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Human-aware Motion Planning with Improved Virtual Doppler Method in Highly Dynamic Environments

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ABSTRACT

Human-aware path planner is essential for achieving harmonious coexistence between humans and robots in highly dynamic environments [1]. In this paper, we propose an integrated framework to find the optimal path in the complex environment with considering collision risk, social norms, and crowded areas. In the proposed framework, a general dynamic group model (g-space) based on the Gaussian Mixed Model (GMM) is proposed as the social norms of dynamic groups, which not only considers the factors of humans (e.g., pose, quantity, distribution, psychology) but also establishes the proximity and human interacting constraints of dynamic groups. An integrated Collision Risk and Human Space (CR&HS) model is applied to achieve human acceptable behaviors, in which both collision avoidance, human comfort, and interference-free constraints have been involved. Moreover, an Improved Virtual Doppler Method (IVDM) has been used to realize safety navigation to avoid the robot falling into crowded areas. Finally, the proposed framework has been utilized with the sampling-based rapidly-exploring random tree. Experimental results demonstrate that the proposed method can generate the optimal human-aware collision-free path in complex environments.

INTRODUCTION

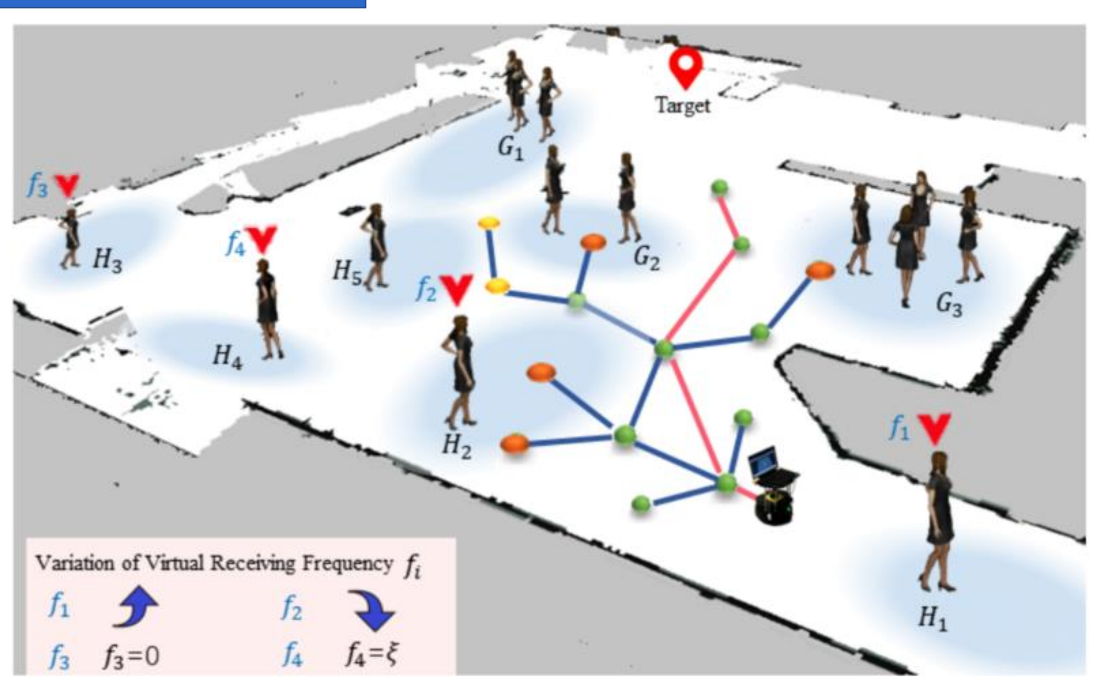

Fig. 1. Illustration of our method. The color points indicate the nodes of paths. The blue areas present the model of human space about the dynamic individual (H_1, H_2, H_4 and H_5), the static individual (H_3), the dynamic group (G_1) and the static groups (G_2, G_3). To measure the human density, $f_{1\text{-}4}$ is proposed to present the relationship between humans and robots. The illustration of fi in the bottom left quarter shows its change while navigating from the current position to the goal. The red path is generated by our method. In the red path, the robot bypasses the crowd and has more human-friendly manners than other methods shown by the orange points and yellow points. Without consideration of human-friendly and human density, the robot in the orange points has a higher probability of generating human-unfriendly manners, and the yellow points lead the robot to fall into the crowd.

