A Principled Approach to Enable Safe and High Performance Maneuvers for Autonomous Rotorcraft

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ABSTRACT

Autonomous rotorcrafts are required to operate in cluttered, unknown, and unstructured environments. Guaranteeing the safety of these systems is critical for their successful deployment. Current methodologies for evaluating or ensuring safety either do not guarantee safety or severely limit the performance of the rotorcrafts. Autonomous vehicles need to operate at their limits to effectively complete their tasks. Safety of the vehicle needs to be ensured while respecting the constraints imposed by sensory and dynamic limitations of the vehicle. To design a guaranteed safe rotorcraft, we have defined safety for an autonomous rotorcraft flying in unknown environments given sensory and dynamic constraints. We have developed an approach that ensures vehicle's safety while pushing the limits of safe operation limits of the vehicle. Furthermore, the presented safety definition and the presented approach are independent of the vehicle and planning algorithm used on the rotorcraft. In this paper we present a real time algorithm to guarantee the safety of the rotorcraft through a diverse set of emergency maneuvers. We prove that the related trajectory set diversity problem is monotonic and sub-modular which enables to develop an efficient, bounded sub-optimal trajectory set generation algorithm. We present safety results for an autonomous Unmanned Little Bird Helicopter flying up to speeds of 56 m/s in partially-known environments. Through months of flight testing the helicopter has been avoiding trees, performing autonomous landing, avoiding mountains while being guaranteed safe. We also present simulation results of the helicopter flying in the Grand Canyon, with no prior map of the environment.

INTRODUCTION

Rotorcraft are used in a wide variety of tasks including cargo delivery, casevac (casualty evacuation), surveillance and people transport. Therefore, the rotorcraft is operating in unstructured and partially-known environments which pose particular challenges for the safety concept of the rotorcraft.

Safe operation of rotorcraft is essential for its applications in these environments, consequently, the problem of motion safety is becoming increasingly important in robotics research. Current safety assessment approaches for autonomous rotorcraft address the problem of safety either conservatively using the distance necessary to slow down the rotorcraft for hovering or do not guarantee safety using swerving distances to determine the maximum safe velocity. These heuristics either do not enable sufficient performance or fail to ensure safety. In this work, we examine the problem of ensuring safety for an autonomous rotorcraft while maintaining the capability to operate the vehicle at its performance limits. The key idea is to ensure that the vehicle is always in a safe state from which it can transition to a loiter pattern or to a

Fig. 1: Autonomous Unmanned Little Bird, coming in for landing in snowy conditions. Helicopter used in experiments

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hovering flight within the known obstacle-free space. All these states are inside the control invariant set of the rotorcraft (Ref. 15), which is a well-known approach to ensure feasibility for model predictive control applications (Ref. 3). Determining loiter patterns or trajectories resulting in hovering flight in various environments is computationally challenging especially when the rotorcraft has non-linear dynamics. Additionally, it is required that the safety evaluation has a low worst-case run time so that it can be used for on-line motion planning at high speeds.

In order to ensure the on-line capability of the safety evaluation, the problem is decoupled in an off-line and an on-line part. The off-line part generates a set of optimized control invariant trajectories allowing the rotorcraft to reach a safe state. The trajectory set is designed to maximize the probability of finding at least one emergency maneuver in the known unoccupied environment. The on-line part determines if the set contains a collision-free trajectory regarding the current state and environment of the rotorcraft. Thereby, the off-line generated trajectory set reduces the search space for the on-line part. This resulting safety evaluation approach serves as a computationally tractable algorithm with bounded run time.

It can be shown, that the problem of generating such kind of trajectory set is NP-hard (Ref. 4). We present an efficient, bounded sub-optimal approximate solution that finds a trajectory set maximizing the probability of containing at least one safe trajectory given a prior obstacle distribution. The proposed novel safety assessment approach based on the emergency maneuver library is compared to other common known approaches such as the stopping distance based safety limits, giving the maximum safe velocity allowed and safe planning reaction times. Therefore, real flight tests from various missions on an Unmanned Little Bird equipped with a range sensor are used. The evaluation also includes results from using the novel emergency maneuver library with a motion planner for autonomous flying. In all evaluated scenarios the novel safety assessment approach outperforms known common approaches by allowing for higher velocities of the rotorcraft while guaranteeing safety for the rotorcraft at all times.

RELATED WORK

Autonomous rotorcrafts and unmanned aerial vehicles(UAVs) have matured over the years. As these systems are developed for field applications (Refs. 1, 11, 13, 17), the need for robust and safe autonomous UAVs is highlighted. The previous work on safety of UAVs can be broadly divided into two paradigms. One of the paradigms is to make sure that the vehicle can stop within the sensor range while applying maximum allowed longitudinal deceleration. Scherer et al. (Ref. 17), Goerzen et al. (Refs. 8, 9) and Adolf et al. (Ref. 2) use the stopping distance of the vehicle to limit vehicle speed, in order to keep it safe. The stopping distance based velocity limit does not exploit the complete dynamics of the vehicle, leading to conservative velocity limits.

Another paradigm is to simplify the non-linear dynamics of the UAVs and plan a path that is guaranteed to stay within the known unoccupied region. Schouwenaars et al. (Ref. 18), uses mixed integer linear programming to plan paths that stay within the known region. Frazzoli et al. (Ref. 5) use simplified dynamics in a sampling based graph, while limiting the maximum planning time to ensure safety. The assumption is that the planner can always plan an obstacle free path if allowed to run until the maximum planning time. Enright et al. (Ref. 11) use Dubins curves to plan paths within the known space. These methods also suffer from not being able to exploit the UAV's full dynamic capabilities.

It is also important to quantify the safety of the autonomous UAV systems. Mettler et al. (Ref. 14) suggested using distance from obstacles as a metric for safety of a UAV navigating through an obstacle field. This metric does not take into account the sensory and dynamics limitations of the vehicle and cannot comment if the vehicle is safe or not.

