Novelty Assessment Report

Paper: InputDSA: Demixing, then comparing recurrent and externally driven dynamics
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Abstract

In control problems and basic scientific modeling, it is important to compare observations with dynamical simulations. For example, comparing two neural systems can shed light on the nature of emergent computations in the brain and deep neural networks. Recently, Ostrow et al. (2023) introduced Dynamical Similarity Analysis (DSA), a method to measure the similarity of two systems based on their recurrent dynamics rather than geometry or topology. However, DSA does not consider how inputs affect the dynamics, meaning that two similar systems, if driven differently, may be classified as different. Because real-world dynamical systems are rarely autonomous, it is important to account for the effects of input drive. To this end, we introduce a novel metric for comparing both intrinsic (recurrent) and input-driven dynamics, called InputDSA (iDSA). InputDSA extends the DSA framework by estimating and comparing both input and intrinsic dynamic operators using a variant of Dynamic Mode Decomposition with control (DMDc) based on subspace identification. We demonstrate that InputDSA can successfully compare partially observed, input-driven systems from noisy data. We show that when the true inputs are unknown, surrogate inputs can be substituted without a major deterioration in similarity estimates. We apply InputDSA on Recurrent Neural Networks (RNNs) trained with Deep Reinforcement Learning, identifying that high-performing networks are dynamically similar to one another, while low-performing networks are more diverse. Lastly, we apply InputDSA to neural data recorded from rats performing a cognitive task, demonstrating that it identifies a transition from input-driven evidence accumulation to intrinsically-driven decision-making. Our work demonstrates that InputDSA is a robust and efficient method for comparing intrinsic dynamics and the effect of external input on dynamical systems.

Core Task Landscape

This paper addresses: **Comparing Intrinsic and Input-Driven Dynamics of Dynamical Systems**

A total of **50 papers** were analyzed and organized into a taxonomy with **22 categories**.

Taxonomy Overview

The research landscape has been organized into the following main categories:

- **Decomposition and Identification Methods for Separating Dynamics**
- **Neuroscience Applications: Neural Dynamics and Behavior**
- **Biological and Ecological Systems Dynamics**
- **Theoretical Foundations and Mathematical Frameworks**
- **Engineering and Control Applications**

Complete Taxonomy Tree

- Comparing Intrinsic and Input-Driven Dynamics of Dynamical Systems Survey Taxonomy
- Decomposition and Identification Methods for Separating Dynamics
  - Koopman Operator-Based Linearization and Embedding (4 papers)
  - [2] Adaptive Koopman embedding for robust control of nonlinear dynamical systems (Rajpal Singh, 2025) View paper
  - [7] Adaptive Koopman Embedding for Robust Control of Complex Nonlinear Dynamical Systems (Singh Rajpal, 2024) View paper
  - [11] Data-Driven Koopman Based System Identification for Partially Observed Dynamical Systems with Input and Disturbance (Patinya Ketthong, 2024) View paper
  - [49] Data-Driven Linearization of Dynamical Systems (George Haller, 2024) View paper
  - Latent Dynamics and Deep Learning Architectures (4 papers)
  - [5] Learning the intrinsic dynamics of spatio-temporal processes through Latent Dynamics Networks (Francesco Regazzoni, 2024) View paper
  - [15] BRAID: Input-driven nonlinear dynamical modeling of neural-behavioral data (Parsa Vahidi, 2025) View paper
  - [16] Modeling and Disentanglement of Intrinsic and Input-Driven Neural Dynamics Underlying Behavior (Unknown, 2025) View paper
  - [45] EEG feature learning with intrinsic plasticity based deep echo state network (Rahma Fourati, 2020) View paper
  - Dynamical Similarity Analysis and Comparison Metrics ★ (2 papers)
  - [0] InputDSA: Demixing, then comparing recurrent and externally driven dynamics (Anon et al., 2026) View paper
  - [1] Modeling and dissociation of intrinsic and input-driven neural population dynamics underlying behavior (Parsa Vahidi, 2024) View paper
  - Statistical and Stochastic Decomposition Approaches (2 papers)
  - [13] Separating intrinsic from extrinsic fluctuations in dynamic biological systems (Andreas Hilfinger, 2011) View paper
  - [27] Separating internal and external dynamics of complex systems (MÃ¡rcio Argollo de Menezes, 2004) View paper
  - Data-Driven Modeling of Autonomous and Forced Systems (2 papers)
  - [3] Learning dynamical systems using dynamical systems (Verzelli, 2022) View paper
  - [6] Data-driven modelling of autonomous and forced dynamical systems (Szalai, 2025) View paper