In this paper, we propose a novel framework to enhance the navigation performance of mobile robots in highly dynamic environments. A universal model that describes dynamic humans has been proposed, in which humans are with an arbitrary number and random distribution in a group. In addition, we propose an improved probability model that combines collision-free factor with human-aware factor. Therefore, different types of social norms and all obstacles can be considered during navigation in a dynamic environment. Besides, relative motion between robots and humans will also be considered in IVDM, as well as the human density. Finally, the proposed framework has been utilized with risk-based, rapidly exploring random tree as the evaluation module [2]. Fig. 1 shows the conception of the proposed method. As shown in the figure, passing through the crowd will increase the probability of potential collision and affect human comfort.

METHODOLOGY

The integrated framework proposed for human-aware path planning is to quickly and stably finish the navigation task while avoiding falling into the crowd without contrary to the social norms. Let $\Gamma_s(q_s(t))$ represents the path s from node $q_s(0)$ to node $q_s(T)$, the problem of this study can be written as:

$$\Gamma_s(q_s(t)) = \{q_s(t)\}_{t=0\ldots T} | q_s(t+\Delta t) = g(q_{s'}(t), u_t^s \Delta t)$$

$g(\cdot)$is the motion model of the robot, u_t^s is the control vector during each time stepΔt of s^{th} path. In each planning step $\Delta t, S$ paths are generated by different control vectors. The cost function $\eth(\cdot)$ is defined to calculate the cost of each node from $\Gamma_s = \{\Gamma_1, \Gamma_2 \ldots \Gamma_S\}$. After that, the path with minimum cost is the final optimum path Γ_{opt}:

$$\boldsymbol{\Gamma_{opt}} = \arg\min \sum_{\Delta t} \eth(\boldsymbol{\Gamma_s}(q_s(t)))$$

$$\eth(\boldsymbol{\Gamma_s}(q_s(t))) = w_1 \prod_{t=1}^{T} P(q_s(t)) + w_2 \sum_{t=1}^{T} \mathcal{A}(q_s(t)) + w_3 \mathcal{C}(\boldsymbol{\Gamma_s})$$

where w_1, w_2, w_3 are the weights to balance the quantities. $\eth(\cdot)$contains the risk of collision and social norms constraints $(P_s(\cdot))$, the IVDM method $(\mathcal{A}_s(\cdot))$, and distance assessment module $(\mathcal{C}(\cdot))$. The distance assessment module is similar to the one in [1]. This algorithm determines how much a cost is when taking an action $u_t^s \in U$ in configuration $q_s(t) \in \Gamma_s$. In addition, the outputs of $P(\cdot)$, $\mathcal{A}(\cdot)$, and $\mathcal{C}(\cdot)$ are normalized.

