness of the robot, which is given by the average of the angle differences of each line that creates the trajectory.

$$SMC = 1 - \frac{\sum_{i=1}^{n}(arctan(y_i - y_{i-1}, x_i - x_{i-1})/\pi)}{n-1} \tag{9}$$

where n is the number of points present in the executed route and x and y are the coordinates of the points. The result varies from 0 to 1, where 1 means that navigation is smoother.

- **Proxemic Coefficient (PRC):** Determines how much the trajectory carried out by the robot respects proxemics in an environment with people. This metrics tries to represent the average degree of comfort of the person closest to the robot in the experiment, given by:

$$PRC = 1 - x, \begin{cases} x \leftarrow d/1.2, & \text{if } d \leq 1.2 \\ x \leftarrow 0, & \text{if } d > 1.2 \end{cases} \tag{10}$$

where d is the distance in meters from the closest person to the robot. The result varies from 0 to 1, where 1 means that navigation respect proxemic rules.

4 Results

For this work, 1000 experiments were carried out for each configuration combination presented in Section 3.2 for simulated environments, defining a subset of tests. In total, 37 subsets of tests were performed, totaling 37000 navigation experiments in simulated environments with random start and goal positions. The main objective of these experiments is to evaluate the robot's navigation behavior in different scenarios and configurations, providing baseline results to compare with future works using learning methods. The scripts for performing these tests can be found on Github repository[4] and all results can be found on OneDrive cloud.[5] The next subsections present the tests and the results of all performance tests proposed in Section 3.

4.1 Stage I: Simple Configuration

The scenarios used in this stage (Fig. 5) have only easy to perceive obstacles or no obstacles at all. The input data for this stage are presented below:

- robot_max_vel: 0.3.
- xy_goal_tolerance: 0.1.
- yaw_goal_tolerance: 3.1415.
- time_factor_tolerance (tft) : 5.
- space_factor_tolerance (sft): 5.
- use_amcl: Yes.
- global_planner: NavFn (NavfnROS).
- local_planner: Base (TrajectoryPlannerROS).
- observation_sources - 3 sensors:
  - laser_scan_front_observation (LaserScan).
  - laser_scan_back_observation (LaserScan).
  - point_cloud_base_front_observation (PointCloud2).
- layers - Common configuration:
  - static_layer (costmap_2d::StaticLayer).
  - obstacles_layer (costmap_2d::VoxelLayer).
  - inflation_layer (costmap_2d::InflationLayer).

From Table 2 shows the results of the experiments performed for this simple configuration. It can be observed that the default configuration obtained excellent results (above 90%) in SR for 2 scenarios (simple and boxes) and poor results (below 50%) in the corridor scenario. For the scenario with a narrow corridor, this configuration had the highest error rates. This configuration does not present problems due to the excess of space traveled (FR_SE). In terms of spatial efficiency, this configuration present small differences towards the environments. In terms of spatial efficiency, this configuration also presented small differences when comparing the three environments. In terms of time efficiency, this configuration presented considerable differences with different scenarios. The behavior that resulted in these values are the same as the space coefficient. The worst result in the narrow corridor was due to small space available to navigate and the necessity to make more corrections in path, planning to avoid collisions with obstacles.

[4] https://github.com/fagnerpimentel/phd

[5] https://feiedu-my.sharepoint.com/:f:/g/personal/fpimentel_fei_edu_br/Ej7C9KvCwXxHo8I45xP0NMIBBZdEmRL1r8MW_qnDNRm5yQ?e=erLRlm

