## Letter

# Online Consensus Control of Nonlinear Affine Systems From Disturbed Data

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Dear Editor,

In this letter, we introduce a novel online distributed data-driven robust control approach for learning controllers of unknown nonlinear multi-agent systems (MASs) using state-dependent representations. The proposed method is formulated as an online optimization problem, based on finite-length disturbed data and expressed in terms of linear matrix inequalities (LMIs), whose solution at each time step yields a stabilizing controller for each agent. The feasibility of the optimization problem ensures the stability of the closed-loop system.

In recent years, the control community has shown significant interest in the distributed control of MASs, driven by their diverse range of applications in different fields such as physics, social sciences, biology, and engineering, as highlighted in [1]–[5]. Direct data-driven control, inspired by the Willems *et al*. [6] fundamental lemma, has gained recurring attention. This approach offers advantages over model-based control, such as avoiding challenges related to model inaccuracies and high computational costs of system identification. As this field has rapidly and continuously developed, data-driven techniques for controlling different systems, albeit complex and nonlinear, have become relatively mature ranging from explicit state feedback control in [7] to model-predictive control in [8].

However, one of the main challenges in data-driven control is building a data-based system representation from disturbed data, as disturbances can undermine the condition of persistency of excitation required by the fundamental lemma. The S-lemma was introduced in [9] as a general framework for handling disturbances and has been widely used in e.g., [10]–[12]. Nonetheless, they assumed that disturbances are only present in the offline data collection process but not during online operation. Recent work [13] has proposed data-driven robust control strategies that consider disturbed data during both learning and closed-loop operation, while ensuring stability and performance. However, these strategies are mainly limited to linear systems, and deriving solutions for nonlinear systems remains challenging. On the other hand, data-driven techniques based on sum-of-squares (SoS) optimization have been developed for polynomial systems [14], but they are computationally expensive. Moreover, while previous research has focused on centralized settings for single systems, the distributed setting for MASs subject to both offline and online disturbances is particularly unexplored.

To address these challenges, we propose a novel online distributed data-driven robust control method for the consensus problem of unknown nonlinear MASs. Our method builds upon the combination of the matrix S-lemma in [9] and the state-dependent representations in [15], to synthesize a state-feedback consensus control protocol by solving an online data-based optimization problem, in the form of LMIs, for each agent at each time step, while simultaneously providing stability guarantees. The main contributions of this work lie in threefold. 1) The proposed method is not limited to rational nonlinearities and simplifies the computational complexity by establishing low-dimensional LMIs, making it comparable to the linear case; 2) An online distributed method for designing the controller for each agent using disturbed data is advocated, which possesses a significantly improved robustness; and 3) Under standard conditions on both offline and online disturbances, uniformly ultimately bounded (UUB) of the closed-loop system is established for the proposed data-driven robust controller.

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**Problem statement:** Consider a discrete-time nonlinear affine MAS with $N$ identical agents indexed by $1,2,\ldots,N$, interacting via a communication network described by a topology $\mathcal{G}$. For $t\in\mathbb{N}$ and $i=1,2,\ldots,N$, the dynamics of each agent is described by

$$x_i(t+1)=\mathbf{f}(x_i(t))+\mathbf{g}(x_i(t))u_i(t)+w_i(t) \tag{1}$$

where $x_i(t)\in\mathbb{R}^n$ and $u_i(t)\in\mathbb{R}^m$ are the state and control input of agent $i$, respectively. $\mathbf{f}\colon\mathbb{R}^n\mapsto\mathbb{R}^n$ and $\mathbf{g}\colon\mathbb{R}^n\mapsto\mathbb{R}^{n\times m}$ are vector fields. The functions of $\mathbf{f}$ and $\mathbf{g}$ are unknown. $w_i(t)\in\mathbb{R}^n$ is the external disturbance obeying $w_i(t)\in\mathcal{L}_2[0,\infty]$. Before proceeding, two assumptions are presented.