In the next section, we present a safety metric that considers both sensory and dynamics constraints of the vehicle to evaluate the vehicle safety. We then present an emergency maneuver library based method that utilizes the true dynamics model of the vehicle to find a positive control invariant set in the known unoccupied space. We formulate the the problem of finding this trajectory set as an NP hard path diversity optimization (Refs. 4, 6, 10). We prove the path diversity problem to be monotonic, sub-modular and present an efficient, bounded sub-optimal algorithm (Ref. 12) to solve for the trajectory set.

DEFINING SAFETY

The safety of an autonomous system is dependent on its sensory and dynamic capabilities. In a fully known environment a rotorcraft is unsafe if it enters a state for which there is no trajectory that avoids a collision, such a state is called Inevitable Collision State (Ref. 7). In a static partially-known environment the unknown regions may contain obstacles. Therefore, to ensure the safety of the vehicle it should be made sure that the vehicle never enters a state for which it cannot transition to a control invariant state within the known region. We now formally define safety for robots operating in uncertain environments. Let, $\mathbf{x}(t)$ be the state of the robot at time t in the state space $\mathcal{X}$ which is in a manifold $\mathcal{X} \subset \mathbb{R}^n$. The workspace of the robot is defined as $\mathcal{W}$ and the occupancy of the robot system in the workspace at a certain state is given as $\mathcal{A}(\mathbf{x}(t)) \subset \mathcal{W}$. Let, $\Omega(\mathbf{x})$ be the function that maps a state $\mathbf{x}$ of the robot to its workspace, $\Omega(\mathbf{x}) \subset \mathcal{W}$. The known space of the workspace at a given time t is denoted as $\mathcal{K}_t \subset \mathcal{W}$. The occupancy of the known obstacles at time t is given by $\mathcal{O}_t \subset \mathcal{K}_t \subset \mathcal{W}$. Let $\Phi_{\mathrm{F}}(s)$ be the search space of trajectories for a given state $\mathbf{x}$, that end in a control invariant state. Let $\phi(\mathbf{x})$ be such a trajectory and let $\phi(\mathbf{x}, \tau)$ be the state of the vehicle at time τ, along the trajectory $\phi(\mathbf{x})$, which is by definition rooted at state $\mathbf{x}$. Then any trajectory followed by the vehicle can be considered safe if at all times on the trajectory there exists a trajectory $\phi(\mathbf{x})$ which completely maps to known obstacle-free space at that time. Equation (1) presents this definition succinctly:

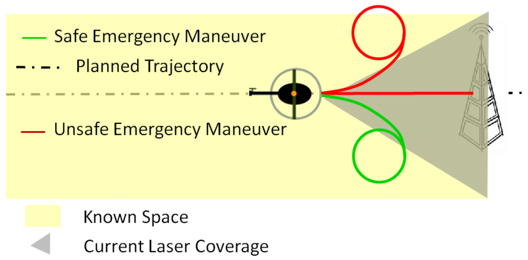


Fig. 2: The helicopter is approaching an obstacle, the stopping distance trajectory is hitting an obstacle but an emergency maneuver is completely in known, obstacle free volume, making the helicopter state safe.

Definition 1 (Motion Safety):

$$\forall t, \forall \tau, \exists \phi(\mathbf{x}) \mid \mathcal{A}(\phi(\mathbf{x},\tau)) \subset (\mathcal{K}_t \setminus \mathcal{O}_t) \tag{1}$$

In the next the section we discuss the real-time application of this safety definition to an autonomous helicopter. We also discuss a time to collision cost function that augments safety.

APPROACH

It is computationally expensive to find a trajectory that satisfies (1) while respecting the non-linear dynamics of a rotorcraft. The problem is made even more challenging by the real-time nature of the constraints, if a trajectory is not found within the temporal constraints, the helicopter might collide into an obstacle. The current methods in use, lead to a very conservative behavior, with helicopters moving well under their dynamic and sensory capabilities. We provide a method that stays independent of the goal directed behavior but ensures safety. We overcome the real-time computation challenges by calculating emergency maneuver trajectory sets offline, that are produced by efficiently sub-sampling the search space of control invariant trajectories. The velocity of the vehicle is then modulated such that the state of the vehicle always satisfies the definition of safety reactively. We provide a solution that ensures the safety of the vehicle irrespective of the planner used to guide the vehicle to the goal.

Emergency Maneuver Library

Instead of solving for dynamically feasible trajectories that end in a control invariant state on-line, we approximate the search space by a set of such trajectories. The trajectory set is designed such that the probability that at least one of the trajectories stays collision free, given a generic prior on the obstacle configuration for a given state is maximized. We formulate this problem as a NP hard optimization (Refs. 4,6) and then prove that it is monotonic sub-modular, providing a sub-optimality bounds for greedily solving the problem and then provide a greedy solution.

Problem Definition

We want to find a trajectory set that maximizes the probability that the set contains at least one collision-free trajectory. The trajectory set should be optimized regarding all possible workspaces of the robot. Therefore, we assume a workspace which is populated by $N_{\mathcal{O}}$ obstacles and which positions in the workspace are distributed by probability density functions (pdfs). We assume that there exists the function $P_{\mathrm{u}}(V)$ which determines the probability of a volume $V \subset \mathcal{W}$ being unoccupied. The volume which is sweeped by the robot following a certain trajectory ϕ is expressed as $V(\mathcal{A}(\phi)) = \text{sweep}(\mathcal{A}(\phi))$, where sweep$(\cdot)$ is the volume which represents all points $\mathbf{p}$ in the workspace which the robot occupies along its path (Ref. 1)

$$\text{sweep}(\mathcal{A}(\phi)) = \{\mathbf{p} | \mathbf{p} \in \mathcal{W}, \exists \tau \;\; \mathbf{p} \in \mathcal{A}(\phi(\tau))\}.$$

