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Curiosity-based Robot Navigation under Uncertainty in Crowded Environments

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ABSTRACT

Mobile robots have become more and more popular in our daily life. In large-scale and crowded environments, how to navigate safely with localization precision is a critical problem. To solve this problem, we proposed a curiosity-based framework that can find an effective path with the consideration of human comfort, localization uncertainty, crowds, and the cost-to-go to the target. Three parts are involved in the proposed framework: the distance assessment module, the curiosity gain of the information-rich area, and curiosity negative gain of crowded areas. The curiosity gain of the information-rich area was proposed to provoke the robot to approach localization referenced landmarks. To guarantee human comfort while coexisting with robots, we propose curiosity gain of the spacious area to bypass the crowd and maintain an appropriate distance between robots and humans. The evaluation is conducted in an unstructured environment. The results show that our method can find a feasible path, which can consider the localization uncertainty while simultaneously avoiding the crowded area.

INTRODUCTION

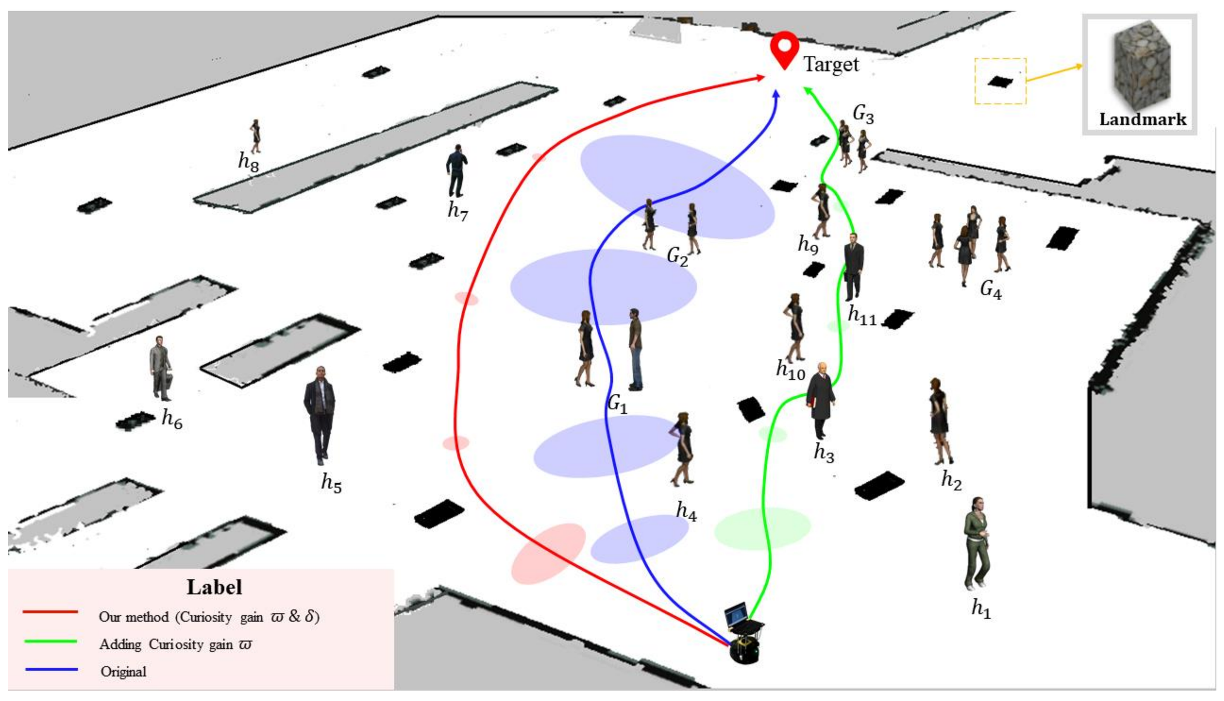

Fig. 1. Illustration of the proposed method. Our method with curiosity gain of information-rich area (ϖ) and curiosity negative gain of crowded area (δ) is able to generate a human-friendly path (red) that can simultaneously avoid crowds and approach landmarks, which makes humans comfortable and minimize state estimation uncertainty. Besides, the method with the curiosity gain (green) ϖ can approach landmarks area while it leads to a high collision risk with humans. The original without these curiosity gains enter both crowded and landmarks deficient areas, resulting in large localization uncertainty and comfort reduction. The smaller the ellipse is, the more accurate the robot localization is. *Hi* presents humans. *G i* presents humans who engage in conversation in a group.

