Convex Computation of the Reachable Set for Hybrid Systems with Parametric Uncertainty

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***Abstract*— Constructing models for systems interacting in highly dynamic environments is difficult. In spite of these challenges, engineers still need to determine the set of configurations of a dynamical model that are able to safely reach a specified configuration under a control law to ensure the correct operation of such systems. This paper presents a convex optimization method to compute the set of configurations of a polynomial hybrid dynamical system that are able to safely reach a user defined target set despite parametric uncertainty in the model. This class of models describes, for example, legged robots moving over uncertain terrains. The presented approach utilizes the notion of occupation measures to describe the evolution of trajectories of a nonlinear hybrid dynamical system with parametric uncertainty as a linear equation over measures whose supports coincide with the trajectories under investigation. This linear equation with user defined support constraints is approximated with vanishing conservatism using a hierarchy of semidefinite programs each of which is proven to compute an outer approximation to the set of initial conditions that can reach the user defined target set safely in spite of uncertainty. The efficacy of this method is illustrated on a pair of nonlinear systems with parametric uncertainty.**

I. Introduction

Computing the set of configurations that are able to safely reach a desired configuration is critical to ensuring the correct performance of a system in dynamic environments where deviations from planned behavior are to be expected. Given its potential, many methods have been proposed to efficiently compute this set of configurations, which is usually referred to as the *backwards reachable set*, for deterministic systems. Unfortunately, the effect of intermittent contact with the world, especially in fluctuating environments, is difficult to model deterministically. A roboticist, for example, may be tasked with ensuring that a control for a legged robot beginning from an initial configuration is able to safely reach a desired goal; however, limitations in sensing or environment variability may render exact modeling of terrain height or friction infeasible. Few numerical methods exist to tractably compute the backwards reachable set of a dynamical system in spite of parametric model uncertainty while providing systematic guarantees on the computed set.

This paper leverages a method developed in several recent papers [1], [2], [3] that describe the evolution of trajectories of a deterministic hybrid dynamical system using measures to describe the evolution of a hybrid dynamical system with parametric uncertainty as a linear equation over measures. As a result of this characterization, the set of configurations that are able to reach a target set despite parametric uncertainty, called the *uncertain backwards reachable set*, can be computed as the solution to an infinite dimensional linear program over the space of nonnegative measures. To compute an approximate solution to this infinite dimensional linear program, a sequence of finite dimensional relaxations semidefinite programs are constructed that satisfy an important property: each solution to this sequence of semidefinite programs is an outer approximation to the uncertain backwards reachable set with asymptotically vanishing conservatism.

Many researchers have attempted to develop efficient tools to compute this uncertain backwards reachable set for hybrid systems with parametric uncertainty. Given its importance to verifying the performance of legged robotic systems locomoting over real world terrain, several researchers have attempted to utilize this backwards reachable set while constructing controllers that are able to walk over terrains of varying heights [4], [6], [7], [5]. These approaches have all relied upon discretizing the height of the terrain under consideration while constructing a controller that performs robustly across these specified heights. In addition to only verifying the performance of the controller over specific heights, these approaches are unable to account for uncertainty associated with imperfect knowledge of terrain friction or parameters affecting the continuous dynamics.

Other approaches have focused

The remainder of the paper is organized as follows: Section II introduces the notation used in the remainder of the paper, the class of systems under consideration, and the backwards reachable set problem under parametric uncertainty; Section III describes how the backwards reachable set under parametric uncertainty is the solution to an infinite dimensional linear program; Section IV constructs a sequence of finite dimensional semidefinite programs that outer approximate the infinite dimensional linear program with vanishing conservatism; Section V describes the performance of the approach on a pair of examples; and, Section VI concludes the paper.

II. Preliminaries

A. Notations

In the remainder of this text, for ease of convenience, the following notations are employed. Finite truncations of the set of natural numbers are expressed as $\mathbb{N}_n := \mathbb{N} \cap [0, n]$. The ring of polynomials on x is denoted by $\mathbb{R}[x]$ and continuous variables supported on set K are represented by $\mathcal{C}(K)$. The degree of a polynomial is equal to degree its largest multinomial; the degree of the multinomial x^α, $\alpha \in \mathbb{R}^n$ is $|\alpha| = \sum_i^n [\alpha]_i$; and $\mathbb{R}_d[x]$ is the set of polynomials in x with degree d. The dual to $\mathcal{C}(K)$, the set of measures on

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K, is identified by $\mathcal{M}(K)$, and the pairing of $\mu \in \mathcal{M}(K)$ and $v \in \mathcal{C}(K)$ is

$$\langle \mu, v\rangle = \int_K v(x)\, d\mu(z).$$

The Lebesgue measure is, as usual, denoted as λ; the support λ is explicitly defined if it is not evident from the context. Sets are labeled in capitalized (K) and their respective boundaries are represented as ∂K; the disjoint union of sets takes the usual definition: $\coprod_{i\in I} A_i = \cup_{i\in I} A_i \times \{i\}$. Supports of measures ($\mu$) are identified as $\sup(\mu)$. The projection operator of both sets and measures are denoted as π_*; for example, $\pi_x A$ is the x-projection of the set $A = \{(x, y) \mid \text{constraints}\}$. Finally, uniform distributions with support $[a, b]$ are denoted as $\mathcal{U}(a, b)$.

