Gatekeeper: Safety Critical Control of Nonlinear Systems with Limited Perception in Unknown and Dynamic Environments

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Abstract—This paper presents the Gatekeeper algorithm, a real-time method to guarantee the safety of a robotic system operating in environments that are unknown and dynamic. Given a nominal planner designed to meet mission objectives, Gatekeeper extends the nominal trajectories using backup controllers, and determines a control policy that is certified safe for all future time using the currently available information. We demonstrate the algorithm on a dynamic aerial firefighting mission, and show reduced conservatism relative to existing methods. The algorithm was also demonstrated onboard a quadrotor, where a map of the environment was built online, and the Gatekeeper algorithm prevented a human pilot from flying the quadrotor into obstacles and unknown regions.

I. INTRODUCTION

Designing controllers that satisfy mission specifications while maintaining strict guarantees of safety is important and challenging. Safety is often posed as requiring the robotic system’s state to lie within a predefined set of allowable states. When the safe set depends on the environment, the robot must sense the environment and devise a plan that is safe (with respect to the available information about the environment), and accomplishes the mission. If the environment is dynamic, then the set of safe states evolves over time, significantly complicating the control design.

Many approaches address safety-critical control design. Recently, Control Barrier Functions (CBFs) [1] have gained interest, since they offer a computationally-efficient method for the online control of nonlinear systems that guarantees the forward invariance of a subset of the safe set. However, a suitable CBF needs to be found, either analytically, or by using computationally expensive offline methods [1], [2]. For some classes of nonlinear systems, constructive methods to find the CBF exist, although these are often only applicable to simple safe sets, and do not handle time-varying or multiple safety conditions well [3]–[5]. To avoid computing a valid CBF, in [6] a backup trajectory is forward propagated from a given state, and by smoothly switching to the backup controller, safety is guaranteed. However, this method ignores the possibility of the nominal trajectory being unsafe, leading to conservatism and off-nominal behaviour. Similarly, in [7], [8], the ability to return to a backup set is determined by approximately computing finite-horizon reachable sets. The method relies on mixed-monotonicity properties of the system considered.

Safety is also often addressed by the higher-level planner. Grid/graph-based [9], and sampling-based [10], [11] planning algorithms can design paths to meet mission objectives while avoiding obstacles and unsafe states. In [12], [13], the robot’s dynamics are simplified to linear dynamics, and the provided safety guarantee assumes the nonlinear system can execute the trajectory generated by the linear dynamics. Alternatively, nonlinear Model Predictive Control (MPC) techniques have also been used, although guaranteeing convergence, stability and recursive feasibility of the solutions remains an open challenge [14], [15].

The main contribution of this paper is the Gatekeeper algorithm (Fig. 1), with which we address the challenge of designing safe controllers for nonlinear systems operating in environments that are unknown and dynamic. The algorithm assumes the following about the robotic system and the en-
environment: (A) the ability to forecast the safe set from online perception, and (B) the existence of a backup controller that can stabilize the robot to a safe terminal set (although the trajectory to the terminal set may be unsafe). In most cases, these assumptions can be verified before the robotic system is deployed, and therefore the guarantee of safety does not depend on data acquired online. In the next section, we motivate the need for Gatekeeper by demonstrating the limitations of existing methods on a simple case study. After presenting the algorithm, we provide remarks on how it can be extended to address disturbances or mismatches due to computational times. Finally, we demonstrate the Gatekeeper algorithm in a simulated aerial firefighting scenario, and in experiments of a quadrotor flying in an unknown environment.

Motivating Examples: Consider two vehicles, where the following vehicle has Adaptive Cruise Control (ACC) (Fig. 2a). The dynamics of the following vehicle is defined by (adapted from [16])

\[ \dot{x}_1 = x_2; \quad \dot{x}_2 = -a_r(x_2) + u \]

