Anticipatory Robot Navigation: Incorporating Estimated Obstacle Behaviors with the Social Force Model

Fengkai LIU¹, Yuichi OHSITA², Kenji KASHIMA³, Shinya YASUDA⁴, Taichi KUMAGAI⁴, Hiroshi YOSHIDA⁴, Masayuki MURATA¹

¹Graduate School of Information Science and Technology, Osaka University, Japan ²Cybermedia Center, Osaka University, Japan ³Graduate School of Informatics, Kyoto University, Japan ⁴Visual Intelligence Research Laboratories, NEC Corporation, Japan

Background

- Increasing demand for automation within warehouses.
- Robots are central to warehouse automation.
 e.g. Automated Guided Vehicles (AGVs).
 Primarily perform transport tasks.
- Some obstacles exist in the operational area of the robot.
 - Static Obstacles: Walls, etc.
 Dynamic Obstacles: Humans, other robots, etc.
- Challenge: Obstacle Avoidance
 - At the situations with unclear obstacle behavior, we focus on:
 - Navigate the robot to achieve an optimal balance between navigation safety and moving efficiency.

1 / 12

Traditional Collision Avoidance Methods

- Drawback: Lack of Interaction-Awareness in some traditional methods.
 - Neglecting the impact of robot's movement on obstacle trajectories.
 Leads to perceiving higher obstacle intrusion and conservative control
 - strategies, e.g., stopping or speed reduction¹.
 - In extreme situations, leads to Freezing Robot Problem².

••• KO

Figure 1: Example: Robot stopped due to lack of Interaction-Awareness.

¹Milos Vasic and Aude Billard. Safety issues in human-robot interactions. In 2013 IEEE International

Conference on Robotics and Automation (ICRA), pages 197-204, 2013. ²Peter Trautman and Andreas Krause. Unfreezing the robot: Navigation in dense, interacting crowds. In 2010 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pages 797-803, 2010 2 / 12

Development of Interaction-Aware Methods

- Introduction of the Social Force Model.
 - To understand and predict the interaction between surrounding entities.
 Drawback: Ignoring individual obstacles behavior.
 - Tendency to use fixed parameter values across different scenarios.
 - Challenges in accurately predicting diverse obstacle behaviors.
 - Potential risk of misjudging obstacle actions leading to collision or inefficient navigation.



Figure 2: Example: Collision risk due to misjudgment in obstacle behavior.

3 / 12

Proposal

Navigating robots while ensuring smooth and efficient movement.

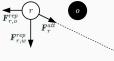
- Model and predict the individual obstacles behavior using observational position data.
 - Utilizing the Social Force Model to simulate obstacle behavior.
 Adapting model parameters based on observed behaviors of different obstacles.
- Calcuate control input of the robot.
 - Based on the model of the behaviors of nearby obstacles.

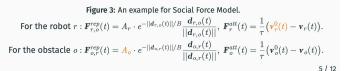
Assumption

- The robots' observation of the obstacles' position $\widetilde{r}_o(t)$ contains noises, potentially due to sensor precision.

4 / 12

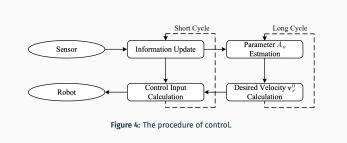
Social Force Model





 \boldsymbol{g}_r

Method Overview



Method: Short Cycle

$$\widehat{\mathbf{r}}_{o}(t) = \widehat{\mathbf{r}}_{o}'(t) + \left[\mathbf{K}(t) \cdot \left(\widetilde{\mathbf{r}}_{o}(t) - \widehat{\mathbf{r}}_{o}'(t)\right)\right]$$

$$\widehat{\mathbf{v}}_o(t) = \frac{\widehat{\mathbf{r}}_o(t) - \widehat{\mathbf{r}}_o(t - \Delta t) + 1/2 \cdot \widehat{\mathbf{a}}_o(\Delta t) \cdot \Delta^2 t}{\Delta t}.$$

Then, the control input of the robot is calculated by

 $\mathbf{v}_r(t + \Delta t) = \mathbf{v}_r(t) + \mathbf{a}_r(t)\Delta t.$

Here, $a_r(t)$, the acceleration, is determined by the Social Force Model. The parameter for the Social Force Model are defined according to the long circle.

Method: Long Cycle

Estimate the value of the parameter A_o using Bayesian Estimation by

$$P(A_o^i | \widetilde{\mathbf{r}}_o(t), \widetilde{\mathbf{r}}_o(t - \Delta t)) = \frac{L(\widetilde{\mathbf{r}}_o(t) | A_o^i, \widetilde{\mathbf{r}}_o(t - \Delta t)) \cdot P(A_o^i)}{\sum_i L(\widetilde{\mathbf{r}}_o(t) | A_o^i, \widetilde{\mathbf{r}}_o(t - \Delta t)) \cdot P(A_o^i)}.$$

This parameter is crucial for dictating the avoidance behavior of obstacles and predicting their movement.

Then, calculate the desired velocity by minimize the objective function

ninimize
$$\mathcal{J}([\mathbf{v}_r^0]) = \mathcal{J}_t([\mathbf{v}_r^0]) + \mathcal{P}_v([\mathbf{v}_r^0]) + \mathcal{P}_d([\mathbf{v}_r^0])$$

based on the prediction of trajectories. This parameter is crucial for calculate the control input of the robot, achieve an optimal balance between navigation safety and operational efficiency.

8 / 12

6 / 12

Evaluation: Experimental Setup

- Environment: Flat area of $3m \times 3m$.
- Robot and Obstacle Settings: Detailed in Table 1.
- Simulation Cases:
 - Obstacle avoids the robot (A_o = 20).
 Obstacle maintains original trajectory (A_o = 0).
 - Table 1: Settings for the Robot and the Obstacle

	Obstacle o	Robot r
Initial position $r(0)$	[1.5, 0.8]	[1.5, 2.2]
Initial velocity $\mathbf{v}(0)$	[0, 1]	[0, -1]
Goal g	[1.5, 2.2]	[1.5, 0.8]
Maximum speed vmax	1.5 m/s	1.5m/s

Figure 5: Setting

9 / 12

Evaluation: Estimation of the Obstacles Behavior

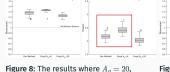




Figure 6: Estimation result \hat{A}_o when the actual value of A_o is set to 20.

Figure 7: Estimation result \widehat{A}_o when the actual value of A_o is set to 0.

Evaluation: Comparison With the Scenario Without Parameter Estimation



avoid the robot.



the robot.

=

Conclusion

Summary of Current Work

- Applied the Social Force Model for understanding and predicting obstacle avoidance behaviors.
- Utilized these insights to refine the robot's control input.
- Achieved a balance between navigation efficiency and safety.

Future Directions

- Exploration of practical application in real-world scenarios.
- Deployment and testing on actual robots in diverse environments.
- Expansion of the model to include human obstacles and account for irrational behaviors.

12 / 12