B. Problem description

The class of uncertain systems considered in this study is constituted by *autonomous*[1] polynomial hybrid systems that have a common trait–in each discrete state, the uncertainty that affects the system's dynamics is constant. More specifically, for every visit of a discrete state, the uncertainty assumes a value drawn from some distribution and retains the value until the system transitions to another discrete state; we term such systems as being *quasi-uncertain*. Def. 1 formalizes the description of quasi-uncertain systems.

Definition 1: A polynomial 'quasi-uncertain' hybrid system is a tuple $\mathcal{H} = (\mathcal{J}, \mathcal{E}, \mathcal{D}, \mathcal{F}, \mathcal{G}, \mathcal{R}, \Gamma)$, where

- $\mathcal{J}$ is a finite set of indices of discrete states in of $\mathcal{H}$; $|\mathcal{J}| = \mathbb{N}_{n_m}$
- $\mathcal{E} \subset \mathcal{J} \times \mathcal{J}$ is the set of tuple of terminals of directed edges; e_{ij} is the edge connecting discrete state i with j
- $\mathcal{D} := \coprod_{j\in\mathcal{J}} \mathcal{X}_j$ is the disjoint union of domains; $\mathcal{X}_j := \{x \in \mathbb{R}^{n_x^i} \mid h_X^i(x) \geq 0, \forall i \in \mathbb{N}_{n_{h_X}^j}\}$
- if $\mu_{\theta_j} \in \mathcal{P}(\Theta_j)$ with $\Theta_j \subset \mathbb{R}^{n_\theta^j}$ (compact) is the distribution of the uncertainty associated with state j, $\Gamma := \coprod_{j\in\mathcal{J}} \mu_{\theta_j}$ is the disjoint union of probability distributions
- $\mathcal{F} := \{f_j\}_{j\in\mathcal{J}}$ where $f_j\colon \mathcal{X}_j \times \Theta_j \to \mathcal{X}_j$, $f_j \in (\mathbb{R}[x,\theta])^{n_{x_j}}$ is a tangent vector to $\mathcal{X}_j$ at (x, θ).
- $\mathcal{G} := \coprod_{p\in\mathcal{E}} \mathcal{G}_p$ is the disjoint union of guards; $\mathcal{G}_{(i,j)} := \{(x,\theta) \in \partial\mathcal{X}_i \times \Theta_j \mid h^k_{g_{(i,j)}}(x,\theta) = 0, \forall k \in \mathbb{N}_{n_{h_g}^{(i,j)}}\}$; $\forall (i, j), (i, k) \in \mathcal{E}$, $\mathcal{G}_{(i,j)} \cap \mathcal{G}_{(i,k)} = \emptyset, \forall j \neq k$
- $\mathcal{R}$ is the set of reset maps with each edge in $\mathcal{E}$ being represented; $R_{(i,j)}\colon \pi_x(\mathcal{G}_{(i,j)}) \to \mathcal{X}_j$ is a continuously differentiable injection, $R_{(i,j)} \in \mathbb{R}[x]$ and denotes the transformation accompanying state transition

and $h_X^j(x,\theta)$, $h^k_{g_{(i,j)}}(x,\theta) \in \mathbb{R}[x]$ for all appropriate values of j, k.

In line with what is standard definition in literature related to switched systems, the discrete state are alternatively referred to as *modes* of the system. In addition, the systems considered are not allowed to undergo infinite mode transitions in a finite time.

[1]Whilst time-invariant systems are typically referred to as being autonomous, in this context, that label is applied to drift, time-invariant systems.

Algorithm 1: Execution of $\mathcal{H}$

Initialization: $t = 0$, $j \in \mathcal{J}$, $(x_0, j) \in \mathcal{D}$, $x(0) = x_0$;
loop
Let θ be drawn according to μ_{θ_j}
Let $\gamma_\theta\colon \mathcal{T} \to \mathcal{X}_j$, abs. ct. st.
1) $\dot\gamma_\theta(s) = f(\gamma_\theta(s), \theta)$ λ_t^*-a.e.
2) $\gamma_\theta(t) = x(t)$

$\Lambda_{(j,t)} := \{r \in [t,\infty) \mid \exists (j,k) \in \mathcal{E}, (\gamma_\theta(r), \theta) \in \mathcal{G}_{(j,k)}\}$
if $\Lambda_{(j,t)} \neq \emptyset$
$t' := \inf \Lambda_{(j,t)}$, k st. $\gamma_\theta(t') \in \pi_x(\mathcal{G}_{(j,k)})$
$x(s) \leftarrow \gamma_\theta(s), \forall s \in [t, t')$
$t \leftarrow t'$, $x(t') \leftarrow R_{(j,k)}(\gamma_\theta(t'))$, $j \leftarrow k$
else
Stop
end
*where λ_t is the Lebesgue measure on $[t,\infty)$

Assumption 1: $\mathcal{H}$ has no zeno execution.