where \( x_1, x_2 \) are (respectively) the position and velocity of the following vehicle along a road. The resistive forces on the vehicle are \( a_r(x_2) \geq 0 \), a known nonlinear function of vehicle speed. The control input is the bounded acceleration, \( u \in [-u_{\text{min}}, u_{\text{max}}] \), with \( u_{\text{min}}, u_{\text{max}} > 0 \). The trajectory of the lead vehicle is defined by \( x_3(t) \), an unknown function of time. The following vehicle is able to use onboard sensors (e.g. a LIDAR) to estimate the distance to the lead vehicle, but has a limited sensing range \( d_{\text{sense}} \). The objective for the following vehicle is to maintain a desired speed \( v_d \), without crashing into the lead vehicle. If we neglect nonlinearities (\( a_r(x_2) = 0 \)), and constrain the lead vehicle to not move backwards (\( x_3'(t) \geq 0 \)), then one analytical solution is to limit the maximum speed of the vehicle to be less than \( v_{\text{max}} = \sqrt{2d_{\text{min}} \min(d_{\text{sense}}, d_{\text{lead}})} \): in this case, the vehicle can stop before hitting the lead vehicle or within its current sensing horizon. Then, one can use a CLF-CBF-QP controller [1] to ensure the system remains within these bounds. Although nonlinear dynamics can be handled by the CLF-CBF-QP, \( v_{\text{max}} \) was derived without considering the nonlinearity, introducing conservatism. Furthermore, if the lead vehicle is allowed to reverse, the safe set changes and one would need to verify if the new safe set can be rendered forward invariant by the CLF-CBF-QP. Similarly, suppose the vehicle is operating in a foggy environment where \( d_{\text{sense}} \) can change over time. If we constructed a CLF-CBF-QP based on assumed worst case bounds on \( d_{\text{sense}} \) (or the rate of change of \( d_{\text{sense}} \)), the controllers will be rather conservative when operating in clear conditions.

Next, consider the Firewatch mission in which a helicopter is tasked to survey the fire-front by flying along the perimeter of the fire. Since the fire is constantly evolving, the helicopter is operating with limited information around a dynamically-changing safe set. To apply a CBF-QP controller [1] one needs to, in real-time, encode the dynamic safe set, and construct a CBF based on \( h(x) \) to certify the forward invariance inner safe set. However, it is computationally impractical to construct CBFs even for static safe sets for systems with a large number (>10) of states [2].

The examples reinforce that the choice of the controller, and how it is adapted or changed, depends highly on the environment, and also that the perception capabilities directly influence the certificate of safety obtained. We need a framework that can reason about safe control policies online, based on the available information, without being too conservative.

II. PROBLEM FORMULATION

Notation: Let \( \mathbb{R} \) denote the set of reals, and \( \mathbb{R} = \mathbb{R} \cup \{\pm \infty\} \) to denote the extended reals. Lowercase \( t \) is used for specific timepoints, while uppercase \( T \) is used for durations. Consider a nonlinear system

\[ \dot{x} = f(x, u), \quad x(t_0) = x_0 \quad (1) \]

where \( x \in \mathcal{X} \subset \mathbb{R}^n \) is the state of the robot and \( u \in \mathcal{U} \subset \mathbb{R}^m \) is the control input. The function \( f : \mathcal{X} \times \mathcal{U} \to \mathbb{R}^n \) is assumed locally Lipschitz continuous wrt both arguments. Given a feedback controller \( u = \pi(t, x) \) that is piecewise-continuous wrt to \( t \) and Lipschitz continuous wrt to \( x \), a unique solution exists to the closed-loop dynamics \( \dot{x} = f_x(t, x) \) over an interval \( t \in T = [0, T_{\infty}) \) [17, Th.3.1]. For simplicity, we assume solutions are forward-complete, i.e., \( T_{\infty} = \infty \).

We assume a nominal planner has been designed to meet the mission objectives, without explicitly considering safety requirements. This nominal planner constructs a trajectory \( P_{\text{nom}} \) for the robot to follow, and at each planning iteration a new trajectory is generated. A trajectory is defined as:

**Definition 1.** A trajectory \( P \) on the interval \([t_0, t_1]\) (where \( t_0, t_1 \in \mathbb{R} \)) is the solution \( x(t; t_0, x_0, u_0) \) to the dynamics (1) for a piecewise-continuous control input \( u : [t_0, t_1] \to \mathcal{U} \). If \( t_1 = \infty \), \( P \) is an infinite-horizon trajectory, else it is a finite-horizon trajectory.

