Multi-Agent Spatial Predictive Control
with Application to Drone Flocking

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Abstract—We introduce Spatial Predictive Control (SPC), a technique for solving the following problem: given a collection of robotic agents with black-box positional low-level controllers (PLLCs) and a mission-specific distributed cost function, how can a distributed controller achieve and maintain cost-function minimization without a plant model and only positional observations of the environment? Our fully distributed SPC controller is based strictly on the position of the agent itself and on those of its neighboring agents. This information is used in every time step to compute the gradient of the cost function and to perform a spatial look-ahead to predict the best next target position for the PLLC. Using a simulation environment, we show that SPC outperforms Potential Field Controllers, a related class of controllers, on the drone flocking problem. We also show that SPC works on real hardware, and is therefore able to cope with the potential sim-to-real transfer gap. We demonstrate its performance using as many as 16 Crazyflie 2.1 drones in a number of scenarios, including obstacle avoidance.

I. INTRODUCTION

A collection of drones can perform tasks that cannot be accomplished by individual drones alone [1]. It can, for example, carry a heavy load while still being much more agile than a single larger drone [2], [3]. In search-and-rescue applications, the drones can explore unknown terrain by covering individual paths that jointly cover the entire area [4]–[6]. These collective maneuvers can be expressed as the problem of minimizing a positional cost function, i.e., a cost function that depends on the positions of the drones (and possibly information about their environment). Such a problem formulation requires a method to localize each drone within a common reference frame, e.g., a Global Navigation Satellite System (GNSS) or an indoor localization system.

Off-the-shelf drones, such as Crazyflie [7], DJI [8], and Parrot [9], come equipped with a positional low-level controller (PLLC). Such a controller takes a position argument as input and maneuvers the drone to this position, where it then hovers. PLLCs are common in other types of robotic systems, including the Landshark [10] and Taurob [11] unmanned ground vehicles, and the Bluefin\textsuperscript{®}-12 [12] unmanned underwater vehicle. Unfortunately, the PLLC’s code is often proprietary, and the exact parameters of the physical drone model might not be available. Since the PLLC and physical drone together form the plant to be controlled, a dynamic model of the plant is often unavailable, for one or both of these reasons.

In this paper, we address the following problem: Design a distributed controller that minimizes a given positional cost function for robotic agents with black-box PLLCs, no available model of the plant dynamics, and only positional observations of their environment.

To solve this problem, we introduce Spatial Predictive Control (SPC), a novel distributed high-level approach to multi-agent control. In SPC, each agent’s controller identifies \( N \) equally-spaced points within a maximum look-ahead distance \( c \cdot N \) from its current position in the direction of the negative gradient of a cost function \( c \). The SPC controller then computes the value of \( c \) for each of these points and chooses the one with minimal cost as the target location to be sent to the PLLC. The PLLC makes a best effort to reach this location, while in the next time-step, SPC provides an updated target.

\textit{SPC vs MPC.} To solve the stated problem, one might consider the PLLC as part of the plant and design a Model Predictive Control (MPC) for the high-level control. Such an approach is not applicable since neither a dynamic model of the physical plant nor the internals of the PLLC are available. Even if an approximate dynamic model could be obtained using system identification techniques, and if the code for the PLLC is available (e.g., for Crazyflies), MPC remains a computationally expensive method [13]. This is especially relevant for embedded processors with limited computing capabilities. MPC needs to calculate the predicted behavior for the plant model over a specified time horizon in order to search for an optimal control input. In contrast, SPC does not require a plant model and avoids extensive prediction calculations.

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SPC vs Planning. Given that (robotic) agents are equipped with PLLCs, one might ask if a controller is actually needed, or would a planning-based approach suffice. Based on the initial positions of agents and obstacles, a plan of way-points could be generated for the PLLC to follow. Since, however, the environment is constantly changing due to the movement of other agents (and possibly obstacles), such a plan would become quickly outdated. This is exactly the type of problem we address with SPC: in every time step, we use the observations of the environment to calculate the next input to the PLLC; the SPC makes a best effort to reach this position. Hence, the key difference between SPC and planning is the granularity of the time horizon: planning uses long time horizons for calculating trajectories, whereas in our approach, feedback from the plant in every time step is used to recalculate the desired next position.

