



# Benchmarking Off-the-shelf Human-Aware Robot Navigation Solutions

Adam Gouguet, Abir B. Karami, Guillaume Lozenguez, Luc Fabresse

## ► To cite this version:

Adam Gouguet, Abir B. Karami, Guillaume Lozenguez, Luc Fabresse. Benchmarking Off-the-shelf Human-Aware Robot Navigation Solutions. IntelliSys, Sep 2023, Amsterdam, Netherlands. hal-04429230

**HAL Id: hal-04429230**

**<https://hal.science/hal-04429230>**

Submitted on 31 Jan 2024

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# Benchmarking Off-the-shelf Human-Aware Robot Navigation Solutions

Adam Gouguet<sup>1,2</sup>, Abir Karami<sup>2</sup>, Guillaume Lozenguez<sup>1</sup>, and Luc Fabresse<sup>1</sup>

<sup>1</sup> IMT Nord Europe - Ecole nationale supérieure Mines-Télécom Lille Douai  
firstname.lastname@imt-nord-europe.fr

<sup>2</sup> FGES, Université Catholique de Lille, F-59000 Lille, France,  
firstname.lastname@univ-catholille.fr

**Abstract.** In recent years, the number of robotic applications in public spaces has been growing. Decades of research have given rise to various methods of human-aware robotic navigation. There are a lot of different navigation solutions to guide a robot in presence of humans. Despite multiple surveys comparing existing navigation solutions, few of them take social criteria into account. In this sense, it is difficult to evaluate existing methods and select the one that performs better in a given context. In this article, we first provide a thorough classification of state-of-the-art solutions regarding human-aware robotic navigation solutions. Then, we select a set of measurable criteria to evaluate both the efficiency and the social-compliance of navigation solutions. Using these criteria, we finally compare representative off-the-shelf navigation solutions using the SEAN Simulator to identify the most suitable for human-aware navigation.

**Keywords:** Mobile robotics, Human-Robot Interaction, Social navigation

## 1 Introduction

Being a fundamental field of robotics, the navigation of mobile robots has been widely studied. The growing necessity to take into account the presence of humans in mobile robotics makes the human-aware robotic navigation, also called social navigation, one of the main challenges of mobile robotics. Indeed, the number of new robotic applications which need to perform human-aware robotic navigation due to their cluttered environment is increasing day by day, such as service robots in airports, hospitals, restaurants, shopping malls, etc. However, traditional robotic navigation approaches do not achieve satisfactory human-robot interaction because of the rudimentary behavior of these approaches which seems strange to humans. In addition, not being used to the presence of a robot in their environment, humans tend to behave differently. By respecting personal space, avoiding separating social groups, moving at a speed that does not disturb present humans and approaching humans from visible spaces, the robot navigation will be more acceptable by humans.

In this context, the study of human-aware robotics navigation is growing nowadays and we can notice different approaches. For each of them, this problematic is tackled using different methods. Many of these methods are based on the proxemics theory [1] and the social force model [2] to achieve human-like suitable behavior. However, most

of these researches only evaluate their solution with classic metrics such as time, path length or distance between the robot's position and the target. Only few methods were assessed with social measures. This raises the question of what methods are least disruptive to humans and yet are effective as a robotic navigation method. In this way, this article provides an overview of off-the-shelf social navigation methods and compares them in regard to different metrics.

The contributions of this paper are : 1) a selection of off-the-shelf human-aware robot navigation methods from different families ; 2) the construction of a set of measurable metrics to evaluate the navigation methods focusing both on efficiency and social criteria ; 3) a benchmarking of the selected navigation methods regarding our set of metrics. The code allowing us to carry out these evaluations is available in our repository<sup>3</sup>

This paper is organized as follows. Foremost, we provide an overview of the state of the art on off-the-shelf human-aware robotic navigation, then we give our selection of representative solutions in Section 2. In Section 3, we detail our metric selection process by giving a non-exhaustive list of existing metrics and specifying which metrics we use and why. Section 4 presents the experiments performed with off-the-shelf social navigation methods and reports the results using the chosen metrics. Finally, we conclude in Section 5 with a discussion of future work.

## 2 Our Selection of Off-the-shelf Navigation Solutions

Robotics navigation consists in planning a path from the current position to a target location and following this path while locally avoiding dynamic obstacles. Human-aware navigation consists in enhancing traditional navigation solutions while avoiding disturbing present humans. As a first abstraction, the humans can be considered as dynamic obstacles by the robots. However, humans follow certain rules of social navigation with each other such as respecting personal distance and that there are implicit expectations that others (humans and robots nowadays) will also respect those rules. The classical method of robot navigation, socially-insensitive robotic navigation such as the Dynamic Window Approach (DWA) [3], Velocity Obstacles (VO) [4], Timed-Elastic-Band (TEB) [5, 6] and more [7, 8, 9], don't guarantee to find a path without violating these social rules by bringing a sense of discomfort to humans in the environment. By taking into account the human in the environment of the robot, it is possible to overcome those problems.

There are many reviews/survey papers dedicated to social navigation. Mavrogiannis et al. [10] are interested on core challenges of social robot navigation (motion planning, behavior design, evaluation methods). Kruse et al. [11] focuses on the themes of comfort, naturalness and sociability of robot motions, giving different methods for each feature category. Möller et al. [12] provides a review of relevant areas of socially compliant robotic navigation, such as active vision, robotic navigation, human-robot interaction, and human activity recognition. Cheng et al. [13] indicate advantages and disadvantages for each social navigation category : Reactive, Predictive, Model-based

<sup>3</sup> [https://github.com/agouguet/benchmarking\\_social\\_robot\\_navigation](https://github.com/agouguet/benchmarking_social_robot_navigation)

and Learning-based. Xiao et al. [14] studies machine learning approaches for mobile robot navigation, with part of their research focusing on learning methods for social navigation.

In the remainder of this section, we first present a state of the art of the off-the-self available solutions. Thereafter, we will summarize this same state of the art by presenting the advantages and disadvantages of each family of solutions. And finally, we will justify a sub-selection of chosen solutions to be part of our benchmarks.

## 2.1 Classification of Off-the-shelf Navigation Solutions

We are looking for human-aware robotic navigation solutions that can be used as is, i.e., they do not require modification or external addition. These kinds of solutions are called “off-the-shelf” or “out-of-the-box” solutions. In Figure 1, we propose a general taxonomy of off-the-shelf approaches in different families; each of them being then described.

