

# Controlled Supermartingale Functions for Stochastic Differential Equations: Inference and Applications.

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**Abstract**—We study the problem of constructing controlled supermartingale functions to synthesize feedback laws that guarantee safety properties of stochastic differential equations (SDE) with control inputs. SDEs are widely used to model continuous time stochastic processes with applications ranging from financial markets to biology. In this paper, we extend classic notions from martingale theory for stochastic processes to prove that a given SDE will not exit a safe region over some finite time horizon with high probability. Our notion considers time-varying supermartingale functions that provide sharper probability bounds when compared to those that are time-independent. Furthermore, we study the controlled version of these supermartingales and the problem of synthesizing feedback control law that will maintain the state within a safe set with high probability over a given finite time horizon. We provide a projection-based algorithm for synthesizing polynomial, time-varying controlled supermartingales and corresponding feedback laws using sum-of-square (SOS) programming techniques. We implement our approach on some challenging numerical examples to demonstrate how it can synthesize control feedback laws that provide upper bounds on the probability of safety violations over a given time horizon.

## I. INTRODUCTION

Stochastic differential equations (SDEs) are models of continuous-time stochastic processes that are built on top of ordinary differential equations by adding terms based on the differential of the Brownian motion. They are naturally used to model many types of stochastic processes in areas such as control systems (e.g., modeling wind disturbances) [1], physics (e.g., modeling noise in solid state devices) [2] and finance (e.g., modeling option prices) [3]. SDEs are defined by combining drift and diffusion terms, wherein the drift term models the evolution of the states over time and the diffusion term introduces a stochastic term that is affected by the “derivative” of white noise [4]. In this paper, we study the problem of proving that given an SDE with initial conditions, its trajectories remain within a safe region for some given finite time horizon  $[0, T]$  with high probability. Furthermore, given a SDE with control inputs, we study the problem of designing a feedback law that ensures bounded time safety with high probability. Tools from supermartingale theory have been used to tackle such problems [5]–[9]. However, these tools often focus on time independent supermartingales. In this paper, we focus on so-called  $\lambda$ -supermartingales that are time dependent through a time varying scaling term  $\lambda(t)$ . This allows us to prove sharper

time varying bounds that tail off exponentially as time increases. Also, the computation of such supermartingales with control inputs is very challenging: leading to bilinear optimization problems that are well-known to be computationally hard. In this paper, we provide a simple iterative scheme for computing such supermartingales using sum-of-squares (SOS) programming [10], [11]. Our iterative scheme formulates a series of semidefinite programming problems that, upon convergence, yield the required supermartingales. Although convergence of our computational scheme is not guaranteed *a priori*, we demonstrate promising results on a set of challenging numerical examples that show the power of our approach to prove nontrivial bounds on probabilities of reaching unsafe sets.

## A. Related Work

The notion of supermartingales [12] and their use in proving properties of stochastic systems is well known [13]. Lyapunov methods have been extended to SDEs to prove stochastic stability [13]–[15]. Techniques for proving safety properties have built upon these results. Prajna et al [5] introduced the notion of stochastic barrier certificates, which serve as supermartingales to verify that stochastic hybrid systems remain within a safe set with high probability. This work laid the foundation for subsequent developments in the formal verification of probabilistic safety properties. For instance, Wisniewski and Bujorianu [8] developed a probabilistic safety analysis framework for Markov processes, further expanding the scope of barrier methods to stochastic settings. More recently, Wang et al [7] introduced the concept of stochastic control barrier functions (SCBFs) for safety-critical control of systems governed by SDEs, bridging the gap between safety verification and control design in stochastic environments. Although Prajna et al demonstrate the use of polynomial supermartingales synthesized using sum-of-squares programming, the later work of Steinhart and Tedrake [6] utilizes exponential barrier functions and semidefinite programming to derive sharper probability bounds for safety properties of discrete and continuous time stochastic systems. However, the computation of exponential supermartingales is a hard problem that also leads to bilinear constraints. In this paper, we try to prove sharp bounds on the probability of safety violations through the use of time-varying supermartingales wherein the probabilities of safety property violations are shown to decay exponentially over time. The contributions of this paper are two-fold: (a) we show how time varying supermartingale functions can

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provide sharp bounds; and (b) we demonstrate an approach to synthesize these functions using SOS programming.

SOS programming techniques allows us to prove properties over polynomial inequalities by encoding the problem of proving that a given polynomial is non-negative over a semi-algebraic set as a semi-definite optimization problem that can be solved efficiently [10], [11], [16]. The approach has been well integrated into packages such as the Julia SumOfSquares package [17]. Our computational approach presented here is an extension of our previous work that uses a similar approach to synthesize vector barrier function for Ordinary Differential Equations (ODEs) [18]. However, the setting of this work is entirely different, and thus, the technique has been suitably adapted.

## II. PRELIMINARIES AND PROBLEM STATEMENT

In this section, we will first recall some classical notions of stochastic processes and define the SDE model. Due to page limitations, we have elided background details and proofs. These will be part of the extended version, available online.

### A. Stochastic Process

We will briefly present some basic concepts from measure theory; further details are available elsewhere [12].