Table 2 Simple configuration

	Simple	Boxes	Corridor
SR	**98.4%**	94.5%	43.1%
FR_SE	0%	0%	0%
FR_TE	0.1%	1.4%	25.7%
FR_A	0.9%	2.6%	25.3%
FR_C	0.6%	1.5%	5.9%
SPC	$\bar{x} = 1$	$\bar{x} = 0.98$	$\bar{x} = 0.98$
	$\sigma = 0$	$\sigma = 0.01$	$\sigma = 0.03$
TEC	$\bar{x} = 0.96$	$\bar{x} = 0.88$	$\bar{x} = 0.74$
	$\sigma = 0.06$	$\sigma = 0.14$	$\sigma = 0.24$
SMC	$\bar{x} = 0.93$	$\bar{x} = 0.84$	$\bar{x} = 0.79$
	$\sigma = 0.06$	$\sigma = 0.01$	$\sigma = 0.12$

The best values are shown in bold

$\bar{x}$ = mean, σ = standard deviation

At this stage, it was possible to notice that the robot presented some location problems. The AMCL showed sudden jumps in position. As such, the robot was lost in the environment resulting in the impossibility of reaching the destination or think that it reached the destination when, in fact, it had not arrived. Preliminary tests in a more complex environment indicated that this type of problem occurred less frequently. This behavior happens because in the complex environments have enough details that serve as a reference for the AMCL, which enables the robot to locate itself. Given this information and since the optimization of the location is not the focus of this initial phase of testing in a simulated environment, it was chosen to use the positioning of the robot that comes directly from the simulator for further testing.

4.2 Stage II: Global Planners

In the second stage of the tests, the same scenarios of the previous stage were used (Fig. 5). In this context, only the use of localization was changed and the global planners. The details of the changed variables are presented below:

- use_amcl=: No.
- global_planner:
    - Navfn (NavfnROS).
    - Global (GlobalPlanner).

From the Table 3 we can see the results of the experiments performed by using localization from the simulator and the two global planners used: Navfn and Global. It can be observed that both planners obtained excellent results (above 90%) in SR for 2 scenarios (simple and boxes), and unsatisfactory results (below 80%) in the corridor scenario. The NavFn planner has For scenario with narrow corridor, it is remarkable that a performance upgrade occurred, when comparing with the previous stage: +36.2% for NavFn Planner and +26.3% for Global planner. Most of the failures were related to the time exceeded (FR_TE). This upgrade is more related to the use of simulation localization. This configuration does not presented problems due to the excess of space traveled (FR_SE). In terms of spatial efficiency (SPC), time efficiency (TEC) and smooth coefficient (SMC), this configuration present a behavior similar to that obtained in the previous stage.

Table 3 Global planner: NavFn x Global

	Navfn			Global		
	Simple	Boxes	Corridor	Simple	Boxes	Corridor
SR	98.8%	**97.9%**	**79.3%**	**99.3%**	97..2 %	69.4%
FR_SE	0%	0%	0%	0%	0%	0%
FR_TE	0%	0.6%	18.4%	0%	0.9%	26.9%
FR_A	0.7%	0.4%	0.5%	0.5%	0.9%	1.2%
FR_C	0.5%	1.1%	1.8%	0.2%	1%	2.5%
SPC	$\bar{x} = 1$	$\bar{x} = 0.98$	$\bar{x} = 0.98$	$\bar{x} = 1$	$\bar{x} = 0.97$	$\bar{x} = 0.97$
	$\sigma = 0$	$\sigma = 0.01$	$\sigma = 0.02$	$\sigma = 0$	$\sigma = 0.01$	$\sigma = 0.03$
TEC	$\bar{x} = 0.96$	$\bar{x} = 0.89$	$\bar{x} = 0.83$	$\bar{x} = 0.96$	$\bar{x} = 0.91$	$\bar{x} = 0.73$
	$\sigma = 0.04$	$\sigma = 0.13$	$\sigma = 0.2$	$\sigma = 0.04$	$\sigma = 0.11$	$\sigma = 0.25$
SMC	$\bar{x} = 0.93$	$\bar{x} = 0.85$	$\bar{x} = 0.85$	$\bar{x} = 0.93$	$\bar{x} = 0.85$	$\bar{x} = 0.81$
	$\sigma = 0.05$	$\sigma = 0.09$	$\sigma = 0.11$	$\sigma = 0.05$	$\sigma = 0.07$	$\sigma = 0.12$

The best values are shown in bold

$\bar{x}$ = mean, σ = standard deviation

4.3 Stage III: Local Planners

In the third stage of the tests, the same scenarios of the previous stage were used (Fig. 5). Here we select the NavFn as global planner due to the best results with this planner and variate the local planners. The details of the changed variables are presented below:

- global_planner: NavFn.
- local_planner:
  - Base (TrajectoryPlannerROS).
  - DWA (DWAPlannerROS).
  - EBand (EBandPlannerROS).
  - TEB (TebLocalPlannerROS).

