People-aware navigation: AI-driven approaches to enhance the robot's navigation capabilities

Gloria Beraldo[1,2], Alberto Bacchin[1] and Emanuele Menegatti[1]

[1]*Department of Information Engineering, University of Padova, UNIPD*
[2]*Institute for Cognitive Science and Technology, National Research Council, ISTC-CNR*

Abstract
Traditional navigation algorithms, optimizing the robot's movements towards a target position, are not appropriate to manage the robot's movements in uncontrolled environment populated by people. In this paper, we propose different AI-driven methodologies related to the challenging topic of *people-aware navigation*, a dynamic and multi-agents navigation task, that aim introducing the social conventions respected by people, both at the reactive level and via a learning process.

Keywords
Social navigation, Shared approaches, Human-robot interaction,

1. Introduction

Robot navigation consists of the capability of efficiently reaching a destination B from the original position A. Traditionally, the standard navigation algorithms rely on optimizing a function based on the distance to the target position B, the number of attempts to reach the current goal and the cost associated with the obstacles [1]. However, in the perspective of introducing robots in social and uncontrolled environments populated by people, such as in the hospital, mall, house, the traditional navigation systems appear not suitable and robust, since they treat people as traditional obstacles. On the contrary, when moving, people care not only about avoiding collisions among them, but also about respecting social conventions in Figure 1. For instance, people usually respect social spaces according to the established relationship [2]. These emerging aspects have led to design *people-aware navigation algorithms*, also known as *social navigation*, namely a navigation task in a dynamic human environment where each agent has private and public objectives: efficiently reach a goal abiding by social norms [3]. Thus, it is necessary to introduce an additional cost depending on social rules and people interaction in the function to optimize behind each navigation system. However, how to implement this cost is challenging and still an opening research question. Indeed, *people-aware navigation* is more dynamic than the traditional where several agents share the same environment. Moreover, each agent is in charge of solving his/her navigation problem that is not known to the other people. Finally, the trajectories performed by each person are influenced by the other.

8th Italian Workshop on Artificial Intelligence and Robotics (AIRO 2021)
gloria.beraldo@dei.unipd.it (G. Beraldo); bacchinalb@dei.unipd.it (A. Bacchin); emg@dei.unipd.it (E. Menegatti)
0000-0001-8937-9739 (G. Beraldo); 0000-0002-2945-8758 (A. Bacchin); 0000-0001-5794-9979 (E. Menegatti)

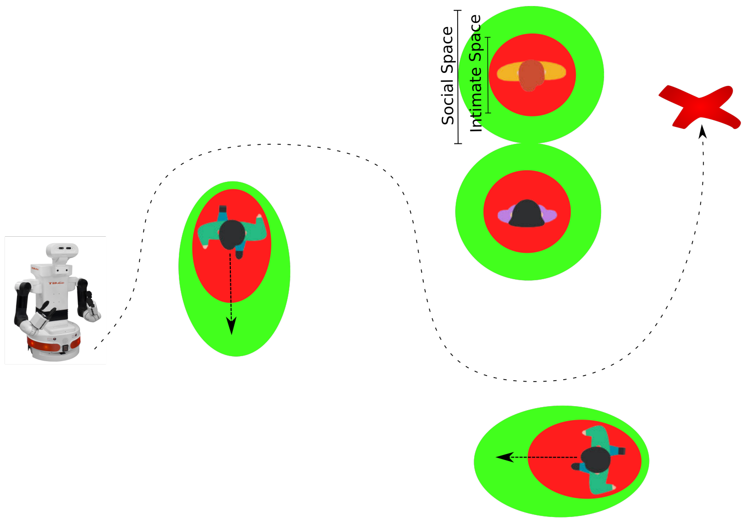

Figure 1: In *people-aware* navigation, the robot should be aware of social rules and conventions such as avoid to cut off the street to walking people or avoid to pass in the middle of a group of interacting people.

In this paper, we present an overview of different questions we are investigating and the proposed AI-based approaches to model *people-aware navigation* in *(semi)-autonomous* applications.