The objective of this work is to estimate the *largest* set of initial conditions from which the flow of trajectories reach the terminal set $\mathcal{X}_T$ in finite time T. The projection of $\mathcal{X}_T$ onto each mode is the following

$$\mathcal{X}_{T_j} = \{x \mid x \in \mathcal{X}_j\}, \quad \forall j \in \mathcal{J}.$$

Assumption 2: $\mathcal{X}_{T_j}$, $\forall j \in \mathcal{J}$, is a compact semi-algebraic set with bounding polynomials $h^i_{T_j}$, $i \in \mathbb{N}_{n^j_{h_T}}$.

Assumption 3: The terminal set and guards are mutually exclusive; i.e. $\forall \pi_x \left(\cup_{(i,j)\in\mathcal{E}} \mathcal{G}_{(i,j)}\right) \cap \mathcal{X}_T = \emptyset$.

The set being approximated can be represented as

$$\mathcal{X}_0 = \bigcup_{i\in\mathcal{J}} \mathcal{X}_{0_i}$$

where

$$\begin{aligned}\mathcal{X}_{0_i} = \{(y, i) \in \mathcal{D} \mid x_0 = y, x\colon [0,T] \to \pi_x(\mathcal{D}),\\ x(T) \in \mathcal{X}_T \text{ using Alg. 1}\}\end{aligned} \tag{1}$$

is the set of initial conditions in each mode from which trajectories that emanate reach $\mathcal{X}_T$ at time T. For convenience, hereafter the times at which the system's state is relevant is denoted by the set $\mathcal{T} := [0, T]$.

III. Problem formulation

The object of interest is a set from which trajectories (piece-wise absolutely continuous functions) that emanate, and are governed by the dynamics of the system, reach another pre-determined set; given the problem structure, one might be better served to formulate the problem as one based in an appropriate functional space; and use measures defined on the sets of interest as surrogates.

The critical idea of the ensuing presentation—related to the definition of *quasi-uncertain* systems—is the following: the uncertainty takes a constant value in each mode, although its value is drawn from a distribution; so, technically, the uncertainty is an unknown parameter of the dynamics which can be added to and used to extend the state-space. That is, the dynamics in each mode j can be represented as

$$\tilde{f}_j = \begin{bmatrix} f_j' & \mathbf{0}_{n_{\theta_j}}' \end{bmatrix}'.$$

In this augmented-state-space—henceforth referred to as the state-space of the system—the object of interest still remains the same, $\mathcal{X}_{0_j}, \forall j \in \mathcal{J}$. Furthermore, as the system transitions out of a mode, say at time τ_k the solution reaches e_{ij}, the uncertainty in mode j is not related to the *actual* value of the uncertainty in mode i at τ_k; in fact, the dimensions of the uncertain parameters n_{θ_j} need not equal n_{θ_i}, much less their distributions.

Since the free variables in the ensuing problem formulation are measures on sets associated with a dynamical system, it is helpful to use the occupation measure $\mu_j(\cdot \mid \tau_k, x_0, \theta) \in \mathcal{M}(\mathcal{T} \times \mathcal{X}_j \times \Theta_j)$ as a template. The occupation measure, introduced in [], is to be interpreted as measuring the time the solution trajectories spend in a particular region of the space. For instance, suppose the system enters mode j at τ_k with states taking initial values $x(\tau_k) = x_0$ and $\theta(\tau_k) = \theta$, the occupation measure is defined as

$$\mu_j(A \times B \times C|\tau_k, x_0, \theta) = \int_0^T I_{A\times B\times C}(t, x(t|\tau_k, x_0, \theta), \theta)dt.$$

From the above definition, the following relation follows naturally

$$\langle \mu_j(\cdot \mid \tau_k, x_0, \theta), v\rangle = \langle \lambda_t, v(t, x(t \mid \tau_k, x_0, \theta), \theta)\rangle, \quad (2)$$

where λ_t is the Lebesgue measure on $\mathcal{T}$.

Note that in its definition, the occupational measure is a conditional measure – conditioned on the arrival-time and initial values of the states in that mode. When considering a set of possible arrival-times and initial conditions, the *average occupation measure* is defined by *averaging* the occupation measure wrt. to a measure on the set of possible initial conditions of the mode ($\check{\mu}_{0_j}$); i.e.

$$\mu_j(A \times B \times C) = \int\limits_{\mathcal{T}\times\mathcal{X}_j\times\Theta} \mu_j(A \times B \times C \mid x_0, \theta)\, d\check{\mu}_{0_j}. \quad (3)$$

Observe that by definition, the uncertain variables are independent of the states' initial conditions; hence $\check{\mu}_{0_i} \in \mathcal{M}(\mathcal{T} \times \mathcal{X}_j \times \Theta)$ is expressible as a product measure:

$$\check{\mu}_{0_j} = \bar{\mu}_{0_j} \otimes \mu_{\theta_j}, \quad (4)$$

where $\bar{\mu}_{0_j} \in \mathcal{M}(\mathcal{T} \times \mathcal{X}_j)$ is the measure on the set of initial conditions, and $\mu_{\theta_j} \in \mathcal{M}(\Theta)$ is provided by in the definition of $\mathcal{H}$.

