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# Autonomous Navigation by Mobile Robots in Human Environments: A Survey

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***Abstract*— With the service robots are well used in more and more indoor environments, autonomous navigation in such a human environment has been explored in recent decades. Different from the traditional navigation schemes, the new scenarios pose challenges about how to deal with the dynamic obstacles, especially the humans. To overcome the challenges, researchers need to consider: 1) the uncertainty of humans motion, 2) the interaction between human and robot, 3) the group information of the people. Also, the energy cost in the navigation process is of vital importance. In this case, the navigation requirements go far from the shortest path. In this paper, we reviewed the related works in the past decade, which can be roughly divided into four categories: reactive based, predictive based, model based and learning based. For each category, we analyzed some state of the arts, and listed the pros, cons and open problems. In the last of the paper, we summarized some evaluation metrics and corresponding methods.**

## I. Introduction

Nowadays, service robots are well used in more and more indoor environments, ranging from homes, offices to shopping malls, airports. In these environments, autonomous navigation by mobile robots is a basic but challenging task. On one hand, the robots need to finish the task assigned by some people efficiently-using as less energy as they can. On the other hand, the robots are required to ensure the physical and psychological safety of the people nearby. As a result, autonomous navigation in a human environment is a multi-objective optimization problem.

To solve this problem, one key challenge is how to deal with the people who share the space with the robots. There are three aspects that induce this challenge. Firstly, the unpredictable human motion. A person is far from a simple moving obstacle, whose motion is affected by both the internal and external factors. Secondly, the interactive information between the human and the robot. A person will have an inference about what the robot is going to do, then react to this inference. Thirdly, group information between the members. More than 70% of humans intend to form interactive groups in social environments [1]. At the very early stage, researchers treated the persons as common moving obstacles. Based on this knowledge, the reactive planners were proposed with a very satisfactory performance for collision avoidance [2]–[4]. Reactive planners can ensure the safety since they consider all the potential collision cases. However, they only focus on the next step which is short-sighted. To plan a long-sight path, human trajectory prediction becomes a focus of the researchers. In a low-density environment, this kind of methods shows great improvement, while when the crowd density increases, the robot tends to stop until the crowd disperses, which is known as a "Freezing Robot Problem" (FRP) [5]. The main reason is that the persons are dealt with separately, and most of the researches ignore the interaction between the social agents. As a result, the cooperative planning strategy is well adopted in the current research trend [6], [7]. To improve the navigation performance, the social cues such as the human-object interaction, the human-human interaction are incorporated in the planning framework [8]. And some multi-policy strategies are applied to deal with the complex environment [9], [10]. Meanwhile, with the good development of deep reinforcement learning, more and more researchers propose to solve this mentioned problem under a learning framework [11]–[13]. Among these methods, researchers should select the suitable one for the specific application. For example, the methods used in airports [14] and homes [15] are different due to the spatial scale and specific functions of the service robot.

This paper provides an overview of the researches in the past decade about autonomous navigation in human environments by mobile robots. Note that, we cannot ensure all of the related papers are reviewed in this paper, but the literature can surely represent the mainstream in this field. Similar work appears in [16], but this work was conducted five years ago which cannot demonstrate the latest trend, such as the application of the deep reinforcement learning. Based on different criteria, we divide the related works into several categories. We will analyze the pros and cons of the state of the arts for each category, then we will summarize the existing works and provide some potential directions.

The remainder of this paper is organized as follows. In section II, based on the horizon criteria, we divide the researches into reactive based and predictive based. Section III gives a comparison of the model based and learning based methods. Section IV describes some evaluation methods. We draw some conclusions in the last section.

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## II. Reactive & Predictive Strategy

### A. Reactive planners

A straightforward method to avoid collisions with the moving obstacles by mobile robots is that go towards the goal, if there is an obstacle in its way, just avoid it as illustrated in Fig. 1(a). One of the state of the arts is the velocity obstacle (VO) proposed by Fiorini et al. [2]. The main idea is to avoid making an action for the mobile robot that may cause a collision with a given obstacle moving at a given velocity. The basis of this idea is well adopted in many other researches [17]–[19]. However, when applied in a multi-agent navigation problem, the traditional way will lead to an oscillation problem, due to the non-consensus selection of actions. To overcome this drawback, Berg at al. proposed reciprocal velocity obstacles (RVO) [3] that considers the reaction of the other agents. Guy et al. [20] extended RVO to enable the mobile robot to behave like a man. To the best of our knowledge, ORCA proposed in [4] is the state of the art for the reactive planner, which provides a multi-robot navigation framework in human environments. Another kind of well used reactive planners is based on Social Force Model [21]. The forces come from the internal motivation such as heading for the goal, the factor that people keep a certain distance and attractive effects. Based on this, the human and robot, human and human, human and object can be modeled, and direct the robot navigating in a safe and friendly way [8]. Choi et al. [22] adopted Gaussian process regression to enable a low-cost robot navigation in a dynamic environment. Gaussian process motion controller (GPMC) and hierarchical Gaussian process motion controller (HGPMC) are integrated to compute the collision avoidance.