SPC vs PFC. Potential Field Controllers (PFCs) are well-known controllers for mobile robots. Prior work has considered their application to flocking. PFCs view the cost function as defining a potential field, and thus, PFCs use the gradient of the potential as the force (or acceleration) the controller needs to apply. There are two issues with using PFCs for our stated problem. First, when the environment has obstacles and a large number of moving drones, the cost function becomes time-varying and nonlinear (as in Figure 1), and local gradients become misleading. Second, in our setting, we cannot set the acceleration directly because we only have access to the PLLC. Nevertheless, we can adapt and use PFC in our setting, but our experiments confirm that it performs poorly compared to SPC, which evaluates the cost function at multiple points in that direction. As the figure illustrates, this enables the drone to see peaks and valleys in the cost function at multiple points in that direction. However, if the cost function is nonlinear (e.g., has many peaks), then gradients can be misleading. The key observation underlying SPC is that each agent should look ahead in the observable state space, in the direction of the negative gradient, to determine the reference value for its observable state. An SPC controller picks $N$ equally-spaced points within a maximum look-ahead distance $\epsilon \cdot N$ from the current observable state and in the direction of the negative gradient, where $\epsilon$ and $N$ are parameters of the controller. At any given state $(x_{io}(t), x_{Hio}(t))$, the set $Q_i$ containing these equally-spaced points is given by:

$$Q_i = \left\{ x_{io}(t) - n \cdot \frac{\nabla c(x_{io}(t), x_{Hio}(t))}{\| \nabla c(x_{io}(t), x_{Hio}(t)) \|} : n = 0, \ldots, N \right\}$$

(3)

Here $\nabla c(x_{io}(t), x_{Hio}(t))$ denotes the evaluation of the gradient of $c$ at the point $(x_{io}(t), x_{Hio}(t))$. Our spatial-predictive controller selects the point in $Q_i$ with minimum cost as the next target position $x_{io}^{(r)}$ for agent $i$:

$$x_{io}^{(r)} = \underset{x_{io} \in Q_i}{\text{argmin}} \left( c(x_{io}, x_{Hio}(t)) \right)$$

(4)

Note that the SPC controller recomputes the reference $x_{io}^{(r)}$ at each time step. This is important because this computation of

II. SPC FOR MULTI-AGENT SYSTEMS

We describe the distributed control problem addressed in this paper and present SPC for solving this problem.

A. Distributed Control for Distributed Cost Minimization in the Presence of PLLCs

We consider a multi-agent system consisting of a set $D$ of agents. Each agent $i \in D$ has a state $(x_{io}(t), x_{ih}(t))$, where $x_{io}$ is the observable part of its state and $x_{ih}$ is the hidden part of its state. Agent $i$ has a control input $u_i$ and its dynamics is assumed to be given by some unknown function $f$:

$$\frac{dx_{io}(t)}{dt}, \frac{dx_{ih}(t)}{dt} = f(t, x_{io}(t), x_{ih}(t), u_i(t))$$

(1)

Agent $i$ has access to the observable state of a subset $H_i \subseteq D$ of agents. $H_i$ will be referred to as the neighborhood of $i$.

The objective for the multi-agent system is given in terms of a cost function $c(x_{io}, x_{Hio})$ that maps the observable state of agent $i$ $(x_{io})$ and of its neighbors $(x_{Hio})$ to a non-negative real value. Here we use $x_{Hio}$ as shorthand for $(x_{jo})_{j \in H_i}$. Agent $i$’s goal is to minimize $c(x_{io}, x_{Hio})$.

In our setting, we do not have ability to directly set $u_i$. Instead, we can only set a reference value $x_{io}^{(r)}$ that is then used by some black-box, low-level controller PLLC to internally set the control input.

$$u_i(t) = PLLC(t, x_{io}(t), x_{ih}(t), x_{io}^{(r)})$$

(2)

Both the dynamics of each agent (function $f$) and the details of the PLLC (function PLLC) are unknown. The cost function $c$ is given. We want to find a procedure that allows each agent to minimize its cost in the above setting.