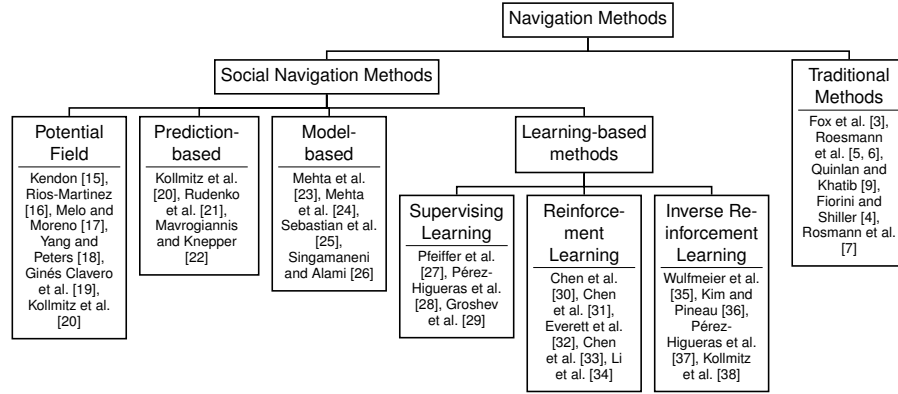


Fig. 1: State-of-the-Art overview of the off-the-shelf navigation methods

*Potential Fields.* To take into account the human in his environment, some works focus on the constraints that robots must respect, such as not entering the personal space of the human [1]. A common way to respect personal space is to use an asymmetric Gaussian function to represent either a personal space of a human or group space. Called as F-formation [15] or O-space [16], different shapes are possible for representing group space depending on individual’s position in the group [17, 18] or depending on the activity of the group [19]. Then, virtual repulsing forces will prevent the robot to move inside the personal spaces.

*Prediction-Based.* In addition to the use of asymmetric Gaussian functions, [20] calls on the prediction of human trajectories to avoid entering the human’s personal space but also to respect certain common rules among humans such as letting someone cross or

not blocking a path. [21] uses a model of Markov Decision Process (MDP) to formulate planning problem and produce a goal-directed global motion policies. [22] presents a navigation planning for dynamic environments composed of a probabilistic inference mechanism predicting the collective avoidance strategy, based on the observation of past behaviors. Even if the prediction models provide a lot of social information to help the navigation of the robot, it requires a significant computational cost, especially when it comes to dense crowded environments. In such cases, the robot might not have possible access without encroaching on the personal space. In this case, the robot will stop until access is freed, this situation is called "Freezing Robot Problem" [39]. This situation is often caused by the individual considerations of each agent present in the environment and the lack of consideration for the interactions between these same agents.

*Model-Based.* We can also cite model-based works, these methods use several models / behavior depending on the situation, such as Multi-Policy Decision-Making [23, 24] which uses the policy with the best expected utility among a set of different policies. Sebastian et al. [25] proposed a Gaussian Mixture Model in order to differentiate people's behavior and choose the most relevant and respectful path towards people. HATEB [26] provides a social navigation method using asymmetric Gaussian function and an architecture composed by 3 modes of planning and shiftable between them based on the situation of the environment, including one which uses trajectory prediction and cooperation between the robot and the human. Although model-based social navigation methods can make smarter decisions due to the consideration of human behavior, the resulting robot movements are not smooth. In addition, the selection of parameters could be complicated to set up.

*Learning-Based Methods.* In recent years, the development of learning methods and their effectiveness has opened up a new possible field for robotic social navigation. Using machine learning for social navigation robot, three subdomains can be distinguished [12, 13, 40] : supervised learning, deep reinforcement learning and inverse reinforcement learning.

*Supervised Learning.* Regarding supervised learning methods, researchers use expert demonstrations for the training of social navigation methods because humans are used to crowd movements and therefore have good performance in navigation taking others into account. Pfeiffer et al. [27] provided a target-oriented end-to-end robot navigation using 2D laser data as input and steering commands as output. They used an existing motion planner to generate expert demonstrations and they demonstrate that it is possible to transfer the learned motion planner on the simulation to an unseen environment or in real-world. Same as [27], Pérez-Higueras et al. [28] used expert demonstration as learning data, but the intended purpose is different. Indeed, Pérez-Higueras et al. used a Fully Convolutional Neural Network to learn a cost map that works as a prediction. Groshev et al. [29] using a deep neural network to perform a reactive policy, i.e., mapping a state of the environment to an action.

*Deep Reinforcement Learning.* Reinforcement learning solutions are useful to generate human-like robot navigation. As mentioned, the prediction task often required

expensive computation, Chen et al. [30] proposed to offload the online computation (prediction) to an offline training process. Chen et al. [31] pointed out that it is easier to specify what the robot should not do than what it should do. They used deep reinforcement learning to achieve robotic social navigation that doesn't violate social rules. Contrary to previous works, Everett et al. [32] assumed that agents do not follow particular behavioral rules. The proposed method (CADRL) allows collecting observations of an arbitrary number of other agents for learning. By rethinking pairwise interactions with a self-attention mechanism and jointly modeling Human-Robot as well as Human-Human interactions, Chen et al. [33] propose a social navigation method (SARL) with the ability to better anticipate humans using the deep reinforcement learning. Li et al. [34] has improved the SARL algorithm (SARL\*) by introducing a dynamic local goal and a map-based safe action space to avoid real-world distance limitation or neglect other obstacles than humans.

*Inverse Reinforcement Learning.* There exist some limitations for reinforcement learning, indeed, if you want to use reinforcement learning, you need to design a handcrafted cost function and in other words, it requires expertise in robotics, sensing and motion planning [35]. Kim and Pineau [36] uses an inverse reinforcement learning module to learn an expert's behavior through a set of demonstration trajectories and represent it as a cost function that respects social rules. Pérez-Higueras et al. [37] combined inverse reinforcement learning with Random Trees (RRT\*) to learn the RRT\*'s cost function from demonstrations. Kollmitz et al. [38] employed inverse reinforcement learning to learn from physical human-robot interaction, so the robot learns social rules and can do profiling on the present humans.