Similarly, measures on terminals sets $\mathcal{X}_{T_j}$, $\mu_{T_j} \in \mathcal{M}(\mathcal{X}_{T_j} \times \Theta)$

$$\mu_{T_j}(A \times B) = \int\limits_{\mathcal{T}\times\mathcal{X}_{T_j}\times\Theta} I_{A\times B}(x(T \mid \tau_k, x_0, \theta), \theta)\, d\check{\mu}_{0_j},$$

and guards, $\mu_{\mathcal{G}_{(j,k)}} \in \mathcal{M}(\mathcal{T} \times \mathcal{G}_{(j,k)}), \forall (j,k) \in \mathcal{E}$

$$\mu_{\mathcal{G}_{(j,k)}}(A \times B\times C) = \int\limits_{\mathcal{T}\times\mathcal{G}_{(j,k)}} I_{A\times B\times C}(t, x(t \mid \tau_k, x_0, \theta), \theta)\, d\check{\mu}_{0_j},$$

are defined. While measure μ_{T_j}—supported on the terminal set at the final time—has an obvious interpretation, measures $\mu_{\mathcal{G}_{(j,k)}}, \forall (j,k) \in \mathcal{E}$ are supported on the guards of mode j and should be interpreted as the hitting times of the guard. For convenience, the *final measure* for each mode j is defined as

$$\check{\mu}_{f,j} = \delta_T \otimes \mu_{T_j} + \sum_{k\in\{l|(j,l)\in\mathcal{E}\}} \mu_{\mathcal{G}_{(j,k)}}. \quad (5)$$

Given a set of initial conditions $\mathcal{X}_0$, the dynamics of the system—under appropriate assumptions—defines a bundle of trajectories of the system states. It is of interest to ensure that this bundle terminates in the desired set $\mathcal{X}_T$, making $\mathcal{X}_0$ a subset of the BRS; stated differently, it is necessary to relate $\coprod_{j\in\mathcal{J}} \check{\mu}_{0_j}$ with $\coprod_{j\in\mathcal{J}} \check{\mu}_{f,i}$ and the dynamics of the system. As a first step towards deducing said relation, linear operators $\mathcal{L}_{\tilde{f}_j} : \mathcal{C}^1(\mathcal{T}\times\mathcal{X}_j\times\Theta_j) \to \mathcal{C}(\mathcal{T}\times\mathcal{X}_j\times\Theta_j)$ satisfying Eqn. (6) in which $v \in \mathcal{C}^1(\mathcal{T}\times\mathcal{X}_j\times\Theta_j; \mathbb{R})$ is an arbitrary test function, are defined.

$$\mathcal{L}_{\tilde{f}_j} v = \langle \nabla_x v, f_j\rangle \quad (6)$$

Suppose the system transitioned to mode j at $t = \tau_{k-1}$ with the states taking initial values $x(\tau_{k-1})$ and θ; the value of v, evaluated along the flow of the system states and at $t = \tau_k$ is computed using the fundamental theorem of calculus according to Eqn. (7).

$$\begin{aligned} v\left(\tau_k, x\left(\tau_k \mid x(\tau_{k-1}), \theta_{k-1}\right)\right) &= v(\tau_{k-1}, x(\tau_{k-1}), \theta_{k-1}) \\ &+ \int_{\tau_{k-1}}^{\tau_k} \mathcal{L}_{\tilde{f}} v(t, x(t \mid \tau_{k-1}, x(\tau_{k-1}), \theta_{k-1}))\, dt. \end{aligned} \quad (7)$$

Using Eqn. (2), Eqn. (7) can be re-written as

$$\begin{aligned} v\left(\tau_k, x\left(\tau_k \mid \tau_{k-1}, x(\tau_{k-1}), \theta_{k-1}\right)\right) &= v(\tau_{k-1}, x(\tau_{k-1}), \theta_{k-1}) \\ &+ \left\langle \mu_j(\cdot \mid \tau_{k-1}, x(\tau_{k-1}, \theta_{k-1}), \mathcal{L}_{\tilde{f}} v\right\rangle \end{aligned} \quad (8)$$

which can be simplified by *averaging* wrt. to the set of initial conditions $x(\tau_{k-1})$ and θ using Eqns. (3)–(5) to arrive at

$$\langle \check{\mu}_{f,j}, v\rangle = \langle \check{\mu}_{0_j}, v\rangle + \left\langle \mu_j, \mathcal{L}_{\tilde{f}} v\right\rangle. \quad (9)$$

Alternatively, using the standard definition of adjoint operators[2], Eqn. (9) is re-written as

$$\langle \check{\mu}_{f,j}, v\rangle = \langle \check{\mu}_{0_j}, v\rangle + \left\langle \mathcal{L}_{\tilde{f}}' \mu_j, v\right\rangle \quad (10)$$

[2]A linear operator $\mathcal{L}$ and its adjoint, $\mathcal{L}'$, satisfy the following relation:

$$\langle \mathcal{L}'\mu, v\rangle = \langle \mu, \mathcal{L}v\rangle = \int\limits_{\mathcal{X}} \mathcal{L}v\, d\mu.$$

Eqn (10) is the desired equation that relates the dynamics of the state to the initial and final measures in each mode of the system.