- Neuroscience Applications: Neural Dynamics and Behavior
  - Motor Cortex Dynamics and Movement Control (5 papers)
  - [9] The roles of internal dynamics and proprioceptive feedback in motor cortex during movement execution (Hongru Jiang, 2025) View paper
  - [25] Feedback control of recurrent dynamics constrains learning timescales during motor adaptation (Harsha Gurnani, 2024) View paper
  - [32] Motor cortex is an input-driven dynamical system controlling dexterous movement (Britton Sauerbrei, 2018) View paper
  - [35] Combatting nonidentifiability to infer motor cortex inputs yields similar encoding of initial and corrective movements (Peter J Malonis, 2021) View paper
  - [47] Interplay between external inputs and recurrent dynamics during movement preparation and execution in a network model of motor cortex. (Ludovica Bachschmid-Romano, 2023) View paper
  - Large-Scale Brain Network Dynamics and Stimulation (3 papers)
  - [12] Modelling and prediction of the dynamic responses of large-scale brain networks during direct electrical stimulation (Yuxiao Yang, 2021) View paper
  - [21] Shaping intrinsic neural oscillations with periodic stimulation (Christoph S. Herrmann, 2016) View paper
  - [42] Intrinsic dynamic shapes responses to external stimulation in the human brain (Maximilian Nentwich, 2025) View paper
  - Attentional States and Cortical Attractor Dynamics (1 papers)
  - [14] Geometry of neural dynamics along the cortical attractor landscape reflects changes in attention (Ha-Young Song, 2025) View paper
  - Neural Criticality and Scaling Phenomena (2 papers)
  - [8] Robust Scaling in Human Brain Dynamics Despite Latent Variables and Limited Sampling Distortions (RubÃ©n Calvo, 2025) View paper
  - [24] Extrinsic vs Intrinsic Criticality in Systems with Many Components (Vudtiwat Ngampruetikorn, 2023) View paper
  - Recurrent Network Dynamics and External Control (1 papers)
  - [33] Input correlations impede suppression of chaos and learning in balanced firing-rate networks (Rainer Engelken, 2022) View paper
- Biological and Ecological Systems Dynamics
  - Animal Locomotion and Motor Control (2 papers)
  - [4] Learning interpretable control inputs and dynamics underlying animal locomotion (TS Mullen, 2024) View paper
  - [46] Identification of intrinsic and reflexive components of human arm dynamics during postural control (F.C.T. van der Helm, 2002) View paper
  - Population Dynamics and Ecological Interactions (4 papers)
  - [18] Dynamics of a stage-structured predatorâ prey system with fear-induced group defense in autonomous and nonautonomous settings (Subarna Roy, 2024) View paper
  - [28] Dynamical behaviours of discrete amensalism system with fear effects on first species. (Qianqian Li, 2024) View paper
  - [31] Dynamics of an autonomous food chain model and existence of global attractor of the associated non-autonomous system (Jyotirmoy Roy, 2019) View paper
  - [38] Intrinsic chaos and external noise in population dynamics (Jorge A. Gonzalez, 2022) View paper
  - Cellular and Molecular Dynamics (2 papers)
  - [29] Adaptive oscillators support Bayesian prediction in temporal processing (K. Doelling, 2023) View paper
  - [30] An enhanced transcription factor repressilator that buffers stochasticity and entrains to an erratic external circadian signal (Steven A. Frank, 2023) View paper
- Theoretical Foundations and Mathematical Frameworks
  - Autonomous Versus Non-Autonomous System Theory (4 papers)
  - [23] Dimension of attractors associated to autonomous and non-autonomous dynamical systems (Rafael de Oliveira Moura, 2025) View paper
  - [39] Useful transformations from non-autonomous to autonomous systems (Alona Ben-Tal, 2021) View paper
  - [43] The onset of chaos in nonautonomous dissipative dynamical systems: a low-order ocean-model case study (Stefano Pierini, 2018) View paper
  - [50] The minimality of g-non-autonomous discrete dynamical systems (Russl Abd Al-Khaliq Abd Al-Rahim, 2023) View paper
  - Intrinsic Dynamics and Temporal Structure (3 papers)
  - [19] The gesture as an autonomous nonlinear dynamical system (Tanner Sorensen, 2016) View paper
  - [22] The intrinsic dynamics of psychological process (Robin R. Vallacher, 2015) View paper
  - [41] The intrinsic cause-effect power of discrete dynamical systemsâfrom elementary cellular automata to adapting animats (Larissa Albantakis, 2015) View paper
  - Forced and Periodically Driven Systems (2 papers)
  - [20] Optimal time averages in non-autonomous nonlinear dynamical systems (Doering, 2020) View paper
  - [44] Nonlinear dynamics and chaos (Steven H. Strogatz, 2002) View paper
  - Perpetual Manifolds and Rigid Body Dynamics (2 papers)
  - [26] Exact augmented perpetual manifolds as a tool for the determination of similar rigid body modes: Corollary for determining backbone curves of autonomous systems (Fotios Georgiades, 2023) View paper
  - [34] Exact Augmented Perpetual Manifolds Define Specifications for the Steady States of Similar Rigid Body Modes, a Corollary for Nonautonomous Systems (Fotios Georgiades, 2022) View paper
  - Intrinsic Versus Extrinsic Criticality (1 papers)
  - [40] Renormalization group analysis of a self-organized critical system: intrinsic anisotropy vs random environment (N. V. Antonov, 2022) View paper
- Engineering and Control Applications
  - Reservoir Computing and Physical Dynamics Exploitation (2 papers)
  - [10] Enhancing traffic dynamics-induced machine learning through heterogeneous driving policies (Kai-Fung Chu, 2025) View paper
  - [48] Improving reservoirs using intrinsic plasticity (Benjamin Schrauwen, 2008) View paper
  - Intrinsic Plasticity and Adaptive Neural Mechanisms (1 papers)
  - [17] Event-driven intrinsic plasticity for spiking convolutional neural networks (An-Guo Zhang, 2021) View paper
  - Astrophysical and Plasma Dynamics (1 papers)