Given a set  $\Omega$  (sample space), a *measurable space* is defined as a pair  $(\Omega, \mathcal{F})$ , where  $\mathcal{F}$  is a  $\sigma$ -algebra on  $\Omega$ . We will refer to key concepts from measure theory and stochastic processes including that of a filtration, stopping time, stopped processes and Doob's inequality. The details of these concepts are available from standard textbooks [12]. Let  $\mathcal{I} \subseteq \mathbb{R}_{\geq 0}$  denote a set of "time instants".

**Definition 1 (Supermartingales):** Given a probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ , the stochastic process  $\{X_t\}_{t \in \mathcal{I}}$  is called a *supermartingale* with respect to a filtration  $\mathcal{M} = \{\mathcal{M}_t\}_{t \in \mathcal{I}}$  iff the following conditions hold:

- $X_t$  is  $\mathcal{M}_t$ -measurable for all  $t \in \mathcal{I}$ ,
- $\mathbb{E}[|X_t|] < \infty$  for all  $t \in \mathcal{I}$ ,
- $\mathbb{E}[X_t | \mathcal{M}_s] \leq X_s$  for all  $t, s \in \mathcal{I}$ ,  $t \geq s$ .

If the stochastic process  $X = \{X_t\}_{t \in \mathcal{I}}$  starts from a specific point  $X_0 = x$ , let  $\mathbb{P}^x$  denote the probability measure satisfying  $\mathbb{P}^x(X_0 = x) = 1$ . When  $X_0$  is a random variable with distribution  $\mu$ , we denote the corresponding probability measure by  $\mathbb{P}^\mu$ . Likewise, we employ the notations  $\mathbb{E}^x(h(X_t)) := \mathbb{E}[h(X_t) | X_0 = x]$  and  $\mathbb{E}^\mu(h(X_t)) := \mathbb{E}[X_t | X_0 \sim \mu]$ .

### B. Stochastic Differential Equation

Consider stochastic differential equation (SDE) as

$$dx = f(x)dt + \sigma(x)dW \quad (1)$$

where  $x \in \mathbb{R}^n$  is the state of system in  $\mathbb{R}^n$ ,  $W$  is  $p$ -dimensional Brownian motion,  $f : \mathbb{R}^n \rightarrow \mathbb{R}^n$  is the drift term, and  $\sigma : \mathbb{R}^n \rightarrow \mathbb{R}^{n \times p}$  is the diffusion term.

**Assumption 1 (Existence and Uniqueness Assumption):** The functions  $f$  and  $\sigma$  satisfy the conditions of [4, Theorem 5.2.1].

Consider the measurable space  $E = \mathbb{R}^n$  equipped with the Borel measure. An observable function  $h$  is defined as  $h : E \rightarrow \mathbb{R}$ . Let  $\mathcal{B}(E)$  be the set of all bounded measurable functions from  $E = \mathbb{R}^n$  to the real line  $\mathbb{R}$ . The space  $\mathcal{B}(E)$  forms a Banach space under the supremum norm defined as  $\|h\| = \sup_{x \in E} |h(x)|$  [19].

**Definition 2 (Semigroup of Operators [20]):** A one-parameter family of linear operators  $\{P_t\}$  which satisfies the following properties is called *semigroup*.

- $P_0 = \text{Id}$ ,
- $P_{t+s} = P_t \circ P_s$ ,  $\forall s, t \geq 0$ .

**Definition 3 (Koopman Operator):** For every  $t \in \mathcal{I}$ ,  $P_t : \mathcal{B}(E) \rightarrow \mathcal{B}(E)$  is a positive linear operator with respect to the Markov process  $\{X_t\}_{t \in \mathcal{I}}$ . Let  $h \in \mathcal{B}(E)$  then

$$P_t h(x) = \mathbb{E}^x [h(X_t)] . \quad (2)$$

$\{P_t\}_{t \in \mathcal{I}}$  has semigroup property. Based on Chapman-Kolmogorov equation [21], for  $s, t \in \mathcal{I}$  we have  $P_{t+s} = P_t P_s$ , and  $P_0 = \text{Id}$ .

**Definition 4 (Generator of Koopman Operator):** The operator  $\mathcal{L} : \mathcal{D}_{\mathcal{L}} \rightarrow \mathcal{B}(E)$  is called the (infinitesimal) generator of the semigroup  $P_t$ , and is defined as

$$\mathcal{L}h(x) = \lim_{t \rightarrow 0} \frac{P_t h(x) - h(x)}{t}, \quad x \in E, \quad (3)$$

where  $\mathcal{D}_{\mathcal{L}}$  be the set of all  $f \in \mathcal{B}(E)$  that the the limit exists.

**Proposition 1: (Dynkin Formula)** Let  $\mathcal{I} = \mathbb{R}_{\geq 0}$ . Suppose  $h \in \mathcal{D}_{\mathcal{L}}$ , then for  $t \geq 0$  (see [22, Proposition 14.10])

$$P_t h(x) = h(x) + \mathbb{E}^x \left[ \int_0^t \mathcal{L}h(X_s) ds \right]. \quad (4)$$

**Remark 1:** The generator of Koopman for the SDE system in (1) for a twice differentiable function  $h$  is given as

$$\mathcal{L}h(x) = \nabla h(x)^\top f(x) + \frac{1}{2} \text{tr}((\sigma(x)\sigma(x)^\top) \times \nabla^2 h(x)). \quad (5)$$

**Example 1:** Consider the SDE:  $dx = -0.5xdt - 0.2xdW$  over  $x \in \mathbb{R}$  and 1D Brownian motion  $W(t)$ . The drift term  $a(x) = 0.5x$  and the diffusion term  $\sigma(x) = 0.2x$ . For the Lebesgue measurable function  $h(x) = x^2$ . We have  $\mathcal{L}h = a(x) \cdot \nabla h + \frac{1}{2} \text{tr}(\sigma \sigma^\top \nabla^2 h) = -x^2 + 0.04x^2 = -0.96x^2$ .