*1) pros:*

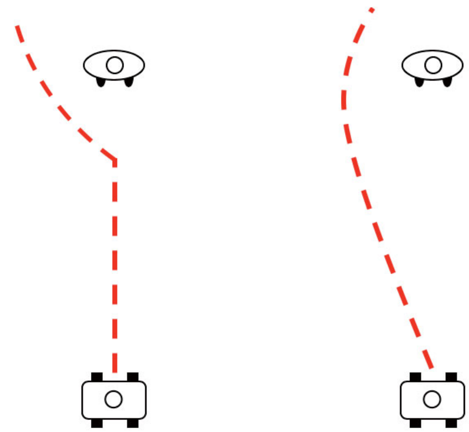
- *Implementation*. The method is easy to implement and applied in the real situations.
- *Physical safety*. The reactive planner considers all the collision cases, and select an action to avoid the collision risk. It can ensure the physical safety of the people nearby.
- *Generalization*. The strategy can be well generalized in a more complex environment.

*2) cons:*

- *Short-sight*. The reactive planner mainly considers the next action and ignores the future states of the agents nearby.
- *Psychological safety.* The strategy cannot ensure that the behavior of the mobile robot is like a person. As a result, there may be social discomfort in the navigation.

*3) open problem:*

- *Prediction ability*. More focus should be on the predictability of the human behavior. In this way, the global navigation can be implemented in a more cost-effective way.
- *Social cues.* Some important social cues should be considered in the planner, such as group information to make the navigation a human-friendly way.



(a) (b)

Fig. 1: (a) Reactive-based planning. The robot changes its direction when a person appears in the way of it. (b) Predictive-based planning. The robot first predicts the future states of the person, then it makes a reaction to avoid collision in advance.

### B. Predictive planners

When a person navigates in a crowd, to avoid a collision with other people, a predictive model will be set up to help decide where to go. Based on this fact, some researches [23]–[27] proposed to estimate the future trajectories of the agents as illustrated in Fig. 1(b). In a predictive navigation framework, the mobile robot estimates the future states of the other agents and makes the reciprocal action. Lu et al. [28] stated the importance of the subtle action difference of the mobile robot on the pedestrians.

In a sparse or semi-dense environment, the robot can find an efficient way to navigate through the crowd. However, in a dense scenario, every path will have a potential collision with some agent. In this case, the robot either stops until the environment gets safer or makes some evasive actions to avoid a collision, which is known as a "Freezing Robot Problem" (FRP). The main reason of FRP is that the future trajectory of one agent is predicted independently with the others. However, in the real-world scenarios, the moving agents usually react to the actions of the others. For example, two people are walking towards each other in a narrow corridor. To avoid a collision, they both make efforts such as passing by the right to make the navigation safe and smooth. As a result, a novel cooperative navigation strategy is well adopted. Trauman et al. [5] used an interaction potential to model the cooperation between agents in the space. Mead et al. [29] extended the definition of interaction potential in [5] to consider it from a multi-feature psychophysical perspective with the goal of maximizing interaction potential along the path to the goal pose. Rosmann et al. [30] first predicted and planned the future trajectories of the agents, and coupled them to reach an agreement that benefits the navigation of the agents in the space. Vemula et al. [31] used the spatial orientation of other agents to predict the velocities of them in the vicinity. Vemula et al. [32] focus on the importance of each person to avoid based on the potential collision. They trained the attention model using the real trajectory data. Mavrogiannis et al. [33] designed a human-inspired probabilistic inference mechanism and used it to interpret the environment and decide what future behaviors are proper for it. it. Fisac et al. [34] considered the uncertainty of the trajectory prediction to generate assured robot motion. To make full use of the group information, Aroor et al. [35] proposed to learn the crowd density and incorporate it into a navigation architecture to improve the performance.

