Data-Driven Stabilization of Nonlinear Polynomial Systems With Noisy Data

Meichen Guo, Claudio De Persis, and Pietro Tesi

Abstract—In a recent article, we have shown how to learn controllers for unknown linear systems using finite-length noisy data by solving linear matrix inequalities. In this article, we extend this approach to deal with unknown nonlinear polynomial systems by formulating stability certificates in the form of data-dependent sum of squares programs, whose solution directly provides a stabilizing controller and a Lyapunov function. We then derive variations of this result that lead to more advantageous controller designs. The results also reveal connections to the problem of designing a controller starting from a least-square estimate of the polynomial system.

Index Terms—Data-driven control, nonlinear control, nonlinear systems, robust control, sum of squares.

I. INTRODUCTION

The idea of designing control laws from measured data alone for a system with unknown dynamics is of high relevance, both theoretically and practically. Following a rough classification, there are two approaches to concretize this idea. The first one is based on identifying a model of the system and then designing a controller that deals with the uncertainty resulting from the identification process. The second one devises methods to directly synthesize controllers from data without explicitly undertaking a model identification, hence the name of direct data-driven control.

Both approaches are viable and appealing but the focus of this article is on direct data-driven control, which will lead us to provide neat compact conditions for the synthesis of nonlinear stabilizing controllers and corresponding Lyapunov functions. The proposed method is also adaptable enough to allow for the synthesis and analysis of controllers based on least-square estimates of the system’s matrices and finite-length data processing, thus revealing connections between the two approaches. Various results on direct data-driven control have been proposed and much attention has been devoted to the specific study of nonlinear systems, which remains an open and challenging problem. Among the contributions on direct data-driven control of nonlinear systems, we recall works such as the virtual reference feedback tuning (VRFT) [1] and iterative feedback tuning [2], the on-line data-driven control of [3], the so-called intelligent PID [4], [5], and reinforcement learning [6], [7].

Related Work: Recent works inspired by Willems et al.’s lemma [8] have revealed a new approach to accomplish direct data-driven control. Specifically, for linear systems, by Willems et al.’s lemma, any input–output trajectory of a linear system can be expressed as a linear combination of finite number of previously measured input–output data. Using this lemma to parameterize a closed-loop linear system controlled by a state-feedback controller, the feedback gain can be directly found via data-based linear matrix inequalities (LMIs) for various control problems [9]. A nonlinear extension of the linear stabilization result was also considered in [9], where the nonlinear remainder after linearization is treated as disturbances and robust data-driven control method is applied to obtain local stabilization result. Recently, the authors in [10] investigated the stabilization of bilinear systems with a characterization of the basin of attraction. Polynomial systems lend themselves to a similar analysis as the one in [9] once one expresses the system’s polynomial vector fields in the span of a suitable basis of polynomial functions and pursues a simultaneous design of controllers and Lyapunov functions based on the second Lyapunov theorem [11]. Independently, and taking a different route, the authors in [12] used the dual stability theory and Farkas’ lemma for direct data-driven design of rational state-feedback controllers for nonlinear systems. A basis of polynomials to express the nonlinearity was considered earlier in [13] and used to perform a right-inversion of the system dynamics based on which a reference tracking controller is derived. Model-inversion errors are then compensated by an outer-loop linear controller designed according to the VRFT technique.

A crucial aspect in data-driven control is that the measured data are affected by unknown noise. For linear systems, the authors in [9] posed a signal-to-noise ratio assumption on the measurement noise and presented sufficient conditions for data-driven stabilizers. This method was further investigated and analyzed in [14] for data-driven design of linear quadratic regulators. The article [15] has remarked that the condition on the noise introduced in [9] can be interpreted as an instance of a quadratic matrix inequality and analyzed via a full-block S-procedure. Another work [16] presented a matrix-valued S-lemma based on the classical S-lemma and apply it to data-driven control of linear systems. Other notable works dealing with direct or indirect data-driven robust control include, but are not limited to, [12], [17].

In this article, we investigate global data-driven stabilization of continuous-time nonlinear polynomial systems at a known equilibrium using noisy data. The focus is on polynomial systems because, first, polynomials systems are widely used to model processes in engineering applications such as fluid dynamics [18] and robotics [19]. In fact, polynomial control systems, and the supporting technical developments in sum of squares (SOS) optimization, have attracted considerable attention over the last twenty years [20]–[26]. Second, as shown in the model-based control [27], nonlinear polynomial systems can be written into a linear-like form and controlled using the Lyapunov method.
This inspires us to adopt the framework of [9] to establish a direct data-driven control synthesis for the nonlinear polynomial systems. Our previous work [11] has presented some preliminary results on data-driven stabilization of polynomial systems with state-independent input vector field and noise-free data. In this article, we enhance the results to handle state-dependent input vector field and noisy data. Besides being of interest in its own right, the study on polynomial systems will help us better understand and gain more insights in direct data-driven control of nonlinear systems.

**Contribution:** The main contribution of this article is to design a controller that renders a known equilibrium of an input-affine nonlinear polynomial system stable using only finite-length noisy data. The measurement noise is unknown and satisfies a quadratic constraint. Using a variation of the data-based closed-loop representation in our work [11], we improve the previous results so that high-order polynomial systems can now be handled more effectively. Following the framework of [9], the first result of this article shows that the data-driven design with measurement noise for linear systems can be extended to nonlinear polynomial systems using the adjusted closed-loop representation. Then, by adopting other forms of the data-based closed-loop representation, more advantageous stabilization results are attained which require less assumptions or have improved computational efficiency. A connection is also established with the problem of designing controllers based on least-square estimates of the system’s dynamics. As the data-driven stabilizing conditions involve semipositive-definiteness of polynomial matrices, we use SOS relaxations to make the computation tractable. We also show that the results can be interpreted as SOS relaxations of pointwise necessary and sufficient conditions for global robust stabilizability of polynomial systems.

**Organization:** The structure of the article is specified as follows. In Section II, we formulate the data-driven control problem. Section III contains the main results where controllers are designed using data corrupted by measurement noise. Theorem 1 can be regarded as an extension of [9, Theorem 5] from linear systems to nonlinear polynomial systems. Next, by slightly modifying the closed-loop system representation, a result in the same spirit of Theorem 1 is proposed that requires less assumptions on the controlled dynamics. A more computationally efficient corollary then follows, where a decision variable is redefined, such that its size is independent of the size of the data. In Section IV, the simulation results on the Van der Pol oscillators are presented to show the effectiveness of the proposed design methods. Finally, we summarize the article and draw the conclusions in Section V.