### C. Controlled SDE

Consider an SDE system where the drift term includes an additional component influenced by a control input:

$$dx = (f(x) + g(x)u)dt + \sigma(x)dW, \quad (6)$$

where  $g : \mathbb{R}^n \rightarrow \mathbb{R}^{n \times m}$ , and the control input  $u \in \mathbb{R}^m$ .

Let  $\mathcal{L}_u$  be the generator of (6), and  $\mathcal{L}$  be the generator of the SDE without the term  $g(x)u$  involving the control input.

$$\mathcal{L}_u h(x) = \mathcal{L}h(x) + \nabla h(x)^\top g(x)u. \quad (7)$$

#### D. Problem Statement

We will now present the problem statement.

**Inputs:** We are given a controlled SDE model according to Eq. (6) defined by functions  $f(x), g(x)$  and  $\sigma(x)$ , a set of initial states  $\mathcal{X}_0$ , unsafe states  $\mathcal{X}_u$  ( $\mathcal{X}_0 \cap \mathcal{X}_u = \emptyset$ ), time horizon  $T > 0$  and probability threshold  $\rho \in (0, 1)$ .

**Output:** A continuous and differentiable control feedback law  $u = \kappa(x)$  such that for all initial conditions  $x_0 \in \mathcal{X}_0$ , the probability that a trajectory of the resulting closed loop system starting from  $x_0$  at time  $t = 0$  reaches a state  $x_t \in \mathcal{X}_u$  for  $t \in [0, T]$  is less than or equal to  $\rho$ .

### III. SUPERMARTINGALE AND $\lambda$ -SUPERMARTINGALE FUNCTIONS

Supermartingales are commonly used to study stochastic systems, and are particularly useful for safety, stability analysis, and stochastic control.

*Definition 5 (Supermartingale Functions):* An observable function  $h : E \rightarrow \mathbb{R}$  is a *supermartingale* for stochastic process  $\{X_t\}$  iff  $\{h(X_t)\}$  is a supermartingale process.

*Lemma 1:* Given the SDE system in (1), and the corresponding infinitesimal generator  $\mathcal{L}$ , an observable function  $h \in D_{\mathcal{L}}$  is supermartingale if  $\mathcal{L}h(x) \leq 0$ .

*Example 2:* The function  $h(x)$  in Example 1 is a supermartingale:  $\mathcal{L}h = -0.96x^2 \leq 0$  for all  $x$ .

#### A. $\lambda$ -Supermartingales

Let  $\lambda : \mathcal{I} \rightarrow \mathbb{R}$  be a continuous function over time. We introduce  $\lambda$ -supermartingales, which generalize the concept of supermartingales.

*Definition 6 ( $\lambda$ -supermartingale):* An observable  $h : E \rightarrow \mathbb{R}$  is called  *$\lambda$ -supermartingale*, if there exists a continuous function  $\lambda : \mathcal{I} \rightarrow \mathbb{R}$  such that  $e^{-\int_0^t \lambda(s)ds}h$  is a supermartingale function.

A sufficient condition for an observable function  $h \in D_{\mathcal{L}}$  to be  $\lambda$ -supermartingale is given in the following lemma.

*Lemma 2:* Given the SDE system in (1), and the corresponding infinitesimal generator  $\mathcal{L}$ , an observable function  $h \in D_{\mathcal{L}}$  is  $\lambda$ -supermartingale with a continuous and differentiable function  $\lambda : \mathcal{I} \rightarrow \mathbb{R}$  if  $\mathcal{L}h \leq \lambda h$ .

All proofs are available in the extended version

*Lemma 3:* Let  $h \in D_{\mathcal{L}}$  be a  $\lambda$ -supermartingale function with a smooth function  $\lambda : \mathcal{I} \rightarrow \mathbb{R}$ , then for all  $x \in \mathbb{R}^n$ ,

$$P_t h(x) \leq e^{\int_0^t \lambda(s)ds} h(x). \quad (8)$$

#### B. Probabilistic Forward Invariance and Safety Inference using Supermartingale Functions

Here, we explore forward invariance and safety probabilities using supermartingale functions.

*Definition 7 (First Hitting Time):* Suppose  $D \in \mathcal{E}$  and  $\omega \in \Omega$ . The *first hitting time*  $\tau_D$  of the process  $X = \{X_t\}_{t \in \mathcal{I}}$  to the set  $D$  is a random variable defined as

$$\tau_D(\omega) := \inf\{t \in \mathcal{I} : X_t(\omega) \in D\}.$$

Note that  $\tau_D(\omega) = \infty$  if  $X_t(\omega) \notin D$  for all  $t \in \mathcal{I}$ .