From the Table 4 we can see the results of the experiments performed by using the four local planners used: Base, DWA, EBand and TEB. Note that the Base planner results is the same as presented in the Table 4 for NavFn. It can be observed that the four planners obtained excellent results (above 90%) in SR for 2 scenarios (simple and boxes) and good results (above 70%) in the corridor scenario. For the scenario with a narrow corridor, again, a noticeable performance upgrade was achieved, when compared to the previous stage: +17.3% for TEB Planner, with most of the failures related to the time exceeded (FR_TE). This configuration did not present problems due to the excess of space traveled (FR_SE). In terms of spatial efficiency (SPC), time efficiency (TEC) and smooth coefficient (SMC) this configuration presented a behavior similar to that obtained in the previous stage

4.4 Stage IV: Observation Sources

In the fourth stage of the tests, the environment was changed to explore more difficult obstacles, such as tables and small objects, both hard to see by a common laser. The environment used in this stage can be seen in the Fig. 6. Here we select the TEB as local planner due to the best results with this planner and variate the sensors observation sources. The details of the changed variables are presented below:

- local_planner: TEB.
- observation_sources:
  - 3 sensors:

    laser_scan_front_observation.
    laser_scan_back_observation.
    point_cloud_base_front_observation.
  - 4 sensors:

    laser_scan_front_observation.
    laser_scan_back_observation.
    point_cloud_base_front_observation.
    point_cloud_torso_front_observation.

Table 4 Local planner base x DWA x EBand x TEB

	Base			Dwa			Eband			Teb		
Simple	Boxes	Corridor	Simple	Boxes	Corridor	Simple	Boxes	Corridor	Simple	Boxes	Corridor	
SR	98.8%	97.9%	79.3%	95%	92%	78.3%	**99.5%**	97.9%	87.4%	98.3%	**98.2%**	**96.6%**
FR_SE	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
FR_TE	0%	0.6%	18.4%	0.7%	0%	1.4%	0%	0%	8%	1.4%	0.09%	0.5%
FR_A	0.7%	0.4%	0.5%	4.3%	8%	20.3%	0.5%	2.1%	4.1%	0.3%	0.04%	0.04%
FR_C	0.5 %	1.1%	1.8%	0%	0%	0%	0%	0%	0.5 %	0%	0%	0%
SPC	$\bar{x} = 1$	$\bar{x} = 0.98$	$\bar{x} = 0.98$	$\bar{x} = 1$	$\bar{x} = 0.98$	$\bar{x} = 0.98$	$\bar{x} = 1$	$\bar{x} = 0.97$	$\bar{x} = 0.93$	$\bar{x} = 1$	$\bar{x} = 0.97$	$\bar{x} = 0.94$
	$\sigma = 0$	$\sigma = 0.01$	$\sigma = 0.02$	$\sigma = 0.02$	$\sigma = 0.02$	$\sigma = 0.02$	$\sigma = 0$	$\sigma = 0.01$	$\sigma = 0.03$	$\sigma = 0$	$\sigma = 0.01$	$\sigma = 0.07$
TEC	$\bar{x} = 0.96$	$\bar{x} = 0.89$	$\bar{x} = 0.83$	$\bar{x} = 0.94$	$\bar{x} = 0.91$	$\bar{x} = 0.9$	$\bar{x} = 0.88$	$\bar{x} = 0.83$	$\bar{x} = 0.28$	$\bar{x} = 0.98$	$\bar{x} = 0.95$	$\bar{x} = 0.94$
	$\sigma = 0.04$	$\sigma = 0.13$	$\sigma = 0.2$	$\sigma = 0.05$	$\sigma = 0.06$	$\sigma = 0.04$	$\sigma = 0.01$	$\sigma = 0.02$	$\sigma = 0.09$	$\sigma = 0.01$	$\sigma = 0.01$	$\sigma = 0.15$
SMC	$\bar{x} = 0.93$	$\bar{x} = 0.85$	$\bar{x} = 0.85$	$\bar{x} = 0.94$	$\bar{x} = 0.89$	$\bar{x} = 0.91$	$\bar{x} = 0.94$	$\bar{x} = 0.86$	$\bar{x} = 0.89$	$\bar{x} = 0.94$	$\bar{x} = 0.88$	$\bar{x} = 0.84$
	$\sigma = 0.05$	$\sigma = 0.09$	$\sigma = 0.12$	$\sigma = 0.03$	$\sigma = 0.04$	$\sigma = 0.04$	$\sigma = 0.02$	$\sigma = 0.02$	$\sigma = 0.03$	$\sigma = 0.02$	$\sigma = 0.02$	$\sigma = 0.08$