## 2.2 Summary

Table 1 summarizes the advantages and disadvantages of each family of navigation solutions based on the following properties:

- **Safety.** The first most important criterion concerns the safety of the generated behavior : the use of a potential field mainly allowing the robot to avoid disturbing the present humans, this method will therefore not be able to cause any collision problems. Prediction-based and model-based methods should not lead to a collision, however, if the prediction is not very efficient or the use of a model is not relevant it can lead to a violation of the personal space of a human. Regarding methods based on learning, there are too many factors depending on the method and the context of use such as how the learning was carried out, which is why it is difficult to give a general answer.
- **Extensibility of Social Information.** This point concerns the potential for evolution of the methods according to the added social information. For example, methods based on prediction or learning will perform better if they are provided with more information, such as the person's activity or profile. In the same line, it is possible to modify the field of potential according to the acquired information, but the possible forms remain rather limited.

	Potential Field	Prediction-Based	Model-Based	Learning-Based
Safety	++	+	+	N/A
Extensibility of Social Information	+	++	-	++
Computation Cost	+	--	-	++
Data Required	++	+	+	--
Adaptability	-	-	++	--

Table 1: Comparison Table of Main Families of Social Navigation Approaches

- **Computation Cost.** Another important aspect concerns the computational cost (online), it is obvious that the learning methods are much more efficient than the other methods on this criterion, the computational cost being generally offline. The use of potential field using asymmetric Gaussian function is not complex to calculate. On the contrary, the methods based on a model or prediction are not very efficient on this criterion.
- **Data Required.** The potential field requires very little data. In order to realize a potential field around a human, it is enough to have its position and its orientation. We dissociate here the prediction module and the navigation method using this prediction, the navigation method will only use data like the positions of the humans and the result of the prediction module (example: the future path of a human). Similarly, model-based solutions only need the information present in the environment, such as location of the robot or human’s position and orientation. Learning methods require a huge amount of data to perform their learning. As a consequence, a recurrent strategy consists in using simulation to learn a first operational model before refining it in the real world.
- **Adaptability.** If a learning-based model encounters an unprecedented situation, it is difficult to know how the robot will react. It is also hard to integrate a model trained in a specific environment into a new environment. Methods based on prediction suffer a bit the same fate, in an unprecedented situation the prediction will surely be less efficient and therefore the navigation plan. It is possible to use the potential fields in any situation, however, the robot might end up in the “Freezing Robot Problem” such as during narrow passage. Conversely, model-based methods will be more adaptable due to the changing behavior of the robot according to its environment.

### 2.3 Selection of Representative Navigation Solutions

This paper aims at benchmarking representative navigation solutions, this is why we selected off-the-shelf navigation solutions for which source code is available and executable among all those different families. The selected solutions are:

- **Dynamic Window Approach (DWA)** [3]. DWA is a collision avoidance strategy. The objective is to find the optimal direction and velocity that brings the robot to the goal without any collision. This is the default local planner in the ROS `move_base` package and the most used one.
- **Timed Elastic Band (TEB)** [5, 6]. TEB uses the given path by the global planner (like A\*), thus it can create a more realistic path in local scope. In recent years, this is one of the most used navigation solution in the ROS community.
- **Human-Aware Timed Elastic Band (HATEB-2)** [26]. HATEB is a navigation planner capable of planning cooperative trajectories. It offers co-navigation solutions by jointly calculating the trajectories of humans and robots using TEB. To compute a human’s trajectory, the local planner use a human motion prediction module. A potential field is also applied to static humans to avoid their personal spaces. HATEB has already been compared with Kollimtz and al. solution[20].
- **Socially Attentive Reinforcement Learning \* (SARL\*)** [34]. SARL\* model is an improvement of SARL method, which is proposed to rethink pairwise interactions with a self-attention mechanism and joint Human-Robot and Human-Human interaction model using deep reinforcement learning framework. Li et al. showed that SARL\* outperforms traditional SARL. For our evaluation of this method, we will use a pre-trained model given by the authors. In fact, SARL\* requires a training step on the deployment scenarios to exploit its full potential. However, as the goal is to target generic and adaptable solutions in a ‘off-the-shelf’ philosophy, we chose to skip the training step.

We argue that this selection is representative. DWA, TEB and HATEB represent the families based on potential fields, prediction and models. SARL\* is a learning-based solution which is already known to outperform its predecessors CADRL [41] and SARL [33].

## 3 Our Selection of Metrics

In the context of human-aware robotic navigation, new evaluation metrics appear and can be more restrictive than the metrics used for classical robotic navigation. In this section, we analyse a wide list of existing metrics (while not non-exhaustive), then we present and justify our selection of metrics for benchmarking the selection of representative solutions.

### 3.1 Evaluating Social Navigation

When it comes to evaluating robotic navigation methods, there are several performance metrics. For example, Cybulski et al. [42] and Naotunna and Wongrataphisan [43]



have evaluated different traditional navigation methods for ROS. They used metrics such as time, robot path length, minimum distance between the robot and its target to be able to quantify the effectiveness of a robotic navigation method. In this section, we describe the criteria we used to compare and assess navigation methods using both standard criteria and social ones. In order to select the metrics of interest in the context of this paper, we have carried out a state of the art of all the existing metrics for the evaluation of robotic navigation methods. In addition to the classic metrics, we can find specific ones for the evaluation of social robotic navigation. Gao and Huang [44] have summarized the different evaluation methods, scenarios, datasets and metrics that exist to achieve this. Wang et al. [45] offered a comparison of four different state-of-the-art learning-based methods under measures of efficiency and social compliance.

As used by [42] and [43], among the classic metrics, we can cite the length of the path, the time required, the average speed and acceleration, whether the robot has reached its goal, the final distance between the robot and the goal, and finally the number of collisions. In addition to these very common metrics, we can find metrics like path efficiency and path irregularity. The efficiency of the path consists in comparing the length of the shortest path with the length of the path made by the robot. The irregularity corresponds to the number of unnecessary turns performed by the robot. Knowing the number of seconds the robot did not move is also interesting, because it can be due to several situations : a period of calculation time, a moment when the robot was blocked by an obstacle or a situation where the robot gave priority to a human. However, it is necessary to observe the path of the robot in more detail to detect the exact reason.

There are also metrics that can assess the robot's ability to be human-aware. A metric that reflects this well is the number of times the robot will strongly disturb a human; we consider that a human is disturbed when a robot enters his personal space [1] (distance less than 1.2 meters). It is possible to differentiate 2 versions of the metric: number of times the robot will violate a human's personal space. The second version does not take into account the situation where the robot is stationary. If the robot is stationary, but the distance becomes less than 1.2 meters, we can say that this has not bothered the human since it was his decision to approach the robot. In addition to the number of times the robot has disturbed a human, we can measure the degree of disturbance by measuring the time the robot has remained in the personal space of the human and also the minimum distance between the robot and human during the navigation. In order to have more information, we differentiate between collisions with a static object and humans.