Let  $E = \mathbb{R}^n$ ,  $\mathcal{I} = \mathbb{R}_{\geq 0}$ ,  $h \in D_{\mathcal{L}}$  be a nonnegative supermartingale function, and  $O_c$  be the super-level set of  $h$  for  $c > 0$ :

$$O_c := \{x \in \mathbb{R}^n \mid h(x) \geq c\}. \quad (9)$$

Suppose  $\tau_{O_c}$  indicates the first hitting time of the solution to the SDE system (1) starting from  $x \in \mathbb{R}^n \setminus O_c$  to the set  $O_c$ . The probability of hitting  $O_c$  within the time interval  $[0, T]$  starting from  $x$ , is formulated as

$$\mathbb{P}^x(\tau_{O_c} \leq T) = \mathbb{P}^x\left(\sup_{t \in [0, T]} h(X_t) \geq c\right). \quad (10)$$

Let us first consider a bound for a fixed time  $t \in \mathcal{I}$ . Let  $h \in D_{\mathcal{L}}$  be a nonnegative  $\lambda$ -supermartingale with smooth function  $\lambda : \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}$ , and let  $O_c$  in (9) be a super-level set of  $h$  for  $c > 0$ . The probability that  $X_t$  enters the set  $O_c$  can be upper bounded directly using Markov inequality follows:

$$\begin{aligned} \mathbb{P}^x(h(X_t) \geq c) &\leq \frac{1}{c} \mathbb{E}^x[h(X_t)] = \frac{1}{c} P_t h(x) \\ &\leq \frac{1}{c} \exp\left(\int_0^t \lambda(s)ds\right) h(x) \end{aligned} \quad (11)$$

Note that the bound above holds for a specific time  $t$ . Our goal is to bound the probability over a time interval  $[0, T]$ . The Lemma below provides us with a required bound. For convenience, let  $\Lambda(t) = \int_0^t \lambda(s)ds$ .

*Lemma 4:* Given the SDE system in (1), and the corresponding infinitesimal generator  $\mathcal{L}$ . Let  $h \in D_{\mathcal{L}}$  be a nonnegative  $\lambda$ -supermartingale function with the continuous function  $\lambda : \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}$ . Let  $O_c$  be as defined (9) and  $S \subseteq \mathbb{R}^n$  be such that  $S \cap O_c = \emptyset$ . For  $x \in S$ ,

$$\mathbb{P}^x(\tau_{O_c} \leq T) \leq \frac{1}{c} \left( \sup_{t \in [0, T]} e^{\Lambda(t)} \right) h(x). \quad (12)$$

If we have initial distribution  $\mu$  with support in  $S$ , then

$$\mathbb{P}^\mu(\tau_{O_c} \leq T) \leq \frac{1}{c} \left( \sup_{t \in [0, T]} e^{\Lambda(t)} \right) \mathbb{E}^\mu[h(X_0)]. \quad (13)$$

*Proof:* Let  $t$  range over the interval  $[0, T]$ . We have

$$\mathbb{P}(\exists t : h(X_t) \geq c) = \mathbb{P}\left(\exists t : e^{-\Lambda(t)} h(X_t) \geq ce^{-\Lambda(t)}\right)$$

$$\begin{aligned}
&= \mathbb{P} \left( \sup_t e^{-\Lambda(t)} h(X_t) \geq \inf_t c e^{-\Lambda(t)} \right) \\
&\leq \frac{\mathbb{E}[h(X_0)]}{\inf_t c e^{-\Lambda(t)}} = \frac{1}{c} \left( \sup_t e^{\Lambda(t)} \right) \mathbb{E}[h(X_0)]
\end{aligned}$$

If  $X_0$  is a Dirac distribution at  $x$ , then  $\mathbb{E}[h(X_0)] = h(x)$ , proving (12). If  $X_0 \sim \mu$ , then we establish (13). ■

*Remark 2:* A supermartingale is, in fact, a  $\lambda$  supermartingale with  $\lambda = 0$ . The term  $\left( \sup_{t \in [0, T]} e^{\Lambda(t)} \right)$  in Eq. (12) is advantageous if  $\lambda(t) \leq 0$  for all  $t \in [0, T]$ . First, the probability bound  $\mathbb{P}^x(h(X_t) \geq c)$  decreases exponentially over time  $t$  yielding a tight bound for a specific time instant  $t$ . This is illustrated through the numerical examples in Section V. For instance the plots in Figs. 1, 2 and 3 show how the probability bounds for reaching an unsafe set tails off over time, thanks to the  $\lambda(t)$  term.

We will now consider the case for controlled SDE (6).

*Lemma 5:* Given the controlled affine SDE in (6), let  $h \in D_{\mathcal{L}}$  be a nonnegative  $\lambda$ -supermartingale function with the continuous function  $\lambda : \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}$ . Suppose  $S \subset \mathbb{R}^n$  and  $h(x) \leq c$  for  $x \in S$ . Let  $O_c = \{x \in \mathcal{X} : h(x) \geq c\}$  be a super-level set of  $h$  for  $c > 0$ . If there exists a differentiable control law  $u = \kappa(x)$  such that for each  $x \in S$ :

$$\mathcal{L}_u h(x) = \mathcal{L}h(x) + \nabla h(x)^\top g(x)u(x) \leq \lambda h(x), \quad (14)$$

then, the probability of reaching  $O_c$  at time  $t$  starting from  $x \in S$  is bounded as:

$$\mathbb{P}(h(X_t) \geq c) \leq \frac{1}{c} e^{\Lambda(t)} \mathbb{E}[h(X_0)].$$