Assumption 1: The graph $\mathcal{G}$ is undirected and connected.

Assumption 2: There exist known basis functions $\mathbf{F}\in\mathbb{R}^{n_f}$ and $\mathbf{G}\in\mathbb{R}^{n_g\times m}$ that span $\mathbf{f}$ and $\mathbf{g}$, respectively.

Assumption 2 means the use of a function library to describe the dynamics of the MAS, which is commonly valid in practical scenarios like mechanical and electrical systems, where the dynamics can be derived from first principles, but the exact systems parameters are unknown. Under Assumption 2, (1) can be represented as

$$x_i(t+1)=\Lambda\mathbf{F}(x_i(t))+\Theta\mathbf{G}(x_i(t))u_i(t)+w_i(t) \tag{2}$$

where $\Lambda\in\mathbb{R}^{n\times n_f}$, $\Theta\in\mathbb{R}^{n\times n_g}$ are unknown coefficients of $\mathbf{f}$, $\mathbf{g}$ with the corresponding size $n_f$, $n_g$ of basis functions.

We commence by defining the combined measurement variable, including the relative state information between neighbouring agents and the absolute states of a portion of agents as follows:

$$z_i(t)=\sum_{j=1}^{N}\Big[a_{ij}(x_i(t)-x_j(t))+d_ix_i(t)\Big] \tag{3}$$

where $t\in\mathbb{N}$, $a_{ij}$ denotes the $ij$th entry of the adjacency matrix $\mathcal{A}$, and $d_i$ are constant scalars satisfying $d_i>0$ for $i=1,2,\ldots,q$ and $d_i=0$ for $i=q+1,2,\ldots,N$ with $q=\{1,2,\ldots,q\}$.

Then, the following distributed state-feedback consensus control law is adopted for the nonlinear MAS (1):

$$u_i(t)=K_i(t)z_i(t) \tag{4}$$

where $K_i(t)\in\mathbb{R}^{m\times n}$ is the feedback gain matrix of agent $i$ to be designed at each time step. To this end, the closed-loop network dynamics resulting from (4) for (2) can be described as

$$x_i(t+1)\ =\Lambda\mathbf{F}(x_i(t))+\Theta\mathbf{G}(x_i(t))K_i(t)z_i(t)+w_i(t). \tag{5}$$

Our goal is to design a state-feedback consensus control protocol (4) to stabilize the unknown nonlinear closed-loop system (5) subject to unknown external disturbance $w_i(t)$. Actually, the asymptotic stability is hard to achieve under the influence of disturbances. In line of this, define the consensus error as $e_i(t):=x_i(t)-(1/\bar{N}_i\sum_{j\in\mathcal{N}_i}x_j(t))$ with total numbers of agent $i$'s neighbors $\bar{N}_i$. A natural idea is to study the robustness of consensus protocols to external disturbances, which is formulated as an issue of additional UUB performance specification. However, the lack of knowledge about dynamics coefficients $\Lambda$, $\Theta$ challenges the controller design and its associated stability analysis. To tackle this, we introduce an advanced data acquisition mechanism. We begin by supposing that the controller side of each agent $i$ possesses a buffer of size $T \in \mathbb{N}_+$. At each $t \in \mathbb{N}$, the buffer records the latest $T$ input-state samples of agent $i$, which are collected in data matrices $X_{i,t+}$, $X_{i,t-}$, and $U_{i,t-}$, given as follows:

$$
\begin{aligned}
X_{i,t+} &:= [x_i(t-T+1) \cdots x_i(t)]\\
X_{i,t-} &:= [\mathbf{F}(x_i(t-T)) \cdots \mathbf{F}(x_i(t-1))]\\
U_{i,t-} &:= [\mathbf{G}(x_i(t-T))u_i(t-T) \cdots \mathbf{G}(x_i(t-1))u_i(t-1)].
\end{aligned} \tag{6}
$$