There are also metrics comparing the behavior of the robot with that of a human, Average Displacement Error [46] calculates the average difference between a predicted trajectory with a human trajectory. In the evaluation of the socially conscious navigation method, this metric is used to compare the trajectory produced by the navigation method with a human trajectory [44]. And Final Displacement Error [46] compares the distance between the final destination of the predicted trajectory with that of the human at each time step.

In the table 2, we compared all these different metrics under four criteria:

- **Interpretable.** Is the metric easily interpretable?

	Interpretable	Efficiency	Socially Aware	Safety
Goal Achieved	++	++	--	--
Path Length	++	++	--	--
Average Velocity/Acceleration	++	+	--	+
Time to Reach Goal	++	++	--	--
Path Efficiency	++	++	--	--
Path Irregularity	++	+	-	--
Error Distance to Target	++	++	--	--
Collision with Static Obstacle	++	+	--	++
Time Not Moving	++	+	-	--
Violation of Human Personal Space	++	--	++	+
Violation of Human Personal Space While the Robot is Stationary	-	--	+	++
Time of Robot Violate Human Personal Space	++	--	++	-
Minimum Distance Between the Robot and the Closest Human	++	--	++	++
Collision with Human	++	++	++	++
Average Displacement Error	+	-	++	--
Final Displacement Error	+	-	++	--

Table 2: Comparison Table of Existing Metrics using Four Criteria

- **Efficiency.** Does the metric permit to evaluate the effectiveness of the navigation method?
- **Socially Aware.** Does the metric measure if the robot is socially aware or not?
- **Safety.** Does the metric give information about the safety of the navigation method?

We can see that the first part of table 2 (until the Time Not Moving metric) represents efficiency metrics, few of them have an impact on whether the robot is aware of the human. Only the irregularity of the path and the time the robot is stationary have a minimum impact. Indeed, the irregularity of the path also represents the behavior of the robot, so if the robot does not act logically, it may seem strange from the human point of view. One of the possibilities for the robot not moving is that it is blocked by a human, and this would then reflect the fact that the robot gives priority to the human. We can see a contrast between the first part of the table which is mainly concerned with the effectiveness of the method and the second part which is dedicated to the social

aspect. Regarding safety, we can see that the majority of metrics that reflect security are in the social part. It can be difficult to interpret a violation of personal space when the robot is stationary, because depending on the method of navigation it can be random or intentional.

### 3.2 Our Set of Measurable Metrics

Our benchmarks target specific scenarios, where humans always have the same goals. Of course, a human reacts to the robots, such as avoiding it, but we make sure that the scenarios are reproducible to be able to compare the different navigation solutions fairly i.e. in the same conditions. In this regard, we selected the following set of metrics:

- **Goal Achieved.** The robot has reached the given goal or not.
- **Path Length (meters).** Total distance traveled by the robot. This shows the overall effectiveness of the method coupled with the time required.
- **Time to Reach Goal (seconds).** Total seconds that the robot took to reach the final goal. It is then possible to know which method is the fastest.
- **Error Distance to Target (meters).** Distance between the final position and the target position. This makes it possible to quantify the error of the method.
- **Total Rotation (degrees).** Total rotations in the robot’s travel. We can compare the total number of rotations between two methods, because they will be evaluated in the same scenario with the same conditions. This reflects the unnecessary rotations compared to other methods.
- **Time Not Moving (seconds).** Total seconds that the robot was not moving. This can correspond for instance to the period of calculation or the time when the robot was blocked.
- **Collision with Static Obstacle.** The number of collision with a static obstacle.
- **Violation of Human Personal Space.** The number of times the robot violated a human personal space. It is then possible to know how many times a robot has disturbed a human. A violation of personal space correspond to a distance between robot and human inferior to 1.2 meters.
- **Violation of Human Personal Space While the Robot is Stationary.** The number of times the robot violated a human personal space while it was stationary. On the contrary, if the robot is static, the human has not been disturbed, because he decided himself to enter the personal space of the robot.
- **Time of Robot Violate Human Personal Space (seconds).** Total seconds that robot was in a human personal space. A data allowing to know which method has disturbed the people the most.
- **Minimum Distance Between the Robot and the Closest Human (meters).** Minimum distance between the robot and the closest human to the robot during navigation. This reflects the degree of disturbance achieved by the robot’s navigation.
- **Collision with Human.** The number of times the robot collided with a human.

We discarded several metrics that exist in the literacy. For example, the average speed and acceleration metric does not indicate much, what is important is to know the speed in difficult situations such as approaching a human or a narrow passage. However,

knowing what speed the robot must have in order to prevent disturbing the human is a measure that we do not have, because it depends a lot on the profile of the person, it then becomes difficult to conclude on this point. Regarding path efficiency and path irregularity, this is due to the fact that we plan to evaluate the methods on repeatable scenarios, so the minimum path length to reach the goal will remain the same, similarly for the minimum number of rotations. This is why the length of the path made by the robot and its total number of rotations is sufficient. Concerning the more social metrics, we ruled out Average Displacement Error and Final Displacement Error, because in our opinion if the robot behaves like a human it is not a guarantee of quality and these metrics depend a lot on the human data.

## 4 Benchmark

The idea of the proposed benchmark is to set up the tools and processes to evaluate and compare different navigation methods. Previous works have proposed simulations and benchmarks to evaluate different methods of social robotic navigation. Gao and Huang [44] yielded several simulators specifically for social navigation. The open source Social Environment for Autonomous Navigation (SEAN) 2.0 simulator [47, 48] appears to be the most appropriate choice. However, SEAN is developed on the philosophy to produce statistical metrics, computed from many randomly generated experiments on a large space scenario. It seems more interesting to us to focus the evaluation and the comparison of navigation methods on repeatable scenarios. Each scenario would be dedicated to highlight a specific configuration challenging for robot navigation.

Within this section, we give the elements composing our benchmark: the evaluation scenarios, the used simulator and the setting up of the experiments. Then, we give the results of the experiments and discuss them.

