Event-triggered and distributed model predictive control for guaranteed collision avoidance in UAV swarms

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Abstract: Distributed model predictive control (DMPC) is often used to tackle path planning for unmanned aerial vehicle (UAV) swarms. However, it requires considerable computations on-board the UAV, leading to increased weight and power consumption. In this work, we propose to offload path planning computations to multiple ground-based computation units. As simultaneously communicating and recomputing all trajectories is not feasible for a large swarm with tight timing requirements, we develop a novel event-triggered DMPC that selects a subset of most relevant UAV trajectories to be replanned. The resulting architecture reduces UAV weight and power consumption, while the active redundancy provides robustness against computation unit failures. Moreover, the DMPC guarantees feasible and collision-free trajectories for UAVs with linear dynamics. In simulations, we demonstrate that our method can reliably plan trajectories, while saving 60% of network traffic and required computational power. Hardware-in-the-loop experiments show that it is suitable to control real quadcopter swarms.

Keywords: Distributed constrained control and MPC, Event-triggered and self-triggered control, Multi-agent systems

1. INTRODUCTION

In the recent years, unmanned aerial vehicle (UAV) swarms have become larger and larger, reaching sizes from 50 up to 100 UAVs (Preiss et al. (2017)). To find trajectories that do not lead to colliding UAVs for such big swarms poses a challenge for path planning algorithms. The planning usually requires a lot of computational power, which can either be centralized or distributed among the UAVs. In the first case, a stationary computer transmits the trajectories to the UAVs over a wireless network. In the latter, the UAVs calculate their paths on-board and have to exchange information among themselves over a wireless network. Central model predictive control (MPC) approaches like Augugliaro et al. (2012) need no powerful processor on board of the UAV. This decreases weight and thus energy consumption of the UAV. However, they do not scale well with an increasing number of UAVs (Luis and Schoellig (2019)) and expose the system to the potential risk of a whole system failure if the central computer fails (AlZain et al. (2012)). Distributed model predictive control (DMPC) based approaches have become increasingly popular (Zhou et al. (2017), Luis and Schoellig (2019), Luis et al. (2020) Park et al. (2021)). First, they do not require any central node since all computations are done on the UAVs. Second, they scale well with increasing number of UAVs. However, the on-board processing needs computational capacity and thus increases weight, leading to a higher energy consumption of the UAVs.

This work uses the “best of both” and combines centralized and distributed features based on a novel event-triggered DMPC (ET-DMPC) design. Our approach consists of multiple stationary computation units (CU, Figure 1). Every CU is placed on the ground and has enough power to replan the trajectory of one UAV at a time. It shares the resulting trajectory with other CUs and the UAVs over a wireless network, leveraging recent advances in low-power wireless technology (Mager et al. (2021)). The UAVs then follow their respective trajectories. However, it is not viable to provide one CU for each UAV in the swarm, which makes the system more expensive and may exceed the available network bandwidth. We thus propose to use fewer CUs than UAVs and present an event-triggering (ET) mechanism that enables trajectory replanning for only a subset of UAVs at a time.

This approach has benefits over purely centralized or distributed approaches. First, the UAVs need less on-board computational power, which saves weight and reduces energy consumption. Second, in contrast to standard centralized approaches, it is more robust against failures, because a failure of one CU does not lead to a whole system failure, as the remaining CUs in combination with ET can still plan the paths of the UAVs. The presented ET-DMPC uses features from existing DMPCs and scales well with the size of the swarm. In summary, this paper makes the following contributions:

● A novel distributed computing method for path planning of large UAV swarms which uses ET for improved resource efficiency;
A video of the method controlling a real quadcopter swarm can be found in https://youtu.be/2QqQ5JoUJCA.
Because some types of UAV need to maintain a higher coordinate system is scaled using a symmetric positive definite matrix $\Theta$ (Luis and Schoellig (2019); Luis et al. (2020); Park et al. (2021)). To simplify the design of the DMPC and the ET, the algorithm fails to find a trajectory.

4. EVENT-TRIGGERED DISTRIBUTED MODEL PREDICTIVE CONTROL

In this section, we will now solve the three subproblems that we have defined in the section above.