Observe that when $t \in [0, T-1]$, the indices of the samples in (6) are negative, indicating that the initial data is acquired through an offline experiment, as shown below, i.e., replacing $t$ in (6) with $T$

$$
\begin{aligned}
X_{i,T+} &:= [x_i(1) \cdots x_i(T)]\\
X_{i,T-} &:= [\mathbf{F}(x_i(0)) \cdots \mathbf{F}(x_i(T-1))]\\
U_{i,T-} &:= [\mathbf{G}(x_i(0))u_i(0) \cdots \mathbf{G}(x_i(T-1))u_i(T-1)].
\end{aligned}
$$

Furthermore, as $t \geq T$, the data matrices are updated at each time step. To be specific, the buffer window is shifted one step forward, removing the oldest sample (i.e., the first column of the data matrices in (6) is removed) and adding the latest sample to the buffer.

Let $W_{i,t-} := [w_i(t-T) \cdots w_i(t-1)]$ denote the disturbance matrices corresponding to the $T$ input-state samples. Then, a quadratic full-block disturbance bound is introduced as follows.

Assumption 3: For agent $i \in \{1, 2 \ldots, N\}$, the disturbance matrix $W_{i,t-}$ belongs to

$$
\mathcal{W}_i = \left\{ W_{i,t-} \in \mathbb{R}^{n \times T} \left| \begin{bmatrix} W_{i,t-}^T \\ I \end{bmatrix}^T \begin{bmatrix} Q_d & S_d \\ * & R_d \end{bmatrix} \begin{bmatrix} W_{i,t-}^T \\ I \end{bmatrix} \geq 0 \right. \right\}
$$

with some known matrices $Q_d \prec 0$, $R_d = R_d^T$, and $S_d$.

Assumption 3 is standard for modeling bounded additive disturbance during the data acquisition phase by quadratic constraints, see e.g., [9]–[11]. Clearly, (2) satisfies $X_{i,t+} = \Lambda X_{i,t-} + \Theta U_{i,t-} + W_{i,t-}$. To provide stability analysis guarantees for the nonlinear MAS (2) with unknown $\Lambda$, $\Theta$, we need to derive a stability criterion for all $[\Lambda, \Theta]$ that are consistent with the input-state data and the given disturbance bound. For this purpose, a data-based representation of $[\Lambda, \Theta]$ is constructed in the following lemma.

Lemma 1: For $i \in \{1, 2, \ldots, N\}$, the set $\Sigma_i$ of all possible system parameters compatible with the disturbed data is expressed by

$$
\Sigma_i := \left\{ (\Lambda, \Theta) \left| \begin{bmatrix} [\Lambda, \Theta]^T \\ I \end{bmatrix}^T \Theta_i \begin{bmatrix} [\Lambda, \Theta]^T \\ I \end{bmatrix} \geq 0 \right. \right\} \tag{7}
$$

where $\Theta_i := \left[\begin{array}{cc} -X_{i,t-} & \mathbf{0} \\ -U_{i,t-} & \mathbf{0} \\ \hline X_{i,t+} & I \end{array}\right] \begin{bmatrix} Q_d & S_d \\ * & R_d \end{bmatrix} [\cdot]^T$.

With the preliminaries above, the problem to be addressed in this letter is formally stated as follows.

Problem 1: Under Assumptions 1−3, consider the nonlinear affine MAS (1) with unknown dynamics $\mathbf{f}$ and $\mathbf{g}$ over the graph $\mathcal{G}$. Given the disturbed experimental input-state data $(X_{i,t+}, X_{i,t-}, U_{i,t-})$, design a distributed state-feedback consensus control law (4) such that the consensus error $e_i(t)$ of each agent is UUB for any initial states.

**Main results:** This section proposes an online distributed data-driven robust control approach to address Problem 1 for the unknown MAS (1). See Fig. 1 for an illustration of the considered data-driven consensus control architecture.