In the execution of system $\mathcal{H}$, each mode can be entered in two ways – at $t = 0$; and because of a reset map, at any time $t \in \mathcal{T}\backslash\{0, T\}$; hence the initial measure in the (t, x)-projection can be decomposed as

$$\bar{\mu}_{0_j} = \delta_0 \otimes \mu_{0_j} + \pi_{t,x}\sigma_{0_j} \tag{11}$$

with $\mu_{0_j} \in \mathcal{M}(\mathcal{X}_j)$ is the measure supported on the initial conditions to the system at $t = 0$, and $\sigma_{0_j} \in \mathcal{M}(\mathcal{T}\times\mathcal{X}_j\times\Theta_j)$ is the measure on initial conditions after the first reset. State resets occur when the states reach the guard and, unless the solution terminates at the guard, contradicting Assumption 3, for every solution terminating in the support of $\mu_{\mathcal{G}_{(i,j)}}$, $\forall (i, j) \in \mathcal{E}$, there must exist a trajectory originating in the support of σ_{0_j}, $\forall j \in \mathcal{J}$; that is, $\mu_{\mathcal{G}_{(i,j)}}, \forall (i, j) \in \mathcal{E}$, and $\sigma_{0_j}, \forall j \in \mathcal{J}$, are related.

To see this relation, σ_{0_j} is first decomposed into measures corresponding to the source of each arrival state; i.e.

$$\sigma_{0_j} = \sum_{i\in\{k|(k,j)\in\mathcal{E}\}} \sigma_{(i,j)} \otimes \mu_{\theta_j}, \tag{12}$$

where $\sigma_{(i,j)}$ is the measure on initial conditions post reset for all trajectories arriving at mode j from guard $\mathcal{G}_{(i,j)}$ of mode i. Upon reaching the guard, the system transitions according to the reset map; in essence, viewing $R_{(j,k)}$ as a nonlinear transformation of the state-space, the relation in Eqn. (13) between $\sigma_{(i,j)}$ and $\mu_{\mathcal{G}_{(i,j)}}$ is established.

$$\left\langle \sigma_{(i,j)}, w \right\rangle = \left\langle \pi_{t,x}\mu_{\mathcal{G}_{(i,j)}}, w \circ R_{(i,j)} \right\rangle \tag{13}$$

where $w \in \mathcal{C}(\mathcal{T} \times \mathcal{X}_j)$ and

$$\left\langle \pi_{t,x}\mu_{\mathcal{G}_{(i,j)}}, s \right\rangle = \left\langle \mu_{\mathcal{G}_{(i,j)}}, s \right\rangle, \forall s \in \mathcal{C}(\mathcal{T} \times \mathcal{X}_i);$$

essentially, $\sigma_{(i,j)}$ is a push-forward measure of $\mu_{\mathcal{G}_{(i,j)}}$.

A. The primal

With the constraints expressed in terms of measures, the problem of approximating the BRS is formulated as an infinite-dimensional Linear Program that supremizes the *volume* of the set of initial condition.

$$\sup_{\Lambda} \sum_{j=1}^{n_m} \left\langle \mu_{0_j}, 1 \right\rangle \tag{P}$$

st.

$$\begin{aligned} \check{\mu}_{0_j} + \mathcal{L}'_{\tilde{f}}\mu_j &= \mu_{f,j} & \forall j \in \mathbb{N}_{n_m} \\ \mu_{0_j} + \hat{\mu}_{0_j} &= \lambda_j & \forall j \in \mathbb{N}_{n_m} \\ \sum_{j=1}^{n_m} \left\langle \mu_{T_j}, 1 \right\rangle &= \sum_{j=1}^{n_m} \left\langle \mu_{0_j}, 1 \right\rangle & (14) \end{aligned}$$

where λ_j is the Lebesgue measure supported on $\mathcal{X}_j$.

$$\Lambda = \{\mu_j, \mu_{0_j}, \mu_{T_j}, \hat{\mu}_{0_j}, \mu_{\mathcal{G}_{(j,k)}} \geq 0, \forall j \in \mathbb{N}_{n_m}, (j, k) \in \mathcal{E}\}.$$

Variables $\hat{\mu}_{0_j} \in \mathcal{M}(\mathcal{X}_j)$ are slack variables introduced to enforce a stronger constraint than absolute continuity of μ_{0_j} wrt. to λ_j

$$\mu_{0_j}(A) \leq \lambda_j(A) \qquad \forall A \subset \mathcal{X}_j$$

The constraint in Eqn. (14) ensures that all trajectories that emanate $\cup_{j\in\mathbb{N}_{n_m}} \text{supp}(\mu_{0_j})$ reach $\mathcal{X}_T$ at $t = T$, and is not *stuck* at any of the guards.

