

Curiosity-based Robot Navigation under Uncertainty in Crowded Environments

Kuanqi Cai^{1,2}, Weinan Chen¹, Chaoqun Wang³, Shuang Song², and Max Q.-H. Meng^{1,2}, *Fellow, IEEE*

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 the 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 co-existing 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.

I. INTRODUCTION

In the past few years, with the rapid development of mobile robots, service robot driving in the large-scale and human-robot coexistence environment has attracted growing attention [1]. Therefore, how to generate a feasible trajectory in such environments becomes an essential problem for service robots [2].

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 [3]. In our curiosity-based framework, curiosity is defined as the unsupervised act of moving through the areas which contain landmarks or few humans based on the robots' current condition. Different from the curiosity-based path planner proposed by Zhang et.al [4], which guides robot only to learn environmental information of obstacles, our proposed method can seek a feasible path considering both low localization uncertainty and human-comfort behavior. We set 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" [5], and have an adverse effect on human

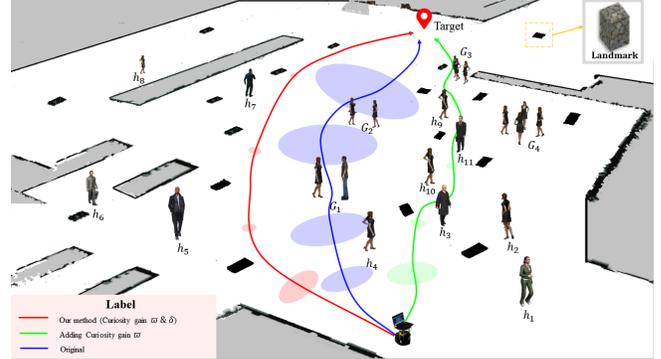


Fig. 1. Illustration of the proposed method. Our method with curiosity gain of information-rich area (ϖ) and curiosity negative gain of crowded area (δ) is able to generate a human-friendly path (red) that can simultaneously avoid crowds and approach landmarks, which makes humans comfortable and minimize state estimation uncertainty. Besides, the method with the curiosity gain ϖ (green) 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. H_i presents humans. G_i presents humans who engage in conversation in a group.

comfort simultaneously. In other words, crowded areas have a curiosity negative gain to prevent robots from navigating in such areas. Besides, 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 [6]. Therefore, robots need to be curious about the information-rich area and then generate the path across these areas to reduce the localization uncertainty. To solve such problems, we present an integrated, curiosity-based approach for mobile robot navigation. This approach can both avoid crowds and consider the localization uncertainty in dynamic environments.

II. PROBLEM FORMULATION

The target of driving the robot in a crowded environment is to find a feasible path bypassing the crowd and reducing the localization uncertainty. 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. The non-linear motion model of

¹Shenzhen Key Laboratory of Robotics Perception and Intelligence, Southern University of Science and Technology, Shenzhen, China.

²School of Mechanical Engineering and Automation, Harbin Institute of Technology, Shenzhen, China.

³School of control science and engineering, Shandong university, Shandong, China.