In this paper, we focus on three aspects of the problem including collision risk and human comfort, crowds, and localization uncertainty. In terms of completing navigation tasks quickly and safely, it is important to endow service robots with fundamental navigation capabilities that meet both collision-free and safe objectives. Our proposed method can seek a feasible path considering both low localization uncertainty and human-comfort behavior. We set two different gains to inspire the "curiosity" in terms of the robot's current condition and propel the path planning.

- Considering the condition of human dense, robot navigation should be effective to avoid driving into the crowded area, which may cause the "freezing robot problem" [1], and have an adverse effect on human comfort simultaneously. In other words, crowded areas have a curiosity negative gain to prevent robots from navigating in such areas.
- The operating scope of serve robots may be relatively large, like airports. In such environments, state estimation may not be accurate because of the lack of landmarks and measurement noise [2]. Therefore, robots need to be curious about the information-rich area and then generate the path across these areas to reduce the localization uncertainty.

METHODOLOGY

We use $\mathbb{M}$ to represent the map of the environment created by the robot. $\mathbb{O}_{obs}(t)$ represents the un-modeled obstacles, which includes humans $\mathbb{O}_h(t)$ and lifeless obstacles $\mathbb{O}_{so}(t)$. These obstacles are newly introduced which are not in $\mathbb{M}$. $\mathbb{O}_{free}(t)$ represents the free space in the map, which excludes the modeled obstacles and un-modeled obstacles (humans). $\mathbb{O}_{mark}$ represents the landmark space in the map. During navigation process, the path planning is repeated at each time step Δt. $\mathcal{Q}_j : \{q_j^1, q_j^2, ..., q_j^i\}$ represents nontrivial trajectories generated in j[th] time step. $q_j^i : \{[x_j(1), u_j(1), z_j(1)]^T, ..., [x_j(n), u_j(n), z_j(n)]^T\}$ contains a number of states, control inputs and observations. The best path from a set of nontrivial trajectories in j[th] time step can be formulated by the first formula of **Evaluation Module** in Fig. 2. where $\mathcal{O}$ represents landmarks in the environment. $\mathcal{L}^*$ is the objective function to find the best path from a set of nontrivial trajectories. The curiosity-based function $\mathcal{L}^*$ is expressed as the second formula. ℓ is the evaluation of localization uncertainty and σ is the location threshold. When $\ell(q_j^i)$ is higher than a given threshold, the robot is regarded as localization fails. ς represents the function of curiosity gain ϖ, which is positively correlated with the curiosity in the information-rich area. When the localization uncertainty increases, a higher value of ς is gotten. This means that the robot becomes more curious about the information-rich area. w is the weight of the curiosity gain ϖ. $\mathcal{L}$ is the social-aware cost function. It consists of the distance assessment module, curiosity negative gain δ, human comfort, and collision risk. When the robot works in increasingly crowded environments, the curiosity negative gain of the crowded areas will increase. In such conditions, the curiosity of crowded areas is lower