### 4.1 Scenarios

We have chosen to carry out our evaluations on specific scenarios representing recurrent situations. Before testing random trials, the methods need to be tested in given social situations, small in terms of space and duration. Indeed, random experiments do not guarantee to cover specific social situations neither to highlight specific failure hidden by the averages. In the literature, there are scenarios well-known to researchers regarding robotic social navigation [44]. These scenarios include moving around static humans, overtaking, crossing, and passing through a narrow space.

We retain 4 scenarios in this study. The scenario with static humans (Figure 2a) is the most basic scenario, we look at whether the robot is aware of the humans in its environment. The overtaking scenario (Figure 2b) makes it possible to see whether the robot favors performance or the attention paid to the human. The crossing scenario (Figure 2c) is interesting, because we can see the difference in attitude of the human in the presence of the robot and how it reacts. And the last scenario: the crossing between the human and the robot in a restricted space like a doorway (Figure 2d). This scenario really makes it possible to see if the robot gives priority to the human and if it does not hinder the human so that he can pass.

In our experiments, we ensure that a scenario is reproducible, i.e., it is executed in the same conditions and with the same parameters (e.g. initial positions and goals of the robot and humans are fixed). Therefore, our results are fair and comparable for different robot’s navigation solutions.

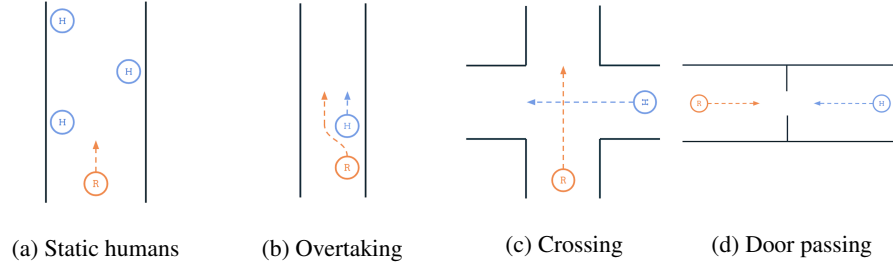


Fig. 2: Common scenario used to evaluate social navigation methods. Orange circle represent the robot (R), the blue circles the humans (H) and the static obstacles are black lines. Dot lines draw expected trajectories toward provided goals.

## 4.2 Simulator

We extended the SEAN 2.0 simulator which is based on the Unity engine. It uses a TCP connector to interface with Robot Operating System (ROS) libraries (Figure 3). SEAN supports two navigation methods to simulate humans: Social Force Model (SFM) [2] or Optimal Reciprocal Collision Avoidance (ORCA) [49]. In our case, we used SFM a popular model mostly used by the community, especially in Pedestrian Simulation<sup>4</sup>. SEAN already implements many of the metrics we want for the evaluation navigation methods, however, some of them were computed offline (such as time not moving metric, the length of the path and the total rotation of the robot). We have implemented those metrics directly in the SEAN API within Unity and we added the Time of Robot Violate Human Personal Space metric. All these metrics are now computed dynamically during the experiment in Unity, sent to ROS via the TCP connector and then stored in csv and json files.

To guarantee reproducible scenarios, we had to modify the behavior of the simulated humans and the robot. All agents (humans and robot) must pass by checkpoints rather than moving along a graph initially planned in the SEAN simulator. This new behavior, allow us to control the movements of the humans and carry out repeatable scenarios. Then, we created each of the scenarios on Figure 2 in SEAN such as the doorway one depicted on Figure 4.

<sup>4</sup> [https://github.com/srl-freiburg/pedsim\\_ros](https://github.com/srl-freiburg/pedsim_ros)

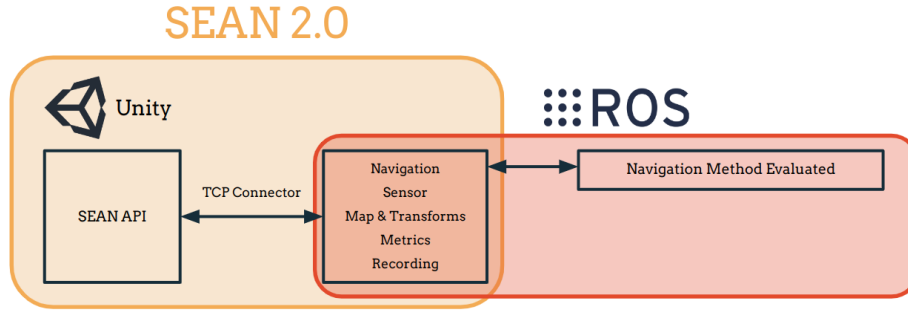


Fig. 3: Architecture of SEAN benchmark

### 4.3 Results

Figure 5 summarizes all the results for each scenario-navigation method coupled according to the metrics chosen in the Section 3.1, metrics separated into two groups, the efficiency metrics and social metrics. Overall, there is no method that stands out positively in terms of pure performance. However, HATEB is by far the best social method, it is the best in almost all scenarios, except the crossover scenario. If, for example, we take the metric of the minimum distance between the robot and the human, over the four scenarios, the minimum distance is 1.19 meters. Knowing that the personal space is often defined at 1.2 meters, the robot hardly disturbs the human. In addition, we note that in all the experiments, the robot violated the human’s personal space only once, and it was immobile, so it was the human who chose to move forward despite the presence of the robot. TEB is a bit better than DWA in the social aspect, especially in crossing and door crossing scenarios, it is therefore better than its direct rival in complex situations. Otherwise, the DWA and TEB methods are a little more efficient than HATEB, but the lack of consideration for humans is a big downside. Moreover, we see that in certain situations, taking the human factor into account leads to better performance. Let’s look at the crossing scenario, with the HATEB method, the robot anticipated the passage of the human, so it slowed down a bit to let the human pass and then resume its pace, thus, it gained in efficiency on all criteria of performance. The learning method, SARL\* is not very good, the fact that it has not been trained specifically on the scenarios may explain this. The method manages to take the human into account and gives him priority, but the behavior is not rational and looks like random behavior as we can see in Figure 6d. It is this behavior that explains why SARL\* is better than HATEB on social metrics on the crossover scenario. And it is this same behavior that also explains its mediocrity regarding efficiency metrics. Concerning the crossing and door passage scenarios, only HATEB and SARL\* give priority to the human, whereas DWA and TEB force the human to back up. We can see the behaviors in doorway scenario in the figure 6. All the videos of the evaluations are available on the project’s git<sup>5</sup>.