2. People-aware navigation for shared teleoperation

In this section, we introduce the research problem of enhancing the robot's capabilities during the remote teleoperation. In this kind of application, the importance of *people-aware navigation* is dual: a) the remote user has difficulty to efficiently and sociably manage the avoidance of dynamic obstacles such as people for instance due to the communication delay of receiving the camera feedback; b) the user would like to interact with one or more people (i.e., the person can be also a target). Specifically, our hypothesis is that *shared autonomy* system that simultaneously performs *people-aware navigation* and takes into account the user's input represents the most suitable kind of interaction. With this purpose, the contribution of this section is the evaluation of a first *people-aware navigation system* for shared teleoperation based on the *Teleoperation Behavior*. The proposed system manages the directional user's commands to drive the robot and the *Social behavior* to make the robot follow a target person autonomously and respecting social distances (e.g., it aims to freed the human to manage any single maneuvers to move towards the person) [4]. Therefore, the system enables the robot to adjust its motion according to the social context and to the user's input. From the technical point of view, we extend the formulas presented in [5] to consider the dynamism of people (i.e., the velocity and direction of humans in addition to their positions are evaluated) and we also integrate them with the "social rules" related to the personal space. Finally, we use the sum of the attractive and the repulsive behaviors to choose a *subgoal* position for the robot (e.g., navigation goal) rather than modify the robot's velocity accordingly.

We have evaluated the system in a pilot test with 10 users that were required to drive a mobile robot remotely from their home[1], and we have considered the following three conditions (e.g., two runs per condition): a) a complete *manual teleoperation* (e.g., any assistance nor robot's behaviors in autonomy); b) *supervisory* (e.g., the user's was required only to select a target person to follow at the beginning, then all the *people-aware behaviors* are autonomously managed by the robot); c) *shared autonomy* (e.g., the user can rely on the autonomous robot's *people-aware behaviors* until he/she sends directional commands). The first results have confirmed our hypothesis. The number of user's commands were decreased three times in *shared autonomy* condition than the *manual teleoperation*, indicating a reduction of user's workload [4], the trajectories were closer to the ground truth and no collisions happened. Any significant differences between the *shared autonomy* and the *supervisory* conditions were found. Furthermore, interestingly, the users relied on the robot's autonomy (e.g., the robot's assistance) in the more challenging part of the navigation task such as the passage through the doors, the corridor when the robot meets a walking person, a bend sharp. Finally, the human evaluation via questionnaire confirmed that participants made less effort in the *shared modality* than the *manual teleoperation.* Despite the easiness of *supervisory* modality (e.g., confirmed via the questionnaire), the participants preferred the *shared autonomy* as the best way to interact and drive the robot.

3. The problem of simulating a natural human walking

In the first experiments presented in the previous section, we faced the problem of simulating people motion to test the system. Gazebo, the traditional tool to simulate robots inside the ROS ecosystem, provides the animated model for people known as *actor*[2]. That tool allows animating both the *skeleton* (e.g., the joints inside the same model) and its motion along a specific trajectory. Furthermore, a set of different animations are included according to the specific actions performed by the actor: *moonwalk, run, sit down, sitting, stand up, talk, walk*. In the previous setup, we have specifically focused on the *talk* and the *walk* actions. It has emerged that especially in the case of *walk* the motion is not completely natural and intuitive (especially during the rotation around himself/herself), because the model simply follows a trajectory achieved by interpolating a set of *waypoints* set a priori. This aspect brings two limitations: a) if the waypoint coincides with an obstacles, a collision occurs; b) each simulated actor has not awareness of the other, with the possibility again of colliding with the the other actors. Although the first limitation was partially solved in the extended approach based on the virtual force model proposed in [6], we have focused on designing a new actor model that improves the *collision-avoidance algorithm* with respect to [6] and, in addition, considers the presence of the other walking people. Specifically, for facing the former aspect, we have applied a repulsive force to the actor when a collision is predicted. The force is inversely proportional to the distance between the obstacle and the actor. As regard the latter, a 3D collision box is associated to each actor for being detectable by the robot's lidar and by the other. Moreover, the motion of

[1]The experiments were made in simulations due to the COVID restrictions
[2]http://gazebosim.org/tutorials?tut=actor&cat=build_robot

the people is characterised by a random speed that is modelled with a Gaussian distribution and for which it is possible to define the area of interest. Finally, it is worth highlighting that the plugin is open-source[3] and can be easily imported inside any Gazebo world.