The best values are shown in bold

$\bar{x}$ = mean, σ = standard deviation

From Table 5 we can see the results of the experiments performed by using the two different sensor's configuration. The first configuration with 3 sensors (base front laser, base back laser and base front 3D camera) and the second configuration with 4 sensors (base front laser, base back laser, base front 3D camera and torso front 3D camera). It can be observed that in scenario with tables, excellent results (above 90%) were obtained in SR for both configurations. It means that the tables can be well perceived by one of the sensors in the robot In the other 2 scenarios in this stage, very poor results were obtained (bellow 30%) for three sensor's configuration and excellent results (above 90%) for the four sensors configuration.

4.5 Stage V: Navigation Layers

In the fifth stage of the tests, the scenarios were changed to explore human populated environments, there are static and dynamic simulated people and person in interaction with others people and objects. The environment used in this stage can be seen in the Fig. 7. Here we select the observation sources from 4 sensors due to the best results with this sensors and variate the costmap layers. The details of the changed variables are presented below:

- observation_sources: 4 sensors.
- layers:
  - Common configuration:

    static_layer (costmap_2d::StaticLayer).
    obstacles_layer (costmap_2d::VoxelLayer).
    inflation_layer (costmap_2d::InflationLayer).
  - Social configuration:

    static_layer (costmap_2d::StaticLayer).
    obstacles_layer (costmap_2d::VoxelLayer).
    inflation_layer (costmap_2d::InflationLayer).
    proxemic_layer (social_navigation_layers::ProxemicLayer).

From Table 6 we can see the results of the experiments performed by using the two different navigation layers configuration. The first configuration has 3 layers (static, obstacles and inflation) and the second configuration with 4 layers (static, obstacles, inflation and proxemic). It can be observed that only the scenario with static people obtained excellent results (above 90%) in SR for both configurations. In the human interaction environment, poor results were obtained (around 50%) for Common configuration and excellent result (above 90%) for Social configuration. In the other 2 scenarios in this stage, very poor results were obtained (bellow 10%) for both configurations.

4.6 Stage VI: Marathon

In the sixth stage of the tests, the scenarios were changed to explore a more realistic and complex environment, by combining all of the elements presented in the previous stages. The environment used in this stage can be seen inthe Fig. 8. The details of the changed variables are presented below:

Table 5 Observation sources: 3 sensors x 4 sensors

	3 Sensors			4 Sensors		
	Tables	Boxes_small	Mix	Tables	Boxes_small	Mix
SR	96.2%	8.5%	29.6%	**97.5**%	**96.1**%	**98.2**%
FR_SE	0%	0%	0%	0%	0%	0%
FR_TE	1.5%	0%	0%	1.2%	2.1%	1%
FR_A	0.4%	0.4%	0.3%	0.6%	0.4%	0.6%
FR_C	1.9%	91.1%	70.1%	0.7%	1.4%	0.2%
SPC	$\bar{x} = 0.98$	$\bar{x} = 0.99$	$\bar{x} = 0.96$	$\bar{x} = 0.98$	$\bar{x} = 0.96$	$\bar{x} = 0.95$
	$\sigma = 0.01$	$\sigma = 0$	$\sigma = 0.04$	$\sigma = 0.01$	$\sigma = 0.04$	$\sigma = 0.04$
TEC	$\bar{x} = 0.96$	$\bar{x} = 0.97$	$\bar{x} = 0.92$	$\bar{x} = 0.96$	$\bar{x} = 0.92$	$\bar{x} = 0.91$
	$\sigma = 0.01$	$\sigma = 0.01$	$\sigma = 0.08$	$\sigma = 0.01$	$\sigma = 0.09$	$\sigma = 0.07$
SMC	$\bar{x} = 0.89$	$\bar{x} = 0.93$	$\bar{x} = 0.85$	$\bar{x} = 0.89$	$\bar{x} = 0.86$	$\bar{x} = 0.84$
	$\sigma = 0.02$	$\sigma = 0.01$	$\sigma = 0.06$	$\sigma = 0.02$	$\sigma = 0.06$	$\sigma = 0.06$

The best values are shown in bold

$\bar{x}$ = mean, σ = standard deviation

Table 6 Navigation layers: common x social

	Common				Social			
	Static people	Dynamic people	Human interaction	Object interaction	Static people	Dynamic people	Human interaction	Object interaction
SR	97.5%	0.2%	51.9%	**9.8%**	**98.5%**	**6.5%**	**93.3%**	0.01%
FR_SE	0%	0%	0%	0%	0%	0%	0%	0%
FR_TE	1.3%	0.1%	0.9%	0%	0.04%	0.2%	1.1%	0%
FR_A	1.2%	4.6%	0.8%	0.9%	1.1%	0.8%	1.8%	0.9%
FR_C	0%	95.1%	0%	0%	0%	92.5%	0%	0%
FR_I	0%	0%	46.4%	89.6%	0%	0%	3.8%	99%
SPC	$\bar{x} = 0.98$	$\bar{x} = 0.71$	$\bar{x} = 0.97$	$\bar{x} = 0.98$	$\bar{x} = 0.98$	$\bar{x} = .88$	$\bar{x} = 0.91$	$\bar{x} = 0.99$
	$\sigma = 0.01$	$\sigma = 0.06$	$\sigma = 0.04$	$\sigma = 0.01$	$\sigma = 0.01$	$\sigma = 0.08$	$\sigma = 0.07$	$\sigma = 0$
TEC	$\bar{x} = 0.96$	$\bar{x} = 0.96$	$\bar{x} = 0.95$	$\bar{x} = 0.96$	$\bar{x} = 0.94$	$\bar{x} = 0.94$	$\bar{x} = 0.85$	$\bar{x} = 0.98$
	$\sigma = 0.01$	$\sigma = 0.01$	$\sigma = 0.02$	$\sigma = 0.01$	$\sigma = 0.03$	$\sigma = 0.03$	$\sigma = 0.06$	$\sigma = 0$
SMC	$\bar{x} = 0.9$	$\bar{x} = 0.9$	$\bar{x} = 0.89$	$\bar{x} = 0.89$	$\bar{x} = 0.88$	$\bar{x} = 0.88$	$\bar{x} = 0.78$	$\bar{x} = 0.89$
	$\sigma = 0.02$	$\sigma = 0.02$	$\sigma = 0.01$	$\sigma = 0.01$	$\sigma = 0.03$	$\sigma = 0.03$	$\sigma = 0.04$	$\sigma = 0$
PRC	$\bar{x} = 0.93$	$\bar{x} = 0.93$	$\bar{x} = 0.87$	$\bar{x} = 0.91$	$\bar{x} = 0.93$	$\bar{x} = 0.93$	$\bar{x} = 0.88$	$\bar{x} = 0.92$
	$\sigma = 0.02$	$\sigma = 0.02$	$\sigma = 0.01$	$\sigma = 0.01$	$\sigma = 0.07$	$\sigma = 0.07$	$\sigma = 0.01$	$\sigma = 0$

