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Exploring Learning Techniques for Developing Socially-Aware Service Robots: Best Practices for Social Comfort

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Abstract. In the past few years, there has been an increase in commercial and research focus on service robots operating in daily surroundings. These machines are anticipated to function independently in busy settings, enhancing movement efficiency and safety parameters, as well as social acceptance. Expanding conventional path planning modules to include socially aware criteria, while sustaining speedy algorithms that can adapt to human behavior without causing distress, presents a significant challenge. To address this challenge, learning methods have gained significant relevance. Among the various techniques, deep reinforcement learning, end-to-end, and inverse reinforcement learning have been the most promising. However, it is difficult to determine which techniques are superior, and sometimes, developers may obtain poor results due to inadequate data or experimental procedures during the learning stage. Therefore, it is essential to evaluate and discuss the best practices and options for an effective training stage that can improve results. As we are specifically referring to social robots, the evaluation of results should take into consideration social comfort as a key factor.

Keywords. Socially aware robotics, deep learning, multi-behaviour navigation, social navigation, social comfort

1. Introduction

One of the challenges in social robotics is expanding conventional path planning modules to include socially aware criteria. Learning methods such as deep reinforcement learning (DRL) approaches like CADRL, SARL, and SOADRL have been proposed for learning

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navigation policies in socially aware criteria. End-to-end learning has shown promise in scenarios where pedestrian positioning is challenging. Inverse reinforcement learning (IRL) offers a potential solution to automate reward function computation, with approaches like maximum likelihood estimation and Bayesian modeling showing promising results. However, poor results can occur due to insufficient data or experimental procedures, emphasizing the importance of evaluating and discussing effective training practices. Social comfort is a crucial factor in evaluating the outcomes of learning methods for social robots.

2. Methodology

This section outlines the criteria that were employed to select the articles included in this review and the criteria to analyze the experiments of the papers.

2.1. Article selection criteria

We meticulously compiled a selection of papers focused on social navigation, with particular emphasis on the topic of learning. Our approach involved a comprehensive review of the literature, drawing from authoritative works such as [19], [4], [12], and [37], as well as recent citations. We identified the most relevant papers that delved into the areas of social navigation, comfort, and learning.

3. Experiments

3.1. Deep Reinforcement Learning and End-to-End approaches

On these collected of papers there are several techniques o combinations of them use on each paper.[1],[2] and [7] use value networks and deep RL for learning social norms in collision avoidance. [32] compares reward functions,[6] evaluates a controller training approach, and [14] employes optimized parameters (OP-DDPG) for collision avoidance training. [9] evaluates Probabilistic roadmap (PRM-RL) on different maps. [22] compares their model with existing ones in randomized environments,[3] trains a gaze-modulated RL network for robot navigation and compare it with SARL.[11] propose a socially normative navigation algorithm,[23] compare their policy with NH-ORCA, and [15] use deep RL to train a robot in a simulated environment with changing obstacles.

[33] proposes curiosity-driven exploration, while [21] presents a simulative learning environment for socially concomitant navigation, both demonstrating their effectiveness through experiments. [24] introduces a deep Q-network (DQN) agent surpassing previous algorithms by learning challenging tasks from pixels and game scores alone. Simulation is widely used for training motion planners in mobile robotics. [34] trains a motion planner in the V-REP simulator for nonholonomic robots, while Fan et al. (2018) efficiently explore the state space with multiple robots using the Stage mobile robot simulator. [29] employs an observable Markov decision process (POMDP) approach to train navigation policies in diverse environments, while [5] trains a navigation algorithm in the Gazebo simulator for obstacle avoidance and autonomous navigation. In contrast,

[10] and [28] focus on expert demonstrations and evaluating path planning algorithms through simulation.

Two studies, [20] and [26], evaluate their navigation methods using simulations.[20] assess the navigation capability of a DQN agent in an unknown indoor environment while avoiding obstacles. [26] trains a neural network-based motion planner to safely guide the robot through environments cluttered with obstacles. Although [26] also evaluates their method in real-world experiments, their simulation results demonstrate its transferability to previously unseen virtual and real-world environments.