- ◦ [36] Particle acceleration in self-driven turbulent reconnection (Jianfu Zhang, 2023) View paper
- ◦ General Dynamical Systems Textbooks and Reviews (1 papers)
- ◦ [37] Dynamical systems in neuroscience (Saeb-Gilani, 2007) View paper

Narrative

Core task: comparing intrinsic and input-driven dynamics of dynamical systems. This field addresses a fundamental challenge in understanding complex systems—distinguishing between behavior arising from a system's internal structure versus behavior shaped by external forcing. The taxonomy reflects a multifaceted landscape organized around five major branches. Decomposition and Identification Methods focus on algorithmic and statistical techniques for separating autonomous dynamics from input effects, often leveraging tools like Koopman operators (Adaptive Koopman Embedding[2], Koopman Partial Observation[11]) and data-driven linearization approaches (Data-Driven Linearization[49]). Neuroscience Applications examine how neural circuits balance intrinsic oscillations with sensory or task-driven inputs (Motor Cortex Input-driven[32], Cortical Attractor Geometry[14]), while Biological and Ecological Systems Dynamics explore similar questions in population models and ecological interactions (Fear-induced Group Defense[18]). Theoretical Foundations provide the mathematical underpinnings—manifold theory, non-autonomous system analysis (Non-autonomous to Autonomous[39], Augmented Manifolds Nonautonomous[34])—and Engineering and Control Applications translate these insights into practical control strategies (Learning Interpretable Control[4], Adaptive Koopman Control[7]).

A particularly active line of work centers on developing metrics and frameworks to quantify dynamical similarity when inputs are present, contrasting with classical autonomous system analysis. Some studies emphasize disentangling intrinsic versus extrinsic contributions through explicit decomposition (Separating Intrinsic Extrinsic[13], Disentanglement Intrinsic Input[16]), while others focus on learning latent representations that capture both modes (Latent Dynamics Networks[5], Learning Dynamical Systems[3]). InputDSA[0] sits within the Dynamical Similarity Analysis cluster, closely aligned with Modeling Intrinsic Input Dynamics[1], and addresses the challenge of comparing systems when traditional autonomous metrics fail. Unlike approaches that primarily model or control input-driven systems, InputDSA[0] emphasizes comparison and similarity measurement, offering a complementary perspective to decomposition-focused methods like BRAID[15] or control-oriented frameworks. This positioning highlights an ongoing tension in the field: whether to isolate components or to develop holistic metrics that respect the interplay between intrinsic and driven dynamics.