Motivated by [15], we proceed by denoting the state-dependent representations $\mathbf{F}(x_i(t)) = \mathbf{A}(x_i(t))x_i(t)$ and $\mathbf{G}(x_i(t)) = \mathbf{B}(x_i(t))$ with $\mathbf{A} \in \mathbb{R}^{n_f \times n}$. Then, for $i \in \{1, 2, \ldots, N\}$, the nonlinear MAS (2) can be recast into the following form:

$$
x_i(t+1) = \Lambda \mathbf{A}(x_i(t))x_i(t) + \Theta \mathbf{B}(x_i(t))u_i(t) + w_i(t). \tag{8}
$$

In this way, a state-dependent model is constructed that captures each agent's dynamics at each time step $t$, which we subsequently stabilize by treating it as a linear time-invariant (LTI) system. Building on this result, the ultimate aim is to design a distributed data-driven robust consensus controller for each agent at each time step directly from data that can effectively address Problem 1 for all linear-like systems in the set $\Sigma_i$.

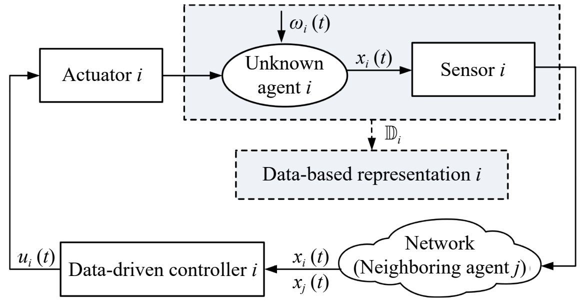


Fig. 1. Distributed data-driven state-feedback consensus control.

For this effort, when matrices $\Lambda$, $\Theta$ in (5) are known, inspired by the results of uncertain MASs in [4], the stabilization problem is addressed if and only if the matrices $A_i(t) + \lambda_i B_i(t) K_i(t)$ are Schur stable, where $\lambda_i$, $i = 1, 2, \ldots, N$, are the eigenvalues of Laplacian matrix $\widehat{\mathcal{L}} = \mathcal{L} + D$. Let $\bar{\lambda}$ and $\underline{\lambda}$ denote the maximize and minimize eigenvalue of $\widehat{\mathcal{L}}$. Define $\rho = \underline{\lambda}/\bar{\lambda}$. The optimal state-feedback consensus controllers can be computed by solving the following linear quadratic regulation (LQR) problem at each time step. For simplify, we omit $x_i(t)$ in the sequel, i.e., using $\mathbf{A}_{i,t}$ for $\mathbf{A}(x_i(t))$ and $\mathbf{B}_{i,t}$ for $\mathbf{B}(x_i(t))$

$$
\min \operatorname{trace}(QP_i(t)) + \operatorname{trace}(RL_i(t)) \tag{9a}
$$

$$
\begin{aligned}
\text{s.t.}\ \ & P_i(t) - (\Lambda \mathbf{A}_{i,t} + \lambda_i \Theta \mathbf{B}_{i,t} K_i(t)) P_i(t)\\
& \times (\Lambda \mathbf{A}_{i,t} + \lambda_i \Theta \mathbf{B}_{i,t} K_i(t))^T \geq 0
\end{aligned} \tag{9b}
$$

$$
L_i(t) - K_i(t) P_i(t) K_i(t)^T \geq 0 \tag{9c}
$$

where $Q \in \mathbb{R}^{n \times n}$, $R \in \mathbb{R}^{n \times n}$ are positive definite symmetric matrices. Consider the Lyapunov function candidate for the closed-loop system (5) as $V_i(t) = e_i^T(t) P_i(t) e_i(t)$. We solve (9) with an additional constraint to provide the stability guarantee

$$
\min \operatorname{trace}(QP_i(t)) + \operatorname{trace}(RL_i(t)) \tag{10a}
$$