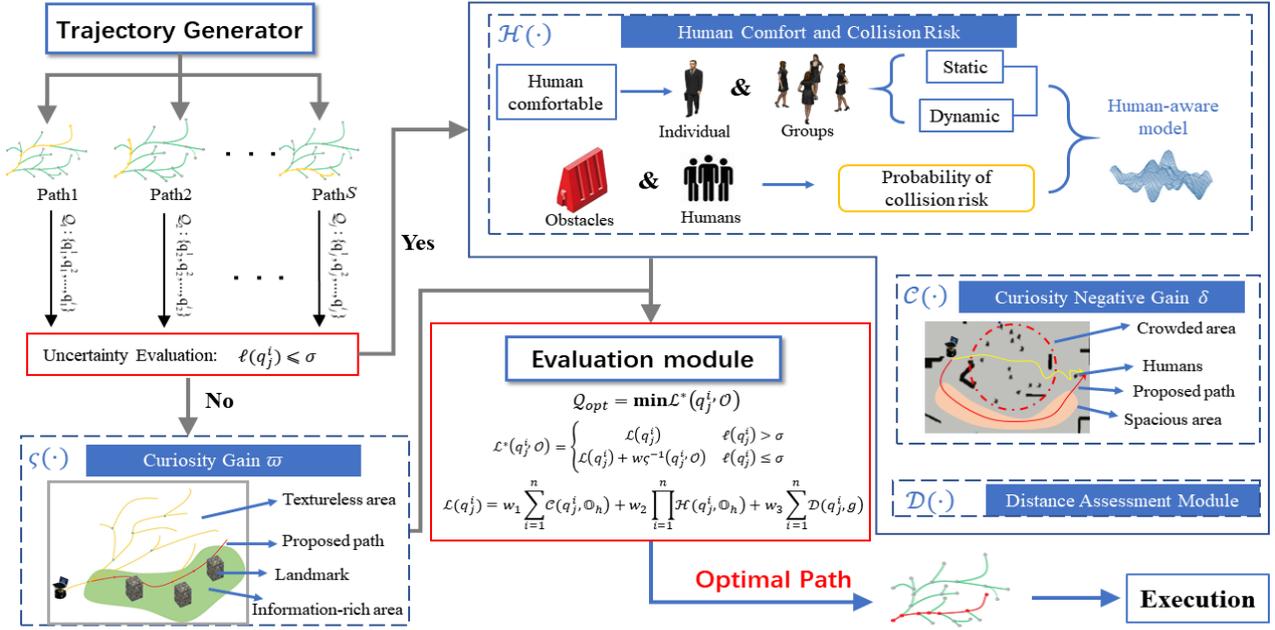


Fig. 2. System diagram of the curiosity-based path planner. **Evaluation Module** calculates the cost of the multiple trajectories generated by the **Trajectory Generator**, and the trajectory with the minimum cost is considered the optimum one.

the robot is depicted as:

$$x(t+1) = f(x(t), u(t), m_t), \quad m_t \sim \mathcal{N}(\mathbf{0}, M_t), \quad (1)$$

$x(t) \in \chi$ is the valid robot state at time t . χ is the state space. $u(t) \in U$ is the control vector in the control space U . m_t is the motion noise with mean 0 and variance M_t . The measurement of the robot at time t is $z(t) \in Z$. Z is the observation set that contains the whole observation information of the robot. The formula of $z(t)$ is as follow

$$z(t) = g(x(t), n_t), \quad n_t \sim \mathcal{N}(\mathbf{0}, N_t). \quad (2)$$

n_t is the measurement noise based on Gaussian distribution with variance N_t . During navigation process, the path planning is repeated at each time step Δt . $\mathcal{Q}_j : \{q_j^1, q_j^2, \dots, q_j^i\}$ represents nontrivial trajectories generated in j_{th} time step. $q_j^i : \{[x_j(1), u_j(1), z_j(1)]^T, \dots, [x_j(n), u_j(n), z_j(n)]^T\}$ contains a number of states, control inputs and observations. n is the index of state along the path. The best path from a set of nontrivial trajectories in j_{th} time step can be formulated by

$$\begin{aligned} \mathcal{Q}_{opt} = \min & \quad \mathcal{L}^*(q_j^i, \mathcal{O}) \\ \text{s.t.} & \quad \mathcal{O} \in \mathcal{O}_{mark} \\ & \quad q_j^i \in \mathcal{Q}_j \\ & \quad q_j^i \in \mathcal{O}_{free}(t), \quad \forall t \in [t, t + \Delta t], \end{aligned} \quad (3)$$

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

$$\mathcal{L}^*(q_j^i, \mathcal{O}) = \begin{cases} \mathcal{L}(q_j^i) & \ell(q_j^i) > \sigma \\ \mathcal{L}(q_j^i) + w\zeta^{-1}(q_j^i, \mathcal{O}) & \ell(q_j^i) \leq \sigma. \end{cases} \quad (4)$$

