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• **Supplementary File** •

Obstacle Avoidance Under Relative Localization Uncertainty

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Appendix A Simulations

To further illustrate the effectiveness of the proposed method, simulations on 2D space are carried out using both the proposed method and the method described in [1]. First, one trial of simulation is carried out to compare the collision avoidance and reference trajectory tracking performance. Further, comparative analysis is carried out based on mento-carlo simulations to test the effectiveness under different localization uncertainties.

The dynamic model of local robot and obstacle are modeled using the second-order linear model as

$$x_{i,k+1} = Ax_{i,k} + Bu_{i,k},$$
$$x_{o,k+1} = Ax_{o,k} + w_{o,k},$$

where $A = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \otimes I_2$ and $B = \begin{bmatrix} 0.5\Delta t^2 \\ \Delta t \end{bmatrix} \otimes I_2$, with control sample time $\Delta t = 1$. The process noise for the obstacle is set as $w_{o,k} \sim \mathcal{N}(0, \text{diag}([0.05^2, 0.05^2, 0.01^2, 0.01^2]))$. The dynamics for the reference state of local vehicle is $x_{r,k} = [k, 0, 1, 0]^\top$. The measurement function for obstacle is

$$z_{i,k} = x_{o,k} + v_k,$$

where v_k is the measurement noise $v_k \sim \mathcal{N}(0, R_i)$, $R_i = \text{diag}([10^2, 20^2])$.

Appendix A.1 Simulation 1

In this part, the local robot and the obstacle are initialized respectively as $x_{i,0} = [0, 0, 1, 0]^\top$ and $x_{o,0} = [0, 10, -1, 0]^\top$. The collision avoidance separation threshold is set as $r_c = 10$, and the collision avoidance confidence is set as $\varepsilon = 0.95$. A typical Kalman filter is implemented to estimate the state of the target. The estimated obstacle trajectory and the corresponding covariance are plotted in Figure A1 in red solid line and red ellipse respectively. The black dashed line indicates the ground truth trajectory of the obstacle. The collision avoidance trajectory of the local robot based on the proposed method as well as the method in [1] are plotted in green and blue solid line respectively. Apparently both methods are able to realize collision avoidance behavior with regard to the obstacle.

To further compare the effectiveness of the two methods, the separation distances and the reference trajectory tracking errors are plotted in Figure A2. According to Figure A2(a), the minimum separation distances of our proposed method and method in [1] are 12.42 and 20.23 respectively and are apparently larger than the predefined separation distance r_c. However, the larger separation distance is achieved, the further the local robot is deviated from the reference trajectory. As shown in Figure A2(b), the tracking error of our method is much small than the method in [1], that is, on the trajectory tracking purpose, our method is more efficient.

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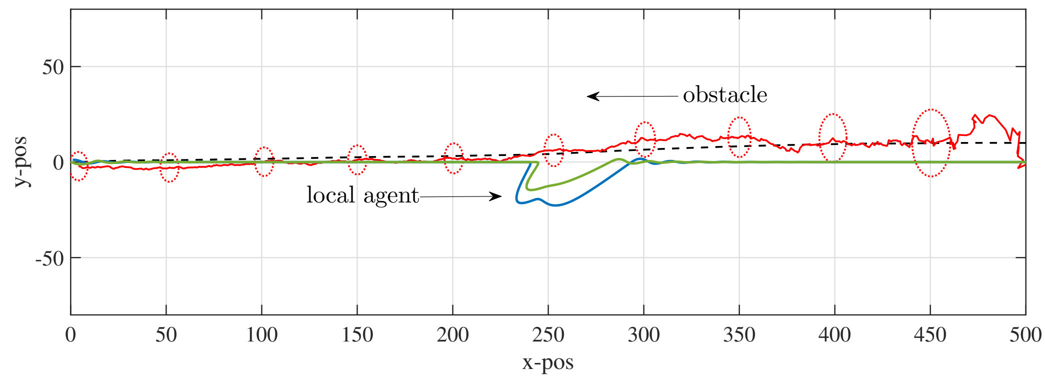

Figure A1 The obstacle collision avoidance trajectories (our method: green solid line, method in [1]: blue solid line) and the obstacle trajectory estimation (red solid line)