$$
\begin{aligned}
\text{s.t.}\ \ & P_i(t) - (\Lambda \mathbf{A}_{i,t} + \lambda_i \Theta \mathbf{B}_{i,t} K_i(t)) P_i(t)\\
& \times (\Lambda \mathbf{A}_{i,t} + \lambda_i \Theta \mathbf{B}_{i,t} K_i(t))^T > 0
\end{aligned} \tag{10b}
$$

$$
L_i(t) - K_i(t) P_i(t) K_i(t)^T \geq 0 \tag{10c}
$$

$$
V_i(t-1) - V_i(t) > 0. \tag{10d}
$$

Now, we are ready to discuss the properties associated to an equivalent data-based version of (10). An online distributed data-driven robust control algorithm for the unknown nonlinear MAS (1) under the control protocol (4), is presented in Algorithm 1, with stability guarantees provided below.

Theorem 1: Consider the nonlinear MAS (1) under the graph $\mathcal{G}$. Suppose Assumptions 1−3 hold. For all $[\Lambda, \Theta] \in \Sigma_i$ and $i \in \{1, 2, \ldots, N\}$, if there exist matrices $P_i(t) = P_i(t)^T > 0$, $H_i(t)$, and $L_i(t)$, and scalars $\tau \geq 0$, $\eta > 0$ such that the following LMIs:

$$
\min \operatorname{Tr}(QP_i(t)) + \operatorname{Tr}(RL_i(t)) \tag{11a}
$$

$$
\begin{aligned}
\text{s.t.}\ \ & \begin{bmatrix} -\mathbf{A}_{i,t} P_i(t) \mathbf{A}_{i,t}^T & -\rho \mathbf{A}_{i,t} H_i^T(t) \mathbf{B}_{i,t}^T & 0 & 0 \\ -\rho \mathbf{B}_{i,t} H_i(t) \mathbf{A}_{i,t}^T & 0 & \rho \mathbf{B}_{i,t} H_i(t) & 0 \\ 0 & \rho \mathbf{H}_i^T(t) \mathbf{B}_{i,t}^T & P_i(t) & 0 \\ 0 & 0 & 0 & P_i(t) - \eta I \end{bmatrix}\\
& - \tau \begin{bmatrix} -X_{i,t-} & 0 \\ -U_{i,t-} & 0 \\ 0 & 0 \\ X_{i,t+} & I \end{bmatrix} \begin{bmatrix} Q_d & S_d \\ * & R_d \end{bmatrix} [\cdot]^T > 0
\end{aligned} \tag{11b}
$$

$$
\begin{bmatrix} L_i(t) & H_i(t) \\ H_i^T(t) & P_i(t) \end{bmatrix} \geq 0 \tag{11c}
$$

$$
\begin{bmatrix} V_i(t-1) & x_i^T(t) \\ x_i(t) & P_i(t) \end{bmatrix} > 0 \tag{11d}
$$

hold, then the UUB is achieved for any initial states under the state-feedback consensus control protocol (4). Moreover, the feedback gain matrix is computed as $K_i(t) := L_i(t)P_i(t)^{-1}/\bar{\lambda}$.

**Algorithm 1** Online distributed data-driven robust control

**Input:** desired lifespan of the MAS $\mathcal{T}$; data size $T$; data-generating input $u_i(0)\in\mathbb{R}^m$; initial states $x_i(0)\in\mathbb{R}^n$; matrices of the disturbance model $Q_d$, $S_d$, and $R_d$; parameters $\tau$, $\eta$; decide basis functions $\mathbf{F}$, $\mathbf{G}$; performance matrices $Q$, $R$; and initial value of the Lyapunov function $V_i(0)$.
**Collect** initial $T$-long stream of state-input data $\mathbb{D}_i$ and construct data matrices $X_{i,T+}$, $X_{i,T-}$, and $U_{i,T-}$.
**while** $t<\mathcal{T}$ **do**
  **for** $i=1,2,\ldots,N$ **do**
    Update data matrices $X_{i,t+}$, $X_{i,t-}$, $U_{i,t-}$
    Solve the data-based optimization problem (11).
    Design controller gain matrix $K_i$ via Theorem 1.
    Broadcast $x_i(t)$ to agent $j\in\mathcal{N}_i$.
    Compute $z_i(t)$ from (5) based on the updated state $x_j(t)$.
    Update the control protocol (4) and the dynamics (5).
  **end for**
**end while**