In the rest of the paper we use the shorter notation $V_\phi = V(\mathcal{A}(\phi))$ to denote the sweeped volume of the robot. The probability of a path being safe is given by the probability of the sweeped volume being unoccupied

$$P_{\mathrm{u}}(\phi) \qquad = P_{\mathrm{u}}(V_\phi)$$

which allows to determine the probability of path ϕ_1 or ϕ_2 being unoccupied

$$P_{\mathrm{u}}(\phi_1 \cup \phi_2) = P_{\mathrm{u}}(\phi_1) + P_{\mathrm{u}}(\phi_2) - P_{\mathrm{u}}(\phi_1 \cap \phi_2)$$

where,

$$P_{\mathrm{u}}(\phi_1 \cap \phi_2) = P_{\mathrm{u}}(V_{\phi_1} \, \cap V_{\phi_2}).$$

Using the inclusion-exclusion principle, we get the probability of a path set $\Phi = \{\phi_1, \phi_2, \ldots, \phi_n\}$ having an obstacle free path as

$$P_{\mathrm{u}}(\Phi) = \sum_{k=1}^{n} (-1)^{k-1} \Big(\sum_{1 \le i_1 \le \ldots \le i_k \le n}^{n} P_{\mathrm{u}}(\phi_{i_1} \cap \ldots \cap \phi_{i_k}) \Big). \tag{2}$$

In order to maximize the safety of the robot, a finite path set Φ must be determined maximizing the probability that at least one path is collision-free. This is formulated as the path diversity problem:

Problem 1 (Path Diversity): *The desired trajectory set Φ_d maximizes the probability of finding at least one obstacle-free path.*

$$\begin{aligned} &\Phi_{\mathrm{d}} := \arg\max P_{\mathrm{u}}(\Phi) \\ &\textit{subject to } \|\Phi_{\mathrm{d}}\| < N_\Phi \\ &\textit{where, } \Phi_{\mathrm{d}} \subseteq \Phi_{\mathrm{F}} \end{aligned} \tag{3}$$

Since the path diversity problem is known to be NP-hard, we present a greedy method to optimize (3). But before that we prove that greedily optimizing equation (3) is bounded sub-optimal. To prove bounded sub-optimality we prove the $P_{\mathrm{u}}(\Phi)$ is sub-modular and monotonically increasing in the cardinality of Φ.

Monotonicity Proof

In the following we show that the probability of at least one path in a path set being collision-free is monotonically increasing by the cardinality of the path set.

Proposition 1 (Monotonicity of Path Sets)**.** *Given a path set Φ_A, a path ϕ_a and a path set $\Phi_B = \{\Phi_A, \{\phi_a\}\}$ the probability that the set Φ_B contains at least one collision-free path is bigger or equal than for the set Φ_A*

$$P_{\mathrm{u}}(\Phi_B) - P_{\mathrm{u}}(\Phi_A) \geq 0.$$

Proof. The probability of the path set Φ_b having at least one obstacle-free path is given by

$$P_{\mathrm{u}}(\Phi_B) = P_{\mathrm{u}}(\Phi_A \cup \{\phi_a\}).$$

Using inclusion exclusion principle lead to

$$\begin{aligned} P_{\mathrm{u}}(\Phi_B) &= P_{\mathrm{u}}(\Phi_A) + P_{\mathrm{u}}(\phi_a) - P_{\mathrm{u}}(\Phi_A \cap \phi_a) \\ P_{\mathrm{u}}(\Phi_B) - P_{\mathrm{u}}(\Phi_A) &= P_{\mathrm{u}}(\phi_a) - P_{\mathrm{u}}(\Phi_A \cap \phi_a). \end{aligned} \tag{4}$$

For all ϕ_a, $P_{\mathrm{u}}(\phi_a) \geq 0$ and $\max[P_{\mathrm{u}}(\Phi_A \cap \phi_a)] = P_{\mathrm{u}}(\phi_a)$, which is the case when all the volume covered by path ϕ_a is already covered by Φ_A. This implies that

$$P_{\mathrm{u}}(\phi_a) - P_{\mathrm{u}}(\Phi_A \cap \phi_a) \geq 0$$

and inserted in (4) leads to $P_{\mathrm{u}}(\Phi_B) - P_{\mathrm{u}}(\Phi_A) \geq 0$ □

Prop. 1 proves that adding more trajectories to a path set, cannot decrease the probability of finding an obstacle-free path in the set. In other words, $P_{\mathrm{u}}(\Phi)$ is monotonically increasing in the cardinality Φ.

Sub-Modularity Proof

In order to show that a greedy algorithm for the path diversity problem (Prop. 1) is bounded sub-optimal, we will that $P_{\mathrm{u}}(\Phi)$ is a submodular set function. This means, that the difference in the probability P_{u} that a single trajectory makes when added to the path set decreases as the size of the path set increases.

Proposition 2. *Let there be a path set $\Phi_\Gamma \subseteq \Phi_\Upsilon \subseteq V$, where $P_{\mathrm{u}} : 2^V \rightarrow R$. Now, assume a path ϕ_e,such that $\phi_e \subseteq V \backslash \Upsilon$ Define $\Phi_{\Gamma+e} = \{\Phi_\Gamma, \phi_e\}$, $\Phi_{\Upsilon+e} = \{\Phi_\Upsilon, \phi_e\}$. For sub-modularity*

$$\triangle(e|\Upsilon) < \triangle(e|\Gamma)$$

where, $\triangle(.)$ is the discrete derivative.

Proof. The discrete derivative of $\triangle(e|\Gamma)$ is defined as

$$\begin{aligned} \triangle(e|\Gamma) &= P_{\mathrm{u}}(\Phi_{\Gamma+e}) - P_{\mathrm{u}}(\Phi_\Gamma) \\ &= P_{\mathrm{u}}(\Phi_\Gamma \cup \phi_e) - P_{\mathrm{u}}(\Phi_\Gamma) \\ &= P_{\mathrm{u}}(\Phi_\Gamma) + P_{\mathrm{u}}(\phi_e) - P_{\mathrm{u}}(\Phi_\Gamma \cap \phi_e) - P_{\mathrm{u}}(\Phi_\Gamma) \\ &= P_{\mathrm{u}}(\phi_e) - P_{\mathrm{u}}(\Phi_\Gamma \cap \phi_e) \end{aligned}$$

and similarly

$$\triangle(e|\Upsilon) = P_{\mathrm{u}}(\phi_e) - P_{\mathrm{u}}(\Phi_\Upsilon \cap \phi_e).$$

