Controlling Chaotic Dynamics with an NGRC-MDS Digital Twin: Minimal-Impact Switching and Stabilization in the Lorenz System

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***Abstract*—We present a data-driven approach to controlling chaotic dynamics using an NGRC-MDS digital twin constructed from partial observations. The Lorenz system is considered with only a single state variable available for measurement and control. The digital twin predicts the system response to candidate pulse inputs and is used to select their timing, amplitude, and duration while minimizing control effort. Two tasks are studied: stabilization on a prescribed lobe of the Lorenz attractor and controlled switching between its lobes. In both cases, the NGRC-MDS digital twin enables sparse control and achieves performance comparable to a model-based reference that uses the true Lorenz equations for prediction. The results demonstrate that a data-driven digital twin trained from a single observable can provide sufficient predictive information for minimal-impact control of chaotic dynamics.**

***Index Terms*—digital twin, chaos control, reservoir computing, NGRC-MDS, Lorenz system, partial observability**

I. Introduction

The concept of the digital twin was originally introduced to represent complex technical and biological systems. Its evolution, definitions, and scope are systematically reviewed in [1], while more recent developments, including links to complex systems theory and machine learning, are discussed in [2]. At the same time, artificial intelligence is increasingly being deployed in critical domains, including clinical diagnostics [3], and is becoming an integral component of digital twins themselves, including human digital twins [4], [5].

Recent advances in data-driven modeling have substantially lowered the technological barrier to constructing digital twins. In many cases, a functional representation of a system can now be learned directly from observational data, without requiring an explicit specification of the governing equations. This paradigm is also gaining traction in biomedical applications [6]. However, the increasing accessibility of digital-twin technologies does not make the underlying problem less demanding. Rather, it shifts the central question from whether a digital twin can be constructed to what it can be reliably used for and under what conditions its predictions and decisions remain valid.

Among the possible applications of digital twins, control is particularly demanding because the twin becomes part of the closed-loop system, so that modeling errors can directly affect control performance and stability. This issue is especially important when the governing dynamics are unknown or cannot be reliably identified from the available measurements. In such settings, data-driven approaches, in which a model suitable for control is constructed directly from observed system behavior, are of particular interest.

Reservoir computing has demonstrated the ability to reconstruct and predict system dynamics from incomplete observations in a variety of settings, including network models [7], systems with hidden variables [8], [9], and real neurophysiological data [10]. Its predictive performance depends strongly on the organization of the reservoir [11] and may also vary substantially over time; in stochastic systems, for example, predictability can exhibit an intermittent character [12]. When a measurement-driven digital twin is continuously driven by observations of the original system, their interaction can be viewed within a master–slave framework. Synchronization regimes in coupled chaotic systems have been studied extensively [13], [14], providing a natural conceptual framework for characterizing when and to what extent the dynamics of the twin remain consistent with those of the original system.

A particularly computationally efficient approach is next-generation reservoir computing (NGRC), which is based on nonlinear vector autoregression [15]. NGRC can be trained on relatively small datasets and is suitable for real-time operation, including applications to experimental signals [16]. Its exten-

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sion, NGRC-MDS, incorporates multiscale delay selection to reconstruct hidden variables from partial observations [17]. Importantly, the feasibility of embedding an NGRC-based model into the control loop as a digital twin of a chaotic system has already been demonstrated [18].

In this study, we investigate the use of an NGRC-MDS-based digital twin for controlling chaotic dynamics with minimal control intervention. The Lorenz system serves as a model system under partial observability, with only one state variable available for measurement. Control is implemented through a step input applied to the observed variable, while the digital twin is used to determine the amplitude, duration, and timing of the intervention. We consider two control tasks: switching the trajectory between the two lobes of the Lorenz attractor and stabilizing it within a single lobe.

II. Methods

A. System and Control Input Class

We consider the Lorenz system with an additive input $u(t)$ applied to the y-equation:

$$\begin{aligned} \dot{x} &= \sigma(y - x), \\ \dot{y} &= x(\rho - z) - y + u(t), \\ \dot{z} &= xy - \beta z, \end{aligned} \tag{1}$$

where $\sigma = 10$, $\rho = 28$, and $\beta = 8/3$. The system is integrated using the fourth-order Runge–Kutta method with a time step of $\Delta t = 0.01$.

The system is assumed to be partially observable: only the scalar variable $y(t)$ is available for measurement, whereas $x(t)$ and $z(t)$ remain unobserved and are not directly available to the control algorithm.