Related Works in Same Category

The following **1 sibling papers** share the same taxonomy leaf node with the original paper:

1. Modeling and dissociation of intrinsic and input-driven neural population dynamics underlying behavior

Authors: Parsa Vahidi, Omid G. Sani, Maryam M. Shanechi, Maryam Shanechi | **Year/Venue**: 2024 | **URL**: View paper

Abstract

Significance Neural dynamics emerge either intrinsically within the recorded brain regions or due to inputs to those regions, such as sensory inputs or neural inputs from other regions. Further, recorded neural dynamics may or may not be related to a specific measured behavior of interest. We first show how intrinsic neural dynamics that underlie a behavior can be confounded by both measured inputs and other intrinsic neural dynamics. To address this challenge, we develop methods that dissociate...

Relationship Analysis

Both papers belong to the Dynamical Similarity Analysis and Comparison Metrics category, focusing on methods to separate and compare intrinsic versus input-driven dynamics in dynamical systems. They overlap in addressing the fundamental challenge of disentangling recurrent dynamics from external input effects in neural and computational systems. The key difference is that the original paper (InputDSA) extends DSA by developing a novel metric based on controllability matrices and DMDc variants to compare both intrinsic and input operators across systems, while the candidate paper focuses on modeling and dissociating behavior-related intrinsic dynamics from both input-driven dynamics and other intrinsic dynamics within a single system.

Contributions Analysis

Overall novelty summary. The paper introduces InputDSA, a metric for comparing both intrinsic and input-driven dynamics across systems, extending the DSA framework by incorporating external forcing. It resides in the 'Dynamical Similarity Analysis and Comparison Metrics' leaf, which contains only two papers total. This is a notably sparse research direction within the broader taxonomy of 50 papers across 22 leaf nodes. The sibling paper focuses on modeling intrinsic and input dynamics rather than comparison metrics, suggesting that quantitative similarity measurement for input-driven systems remains an underexplored niche despite the field's broader interest in decomposition and identification methods.

The taxonomy reveals that neighboring leaves are densely populated with decomposition techniques: Koopman operator methods (4 papers), latent dynamics architectures (4 papers), and statistical approaches (2 papers). These adjacent directions emphasize separating or modeling intrinsic versus input-driven components, whereas InputDSA's leaf focuses on comparison after decomposition. The scope notes clarify that decomposition methods aim to identify components, while the comparison metrics category addresses quantifying similarity across systems. This structural positioning suggests InputDSA bridges a gap between decomposition-heavy approaches and the need for cross-system evaluation, occupying a distinct methodological space.

Among 30 candidates examined, the core InputDSA metric contribution shows no clear refutation (10 candidates examined, 0 refutable). However, the Subspace DMDc variant and the fast optimization algorithm each face one refutable candidate among 10 examined. The limited search scope means these statistics reflect top-30 semantic matches rather than exhaustive coverage. The metric itself appears more novel than its algorithmic components, which may overlap with existing DMDc or optimization literature. The contribution-level analysis suggests the conceptual framework for comparing input-driven dynamics is less anticipated by prior work than the technical implementation details.

Based on the limited 30-candidate search, InputDSA occupies a sparse research direction with minimal direct competition in its specific comparison-focused niche. The taxonomy structure and sibling paper context suggest the work addresses an underserved need, though the algorithmic contributions show some overlap with existing techniques. The analysis does not cover exhaustive DMDc or optimization literature, so the novelty assessment remains provisional and tied to the semantic search scope employed.

This paper presents **3 main contributions**, each analyzed against relevant prior work:

Contribution 1: InputDSA: a novel metric for comparing intrinsic and input-driven dynamics

Description: The authors propose InputDSA, which extends the Dynamical Similarity Analysis framework to account for external inputs by estimating and comparing both input and intrinsic dynamic operators. This enables quantitative comparison of how inputs affect dynamics in addition to recurrent dynamics.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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1. Disentangling recurrent neural dynamics with stochastic representational geometry

URL: View paper

Brief Assessment

Disentangling Recurrent Dynamics[78] focuses on using stochastic shape distances (SSDs) to compare noisy neural dynamics by analyzing trial-to-trial variability and covariance structures, not on developing metrics for comparing input and intrinsic dynamic operators as InputDSA does.