**Notation:** The following notations are adopted throughout the article.
- $\mathbb{A} \geq 0$: Matrix $A$ is positive semidefinite.
- $\mathbb{A} > 0$: Matrix $A$ is positive definite.
- $\mathbb{A} \succeq \mathbb{B}$: Matrix $A - B$ is positive semidefinite.
- $\mathbb{N}_{\geq 0}$: Set of natural numbers excluding 0.
- $\mathbb{R}$: Set of real numbers.
- $\mathbb{R}_{\geq 0}$: Set of positive real numbers.
- $\mathbb{P}$: Set of polynomials.
- $\mathbb{P}^*$: Set of SOS polynomials.
- $\mathbb{P}^*_{\text{r}\times s}$: Set of $r \times s$ polynomial matrices.
- $\Sigma^*$: Set of $r \times r$ SOS polynomial matrices.

### II. Problem Formulation

Consider the input-affine polynomial system

$$\dot{x} = f(x) + g(x)u$$

where $x \in \mathbb{R}^n$ is the state, $u \in \mathbb{R}^m$ is the control input, $f(x)$ and $g(x)$ are polynomial vector fields of sizes $n \times 1$ and $n \times m$, respectively. The specific expressions of $f(x)$ and $g(x)$ are unknown. We will consider the following assumption.

**Assumption 1:** For the nonlinear polynomial system (1)

a) the origin is a known equilibrium, i.e., $f(0) = 0$;

b) an upper bound on the maximum degree $d$ of $f(x)$ and $g(x)$ is known.

Assumption 1 a) results in no loss of generality as long as the desired equilibrium to stabilize is known. In fact, if the desired equilibrium is not the origin then we can reduce the analysis to the case considered in Assumption 1 a) by a change of coordinates. On the other hand, the assumption that the equilibrium to stabilize is known is satisfied in many practical cases involving mechanical and electrical systems, where the knowledge of the equilibrium points can be inferred from physical considerations. Assumption 1 b) makes it possible to write (1) in the linear-like form

$$\dot{x} = AZ(x) + BW(x)u$$

where $A \in \mathbb{R}^{n \times N}$ and $B \in \mathbb{R}^{n \times q}$ are unknown constant matrices; the $N \times 1$ vector $Z(x)$ collects all the distinct monomials in $x$ that appear in $f(x)$, and satisfies $Z(0) = 0$; finally, the $q \times m$ matrix $W(x)$ contains all the monomials that appear in $g(x)$. We note that more insights into system (1) help to choose $Z(x)$ in a more precise manner, which improves the efficiency of the subsequent computations. Nonetheless, in this work, we assume that only the information listed in Assumption 1 is available for control design. We note that Assumption 1 thus amounts to considering grey-box models, i.e., models with known structure but unknown parameters. As previously noted, this happens in many practical cases such as with mechanical and electrical systems, where information about the system to control is usually derived using first principles, while the exact systems parameters are not known.

For nonlinear systems having high order, $Z(x)$ can have notably large size and high order, which may cause issues in the controller design. As pointed out in [27] for the model-based control of polynomial systems, the choice of $Z(x)$ affects the success of the design method. A big vector $Z(x)$ containing high-order monomials can cause computational issues in the SOS program and fail to give a solution. To overcome this issue, we use another vector $\hat{Z}(x)$ having smaller size and lower degree than $Z(x)$ for the controller design and stability analysis. Specifically, the $p \times 1$ vector $\hat{Z}(x)$ satisfies that

$$Z(x) = H(x)\hat{Z}(x)$$

with polynomial matrix $H(x) \in \mathbb{P}^{N \times p}$. Our controller design and stability analysis will be based on the Lyapunov function $V(x) = Z(x)^\top P^{-1}Z(x)$, with $P$ a positive definite matrix. Since in this article we restrict ourselves to consider a global stabilization problem, we choose $\hat{Z}(x)$ to be radially unbounded and that $\hat{Z}(x) = 0$ if and only if $x = 0$. The choice of matrix $H(x)$ is not unique and it plays a minor role in the success of the proposed design. A straightforward choice of $\hat{Z}(x)$ is a vector whose first $n$ components coincide with $x$. This choice will be used in the subsequent sections of this article. Note that $\hat{Z}(x) = 0$ if and only if $x = 0$ implies that $Z(x) = 0$ if $x = 0$, i.e., the autonomous system $\dot{x} = f(x)$ must have an equilibrium at the origin, in agreement with Assumption 1a). On the other hand, even though the matrix $W(x)$ having larger size also increases computational burden in the SOS program, it does not directly affect the design of the Lyapunov function or the sizes of the decision variables. Hence, the choice of $W(x)$ has much less impact on the success of the synthesis and will not be a focus of this article.

To design a data-driven controller, we first run an off-line experiment to collect the input-state data. The experiment is conducted over the time interval $[t_0, t_0 + (T - 1)\tau]$, where $T \in \mathbb{N}_{>0}$ is the number of sampled data and $\tau \in \mathbb{R}_{>0}$ is the sampling time. The choice of $\tau$ is arbitrary and all the results which follow continue to hold even with the same sampling time. The experiment is conducted over the time interval $[t_0, t_0 + (T - 1)\tau]$, where $T \in \mathbb{N}_{>0}$ is the number of sampled data and $\tau \in \mathbb{R}_{>0}$ is the sampling time. The choice of $\tau$ is arbitrary and all the results which follow continue to hold even with the same sampling time.
unevenly spaced sampled measurements. The matrices containing the sampled input-state data are arranged as

\[ U_0 := \begin{bmatrix} u(t_0) & u(t_0+\tau) & \cdots & u(t_0 + (T-1)\tau) \end{bmatrix}, \]

\[ X_0 := \begin{bmatrix} x(t_0) & x(t_0+\tau) & \cdots & x(t_0 + (T-1)\tau) \end{bmatrix}, \]

\[ \hat{X}_1 := \begin{bmatrix} \hat{x}(t_0) & \hat{x}(t_0+\tau) & \cdots & \hat{x}(t_0 + (T-1)\tau) \end{bmatrix}. \]

Then, we can compute the data

\[ Z_0 := [Z(x(t_0)) \; Z(x(t_0+\tau)) \; \cdots \; Z(x(t_0 + (T-1)\tau))], \]

\[ \overline{U}_0 := [W(x(t_0))u(t_0) \; W(x(t_0+\tau))u(t_0+\tau) \; \cdots \; W(x(t_0 + (T-1)\tau))u(t_0 + (T-1)\tau)]. \]