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. ζ 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 ζ 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 than the spacious area. Therefore, the robot will be attracted by the spacious area to bypass the crowds. The formula of \mathcal{L} is:

$$\mathcal{L}(q_j^i) = w_1 \prod_{i=1}^n \mathcal{C}(q_j^i, \mathcal{O}_h) + w_2 \prod_{i=1}^n \mathcal{H}(q_j^i, \mathcal{O}_h) + w_3 \sum_{i=1}^n \mathcal{D}(q_j^i, g), \quad (5)$$

where \mathcal{D} is the distance assessment module, which is similar to the tradition method [7]. \mathcal{H} is gaussian process-based model considering human comfort and collision risk, which is similar to the [8]. \mathcal{C} represents curiosity negative gain δ .

III. METHODOLOGY

In this study, we combine the curiosity-based function with the systematic sampling-based planner to find the feasible trajectory. The diagram of the system for trajectory generation and assessment in the planning step is illustrated in Fig. 2. First, the **Trajectory Generator** accounts for generating a series of path candidates from the robot's current position to

Algorithm 1: Trajectory Generation

Input: Map \mathbb{M} , Goal g
Output: Trajectory candidates \mathcal{Q}_j

- 1 $g = read(), \mathcal{Q}_j = \emptyset;$
- 2 $\mathcal{O}_{mark} = load(), \mathbb{M} = load();$
- 3 $Tree \leftarrow InitializeTree();$
- 4 **while** $t < \Delta t$ **do**
- 5 $q_{rand} \leftarrow Sampling(\mathbb{M});$
- 6 $q_{near} \leftarrow Nearest(q_{rand}, Tree);$
- 7 $[q_{new}, \tau] \leftarrow Steer(q_{rand}, q_{near});$
- 8 $Tree = Extend(q_{near}, q_{rand});$
- 9 **if** $ObstacleFree(q_{new})$ **then**
- 10 $Tree.add(q_{near}, \tau);$
- 11 $q_{neighbor} \leftarrow FindNearNeighbor(Tree, q_{new});$
- 12 $Tree \leftarrow Rewire(q_{neighbor}, q_{new}, Tree);$
- 13 $\mathcal{Q}_j \leftarrow FindPathCandidates(Tree);$

the next position with the sampling-based planning scheme. Second, we calculate the localization uncertainty of the current robot position. If the localization uncertainty of the robot is higher than the threshold, the curiosity gain in the information-rich area will be introduced in the **Evaluation Module** and the trajectory pass through this area will be rewarded and vice versa. Third, the **Evaluation Module** is leveraged for the best path with minimum cost.

The workflow of **Trajectory Generator** which is similar to [9] can be seen in Alg. 1. $Sampling(\cdot)$ is used to generate the random point q_{rand} in the \mathbb{O}_{free} . $Nearest(\cdot)$ is to search $Tree$ for finding the nearest point q_{near} to q_{rand} . $Steer(\cdot)$ extends $Tree$ from q_{near} to q_{rand} with path τ considering the kinematic constraint of robots. q_{new} represents the end of the path τ . q_{near} is the neighbor point of the q_{new} . $FindNearNeighbor(\cdot)$ is the function to reselect the neighbor point of the q_{new} on the $Tree$. $Rewire(\cdot)$ is the rewiring process of $Tree$ to reduce redundant length. These processes is repeated and the $Tree$ continuous updates during each time step Δt . When time runs out, trajectories candidates on $Tree$ for robot navigation are generated through $FindPathCandidates(\cdot)$. $FindPathCandidates(\cdot)$ is the function to select the trajectories that are collision free and conform to the robot motion model as candidates.

The procedure of effective path generation based on **Evaluation Module** is shown in Alg. 2. During the navigation process, the robot updates its observation (see lines from 3 to 5 in Alg. 2). In addition, real-time constraints of **Evaluation Module**, which contain curiosity gain ϖ , collision risk, and human comfort, curiosity negative gain δ , and distance assessment module are considered to find the best trajectory from a set of candidates (see lines from 6 to 23 in Alg. 2). Different from the artificial potential field-based methods [10], which may lead to local minima and computationally heavy, the collision risk and curiosity-based components in our method are based on a probability model.

