Autonomous vehicle, Mobile robot, Drone

Uncertainty-exploiting energy-efficient AI Control: integrating event-triggered control with probabilistic inference

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Abstract

Event-triggered control strategies reduce the number of times a controller must execute expensive updates while still achieving the desired control performance. This work proposes a learning-based event-triggered model predictive control (MPC) for systems whose dynamics are initially unknown. A Gaussian process (GP) model is trained online and used to predict future states; crucially, it also provides a variance that quantifies prediction uncertainty. The controller converts this uncertainty into a bound on the possible prediction error and solves the optimal control problem (OCP) only when the discrepancy between predicted and measured states exceeds a threshold. The OCP is formulated using GP-based predictive states and includes terminal constraints that help enforce stable behavior. The paper studies convergence and shows that, once the GP uncertainty becomes sufficiently small, the closed-loop state reaches the terminal set within finite time. Simulations demonstrate effectiveness on a path tracking control of mobile robot example.

Background & Results

MPC is a receding-horizon optimization method: at each sampling time, it predicts future trajectories, optimizes an input sequence to minimize a cost such as tracking error and control effort under constraints, applies the first input, and repeats. Although MPC is popular in robotics, vehicles, and process control because it handles constraints explicitly, solving a nonlinear OCP every time step can be too slow for embedded processors, and inaccurate models can force conservative operation. Prior event-triggered MPC reduces optimization frequency, but typically assumes known dynamics. The proposed method learns the unknown dynamics with a GP and uses its variance to decide whether to replan, so updates naturally become rarer as the model improves. In a leader–follower tracking task for a nonholonomic (unicycle) mobile robot, the learning process increases data points from 25 to 82 and reduces the number of OCP solves from 11 triggers (iteration 1) to 1 trigger (iteration 10), while periodic MPC solves 40 times. The accumulated cost improves from 51.2 to 14.6, close to periodic MPC's 13.9, and total computation time drops from 520 ms to 68 ms (periodic baseline: 1073 ms).

Significance of the research and Future perspective

These results show that model uncertainty can be used not only to improve prediction, but also to schedule optimization effort adaptively. The resulting "replan only when needed" rule is explainable and offers a clear performance–computation trade-off. It can save compute, battery power, and communication frequency for drones, mobile robots, and autonomous vehicles. Future directions include handling higher-dimensional dynamics and multi-agent mobile robots, incorporating stronger safety guarantees under disturbances and sensor noise, and validating the approach on real hardware with latency-aware triggering and automatic threshold tuning.

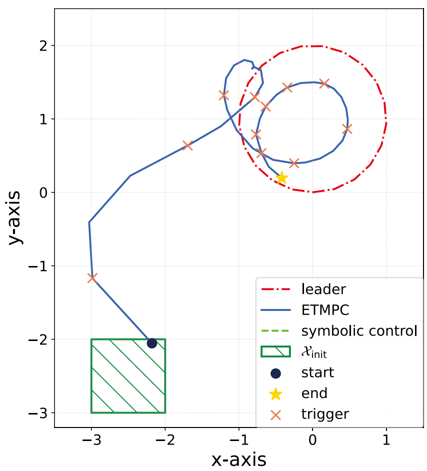

Figure 1

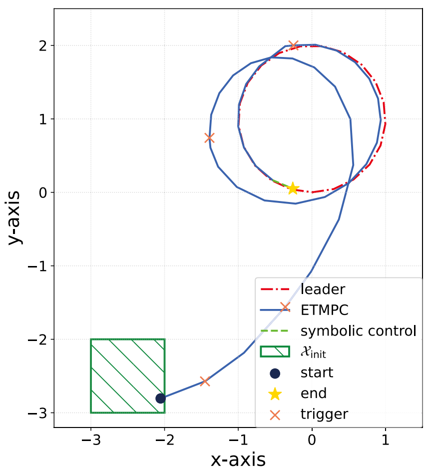

Figure 2

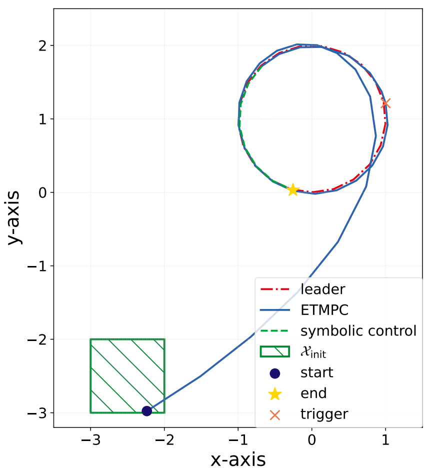

Figure 3

The reference trajectory of the mobile robot (red dash-dotted line) and the robot trajectory obtained by the event-triggered MPC (blue solid line) are shown.
The yellow star markers indicate the time instants when the control-input optimization was recomputed.
Figure 1 shows the result after 1 iteration, Figure 2 after 5 iterations, and Figure 3 after 10 iterations. As shown in the figures, as the number of iterations increases, the tracking performance improves, while the frequency of control re-optimization (recomputation) decreases simultaneously.

Patent	
Treatise	Hashimoto, Kazumune; Onoue, Yuga; Wachi, Akifumi et al. Learning-based event-triggered MPC with Gaussian processes under terminal constraints. IEEE Transactions on Cybernetics. 2025, 55(4), 1512-1525. doi: 10.1109/TCYB.2025.3536606
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