<sup>5</sup> [https://github.com/agouguet/benchmarking\\_social\\_robot\\_navigation](https://github.com/agouguet/benchmarking_social_robot_navigation)

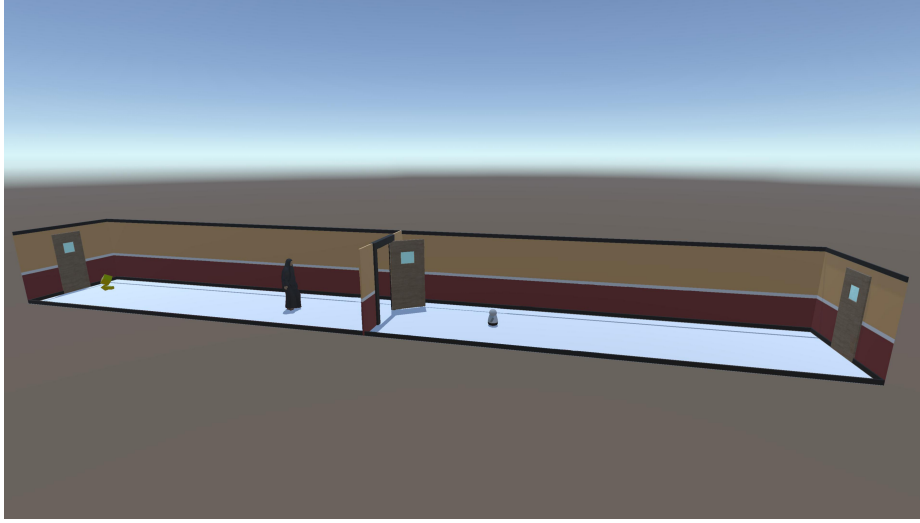


Fig. 4: Screenshot from SEAN benchmark, door passing scenario

## 5 Conclusion

In this paper, we compared representative and off-the-shelf social robot navigation methods under a set of measurable metrics, some on the efficiency of the method and others on the social compliance. Through the SEAN benchmark, we showed that the HATEB method is the best on specific social scenarios from the literature. We performed the evaluations on few scenarios representing complex situations involving a human and a robot. From the performance point of view, it is not possible to really differentiate DWA, TEB and HATEB. However, social metrics really help to assess the social dimension showing that HATEB performs better from this perspective.

In future research, we plan to improve this benchmark by adding new representative and denser scenarios (more humans, crowds) where the robot is surrounded by humans. We also plan to study the impact of the simulated human model on the results by supporting other human models [50]. Finally, we would like to evaluate some of these navigation solutions in a real-world setup.

## Acknowledgment

We thank all researchers who have shared their code publicly. Special thanks to the SEAN 2.0 team for sharing the code of their simulator.

	Static Humans				Overtaking				Crossing				Door Passing			
	DWA	TEB	HATEB	SARL*	DWA	TEB	HATEB	SARL*	DWA	TEB	HATEB	SARL*	DWA	TEB	HATEB	SARL*
Goal Achieved	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Path Length (m)	<b>21.75</b>	21.80	22.05	-	21.87	<b>21.55</b>	22.12	28.35	22.73	21.87	<b>21.78</b>	26.38	<b>21.98</b>	22.46	24.86	56.87
Time to Reach Goal (s)	<b>190.0</b>	194.0	191.0	-	<b>169.0</b>	201.0	188.0	345.0	189.0	201.0	<b>178.0</b>	250.0	<b>206.0</b>	240.0	212.0	633.0
Error Distance to Target (m)	0.24	0.19	<b>0.18</b>	14.46	<b>0.24</b>	0.59	0.28	0.67	0.24	0.36	<b>0.17</b>	0.85	0.24	<b>0.17</b>	0.18	0.54
Total Rotation (degree)	<b>22.69</b>	31.02	235.73	218.09	208.09	<b>160.99</b>	235.83	2839.79	294.52	117.12	<b>89.98</b>	3274.92	250.12	<b>150.21</b>	279.16	8432.11
Time Not Moving (s)	<b>0.0</b>	2.0	5.0	-	<b>1.0</b>	9.0	<b>1.0</b>	253.0	3.0	6.0	<b>1.0</b>	111.0	35.0	33.0	<b>13.0</b>	354.0
Collision with Static Obstacle	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Violation of Human Personal Space	3	3	<b>0</b>	-	1	1	<b>0</b>	1	2	<b>0</b>	<b>0</b>	<b>0</b>	<b>0</b>	<b>0</b>	<b>0</b>	1
Violation of Human Personal Space While the Robot is Stationary	0	0	0	-	0	0	0	0	1	<b>0</b>	<b>0</b>	<b>0</b>	1	1	1	1
Time of Robot Violate Human Personal Space (s)	47.53	47.79	<b>0.0</b>	-	22.71	24.23	<b>0.0</b>	1.16	26.02	<b>0.0</b>	<b>0.0</b>	<b>0.0</b>	28.44	17.87	<b>7.56</b>	61.28
Minimum Distance Human (m)	0.92	0.99	<b>1.36</b>	-	0.82	1.06	<b>1.53</b>	1.38	0.97	1.50	3.56	<b>3.75</b>	0.97	1.02	<b>1.19</b>	0.88
Collision with Human	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0

Fig. 5: Performance and Social Metrics of Four Different Methods on Proposed Scenarios