In real-world experiments, various navigation methods were evaluated. SA-CADRL [1] and GA3C-CADRL [7] policies were implemented on robotic vehicles in pedestrian environments, while [14] performed real indoor experiments with the IVO robot.[9] used a PRM-based approach, [22] employed deep RL with 3D lidar and stereo camera, and [33] tested their algorithm using a laser ranging sensor.[21] evaluated the transferability of their policy by comparing it with humans in real-world scenarios. [20] evaluated the DQL algorithm for autonomous mobile robot navigation in both simulation and real-world experiments. [26] focused on generating training data for navigating a maze-like area, while [27] demonstrated the generalization and robustness capabilities of models trained purely in simulation. [34] evaluated the real-world performance of robot navigation to reach targets.[8] successfully tested a collision avoidance policy on various mobile platforms in different real-world environments.[10] trained a robot to navigate in a real-world scenario using data collected by human experts. [5] trained a model in a simulation environment and demonstrated its adaptability to real-world uncertainties by testing it on a real tracked robot without fine-tuning.

3.2. *Inverse Reinforcement Learning*

In [38], real-world routing preferences are modeled using GPS data, while [16] demonstrates successful navigation path learning from demonstrations using a crowd motion simulator. [13] generates feasible velocity trajectories resulting in smooth paths for robot navigation, while [35] introduces a software platform with various contributions including GPU-based learning algorithms and teleoperation. [18] evaluates their approach's generalization to new situations using datasets of interacting pedestrians, while [36] collects data for a robot's path planning algorithm using lidar and remote control. [31] uses Bayesian Inverse Reinforcement Learning to learn reward functions for adventure games, and [25] demonstrates the effectiveness of their learning approach in enabling robots to learn complex navigation behaviors with experiments on a real robot and a pedestrian simulator.

However for real experiments [30] and [18] demonstrate successful social behavior for mobile robots in crowded environments. [35] showcases the potential for robots to provide helpful services in public spaces. [17] and [25] focus on robot behavior similar to human drivers and respecting personal spaces, respectively. The IRL planner was faster but more conservative, while the robot in [25] maintained personal spaces with the help of a social relation tracker.

4. Social Comfort

4.1. Deep Reinforcement Learning and End-to-End approaches

These methods ensure human-aware navigation and achieve socially compliant in dynamic pedestrian environments. They include SA-CADRL [1],long short-term memory (LSTM) extension [7], the SOADRL algorithm [22], the neural network-based approach [21], the danger-zone prediction method proposed by [32], the approach proposed by [14] that combines machine learning techniques with the Social Force Model, the method proposed by [11] that models both human-robot cooperation and inter-human interactions, the attention mechanism-based system proposed by [28], and the approach proposed by [29] that adapts to pedestrians in real-time while ensuring trajectory planning.

4.2. Inverse Reinforcement Learning

Several studies aim to develop socially compliant path planning frameworks for robots in human environments. [16] replicates human pedestrian behavior, while [30] imitates human behavior for socially compliant motions. [35] replicates human interactions, and [18] focuses on learning pedestrian behavior to predict and navigate through them. Meanwhile, [36], [17], and [25] propose approaches that generate socially adaptive paths by learning from demonstrated paths and taking social variables into account.

5. Discussion and Conclusion

The aim of this paper is to analyze the collected papers' ideas to provide future navigation algorithms with a source of methods that can be combined to improve social navigation and achieve better results.

To ensure effective learning models, diverse datasets should be used instead of relying on limited recorded datasets. The selected datasets should encompass various locations and environments for different purposes, not just a specific service or objective. Examples of valuable datasets include ETH, EWAP, Motion Capture, ZARA, and UCY, as used by [21]. Other notable datasets include Students [3] and WALLS [29]. Providing these references is an important contribution of the paper.

Not all studies are evaluated through real experiments due to the difficulties of simulating and generating scenarios. These limitations may include a lack of available robots or test subjects. Nonetheless, studies like those by [30], which test algorithms in a tourist environment, [34], which test algorithms in an office, and [8], which test them in a crowded street and mall, provide crucial insights into different scenarios and random people for evaluating and achieving robust coverage of situations.

In terms of social comfort, various strategies can be incorporated into navigation. For instance, [3] and [21] add social norms, [32] presents the concept of danger zones, [22] learns motion patterns, [10] and [28] propose adaptive robots, and [35] replicate human-social interaction, and [18] discusses cooperative navigation.

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