For brevity, we assume that only the derivatives are affected by measurement noise, while \( Z_0 \) and \( \overline{U}_0 \) are measured exactly. This is motivated by the fact that getting exact measurements of signals derivatives is usually more challenging. Later on in Remark 8, we will also comment on the case where even \( Z_0 \) and/or \( \overline{U}_0 \) are corrupted by noise or disturbance. Let

\[ D_0 := \begin{bmatrix} d(t_0) & d(t_0+\tau) & \cdots & d(t_0 + (T-1)\tau) \end{bmatrix}, \]

where \( d(t) \in \mathbb{R}^n \). We will denote by

\[ X_1 := \hat{X}_1 + D_0 \]

the matrix containing information about \( \hat{X}_1 \), where \( D_0 \) thus represents a measurement noise. We note that, in view of (2), the following relation on the data holds:

\[ X_1 = AZ_0 + B\overline{U}_0 + D_0. \]  

The data-driven stabilization problem of (1) is to design a state-dependent control gain \( F(x) \) using the noisy experimental input-state data alone, such that under the state-feedback controller

\[ u = F(x)\hat{Z}(x) \]  

the closed-loop system is globally asymptotically stable at the origin.

III. DATA-DRIVEN STABILIZATION WITH NOISY DATA

In this section, we present conditions for the stabilization of unknown polynomial systems with data affected by noise. It is unrealistic to expect to stabilize the system using data that are affected by arbitrary noise. Hence, we introduce the following assumption on \( D_0 \).

Assumption 2: The unknown matrix \( D_0 \) satisfies \( D_0D_0^\top \preceq R_BR_D^\top \) for some known \( R_D \in \mathbb{R}^{n \times T} \).

Assumption 2 is in a similar form as [9, Assumption 2], where a signal-to-noise ratio assumption is posed on the noise \( D_0 \) to solve the data-driven control problems. The bound \( R_D \) is obtained by prior information on the noise. In fact, if we set \( R_B = \gamma X_1 \) for some constant \( 0 < \gamma < 1 \), Assumption 2 becomes the same as [9, Assumption 2]. Interestingly, the noisy data result in [9, Th. 5] can be extended to nonlinear polynomial systems, which will be presented in Section III-A. Then, in Sections III-B and III-C, by slightly changing the data-based closed-loop representation and the decision variable, we can derive the result under more advantageous conditions.

Remark 1 (Generality of quadratic bounds on the noise): Assumption 2 is satisfied whenever the prior knowledge on the maximum noise amplitude is known, i.e., \(|d(k)|^2 \leq \bar{d} \) for some known constant \( \bar{d} \). In this case, Assumption 2 holds true with \( R_BR_D^\top = \bar{d}T I_n \). A quadratic bound also holds in case of Gaussian noise. Specifically, assuming that the noise samples are i.i.d. with normal distribution, i.e.,

\[ d(k) \sim \mathcal{N}(0, \sigma^2 I_n) \; \forall k, \]

it holds that [28, Th. 6.1]

\[ D_0D_0^\top \preceq \sigma^2 T \left( 1 + \mu + \sqrt{\frac{2}{n}} \right)^2 I_n \]  

for any \( \mu > 0 \) with probability at least \( 1 - e^{-c_T \mu^2/2} \), where \( n \) is the dimension of \( d \). By letting \( R_BR_D^\top \) be equal to the right-hand side of (6), we thus obtain a quantitative bound on the probability that Assumption 2 is satisfied in case of Gaussian noise. In the remainder of the article a few results are given which state that, under Assumption 2 and other conditions, if suitable SOS programs are feasible then their solutions return a stabilizing controller. A consequence of (6) is that, in case of Gaussian noise, the solutions to these SOS programs return a controller that is stabilizing with probability at least \( 1 - e^{c_T \mu^2/2} \).

A. Data-Driven Stabilization With Noisy Data

In the result below, inspired by the results of [9], we will introduce a controller of the form \( u = F(x)\hat{Z}(x) \), where \( F(x) = U_0Y(x)P^{-1} \) and \( Y(x), P \succ 0 \) are matrices that satisfy the condition (b) \( Z_0Y(x) = H(x)P \). This choice allows us to express the closed-loop dynamics as

\[ \dot{x} = AZ(x) + BW(x)u \]

\[ = (A\hat{H}(x)P^{-1} + BW(x)U_0Y(x)P^{-1})\hat{Z}(x) \]

\[ = (A\hat{Z}_0(x)P^{-1} + BW(x)U_0Y(x)P^{-1})\hat{Z}(x) \]

\[ = (X_1 + D_0B\overline{U}_0 + BW(x)U_0Y(x)P^{-1})\hat{Z}(x) \]

having introduced the symbols

\[ E := [B \; D_0]; \]

\[ \hat{U}_0 := \begin{bmatrix} \overline{U}_0 - W(x)U_0 \\ I_T \end{bmatrix} \]

to obtain the last identity.

To design the stabilizing gain \( F(x) \), we need another assumption on the unknown matrix \( B \).

Assumption 3: The matrix \( B \) satisfies \( BB^\top \preceq R_BR_D^\top \) for some known \( R_B \in \mathbb{R}^{n \times q} \).

Remark 2 (A replacement of Assumption 3 checkable from data): It is possible to replace Assumption 3 with the condition

\[ \begin{bmatrix} I & 0 \\ 0 & 0 \end{bmatrix} \preceq \begin{bmatrix} U_0 & \overline{U}_0 \\ Z_0 & Z_0 \end{bmatrix}, \]

for some \( \gamma > 0 \). The latter can be checked from data and is trivially satisfied if the matrix \( \overline{U}_0/Z_0 \) has full row rank. Under Assumption 2, the condition above and identity (4) yield

\[ BB^\top \preceq \gamma(X_1 - D_0)(X_1 - D_0)^\top \preceq 2\gamma(X_1X_1^\top + D_0D_0^\top) \preceq 2\gamma(X_1X_1^\top + R_BR_D^\top) \]

which shows the fulfillment of Assumption 3 with

\[ R_B = \sqrt{2\gamma} \begin{bmatrix} X_1 & R_D \end{bmatrix}. \]

Under Assumptions 2 and 3

\[ EE^\top = BB^\top + D_0D_0^\top \preceq R_BR_D^\top + R_BR_D^\top \]

Define \( R_K := [R_B \; R_D] \). Then, it holds that

\[ EE^\top \preceq R_K^\top \]