**Numerical example:** This part provides a numerical example to verify the efficiency of the proposed approach. Consider a nonlinear MAS consisting of four inverted pendulums, treating as agent $i=1,2,3,4$. The dynamics of each agent is described as follows with $T_c=0.1$:

$$x_i(t+1)=\begin{bmatrix} x_{i1}(t)+T_c x_{i2}(t)\\ x_{i2}(t)+T_c\sin x_{i1}(t)-T_c x_{i2}(t)\end{bmatrix}+\begin{bmatrix}0\\T_c\end{bmatrix}u_i(t)+w_i(t).$$

Agents 1−4 are connected in a line. It is evident that the communication topology among them satisfies Assumption 1. Choose the basis $\mathbf{F}(x_i(t))=[x_{i1}(t);x_{i2}(t);\sin(x_{i1}(t))]^T$, $\mathbf{G}(x_i(t))=1$. Set $Q=I$, $R=I$, and $V_i(0)=1000$. The disturbance $w_i(t)$ is bounded by Assumption 3 for all $t\in\mathbb{N}$ with $Q_d=-I$, $S_d=0$, and $R_d=\bar{w}I$. The initial states and inputs obey the normal distribution, and the disturbance obey Gaussian distribution with standard deviation $\bar{w}=0.01$. To implement the proposed method, Algorithm 1 was applied to excite the open-loop MAS offline for the first 20 time steps, denoted as $T=20$. Subsequently, for $t\in[20,120]$, an online process was carried out by implementing the distributed controllers obtained at each time step on the MAS. The state trajectories of all agents under the proposed data-driven controller (solid line) and the model-based one (dashed line) are shown in Fig. 2. The proposed controller achieves similar performance to the model-based one, implying superiority of the data-driven approach since no system model information is required during implementation.

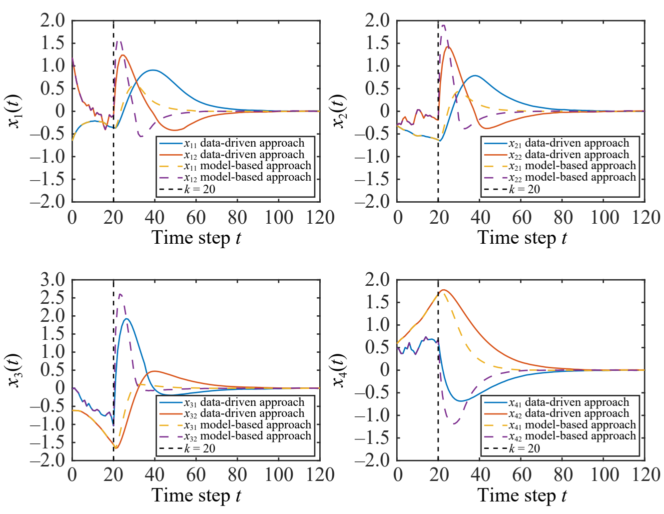


Fig. 2. State trajectories of all agents under different approaches.

**Conclusions:** The consensus control problem of unknown nonlinear MASs has been addressed in this letter. An online distributed data-driven robust control approach was proposed to design controllers directly from disturbed data, along with rigorous stability guarantees. The resulting computational complexity at each step is comparable to that of designing a controller for a linear MAS of the same dimensions. Numerical examples have been provided under data-driven and model-based approaches, which showcases the effectiveness of the proposed method in terms of control performance and robustness dealing with disturbed data. Generalizing the results to the general directed topology constitutes interesting directions for future study.

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