Taking the difference of the discrete derivatives

$$\begin{aligned} &\triangle(e|\Gamma) - \triangle(e|\Upsilon) = \\ &\quad = P_{\mathrm{u}}(\phi_e) - P_{\mathrm{u}}(\Phi_\Gamma \cap \phi_e) - P_{\mathrm{u}}(\phi_e) + P_{\mathrm{u}}(\Phi_\Upsilon \cap \phi_e) \\ &\quad = P_{\mathrm{u}}(\Phi_\Upsilon \cap \phi_e) - P_{\mathrm{u}}(\Phi_\Gamma \cap \phi_e) \\ &\quad = P_{\mathrm{u}}((\Phi_\Gamma \cup \Phi_{\Upsilon/\Gamma}) \cap \phi_e) - P_{\mathrm{u}}(\Phi_\Gamma \cap \phi_e) \\ &\quad = P_{\mathrm{u}}((\Phi_\Gamma \cap \phi_e) \cup (\Phi_{\Upsilon/\Gamma} \cap \phi_e)) - P_{\mathrm{u}}(\Phi_\Gamma \cap \phi_e) \\ &\quad = P_{\mathrm{u}}(\Phi_\Gamma \cap \phi_e) + P_{\mathrm{u}}(\Phi_{\Upsilon/\Gamma} \cap \phi_e) \\ &\quad\quad - P_{\mathrm{u}}(\Phi_\Gamma \cap \phi_e \cap \Phi_{\Upsilon/\Gamma}) - P_{\mathrm{u}}(\Phi_\Gamma \cap \phi_e) \\ &\quad = P_{\mathrm{u}}(\Phi_{\Upsilon/\Gamma} \cap \phi_e) - P_{\mathrm{u}}(\Phi_\Gamma \cap \phi_e \cap \Phi_{\Upsilon/\Gamma}) \end{aligned}$$

Applying Baye's Rule
$P_{\mathrm{u}}(\Phi_\Gamma \cap \phi_e \cap \Phi_{\Upsilon/\Gamma}) = P_{\mathrm{u}}(\Phi_\Gamma | (\phi_e \cap \Phi_{\Upsilon/\Gamma})) P_{\mathrm{u}}(\Phi_{\Upsilon/\Gamma} \cap \phi_e)$
it follows that

$$\triangle(e|\Gamma) - \triangle(e|\Upsilon) = P_{\mathrm{u}}(\Phi_{\Upsilon/\Gamma} \cap \phi_e)(1 - P_{\mathrm{u}}(\Phi_\Gamma | \phi_e \cap \Phi_{\Upsilon/\Gamma})).$$

With $P_{\mathrm{u}}(\Phi_{\Upsilon/\Gamma} \cap \phi_e)(1 - P_{\mathrm{u}}(\Phi_\Gamma | \phi_e \cap \Phi_{\Upsilon/\Gamma})) \geq 0$ the equation can be rewritten as

$$\triangle(e|\Gamma) - \triangle(e|\Upsilon) \geq 0.$$

□

Greedy Algorithm

Since, $P_{\mathrm{u}}(\Phi)$ is monotonic sub-modular, the path diversity problem (Prop. 1) can be greedily optimized while maintaining a sub-optimality bound of $(1 - 1/e) \approx 63\%$ (Refs. 12,16). We describe the greedy algorithm in Alg. 1. We start with

Algorithm 1: Greedy Optimization for a Emergency Maneuver Trajectory Set

```
Initialize: Φ_G = ∅

while |Φ_G| < N_φ do
    φ_s = argmax_{φ ∈ Φ_F/Φ_G} P_u(Φ_G ∪ {φ})
    Φ_G = {Φ_G ∪ {φ_s}}
end
```

an empty trajectory set and search through Φ_F to find the trajectory that maximizes P_{u}. This trajectory is saved in Φ_G and in the next step, the search for trajectory that maximizes P_{u} is conducted in Φ_F/Φ_G, and added to Φ_G. The process of greedily selecting trajectories from Φ_F/Φ_G and adding them to Φ_G is repeated till the desired number of trajectories N_ϕ have been added. In the next section we explain how to use this greedily generated set to guarantee safety.

Safety Algorithm

We ensure the safety of the rotorcraft by using the emergency maneuver library to enforce the constraint that the current and next state of the helicopter always lies in the positive invariant set, which does not intersect the obstacles and stays within the

Algorithm 2: Emergency Maneuver Trajectory Set Application for Reactive Safety

```
Initialize: Φ_Previous = Φ_{S_1}

while mission active do
    Φ_New = {∅}
    for ∀φ_c ∈ Φ(s_{t+1}) do
        if ∀τ  A(φ_c(τ)) ⊆ (K_t \ O_t) then
            Φ_New = {Φ_New, {φ_c}}
        end
    end
    if Φ_New = {∅} then
        execute φ_e ∈ Φ_Previous
    else
        Φ_Previous = Φ_New
    end
end
```

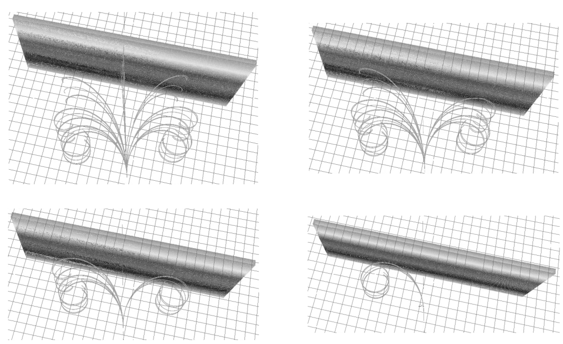


Fig. 3: Data from a flight test conducted on 18th December 2013 in Manassas,Virgina. a) Helicopter approaches a large simulated wall with the emergency trajectory libraries wih no emergency maneuver in contact with the wall. b) As the helicopter gets closer to the wall, the emergency maneuvers intersect the wall and become invalid. Only valid maneuver are displayed. c) More emergency maneuvers pruned away as they come in contact with the wall d) Emergency maneuver is executed as the future state is no longer safe.

known volume. The algorithm to ensure safety is explained in Alg. 2.