The input $u(t)$ is a train of non-overlapping rectangular pulses,

$$u(t) = \sum_i a_i \left[H(t - t_i) - H(t - t_i - \tau_i \Delta t) \right], \tag{2}$$

where $H(\cdot)$ denotes the Heaviside step function, a_i is the pulse amplitude bounded by $|a_i| \le a_{\max} = 5$, t_i is the onset time, and $\tau_i \in \mathbb{N}$ is the pulse duration expressed in integration steps. Thus, the corresponding duration in time units is $\tau_i \Delta t$. The pulses are constrained to be non-overlapping,

$$t_{i+1} \ge t_i + \tau_i \Delta t, \tag{3}$$

which ensures that $|u(t)| \le a_{\max}$ at all times.

The control effort is quantified by the L^1 norm of the input,

$$C = \int_0^T |u(t)|\, dt = \sum_i |a_i|\, \tau_i \Delta t. \tag{4}$$

This criterion jointly penalizes the amplitude and duration of the applied pulses.

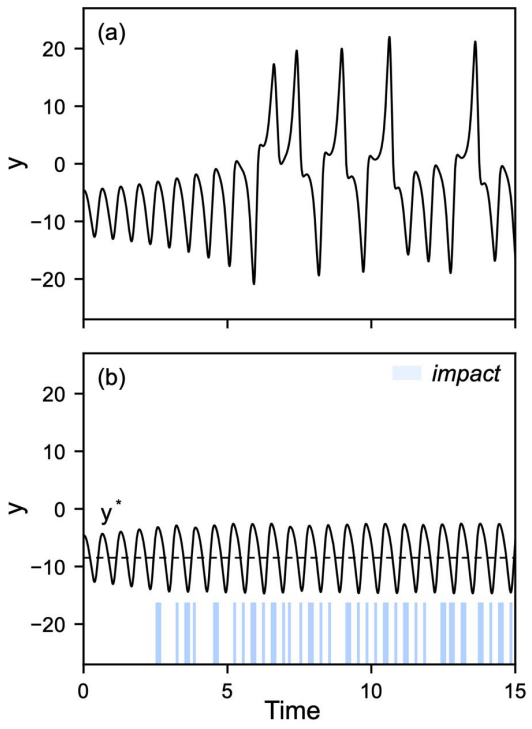


Fig. 1. Stabilization of the Lorenz system on the target lobe using the NGRC-MDS digital twin. The controlled trajectory remains on the target lobe through sparse pulse inputs, while the uncontrolled trajectory switches between the two lobes.

B. Training Data

The digital twin is trained from a single continuous trajectory of 500 time units (50 000 samples). Only the measured variable $y(t)$ and the corresponding input $u(t)$ are provided to the model; the unobserved variables $x(t)$ and $z(t)$ are not used for training or control.

The training trajectory contains three segments. The first 100 time units correspond to autonomous dynamics ($u = 0$). During the next 200 time units, the system is driven by random step inputs with amplitudes uniformly sampled from $[-5, 5]$ and durations between 0.5 and 2 time units. The final 200 time units contain sparse rectangular pulses with absolute amplitudes uniformly sampled from $[0.2, 5]$, random signs, and durations of 5–20 integration steps. Pulse durations of 25–45 steps are intentionally excluded from the training data to provide an out-of-distribution test range.

C. Control Objective

Since only $y(t)$ is observed, the current lobe is determined from the smoothed signal

$$\tilde{y}(t) = \frac{1}{T_s} \int_{t - T_s}^{t} y(\xi)\, d\xi, \qquad T_s = 0.2, \tag{5}$$

with $s(t) = \operatorname{sign} \tilde{y}(t) \in \{-1, +1\}$. The target lobe is specified by $r(t) \in \{-1, +1\}$.

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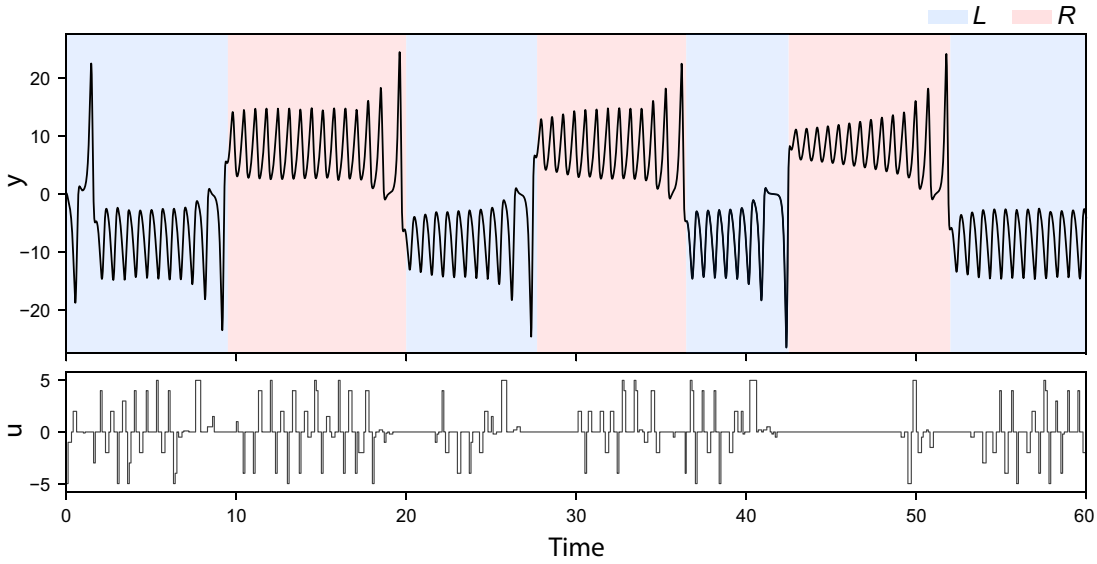