The best values are shown in bold

$\bar{x}$ = mean, σ = standard deviation

- robot_max_vel: 0.3.
- xy_goal_tolerance: 0.1.
- yaw_goal_tolerance: 3.1415.
- time_factor_tolerance (tft): 5.
- space_factor_tolerance (sft): 5.
- use_amcl=: No.
- global_planner: NavFn.
- local_planner: TEB.
- observation_sources: 4 sensors.
- layers: Social configuration

From Table 7 we can see the results of the experiments performed by using a complex environment, with obstacles, small obstacles, tables, and people. In the previous stages, a poor performance was observed in the environments with dynamic humans and humans interacting with objects. Therefore, at this stage, the environment was evaluated in a scenario with all these elements (M1), an environment without human interacting with objects (M2), and an environment without humans interacting with objects and without dynamic humans altogether (M3). It can be observed that only environment M3 obtained excellent results, equal to 97.6% in SR as expected due to small performance in the environments with dynamic humans and humans interacting with objects.

4.7 Result Discussion

In a previous study [19], 24000 experiments were carried out. That work explore two test environments, with and without furniture; 3 sensors (1 front laser, 1 back laser and 1 depth camera); and 4 local planners (Base, DWA, EBand and TEB). As future work, proposed in [19] it was expected to optimize the parameters of the local planning methods in simulated environment and to also optimize human comfort and robot sociability. Furthermore, it was proposed to conduct experiments in a simulated environment with specific situations, such as navigating in environments with obstacles out of laser range and interaction with people.

Table 7 Marathon

	FEI_K5_M1	FEI_K5_M2	FEI_K5_M3
SR	1%	77.9%	**97.6%**
FR_SE	0%	0%	0%
FR_TE	0.1%	0.1%	0%
FR_A	0.7%	1.9%	2.3%
FR_C	0.2%	20.1%	0.1%
FR_I	98%	0%	0%
SPC	$\bar{x} = 0.97$	$\bar{x} = 0.94$	$\bar{x} = 0.94$
	$\sigma = 0.01$	$\sigma = 0.03$	$\sigma = 0.03$
TEC	$\bar{x} = 0.93$	$\bar{x} = 0.88$	$\bar{x} = 0.89$
	$\sigma = 0.02$	$\sigma = 0.04$	$\sigma = 0.05$
SMC	$\bar{x} = 0.46$	$\bar{x} = 0.46$	$\bar{x} = 0.46$
	$\sigma = 0.01$	$\sigma = 0.01$	$\sigma = 0.01$
PRC	$\bar{x} = 0.09$	$\bar{x} = 0.89$	$\bar{x} = 0.91$
	$\sigma = 0.02$	$\sigma = 0.02$	$\sigma = 0.01$

The best values are shown in bold

$\bar{x}$ = mean, σ = standard deviation

In this study, some metrics were used to test e the robustness, safety and human comfort. This metrics evaluates only the robot's movement and interaction with people over 37000 experiments performed gradually in order to test each one of the navigation system components. The robot was able to perceive and avoid small obstacles and 3D objects such as tables. It was possible to note that depending on the shape and position of the sensors, adding a 3D camera is not enough to carry out the task safely. For the HERA platform, two 3D cameras were required for this purpose. Nonetheless, it is possible that for other less complex and smaller robots, only one sensor is enough.