The algorithm queries the emergency maneuver library at a future state of the rotorcraft, and ensures it can transition to an emergency maneuver which lies in known obstacle free space. If the there are no such maneuvers, one of the emergency maneuvers computed at the previous step (for the current state) are executed. This operation has a maximum limit on run-time and is guaranteed to keep the vehicle safe. The algorithm is explained with a working example in Fig. 3.

RESULTS

We implemented the emergency maneuver trajectories to ensure the safety of the autonomous Unmanned Little Bird Helicopter, equipped with a large field of view range sensor. The dynamic constraints of the helicopter are given in Tab. 1.

Table 1: Constraints on trajectory

Constraint	Velocity $\|v(t)\|$	
	$\geq 20\,\text{m/s}$	$< 20\,\text{m/s}$
Roll [°]	25.00	28.50
Roll rate [°/s]	15.00	–
Heading rate [°/s]	–	28.50
Longitudinal vel. [m/s]	60.00	20.00
Vertical vel. [m/s]	5.00	5.00
Longitudinal accel. [m/s²]	0.75	0.75
Vertical accel. [m/s²]	1.00	1.00

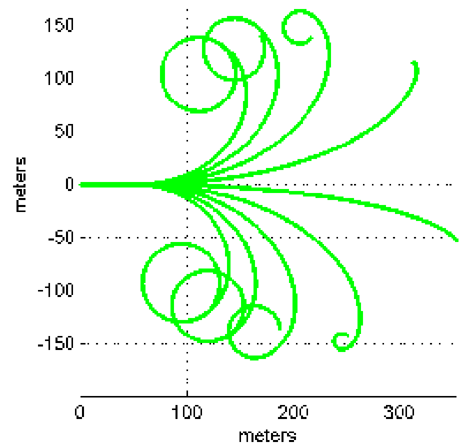


Fig. 4: Emergency Maneuver Library for a rotorcraft at 25 m/s

Given these constraints we approximate $\Phi_F(s)$, by five hundred trajectories each forming a positive control invariant set. The trajectories for this application end in a hover and can trivially be extended to end in a loiter if desired. Each trajectory slows down the helicopter using the maximum allowed deceleration. The trajectories are generated by sampling the roll rate and z acceleration uniformly. Once the helicopter has made a 180° co-ordinated turn the radius of the turn is fixed and the vertical velocity is forced to be 0 m/s. We use a constant resolution three dimensional grid as our representation and assume uniform probability of occupation of each voxel. The probability of a trajectory set containing at least one unoccupied trajectory is calculated using inclusion-exclusion principle as suggested by Branicky et. al (Ref. 4). Thirty three trajectories out of these five hundred trajectories are selected greedily. Fig. 4 shows the top view of a trajectory set calculated at 25 m/s. Given a trajectory set we can calculate the sensor range required for different velocities. Equation 5 tells the minimum sensor range required for a velocity, given an emergency maneuver library.

$$\text{range} = \min_{\phi_c}(\max(\zeta(\phi_c))) \tag{5}$$

where, $\phi_c \in \Phi_G(s)$ ζ returns a vector of the euclidean distance between starting state s and all the states in ϕ_c.

The best case sensor range required while using the emergency maneuver library is given by (5). The worst case is the same as the stopping distance. Hence, the emergency maneu-

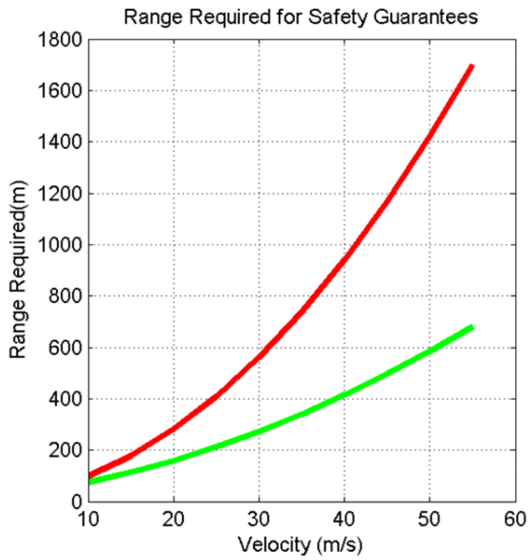


Fig. 5: Changes in Sensor Requirements. The sensor range required for safe operation of the vehicle when using stopping distance for safety is displayed in red, in green is the sensor range required for safe operation of the vehicle when using emergency maneuver library for helicopter safety.

ver library is guaranteed to provide at least as much performance as the stopping distance safety enforcer, Fig. 5.

Fig. 6 shows the mountain avoidance case during flight tests in Mesa, Phoenix. As the helicopter approaches the mountain the maximum safe speed is $30\,{}^{m}/_{s}$. While the helicopter is avoiding the mountain some of the emergency maneuvers intersect the mountain and are unavailable for execution. Yet the safe speed does not decrease as the helicopter still has the option of taking other emergency maneuvers at the safe speed. This shows that the emergency maneuver library works well under partial obstruction/occlusion and allows maximum time to the planner before the execution of the emergency maneuver.

We can quantify the performance of an emergency maneuver trajectory by calculating the maximum safe velocity it allows the helicopter during a mission and the planning time it allows the planner before it becomes imperative for the helicopter to execute the emergency maneuver library. Fig. 7 shows the maximum safe velocity and allowed planning times for a flight test conducted in Quantico, Virginia. The red line shows the path where the helicopter is travelling to turn towards the landing zone. The orange part of the path corresponds to the part of the mission for which the sensor on the helicopter focuses on the landing zone for its evaluation. This implies, when the helicopter is travelling through the path in orange the sensor stops looking for obstacles and helicopter comes increasingly close to the known/unknown volume boundary, leading to drop in maximum safe velocity and allowed planning time. The red part of the path corresponds to turns, it should be noticed how the maximum safe velocity according to the stopping distance decreases as the vehicle turns. This happens due to reduction in effective range of the sensor beacause of sparsity of observations in front of the vehicle while turning. The maximum safe speed by the emergency maneuver library is unaffected, as it efficiently utilizes the known space.