Safety is expressed as requiring the robotic system state to lie within a set of allowable states \( S(t) \subset \mathcal{X} \). We assume that \( S(t) \) is unknown, yet also that the perception system forecasts an under-approximation of the safe set,\(^2\) denoted \( B(\tau) \) for all \( \tau \geq t \), i.e.,

\[ B(\tau) \subset S(\tau) \quad \forall \tau \geq t. \quad (2) \]

\(^1\)The notation \( S(t) \) emphasizes that the safe set is time-varying.

\(^2\)Although \( B \) can be challenging to represent computationally, this module can be implemented lazily: the only requirement is that given a pair \( (\tau, x) \) it be able to answer whether \( x \in B(\tau) \).
For example, in the firefighting scenario, suppose the helicopter is mounted with an infrared camera to detect the fire line. Then using a reasonable upper-bound on the fire spread rate, one can forecast the location of the fire in the future. To summarize, the problem is as follows:

Problem 1. Given a dynamical system (1) with a nominal planner that produces finite-horizon trajectories $P_{nom}$, and a perception module that can forecast an under-approximation $B(\tau)$ of the safe set $S(\tau)$ (as in (2)), design a method to follow $P_{nom}$ while guaranteeing the system remains safe, i.e., $x(t) \in S(t)$ for all $t \geq 0$.

III. THE ALGORITHM: GATEKEEPER

The architecture of Gatekeeper is described in Fig. 1. First, the nominal planner produces a finite-horizon nominal trajectory, $P_{nom}$. Next, Gatekeeper extends this into an infinite horizon trajectory, $P_{ext}$, using the algorithms described below. It evaluates whether $P_{ext}$ is safe based on the available information, and if so, $P_{ext}$ becomes the committed trajectory $P_{com}$. In this way, Gatekeeper maintains access to a trajectory that is defined for all future time, and is known to be safe. By requiring the low-level controller to track $P_{ext}$ at all times, we guarantee the robot can remain safe. In order to describe these steps, we first introduce some definitions.

A. Definitions and Subroutines

Backup Controllers: We assume a backup controller has been designed, using a definition adapted from [6], [18].

Definition 2. Let $S_B(t) \subset X$ be a set of states known to be safe, i.e., $S_B(t) \subset S(t)$ for all $t$. A backup controller is a Lipschitz continuous feedback controller $\pi_b : X \to U$ that under the system dynamics (1) renders the set $S_B(t)$ (i) forward invariant, and (ii) reachable within a finite duration $T_b$ from any $x \in D(t) \subset X$, where $D(t)$ is the $T_b$-domain of attraction of $S_B(t)$.

In words, a backup controller $\pi_b$ drives the system to a state in the set $S_B(t)$, called the terminal set, which is known to be safe, although the path taken to enter $S_B(t)$ might not be safe. The set $S_B(t)$ is assumed known, but the set $D(t)$ does not need to be known. In the Firewatch scenario, we can define a backup controller that flies the helicopter at a high speed normal to and away from the fire-front.

Extend: The extend function takes a section of a finite-horizon feasible trajectory $P_{nom}$, and extends it into an infinite-horizon trajectory using the backup controller:

Definition 3. Let $P_{nom}$ be a nominal trajectory $x_{nom}(t; t_0, x_0, u_{nom})$. Let $t_{ext} \in [t_0, t_1]$. The function $\text{extend}(P_{nom}, t_{ext})$ returns a trajectory $P_{ext}$ defined over the interval $[t_0, \infty)$ where $x_{ext}(t; t_0, x_0, u_{ext})$ is the solution to (1) using the control input

$$u_{ext}(t) = \begin{cases} u_{nom}(t) & \text{for } t \in [t_0, t_{ext}] \\ \pi_b(x_{ext}(t)) & \text{for } t > t_{ext} \end{cases}$$

(isSafe): Whether a trajectory $P_{ext}$ is safe can be determined by the isSafe routine:

| Algorithm 1: isSafe |
|---------------------|
| function isSafe(Pext, tpred); |
| let $x_{ext}(t) = x_{ext}(t; t_0, x_0, u_{ext})$ |
| if $x_{ext}(t) \in B(t) \forall t \in [t_0, t_{pred}]$ then |
| if $x_{ext}(t_{pred}) \in S_B(t_{pred})$ then |
| return True |
| return False |

The three checks involved are interpreted as follows: In line 3 we check whether the trajectory between $[t_0, t_{pred}]$ lies within $B(t)$, the perceived safe set. In line 4, we check that the terminal set $S_B$ is reached. In line 5 we verify that after reaching $S_B$ the controller remains within $S_B$. This method allows the safety of an infinite-horizon trajectory to be checked using only information from a finite interval $[t_0, t_{pred}]$. See Lemma 1 for the proof of correctness.