Another kind of the prediction planners is based on the understanding of the social rules [36]–[42]. Chung et al. [36] proposed a framework to understand the social behaviors of the people in the space and make an human-friendly action. Lam et al. [37], [38] proposed six rules to help conduct a human-centered navigation task. Similar approaches appeared in [39], [40]. Mavrogiannis et al. [41] stated that the robot should make an action based on the avoidance protocols between the navigating agents to facilitate the inference and decision making for everyone. Johnson et al. [42] enabled the robot to learn the social norms from the observed data and incorporate them into its motion planning.

*1) pros:*

- *Feasibility*. The predictive methods conform to the laws of the human navigation. They're feasible in a human environment.
- *Social information*. The strategy can incorporate much social information to help with navigation.

*2) cons:*

- *Expensive computation*. The prediction of the trajectories for the agents requires much computation resources. When the crowd density gets higher, the algorithm is hard to work in real time.
- *Prediction uncertainty.* Due to the stochasticity of the human motion, the prediction presents uncertainty especially when the horizon gets further.

*3) open problem:*

- *Simplification*. Not all of the agents will have a potential collision with the robot. As a result, how to use the spatial and group information to offload the expensive computation remains an open problem.
- *Prediction bias*. The prediction result is not always reliable. When prediction biases appear, the robot needs to compensate them.

## III. Model-based & Learning-Based Strategy

### A. Model-based Strategy

For a large amount of works, researchers make efforts to solve the navigation problem in a human environment using different models. The navigation process is based on decision making considering the spacial interaction of the agents. Mehta et al. [9] proposed to use a Multi-Policy Decision Making framework extended from MPDM [43]. A forward simulation is conducted to evaluate the utility of the action generated from the proposed framework. The social interaction between the mobile robot and the moving pedestrians are considered in the prediction process. Mehta et al. [10] extended [9] through improving the efficiency of discovering influential outcomes. The Multi-policy strategy is well suited for the dynamic environments, since these scenes are changing all the time and many emergencies will come out. Sebastian et al. [44] adopted a Gaussian Mixture Models (GMM) to distinguish the different behaviors of the people and selected a trajectory with a high social-appropriateness score. Truong et al. [8], [45] proposed a social navigation framework that incorporates the interaction between human and human, human and objects. To ensure safety and be consistent with the characteristics of human navigation, social force model (SFM) is well used and extended in many methods. Zanlungo et al. [46] used an SMF-based method to replicate the behavior of people in a group. In [47], Chik et al. used Social-Force Gaussian Pedestrian Proxemics model to represent the pedestrian social space. Chen et al. [48] combined RRT-star with generalized velocity obstacles (GVO) to reduce the uncertainty of the trajectory. Forer et al. [49] regarded the navigation as a non-linear multi-objective optimization problem. They used the Pareto Concavity Elimination Transformation (PaCcET) to capture the human behavior and select the optimal trajectory point.

*1) pros:*

- *Implementation*. The method doesn't need any training process and requires no experts knowledge.
- *Behavior*. With more information than humans collected from the sensors, the robot can make more intelligent decisions.
- *Generalization*. The strategy can be well generalized in a more complex environment.

*2) cons:*

- *Human-like behavior*. Separation with the real trajectory data from the humans will make the navigation less natural.
- *Parameters*. To make the model work well in a specific environment, the parameter selection is a tough process.

*3) open problem:*

- *Social information*. The model needs to consider more social information to make the robot behave more like a person.
- *Integration.* The single model usually suffers from uncertainty or incompleteness. How to intelligently integrate different models remains an open problem.

### B. Learning-based Strategy

The development of deep neural network opens up a new way to make the robot's navigation safer and friendly. Based on the different functions, the models can be divided into three categories: supervised-learning based, deep reinforcement learning based, inverse reinforcement learning based methods.

*1) Supervised-learning based method:* To a large extent, the robotic experts can instruct the navigation by mobile robots. The people have the good performance in navigating in a crowd. Based on this fact, many researches are conducted using supervised learning. Pfeiffer et al. [50] proposed a target-oriented end-to-end navigation model that input the raw 2D laser data and output the steering commands. Perez-Higueras et al. [51] used Fully Convolutional Neural Networks (FCNs) to predict the cost map that helps the robot behave like a person. Hamandi et al. [52] adopted the imitation learning strategy to mimic humans navigation behaviors. Groshev et al. [53] used a deep neural network to represent a generalized reactive policy (GRP) that maps the state of the environment to an action. Li et al. [54] adopted a role playing learning scheme to help robot socially navigate. Han et al. [55] proposed Sequence-based Multimodal Apprenticeship Learning (SMAL) to learning robotic demonstrations directly from the expert. They also solved the perceptual aliasing by fusing temporal information and multimodal data to help the robot make a decision. Ahn et al. [56] learned different personal space for different people to approach them.