Likewise, if  $t \in [0, T]$ , then

$$\mathbb{P}(\exists t : h(X_t) \geq c) \leq \frac{1}{c} \left( \sup_t e^{\Lambda(t)} \right) \mathbb{E}[h(X_0)].$$

The proof directly follows by applying Lemma 5 to the closed-loop SDE obtained by plugging-in  $u = \kappa(x)$ . Returning to the overall problem statement in Section II-D, we seek a  $\lambda$ -supermartingale  $h(x)$  and feedback law  $\kappa$  that satisfy the following criteria:

$$\left. \begin{aligned}
&h(x) \geq 0, \forall x \in \mathcal{X}; \quad \lambda(t) \leq 0, \forall t \in [0, T]; \\
&h(x) \leq \rho, \forall x \in \mathcal{X}_0; \quad h(x) \geq 1, \forall x \in \mathcal{X}_u; \\
&\mathcal{L}h(x) + \nabla h(x)^\top g(x)\kappa(x) \leq \lambda(t)h(x), \\
&\quad \forall x \in \mathcal{X}, t \in [0, T].
\end{aligned} \right\} \quad (15)$$

*Theorem 1:* Let  $h(x), \kappa(x)$  satisfy (15) over  $x \in \mathcal{X}$  and  $t \in [0, T]$  for given controlled SDE involving  $f, g, \sigma$ , sets  $\mathcal{X}_0, \mathcal{X}_u$ , time horizon  $T > 0$  and probability threshold  $\rho \in (0, 1)$ . The controlled SDE (6) under the feedback  $u = \kappa(x)$  satisfies  $\mathbb{P}(\tau_{\mathcal{X}_u} \leq T) \leq \rho$ .

#### IV. SYNTHESIS OF SUPERMARTINGALES

In this section, we use an iterative approach to synthesize polynomial  $\lambda$ -supermartingale functions and control feedback laws for a given SDE. We will restrict our attention to nonlinear SDEs whose drift and diffusion functions are described by polynomials over  $x, t$ . Furthermore, we will

synthesize  $\lambda$ -supermartingales  $h(x)$ , wherein  $\lambda(t)$  and  $h(x)$  are polynomials over  $t, x$ , respectively.

Let  $\mathbb{R}[x]$  denote the set of all polynomials for  $x \in \mathbb{R}^n$ . We assume that the SDE system in (6) is polynomial, the functions  $f, g, \sigma$  are polynomials.

*Definition 8 (Sum-of-Squares):* A polynomial  $g \in \mathbb{R}[x]$  is a *sum-of-squares* if  $g = \sum_{i=1}^r p_i^2$  for  $r \in \mathbb{N}$  and  $p_i \in \mathbb{R}[x]$ . The set of SOS polynomials is denoted by  $\text{SOS}[x]$ .

We use monomial basis functions to express each polynomial as the inner product of a coefficient vector with a monomial vector. Suppose  $\phi_d(x)$  denotes the monomial vector that contains all monomials over  $x$  with degree  $\leq d$ . Then, each polynomial  $p(x)$  of maximum degree  $d$  can be expressed as  $p(x) = v^\top \phi_d$  where  $v \in \mathbb{R}^{r_d}$  is the coefficient vector and  $r_d = \binom{n+d}{n}$ . We define the (coefficient) distance between two polynomials  $h_i(x) = v_i^\top \phi_d$  and  $h_j(x) = v_j^\top \phi_d$  as

$$d(h_i, h_j) := \|v_i - v_j\|_2. \quad (16)$$

First, we consider polynomial SDEs without control inputs. Our goal is to synthesize a  $\lambda$ -supermartingale function  $h(x) \in \mathbb{R}[x]$  and  $\lambda(t) \in \mathbb{R}[t]$  that satisfies the condition:

$$\forall x \in \mathcal{X} \subset \mathbb{R}^n, \mathcal{L}(h(x)) \leq \lambda h(x) \quad (17)$$

Let  $d$  be an *a priori* fixed degree bound for  $h(x)$ . We write  $h(x) = v_h^\top \phi_d$  for an unknown vector  $v_h \in \mathbb{R}^{r_d}$ . We do the same for  $\lambda$  as a function of  $t$ ,  $\lambda(t) = \omega_\lambda^\top \psi_q(t)$ , where  $\psi_q(t)$  is a basis of monomials up to some degree  $q$  in  $t$ .

Since  $\mathcal{L}$  is a linear operator, we have that  $\mathcal{L}h(x) = \mathcal{L}(v_h^\top \phi_d) = v_h^\top \mathcal{L}\phi_d$ . Note that  $\mathcal{L}\phi_d$  is a vector of polynomials whose degrees can exceed  $d$ . We relax condition (17) using the sum-of-squares (SOS) approach [10], [11], [16]:

$$\left. \begin{aligned}
&\text{find } v_h, \omega_\lambda \text{ s.t.} \\
&(\omega_\lambda^\top \psi_q(t)) \times (v_h^\top \phi_d(x)) - (v_h^\top \mathcal{L}\phi_d(x)) \text{ is SOS}
\end{aligned} \right\} \quad (18)$$

