PANDA: Priority-Based Collision Avoidance Framework for Heterogeneous UAVs Navigating in Dense Airspace

Extended Abstract

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ABSTRACT

With increasing unmanned aerial vehicle (UAV) applications, the airspace is expected to be crowded with heterogeneous (quadrotors, fixed wings and hybrid UAVs) UAVs sharing a dense airspace. In this complex airspace, efficient collision avoidance techniques that respect right-of-way rules are essential. Further, UAVs may have different priorities depending on their tasks e.g. medical, logistics, etc. Due to this coupling of right-of-way with priority, collision avoidance in dense airspace becomes challenging. In this paper, we propose PANDA, a novel potential-field based approach that addresses these constraints in a unified way. Simulations show that PANDA achieves 21% faster completion time for the highest priority UAVs over a no priority baseline and a 60% faster completion time over the lowest priority UAVs.

KEYWORDS

Collision avoidance, potential field, unmanned aerial vehicles

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The utilization of UAVs in urban regions has increased significantly with applications in logistics [10], surveillance and security systems [16], medical emergency, healthcare [6], delivering of products [7], motion and traffic analysis, and various other research purposes [18, 21]. With the increasing applications leading to a significant increase in the number of UAVs operating in a shared, highly dense airspace, it is crucial to manage flight paths and operational tasks in an efficient manner. Consider a situation where a logistic UAV, a food delivery UAV and a medical emergency UAV are on collision course. Drawing a parallel inference to terrestrial traffic norms, where passenger and commercial vehicles make their way for an ambulance, we expect the medical emergency UAV to get right of way. In this case, assigning priorities to the UAVs might be useful. These priorities help in coordinating the movements of diverse UAVs while maintaining orderly and safe airspace for all agents.

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In order to navigate effectively in this complex environment, priority-based collision avoidance systems with deterministic behavior are essential. These systems provide distinct UAVs different priority levels so that aerial vehicles performing urgent and time-sensitive tasks, like emergency response or medical delivery, obtain higher priority over other vehicles to reach the destination directly.

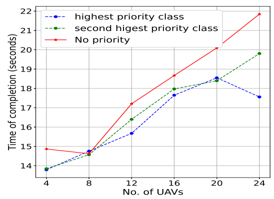
Several collision avoidance algorithms for aerial vehicles have been developed over the years [1, 8, 20, 26]. These algorithms can be broadly classified based on the techniques employed – (i) geometric [4] (ii) field-based which include potential fields [5, 9, 23], (iii) navigation function [3, 22], vector field [15, 17, 25], (iv) guidance-based [13, 14] (v) control theoretic-based [11, 12, 19] and (vi) negotiation-based [2, 24]. All the above algorithms assume that the agents are (a) homogeneous and (b) reactive. Directly extending them to include priority and determinism is challenging.

In order to consider priorities and determinism, we develop a novel priority-based collision avoidance framework using potential field-based approach called as PANDA. We use tangential potential fields to mitigate local minima and achieve determinism by rotating in the same direction. Further, to consider priority, we dynamically scale the repulsion potential field as a function of the vehicle priorities. The vehicle with higher priority will have greater repulsion radius and hence the lower priority vehicle will change its course resulting in minimal course change for the higher priority vehicle. This simple approach of using tangential scalable potential fields achieves both priority and determinism essential for shared unmanned airspace. As PANDA generates prescribed velocity and heading angle for each vehicle, and hence PANDA can be used for any type of vehicle – fixed-wing/multi-copter directly.

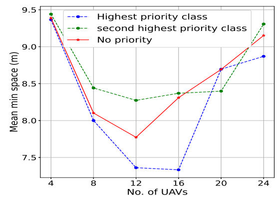
1 PANDA FRAMEWORK

Assume, there are n different UAVs in the shared airspace. Each vehicle u_k has velocity v_k and is at location $s_k = (x_k, y_k)$, with heading ψ_k and is moving towards its goal position g_k. Each UAV u_k is assigned a priority p_k based on its mission. A higher p_k implies the criticality of the UAV mission in the airspace. All UAVs are assumed to have an ADS-B like system to relay their position and velocities to other UAVs. Each UAV also has a maximum operable speed $\bar{v_k}$ along with minimum speed 0 for multi-rotors and > 0 for fixed wing vehicles. While traversing towards the goal, PANDA will prescribe new velocity $|v_k| \leq \bar{v_k}$ for each vehicle.

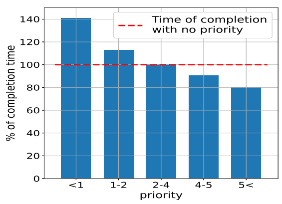
PANDA framework is structured into several distinct phases - (a) predict potential collisions between various vehicles (b) determine the attractive and repulsive forces acting on each vehicle if they are on collision course and (c) limit the maximum velocity to $\bar{v_k}$.



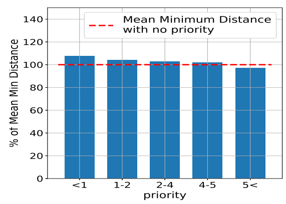
(a) Completion Time



(b) Mean min space



(c) Completion time (24 UAVs)



(d) Mean min space (24 UAVs)

Figure 1: Effect on mission completion time and mean minimum distance due to priority and number of vehicles.