4. Robot's Learning to plan people-aware trajectories

In the previous section, we have considered a *people-aware navigation* system purely reactive where the remote user triggers the autonomous *people-following* behaviors and it changes accordingly to the specific situation (e.g., the presence or not of other directional commands from the user, the perception of the environment, etc). Herein, instead, we aim proposing a different strategy consisting of introducing a learning component in the system, namely we "a priori" train the robot to plan social trajectories respecting the Hall conventions. Considering that objective, we have proposed a genetic algorithm to directly optimize the parameters of the *local planner* inside the standard ROS navigation stack [4] with the aim of taking into account the presence of dynamic people [7]. The proposed approach has the main advantage of being fully integrated in the traditional ROS framework to manage goal-based navigation. However, the proposed method is facing two challenges: a) the performance of the *local planner* is strongly affected by the tuning of these parameters that is tedious and time-consuming task; b) it is complex to determine how to set them manually in environment populated by people because of their irregular movements as confirmed in other previous works [8].

With this purpose, we have exploited the actors plug-in described in Section 3 to simulate walking people that randomly move inside a specific area and, the robot is forced to meet people and learn to respect social distances. In detail, the robot repeats a navigation task (e.g., the robot has to reach a specific navigation goal) several times during the training phase, while it is disturbed by people walking around it. The task is represented in Figure 2. Each training run corresponds to a specific parameters configuration and is associated to a *score* computed in accordance to the proposed genetic algorithm [7]. Such a score depends on three metrics: a) the *minimum distance* from people measured during the execution of the navigation task (i.e., the *social score*); b) the distance from the navigation goal (i.e., the *distance score*); c) the execution time (i.e., the *time score*). We have combined all of these sub-scores, by assigning an higher weight to the *social score*, since our main aim was to enable the robot to plan social compliant trajectories. The other two were included in order to push the robot to successfully reach the goal in lower time (e.g., in accordance to the standard navigation). The final setting is determined by the configuration parameters with the best score.

Then, we have validated the final parameter setting by repeating the execution of the same navigation tasks per 200 times per condition and providing a statistical analysis to compare it with respect to the standard setting. Although the simplicity behind the algorithm, the preliminary results are very encouraging. The probability of overcoming the *intimate space* of people in the Hall's proxemics [2] has been three times lower with the optimization of the parameters than the default settings. Another relevant result have emerged by comparing our approach to the ROS standard algorithm for *people-aware navigation*, i.e. the *social_navigation_layers* [9].

[3]It is available at https://github.com/bach05/gazebo-plugin-autonomous-actor
[4]http://wiki.ros.org/navigation

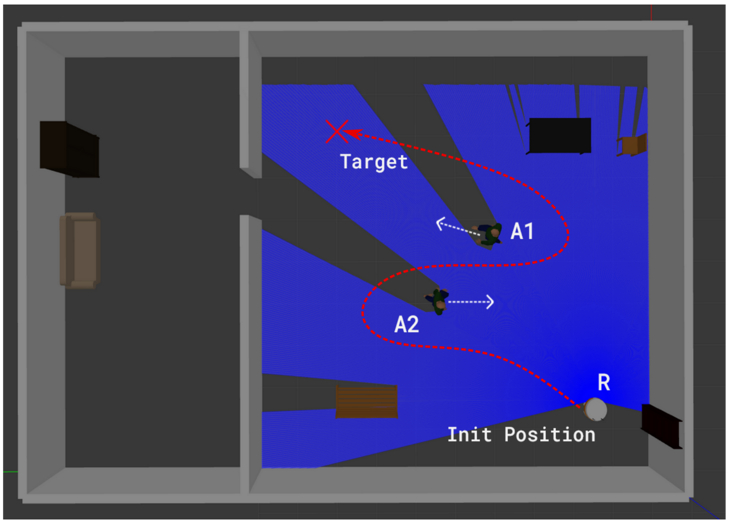

Figure 2: An illustrative representation of the simulated set up for the training of the genetic algorithm. The navigation task have been executed multiple times with different parameter sets, progressively optimized.

The results achieved from the optimized set of parameters have been statistically equivalent to the results obtained enabling the *social_navigation_layers* with the default values. In other words, we have demonstrated that is possible to plan *people-aware trajectories* without additional tools.