Obtaining stabilization results requires to impose positive conditions on polynomial matrices, which is often computationally intractable. To resolve this issue, we use SOS relaxations in the subsequent results.
Theorem 1: For the polynomial system (1), under Assumptions 1 to 3, if there exist a positive definite matrix $P \in \mathbb{R}^{n \times n}$, and the coefficients of $x$ should satisfy
\[ -\frac{\partial Z(x)}{\partial x}(X_1 - E\hat{U}_0(x)) Y(x) - Y(x) = -\frac{\partial \hat{Z}(x)}{\partial x}(X_1 - E\hat{U}_0(x))^\top Y(x) \] for all $x \in \mathbb{R}^n$. Then, the derivative of $V(x)$ satisfies
\[ \dot{V}(x) \leq -\epsilon_1(x) \hat{Z}(x)^\top P^{-1} \hat{Z}(x) \] for all $x \in \mathbb{R}^n$. Therefore, the closed-loop system is stable. Moreover, if $\epsilon_1(x) > 0$ for all $x \neq 0$, then $V(x)$ is bounded, and thus, the origin is globally asymptotically stable since $V(x)$ is radially unbounded (recall that $\hat{Z}(x)$ contains $x$ as a subvector).

To find $P$ and $Y(x)$ in Theorem 1, one can use MATLAB-based tools such as the SOSTOOLS [29]. The decision variables of the SOS program include the constant matrix $P$ and the coefficients of $Y(x)$. The coefficients of $\epsilon_1(x)$ and $\epsilon_2$ can also be set as decision variables.

Remark 3 (Input vector field independent of $x$): In the case where the input vector field is independent of $x$, Theorem 1 can achieve data-driven stabilization without Assumption 3. In this case, the polynomial system can be written into the linear-like form
\[ \dot{x} = Az(x) + Bu \]
where $B \in \mathbb{R}^{n \times m}$, and the corresponding closed-loop dynamics can be expressed using data as
\[ \dot{x} = (A - D_0)y(x)P^{-1}\hat{Z}(x). \]
Then, a stabilization result in the same fashion as Theorem 1 can be derived by changing (10) into
\[ \left[ Y(x) - \epsilon_1(x) I_p \right]^\top P^{-1} \hat{Z}(x) \]
where
\[ Y(x) := -\frac{\partial \hat{Z}(x)}{\partial x} (X_1 - E\hat{U}_0(x))^\top Y(x) - Y(x) \]
and the coefficients of $x$ should satisfy
\[ -\frac{\partial \hat{Z}(x)}{\partial x}(X_1 - E\hat{U}_0(x))^\top Y(x) \leq \epsilon_1(x) I_p \]

Remark 4 (Rank condition on $Z_0$): The feasibility of condition (9) implies a rank condition of $Z_0$. In fact, since $P > 0$, then rank$(H(x)P) \leq \text{rank}(H(x))$. Based on the assumptions on $Z(x)$ and $\hat{Z}(x)$, the rank of $H(x) \in \mathbb{R}^{N \times p}$ should satisfy $1 \leq \text{rank}(H(x)) \leq p$. This means that $Z_0 \hat{Y}(x)$ should also have the same rank between 1 and $p$. Hence, the rank condition needed for $Z_0$ is $\text{rank}(Z_0) \geq \text{rank}(H(x))$. Depending on $H(x)$, in many practical cases $Z_0$ must have full row rank in order to fulfill condition (9). These conditions on $Z_0$ imply that the number $T$ of sampling data must be sufficiently large, since $Z_0 \in \mathbb{R}^{N \times T}$. It is noted that, a large $T$ will increase the computational burden as it affects the size of the decision variable $Y(x)$. Designing experiments that enforce the desired conditions on $Z_0$ is beyond the scope of the article but preliminary results for nonlinear systems are given in [30].

B. Data-Driven Stabilization Without Bounds on the Input Matrix $B$

By defining $S := [B \ A]$ and $W_0(x) := [\hat{U}_0 \ W(x)]$, the chain of equalities in (7) has highlighted the identity
\[ X_1 - E\hat{U}_0(x) = SW_0(x). \]
We can expect then that the analysis carried out in the previous subsection for the representation $\dot{x} = (X_1 - E\hat{U}_0(x))Y(x)P^{-1}\hat{Z}(x)$ can be repeated for the representation
\[ \dot{x} = SW_0(x)Y(x)P^{-1}\hat{Z}(x) \]
and the same stability result can be established. In doing so, we obtain a few advantages compared to Theorem 1, including the relaxation of Assumption 3 on the unknown matrix $B$.

**Theorem 2:** For the polynomial system (1), under Assumptions 1 and 2, if there exist a positive definite matrix $P \in \mathbb{R}^{p \times p}$, polynomial matrix $Y(x) \in \mathbb{P}^{p \times p}$, $\epsilon_1(x) \in \Sigma$, and $\epsilon_2(x) \in \Sigma$, such that

$$
Z_0Y(x) = H(x)P,
$$

(16)

where

$$
T_D(x) = \epsilon_2(x)\frac{\partial \hat{Z}(x)}{\partial x}(X_1X_1^\top - R_D R_D^\top)\frac{\partial \hat{Z}(x)}{\partial x}
$$

(17)

with $\bar{W}_0 := [\bar{U}_0^\top \bar{Z}_0^\top]^\top$, then the state-feedback controller (11) renders the origin stable. Moreover, if $\epsilon_1(x) > 0$ for all $x \neq 0$, the origin is globally asymptotically stable.

**Proof:** First, standard calculations show that the derivative of the Lyapunov function $V(x) = \hat{Z}(x)^\top P^{-1} \hat{Z}(x)$ along the closed-loop system $\dot{x} = S \bar{W}_0(x)Y(x)P^{-1}\hat{Z}(x)$ is

$$
\dot{V}(x) = - \hat{Z}(x)^\top P^{-1} \left[ I_p \begin{bmatrix} I_p \& S^\top \frac{\partial \hat{Z}(x)}{\partial x} \end{bmatrix}^\top - \begin{bmatrix} 0_{p \times p} \& -Y(x)^\top W_0(x)^\top \\ -W_0(x)Y(x) \& 0_{(q+N) \times p} \end{bmatrix} \right] P^{-1} \hat{Z}(x).
$$

(19)