In the last stage of the experiments, in addition to safety, the respect for social norms and people's comfort was also assessed. With the presented method, it was possible to observe that problems with dynamic people did not achieve a satisfactory result. Analyzing the failure cases, it was observed that the robot tries to evade people in a safe way and respecting the proxemics. However, the simulated human who is programmed to walk in a certain space continuously, walks towards the robot. It cause a collision, since the robot has a slower speed and it was unable to deviate in time. This behavior of the simulated human is not an attitude expected in a real environment and does not match the behavior of the human being. The human is a conscious obstacle and manages to avoid collisions. In preliminary experiments in a real environment, the robot manages to deviate from the human in a satisfactory way. As future work, the behavior of the virtual human will be replaced by a behavior generated by PedSim simulator [10] using Social Force Models to avoid this unrealistic behavior. Formal experiments will be carried out in a real environment to assess the people comfort.

At this stage, the following conclusions were reached. The global planners NavFnPlanner and GlobalPlanner performed similarly, however NavFn had better results. In a corridor environment, NavFn obtained approximately 10 percentage points more than GlobalPlaner and a lower collision rate. Among the local planners, the analyzed methods had a greater discrepancy for the corridor environments, where it was observed that the success rate increased by approximately 17 percentage points and the collision rate was 0% for the TEB planner. Unlike DWA and Base planners, the Eband and TEB planners were designed to smooth your curves, which makes the methods more suitable for social navigation. TEB differs from EBand in order to optimize its temporal performance, proven in the experiments realized. TEB is also more suitable to be used with mobile obstacles and for car-like robots. Moving like a car is not what is expected for the HERA platform, however this behavior was the one that best suited this platform. TEB was also presented as a trend in [15].

For environments with people, we explore the use of the proxemic layer which makes up the social configuration of stage V. This layer of costmap was presented in [13]. In these scenarios, it was observed that the use of a new layer of costmap improved performance in almost all scenarios. However, some points need to be noted. For scenarios with static people, there was not a considerable difference (1%). The planner ends up treating the static people as a common obstacle, already analyzed in the previous stages. The people's social space is respected, but for the environment with dynamic people, the results with both configurations (common and social) were lower than expected with a high collision rate (95.1% for the common configuration and 92.5% for the social configuration). For the human interaction environment, there was a significant improvement of 41.4% points. The biggest cause of failures in this scenario was due to the invasion of the people's interaction space, 46.4% for the common configuration and 3.8% for the social configuration. This behavior can be improved by using a new simulator to represent human behavior more appropriately.

The last stage was inspired in [16], which presents a navigation marathon in an office setting and in [26] which presents a series of robot social gatherings. In this scenario, the behavior was consistent with that observed in previous stages. 1% of success rate was observed with 98% of invasion in the area of interaction in the environment with interaction between human and object; 77% of success rate with 20% of collision in the presence of dynamic people, the success rate is greater than that presented in the Table 6. In the last scenario (M3), without dynamic people and without interaction with objects, the success rate was 97.6%, compatible with was already observed in the previous steps.

In relation to the spatial and temporal coefficients, there were changes in the results related to the previous work which must be considered. The results of these metrics for the SPC and TEC will be analyzed, which measure how much the path executed by the robot approaches the planned path in spatial and temporal terms.

In relation to the SPC, there was no significant difference in spatial performance. The SPC getting close to 1 in practically all experiments. The observed drop is due to the fact that the environment in the previous work was mapped with the objects already positioned in their places. In other words, the planning takes these objects into account when carrying out the initial planning. In this work, no object was positioned in the environment for the mapping, therefore, they are not considered in the initial planning, and it is necessary to deviate from the globally planned trajectory in order to avoid these obstacles. The results in this work indicate that all the configurations used are able to satisfactorily respect the trajectory planning, with a maximum standard deviation of 0.08. The worst values were observed in more complex environments, as in the case of stage VI, with different types of objects and people, with an average SPC of 0.95 and standard deviation of 0.03.

It is possible to notice that these values fall in the stage VI (Fig. 8). That influence of scenarios at TEC values is because the complexity of the environment is proportional to the need to make adjustments in navigation. Adjustments such as reducing the speed of the robot at certain points and rotating movements of the robot that generates a lot of time loss. Possible solutions to this problem are to take into account such reductions in speed and time spent with turning when planning the time of execution of the experiment as well as modifying the navigation behavior of the robot to perform smoother.