Algorithm 2: Optimal Trajectory Generation

Input: Trajectory candidates \mathcal{Q}_j , Current state x_c
Output: Best path from a set of candidates \mathcal{Q}_{opt}

- 1 Humans \mathbb{O}_h , Landmark \mathbb{O}_{mark} , Un-modeled Obs $\mathbb{O};$
- 2 **while** g not reached **do**
- 3 Observe($\mathbb{O}_{mark}, \mathbb{O}_{obs}$);
- 4 Delete unreachable trajectories(\mathcal{Q}_j, x_c, t);
- 5 predict \mathbb{O}_h at time $t, \dots, t+N * \Delta t$;
- 6 $\ell = UncertaintyCal(x_c);$
- 7 **if** $\ell > \sigma$ **then**
- 8 $IntroCuriosityGain P_{\varpi} = \varsigma^{-1}(q_j^i, \mathbb{O}_{mark});$
- 9 **else**
- 10 $P_{\varpi} = 0;$
- 11 **for** $j < Number\ of\ candidates$ **do**
- 12 **for** $i < size(\mathcal{Q}_j)$ **do**
- 13 $Collision \ \& \ Human P_{Risk} = \mathcal{H}(q_j^i, \mathbb{O}_h);$
- 14 $DistanceAssessment P_{Dis} = \mathcal{D}(q_j^i, g);$
- 15 $IntroCurNegGain P_{\delta} = \mathcal{C}(\mathbb{O}_h, q_j^i);$
- 16 $\mathcal{Q}_{cost} = CostCal(P_{Risk}, P_{Dis}, P_{\delta}, P_{\varpi});$
- 17 $i++;$
- 18 $j++;$
- 19 $\mathcal{Q}_{opt} \leftarrow Min(\mathcal{Q}_{cost});$
- 20 **if** $\mathcal{Q}_{opt} = \emptyset$ **then**
- 21 **break;**
- 22 **else**
- 23 $\left| \right.$ move along \mathcal{Q}_{opt} for one step;

A. Curiosity gain of information-rich areas

The curiosity gain ϖ is a probabilistic model which is designed to reduce the localization uncertainty of the robot when driving in dynamic environments. The higher the probability, the more curious the robot is about the area. Curiosity gain ϖ contains three parts: collision region, curiosity region, and overlap region.

1) *Collision Region:* Landmark often refers to the known obstacles in the map, which can be used for robot localization. The collision region is the area where the robot would collide with the landmarks. The collision region of the landmark is the inflation of the landmark. The inflation radius is the robot's inscribed radius. The probability of curiosity gain ϖ in this area is zero, which presents this area as not attractive to robots.

2) *Curiosity Region:* The curiosity region is the expansion of the landmarks, whose inflation radius is according to the laser range. In such an area, the robot has a high probability observe the information of the landmark to locate. The curiosity gain ϖ in this area corresponds to the information content observed by the robot. Hence, it decreases from the inside that is close to the landmark to the outside.

3) *Overlap Region:* In a crowded area, humans may walk around or stay in the curiosity region. The observation in the human body will introduce localization error, which leads to the failure of the robot localization and even collides with