B. Algorithm Description

The main component of Gatekeeper is the algorithm that updates the committed trajectory when the nominal planner yields a new nominal trajectory. This is done using either of the following two algorithms.

In the full algorithm (Alg. 2) we find the largest $t_{ext}$ such that the extended trajectory is safe (Alg. 2, line 3). This is in general a nonlinear, nonconvex optimization, but since it is an optimization over a single and bounded scalar variable, standard line search or discrete grid search methods can be used. If a suitable $t_{ext}$ is found, the committed trajectory gets updated (Alg. 2, line 5).

In the simple algorithm (Alg. 3), $t_{ext}$ is not optimized for, but is based on fixed horizon the user defines (Alg. 3, line 3). The rest of the algorithm is the same as the full algorithm: if the extended trajectory is safe, the committed trajectory gets updated (Alg. 3, line 7). This removes the need to perform the $\text{argmax}$ online, reducing the computational complexity. In our limited experience, by choosing a small nominal horizon (i.e., small $T_n$) has allowed the nominal plan to be followed more closely. Intuitively, if a large $T_n$ is selected, it is more likely for the extended trajectory to reach states not in $B$, and therefore be rejected.

Both algorithms need to be initialized with an infinite horizon committed trajectory. While this can be done in any number of ways, one option is to use the backup controller, i.e., $P_{com}$ is defined over the interval $[t_0, \infty]$ using the control input $u_{com}(t) = \pi_b(x_{com}(t))$. 

In general, the controller that brings $x \in D(t)\backslash S_B(t)$ to $S_B(t)$ can be different from the controller that renders $S_B(t)$ forward invariant, but for simplicity we assume they are the same.
Algorithm 2: FullGatekeeper
1 Parameters: $T_b$
2 function fullGatekeeper($P_{nom}, P_{com}^\text{old}$):
3 \hspace{1cm} $t_{ext} \leftarrow \arg\max_{t \in [t_0, t_1]} \{ t : \text{isSafe}(P, t + T_b) \}$
4 \hspace{1cm} where $P = \text{extend}(P_{nom}, t)$
5 if $t_{ext}$ exists then
6 \hspace{2cm} $P_{com}^\text{new} \leftarrow \text{extend}(P_{nom}, t_{ext})$
7 else
8 \hspace{2cm} $P_{com}^\text{new} \leftarrow P_{com}^\text{old}$
9 \hspace{1cm} return $P_{com}^\text{new}$

Algorithm 3: SimpleGatekeeper
1 Parameters: $T_b, T_n$
2 function simpleGatekeeper($P_{nom}, P_{com}^\text{old}$):
3 \hspace{1cm} $t_{ext} \leftarrow t_0 + T_n$
4 \hspace{1cm} $t_{pred} \leftarrow t_{ext} + T_b$
5 \hspace{1cm} $P_{ext} \leftarrow \text{extend}(P_{nom}, t_{ext})$
6 if isSafe($P_{ext}$, $t_{pred}$) then
7 \hspace{2cm} $P_{com}^\text{new} \leftarrow P_{ext}$
8 \hspace{1cm} else
9 \hspace{2cm} $P_{com}^\text{new} \leftarrow P_{com}^\text{old}$
10 \hspace{1cm} return $P_{com}^\text{new}$

C. Theoretical Guarantees

We prove that either version of Gatekeeper provides a recursive guarantee of safety. In Lemma 1 we prove correctness of the isSafe algorithm, and in Theorem 1 we show that the proposed Algorithms ensure safety.

Lemma 1. Given a committed trajectory $P_{com}$ that satisfies $\text{isSafe}(P_{com}, t_{pred}) = \text{True}$ for some $t_{pred} \geq t_0$, executing $P_{com}$ ensures the robot remains safe for all $t \geq t_0$.