On the other hand, since we choose a $\hat{Z}(x)$ whose first $n$ components coincide with $x$, $\frac{\partial \hat{Z}(x)}{\partial x}$ has full column rank. Hence, the quadratic constraint in Assumption 2 can be equivalently written as

$$
\frac{\partial \hat{Z}(x)}{\partial x} D_0 \frac{\partial \hat{Z}(x)}{\partial x}^\top - \frac{\partial \hat{Z}(x)}{\partial x} R_D R_D^\top \frac{\partial \hat{Z}(x)}{\partial x} \preceq 0
$$

and then expressed as


$$
\begin{bmatrix}
I_p \\
D_0 \frac{\partial \hat{Z}(x)}{\partial x}^\top \\
-D_0 \frac{\partial \hat{Z}(x)}{\partial x} R_D R_D^\top \frac{\partial \hat{Z}(x)}{\partial x}^\top
\end{bmatrix} \preceq 0_{N \times T}
$$

(20)

where $D_0 = X_1 - S\bar{W}_0$ which follows from (4). Then, we can derive the following condition equivalent to (20):

$$
\begin{bmatrix}
I_p \\
S^\top \frac{\partial \hat{Z}(x)}{\partial x}^\top \\
\frac{\partial \hat{Z}(x)}{\partial x} (X_1X_1^\top - R_D R_D^\top) \frac{\partial \hat{Z}(x)}{\partial x}^\top - \frac{\partial \hat{Z}(x)}{\partial x} X_1 \bar{W}_0^\top \\
-W_0 X_1 \frac{\partial \hat{Z}(x)}{\partial x} \bar{W}_0 \bar{W}_0^\top
\end{bmatrix} \preceq 0.
$$

(22)

Under condition (17), it holds that

$$
\begin{bmatrix}
T_D(x) \\
-Y(x)^\top W_0(x)^\top - \epsilon_2(x)\frac{\partial \hat{Z}(x)}{\partial x} X_1 \bar{W}_0^\top
\end{bmatrix}^\top
$$

$$
\begin{bmatrix}
\epsilon_2(x) \bar{W}_0 \bar{W}_0^\top
\end{bmatrix}
$$

$$
\geq
$$

$$
\begin{bmatrix}
\epsilon_1(x)I_p \\
0_{p \times (q+N)} \\
0_{(q+N) \times p} & 0_{(q+N) \times (q+N)}
\end{bmatrix}.
$$

Recall the expression of $\dot{V}(x)$ (19) along the closed-loop system and the expression (22) of Assumption 2. Then, using the classic S-procedure [31] with a polynomial multiplier $\epsilon_2(x)$, it holds that for any $\epsilon_2(x) \geq 0 \forall x \in \mathbb{R}^n$

$$
\dot{V}(x) \leq - \hat{Z}(x)^\top P^{-1} \begin{bmatrix}
I_p \\
S^\top \frac{\partial \hat{Z}(x)}{\partial x}^\top \\
\frac{\partial \hat{Z}(x)}{\partial x}
\end{bmatrix}^\top
$$

$$
\begin{bmatrix}
T_D(x) \\
-Y(x)^\top W_0(x)^\top - \epsilon_2(x)\frac{\partial \hat{Z}(x)}{\partial x} X_1 \bar{W}_0^\top
\end{bmatrix}^\top
$$

$$
\begin{bmatrix}
\epsilon_2(x) \bar{W}_0 \bar{W}_0^\top
\end{bmatrix}
$$

$$
\leq
$$

$$
\begin{bmatrix}
I_p \& S^\top \frac{\partial \hat{Z}(x)}{\partial x} \& \frac{\partial \hat{Z}(x)}{\partial x}
\end{bmatrix}^\top P^{-1} \hat{Z}(x).
$$

(23)

Using this inequality and condition (17), we can conclude that

$$
\dot{V}(x) \leq -\epsilon_1(x) \hat{Z}(x)^\top P^{-1} \cdot P^{-1} \hat{Z}(x) \forall x \in \mathbb{R}^n
$$

and the thesis follows.

Theorems 1 and 2 use the same stabilizing approach but different data parameterizations of the closed-loop system. Comparing these two results, Theorem 2 is more advantageous in a few aspects. First, by pulling out the unknown dynamics $A$ and $B$ in one matrix $S$, Theorem 2 no longer requires Assumption 3. Second, the SOS condition (17) can be made more computationally efficient by a change of decision variable, as we discuss in the next subsection. Nonetheless, Theorem 1 is important because it provides insights on how to arrive at Theorem 2 while establishing connections with the robust stabilization results of [9].

**Remark 5 (A least-square-based design):** Identity (4) can be used to establish a variation of Theorem 1 that has a similar feature as Theorem 2 but is based on a system’s representation that uses a least-square estimate of the system’s matrices. By (4), we can adopt an estimate of the model $S$ that minimizes the Frobenius norm of $X_1 - S\bar{W}_0 = D_0$. This choice returns the least-square estimate $S_* := X_1\bar{W}_0$ of $S$, with $\bar{W}_0$ the pseudoinverse of $\bar{W}_0$, and entails an estimation error $S_* - S$. We note that the estimate $S_*$ can be used for a model-based control design in which the actual model $S$ is replaced by the estimate $S_*$, with the expectation that for smaller $S_* - S$, the result will be increasingly accurate. To show this, let us consider the case of a full-row rank matrix $\bar{W}_0$, so that $S_* - S$ is given by $D_0\bar{W}_0$. Then, we obtain the representation

$$
X_1 - E\tilde{U}_0(x) = S\bar{W}_0(x) = S_*\bar{W}_0(x) - D_0\bar{W}_0\bar{W}_0\bar{W}_0^\top.
$$

Based on this representation and on the same arguments of the proof of Theorem 1, one realizes that, under Assumption 2 and without Assumption 3, an analogous of Theorem 1 holds provided that in condition (10) the matrices $X_1, \tilde{U}_0(x)$ are replaced by $S_*\bar{W}_0(x), \bar{W}_0\bar{W}_0\bar{W}_0^\top$, respectively.

**C. Computationally More Efficient Stabilization Conditions**

Recalling that $F(x) = U_0 Y(x) P^{-1}$, we can obtain $F(x) P = U_0 Y(x)$. Defining $K(x) := F(x) P$, we can write the term $W_0(x)Y(x)$ in (19) as
\[
W_0(x)Y(x) = \begin{bmatrix} W(x) & U_0 \end{bmatrix} Y(x) = \begin{bmatrix} W(x)F(x) & P \\ H(x) & P \end{bmatrix} = \begin{bmatrix} W(x)K(x) & P \\ H(x) & P \end{bmatrix}
\]

which suggests to adopt \( K(x) \) as a new decision variable, modify condition (17) and obtain the following result.