B. Spatial Predictive Control (SPC)

Let $\nabla c(x_{io}, x_{Hio})$ denote the gradient of cost function $c$ with respect to $x_{io}$. One way to minimize the cost $c(x_{io}, x_{Hio})$ would be to follow the negative of the gradient at every point. However, if the cost function is nonlinear (e.g., has many peaks), then gradients can be misleading. The key observation underlying SPC is that each agent should look ahead in the observable state space, in the direction of the negative gradient, to determine the reference value for its observable state. An SPC controller picks $N$ equally-spaced points within a maximum look-ahead distance $\epsilon \cdot N$ from the current observable state and in the direction of the negative gradient, where $\epsilon$ and $N$ are parameters of the controller. At any given state $(x_{io}(t), x_{Hio}(t))$, the set $Q_i$ containing these equally-spaced points is given by:

$$Q_i = \left\{ x_{io}(t) - n \cdot \frac{\nabla c(x_{io}(t), x_{Hio}(t))}{\| \nabla c(x_{io}(t), x_{Hio}(t)) \|} : n = 0, \ldots, N \right\}$$

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$$x_{io}^{(r)} = \underset{x_{io} \in Q_i}{\text{argmin}} \left( c(x_{io}, x_{Hio}(t)) \right)$$

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Note that the SPC controller recomputes the reference $x_{io}^{(r)}$ at each time step. This is important because this computation of
The mission-specific target seeking term sets a target location, denoted by $p_{\text{tar}}$, for the entire flock. The obstacle avoidance term prevents the drones from colliding with infinitely tall cylindrical objects. Let $K$ denote the set of obstacles. For $k \in K$, let $r_k$ denote the radius of obstacle $k$, and let $p_k$ denote its center on the xy-plane. 

Target-seeking term:

$$
    c_{\text{tar}}(p_i, p_{H_i}) = \omega_{\text{tar}} \cdot \left\| p_{\text{tar}} - \frac{p_i + \sum_{j \in H_i} p_j}{|H_i| + 1} \right\|^2 (8)
$$

Obstacle-avoidance term:

$$
    c_{\text{obs}}(p_i) = \omega_{\text{obs}} \cdot \frac{1}{|K|} \cdot \sum_{k \in K} \frac{1}{\max(\|p_i - p_k\| - r_k - r_d, 0)}^2 (9)
$$

The function $\mathcal{P}(. )$ projects a vector to the xy-plane.

C. Gradient of the cost function

For SPC, the gradient of the cost function is required in Eq. (3), and is given by (for readability, we elide function arguments):

$$
    \nabla_{p_i} c = \nabla_{p_i} c_{\text{coh}} + \nabla_{p_i} c_{\text{sep}} + \nabla_{p_i} c_{\text{tar}} + \nabla_{p_i} c_{\text{obs}} (10)
$$

Cohesion gradient:

$$
    \nabla_{p_i} c_{\text{coh}} = 2 \cdot \omega_{\text{coh}} \cdot \left( p_i - \frac{1}{|H_i|} \cdot \sum_{j \in H_i} p_j \right) (11)
$$

Separation gradient:

$$
    \nabla_{p_i} c_{\text{sep}} = \frac{2}{|H_i|} \cdot \sum_{j \in H_i} \frac{p_j - p_i}{\|p_i - p_j\|-2r_d} \cdot \|p_i - p_j\| (12)
$$

Target-seeking gradient:

$$
    \nabla_{p_i} c_{\text{tar}} = \frac{2}{|H_i| + 1} \cdot \left( p_i - \frac{\sum_{j \in H_i} p_j}{|H_i| + 1} - p_{\text{tar}} \right) (13)
$$

Obstacle-avoidance gradient:

$$
    \nabla_{p_i} c_{\text{obs}} = \frac{2\omega_{\text{obs}}}{|K|} \cdot \sum_{k \in K} \frac{p_k - \mathcal{P}(p_i)}{\|\mathcal{P}(p_i) - p_k\| - r_k - r_d} \cdot \|\mathcal{P}(p_i) - p_k\| (14)
$$

D. Flock-Formation Quality metrics

Collision avoidance: To avoid collisions, the distance between all pairs of drones must remain above a specified threshold $\text{dist}_{\text{thr}}$. We define a metric for the minimum distance between any pair of drones as follows:

$$
    \text{dist}_{\text{min}} = \min_{i,j \in D; i \neq j} \|p_i - p_j\| (15)
$$

We set $\text{dist}_{\text{thr}} = 2 \cdot r_d + r_{\text{safety}}$, where $r_d$ is the radius of the drone, and $r_{\text{safety}}$ is a safety margin.