Proof. By construction isSafe only returns true if (A) $x_{com}(t) \in \mathcal{B}(t) \subset \mathcal{S}(t)$ for all $t \in [t_0, t_{pred}]$ and (B) $x_{com}$ reaches the set $S_B$ in the finite time $t_{pred}$. The final check ensures the trajectory remains within $S_B$ for all $t \geq t_{pred}$, since the set $S_B$ is forward invariant using the backup controller. Hence, for all $t \geq t_0$, $x_{com}(t) \in \mathcal{S}(t)$.

Theorem 1. Suppose at $t_0$, the committed trajectory $P_{com}$ satisfies $\text{isSafe}(P_{com}, t_0 + T_b) = \text{True}$. Then, if either Alg. 2 or Alg. 3 are used to update $P_{com}$ based on new nominal trajectories $P_{nom}$, the system will remain safe for all time, i.e., $x(t) \in \mathcal{S}(t)$ for all $t \geq t_0$.

Proof. By Lemma 1, $x(t) \in \mathcal{S}(t)$ for all $t \geq t_0$ if $P_{com}$ is not replaced. $P_{com}$ is replaced either in Alg. 2, line 5 or in Alg. 3, line 7. Suppose the switch occurs at some time $t_s$. In either case, $P_{com}$ is replaced with a trajectory $P_{ext}$ for which there exists a $t_{pred} \geq t_s$ such that $\text{isSafe}(P_{ext}, t_{pred}) = \text{True}$. Therefore, by Lemma 1, executing $P_{ext}$ guarantees $x(t) \in \mathcal{S}(t)$ for all $t \geq t_0$. Therefore, even as $P_{com}$ gets replaced, we have that $x(t) \in \mathcal{S}(t)$ for all $t \geq t_0$.

This has the useful property that if the nominal plan is safe, Gatekeeper will not modify it.\footnote{This corollary only holds true for the full version of Gatekeeper, not the simplified version.}

Corollary 1. Suppose at some time $t_s$, the robot state is $x_s$ and $P_{nom}$ is a new nominal trajectory defined over the interval $[t_s, t_1]$. Suppose the trajectory satisfies $x_{nom}(t; t_s, x_s, u_{nom}) \in \mathcal{B}(t)$ for all $t \in [t_s, t_1]$ and $x_{nom}(t; t_s, x_s, u_{nom}) \in S_B$, then under Alg. 2, the robot will follow $x(t) = x_{nom}(t) \in \mathcal{T}$ for $t \in [t_s, t_1]$.

Proof. The solution to argmax in Alg. 2, line 3 is $t_{ext} = t_1$. Therefore, for any parameter $T_b \geq 0$, the committed trajectory is updated to match $P_{nom}$ for the interval $[t_s, t_1]$. Therefore the robot will follow this trajectory.

Remark 1. While apparent, this is an important property that differentiates our work from many safety-critical controllers currently used in the literature. For example, in [6], the switch between the nominal control input and the backup control input is determined based solely on a prediction of the behaviour of the backup controller. Therefore, even if the nominal trajectory is safe (as defined in the corollary), the backup filter will of [6] will always modify the control input to include some of the backup control input: since the proposed control input is $u = \lambda \pi_n(x) + (1 - \lambda) \pi_b(x)$ for $\lambda \in [0, 1)$, one can never have $u = \pi_n(x)$. Similarly, in CLF-CBF-QP controllers [1], the QP-based controller will modify nominal control inputs based on local safety functions and derivatives, without considering whether the nominal controller might yield a safe input over a time horizon.

D. Implementation Considerations

Computation Time: While the computations required for Gatekeeper are lightweight (it only requires a forward propagation of dynamics over a bounded interval), in our experiments they take on the order of ones to tens of milliseconds. Suppose the computation time can be upper-bounded by $T_c$. Then, if a new nominal plan is proposed at time $t_0$, instead of extending from $t_0$, we can extend the nominal trajectory from $t = t_0 + T_c$, assuming the committed trajectory continues to be used for the first $T_c$ seconds. Then, if the extended trajectory is still safe, it can become the committed trajectory at $t = t_0 + T_c$. Furthermore, the Gatekeeper can alleviate strict timing requirements on the high-level planners: the algorithm gets triggered when new nominal trajectories are proposed, but retains safety guarantees even if the nominal planner fails to propose new trajectories.