**Corollary 1:** For the polynomial system (1), under Assumptions 1 and 2, if there exist a positive definite matrix \( P \in \mathbb{R}^{n \times n} \), polynomial matrix \( K(x) \in \mathbb{P}^{m \times P} \), \( \epsilon_1(x) \in \Sigma \), and \( \epsilon_2(x) \in \Sigma \), such that

\[
\begin{bmatrix} \Upsilon_D(x) - \epsilon_1(x)I_p & -W(x)K(x) & \epsilon_2(x) \end{bmatrix} \begin{bmatrix} W(x)K(x) \\ H(x)P \end{bmatrix} + \epsilon_2(x)\frac{\partial \hat{z}(x)}{\partial x}X \bar{W}_0 = 0 \\
\epsilon_2(x)\bar{W}_0 \bar{W}_0^\top \end{bmatrix} \in \Sigma^{P+q+1}_0 
\]

renders the origin stable. Moreover, if \( \epsilon_1(x) > 0 \) for all \( x \neq 0 \), the origin is globally asymptotically stable.

**Proof:** Under the control law (25), the closed-loop system can be expressed as

\[
\dot{x} = S \begin{bmatrix} W(x)K(x)P^{-1} \\ H(x) \end{bmatrix} \hat{z}(x).
\]

Then, the time derivative of the Lyapunov function \( V(x) = \hat{z}(x)^\top P^{-1} \hat{z}(x) \) is

\[
\dot{V}(x) = \hat{z}(x)^\top P^{-1} \begin{bmatrix} \frac{\partial \hat{z}(x)}{\partial x}S & W(x)K(x) \\ H(x)P \end{bmatrix} + \begin{bmatrix} W(x)K(x) & P \\ H(x) & P \end{bmatrix} \hat{z}(x) = -\hat{z}(x)^\top P^{-1} \begin{bmatrix} \frac{\partial \hat{z}(x)}{\partial x}S & I_p \\ S^\top & I_p \end{bmatrix} \hat{z}(x).
\]

Using the expression (22) of Assumption 2 and the condition (24), we can conclude that

\[
\dot{V}(x) \leq -\epsilon_1(x)\hat{z}(x)^\top P^{-1} \hat{z}(x) \quad \forall x \in \mathbb{R}^n.
\]

The thesis follows. \( \square \)

In Theorem 2, the size of decision variable \( Y(x) \) is dependent on the number of sampled data \( T \). For systems having higher order and degree, \( T \) can be large which will result in heavy computational burden in the SOS programming. Hence, by changing the decision variable \( Y(x) \) used in Theorem 2, the SOS condition (17) becomes (24), which is independent of \( T \), and the controller design is more computationally efficient.

**Remark 6 (An SOS relaxation of a pointwise necessary and sufficient condition):** Observe that investigating the stabilization problem via the Lyapunov function \( V(x) = \hat{z}(x)^\top P^{-1} \hat{z}(x) \) and the feedback controller \( u = K(x)P^{-1} \hat{z}(x) \) (cf. [16]), the problem becomes one of finding the matrix \( P \succ 0 \) and the matrix \( K(x) \), such that for all \( x \in \mathbb{R}^n \setminus \{0\} \), the matrix in the proof of Corollary 1 satisfies

\[
\begin{bmatrix} I_p \\ S^\top \frac{\partial \hat{z}(x)}{\partial x} \end{bmatrix}^\top \begin{bmatrix} 0_{p \times p} & -K(x)^\top W(x) & -PH(x)^\top \\ -W(x)K(x) & 0_{q \times q} & 0_{q \times N} \\ -H(x)P & 0_{N \times q} & 0_{N \times N} \end{bmatrix} \begin{bmatrix} I_p \\ S^\top \frac{\partial \hat{z}(x)}{\partial x} \end{bmatrix} \succ 0
\]

for all \( S \), such that (22) holds. For each fixed \( x \in \mathbb{R}^n \setminus \{0\} \), one can pointwise apply the matrix S-lemma of [16] to this formulation. Under the technical condition that \( \hat{z}(x) = x \), and for each \( x \in \mathbb{R}^n \setminus \{0\} \), there exists a matrix \( S \) for which (22) with \( S \) replaced by \( \hat{S} \) holds, the stabilization problem is solvable if and only if there exist a matrix \( P \succ 0 \) and a matrix \( K(x) \), such that for all \( x \in \mathbb{R}^n \setminus \{0\} \) there exist \( \epsilon_1(x) > 0 \) and \( \epsilon_2(x) \geq 0 \) for which the matrix (24) is positive semidefinite. Having this condition satisfied leads to an infinite dimensional problem. A natural way to overcome this obstacle is to relax the positive semidefiniteness condition by requiring \( K(x) \), \( \epsilon_1(x) \), \( \epsilon_2(x) \) to be polynomial matrices and the resulting polynomial matrix (24) to be an SOS matrix, which is the condition in Corollary 1. Among other tools, Corollary 1 is obtained by exploiting the condition (22) and S-procedure arguments, analogous to those that in the case of linear systems were considered in [15] and [16].

**Remark 7 (Another convex relaxation):** The stabilization problem of polynomial systems from data has been tackled in [12] using density functions and polyhedral constraints on the uncertainties, which leads to quadratically constrained quadratic program whose convex relaxation is solved via moments-based techniques. Stemming from the results in [9] and [11], our approach uses Lyapunov second stability theorem and quadratic constraints, leading to SOS programs whose solutions directly provide stabilizing controllers and Lyapunov functions.

**Remark 8 (Noisy state and input data):** Noise/disturbance affecting state measurements/inputs does not hinder the analysis. In such a case, instead of the noiseless matrices of data \( Z_0 \) and \( \bar{U}_0 \), one should consider the noisy matrices \( \tilde{Z}_0 = Z_0 + D_Z \) and \( \tilde{U}_0 = \bar{U}_0 + D_U \), where \( D_Z \), \( D_U \) are unknown matrices of noise/disturbance samples. Arguments similar to those used in the proof of [9, Corollary 1], which are not reported here due to space constraints, allow one to derive the analogous versions of Theorems 1 and 2 and Corollary 1 under the additional assumption that

\[
\begin{bmatrix} D_U \\ D_Z \end{bmatrix} \begin{bmatrix} D_U \\ D_Z \end{bmatrix}^\top \leq \tilde{\gamma} \begin{bmatrix} \tilde{U}_0 \\ \tilde{Z}_0 \end{bmatrix} \begin{bmatrix} \tilde{U}_0 \\ \tilde{Z}_0 \end{bmatrix}^\top
\]

for some \( \tilde{\gamma} \in (0, 1/2) \).