**Communication architecture.** The choice of the communication architecture is mainly influenced by related works (Zhou et al. (2017); Cai et al. (2018); Luis and Schoellig (2019); Luis et al. (2020); Park et al. (2021)). To simplify the design of the DMPC and the ET, the algorithms should not have to deal with different timing and information states of the agents. Therefore, we choose a round based many-to-all architecture. During every round, it distributes all messages sent to all agents in the network. This synchronizes the agents, i.e. they send/receive at the same time, and all agents have the same knowledge about the data sent in the network. From an implementation based point of view, this choice is reasonable too. There exist real world implementations of round based many-to-all architectures like Glossy (Ferrari (2011)) or Mixer (Herrmann et al. (2018)), which have been shown to meet the strict real-time and reliability requirements needed for fast control (Mager et al. (2019); Mager et al. (2021)).

During the communication round, the UAVs send their current state and the CUs share their results of the path planning, which the corresponding UAVs and all CUs save in a buffer. After the communication round, the CUs decide which CU replans the path of which UAV using ET. Because of the many-to-all protocol, every CU has the same information and thus knows which UAV will be selected by the other CUs. This avoids the case of two CUs replanning the trajectory of the same UAV. Afterwards, each unit replans the trajectory of its chosen UAV. The maximum duration for the scheduling and replanning $T_{calc}$ is constant for every agent and time. A new communication round (length $T_{com}$) starts afterwards. The combined duration between the starts of two rounds is $T = T_{calc} + T_{com}$.

**ET-DMPC.** The event trigger decides if during the $k$-th round, CU $q$ replans the path of UAV $i$ ($\gamma_{qi}(k) = 1$) or not ($\gamma_{qi}(k) = 0$). Every CU can only replan the path of one UAV in one round and every CU should replan the path of a different UAV. In this work, we use a priority based trigger rule (PBT) (Mager et al. (2021)), which we present at the end of this section, because it uses features from the DMPC, which we present next.

The control input for each UAV is piecewise-constant with sampling time $T_s$ and horizon $h_s$

$$
\mathbf{u}_i(\tau + T|kT) = \sum_{\kappa=0}^{h_s-1} \Gamma_{T_s} (\tau - \kappa T_s) \mathbf{u}_{i,k|k},
$$

where $\Gamma_{T_s}(t)$ is equal to 1 for $0 \leq t < T_s$ and 0 otherwise, and $\mathbf{u}_{i,k|k}$ are the time-discrete inputs. Additionally, we require $\mathbf{r} - \mathbf{r}_{\min} < \mathbf{r}_{\max}$ and 0 otherwise, where $\mathbf{r}_{\max}$ is constant for every agent and time. A coordinate system is scaled using a symmetric positive definite matrix $\Theta$ (Luis and Schoellig (2019); Luis et al. (2020); Park et al. (2021)). Additionally, the whole system has to guarantee that the DMPC problem is feasible at all time. Otherwise, the UAVs might collide because the algorithm.

$$
\min_{\mathbf{u}_{i,k|k}} \sum_{\kappa=0}^{h_s} \left[ ||\mathbf{x}_i(\kappa T_s + T|kT) - \mathbf{x}_{i,target}||_Q^T \right. \\
+ ||\mathbf{u}_i(\kappa T_s + T|kT)||_R^T \right] \\
\text{s.t.} \mathbf{x}_i(\kappa T_s + T + \delta|kT) \\
= e^{\mathbf{A}_i(\kappa T_s + \delta)} \mathbf{x}_i(2T|(k-1)T) + \int_0^\delta e^{\mathbf{A}_i \tau \mathbf{B}_i \tau \mathbf{u}_{i,k|k}} \\
+ \sum_{\ell=0}^{\kappa-1} e^{\mathbf{A}_i(\kappa - \ell - 1) T_s + \delta)} \int_0^\delta e^{\mathbf{A}_i \tau \mathbf{B}_i \tau \mathbf{u}_{i,k|k}} \\
\text{with } 0 \leq \delta < T_s \\
\mathbf{u}_{i,k|k} \leq \mathbf{u}_{i,k|k} \leq \mathbf{u}_{i,k|k}, \forall \ell \in \{0, ..., h_s - 1\} \\
\mathbf{x}_{i,k|k} \leq \mathbf{x}_i(\kappa T_s + T|kT) \leq \mathbf{x}_{i,k|k}\forall \kappa \in \{0, ..., h_b\} \\
\mathbf{y}_i(HT + T|kT) = 0, \mathbf{y}_i(HT + T|kT) = 0 \\
\mathbf{A}_{i,j,c} \begin{bmatrix} p_i(T|kT) \\
\mathbf{p}_i(T_s + T|kT) \\
\vdots \\
\mathbf{p}_i(h_s T_s + T|kT) \\
\end{bmatrix} \leq \mathbf{b}_{i,j,c},
$$