Lemma 1: The optimal value of (P) is equal to $\sum_{j\in\mathbb{N}_{n_m}} \lambda_j(\mathcal{X}_{0_j})$, the sum of *volumes* of the BRSs in each mode. In addition, $\sum_{j\in\mathbb{N}_{n_m}} \text{supp}(\mu_{0_j})$ is the BRS of the system.

B. The dual

The dual corresponding to (P) is derived using standard techniques and is presented below.

$$\inf \sum_{j\in\mathbb{N}_{n_m}} \langle \lambda_j, w_j \rangle$$

st.

$$\begin{aligned} & w_j \geq 0 & \forall (x, j) \in \mathcal{D} \\ & v_j(T, \cdot) + q \geq 0, & \forall (x, j, \theta) \in \mathcal{D} \times \Theta \\ & -\mathcal{L}_{\tilde{f}} v_j \geq 0, & \forall (t, x, j, \theta) \in \mathcal{T} \times \mathcal{D} \times \Theta \\ & w_j - \left\langle \mu_{\theta_j}, v(0, \cdot) \right\rangle - q \geq 1, & \forall (x, j) \in \mathcal{D} \\ & v_j \geq \left\langle \mu_{\theta_k}, v_k \right\rangle \circ R_{(j,k)}, & \forall (t, x, \theta, (j, k)), \in \mathcal{T} \times \mathcal{G} \times \mathcal{E} \end{aligned}$$

where $q \in \mathbb{R}$, $v_j \in C^1(\mathcal{T} \times \mathcal{X}_j \times \Theta_j)$ and $w_j \in C(\mathcal{X}_j)$.

Lemma 2: If (w, v, q) is a solution to the dual problem, then the super-level set

$$\bigcup_{j\in\mathcal{J}} \{x \mid w_j(x) \geq 1\}$$

is an outer approximation of the BRS of the system whose dynamics is described by Alg. 1.

Lemma 3: The optimal value of problem (P) is the sum of volumes of the BRS in each discrete state.

Lemma 4: (D) is a perfect dual of (P)

Remark 1: There are two key aspects of the presentation in this section that deserve re-iteration: (1) by definition, the uncertainties that influence the dynamics can be visualized as a discrete random process with updates to the instantiation of the uncertainty occurring upon entering a new mode; (2) the estimated BRS is the set of initial conditions from which *all* trajectories that emanate reach the terminal set for *all* possible discrete sequence of uncertainty. As a direct implication of the second point, the solution of the problem is the intersection of the BRS of every possible sequence of uncertainty.

IV. Numerical Implementation

The infinite-dimensional problems described in Secs. III-A and III-B are hard to implement and solve directly. In this section, a sequence of *relaxed* SDPs—that contains a sub-sequence whose optimal values converges to the optimal value of the problems introduced in Secs. III-A and III-B—is introduced.

The fundamental idea behind this sequence of relaxations is that measures supported on a compact can be characterized by their moments[3]. Much like Taylor approximations, longer

[3]The nth moment of a measure (μ) is obtained by evaluating the following expression

$$y_{\mu,n} = \langle \mu, x^n \rangle .$$

the length of the sequence of moments (higher the order of moments considered), better is the approximation of the measure. For any finite d-degree truncation of the sequence, the *relaxed* primal P can be transformed into a SDP P_d in the moments.

The dual to P_d, D_d, can be expressed as a sub-of-squares program (SOS program) by considering d-degree polynomials in place of the continuous variables in D. In the following presentation of D_d, the set $Q_d(h^i_{T_j}), \forall (i,j) \in \mathbb{N}_{n^j_{h_T}} \times \mathcal{J}$ and the like are defined as the follows.

$$Q_d(h^i_{T_j}) = \left\{ q \in \mathbb{R}_d[x] \,\middle|\, \exists s_k \in \mathbb{R}_{\leq d}[x], k \in \mathbb{N}_{n^j_{h_T}} \cup \{0\}, \right. \\ \left. q = s_0 + \sum_{l \in \mathbb{N}_{n^j_{h_T}}} h^l_{T_j} s_l \right\}$$

Using the above notation, the d-degree relaxation of the dual is presented below.

$$\inf_{\Xi_d} \sum_{j \in \mathcal{J}} l' \operatorname{vec}(w_j) \qquad (D_d)$$

st.

$$w^d_j \in Q_d(h^i_{T_j}) \qquad \forall (i,j) \in \mathbb{N}_{n^j_{h_T}} \times \mathcal{J}$$
$$v^d_j(T,\cdot) + q \in Q_d(h^i_{X_j}) \qquad \forall (i,j) \in \mathbb{N}_{n^j_{h_X}} \times \mathcal{J}$$
$$-\mathcal{L}_{\tilde{f}_j} v^d_j \in Q_d(h_\tau, h^i_{X_j}) \qquad \forall (i,j) \in \mathbb{N}_{n^j_{h_X}} \times \mathcal{J}$$
$$w^d_j - \left\langle \mu_{\theta_j}, v^d_j(0,\cdot) \right\rangle - q - 1 \in Q_d(h^i_{X_j}) \qquad \forall (i,j) \in \mathbb{N}_{n^j_{h_X}} \times \mathcal{J}$$
$$v^d_j - \left\langle \mu_{\theta_k}, v^d_k \right\rangle \circ R_{(j,k)} \in Q_d(h_\tau, h^i_{X_j}) \qquad \forall (i,j,k) \in \Upsilon$$

where $\Xi_d = \{v^d_j, w^d_j, q\} \in (\mathbb{R}_d[t,x,\theta])^{n_m} \times (\mathbb{R}_d[x])^{n_m} \times \mathbb{R}$, $\Upsilon = \{(a,b,c) \mid b \in \mathcal{J}, a \in \mathbb{N}_{n^b_{h_X}}, (b,c) \in \mathcal{E}\}$ and the other variables are from the given hybrid system $\mathcal{H}$.