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2. Suppression of chaos in a partially driven recurrent neural network

URL: View paper

Brief Assessment

Suppression Chaos Recurrent[71] focuses on how input strength and proportion of input neurons affect chaotic dynamics in RNNs, not on developing metrics to compare dynamics across different systems.

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3. BRAID: Input-driven nonlinear dynamical modeling of neural-behavioral data

URL: View paper

Brief Assessment

BRAID[15] focuses on learning nonlinear neural-behavioral dynamics with measured inputs in a deep learning framework, not on comparing dynamics across different systems using similarity metrics like InputDSA.

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4. Interpreting multi-stable behaviour in input-driven recurrent neural networks

URL: View paper

Brief Assessment

Multi-stable Input-driven RNN[72] focuses on nonautonomous dynamical system theory and the echo state property in RNNs, not on developing metrics to compare dynamics across different systems. The candidate does not propose similarity metrics or comparison frameworks.

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5. A connectivity gradient in structured reservoir computing predicts a hierarchy for mixed selectivity in human cortex

URL: View paper

Brief Assessment

Connectivity Gradient Reservoir[73] focuses on mixed selectivity gradients in structured reservoir computing and human cortex, not on metrics for comparing recurrent and input-driven dynamics in neural networks.

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6. On the dimension of pullback attractors in recurrent neural networks

URL: View paper

Brief Assessment

Pullback Attractors RNN[79] focuses on the dimension of pullback attractors in recurrent neural networks using non-autonomous dynamical systems theory, not on developing metrics to compare intrinsic versus input-driven dynamics across systems. The paper studies how input sequences affect the dimensionality of attractors rather than proposing similarity metrics between different systems' dynamics.

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7. Input-driven circuit reconfiguration in critical recurrent neural networks

URL: View paper

Brief Assessment

Input-driven Circuit Reconfiguration[77] focuses on how inputs spatially pattern neural activity to create dynamic circuits in critical RNNs, not on developing metrics to compare dynamics across systems. The candidate does not propose methods for quantitative comparison of recurrent versus input-driven dynamics.

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8. Echo state property linked to an input: Exploring a fundamental characteristic of recurrent neural networks

URL: View paper

Brief Assessment

Echo State Property[74] focuses on passivity conditions and entrainment in reservoir computing networks driven by ergodic inputs, not on quantitative metrics for comparing recurrent versus input-driven dynamics across systems.

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9. Inferring context-dependent computations through linear approximations of prefrontal cortex dynamics

URL: View paper

Brief Assessment

Linear Approximations Prefrontal[76] focuses on fitting linear dynamical models to prefrontal cortex data to infer context-dependent computations, not on developing a general metric for comparing dynamics across systems. The paper does not propose a similarity metric framework like InputDSA.

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10. Opening the black box: low-dimensional dynamics in high-dimensional recurrent neural networks

URL: View paper

Brief Assessment

Opening Black Box[75] focuses on finding fixed points and slow points in RNNs to understand their computational mechanisms through linearization, not on comparing dynamics across different systems or quantifying similarity between input-driven and intrinsic dynamics as InputDSA does.

Contribution 2: Subspace DMDc: a variant of DMD with control for partially observed systems

Description: The authors develop Subspace DMDc, a novel variant of Dynamic Mode Decomposition with control based on subspace identification. This method addresses the failure mode of standard DMDc in partially observed systems where inputs affect both observed and unobserved components.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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1. Dynamic-mode decomposition and optimal prediction.

URL: View paper

Brief Assessment

Dynamic Mode Decomposition[62] focuses on optimal prediction and memory-dependent DMD for partially observed systems without control inputs. The candidate does not address DMD with control (DMDc) for systems with external inputs, which is the core novelty of the original paper's Subspace DMDc contribution.

2. A scaled derivative-based DMDc method for modelling multiple-input multiple-output mechanical systems

URL: View paper

Brief Assessment

Scaled Derivative DMDc[63] focuses on mechanical systems with multiple inputs/outputs and uses derivative-based scaling, not subspace identification methods for partial observability.

3. Observerâbased eventâtriggered distributed model predictive control for a class of nonlinear interconnected systems

URL: View paper

Brief Assessment

Observer Event-triggered MPC[66] focuses on observer-based event-triggered distributed model predictive control for nonlinear interconnected systems, not on dynamic mode decomposition methods for partially observed systems.

4. Delay-structured noise robust dynamic mode decomposition for power system modal estimation with faulty PMU data

URL: View paper

Brief Assessment

Delay-structured DMD[64] focuses on power system modal estimation with faulty PMU data, not on developing DMD variants for partially observed systems with control inputs.