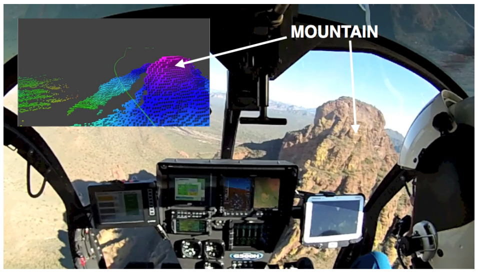
Fig. 9 shows the maximum safe velocity and allowed planning times for seven flight tests, Fig. 8, conducted in Quantico, Virginia. As can be seen in Fig. 9, the maximum safe speed is always greater that the helicopter speed, which means the helicopter is always safe. The stopping distance based safe velocity limit is always well below the flying speeds at which the missions are conducted. The use of emergency maneuver library also allows higher available planning times, while keeping the vehicle safe. Thus results in a vehicle traveling safely at higher speeds with the option of using higher planning times for better quality solutions

Fig. 10 shows a simulated grand canyon mission. The example, Fig. 11, emphasizes the coupling between a gradient based planner and the emergency maneuver library. The planner optimistically assumes that the known space is empty, and plans through an occluded canyon wall. By the time the canyon wall is observed the local gradient based planner cannot plan out of the wall. The emergency maneuver library rescues the helicopter and immediately leads to a change in the direction in which the helicopter is headed. This leads the planner to search in a different region in the search space, allowing the robot to follow a goal based trajectory before it comes to the end of the emergency maneuver. This strong coupling between the emergency maneuver library and the planner leads to a guaranteed safe robot which can recover from the breakdowns in the motion planning system.

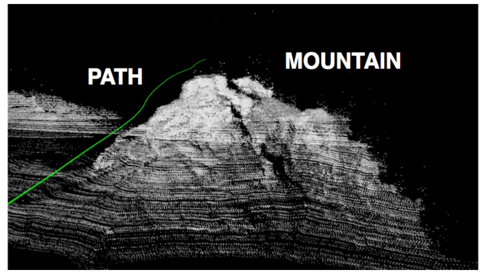
CONCLUSIONS

The main contributions of this paper is to define a metric to guaranty safety of autonomous flying vehicles operating in unknown environments. We use the metric to design an algorithm to guarantee the safety of any autonomous robot flying in unknown environments. The algorithm is independent of the planner guiding the vehicle to the goal. It allows the robot to follow the planned goal directed behavior for as long as possible. We demonstrated how the safety library may be used to find velocity limits and sensor requirements. We have also shown improvements in performance for systems using the emergency maneuver library as a safety governor than using guaranteed safe receding horizon or stopping distance based safety governors and present results from real flight test data. We have shown a clear benefit of using our approach over existing stopping distance based approaches.

In the future, we want to develop a closer coupling between emergency maneuvers and planners, such that the planner proactively responds to potentially unsafe situations rather than just react to them. Another focus of our current research is to include wind and obstacle distributions to augment the emergency maneuver library further.



(a)



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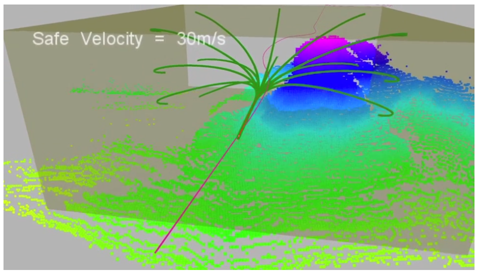
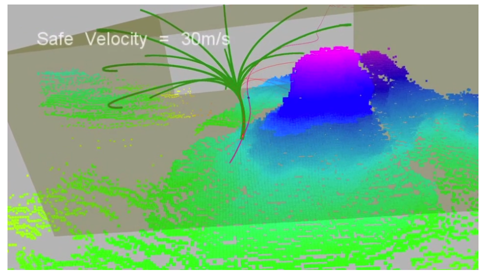
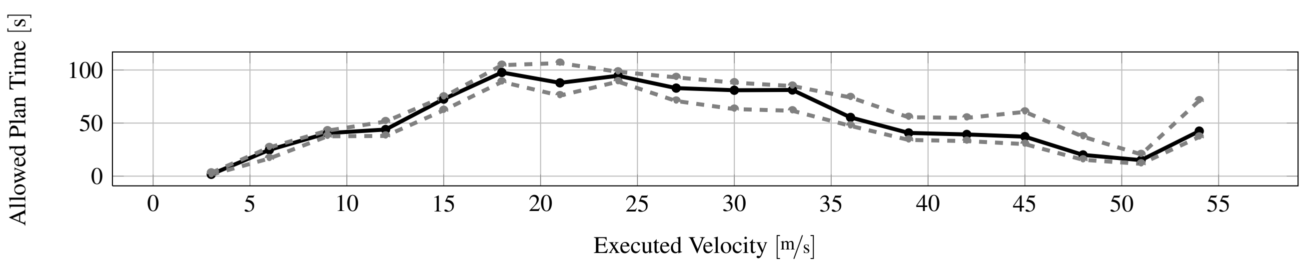


(c)

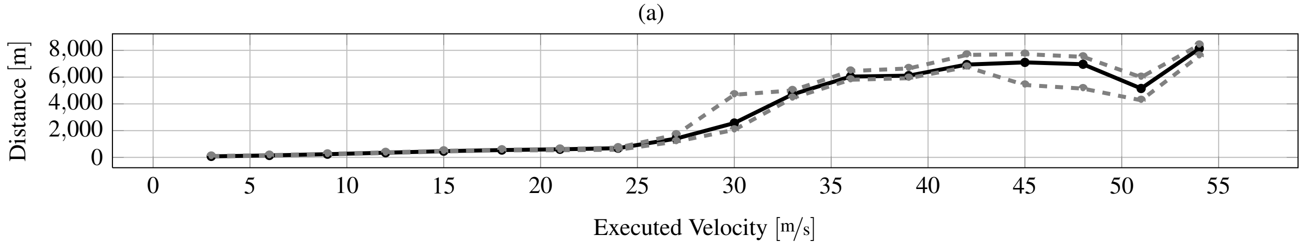


(d)

