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Obstacle avoidance under relative localization uncertainty

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Dear editor,
Collision avoidance is one of the classical topics in robotics research. Collision avoidance control is guided by implementing typical collision avoidance methods, such as potential field [1], dynamic programming [2], and geometrical calculation [3], to various platforms. Since these methods usually assume the perfect localization of an obstacle, they may not guarantee collision-free operations during the stochastic operation of robots wherein the obstacle is localized using noisy sensors. In particular, for micro aerial vehicles (MAVs), the potential obstacles are detected using low-resolution sensors, such as cameras [4] and low-cost radars [5], leading to obstacle localization with high uncertainty. This study considers collision avoidance tasks with relative localization uncertainty to ensure an optimum operation safety of MAVs using low-cost sensors, which have imperfect sensing mechanism.

The localization uncertainty in collision avoidance can be mitigated by increasing the separation distance by an extra portion that denotes the position uncertainty [6–8]. Collision avoidance separation distance is defined as the isometric covariance of the relative localization [6]. Similarly, a minimum radius is defined to realize collision avoidance with a predefined probability [7]. A conservative separation distance is obtained by summing the uncertainties between two vehicles with the predefined separation distance [8]. These methods can be used for the conservative approximation of the uncertainty distribution rather than explicitly considering the shape of the uncertainty for easy calculations, which may lead to excessive avoidance maneuver.

This study addresses the collision avoidance problem with a relative localization uncertainty by proposing a particle representation (PR)-based collision detection method. Collision probability is calculated herein without considering explicit integration over the localization distribution. Furthermore, a particle-wise potential field-based collision avoidance controller is designed herein to achieve the collision avoidance with a predefined confidence rather than a predefined separation distance, which is more reliable in uncertain scenario. The proposed collision detection and avoidance control method is validated using experimental MAV platforms and off-the-shelf sensors. A demonstration video is attached in supporting information.

Methodology. Initially, the dynamics of a local robot i and an obstacle o are defined respectively as $x_{i,k+1} = f_i(x_{i,k}, u_{i,k}, w_{i,k})$ and $x_{o,k+1} = f_o(x_{o,k}, w_{o,k})$. $x_{i,k}$ and $x_{o,k}$ denote the state of the local robot and obstacle at time instance k, respectively. The uncooperative measurement process is represented as $z_k = h_{oi}(x_{i,k}, x_{o,k}, v_{oi,k})$. Let $x_{oi,k} = x_{o,k} - x_{i,k}$ denote the relative state; then, an estimation of $x_{oi,k}$, denoted as $\hat{x}_{oi,k}$ can be obtained using target tracking methods based on the

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observation of z from 1 to k as follows:

$$\hat{x}_{oi,k} \sim p_{oi}(x_{oi,k}|z_{1:k}). \tag{1}$$

Collision can be avoided by keeping a minimum separation distance between the local robot and the obstacle as

$$\|x_{oi,k}\| = \|x_i - x_o\| \geqslant r_c, \tag{2}$$

where r_c denotes the predefined separation distance. Consequently, a collision zone $\mathcal{S}$ can be defined as a 2D disc or a 3D spherical area as follows:

$$\mathcal{S} = \{x|\|x\| \leqslant r_c\}. \tag{3}$$

As the true value of $x_{oi,k}$ is unknown in practical scenarios, a collision probability can be defined as the probability of obstacle that belongs to $\mathcal{S}$:

$$p(x_{oi,k} \in \mathcal{S}|z_{1:k}) = \int_{\mathcal{S}} p_{oi}(x|z_{1:k})\mathrm{d}x. \tag{4}$$

To realize collision avoidance with a confidence threshold ε, a collision needs to be declared when

$$p(x_{oi,k} \in \mathcal{S}|z_{1:k}) \geqslant 1 - \varepsilon. \tag{5}$$

Integration in (4) is normally difficult to execute; therefore, the PR technique is implemented by drawing N weighted particles $\{x^j_{oi,k}, w^j_{oi,k}\}, j \in \{1, 2, \ldots, N\}$ according to the distribution equation (1) to approximate collision probability as follows:

$$p(x_{oi,k} \in \mathcal{S}|z_{1:k}) \approx \frac{1}{N} \sum_{x^j_{oi} \in \mathcal{S}} \delta_{r_c}\left(x^j_{oi}\right), \tag{6}$$

where

$$\delta_{r_c}\left(x^j_{oi}\right) = \begin{cases} 1, & \|x^j_{oi}\| \leqslant r_c, \\ 0, & \|x^j_{oi}\| > r_c. \end{cases}$$

Collision avoidance is adopted after declaring the collision according to (5). Using the proposed PR method, the collision avoidance maneuvers the collision zone $\mathcal{S}$ away from high-particle to low-particle densities to lower the collision probability. To realize this, a particle-wise potential function is defined as follows:

$$U^j_{oi} = \begin{cases} w^j_{oi,k} g(x^j_{oi,k}), & p_{oi,k} \geqslant 1 - \varepsilon, \\ 0, & p_{oi,k} < 1 - \varepsilon, \end{cases} \tag{7}$$

where $g(\cdot)$ is a pairwise potential function with regard to the relative distance between particle $j \in S$ and agent i represented as follows:

$$g\left(x^j_{oi,k}\right) = \frac{\kappa}{2}\left(\frac{1}{\|x^j_{oi,k}\| + \epsilon} - \frac{1}{r_c + \epsilon}\right)^2, \tag{8}$$

where κ and ϵ are the potential field parameters [1]. Finally, the collision avoidance control with regard to obstacle o can expressed as the collective potential force of all particles within $\mathcal{S}$ as follows:

$$u_{oi,k} = -\sum_{x^j_{oi,k} \in \mathcal{S}} \nabla_{x^j_{oi,k}} U^o_i(x^j_{oi,k}). \tag{9}$$