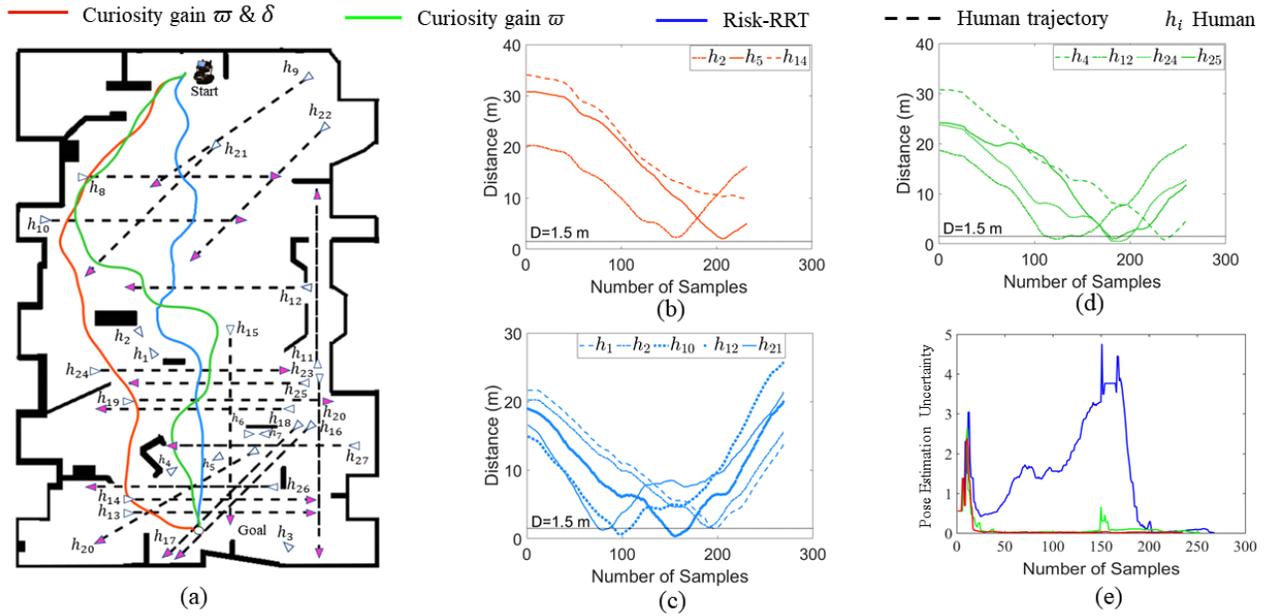


Fig. 3. Experimental results of the simulation environment. (a) Simulation environment and navigation paths. (b)-(d) Distances between humans and robot. (e) Uncertainty of paths.

humans. Therefore, we set the overlap region according to the area occupied by humans. The probability of curiosity gain ϖ in this area will be reduced.

B. Curiosity negative gain of crowded areas

We proposed curiosity negative gain δ which is presented by a two-dimensional Gaussian mixture model to describe the crowded area in the dynamic case at a certain moment. The mean of this model is the center of the crowd and its covariances are depend on the humans at the crowd boundary. The value of curiosity negative gain δ is inversely proportional to the distance between the robot and the center of the crowd. At each time step, curiosity negative gain of crowded areas will be calculated based on the change in the environment to update the trajectory.

IV. SIMULATIONS AND RESULTS

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) [11] for localization. The simulation scenario is shown in Fig. 3(a), which is a large-scale and crowded environment with 27 humans. Humans move in different directions and speeds within the environment. The velocity of different humans is set to be a random value in a range of $[0, 1]$ (m/s). The global information of humans moving in the environment is available to the robot during online planning. 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 [7], 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 the robot. $D=1.5$ m is the defined threshold [12], 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.

The experiment is repeated 10 times. PE, MD, TD, and NT are used for evaluations comprehensively. PE is the pose estimate uncertainty. MD is the minimum distance between humans and the robot while completing the navigation task. TD is the ratio of the duration (when D is smaller than the

¹Video demonstration is available at <https://youtu.be/O2JJWS2Vpck>

TABLE I

STATISTICS OF THE THREE METHODS IN SIMULATION ENVIRONMENTS.

	PE	NT	TD	MD
Curiosity gain ϖ & δ	0.096	0	0	2.065
Curiosity gain ϖ	0.119	3.7	0.238	0.509
Risk-RRT	1.315	4.2	0.266	0.385

threshold) to the total time of the robot moving. NT is the average number of times that the robot's minimum distance is lower than the given threshold. As shown in Table I, the proposed method has the minimums value of NT and TD, and it also has a maximum value of MD. This indicates that the proposed method can maintain an appropriate distance from humans. Besides, it can be seen that the proposed method has the minimum PE, which indicates that our method has the lowest localization uncertainty among the other methods. The simulation demonstrates the effectiveness of our curiosity-based method.

V. CONCLUSIONS AND FUTURE WORK

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.

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