The SOS constraints are translated into semi-definite programming problems. In this case, however, the constraints obtained are *bilinear*, since they involve a product of the unknowns  $v_h$  and  $\omega_\lambda$ . The resulting feasibility problem is therefore non-convex and hard to solve, in general [23]. Inspired by Alternating Minimization Algorithm [24, Section 1.6.3], we propose a projection-based approach that allows all the decision variables  $v_h, \omega_\lambda$  to potentially change during each iteration but nevertheless yields convex optimization problems. For simplicity, we write  $v = v_h$  and  $\omega = \omega_\lambda$ . Let  $h_0$  be an initial *guess*,  $h_0 = v_0^\top \phi_d$ . The proposed iterative scheme solves a the following optimization problem to find  $h_{i+1} = v_{i+1}^\top \phi_d$  given  $h_i = v_i^\top \phi_d$  for  $i \geq 0$ :

$$\left. \begin{aligned}
&\min_{v, \omega} \quad \|v - v_i\|_2 \\
&\text{s.t.} \quad (v_i^\top \phi_d(x)) \times (\omega^\top \psi_q(t)) - v^\top \mathcal{L}\Phi_d \text{ is SOS} \\
&\quad \text{Additional constraints over } v, \omega
\end{aligned} \right\} \quad (19)$$

Eq. (19) computes  $(v_{i+1}, \omega_{i+1})$  as a function of  $v_i$ . Note that  $\omega_i$  is not used.

**Lemma 6:** At any iteration  $i$ , if the optimization problem (19) has an optimal value of 0, then  $v_{i+1} = v_i$  and the values  $(v_h, \omega_\lambda) = (v_{i+1}, \omega_{i+1})$  satisfy Eq. (18).

**Controlled Supermartingale Synthesis:** We will now extend our approach to controlled supermartingale synthesis. Consider a controlled SDE as specified in (6). Suppose we parameterize the feedback  $u = \kappa(x)$  as a polynomial function  $u = K\phi_d$  with an unknown matrix of coefficients  $K \in \mathbb{R}^{m \times r_d}$  and over the same monomial basis  $\phi_d$  (for convenience). The approach of alternating projection can be extended wherein at each iteration we update a triple  $(v_i, \omega_i, K_i)$  starting with some initial guess  $v_0, K_0$ .

$$\begin{aligned} \min_{v, w, K} \quad & \|v - v_i\| + \|K - K_i\| \\ \text{s.t.} \quad & (v_i^\top \phi_d(x)) \times (\omega^\top \psi_q(t)) - (v^\top \mathcal{L}\phi_d(x)) \\ & + (v_i^\top \nabla \phi_d(x)) \times g(x) \times (K\phi_d(x)) \text{ is SOS,} \\ & \text{Additional constraints over } v, w, K. \end{aligned} \quad (20)$$

Once again, we can apply a modified version of the iterative scheme given a controlled SDE: (a) We initialize using a guess  $(v_0, K_0)$ ; (b) at each iteration, we update  $(v_{i+1}, \omega_{i+1}, K_{i+1})$  by solving Eq. (20); and (c) if we achieve convergence, we apply Eq. (20) to check our final result.

Finally, we conclude by focusing on the solution to the problem statement in Section II-D. Given initial set  $\mathcal{X}_0$ , unsafe set  $\mathcal{X}_u$ , time horizon  $T$  and probability bounds  $\rho$ , we find a solution to Eq. (15) by solving the following SOS program iteratively.

$$\left. \begin{aligned} \min_{v, w, K} \quad & \|v - v_i\| + \|K - K_i\| \text{ s.t.} \\ \text{C1: } & v_i^\top \phi_d(x) \text{ is SOS on } x \in \mathcal{X}, \\ \text{C2: } & -w^\top \psi_q(t) \text{ is SOS for } t \in [0, T], \\ \text{C3: } & v_i^\top \phi_d(x) \leq \rho \text{ for } x \in \mathcal{X}_0, \\ \text{C4: } & v_i^\top \phi_d(x) \geq 1 \text{ for } x \in \mathcal{X}_u, \\ \text{C5: } & (v_i^\top \phi_d) \times (w^\top \psi_q) - v^\top \mathcal{L}\phi_d \\ & + (v_i^\top \nabla \phi_d) \times g(x) \times (K\phi_d) \\ & \text{is SOS } (t, x) \in [0, T] \times \mathcal{X}. \end{aligned} \right\} \quad (21)$$

The constraint **C1** imposes non-negativity of  $h(x)$ , **C2** enforces the negativity of  $\lambda(t)$  over  $[0, T]$ , **C3**, **C4** places limits for  $h(x)$  on the initial set  $\mathcal{X}_0$  and unsafe set  $\mathcal{X}_u$ , **C5** denotes the  $\lambda$  supermartingale property.

## V. EXPERIMENTAL RESULTS

We now present the results of our approach on a few selected numerical examples of SDEs. In each case, we solve an instance of the problem stated in Section II-D for various controlled SDEs with given  $\mathcal{X}_0, \mathcal{X}_u$ , threshold  $T$  and probability bounds  $\rho$  using the iterative algorithm from Section IV and the constraints shown in (21). Our

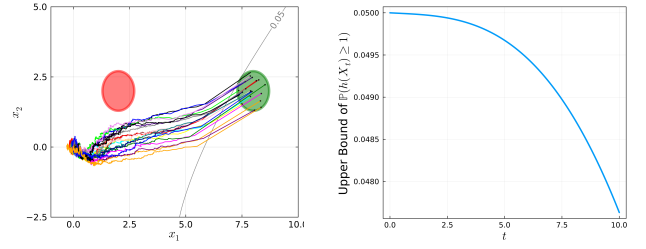


Fig. 1: **(Left)** Twenty randomly sampled trajectories of the closed loop synthesized for Example 3 and **(Right)** upper bound of probability of reaching unsafe set obtained by applying Eq. (11) .

implementation uses the Julia programming language and the SumOfSquares.jl package of Legat et al [17]. Our implementation and the results of the numerical examples will be made available through our GitHub repository <sup>1</sup>.