Lemma 5: The sequence $(\cup_{j \in \mathcal{J}} \{x \mid w^d_j \geq 1\})_d$ is a convergent sequence of outer approximation of the BRS.

V. Examples

In this section, the efficacy of the proposed method is evaluated through three examples. The relaxed problems were parsed using the SPOTLESS toolbox and were numerically solved using MOSEK on a computer equipped with a Intel Xeon W3540 processor and 12GB of RAM. The following points on the examples considered are obligatory.

1) It is a characteristic trait of the problem formulation considered in this paper that the actual distribution of the uncertainty is immaterial. Consequently, in all examples, it is assumed that the disturbance is uniformly distributed.
2) For reasons related to numerics, all problems are normalized such that the state-space is given by $[-1,1]^n$, for an appropriate value of n.

Also, since has been established that the solution of relaxed problems provides an outer approximation of the BRS, in this section, the qualifier 'approximate' is suppressed.

By this definition, the mean of a probability distribution (read probability measure) is y^1_μ and its variance is $y^2_\mu - (y^1_\mu)^2$.

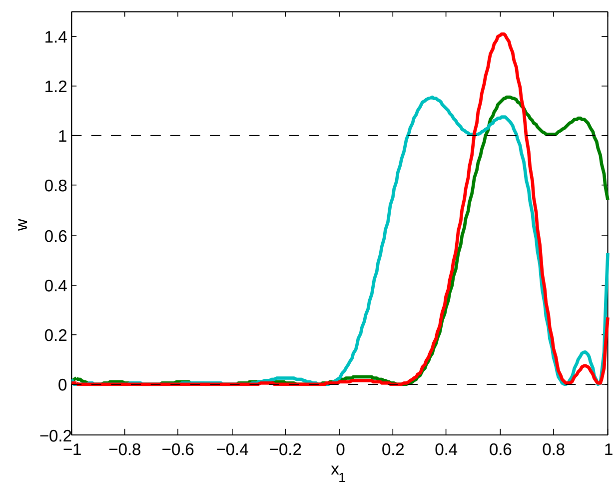

Fig. 1. Outer approximations of the BRS of the extreme deterministic cases and the stochastic case.(green) $\theta = 0$, (blue) $\theta = 1$ and (red) μ_θ

A. 1-D linear dynamics

The first example under consideration is that of a one-state system whose dynamics is described by

$$\dot{x} = -0.7x + 0.2\theta - 0.1, \qquad (15)$$

where θ is an uncertain parameter. Note that this system is not a hybrid system; however, by setting $n_m = 1$ and using identity reset maps, the dynamics can be hybridized. In the implementation whose results are depicted in Fig. 1, the guard is set at $x = 1$ and the degree relaxation, $d = 12$.

Figure 1 presents the graph of w^{12}_1 computed for each of the following cases – (1) $\theta = 0$ (green), (2) $\theta = 1$ (cyan), and (3) $\theta \in \mathcal{U}(0,1)$ (red); when the terminal time is $T = 1$ and the terminal set is $\mathcal{X}_T = [0.2, 0.4]$. Observe that the BRS corresponding to case (3) encloses the intersection of those of cases (1) and (2); this is the desired outcome.

B. Rimless wheel

The planar rimless wheel—constituted by a massless axle to which n equidistant (angular) spokes are connected—is one of the simplest models of legged locomotion. Figure 2 presents a schematic of a rimless wheel—with spokes separated by an angle 2α—rolling down an infinite wedge. The dynamics of this rimless wheel between transitions is described by

$$\begin{bmatrix}\dot{\theta} & \ddot{\theta}\end{bmatrix}' = \begin{bmatrix}\dot{\theta} & \sin(\theta)\end{bmatrix}',$$

where θ is the angle between the pivoted spoke and the vertical. Once the marching spoke makes contact with the terrain, the states are reset using the maps

$$\begin{bmatrix}\theta^+ & \dot{\theta}^+\end{bmatrix}' = \begin{bmatrix}2\gamma - \theta^- & \cos(2\alpha)\,\dot{\theta}^-\end{bmatrix}'.$$

In this example, it is assumed that the slope (terrain) is not flat and that the relative depth of the next step is δ; this translates to an angle β_δ relative to the slope of the wedge. The disturbance to the dynamics of the rimless wheel, β_δ, manifests itself in the guard of the only mode in this hybrid

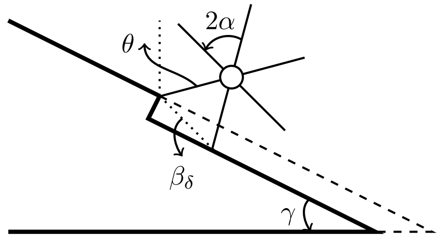

Fig. 2. Schematic of the rimless wheel with β_δ being the disturbance.