Compactness: Compactness of the flock is measured by the maximum distance of any drone from the centroid of the flock. It is defined as follows:

$$
    \text{comp}_{\text{max}} = \max_{i \in D} \left\| \sum_{j \in D} p_j - p_i \right\| (16)
$$

It is expected to stay below some threshold $\text{comp}_{\text{thr}}$; otherwise, the drones are too far apart.
Obstacle clearance: Keeping a safe distance from obstacles is required to avoid collisions. We therefore measure the minimum distance from any drone to any obstacle:

\[
\text{clear}_{obj} = \min_{i \in D, k \in K} \| P(i) - p_k \| \quad (17)
\]

For safety, this should always be greater than some threshold \( \text{clear}_{thr} = r_d + r_k + r_{safety} \).

IV. EXPERIMENTAL EVALUATION

We evaluated SPC on the drone flocking problem using simulations and experiments with Crazyflie 2.1 drones.

A. Simulation Experiments

As a simulation framework, we use crazys [16], which is based on the Gazebo [17] physics and visualization engine and the Robotic Operating System (ROS) [18]. Our SPC algorithm is implemented in C++ as a separate ROS node. It receives position messages from neighboring drones, and control messages, such as the target location or a stop command, from the human operator. It outputs a set-point to the PLLC. The SPC we implemented is fully distributed: there is no central optimizer and no further information is exchanged between ROS nodes. The SPC node calculates the gradient according to Eqs. (11)-(14). The spatial look-ahead parameter \( N \) is determined dynamically based on the distance to the target location, where \( N^* \in \mathbb{N}^+ \) is a system parameter:

\[
N = \left\lceil N^* \cdot \max(1, \min(1.5 \cdot (\| p_i - p_{tar} \| + 0.5), 3)) \right\rceil \quad (18)
\]

This allows the drones to more quickly reach distant target locations and reduces the controller’s computational cost (by reducing \( |Q_i| \)) once the flock reaches the target. Thereafter, the set-point position \( x_{io}^{(r)} \) is determined by Eqs. (3)-(4). Auxiliary functions, like hovering at the starting position, are also implemented in this node. In the simulations, we added Gaussian sensor noise, with \( \sigma = 10 \text{cm} \), for drone position measurements. Cost-function weights and controller parameters (Table I) were determined empirically by analysis of the controller behavior. Note that the maximum look-ahead distance \( \epsilon \cdot N \) should not be too large, to avoid “seeing through” other drones or obstacles. On the other hand, a small value for \( N \) reduces the granularity of the controller action space, leading to a bang-bang controller if \( N = 1 \).

| Cost weights | PLLC A | PLLC B | Hardware |
|--------------|--------|--------|----------|
| \( \omega_{loch} \) | 20 m\(^{-1} \) | 20 m\(^{-1} \) | 20 m\(^{-1} \) |
| \( \omega_{exp} \) | 12 m\(^{-1} \) | 12 m\(^{-1} \) | 12 m\(^{-1} \) |
| \( \omega_{rar} \) | 150 m\(^{-1} \) | 150 m\(^{-1} \) | 150 m\(^{-1} \) |
| \( \omega_{obj} \) | 18 m\(^{-1} \) | 18 m\(^{-1} \) | 35 m\(^{-1} \) |
| \( N^* \) | 6 | 3 | 3 |
| \( \epsilon \) | 0.05 m | 0.05 m | 0.04 m |
| \( k \) | 0.003 m | 0.0015 m | n.a. |
| \( r_d \) | 0.07 m | 0.07 m | 0.07 m |
| \( r_k \) | 0.25 m | 0.25 m | 0.25 m |
| \( r_{safety} \) | 0.06 m | 0.06 m | 0.06 m |

TABLE I: Parameters used in simulation experiments and hardware experiments.