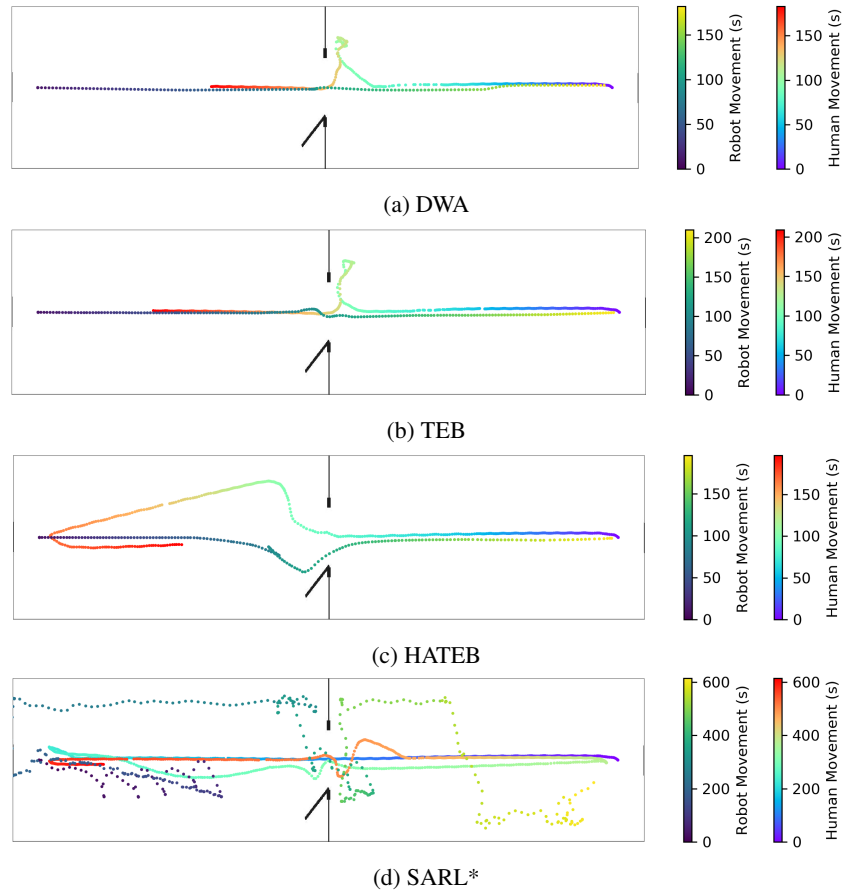


Fig. 6: All robot and human positions at each time step in the door passing scenario for each navigation method

## Bibliography

- [1] E.T. Hall. *The Hidden Dimension: Man's Use of Space in Public and Private*. Bodley Head, 1969.
- [2] Dirk Helbing and Péter Molnár. Social force model for pedestrian dynamics. *Phys. Rev. E*, pages 4282–4286 vol. 51,
- [3] Dieter Fox, Wolfram Burgard, and Sebastian Thrun. The dynamic window approach to collision avoidance. *Robotics & Automation Magazine, IEEE*, pages 23–33 vol. 4, 1997.
- [4] Paolo Fiorini and Zvi Shiller. Motion planning in dynamic environments using velocity obstacles. *The International Journal of Robotics Research*, 17(7):760–772,
- [5] Christoph Roesmann, Wendelin Feiten, Thomas Woesch, Frank Hoffmann, and Torsten Bertram. Trajectory modification considering dynamic constraints of autonomous robots. In *ROBOTIK 2012; 7th German Conference on Robotics*, pages 1–6,
- [6] Christoph Rösman, Wendelin Feiten, Thomas Wösch, Frank Hoffmann, and Torsten Bertram. Efficient trajectory optimization using a sparse model. In *2013 European Conference on Mobile Robots*, pages 138–143, 2013.
- [7] Christoph Rosmann, Artemi Makarow, and Torsten Bertram. Online motion planning based on nonlinear model predictive control with non-euclidean rotation groups. In *2021 European Control Conference (ECC)*. IEEE, jun 2021.
- [8] R.B. Tilove. Local obstacle avoidance for mobile robots based on the method of artificial potentials. In , *IEEE International Conference on Robotics and Automation Proceedings*, pages 566–571 vol. 1.
- [9] S. Quinlan and O. Khatib. Elastic bands: connecting path planning and control. In *[1993] Proceedings IEEE International Conference on Robotics and Automation*, pages 802–807 vol.2, 1993.
- [10] Christoforos Mavrogiannis, Francesca Baldini, Allan Wang, Dapeng Zhao, Pete Trautman, Aaron Steinfeld, and Jean Oh. Core challenges of social robot navigation: A survey. *J. Hum.-Robot Interact.*, feb 2023.
- [11] Thibault Kruse, Amit Kumar Pandey, Rachid Alami, and Alexandra Kirsch. Human-Aware Robot Navigation: A Survey. *Robotics and Autonomous Systems*, pages 1726–1743 vol. 61,
- [12] Ronja Möller, Antonino Furnari, Sebastiano Battiato, Aki Härmä, and Giovanni Maria Farinella. A survey on human-aware robot navigation. *Robotics and Autonomous Systems*, 145:103837, 2021. ISSN 0921-8890.
- [13] Jiyu Cheng, Hu Cheng, Max Q.-H. Meng, and Hong Zhang. Autonomous navigation by mobile robots in human environments: A survey. In *2018 IEEE International Conference on Robotics and Biomimetics (ROBIO)*, pages 1981–1986.
- [14] Xuesu Xiao, Bo Liu, Garrett Warnell, and Peter Stone. Motion planning and control for mobile robot navigation using machine learning: a survey. *Autonomous Robots*, 46(5):569–597,

- [15] Adam Kendon. *Conducting interaction: Patterns of behavior in focused encounters*, volume 7. CUP Archive,
- [16] Jorge Rios-Martinez. Socially-aware robot navigation : combining risk assessment and social conventions.
- [17] Francisco Melo and Plinio Moreno. Socially reactive navigation models for mobile robots. In *2022 IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC)*, pages 91–97.
- [18] Fangkai Yang and Christopher Peters. Social-aware navigation in crowds with static and dynamic groups. In *2019 11th International Conference on Virtual Worlds and Games for Serious Applications (VS-Games)*, pages 1–4, 2019.
- [19] Jonatan Ginés Clavero, Francisco Martín Rico, Francisco J Rodríguez-Lera, José Miguel Guerrero Hernández, and Vicente Matellán Olivera. Defining adaptive proxemic zones for activity-aware navigation. In *Advances in Physical Agents II: Proceedings of the 21st International Workshop of Physical Agents (WAF 2020), November 19-20, 2020, Alcalá de Henares, Madrid, Spain*, pages 3–17. Springer,
- [20] Marina Kollmitz, Kaijen Hsiao, Johannes Gaa, and Wolfram Burgard. Time dependent planning on a layered social cost map for human-aware robot navigation. In *Proc. of the IEEE Eur. Conf. on Mobile Robotics (ECMR)*, 2015.
- [21] Andrey Rudenko, Luigi Palmieri, Achim J. Lilienthal, and Kai O. Arras. Human motion prediction under social grouping constraints. In *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 3358–3364. ISSN: 2153-0866.
- [22] Christoforos Mavrogiannis and Ross Knepper. Multi-agent path topology in support of socially competent navigation planning. *The International Journal of Robotics Research*, 38:338–356, 03 2019.
- [23] Dhanvin Mehta, Gonzalo Ferrer, and Edwin Olson. Autonomous navigation in dynamic social environments using multi-policy decision making. In *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 1190–1197. IEEE, . ISBN 978-1-5090-3762-9.
- [24] Dhanvin Mehta, Gonzalo Ferrer, and Edwin Olson. Fast discovery of influential outcomes for risk-aware MPDM. In *2017 IEEE International Conference on Robotics and Automation (ICRA)*, pages 6210–6216, .
- [25] Meera Sebastian, Santosh Balajee Banisetty, and David Feil-Seifer. Socially-aware navigation planner using models of human-human interaction. In *2017 26th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*, pages 405–410. ISSN: 1944-9437.
- [26] Phani Teja Singamaneni and Rachid Alami. Hateb-2: Reactive planning and decision making in human-robot co-navigation. In *International Conference on Robot & Human Interactive Communication*, 2020.
- [27] Mark Pfeiffer, Michael Schaeuble, Juan Nieto, Roland Siegwart, and Cesar Cadena. From perception to decision: A data-driven approach to end-to-end motion planning for autonomous ground robots. In *2017 IEEE International Conference on Robotics and Automation (ICRA)*, pages 1527–1533.
- [28] Noé Pérez-Higueras, Fernando Caballero, and Luis Merino. Learning human-aware path planning with fully convolutional networks. In *2018 IEEE international conference on robotics and automation (ICRA)*, pages 5897–5902. IEEE,