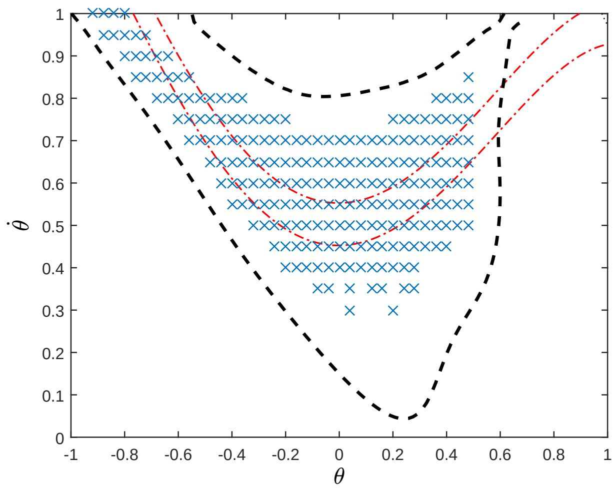

Fig. 3. Outer approximation and estimated BRS based on 100 iterations and T=4. Red band is the terminal set and the black outer is the boundary of the estimated BRS; the crosses correspond to results of MC simulation.

system. The angle at which the marching spoke lands on the surface satisfies

$$\theta = \gamma + \alpha + \beta_\delta.$$

An analytically computable stable limit cycle for the disturbance-free rimless wheel exits []; however, for the case considered in this example, the definition of a limit cycle less clear. Consequently, a notion of *meta-stability*—when the system states arrive within ϵ of the stable limit cycle of the disturbance-free system—is adopted.

Figure 3 presents the degree 12 BRS (black dashed) for the rimless wheel (with $\alpha = 0.4$) which is tasked with arriving within the red band in $T = 4$ seconds, as it is rolling down a wedge with slope $\gamma = 0.2$ withstanding an a sequence of random changes to terrain drawn from $\beta_\delta \sim \mathcal{U}([-0.1, 0.1])$. The relative depths/height of the disturbance is about 25% the length of each spoke.

The BRS is validated by performing Monte Carlo simulations; the box I^2 is discretized into 51 points both ways and 100 independent trajectories are simulated (using MATLAB's ode45 function) from each initial condition. The blue $\times$s depict the initial conditions that arrived within the terminal set at the desired time without violating any of the other constraints. Note that the set of points that succeeded in the MC simulation is entirely contained in the BRS.

At this juncture, a remark about the tightness of the BRS is warranted. Clearly, the BRS in Fig. 3 is not tight; and we attribute this to the set of basis functions with which are currently working–monomials; and the degree relaxation. As commented in [], adopting an alternate basis set is likely to increase the rate of convergence and the tightness. As it stands, there are alternate ways to improve the tightness, primary amongst which is to create phantom modes using identity reset maps; this approach however, needs some care and is deferred for a future work.

VI. Conclusions

In this paper, a convex approximation of the reachable sets of a class of uncertain polynomial hybrid drift systems is presented. The presented method optimizes over the set of unsigned measures using converging moment relaxations and SDPs. A commentary on the accuracy and the adequacy of the proposed method is provided using examples. A future work will extend the work herein by synthesizing *cautious* feedback control laws that guarantee constraint satisfaction.

References

[1] D. Henrion and M. Korda, "Convex computation of the region of attraction of polynomial control systems," *IEEE Transactions on Automatic Control*, vol. 59, no. 2, pp. 297–312, 2014.

[2] A. Majumdar, R. Vasudevan, M. M. Tobenkin, and R. Tedrake, "Convex optimization of nonlinear feedback controllers via occupation measures," *The International Journal of Robotics Research*, p. 0278364914528059, 2014.

[3] V. Shia, R. Vasudevan, R. Bajcsy, and R. Tedrake, "Convex computation of the reachable set for controlled polynomial hybrid systems," in *2014 IEEE 53rd Annual Conference on Decision and Control (CDC)*, pp. 1499–1506, IEEE, 2014.

[4] K. Byl, *Metastable legged-robot locomotion*. PhD thesis, Massachusetts Institute of Technology, 2008.

[5] C. O. Saglam and K. Byl, "Switching policies for metastable walking," in *2013 IEEE 52nd Annual Conference on Decision and Control (CDC)*, pp. 977–983, IEEE, 2013.

[6] H. Dai and R. Tedrake, "Optimizing robust limit cycles for legged locomotion on unknown terrain," in *2012 IEEE 51st Annual Conference on Decision and Control*, pp. 1207–1213, IEEE, 2012.

[7] B. Griffin and J. Grizzle, "Walking gait optimization for accomodation of unknown terrain height variations," in *American Control Conference 2015*, 2015.