To evaluate SPC and its implementation, we defined four path-based scenarios (trajectories), as shown in Figure 3. The end points on the path (shown in red) are provided in a timed sequence as target location \( p_{tar} \). There are four scenarios: without obstacles (Figure 3a), with 1 obstacle (Figure 3b), with 2 obstacles (Figure 3c), and with 13 obstacles (Figure 3d). Simulations were conducted with flocks of size \( |D| = 4, 9, 15, \) and 30. Using radius \( r_H = 0.9 \text{m} \), the neighborhood is defined by:

\[
H_i = \{ j \in D : \| i \| \wedge \| p_i - p_j \| < r_H \} \quad (19)
\]

To check SPC’s robustness to different PLLCs, we experimented with two PLLCs with different step responses. PLLC B reaches its set-point for \( x \)- and \( y \)-dimensions in less than half the time of PLLC A, while overshooting by about 50% more. The PLLCs behave very similarly in the \( z \)-dimension. Figure 4 show snapshots of the simulations. A video is provided in the Supplementary Material and available at: https://youtu.be/iUkaYrnZz9k.

1) Results: The analysis of the quality metrics for collision avoidance, compactness, and obstacle clearance show that our SPC-based approach successfully maintains a stable flock. In Figure 5, metrics are plotted over time for three representative simulations. Data from the prefix of an execution, when the drones move from random starting positions into flock formation, are omitted when computing the metrics.

2) Computational complexity: The computation time of Eq. (4) is \( O(|Q| \cdot (|H_i| + |K|)) \). \( |H_i| \) is bounded by \( |D| \) and also depends on \( r_H \). Introducing a concept of neighborhood for obstacles can reduce the computation time.

3) Comparison with PFC: To compare SPC with [14], [15], we also experimented with a PFC controller based solely on gradients. In this controller, the gradient vector \( \nabla c(p_i) \) is used to determine the next set-point \( x_{io}^{(r)} \) for the PLLC as follows:

\[
x_{io}^{(r)} = p_i - k \cdot \nabla c(p_i) \quad (20)
\]
Fig. 5: Quality metrics over time for SPC simulations using PLLC B for exemplary scenarios of: a) 30 drones with 0 obstacles, b) 9 drones with 1 obstacle, and c) 15 drones with 2 obstacles. Results for other simulation experiments were very similar. While the flock is passing the obstacle(s) the metrics temporarily degrade, however values \(d_{\text{min}}\) and \(\text{clear}_\text{obj}\) stay above the respective thresholds, meaning there are no collisions, throughout the whole simulation. Analogously \(\text{comp}_{\text{max}}\) stays below the threshold (5m), indicating that a compact flock is continuously maintained.

The control law stated in [14] provides an acceleration vector, which we adapted in Eq. (20) to a positional variant as required by the PLLC. We determined the gain \(k\) empirically such that the target of the flock was reached within the same time as our SPC implementation. The gain determines how aggressively the controller moves the drone toward the target location. In the experiments detailed below, the gain is constant, as in [14], [15]. We also briefly experimented with dynamic gain, where \(k\) is computed using a function similar to the one in Eq. (18). This had relatively small effects. Compared to the results with static gain reported below: collision avoidance improved slightly for some scenarios; obstacle clearance improved for some cases with PLLC A, while it worsened with PLLC B; and compactness improved moderately.

Figure 6 shows performance metrics for simulations of SPC and PFC controllers. While both perform reasonably well without obstacles, SPC’s performance is superior in the presence of obstacles. This validates our hypothesis that SPC is particularly valuable when the cost function is more nonlinear (adding obstacles has that effect). Whenever a drone enters or leaves another drone’s neighborhood, the cost function instantaneously changes its value; the gradient changes too. This causes the PFC controller to fail: in these simulations, we observed oscillating behavior and multiple collisions. SPC successfully deals with all of these situations. In short, SPC is more robust to nonlinearities in the cost function and differences in the behavior of the PLLC.

B. Hardware Experiments

We also experimented with real drones, specifically, Crazyflie 2.1 quadcopters [7]; see Figure 7a. For localization, we used the Loco-Positioning system [19]. The drones seamlessly integrated with the localization system, resulting in a (internal) PLLC that enables a drone to hold its position at a given set-point. Stability, however, depends on both the accuracy of the localization system and on the mechanical limitations of the drone. When hovering at a given set-point, we observed noise in the drone’s position in the range of 15 cm. This was also noted in [20].

In the hardware implementation, we used ROS with the same software node as in Section IV-A, with only minor parameter modifications. This demonstrates the robustness of SPC with respect to a potential sim-to-real transfer gap. Since Crazyflies are incapable of running ROS on-board, we transmit the position updates to a PC that runs the controller and transmits the set-point position to the drone. Our experiments therefore also show that SPC is resilient to the additional delay introduced by radio transmission of position updates and set-point messages. Our controller, however, could be ported to run directly on ROS-capable drones, since we run it separately for each drone.