where $\mathbf{r}$ is the current state and the CUs share their results of the path
with $\frac{\varphi_j^i}{\alpha^i} = \frac{h^i}{T^i} - \frac{T^i}{T^i} = \frac{h^i}{T^i} - \frac{\alpha^i}{T^i} \in N$. The solution of the optimization problem results in input values of the linear system (1) such that a quadratic term between the planned trajectory and the desired target $x_i^{\text{target}}$, and of the input with positive definite weights $Q_j, R_j$ is minimized under several conditions. All conditions are time-discrete and the state is obtained using the solution of linear state space systems (4b). The different sample times $T_o, T_n, T_d, T_c$ allow us to tune the time density of the constraints independent of the inter-round time $T$, which cannot be tuned freely, because it depends on $T_{\text{calc}}$ and $T_{\text{com}}$. The sample times are chosen such that the ends of communication rounds fall on sample time points and the corresponding horizons $h_n, h_o, h_i, h_c$ are chosen such that all last sample time points fall on the same time $H$, with prediction horizon $H$. This is important to ensure recursive feasibility (Park et al. (2021)). Because of the delay of calculation and communication, the trajectory starts in the next step $(k+1)T$. The inputs and states are limited to a minimum and maximum (4c)–(4d) according to dynamic limits of the UAV. Equation (4e) is important for the feasibility at the next sample time point $(k+1)T$ (Park et al. (2021)). The property $u_i(\tau + T[kT]) = 0$ for all $\tau \geq H$ then leads to $x_i(\tau + T[kT]) = x_i(H + T[kT])$ for all $\tau \geq H$. Thus, at the end of the horizon, the UAV stops and stays at its position $p_i(H + T[kT])$.

The last constraint (4f) ensures that the UAV does not collide with others. The matrices $A_{i,j,c}$ and $b_{i,j,c}$ are calculated using TV-BVC (Van Parys and Pipeleers (2017)), which Figure 2 illustrates. For every sample time point, the UAV calculates the difference vectors between UAV $i$’s and UAV $j$’s last planned trajectory for all $h \in \{0, ..., h_c\}$

$$n_{ij}(hT_e + 2T)(k-1)T = \Theta^{-1}\left[p_j(hT_e + 2T)(k-1)T - p_i(hT_e + 2T)(k-1)T\right].$$

Then a plane with the normal vector $n_{ij}$ is spanned in the center between the UAVs positions. UAV $i$ has to stay on the plane’s right side with distance of at least $0.5r_{\text{min}}$

$$n_{0,i,j}(hT_e + 2T)(k-1)T = \Theta^{-1}\left[p_j(hT_e + 2T)(k-1)T - p_i(hT_e + 2T)(k-1)T\right].$$

The distance $r_{\text{min}}$ is selected such that both holds in Theorem 2. Combining (5) for all $h \in \{0, ..., h_c\}$, leads to constraint (4f).

After the CU has solved optimization problem (4), it sends the calculated trajectory and inputs to the UAV and all other CUs via the wireless network. The UAV sets $u_i(\tau + kT) = u_i(\tau | kT)$ for $\tau \in [T, 2T]$. In cases of no recalculation ($\gamma_{qi}(k) = 0, \forall q$), the UAV reuses the previously planned trajectory similar to Cui et al. (2018)

$$x_i(t; kT) = x_i(t + T(k - 1)T)$$

$$u_i(t; kT) = u_i(t + T(k - 1)T),$$

for all $t \geq T$ in both situations, replanning or reusing, the resulting trajectories are not closer than $r_{\text{min}}$ at the sampling points.