- [29] Edward Groshev, Maxwell Goldstein, Aviv Tamar, Siddharth Srivastava, and Pieter Abbeel. Learning generalized reactive policies using deep neural networks. In *Proceedings of the International Conference on Automated Planning and Scheduling*, volume 28, pages 408–416,
- [30] Yu Fan Chen, Miao Liu, Michael Everett, and Jonathan P How. Decentralized non-communicating multiagent collision avoidance with deep reinforcement learning. In *2017 IEEE international conference on robotics and automation (ICRA)*, pages 285–292. IEEE,
- [31] Yu Fan Chen, Michael Everett, Miao Liu, and Jonathan P How. Socially aware motion planning with deep reinforcement learning. In *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 1343–1350. IEEE,
- [32] Michael Everett, Yu Fan Chen, and Jonathan P How. Motion planning among dynamic, decision-making agents with deep reinforcement learning. In *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 3052–3059. IEEE,
- [33] Changan Chen, Yuejiang Liu, Sven Kreiss, and Alexandre Alahi. Crowd-robot interaction: Crowd-aware robot navigation with attention-based deep reinforcement learning. *2019 International Conference on Robotics and Automation (ICRA)*, pages 6015–6022,
- [34] Keyu Li, Yangxin Xu, Jiankun Wang, and Max Q.-H. Meng. Deep reinforcement learning based human-aware navigation for mobile robot in indoor environments. In *2019 IEEE International Conference on Robotics and Biomimetics (ROBIO)*, pages 688–694.
- [35] Markus Wulfmeier, Dushyant Rao, Dominic Zeng Wang, Peter Ondruska, and Ingmar Posner. Large-scale cost function learning for path planning using deep inverse reinforcement learning. *The International Journal of Robotics Research*, 36(10):1073–1087,
- [36] Beomjoon Kim and Joelle Pineau. Socially adaptive path planning in human environments using inverse reinforcement learning. *International Journal of Social Robotics*, 8:51–66,
- [37] Noé Pérez-Higueras, Fernando Caballero, and Luis Merino. Teaching robot navigation behaviors to optimal rrt planners. *International Journal of Social Robotics*, 10:235–249,
- [38] Marina Kollmitz, Torsten Koller, Joschka Boedecker, and Wolfram Burgard. Learning human-aware robot navigation from physical interaction via inverse reinforcement learning. In *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 11025–11031. ISSN: 2153-0866.
- [39] Peter Trautman and Andreas Krause. Unfreezing the robot: Navigation in dense, interacting crowds. In *2010 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 797–803. IEEE. ISBN 978-1-4244-6674-0.
- [40] Neziha Akalin and Amy Loutfi. Reinforcement learning approaches in social robotics. *Sensors*, 21(4):1292,
- [41] Michael Everett, Yu Fan Chen, and Jonathan P. How. Motion planning among dynamic, decision-making agents with deep reinforcement learning. In *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Madrid, Spain,

- [42] B. Cybulski, A. Wegierska, and G. Granosik. Accuracy comparison of navigation local planners on ros-based mobile robot. In *2019 12th International Workshop on Robot Motion and Control (RoMoCo)*, pages 104–111, 2019.
- [43] Isira Naotunna and Theeraphong Wongratanaphisan. Comparison of ros local planners with differential drive heavy robotic system. In *2020 International Conference on Advanced Mechatronic Systems (ICAMechS)*, pages 1–6, 2020.
- [44] Yuxiang Gao and Chien-Ming Huang. Evaluation of socially-aware robot navigation. *Frontiers in Robotics and AI*, 8:420,
- [45] Junxian Wang, Wesley P. Chan, Pamela Carreno-Medrano, Akansel Cosgun, and Elizabeth Croft. Metrics for evaluating social conformity of crowd navigation algorithms. In *2022 IEEE International Conference on Advanced Robotics and Its Social Impacts (ARSO)*, pages 1–6, 2022.
- [46] Stefano Pellegrini, Andreas Ess, Konrad Schindler, and Luc Van Gool. You’ll never walk alone: Modeling social behavior for multi-target tracking. *2009 IEEE 12th International Conference on Computer Vision*, pages 261–268,
- [47] Nathan Tsoi, Mohamed Hussein, Jeacy Espinoza, Xavier Ruiz, and Marynel Vázquez. Sean: Social environment for autonomous navigation. In *Proceedings of the 8th International Conference on Human-Agent Interaction (HAI)*,
- [48] Abhijat Biswas, Allan Wang, Gustavo Silvera, Aaron Steinfeld, and Henny Admoni. Socnavbench: A grounded simulation testing framework for evaluating social navigation. *ACM Transactions on Human-Robot Interaction*,
- [49] Jur van den Berg, Stephen J. Guy, Ming Lin, and Dinesh Manocha. Reciprocal n-body collision avoidance. In Cédric Pradalier, Roland Siegwart, and Gerhard Hirzinger, editors, *Robotics Research*, pages 3–19 vol. 70.
- [50] Anthony Favier, Phani Teja Singamaneni, and Rachid Alami. An intelligent human avatar to debug and challenge human-aware robot navigation systems. In *2022 17th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, pages 760–764, 2022.