5. Online learning and control of complex dynamical systems from sensory input

URL: View paper

Brief Assessment

Online Learning Control[70] focuses on learning embeddings for control from sensory input using standard DMDc approaches, not on developing novel variants for partially observed systems.

6. SelfâTriggered Distributed Model Predictive Control via Path Parameter Synchronization

URL: View paper

Brief Assessment

Self-Triggered MPC[67] focuses on formation tracking for mobile robots using distributed model predictive control with path-parameter synchronization. It does not address dynamic mode decomposition methods or partially observed system identification, which are central to the original paper's contribution.

7. Learning Bilinear Models of Actuated Koopman Generators from Partially-Observed Trajectories

URL: View paper

Prior Art Analysis

Learning Bilinear Koopman[68] demonstrates prior work on handling partially-observed systems with control inputs through their bilinear hidden Markov model formulation and EM algorithm approach. The candidate paper explicitly addresses the same failure mode that the original paper claims to solve: the bias in estimating input operators when inputs affect both observed and unobserved components. The candidate provides a different methodological solution (EM algorithm with Kalman filtering) to the same problem that Subspace DMDc addresses, indicating that the challenge of partial observability in control-affine systems was recognized and addressed before the original paper's submission.

Evidence

Evidence 1 - **Rationale**: Both papers identify the same fundamental challenge: partial observability in actuated systems where inputs affect both observed and unobserved states. The candidate paper explicitly recognizes this as a central problem to address. - **Original**: issues of partial observation while estimating a and b via dmdc is an intuitive extension to input-driven systems, it has a hidden failure mode in the analysis of partially-observed systems. this is particularly important in the analysis of neural data, in which a small subset of neurons in a vast p... - **Candidate**: the situation when the full state is not available and we only have access to actuated trajectories of noisy partial observations of the state is significantly more difficult. however, it is also the one most likely to be encountered in experimental applications where one forces the system with vari...

Evidence 2 - **Rationale**: Both papers propose solutions to the partial observation problem in control-affine systems. The candidate's EM-based approach predates the original paper's Subspace DMDc method, demonstrating that solutions to this problem existed prior to the original work. - **Original**: we develop a formal description of this problem for linear systems in appendix d. we solve this problem by introducing subspace dmdc, an extension of subspace dmd (takeishi et al., 2017b) that incorporates input. - **Candidate**: to remedy the problems associated with input dependence and partial observations in koopman generator approximations, we treat the observed trajectories as if they come from a hidden markov model (hmm) whose hidden dynamics are governed by an input-affine combination of finite-dimensional koopman ge...

Evidence 3 - **Rationale**: Both papers work with the same problem formulation: identifying system dynamics from partial observations and control inputs. The candidate paper's approach using bilinear models and EM algorithm represents an alternative solution to the same identification problem. - **Original**: in brief, subspace dmdc utilizes subspace identification algorithms from classical control theory (verhaegen & verdult, 2007), which seek to identify linear dynamical systems of the form: xt+1 = axt + but yt = cxt here, only yt and ut are observed. the situation of partial observability is a special... - **Candidate**: let us suppose that we are given a collection of finely sampled time histories of inputs {u(m) l }l-1 l=0 and observations {y(m) l }l l=0 along trajectories m = 1, . . . , mfrom a control-affine system. we seek to identify matrix approximations of the koopman generators {vk} together with an appropr...

8. Bridging Autoencoders and Dynamic Mode Decomposition for Reduced-order Modeling and Control of PDEs

URL: View paper

Brief Assessment

Autoencoders Dynamic Mode[61] focuses on autoencoding methods for reduced-order modeling of PDEs, not on subspace identification methods for partially observed systems with control.

9. Traffic forecasting with missing data via low rank dynamic mode decomposition of tensor

URL: View paper

Brief Assessment

Traffic Low Rank[69] focuses on tensor-based dynamic mode decomposition for traffic forecasting with missing data, not on DMD with control for partially observed systems with inputs.

10. A Supervised and Transfer Learning Based Two-Stage Framework for UAV Swarm Multi-Target Tracking

URL: View paper

Brief Assessment

UAV Swarm Tracking[65] focuses on multi-target tracking using supervised and transfer learning for UAV swarms, not on dynamic mode decomposition methods for partially observed systems.