Fig. 2. Switching between the two lobes of the Lorenz attractor using the NGRC-MDS digital twin. The controller follows the prescribed target sequence using pulse inputs to initiate transitions and stabilize the trajectory on the target lobe.

The control goal is to follow the target lobe with minimal control effort. The total time spent on the wrong lobe is

$$Q = \frac{1}{2}\int_0^T |s(t) - r(t)|\, dt, \tag{6}$$

while the control effort C is defined in (4). Thus, Q penalizes both delayed switching and departures from the target lobe.

Two scenarios are considered. For stabilization, $r(t)$ is fixed. For switching, $r(t)$ alternates between the two lobes with random dwell times of 6–12 time units.

Since Q depends on the future trajectory, control decisions are based on predictions of the digital twin. Every 0.1 time units, candidate rectangular pulses are tested over a prediction horizon of $H = 3$ time units, with pulse onset times sampled at 0.1-unit intervals up to 0.5 time units ahead. Their amplitudes are $|a| \in \{0.1, 0.2, 0.5, 1, 1.5, 2, 3, 4, 5\}$ and durations are $\tau \in \{10, 20, 30, 40, 50, 70, 100\}$ integration steps. Both signs and the null action $u = 0$ are considered.

For each candidate, the predicted mismatch time Q_H is evaluated. Among candidates with Q_H within $\varepsilon = 0.15$ time units of the minimum, the one with the lowest control effort is selected and applied in full.

D. NGRC-MDS Digital Twin

The digital twin is constructed using the NGRC-MDS method [17] with parameters $p = 3$, $\rho = 0.1$, $n = 4$, and two retained modes. The model takes the measured variable $y(t)$ and the control input $u(t)$ as inputs and predicts the next value $y(t + \Delta t)$. During training, Gaussian noise is added only to the inputs, while the target values remain those of the unperturbed trajectory. This encourages the model to return toward the original trajectory after small perturbations and improves the stability of recursive prediction. Multi-step forecasts are obtained recursively using the predicted values together with the prescribed control input.

III. Results

The controller was evaluated in the stabilization and switching scenarios. In both cases, control was planned using predictions of the digital twin. For comparison, the same planner was also run using the true Lorenz equations as the predictor, providing a model-based reference. Thus, the two cases differ only in the predictor used for control planning.

In the stabilization scenario, the uncontrolled trajectory switches irregularly between the two lobes, whereas the controlled trajectory remains on the target lobe, Fig. 1. Control is applied intermittently, with long intervals of zero input between pulses.

In the switching scenario, the controller follows the prescribed target sequence, combining stabilization on each lobe with controlled transitions between them, Fig. 2. Switching generally requires stronger control than stabilization, while the trajectory between transitions is maintained by sparse pulses.

The digital twin and the model-based reference show comparable performance in both scenarios. Similar mismatch times, switching latencies, and control effort indicate that the NGRC-MDS digital twin provides sufficient predictive accuracy for the considered control tasks using only the scalar observation $y(t)$.

IV. Conclusion

We demonstrated that an NGRC-MDS digital twin constructed from a single observed variable can be used for control of chaotic dynamics under partial observability. Using the Lorenz system, we considered two tasks: stabilization on a prescribed attractor lobe and controlled switching between the lobes. In both cases, the digital twin was used to predict the response to candidate pulse inputs and select sparse interventions with low control effort.

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The resulting control performance was comparable to a model-based reference using the true Lorenz equations for prediction. This shows that explicit knowledge of the full system state and governing equations is not required for the considered control tasks. These results support the use of data-driven digital twins as predictive components of control systems when only limited observations of the underlying dynamics are available.

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