Results and discussion. The effectiveness of the proposed collision avoidance method under obstacle estimation uncertainty is experimentally validated. Two DJI M100 quadrotors that function as the local robot and obstacle are used in a head-on experiment scenario. The dynamics models of local robot and obstacle are modeled using the second-order linear system as follows:

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

where $A = \left[\begin{smallmatrix} 1 & \Delta t \\ 0 & 1 \end{smallmatrix}\right] \otimes I_3$ and $B = \left[\begin{smallmatrix} 0.5\Delta t^2 \\ \Delta t \end{smallmatrix}\right] \otimes I_3$, with control sample time $\Delta t = 0.1$. The same process noise is set as $w_{i,k}, w_{o,k} \sim \mathcal{N}(0, \mathrm{diag}([0.2^2, 0.2^2, 0.2^2, 0.05^2, 0.05^2, 0.05^2]))$. Then, the obstacle is sensed using the onboard camera and UWB sensors as

$$z^a_k = h_c\left(\frac{x_{o,k} - x_{i,k}}{\|x_{o,k} - x_{i,k}\|}\right) + v^a_k,$$
$$z^d_k = \|x_{o,k} - x_{i,k}\| + v^d_k,$$

where z^a and z^d denote the 2D obstacle position in pixel and the relative distance in meter, respectively; z^a is obtained using the YOLO v3 detector running on a Nvidia TX2 onboard computer. $h_c(\cdot)$ is the projection function that projects the obstacle to a 2D image plane (see [9] for details). The measurement noises are assumed to be subjected to Gaussian distribution as $v^a_k \sim \mathcal{N}(0, \mathrm{diag}(5^2, 5^2))$, $v^d_k \sim \mathcal{N}(0, 0.05^2)$. Then, extended Kalman filter is employed to estimate the relative position $\hat{x}_{oi,k}$ and the approximated covariance denoted by $\Sigma_{oi,k}$ at 10 Hz. In the proposed PR-based potential collision avoidance algorithm, the separation distance is set as $r_c = 15$ and the collision avoidance confidence is set as 95%. $N = 1000$ particles are used to approximate the relative localization distribution. The final controller in the head-on scenario is designed as follows:

$$u_{i,k} = c(x_{r,k} - x_{i,k}) - u_{oi,k}, \tag{10}$$

where $x_{r,k}$ represents the time-varying reference state for the local robot i and c is a proper tracking gain.

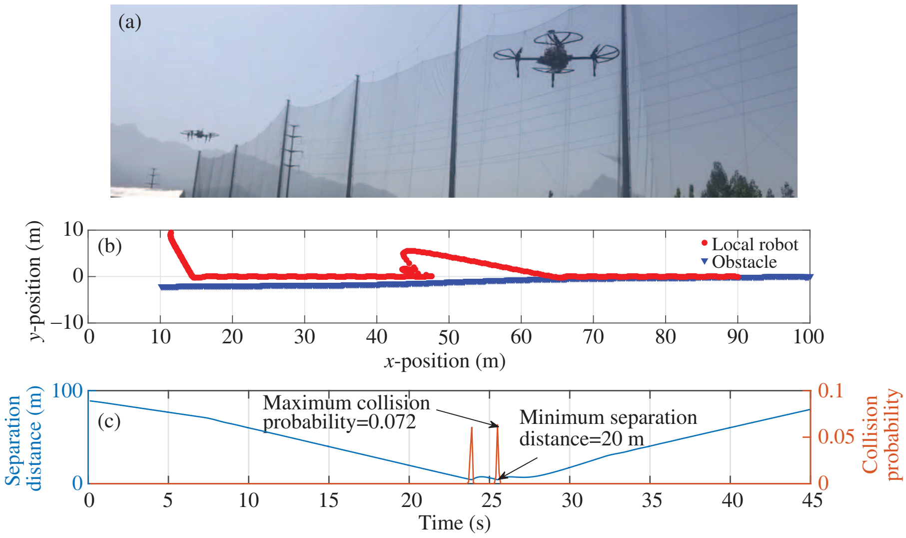

Figure 1 (Color online) Experimental results of the two DJI M100 quadrotors in the head-on collision avoidance scenario. (a) Two DJI M100 quadrotros in the head-on scenario; (b) collision avoidance trajectory of local robot (red) to the obstacle (blue); (c) the separation distance and the collision probability.

The head-on scenario setup is shown in Figure 1(a). The collision avoidance trajectories of both local robot and obstacle are plotted in Figure 1(b). The separation distance and collision probability based on 5 are plotted in Figure 1(c). The collision avoidance is declared during time $k \in [23.5, 24.1] \cup [25.1, 25.9]$ and is achieved at the minimum separation distance of 20.4 m.

Conclusion. A collision avoidance method that considers the obstacle localization uncertainty is developed herein. A particle-wise collision avoidance scheme combined with the PR and potential field method is introduced to achieve the collision avoidance based on a predefined collision probability rather than a certain distance. This method can be used in stochastic robot operation environments.

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Supporting information Videos and other supplemental documents. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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