Choice of Parameters: In both Gatekeeper algorithms the backup prediction horizon, $T_b$, is a user-defined parameter. Increasing this will always make the set of nominal trajectories that can be committed larger: if the extended

Parameters: $T_b,$ $T_n$
trajectory can reach $S_B$ in a time $T_{b1}$, it can also reach $S_B$ in time $T_{b2} > T_{b1}$. Increasing $T_b$ however leads to additional computation, and is therefore a balance.

**Robustness:** When the robot dynamics are described by $\dot{x} = f(x, u, e) + d(t)$, the algorithm needs to be robustified. Suppose the tracking controller used in Fig. 1 guarantees the robot’s state lies within a tube of $P_{com}$ (e.g. using [4], [19], [20]). Then the issSafe function can be modified to validate that the tube lies within the safe sets. The terminal set $S_B(t)$ also needs to be robustly forward invariant.

**Backup Controllers:** The proposed method relies heavily on the ability to design a suitable backup controller, and on identifying a terminal backup set $S_B(t)$ that is control invariant and safe wrt to a dynamic and time varying safe set. This is a limitation of the proposed algorithm, and future works will attempt to relax this assumption.

IV. Simulation Results

We simulate an autonomous helicopter performing a Firewatch mission, around a fire with an initial perimeter of 16 km. The helicopter begins 0.45 km from the fire front, and is tasked to fly along the perimeter, without entering the fire, while maintaining an airspeed of 54 km/h (30 knots). The helicopter model is a nonlinear, not control-affine system:

\[
\begin{align*}
\dot{x}_1 &= x_3 \cos x_4 \\
\dot{x}_2 &= x_3 \sin x_4 \\
\dot{x}_3 &= u_1 \\
\dot{x}_4 &= g \frac{\tan u_2}{x_3}
\end{align*}
\]

where $x_1, x_2$ are the cartesian position coordinates of the helicopter wrt an inertial frame, $x_3$ is the speed of the vehicle along its heading, $x_4$ is the heading angle of the vehicle, and $g$ is the acceleration due to gravity. The control inputs are $u_1$, the acceleration magnitude along the vehicle’s heading, and $u_2$ the roll angle. This system models a vehicle that can control its forward airspeed and makes coordinated turns.

The fire is modeled using level-set methods [22]. In particular, the fire is described using the implicit function $\phi : \mathbb{R} \times \mathbb{R}^2 \to \mathbb{R}$, where the fire-front at time $t$ is the set of points $\{p \in \mathbb{R}^2 : \phi(t, p) = 0\}$. If $\phi(t, p) > 0$, the fire has not reached $p$ at time $t$. Hence, the set of safe states are

\[S(t) = \{x : \phi(t, [x_1, x_2]^T) \geq 0\}\]

where $[x_1, x_2]^T \in \mathbb{R}^2$ refer to the cartesian position of the helicopter. The evolution of the fire is based on the Rothermel 1972 model [23]. Each point $p$ on the fire-front travels normal to the front at a speed $R(t)$, satisfying:

\[
\frac{\partial \phi}{\partial t}(t, p) + R(p) \| \nabla \phi(t, p) \| = 0,
\]

where $R : \mathbb{R}^2 \to \mathbb{R}$ defines the Rate of Spread (RoS). The RoS depends on various environmental factors including terrain topology, vegetation type, and wind speeds [23], [24]. The simulated environment was randomly assigned an RoS function, but the helicopter did not have access to the true RoS map. The only information the helicopter was allowed to use for control design was the onboard IR sensor (to detect the fire within a 1 km range) and that the rate of spread was upper-bounded by 8 km/h (based on estimates in [25]).

Three controllers are compared in Fig. IV. The black line defines the behaviour with a nominal controller, a PD-type controller. The blue line defines the behaviour using the backup filter approach in [6]. The backup controller is a controller that drives the helicopter to fly in a direction normal to the fire-front. Finally, the green line indicates the behaviour using the proposed Gatekeeper algorithm. The same nominal and backup controllers were used in all three simulations. In the Gatekeeper implementation, the nominal plans were generated by forward propagating the nominal controller over $T_n = 20$ seconds. The paths were extended using the backup controller over an additional horizon $T_b = 100$ seconds. For fairness, in the backup filter simulations (blue lines) the same 120 s forward propagation was used. The computation time of both methods was similar, between 3-6 ms. We also implemented a nonlinear MPC (using NLOPT_LN_COBYLA [26], [27]), but each iteration (for the same discretization) took in excess of 1.0 seconds to solve, and would not always converge to a feasible solution.