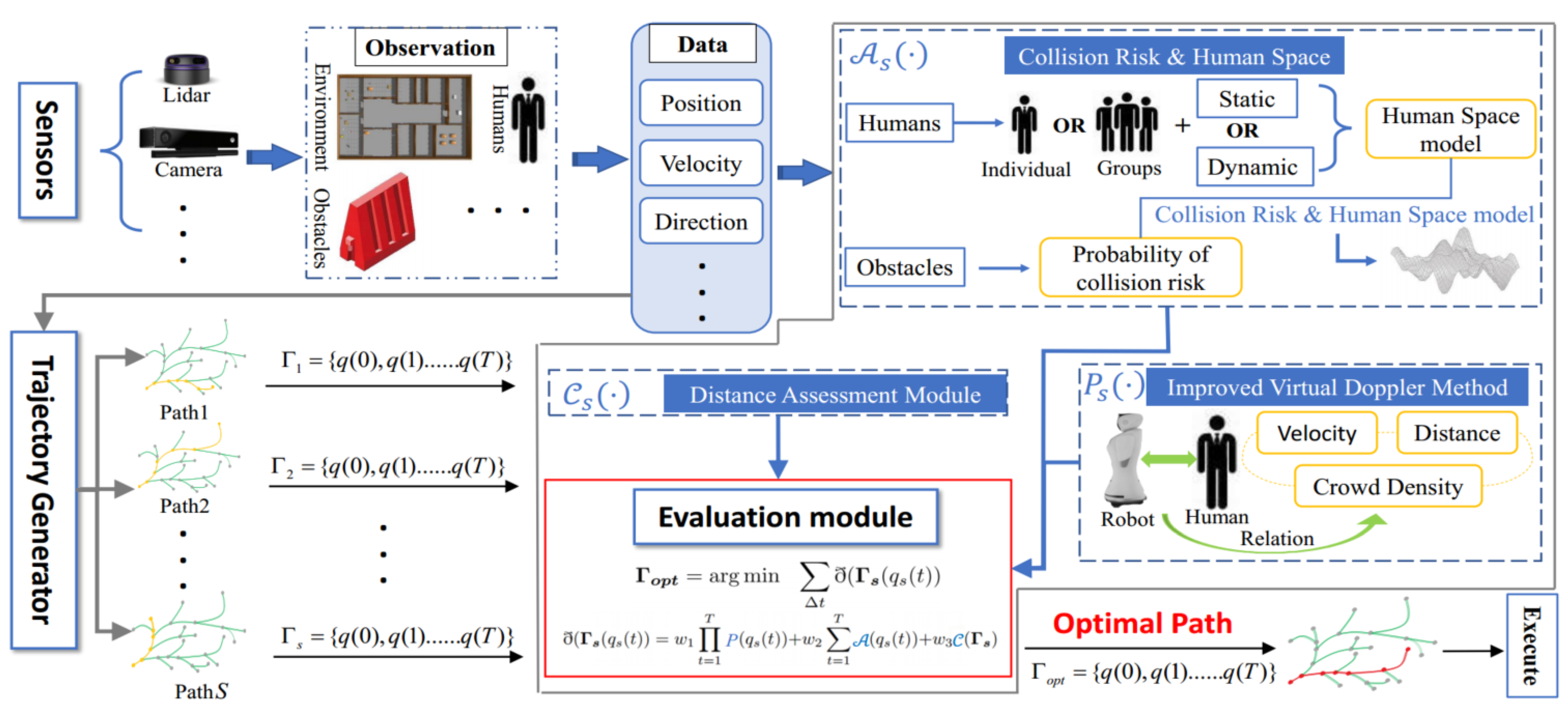

Figure 2. System diagram of the proposed path planning method. In a planning step, according to the data flows from the Sensor, the Evaluation Module calculates the cost of the multiple trajectories generated by the Trajectory Generator, and the path with the minimum cost is taken as the optimal path. The Evaluation Module include CR &HS, IVDM and distance assessment module. Their processes are outlined in the blue dotted box, and the details are described below.

EXPERIMENT

We conduct the simulation in Robot Operation System (ROS). Stage simulator is used and the non-holonomic robot and simulated virtual humans have been implied. The simulation environment with a size of 41 m ×28 m can be seen in Fig. 3. Two sampling-based human-aware methods have been compared: R-RRT and R-CCR. In comparison, R-RRT and R-CCR do not have CR&HS and IDVM model. The experiment in each scenario has been repeated 20 times. Results showed that the trajectories generated by the proposed method are smoother than those generated by other methods. Fig. 4(a) and (c) show the distances (D) between humans and the robot under three methods. We use D=1.5m as the threshold of human comfort, which is defined by anthropologist Hall.[3] When D is

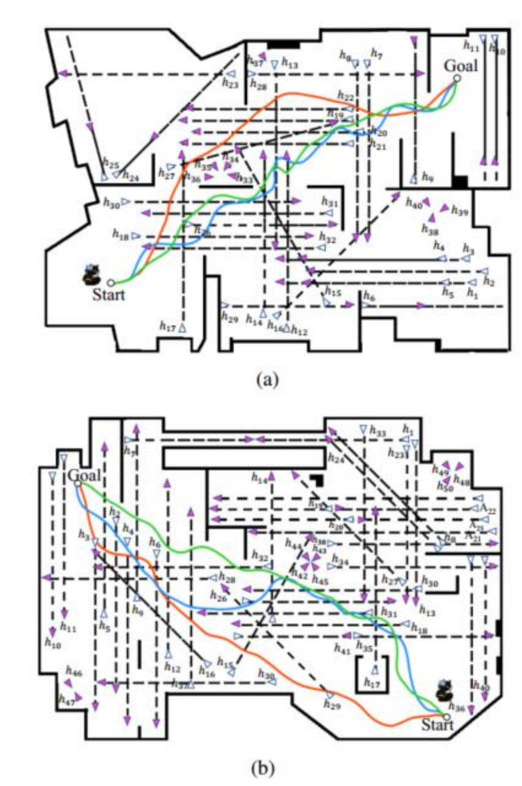

Figure 3. The comparative experiments in exhibition hall environments. (a) The exhibition hall A with 40 humans. (b) The exhibition hall B with 50 humans. The green, blue, and red lines denote the trajectory generated by RRRT, R-CCR, and our method. The black dotted lines are the track of humans. The pink (white) triangle presents the final (initial) position of humans, and the vertex angle of the triangle presents the direction.