**Example 3:** Consider the following controlled SDE

$$dx = (f(x) + g(x)u)dt + \sigma(x)dW, \quad (22)$$

where  $f(x) = \begin{pmatrix} -x_1^3 + 0.5x_2 \\ -x_1 - 2.0x_2 \end{pmatrix}$ ,  $g(x) = I_{2 \times 2}$ , and  $\sigma(x) = \begin{pmatrix} 0.2x_1 & 0.1x_2 \\ -0.1(x_1 + x_2) & 0.2 \end{pmatrix}$ . Suppose the initial set is  $\mathcal{X}_0 = \{x \in \mathbb{R}^2 : (x_1 - 8)^2 + (x_2 - 2)^2 \leq 0.5\}$ , and the unsafe set is  $\mathcal{X}_u = \{x \in \mathbb{R}^2 : (x_1 - 2)^2 + (x_2 - 2)^2 \leq 0.5\}$ . Applying the iterative algorithm to the problem in (21), the feedback control law and the  $\lambda$ -supermartingale observable function  $h$  are generated for  $T = 10$ , and  $1 - \rho = 0.95$ . Figure 1 (left) shows twenty trajectories generated from various initial states  $\mathcal{X}_0$ . The probability of reaching the super-level set of  $h$  at each  $t$  calculated using Eq. (11) (i.e.  $\mathbb{P}(h(X_t) \geq 1)$ ) as a function of time  $t$  is shown in Figure 1 (right).

The maximum degree  $d$  of monomials  $\phi_d(x)$  was taken to be 8, and that for  $\lambda(t)$  was 2. The stopping threshold for the algorithm is  $\epsilon = 10^{-10}$ .

**Example 4:** Consider a controlled Lotka Volterra system with  $f(x) = \begin{pmatrix} 1.5x_1 - x_1x_2 \\ -x_2 + 1.2x_1x_2 \end{pmatrix}$ ,  $g = I$ , and  $\sigma = \begin{pmatrix} 0.2x_1 & 0 \\ 0 & 0.2x_2 \end{pmatrix}$ . Suppose  $\mathcal{X}_0, \mathcal{X}_u$  are given as

$$\mathcal{X}_0 = [0.5, 2]^2, \quad \mathcal{X}_u = \{x \in \mathbb{R}^2 : x_1 + x_2 \geq 5\}.$$

Applying the iterative approach to the problem in (21), the feedback control law and the  $\lambda$ -supermartingale observable function  $h$  are generated for  $T = 10$ , and  $1 - \rho = 0.95$ . Figures 2(left) show the normalized feedback law, while Figure 2 (right) plots the bounds on probability for specific time instants. The maximum degree for  $\phi_d(x)$  was taken to be 8 and that for  $\psi_q(t)$  was taken to be 2.  $\epsilon$  was set to  $10^{-8}$ .

<sup>1</sup><https://github.com/MasoumehGHM/timedKoopmanScalar>

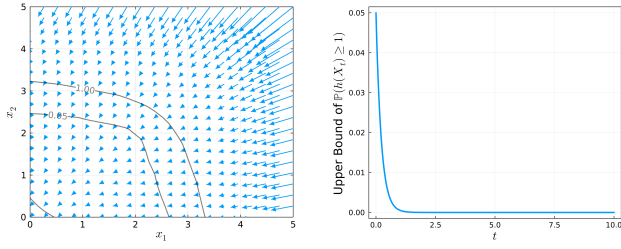


Fig. 2: **(Left)** Closed loop feedback control law of Example 4 and the 0.05, 1-level sets of the supermartingale function; and **(Right)** upper bound of probability of reaching unsafe set as a function of time.

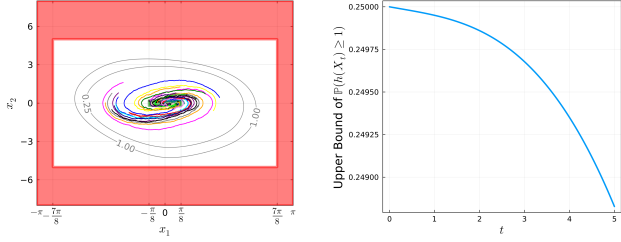


Fig. 3: **(Left)** Twenty trajectories of Example 5 from randomly generated initial points in  $\mathcal{X}_0$ , the red shadowed area indicates the unsafe set; and **(Right)** upper bound of probability of reaching unsafe set as a function of time.