**IV. EXAMPLE**

In this section, we apply the data-driven control method to the stabilization of the Van der Pol oscillator, which is a popular benchmark to test data-driven control results. The simulations are conducted using the SOSTOOLS in MATLAB.

Consider the controlled Van der Pol oscillator

\[
\begin{align*}
\dot{x}_1 &= x_2, \\
\dot{x}_2 &= -x_1 + (1 - x_1^2)x_2 + u.
\end{align*}
\]
Let $Z(x)$ be the power vector that contains all monomials of $x$ having degrees 1 to 3. Choose $Z(x) = [x_1 \ x_2]^T$, then

$$H(x) = \begin{bmatrix} 1 & x_2 & x_1 & 0 & x_1 x_2 & 0 & x_1^2 & 0 \\ 0 & 1 & 0 & 0 & x_2 & 0 & x_1 x_2 & 0 & x_2^2 \end{bmatrix}.$$  

Run an experiment with initial condition $x_0 = [-0.1 \ 0.1]^T$ and input $u = \sin t$ from $t = 0$ to $t = 10$. The sampling period is 0.5.

The data $X_1$ is corrupted by a noise $D_0 = 0.05 X_1$. We set $T = 12$ and $R_D R_D^T = 0.1 X_1 X_1^T$. SOS programs are then formulated to search for $P, \epsilon_2$, and the coefficients of $\epsilon_1(x)$ and $Y(x)$ with both $\epsilon_1(x)$ and $Y(x)$ having degree 2.

First, we apply the special case of Theorem 1, where the input vector field is independent of $x$ (Remark 3). The SOSTOOLS obtains the solution

$$P = \begin{bmatrix} 8.67 \times 10^{-7} & -2.199 \times 10^{-7} \\ -2.199 \times 10^{-7} & 1.925 \times 10^{-7} \end{bmatrix},$$

$$\epsilon_1(x) = x_1 (5.293 \times 10^{-5} x_1 + 1.627 \times 10^{-6} x_2) + x_2 (1.627 \times 10^{-6} x_1 + 5.39 \times 10^{-5} x_2),$$

$$\epsilon_2 = 5.71 \times 10^{-7}.$$

The controller is calculated as

$$u = -x_1 (9.2 x_1^2 + 2.2 x_1 x_2 + x_1 + 8.1 x_2^2 + 0.24 x_2 + 9.7)$$
$$-x_2 (38 x_1^2 + 6.1 x_1 x_2 + 5.5 x_1 + 33 x_2^2 + 2.3 x_2 + 29).$$

Using the design conditions in Theorem 2, the solution given by SOSTOOLS is

$$P = \begin{bmatrix} 1.692 \times 10^{-6} & 1.311 \times 10^{-7} \\ 1.311 \times 10^{-7} & 1.104 \times 10^{-6} \end{bmatrix},$$

$$\epsilon_1(x) = x_1 (9.165 \times 10^{-6} x_1 + 6.389 \times 10^{-10} x_2) + x_2 (6.389 \times 10^{-10} x_1 + 9.258 \times 10^{-6} x_2),$$

$$\epsilon_2 = 1.061 \times 10^{-6}.$$

The designed controller is

$$u = -x_1 (3.7 \times 10^{-7} x_1^2 + 5.1 \times 10^{-5} x_1 x_2 - 0.021 x_1 + 2.2 \times 10^{-4} x_2^2 - 0.092 x_2 + 0.94)$$
$$-x_2 (-1 \times 10^{-4} x_1^2 - 5.3 \times 10^{-3} x_1 x_2 - 3.1 \times 10^{-3} x_1 + 5.5 \times 10^{-4} x_2^2 - 0.064 x_2 + 1.2).$$

Alternatively, we can set $K(x)$ having degree 2 as a decision variable and utilize Corollary 1 to design the data-driven controller. The solution to the SOS program is

$$P = \begin{bmatrix} 6.332 \times 10^{-7} & -5.787 \times 10^{-8} \\ -5.787 \times 10^{-8} & 6.934 \times 10^{-7} \end{bmatrix},$$

$$\epsilon_1(x) = x_1 (5.125 \times 10^{-6} x_1 + 1.366 \times 10^{-10} x_2).$$
$$\epsilon_2 = 7.184 \times 10^{-7}.$$  

The controller is

$$u = -x_1 (1.9 \times 10^{-4} x_1^2 - 8.9 \times 10^{-5} x_1 x_2 - 0.026 x_2 + 4.2 \times 10^{-4} x_2^2 - 0.091 x_2 + 1.5)$$

$$- x_2 (4.8 \times 10^{-5} x_1^2 - 1.1 \times 10^{-4} x_1 x_2 - 3.6 \times 10^{-3} x_2 - 2.4 \times 10^{-4} x_2^2 + 0.072 x_2 + 1.4).$$

The phase portraits of the closed-loop systems under the designed controllers are illustrated in Figs. 1 to 3, respectively. The figures show that, designed using the same dataset, the controllers stabilize system (26) at the origin with different transient performances. The computational time needed for formulating and solving the SOS program and then obtaining the control gain $F(x)$ is 146.5957 s for Theorem 1, 151.3056 s for Theorem 2, and 10.6662 s for Corollary 1. This verifies that Corollary 1 is more computationally efficient than Theorems 1 and 2.

V. CONCLUSION

We have shown how to synthesize controllers and Lyapunov functions for unknown nonlinear polynomial systems starting from noisy data and using Lyapunov second theorem. We do not assume the unknown noise to have any specific form as long as it has a known quadratic bound over the experiment. The state-dependent stabilizing gain is solved via SOS programs that are computationally tractable. Interestingly, the efficiency of the stabilization design can be improved by changing the data parameterization of the closed-loop system even when the same design method is utilized.

Nonlinear data-driven stabilization is a fundamental and important problem that lays the foundation for our ongoing works on nonlinear polynomial systems such as local control with guaranteed domain of attraction and optimal control with quadratic costs. Another interesting topic, is looking into the computational aspects of SOS programming and further improving the efficiency of the data-driven designs. Our results can play an important role in learning control policies for those manifold applications, where polynomial systems and SOS optimization have found wide use.

REFERENCES

[1] M. Campi and S. Savaresi, “Direct nonlinear control design: The virtual reference feedback tuning (VRFT) approach,” IEEE Trans. Autom. Control, vol. 51, no. 1, pp. 14–27, Jan. 2006.

[2] H. Hjalmarsson, M. Gevers, S. Gunnarsson, and O. Lequin, “Iterative feedback tuning: Theory and applications,” IEEE Control Syst. Mag., vol. 18, no. 4, pp. 26–41, Aug. 1998.