While both the Gatekeeper algorithm and the backup filters are able the keep the system safe, Gatekeeper tracks the nominal controller more closely, and is less conservative: the backup controller maintains an average distance from the fire-front of 0.72 km, significantly larger than Gatekeeper’s average distance of 0.16 km (Fig. d). Furthermore, as seen in the snapshots (Fig. a), the backup filter controller results in trajectories that have a lower speed. This is because the backup controller is driving the vehicle perpendicular to the fire, while the nominal controller is tangential to the fire - with Gatekeeper, the two controllers are not mixed. An interesting behaviour of the Gatekeeper is demonstrated in Fig. c: even though the nominal controller drives the helicopter into the pocket, the Gatekeeper rejects this trajectory by predicting that the helicopter’s turning radius is too large to successfully trace the perimeter. While this deviates from the mission objective, it maintains safety.

V. Experimental Results

We implemented Gatekeeper for a quadrotor flying in an unknown environment, where a map of the static obstacles in the world are constructed online using a depth camera, the Intel Realsense D435. The pointcloud generated by the depth camera is integrated into an Octomap [28]. To verify if a given state $x$ along the trajectory is safe, we check that a ball of radius 0.15 m does not intersect with unknown regions or occupied regions. All computations related to the Gatekeeper and the Octomap are run onboard a Raspberry Pi 4B in real time. Each pointcloud integration took 40-50 ms, and each iteration of Gatekeeper took under 3 ms. The hardware control and state estimation are performed on a Pixhawk CubeOrange, running a customized version of PX4. A Vicon motion capture system provides position feedback.

The nominal trajectories were generated by a human pilot, by interpreting joystick commands as desired linear

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6For details, see the code [21].

7The method was modified to ensure safety with time-varying safe sets, using the same upperbound on the rate of spread.
velocities and yaw rates. The Gatekeeper filtered the commands such that the quadrotor flew without crashing into scattered obstacles, and prevented the user from flying the quadrotor into unknown territories. Videos of the experiment, visualizing the nominal, extended and committed trajectories are available in the accompanying video [21].

VI. CONCLUSION

This paper proposes an algorithm (“Gatekeeper”) to safely control nonlinear robotic systems while collecting information about dynamically-evolving safe states. The algorithm constructs an infinite-horizon committed trajectory from a nominal trajectory using backup controllers. By extending a section of the nominal trajectory with the backup controller, Gatekeeper is able to follow nominal trajectories closely, while guaranteeing a safe control input is known at all times. We applied the algorithm to an aerial firefighting mission, where we demonstrated the trajectories executed by Gatekeeper is less conservative than similar methods, without increasing the computational complexity. In hardware experiments, we demonstrated Gatekeepers ability to prevent a human pilot from flying the quadrotor into obstacles in an unstructured environment. Future directions for work involve addressing the design of backup controllers, and developing techniques allow greater flexibility in their design.

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Fig. 3. Simulation results from Firewatch mission. (a) Snapshots of the fire and trajectories executed by each of three controller. The fire is spreading outwards, and the helicopters are following the perimeter. The black line traces the nominal controller, the blue line is based on the backup filter adapted from [6] and the green line shows the proposed controller. (b, c) show specific durations in greater detail. At $t = 0$, the Gatekeeper controller behaves identically to the nominal controller, and makes small modifications when necessary to ensure safety. The backup filter is conservative, driving the helicopter away from the fire and slowing it down. (d) Plot of minimum distance to fire-front across time for each of the controllers. The nominal controller becomes unsafe 3 times, while both the backup controller and the Gatekeeper controllers maintain safety. Animations are available at [21].

Fig. 4. Experimental scenario (top) with the perceived environment (bottom). Gatekeeper is able to ensure the quadrotor only flies in regions that are known to be safe.