Potential collision between vehicles is determined using the time of closest distance of approach $t_{k,i}$ between u_i and u_k as $t_{k,i} = -\frac{(s_i-s_k)\cdot(v_i-v_k)}{(v_i-v_k)\cdot(v_i-v_k)}$, where, $\cdot$ represents the dot product. If $t_{k,i} < 0$ then the UAVs are on a diverging path, while $t_{k,i} > 0$ implies the UAVs will be closest approach at a distance $S_{k,i}$. The approach is computed as $S_{k,i}^2 = (s_i-s_k)\cdot(s_i-s_k)+2(s_i-s_k)\cdot(v_i-v_k)t_{k,i}+(v_i-v_k)\cdot(v_i-v_k)t_{k,i}^2$. Assuming S as our safe distance, we need to determine whether $S_{k,i} < S$ in order to determine if a collision will occur and perform a collision avoidance maneuver.

If u_k needs to avoid n other UAVs, then we need to sum over the attractive and repulsive forces to obtain the net force $F_k = F_k^a + \sum_i^n F_k^r(i)$ acting on the vehicle. F_k^a is the attractive force on u_k from its goal and $F_k^r(i)$ is the repulsive force experienced by u_k due to $u_i (i = 1, \ldots n, i \neq k)$. Then, one can determine the new desired velocity for vehicle U_k as $v_k \leftarrow v_k + \frac{F_k}{m_k}\Delta t$, where m_k is the mass of the UAV and Δt is the refresh rate (time step) of its controller.

This formulation lends itself naturally to priority based collision avoidance. Since the repulsive forces are calculated pairwise, we need to modify the pairwise repulsive forces to account for priority and sum over them. We define attractive and repulsive forces as follows: $F_k^a = \kappa^a \left(1 - e^{b_a||g_k-s_k||^2}\right) \frac{g_k-s_k}{||g_k-s_k||}$, where $\kappa^a > 0$ represents the positive attractive gain parameter that influences the intensity of the attractive field. The repulsive force felt by u_k from u_i is $F_k^r(i) = \frac{p_i}{p_k}\kappa^r \left(e^{-b^r||s_i-s_k||^2} \frac{s_i-s_k}{||s_i-s_k||}\right) R$, where $\kappa^r > 0$ is the repulsive gain parameter to tune the strength of the repulsive force, b^r determines the spread of the repulsive field and $R = [0\ 1; -1\ 0]$ is the rotation matrix which rotates the force vector by $\frac{\pi}{2}$ to be tangential to the obstacle. To account for priority in the repulsive force, there is a scaling factor of $\frac{p_i}{p_k}$.

As the potential field prescribes the desired velocity and heading angle for the vehicle, we assume that the autopilot of these vehicles will generate the required speed and control commands to meet the requirements. Let the net force exerted by the goal and other agents in the vicinity be F_k which can decomposed in x and y directions as F_k^x and F_k^y. The mass of the vehicle is m_k and the corresponding accelerations are given as $a_k^x = \frac{F_k^x}{m_k}$ and $a_k^y = \frac{F_k^y}{m_k}$. The total acceleration magnitude is $a_k = \sqrt{a_k^{x2} + a_k^{y2}}$. The desired heading is $\psi_k^d = \text{atan2}(a_k^y, a_k^x)$, and the angular velocity is given as $\omega_k = k_\psi(\psi_k^d - \psi_k)$ where k_ψ is a control gain. The a_k and ω_k are the control inputs.

Agents under the influence of the tangential repulsive field rotate in a clockwise direction. This can result in cases where a high priority UAV u_i rotates a low priority UAV u_k in the same direction, effectively dragging u_k parallel to itself till it reaches its goal. To avoid this, u_k must slow down enough to let u_i pass through. To achieve this, we set the maximum velocity magnitude of u_k as $\hat{v}_k = \bar{v_k}\frac{p_k}{\max\{p_i \mid i \in N_k^*\}}$, where N_k^* is the collision neighbourhood of u_k. This scales down u_k's maximum velocity based on the highest priority UAV in its collision neighbourhood. We then clip the velocity of u_k as $v_k = \min(|v_k|, \hat{v}_k)\frac{v_k}{|v_k|}$ where $\min(|v_k|, \hat{v}_k)$ is the magnitude of the velocity and $\frac{v_k}{|v_k|}$ is the direction vector.

2 RESULTS AND CONCLUSIONS

We evaluate the performance of PANDA using simulations for varying number of aerial vehicles in the airspace. The priority for each UAV was drawn from a normal distribution with $\mu = 3$ and $\sigma = 1$, which is the representative of a real life situation where most of the UAVs (eg. goods delivery) are of similar priority while a few are of high priority (eg. medical package) and few are of low priority (eg. surveillance). These priorities were then binned into five classes $\{\underline{1}, 1-2, 2-4, 4-5, \bar{5}\}$ with $\bar{5}$ representing the highest priority class and $\underline{1}$ representing the least priority.

Fig. 1a shows the efficacy of PANDA increases as the number of UAVs increases. We can see that the high-priority vehicles reach their destinations much quicker than those without priority. Especially for the 24 UAV case, priority classes $4-5$ and $\bar{5}$ respectively show a 9.3% and 21.84% improvement in completion time over the no-priority time and a 60% faster completion time than the lowest priority class. From Fig. 1c, we can see that the lower priority classes take more time for mission completion; this is due to their larger path deviation and slowing down to make space for high priority UAVs. Subsequently, the high priority UAVs take less time to complete their missions as they have clearer paths. The mean minimum distance for almost all priority classes' UAVs improves as seen in Fig. 1d. We hypothesize this is due to the establishment of order and right-of-way rules in the path planning of the UAVs. Since low-priority UAVs are moving away and slowing down, they make space for high-priority UAVs and the airspace becomes less dense once the high-priority UAVs pass through.

PANDA can be further extended to include dynamics of the vehicle, extend in 3D and also include hard constraints like control barrier function to ensure no vehicle enter the safe of another vehicle.

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