The next metrics analyzed make reference to the main points presented in [12] as fundamental for social navigation. The SMC that verifies the smoothness of the paths taken by the robot, related to naturalness in social navigation and the PRC that verifies the application of proxemics and is related to the comfort of the human being. In a future work, a new metric related to sociability will be inserted.

In the results related to SMC, we observed an improvement in the values, as well as observed for the TEC for stages I to V and a drop in stage VI. This variation is due to the same reasons given by the TEC. Since in a more complex environment the robot will need to make more turns to reach its destination, thus influencing the SMC values.

The results related to the PRC appear only in stages V and VI, where people are present. For stage V, both experiments that used common configuration and experiments that used social configuration obtained similar results, around 0.9. These results show that the social layer did not contribute significantly to social navigation in comparison with the applied common layer, that is, the path executed with the common layer already satisfies the requirements of proxemics in a satisfactory way. However, it is still possible to make improvements to the configuration of the social layer so that it better satisfies proxemics. These improvements will be presented in a future work.

5 Conclusion

This paper presented a comparative study of social navigation components. The methods were evaluated using the ROS navigation stack. The comparative study is one of the steps to implement social navigation in a social robot. This aims to improve the naturalness behavior in the movement of the robot and the comfort for the human. The evaluation was made independently of the sensors or environment in which it is acting.

In this work, it was possible to carry out an incremental development of the environment. Also, an evaluation of several elements in this test scenarios. Environments, global and local planners, sources of sensing and custom map layers were varied. The tests explored from simple scenarios to more complex ones. The study explores scenarios with no objects and with objects of different natures. Some static and dynamic people were also explored in such environments.

With the results in Section 4, it was possible to select a configuration for the navigation system. Some problems are still present with dynamic people, however, the results have reached 97.6% success in a more complex environments.

Although tests were not carried out in a real environment, we had a better analysis of the results carried out gradually increasing the complexity of the environment and components of the navigation system, as well as more metrics and more tests regarding in [16]. Compared to [26], this study have few variations in social situations, however a greater variety of these situations is expected in a future works.

In relation to experiments in real environments, which will also be performed in a future work. The authors expect a drop in success rates in real environments. This drop is common in this type of transition due to noises with real actuator and sensors. However, due to experiments carried out in the simulation, it will be possible to identify and treat errors easily and quickly. The Home Environment Robot Assistant (HERA) will be used with the same configuration utilized in the test stage VI of this work. A smaller number of experiments will be carried out in the real environment, so that it does not overwhelm the humans involved in the experiment. In addition to the metrics used, a questionnaire will also be carried out to assess the degree of comfort of people during the real experiments. It is hoped that it will be possible to improve the values of social metrics without the need to change the environment. The robot must be able to produce better values for social metrics just by changing the way it interprets and acts on the world, even in the most complex and populous environments.

As a future work, the test environment will be integrated with the OpenAI [4] learning environment to carry out comparative tests with state-of-the-art approaches that use reinforcement learning and carry out comparative tests with a new approach using ontology to the problem of social navigation. They will be considered and evaluated to measures of naturalness, sociability and comfort. The results presented in this work will be used as a baseline for comparison with state-of-the-art approaches.

Author's Contributions

– Fagner de Assis Moura Pimentel: PhD candidate responsible for the research, experiment execution, writing and review.
– Plinio Thomaz Aquino-Jr: Advisor responsible for directing the research and the review.

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Data Availability All data and materials are available at the following addresses:

– Code: https://github.com/fagnerpimentel/phd
– Data result: https://feiedu-my.sharepoint.com/:f:/g/personal/fpimentel_fei_edu_br/Ej7C9KvCwXxHo8I45xP0NMIBBZdEmRL1r8MW_qnDNRm5yQ?e=erLRlm

Declarations

Conflict of Interests The authors declare that they have no conflict of interest.

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