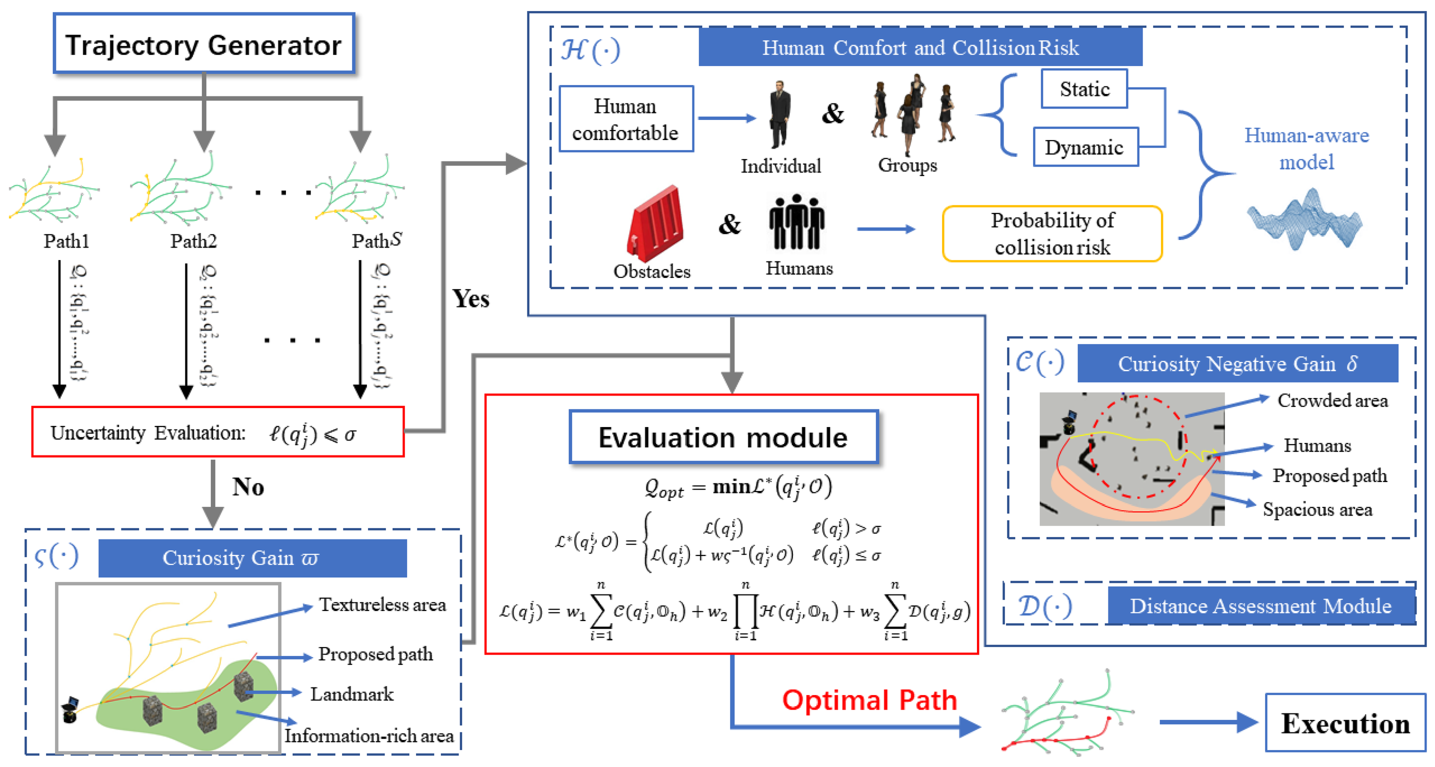

Fig. 2. System diagram of the curiosity-based path planner. **Evaluation Module** calculates the cost of the multiple trajectories generated by the **Trajectory Generator**, and the trajectory with the minimum cost is considered the optimum one.

than the spacious area. Therefore, the robot will be attracted by the spacious area to bypass the crowds. The formula of $\mathcal{L}$ is shown in the third row of the Fig. 2. $\mathcal{D}$ is the distance assessment module, which is similar to the tradition method [3]. $\mathcal{H}$ is gaussian process-based model considering human comfort and collision risk, which is similar to the [4]. $\mathcal{C}$ represents curiosity negative gain δ.