*2) Deep reinforcement learning based method:* With the development of the navigation in dynamic environments, the robots are required not only to avoid collisions, but also behave like a real person. Based on this, the utility of deep reinforcement learning attracts lots of the researchers. Chen et al. [57] pointed out the expensive computation for a predictive model and they proposed to offload the expensive online computation to an offline training process. Chen et al. [58] focused on the problem that what the robot should not do to release the trouble that learning about what should do. Riccio et al. [59] used reinforcement learning to conduct a cooperative planning task. Everett et al. [60] broke the assumption that the agents follow particular moving patterns. The learning-based model can deal with an arbitrary number of agents. Long et al. [61] developed a multi-robot collision avoidance algorithm using deep reinforcement learning.

*3) Inverse reinforcement learning based method:* Using reinforcement learning, researchers need to design the handcrafted cost function. However, the manual handcrafting requires the expertise in robotics, sensing and motion planning [62]. To overcome these limitations, researchers propose to use inverse reinforcement learning to generate the cost function. Wulfmeier et al. [62] proposed a maximum-entropy-based, non-linear inverse reinforcement learning (IRL) framework which is used in a path planning task. Ramirez et al. [11] used IRL to learn where and how to approach a person. Kim et al. [12] first extracted features to represent the state information. After that, they used IRL to generate a cost function with the help of the expert. Finally, the features and cost function are both integrated into a planning framework. Kretzschmar et al. [13] modeled the cooperation behavior of people that considers both the navigation decisions and the natural variance of the human trajectories based on IRL. Perez-Higueras et al. [63] combined IRL with RRT-star to learn the cost function.

*4) pros:*

- *Natural behavior*. The neural network model is trained using the real trajectory data. As a result, it reproduces the human behavior to a large extent.
- *Computation*. The expensive computation is conducted offline in the training process. As a result, the application is cost-effective.

*5) cons:*

- *Training data*. The training process needs a great amount of data, especially when the crowd density increases.
- *Generalization*. For a scenario which is different from the training ones, the neural network cannot generalize very well.

*6) open problem:*

- *Social features*. More social features should be exploited to generate a more human-friendly navigation behavior.
- *Generalization.* In a dynamic scenario, the environment is changing all the time, especially the states of the humans. The model should deal with the generalization problem efficiently.

## IV. Evaluation Methods

To demonstrate the feasibility and efficiency of the proposed planning methods or frameworks, various evaluation experiments are conducted. The evaluation metrics can be mainly divided into three categories.

- *Safety*. The rate of the collision avoidance.
- *Comfort*. The feeling of the co-existing people.
- *Energy cost*. The execution time and trajectory length.

For the *safety* metric, a safety zone can be defined manually. If the robot invades the zone, the behavior will be regarded as an unsafe one. In this way, the quantitative result can be represented using the collision rate and the minimum distance to dynamic obstacles [64].

For the energy cost, researchers usually use qualitative results like trajectory illustrations and quantitative values to evaluate the performance. Lu et al. [28] used the metrics speed and signaling distance to evaluate the navigation in a corridor. Aoude et al. [23] used the path duration time to show the efficiency of the proposed method.

Among these metrics, the comfort is hard to define and evaluate due to its subjective and context dependent. To overcome this problem, some researchers change the implicit index into an explicit one. Truong [65] defined the dynamic social zone concept and they used collision index (CI), interaction index (II), and psychological index (PI) to evaluate the performance of the robot. The same concept was also used in [66]. Bevilacqua et al. [67] proposed three discomfort indices: target value, the computation time and the path length. Chen et al. [68] introduced the social interaction space concept. Chen et al. [69] conducted the evaluation experiments to show the effect of passive HRI. Some researchers use the distance to approximate the discomfort [70]–[72]. In a more convincing way, some researchers use a questionnaire to reveal the feeling of the people [73].

## V. Conclusion

In this paper, we provide a review of the papers in the last decade about autonomous navigation in human environments. To achieve this object, the planners need to consider not only the traditional navigation requirements such as execution time, trajectory length, free collision with static obstacles, but also the human factor. The main trends in this field are analyzed through some state of the arts. For a single person, the robot needs to account for the comfort of the person which needs the trajectory prediction and human robot interaction. For a social group, the robot is required to show respect for the group, and use the group information to improve the navigation performance. For evaluation, the comfort is hard to define and evaluate. Some researchers use the explicit metric - distance to reveal the implicit feelings of the people. Some other researchers use a questionnaire to learn about the preference scores for the robot behavior.

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