5. Shared intelligence for people-aware navigation

Despite the goodness of the preliminary results, the approaches presented in Section 2 and Section 4 have several limitations: a) the robot's autonomy is simply related to follow a target person and respect social distances according to the Hall's formulations; b) any information about the reactions and perception of the other people in the environment are considered; c) the human-robot interaction is very limited. This section aims presenting a different *people-aware navigation* approach that is oriented not only to respect the social intervals formulated by Hall and mix the contribution of the robot's perception with the user's commands, but also to infer the will of interaction from the other people in the environment. Our objective is to make the robot capable of autonomously contextualizing the following social conditions and behave consequently with the possibility of taking choices independently from the remote user's commands. We have focused on the following situations: a) avoiding walking people in an acceptable manner (e.g., in accordance to the Hall intervals) and avoid collisions with both static and dynamic obstacles, b) stopping in front of a target person when the remote user's moves the robot toward the direction of a specific person, c) stopping at the appropriate distance from a person when the latter gazes the robot. Moreover, one of the strengths of the proposed approach is that we have chosen not to explicitly code the possible behaviors in a sort of state machine as in the traditional algorithm of behavioral robotics, but they are achieved directly by the fusion of several *policies* managing specific information influencing the robot's behavior. In detail, the system has been implemented by extending the *shared intelligence* approach based on *policies* proposed in [10] to include the following social components: a) a *motion prediction policy* to estimate the next position occupied by people while walking and to strengthen the *obstacle avoidance*; b) a *user intention policy* to model the intention of the remote user to interact with the people in the environment; c) a *person attention policy* to favor the interaction with people that focus on the robot. Coherently with the original system [10], each *policy* provides a probability grid in the robot's neighborhood, representing the probability distribution of setting the *subgoal* in a specific location considering a specific source of information. As regards the social *policies*, the *motion prediction policy* assigns low probabilities to those cells corresponding to the positions occupied by walking people at time t+1 (we estimate the human motion as linear and we suppose that the robot should avoid the collisions in a social manner). The *user intention policy* and the *person attention policy* take into account the distance between the robot and each person and the time in which the gaze is kept (by the robot or by the people around the robot respectively) to shape the probability distribution. Finally, the fusion of all the *policies* outputs is computed as the product of each probability distribution. A schematic representation of the system is shown in Figure 3.