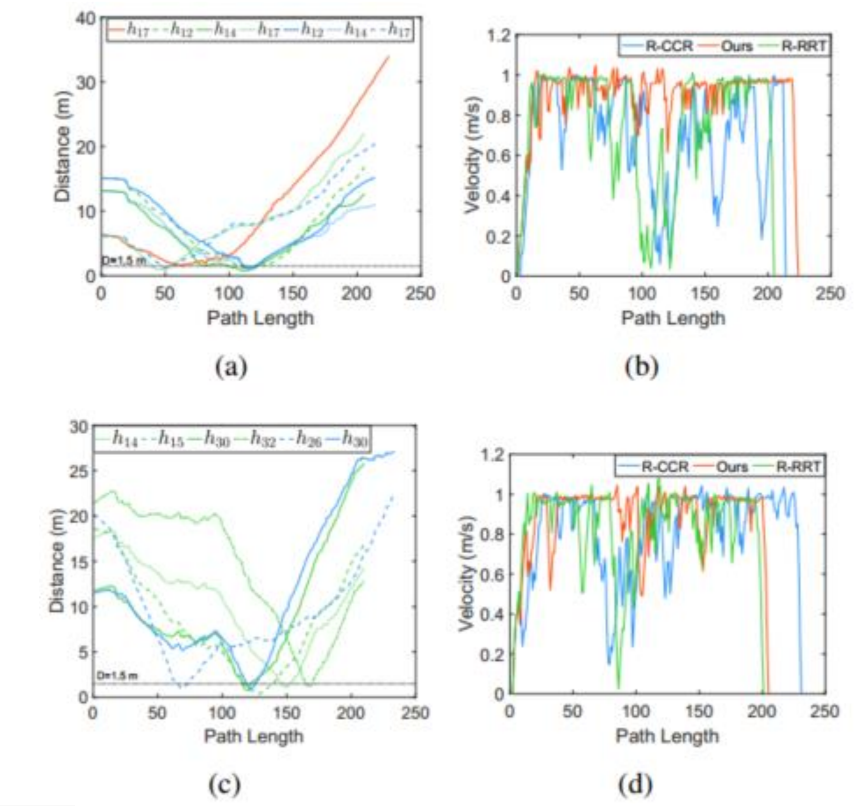

Figure 4. Experimental performance in environment A and B. (a) The distances (D) between humans and robot in environment A. (b) The velocity of different methods in environment B. (c) The distances (D) between humans and robot in environment B. (d) The velocity of different methods in environment B. The green, blue, and red lines in four subfigures denote the performance generated by R-RRT, R-CCR, and our method. D= 1.5m is the threshold of human comfort.

less than the threshold, the human will feel uncomfortable. The smaller the D value is, the more uncomfortable the human will feel. To display results clearly, we only show the three minimum distances (D) between humans and the robot under the threshold in each method. The velocity results can be seen in Fig. 4(b) and (d), which show that the velocity curve under the proposed method has a minimum fluctuation. Although the trajectories planned by the R-RRT are the shortest among all the methods, the velocity curve wavily fluctuates. As shown in Fig. 4(a) and (c), at least three humans may feel uncomfortable under R-RRT and R-CCR methods in both exhibition hall environments. However, only human h_{17} has a distance less than the threshold with the proposed method, which is shown in Fig. 4(a) with the red curve. The above experimental results show that the proposed method is able to consider human awareness and more efficient than the two other methods in large complex environments. The reason is because that based on the ability of navigation in crowded areas introduced by CR&HS and IDVM, the proposed method can drive the robot to bypass crowds smoothly and robustly. Besides, when operating in spacious areas, the proposed method is easier to maintain a proper distance from humans than the other two methods operating in crowded areas. Therefore, the proposed method has a good performance.

CONCLUTION

In this paper, we proposed an integrated framework to find the optimal path in the complex environment. Experimental results demonstrate that the proposed method can move away from the crowd to avoid a potential collision. In the future, we will consider the potential corresponding approaches to improve the efficiency of the proposed method.

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