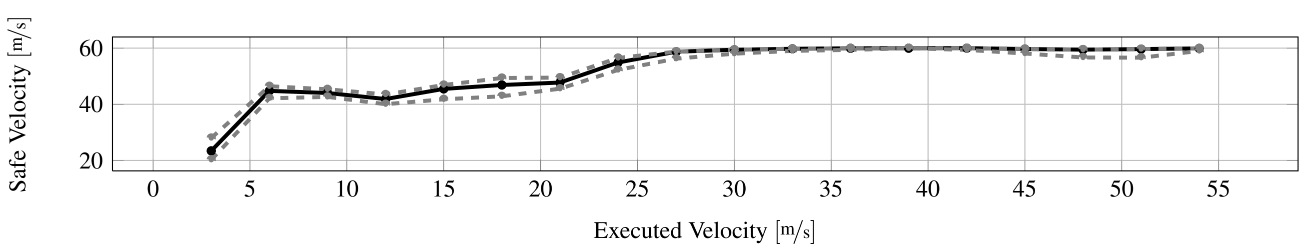
Fig. 6: Mountain avoidance, flight test conducted in Mesa, AZ a) View of the mountain form the helicopter cockpit. b) Point cloud data and planned path around the mountain. c) Emergency Maneuver library before the helicopter starts avoiding the mountain. d) Emergency trajectories intersect the mountain(shown in red) and become invalid, rest of the emergency maneuver trajectories are still valid and the helicopter stays in a safe statement.



(a)



(b)



(c)

Fig. 9: The figures show the allowed plan time, distance to the landing zone and safe velocity relative to the executed velocity of the helicopter. The black line shows the mean and the gray dashed line illustrates the upper and the lower bound of the measurements of all considered flight tests.

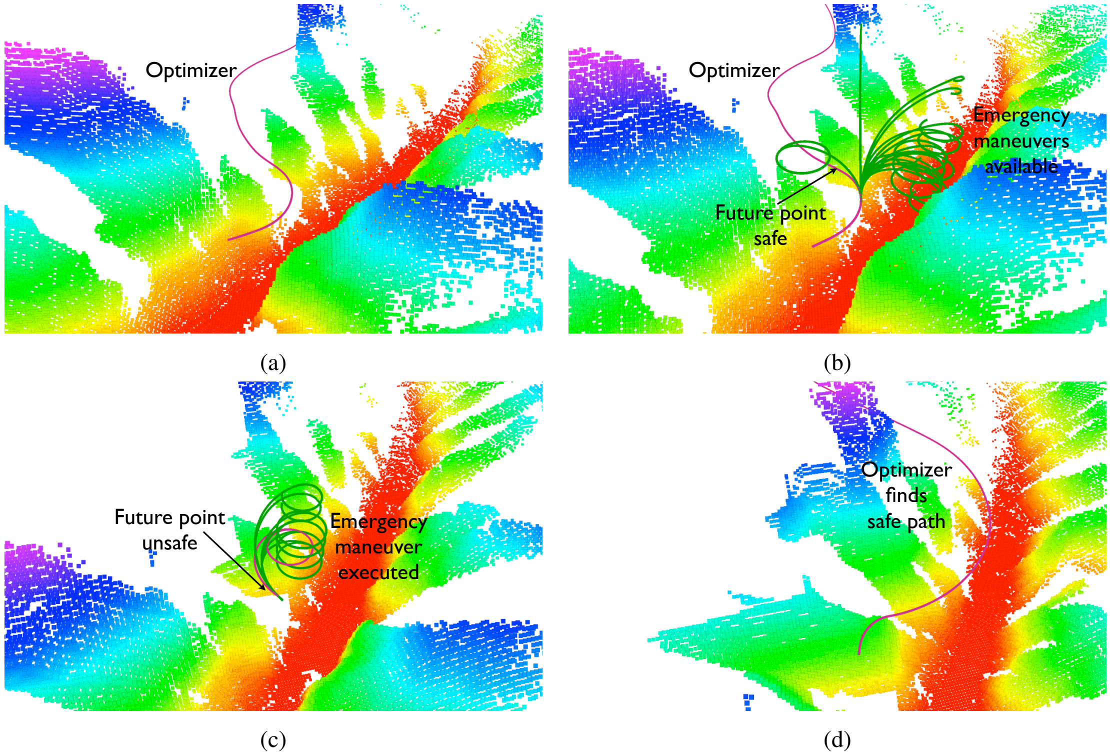


Fig. 11: Emergency maneuver takes the system out of an undesired configuration. (a) Since we run the experiment with a gradient based optimizer. This lies in a local minimum between two walls of the grand canyon (b) The system follows this path since the future point is safe (c) The future point is no longer safe and an emergency maneuver is selected (d) The optimizer is now in a configuration where it can find a safe path again.

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REFERENCES

[1] Karim Abdel-Malek, Yingzhou Yang, Denis Blackmore, and Ken Joy. Swept volumes: Foundations, perspectives, and applications. *Int. J. Shape Modeling*, 12(1):87–127, 2006.

[2] F Adolf and J. S. Dittrich. Evaluation of the artis sampling-based path planner using an obstacle field navigation benchmark. In *Proceedings of the American Helicopter Society 68th Annual Forum. Ft. Work, TX*, 2012.

[3] F. Blachini. Set invariance in control. *Automatica*, 35(11):1747–1767, 1999.

[4] Michael S Branicky, Ross A Knepper, and James J Kuffner. Path and trajectory diversity: Theory and algorithms. In *Robotics and Automation, 2008. ICRA 2008. IEEE International Conference on*, pages 1359–1364. IEEE, 2008.

[5] M. A. Dahleh E. Frazzoli and E. Feron. Real-time motion planning for agile autonomous vehicles. *AIAA Journal of Guidance and Control*, 25(1):116–129, 2002.