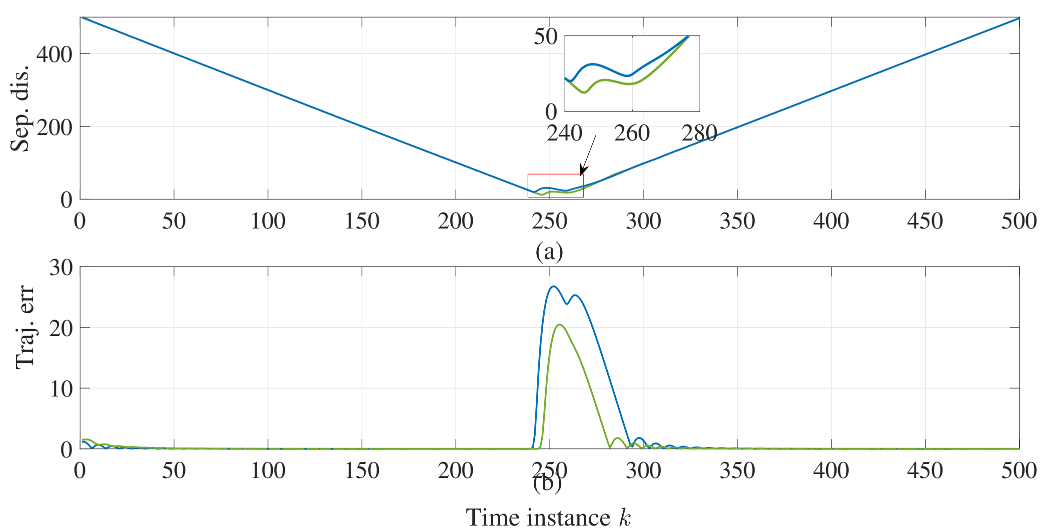

Figure A2 The separation distance and reference trajectory tracking error of the proposed method (green solid line) and the method in [1] (blue solid line).

Appendix A.2 Simulation 2

Mento-carlo simulations are carried out to illustrate the effectiveness of the proposed method in this part. The simulation setup is similar to scenario 1 except with different measurement noise, which means the collision avoidance simulations are carried out under different localization uncertainties. Specifically, the relative measurement covariance is set as $R = \alpha\mathrm{diag}([2^2, 1^2])$ with $\alpha \in \{1, 10, 100, 200, 300, 400\}$. For each possible α, a set of 1000 Monte Carlo simulations is carried out.

Box plots of the distribution of the minimum separation distance between local robot and the obstacle, using both the our algorithm and the method described in [1] are plotted in Figure A3 for each selected *alpha*. As observed, as the measurement covariance, or the localization uncertainty grows, the minimum separation distance grows in order to guarantee the collision avoidance probability. Also, it can be observed that the separation distance of our method is smaller than that of the method in [1]. This is due to better characterization of the uncertainty of our PR based method in comparison with the method in [1].

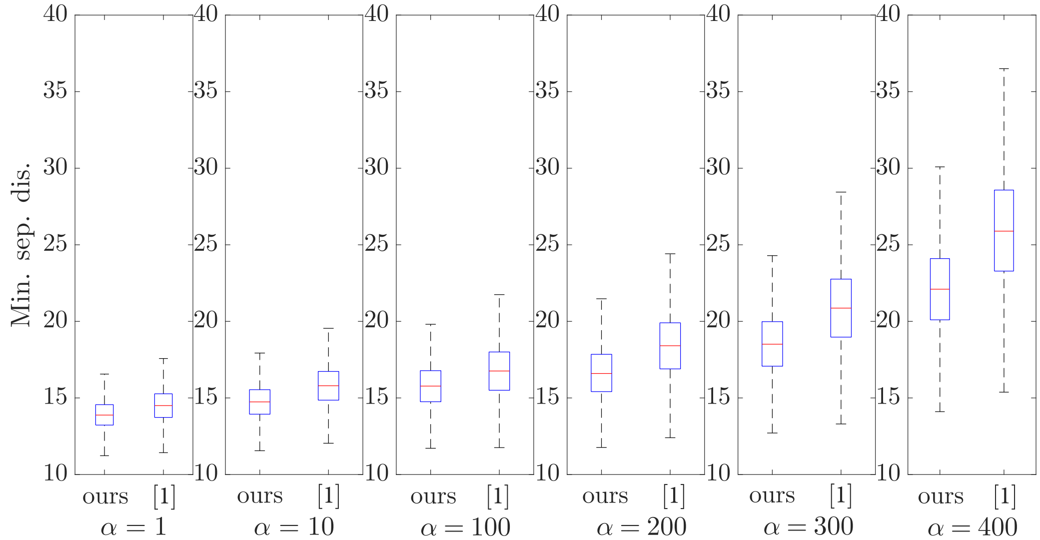

Figure A3 The minimum separation distance with different measurement covariance.

References

1 Hennes D, Meeussen W, Tuyls K. Multi-robot collision avoidance with localization uncertainty. In: Proceeding of International Conference on Autonomous Agents and Multiagent Systems, Singapore, 2016,147–154.