*Example 5:* Consider the approximate pendulum SDE system with  $f(x) = \begin{pmatrix} x_2 \\ -x_1 - x_1^3 \end{pmatrix}$ ,  $g = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$ , and  $\sigma = \begin{pmatrix} 0 & 0 \\ 0 & 0.1 \end{pmatrix}$ . Suppose  $\mathcal{X}_0, \mathcal{X}_u$  are given as

$$\mathcal{X}_0 = \left[-\frac{\pi}{8}, \frac{\pi}{8}\right] \times [-0.2, 0.2],$$

$$\mathcal{X}_u = \left\{x \in \mathbb{R}^2 : |x_1| \geq \frac{7\pi}{8}, |x_2| \geq 5\right\}.$$

The feedback control law and the  $\lambda$ -supermartingale observable function  $h$  are generated for  $T = 5$ , and  $1 - \rho = 0.75$ . Figure 3 (left) shows the trajectories of twenty random generated initial points from  $\mathcal{X}_0$ . Figure 3(right) illustrates the degree of polynomial in  $x$  was taken to be 8, and the maximum degree for  $\lambda$  was 2. The stopping threshold for the algorithm was set to  $\epsilon = 10^{-10}$ .

## VI. CONCLUSION

Thus, our proposed approach effectively leverages supermartingale functions to compute feedback laws that guarantee probabilistic safety properties of SDE models in the presence of control inputs. Future work will aim to extend this methodology to accommodate multiple observable functions, extending to stochastic jump differential equations and stochastic hybrid systems.

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## REFERENCES

- [1] R. Zárate-Miñano, M. Anghel, and F. Milano, “Continuous wind speed models based on stochastic differential equations,” *Applied Energy*, vol. 104, pp. 42–49, 2013.
- [2] R. Narayanan, M. H. Zaki, and S. Tahar, “Using stochastic differential equation for verification of noise in analog/rf circuits,” *J. Electron. Test.*, vol. 26, p. 97–109, Feb. 2010.
- [3] S. Shreve, *Stochastic Calculus for Finance II: Continuous-Time Models*. Springer Finance, Springer, 1 ed., 2004.
- [4] B. Oksendal, *Stochastic differential equations: an introduction with applications*. Springer Science & Business Media, 2013.
- [5] S. Prajna, A. Jadbabaie, and G. J. Pappas, “A framework for worst-case and stochastic safety verification using barrier certificates,” *IEEE Transactions on Automatic Control*, vol. 52, no. 8, pp. 1415–1428, 2007.
- [6] J. Steinhardt and R. Tedrake, “Finite-time regional verification of stochastic non-linear systems,” *The International Journal of Robotics Research*, vol. 31, no. 7, pp. 901–923, 2012.
- [7] C. Wang, Y. Meng, S. L. Smith, and J. Liu, “Safety-critical control of stochastic systems using stochastic control barrier functions,” *2021 60th IEEE Conference on Decision and Control (CDC)*, pp. 5924–5931, 2021.
- [8] R. Wisniewski and L.-M. Bujorianu, “Safety of stochastic systems: An analytic and computational approach,” *Automatica*, vol. 133, p. 109839, 2021.
- [9] S. Feng, M. Chen, B. Xue, S. Sankaranarayanan, and N. Zhan, “Unbounded-time safety verification of stochastic differential dynamics,” in *International Conference on Computer Aided Verification*, pp. 327–348, Springer, 2020.
- [10] J. B. Lasserre, “Global optimization with polynomials and the problem of moments,” *SIAM Journal on optimization*, vol. 11, no. 3, pp. 796–817, 2001.
- [11] P. A. Parrilo, *Polynomial Optimization, Sums of Squares, and Applications*, ch. 3, pp. 47–157.
- [12] D. Williams, *Probability with Martingales*. Cambridge Mathematical Textbooks, Cambridge: Cambridge University Press, 1991.
- [13] H. J. Kushner, *Stochastic Stability and Control*, vol. 33 of *Mathematics in Science and Engineering*. New York: Academic Press, 1967.
- [14] S. P. Meyn and R. L. Tweedie, *Markov Chains and Stochastic Stability*. Communications and Control Engineering, London: Springer, 1993.
- [15] R. Khasminskii and R. Khasminskii, “Stability of stochastic differential equations,” *Stochastic Stability of Differential Equations*, pp. 145–176, 2012.
- [16] N. Z. Shor, “An approach to obtaining global extrema in polynomial problems of mathematical programming,” *Kibernetika (Kiev)*, no. 5, p. 102–6, 1987.
- [17] B. Legat, C. Coey, R. Deits, J. Huchette, and A. Perry, “Sum-of-squares optimization in Julia,” in *The First Annual JuMP-dev Workshop*, 2017.
- [18] G. O. Berger, M. Ghanbarpour, and S. Sankaranarayanan, “Cone-based abstract interpretation for nonlinear positive invariant synthesis,” in *Hybrid Systems: Computation and Control (HSCC)*, pp. 12:1–12:16, ACM, 2024.
- [19] P. Gettoor and R. M. Blumenthal, *Markov Processes and Potential Theory: Markov Processes and Potential Theory*. Academic press, 2011.
- [20] G. A. Pavliotis, *Stochastic processes and applications*. Springer, 2016.
- [21] E. Cinlar, *Probability and stochastics*, vol. 261. Springer, 2011.
- [22] M. H. Davis, *Markov models & optimization*. Routledge, 2018.
- [23] O. Toker and H. Ozbay, “On the NP-hardness of solving bilinear matrix inequalities and simultaneous stabilization with static output feedback,” in *Proceedings of 1995 American Control Conference - ACC’95*, vol. 4, pp. 2525–2526 vol.4, 1995.
- [24] S.-I. Amari, *Information geometry and its applications*, vol. 194. Springer, 2016.