[6] Lawrence H Erickson and Steven M LaValle. Survivability: Measuring and ensuring path diversity. In *Robotics and Automation, 2009. ICRA'09. IEEE International Conference on*, pages 2068–2073. IEEE, 2009.

[7] T. Fraichard and H. Asama. Inevitable collision states. a step towards safer robots? *Advanced Robotics*, 18(10):1001–1024, 2004.

[8] C Goerzen and M Whalley. Minimal risk motion planning: a new planner for autonomous uavs in uncertain environment. In *AHS International Specialists Meeting on Unmmaned Rotorcraft, Tempe, Arizona*, 2011.

[9] C Goerzen and M Whalley. Sensor requirements for autonomous flight. In *Proceedings of the International Conference on Unmanned Aircraft Systems, 2012, Philadelphia,PA*, 2012.

[10] Colin J. Green and Alonzo Kelly. Toward optimal sampling in the space of paths. pages 281–292, 2011.

[11] K. Savla J. J. Enright, E. Frazzoli and F. Bullo. On multiple uav routing with stochastic targets: Performance bounds and algorithms. In *Proceedings AIAA Guidance, Navigation, and Control Conference and Exhibit, Aug. 2005.*

[12] Andreas Krause and Carlos Guestrin. Near-optimal observation selection using submodular functions. In *AAAI*, volume 7, pages 1650–1654, 2007.

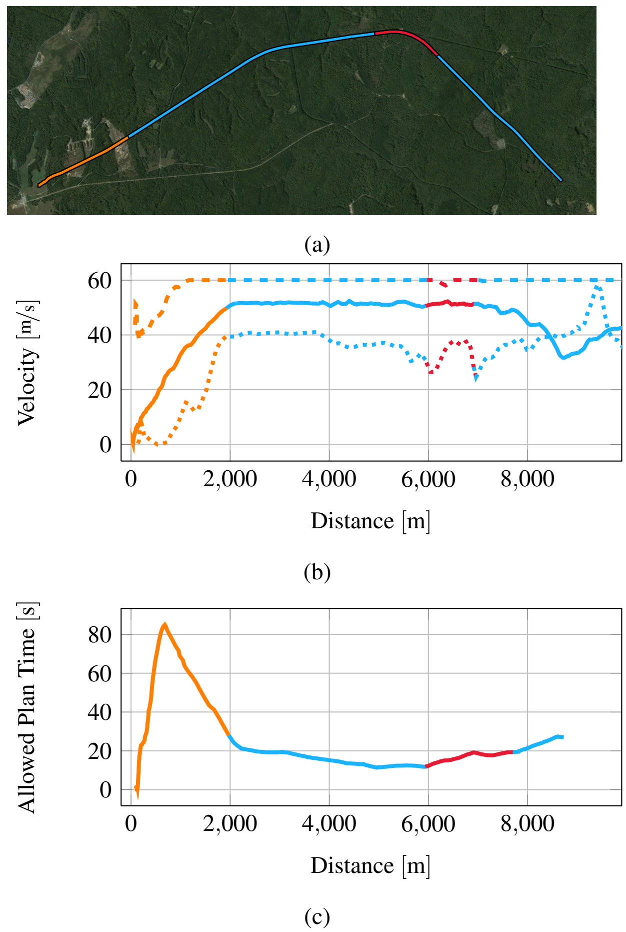

Fig. 7: Safety Quantization: Flight test in Quantico, Virginia. a) Shows an autonomous landing mission conducted in Quantico, Virginia on Unmanned Little Bird. b) Shows the safe velocity of the helicopter with the emergency maneuver library during the flight tests in dashed line, the executed velocity in solid line and the safe velocity if stopping distance is used in dotted line. c) This figure shows planning time available to the planner, before the vehicle will reach the edge of known space and execute one of the emergency maneuvers. The planning time calculated assuming the helicopter will follow the current planned trajectory.

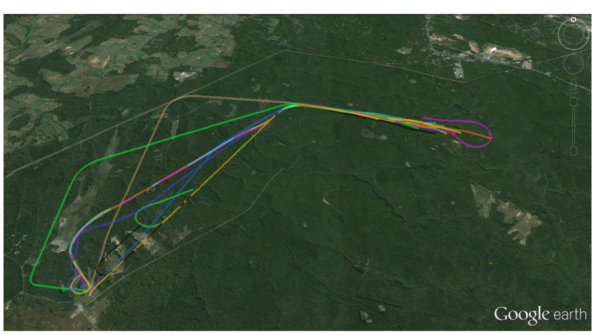

Fig. 8: Paths taken by the autonomous Unmanned Little Bird during landing and wave-off missions conducted in Quantico, on 26 Feb. 2014.

Fig. 10: A mission to land at a helipad in the Grand Canyon. The planner is not given a prior map and has to follow the canyon as it senses it.

[13]Langelaan J.W. Marlow, S.Q. Local terrain mapping for obstacle avoidance using monocular vision. In *AHS Unmanned Vehicles Specialist's Forum, AHS*, 2009.

[14]B Mettler, Z Kong, C Goerzen, and M Whalley. Benchmarking of obstacle field navigation algorithms for autonomous helicopters. In *Proceedings of the American Helicopter Society 66th Annual Forum. Phoenix, AZ*, 2010.

[15]H. Michalska and D.Q. Mayne. Robust receding horizon control of constrained systems. *IEEE Transactions on Automatic Control*, 38(11):1623–1633, 1993.

[16]G. L. Nemhauser, L. A. Wolsey, and M. L. Fisher. An analysis of approximations for maximizing submodular set functions—I. *Mathematical Programming*, 14(1):265–294, 1978.

[17]Achar S. Cover H. Chambers A. D. Nuske S. T. Scherer S., Rehder J. and Singh S. River mapping from a flying robot: state estimation, river detection, and obstacle mapping. *Autonomous Robots*, 32(5):1–26, 2012.

[18]Tom Schouwenaars, Jonathan How, and Eric Feron. Receding horizon path planning with implicit safety guarantees. In *American Control Conference, 2004. Proceedings of the 2004*, volume 6, pages 5576–5581. IEEE, 2004.