For the hardware experiments we used the same scenarios, as in the simulation experiments (Figure 3), except with 13 obstacles. Flocks of size \(|D| = 2, 4, 9,\) and 16 were used.

1) Results: Figures 7b and 7c show pictures of our experiments in a lecture hall. A video is provided in the Supplementary Materials. To show the drone movements for one example experiment with 16 drones, the recorded traces of the localization system are plotted in Figures 7d, 7e, and 7f. Figure 8 presents performance metrics for our hardware experiments. Data from the prefix of an experiment, when the drone moves from initial starting positions into flock formation, are omitted when computing the metrics. Figure 8 shows that our SPC-based approach successfully maintains a stable flock of Crazyflie drones satisfying thresholds for collision avoidance, compactness, and obstacle clearance in nearly every scenario for the full duration of the experiment.

Fig. 7: Hardware experiments. a) Crazyflie 2.1 quadcopters were used. b) A flock of 16 drones and c) 9 drones with 2 obstacles in our lecture hall (a video is in the Supplementary Materials). d, e, f: Recorded traces show the movements of the 16 drones for one exemplary experiment.
SPC can be viewed as combining features of MPC and PFC. MPC does a lookahead in time to decide the best control action. It requires a model of the system to compute states at future time points. Intuitively, MPC computes all the states that can be reached in $k$ time steps using different control inputs, picks the best feasible trajectory, and returns the associated control action. In contrast, SPC ignores the system model and feasibility altogether and instead searches for good control states by enumerating promising candidates. Both MPC and SPC recompute their action in each time step using an optimization procedure to handle noise and variability in environment. PFC uses the gradient of the cost to pick the next action, just like SPC, but PFC does not perform any optimization.

Reynolds [21] was the first to propose a flocking model, using cohesion, separation, and velocity alignment force terms to compute agent accelerations. Reynolds model was extensively studied [22] and adapted for different application areas [23]. Alternative flocking models are considered in [24]–[28], and [14]. Other formulations consider swarm control in the context of formation rigidity [29]–[31]. In these approaches, flocks are described using point models. This means that physical properties of agents (e.g., drones) such as mass and inertia, are not taken into account. In our work, we evaluate SPC on a realistic physical drone model, as well as on real hardware.

In addition to these largely theoretical approaches, in [32]–[34], flocking controllers are implemented and tested on real hardware. However, the approach of [33], [34] involve the use of model-predictive control, which is computationally more expensive than SPC. In contrast to SPC, [32] requires the velocity of neighboring drones. Gradient optimization for robot control has been studied in [15]. In contrast, SPC uses spatial look-ahead as opposed to pure gradient descent.

VI. CONCLUSIONS

We introduced the concept of Spatial Predictive Control (SPC), and demonstrated its utility on the drone flocking problem. SPC is fully distributed. It is based only on the position of the individual drone itself, and on those of neighboring drones. This information is used to compute the gradient of the local cost function and to perform a spatial prediction for the best next action.

We performed an extensive experimental evaluation of SPC on the drone flocking problem. Our simulation experiments used a physics engine with a detailed drone model. Our results demonstrated SPC’s ability to form and maintain a flock, avoid obstacles, and move the flock to multiple target locations. They also highlighted SPC’s robustness to sensing noise and PLLC variability, and its role in the controller hierarchy.

We also evaluated the same controller implementation on a flock of Crazyflie 2.1 quadcopters in different scenarios, thereby demonstrating the effectiveness of SPC in controlling real hardware. Needing only a minor parameter adjustment, and no modifications to the control algorithm, SPC proved to be very robust in terms of a potential sim-to-real transfer gap. The hardware experiments also highlighted SPC’s capability to perform properly in the presence of significant sensor noise introduced by the localization system and the extra latency introduced by radio transmission of positional and control signals.

We also experimentally compared SPC with a related PFC-based approach of [15]. We found that SPC exhibits superior performance and stability, as its discrete search for an optimal solution enables it to avoid oscillations. SPC is a general technique for designing middle-level controllers sandwiched between high-level planners and PLLCs that often come integrated with the hardware.

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