Lemma 1. If $||n_{ij}(hT_e + 2T)(k-1)T||_2 \geq r_{\text{min}}$ for $i \neq j$ and $\forall h \in \{0, ..., h_c\}$, and if (4f) holds for both $i$ and $j$, independent of $\gamma_{qi}(k)$ and $\gamma_{qj}(k) \in \{1, ..., M\}$, then

$$||\Theta^{-1}\left[p_j(hT_e + T[kT]) - p_i(hT_e + T[kT])\right]||_2 \geq r_{\text{min}}$$

Proof: If agent $j$’s trajectory is not recalculated ($\gamma_{qi}(k) = 0, \forall q$), it is with $r_1 = H + T$: $||\Theta^{-1}\left[p_j(\tau | kT) - p_i(\tau | kT)\right]||_2 = ||n_{0,i,j}(\tau + T (k - 1)T)||_2 \\
\geq \frac{1}{2}(r_{\text{min}} + ||n_{ij}(hT_e + 2T)(k-1)T||_2).$$.}

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\geq \frac{1}{2}(r_{\text{min}} + ||n_{ij}(hT_e + 2T)(k-1)T||_2).$$.}
To evaluate the proposed method, we chose PBT (Mager et al. (2021)). With PBT, every CU gets assigned a priority $q$ due to the many-to-all communication. CU $i$ then replans the trajectory of the UAV with $q_i$ when the algorithm is able to lead all UAVs to their target position (right plot). Dotted lines are planned, solid lines real trajectories.

In the mean, PBT is faster and more UAVs reach their target (98.10). It simulates a swarm of Crazyflie drones using gym-pybullet-drones (Panerati et al. (2021)). We approximate the quadcopter dynamics as a triple integrator for the DMPC (Wang et al. (2021)). Because it does not represent the real quadcopter dynamics accurately, the predicted positions using the linear model are set as setpoints of all local position controllers of the UAVs (Luis and Schoellig (2019)). We chose a sampling time of $T = 333.33$ ms ($T_{calc} = 233.33$ ms, $T_{com} = 100$ ms). We set the minimal distance $r_{min} = 0.7$ m and $\theta = \text{diag}[1, 1, 2]$. The space where the UAVs can fly is limited to a cuboid of $5 \times 5 \times 5$ m. Initial and target positions are generated randomly using a truncated uniform distribution such that initial/target positions scaled with $\theta$ are not closer to each other than $r_{min}$. We call one realization of initial and target positions scenario in the following. We could fit up to 25 UAVs in the space.

**Influence of ET.** To determine the influence of ET, we compare PBT to a round-robin trigger. Figure 3 shows experiments with 15, 20 and 25 UAVs for $M = 10$ CUs and TV-BVC with 1000 scenarios for each setup. In all setups, PBT steered the UAVs faster to their targets than round-robin. Additionally, the number of UAVs reaching their target is higher for PBT ($98.5\%$) than round-robin ($92.7\%$). But PBT cannot avoid completely that some UAVs are not able to reach their target. This phenomenon is called deadlock and caused by the absence of a centralized coordinator (Luis and Schoellig (2019); Park et al. (2021)). Every UAV’s trajectory is just optimal regarding the corresponding UAV. It thus would not make room for another UAV if this trajectory moved away from the target position. We noticed that some deadlocks lead to infeasibility due to numerical issues of the solver, which

5. EXPERIMENTS AND DISCUSSION

**Simulation environment.** To evaluate the proposed methods, we have built a simulation of the system. The code with all parameters can be found in https://github.com/Data-Science-in-Mechanical-Engineering/ET-distributed-UAV-path-planner.

**Theorem 2.** If $x_i(t) - T)$ fulfills the conditions of Theorem 1, then $x_i(T) - T = x_i(0)$, and if $r_{min} - \Delta p_{i,max}(T_c) - \Delta p_{j,max}(T_c) \geq r_{min}$ for all $i,j \in \{1,...,N\}, i \neq j$

\[
\Delta p_{i,max}(T) = \max_{x_i \in [x_i,min,x_i,max], u_i(t) \in [u_i,min,u_i,max], \tau \in [0,T]} \left| \| \Theta_0 \| \left( e^{A\tau} - 1 \right)x_i + \int_0^T e^{A\tau}Bu_i(\tau - \tau)\right|_{\tau = 0}^{\tau = T} \]

as upper bounds of the maximum distance, the position can travel between two sample time points with a sample time $T$, then the UAV swarm fulfills (2).

Proof: Feasible solutions of the trajectory planning exist for every $k \geq 0$ (Theorem 1). We select $k,h_c \in \mathbb{N}$ and $0 \leq \delta \leq T_c$ such that $h_c T_c < T$ and $t = kT + T$ with $T = h_c T_c + T + \delta$. Using Theorem 1 we know that $\| (\Theta^{-1} - 1)x_i + \int_0^T e^{A\tau}Bu_i(\tau - \tau)d\tau \|_2 \geq \| (\Theta^{-1} - 1)x_i + \int_0^T e^{A\tau}Bu_i(\tau - \tau)d\tau \|_2 + \Delta p_0(T) - \Delta p_{j,max}(T_c)$.