[3] M. Tanasovíc, L. Fagiano, C. Novara, and M. Morari, “Data-driven control of nonlinear systems: An on-line direct approach,” Automatica, vol. 75, pp. 1–10, 2017.

[4] M. Flies and C. Join, “Model-free control and intelligent PID controllers: Towards a possible trivialization of nonlinear control?,” IFAC Proc. Volumes, vol. 42, no. 10, pp. 1531–1535, 2009.

[5] P. Tabuada, W. L. Ma, J. Grizzle, and A. D. Ames, “Data-driven control for feedback linearizable single-input systems,” in Proc. 56th IEEE Conf. Decis. Control, Melbourne, VIC, Australia, 2017, pp. 6265–6270.

[6] J. M. Lee and J. H. Lee, “Approximate dynamic programming-based approaches for input-output data-driven control of nonlinear processes,” Automatica, vol. 41, no. 7, pp. 1281–1288, 2005.

[7] V. G. Lopez and F. L. Lewis, “Dynamic multiobjective control for continuous-time systems using reinforcement learning,” IEEE Trans. Autom. Control, vol. 64, no. 7, pp. 2869–2874, Jul. 2019.

[8] J. Willems, P. Rapisarda, I. Markovsky, and B. De Moor, “A note on persistency of excitation,” Syst. Control Lett., vol. 54, no. 4, pp. 325–329, 2005.

[9] C. De Persis and P. Tesi, “Formulas for data-driven control: Stabilization, optimality, and robustness,” IEEE Trans. Autom. Control, vol. 65, no. 3, pp. 909–924, Mar. 2020.

[10] A. Bisoffi, C. De Persis, and P. Tesi, “Data-based stabilization of unknown bilinear systems with guaranteed basin of attraction,” Syst. Control Lett., vol. 145, 2020, Art no. 104788.

[11] M. Guo, C. De Persis, and P. Tesi, “Learning control for polynomial systems using sum of squares relaxations,” in Proc. 59th IEEE Conf. Decis. Control, 2020, pp. 2436–2441.

[12] T. Dai and M. Sznaier, “A semi-algebraic optimization approach to data-driven control of continuous-time nonlinear systems,” IEEE Control Syst. Lett., vol. 5, no. 2, pp. 487–492, Apr. 2021.

[13] C. Novara, S. Formentin, S. Savaresi, and M. Milanese, “Data-driven design of two degree-of-freedom nonlinear controllers: The D2-IBC approach,” Automatica, vol. 72, pp. 19–27, 2016.

[14] C. De Persis and P. Tesi, “Low-complexity learning of linear quadratic regulators from noisy data,” Automatica, vol. 128, 2021, Art no. 109548.

[15] J. Berberich, A. Koch, C. W. Scherer, and F. Allgöwer, “Robust data-driven state-feedback design,” in Proc. Amer. Control Conf., Denver, CO, USA, 2020, pp. 1532–1538.

[16] H. J. van Waarde, M. K. Camlibel, and M.Mesbah, “From noisy data to feedback controllers: Non-conservative design via a matrix S-lemma,” IEEE Trans. Autom. Control, to be published. doi: 10.1109/TAC.2020.304777.

[17] T. Dai and M. Sznaier, “A moments based approach to designing MIMO data driven controllers for switched systems,” in Proc. IEEE Conf. Decis. Control, 2019, pp. 5652–5657.

[18] S. I. Chernyshenko, P. Goulart, D. Huang, and A. Papachristodoulou, “Polynomial sum of squares in fluid dynamics: A review with a look ahead,” Philos. Trans. Roy. Soc. A: Math., Phys. Eng. Sci., vol. 372, no. 2020, 2014, Art no. 20130350.

[19] A. Majumdar, A. A. Ahmadi, and R. Tedrake, “Control design along trajectories with sums of squares programming,” in Proc. IEEE Int. Conf. Robot. Automat., Karlsruhe, Germany, 2013, pp. 4054–4061.

[20] P. A. Parrilo, “Structured semidefinite programs and semialgebraic geometry methods in robustness and optimization,” Ph.D. dissertation, Dept. Elect. Eng., California Inst. Technol., Pasadena, California, 2000.

[21] D. Henrion and A. Garulli, Positive Polynomials in Control, vol. 312. Berlin, Germany: Springer, 2005.

[22] G. Chesi and D. Henrion, “Guest editorial: Special issue on positive polynomials in control,” IEEE Trans. Autom. Control, vol. 54, no. 5, pp. 935–936, May 2009.

[23] G. Chesi, “LMI techniques for optimization over polynomials in control: A survey,” IEEE Trans. Autom. Control, vol. 55, no. 11, pp. 2500–2510, Nov. 2010.

[24] E. Hancock and A. Papachristodoulou, “Generalised absolute stability and sum of squares,” Automatica, vol. 49, no. 4, pp. 960–967, 2013.

[25] G. Valmorica and J. Anderson, “Region of attraction estimation using invariant sets and rational Lyapunov functions,” Automatica, vol. 75, pp. 37–45, 2017.

[26] A. Ahmadi and A. Majumdar, “DSOS and SDSOS optimization: More tractable alternatives to sum of squares and semidefinite optimization,” SIAM J. Appl. Algebra Geometry, vol. 3, no. 2, pp. 193–230, 2019.

[27] S. Prajna, A. Papachristodoulou, and F. Wu, “Nonlinear control synthesis by sum of squares optimization: A Lyapunov-based approach,” in Proc. 5th Asian Control Conf., Melbourne, VIC, Australia, 2004, pp. 157–165.

[28] M. Wainwright, High-Dimensional Statistics: A Non-Asymptotic Viewpoint. New York, NY, USA: Cambridge Univ. Press, 2019.

[29] A. Papachristodoulou, J. Anderson, G. Valmorica, S. Prajna, P. Seiler, and P. Parrilo, “SOSTOOLS sum of squares optimization toolbox for MATLAB user’s guide,” 2018, arXiv:1310.4716.

[30] C. De Persis and P. Tesi, “Designing experiments for data-driven control of nonlinear systems,” in Proc. 24th Int. Symp. Math. Theory Netw. Syst., Cambridge, U.K., IFAC PapersOnLine 54-9, 2021, pp. 285–290.

[31] V. A. Yakubovich, G. A. Leonov, and A. K. Gelig, Stability of Stationary Sets in Control Systems With Discontinuous Nonlinearities, vol. 14. Singapore: World Scientific, 2004.