EXPERIMENT

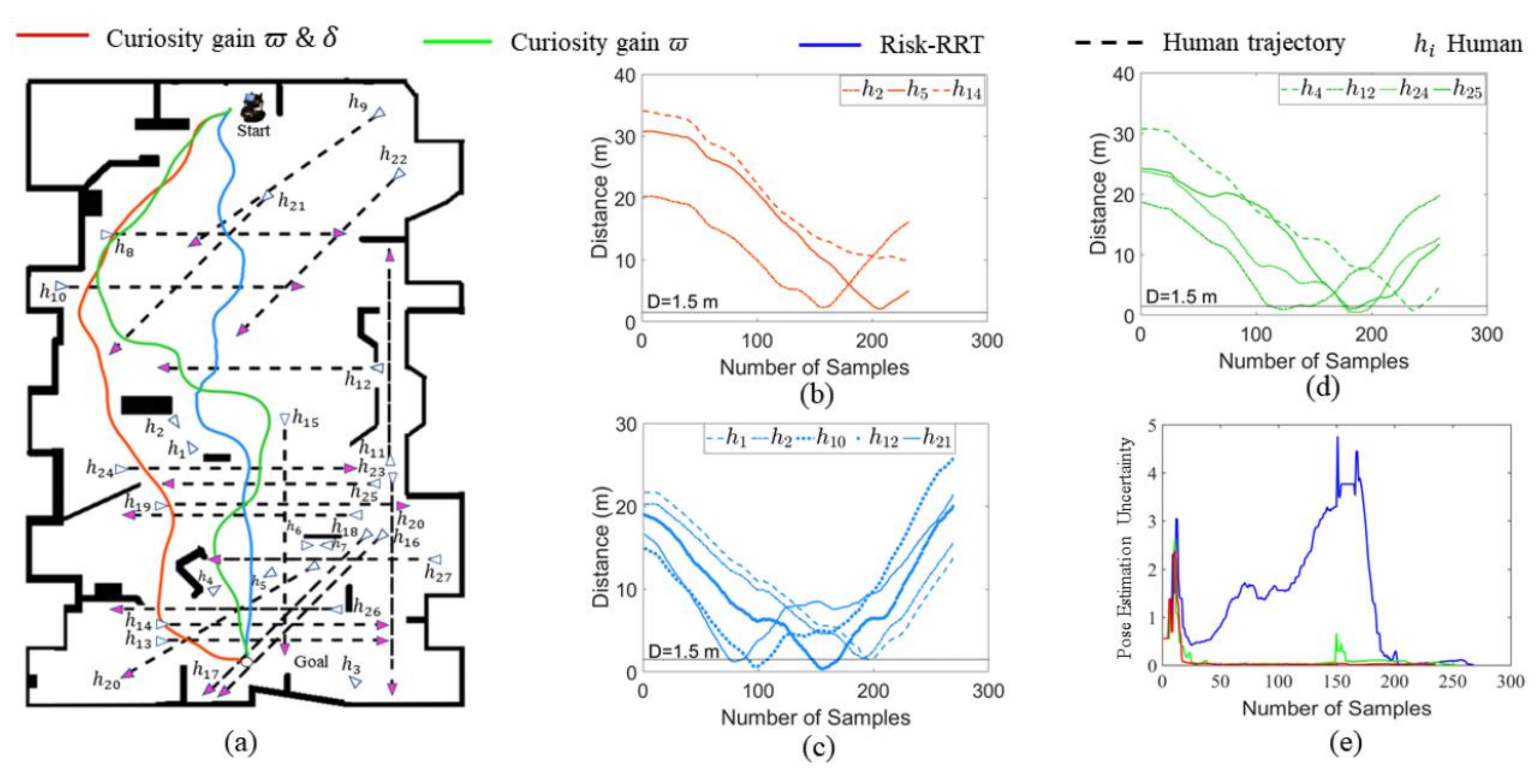

Fig. 3. Experimental results of the simulation environment. (a) Simulation environment and navigation paths.(b)-(d) Distances between humans and robot. (e) Uncertainty of paths.

We conduct the simulation by using the stage simulator in Robot Operation System (ROS). 1 The robot in the simulation environment is mounted with a laser sensor. Besides, we use Adaptive Monte Carlo Localization (AMCL) for localization. The simulation scenario is shown in Fig. 3(a), which is a large-scale and crowded environment with 27 humans. There are few landmarks in the central area of the upper part of the scenario. Our method and the compared methods are shown in different colors in Fig. 3. The red results (path in Fig. 3(a) and curves in Fig. 3(b), (e)) are generated by our method, which considers both the curiosity gain ϖ and curiosity negative gain δ. The green results are generated by the method only considering the curiosity gain ϖ , and the blue results are generated by Risk-RRT [3], which does not consider the curiosity gain. The other two methods drive the robot into a crowded area where it is unable to keep a proper distance from humans. Intuitively, compared with the other two methods, our proposed method can generate the trajectory closer to the landmark and bypass the crowded area more smoothly. The other two methods without considering the curiosity negative gain δ drive the robot into the crowd, which has to make a detour for avoiding humans. Besides, the distances between the nearest humans and the robot in crowded areas are shorter than that in the spacious area. Fig. 3(b)-(d) show the distances between the humans and robot. *D*=1.5m is the defined threshold [5], below which the human will feel uncomfortable. To display results clearly, we show the three minimum distances (D) or distances (*D*) less than or equal to the threshold. The distances in our method are always higher than the threshold. However, this indicator cannot be satisfied by other methods. Such results demonstrate that our method enables the robot to maintain an appropriate distance from humans without affecting human comfort. In addition, in Fig. 3(e), both the red curve and green curve, which both consider the uncertainty effect have lower pose estimation uncertainty than others.

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CONCLUTION

The curiosity-based method can plan a collision-free path with the consideration of the robot state estimation and the distribution of the crowd. Simulations are carried out to demonstrate the advantage of the proposed method. In the future, we will further study the possibility of applying the proposed method to more complex scenarios.