Theorem 2 is independent of the chosen ET. There are two reasons for this independence. First, the swarm must have collision-free initial trajectories for Theorem 2 to hold. Second, each UAV can recursively generate collision-free trajectories with (6) without triggering. However, when a UAV’s replanning is not triggered for $H$ consecutive times, it will stop and stay at a position which might not be its target position. The choice of the ET is thus important to quickly steer the UAVs into their targets.

**Priority based trigger rule.** As a possible trigger rule, we chose PBT (Mager et al. (2021)). With PBT, every UAV gets assigned a priority $g_i(kT)$. Because all CUs have the same information due to the many-to-all communication architecture, they can calculate the priorities of all UAVs locally without any additional communication. CU $q$ then replans the trajectory of the UAV with $q$-th highest priority. The choice of the priority and its parameters allow us to tune the selection of UAVs and thus the performance of the overall system. We chose the following priority:

$$
\begin{align*}
g_i(kT) &= a_1 \| d_{i,target} \|_2 + \alpha_3 \Delta t_i(kT) \\
&= -\alpha_3 \max \left( \cos(\beta), \sum_j \xi \left( \frac{d_{i,target} - d_{j,target} - d_{ij}}{\| d_{i,target} \|_2} \right) \right), \quad (9)
\end{align*}
$$

where $d_{ij} = p_i(2T)((k-1)T) - p_i(2T)((k-1)T)$, $d_{i,target} = p_i(2T)((k-1)T)$ and $\xi$ is max (0, $\| d_{i,target} \|_2 - \| d_{ij} \|_2$). $\Delta t_i(kT)$ describes how long the trajectory of UAV $i$ was not replanned. $\alpha_1, \alpha_2, \alpha_3 \geq 0$ are weights of the summands. The last term measures how many UAVs lie in a cone with angle $\pm \beta$ between the UAV $i$ and its target and how close they are (factor $\xi$). The more UAVs, the more likely $i$ will get blocked by others and thus replanning is ineffective.
also hinders to dissolve them. Soft constraints could help to avoid this issue (Luis and Schoellig (2019)). To avoid deadlocks completely, the targets $p_{i, \text{target}}$ itself can be changed using a cooperative planner (Park et al. (2021)). Furthermore, we compared the performance of a swarm with an equal number of UAVs and CUs ($N = M = 25$) to one with less CUs than UAVs ($M = 10 < N = 25$). We noticed that although some UAVs reached their target faster, there were a lot of deadlocks for $M = 25$. This leads to the shape of the mean distance to target in Figure 3. Thus, in this scenario, ET not only saves 60% of bandwidth and computing hardware, it also improves the performance in the mean.

**Hardware-in-the-loop experiments.** To validate the sufficiency of the choice of a linear model for quadcopter trajectory generation, we tested our method using a hardware-in-the-loop (HIL) simulation with six real Crazyflies flying indoor. We simulated the wireless network and one CU on a local PC, which runs Crazyswarm (Preiss et al. (2017)) and is connected to a motion capture system to obtain the positions of the crazyflies. Figure 4 shows an example trajectory of our HIL-simulation, where UAVs swap positions. We observed no dangerous flight maneuver and unstable behavior of the quadcopters when following the trajectory as can be seen in https://youtu.be/2UzqOnUJQCA. The choice of a linear model in our ET-DMPC seems to be sufficient for real quadcopters.

6. CONCLUSIONS

This paper presented an event-triggered path-planning algorithm for UAV swarms. The developed computation scheme selects a subset of UAVs and replans the trajectories of only these on stationary computation units. The DMPC based path planner guarantees recursive feasibility and collision free trajectories for linear UAV dynamics. Our approach has been demonstrated to reliably steer UAVs without any collisions. This shows that event-triggering can be used to lower the communications and computational resources needed for path planning while guaranteeing collision free trajectories. In future work, we will add static obstacle avoidance to ET-DMPC using a safe flight corridor (Park and Kim (2020); Park et al. (2021)). Additionally, we will investigate distributed cooperative planners to avoid deadlocks.

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