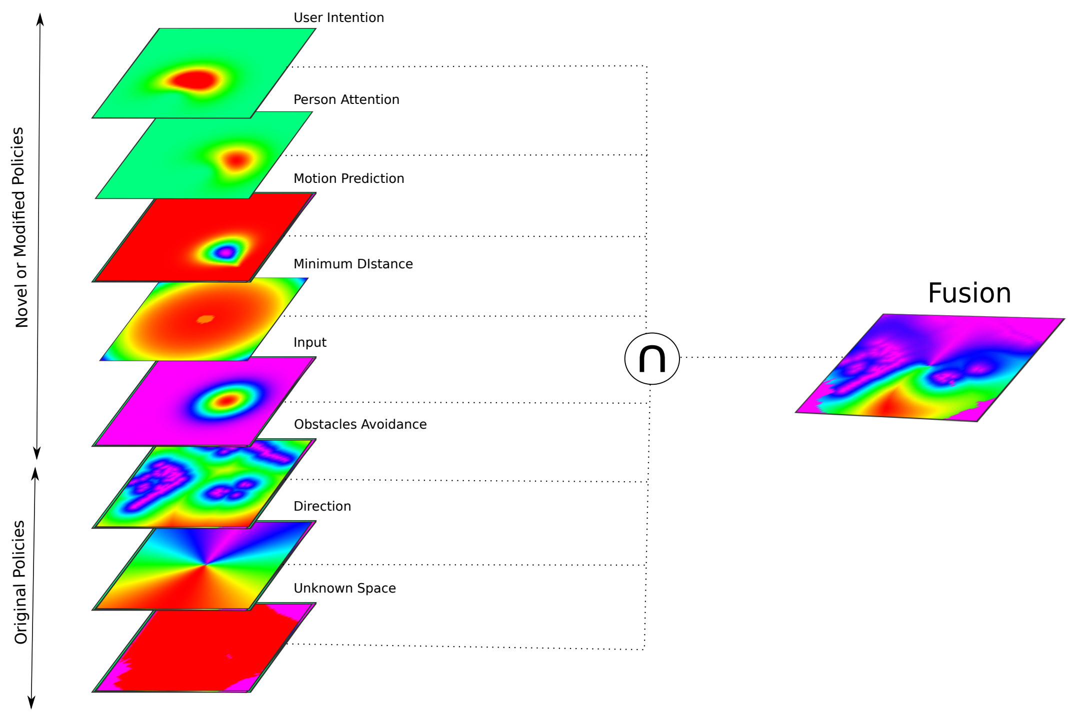

Figure 3: An illustrative representation of the *policies* behind the proposed shared intelligence for *people-aware navigation*.

The preliminary tests, both in simulation and on a real robot, have spotlighted the expected robot's behavior from the fusion of the *social policies* and the original ones. For instance, the robot was able to autonomously infer when it was suitable to stop for starting an interaction between the remote driver and the people. Furthermore, the robot respected the distance from the robot thanks to the combined effect of the *obstacle avoidance* and the *motion prediction policies* and moved in the environment in a reliable way (e.g., no collision) and without passing in the middle of group of people. However, further tests are necessary to confirm the potentialities of this approach in a complete navigation scenario and compare it with standard approaches such as the *social_navigation_layers* [9].

6. Conclusion

In this paper, we have presented possible AI-driven approaches to enhance the robot's navigation capabilities in respecting the social proxemics and promoting the interaction through the robot (e.g., follows a person, interact with people according to the intention of both the remote user and the other people). Future works will include further tests on the real robot and a systematic comparison of the proposed methods.

Acknowledgments

Part of this work was supported by MIUR (Italian Minister for Education) under the initiative "Departments of Excellence" (Law 232/2016). GB is also supported by "SI-Robotics: SocIal ROBOTICS for active and healthy ageing" project (Italian M.I.U.R., PON – Ricerca e Innovazione 2014-2020 – G.A. ARS01 01120).

References

[1] E. Marder-Eppstein, E. Berger, T. Foote, B. Gerkey, K. Konolige, The office marathon: Robust navigation in an indoor office environment, in: 2010 IEEE international conference on robotics and automation, IEEE, 2010, pp. 300–307.
[2] E. T. Hall, The hidden dimension : man's use of space in public and private, The Bodley Head, 1966.
[3] C. Mavrogiannis, F. Baldini, A. Wang, D. Zhao, P. Trautman, A. Steinfeld, J. Oh, Core challenges of social robot navigation: A survey, arXiv preprint arXiv:2103.05668 (2021).
[4] G. Beraldo, K. Koide, A. Cesta, S. Hoshino, M. Salvà, E. Menegatti, Shared autonomy for telepresence robots driven by people-aware navigation, Proceedings of the IEEE International Conference on Intelligent Autonomous Systems (IAS-16) (2021).
[5] S. Hoshino, K. Maki, Safe and efficient motion planning of multiple mobile robots based on artificial potential for human behavior and robot congestion, Advanced Robotics 29 (2015) 1095–1109.
[6] D. Helbing, P. Molnar, Social force model for pedestrian dynamics, Physical Review E 51 (1998). doi:10.1103/PhysRevE.51.4282.

[7] A. Bacchin, G. Beraldo, E. Menegatti, Learning to plan people-aware trajectories for robot navigation: A genetic algorithm, in: 2021 European Conference on Mobile Robots (ECMR), IEEE, 2021, pp. 1–6.
[8] K. Zheng, Ros navigation tuning guide, in: Robot Operating System (ROS), Springer, 2021, pp. 197–226.
[9] D. V. Lu, D. Hershberger, W. D. Smart, Layered costmaps for context-sensitive navigation, in: 2014 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2014, pp. 709–715. doi:10.1109/IROS.2014.6942636.
[10] G. Beraldo, L. Tonin, E. Menegatti, Shared intelligence for user-supervised robots: From user's commands to robot's actions, in: International Conference of the Italian Association for Artificial Intelligence, Springer, 2020, pp. 457–465.