Contribution 3: Fast optimization algorithm for InputDSA metric computation

Description: The authors introduce an optimization algorithm that solves the InputDSA metric via Procrustes alignment rather than iterative optimization, providing exponential acceleration compared to prior methods while maintaining theoretical grounding.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Face recognition with pose variations and misalignment via orthogonal procrustes regression

URL: View paper

Brief Assessment

Face Recognition Procrustes[56] applies orthogonal Procrustes to face image alignment and pose correction, not to dynamical similarity metrics or Koopman operator approximation. The domains and problem formulations are fundamentally different.

2. Scalable Multi-Kernel Clustering with Dynamic Procrustes

URL: View paper

Brief Assessment

Multi-Kernel Dynamic Procrustes[55] focuses on multi-kernel clustering using SVD for efficiency, not on dynamical similarity metrics or Procrustes alignment for comparing recurrent dynamics in neural systems.

3. Differentiable Optimization of Similarity Scores Between Models and Brains

URL: View paper

Brief Assessment

Differentiable Optimization Similarity[51] focuses on differentiating through similarity measures (CKA, Procrustes, etc.) to maximize scores for understanding what drives similarity, not on accelerating dynamical similarity metric computation via Procrustes alignment as in the original paper's InputDSA framework.

4. Geometric Knowledge Distillation via Procrustes Analysis for Efficient Motion Sequence Classification

URL: View paper

Brief Assessment

Geometric Knowledge Distillation[57] focuses on knowledge distillation for motion sequence classification using Procrustes analysis to align shapes, not on optimizing dynamical similarity metrics for comparing recurrent systems. The candidate addresses a different problem domain (motion classification) rather than dynamical systems comparison.

5. Procrustean regression: A flexible alignment-based framework for nonrigid structure estimation

URL: View paper

Brief Assessment

Procrustean Regression[58] addresses non-rigid structure estimation in computer vision using shape alignment and regression frameworks. This is fundamentally different from InputDSA's focus on comparing dynamical systems through Procrustes alignment of state-transition operators and controllability matrices.

6. 3D Human Pose Estimation from Multiple Dynamic Views via Single-view Pretraining with Procrustes Alignment

URL: View paper

Brief Assessment

3D Pose Procrustes[52] applies Procrustes alignment to multi-view 3D pose estimation from camera views, not to dynamical similarity metrics or Koopman operator comparisons. The technical domains are entirely distinct.

7. Quantized Wasserstein Procrustes Alignment of Word Embedding Spaces

URL: View paper

Brief Assessment

Quantized Wasserstein Procrustes[59] addresses alignment of word embedding spaces using optimal transport, not dynamical similarity metrics or Procrustes alignment for recurrent neural network dynamics as in the original paper.

8. HackGAN: Harmonious Cross-Network Mapping Using CycleGAN With Wassersteinâ Procrustes Learning for Unsupervised Network Alignment

URL: View paper

Brief Assessment

HackGAN Procrustes[53] focuses on unsupervised network alignment using Procrustes for mapping network embeddings, not for computing dynamical similarity metrics in recurrent systems. The application domains and technical problems are fundamentally different.

9. Fast dynamical similarity analysis

URL: View paper

Prior Art Analysis

Fast Dynamical Similarity[54] demonstrates that prior work exists for solving the DSA alignment problem via Procrustes methods with exponential acceleration. The candidate paper explicitly describes solving the alignment problem through Procrustes alignment and SVD-based closed-form solutions, achieving computational speedups of multiple orders of magnitude. Both papers address the same computational bottleneck (the orthogonal alignment optimization in DSA) and propose Procrustes-based solutions that avoid iterative optimization, directly challenging the novelty claim that the original paper was first to introduce this approach.

Evidence

Evidence 1 - **Rationale**: Both papers address the same optimization problem for DSA alignment. The candidate demonstrates alternative optimization approaches that avoid iterative constraint enforcement, similar to the original's Procrustes approach. - **Original**: although eq. 2 requires iterative optimization, eq. 8 is solved via procrustes alignment, which yields an exponential acceleration of prior work. - **Candidate**: the field$\psi(C)$ $\in T$ $CO(n)$therefore, represents a first-order riemannian descent direction on$O(n)$, steering updates that preserve orthogonality to infinitesimal order... this construction gives a conceptually distinct variant of fastdsa in which the orthogonality constraint is not enforced at every iterati...

10. The continuous Procrustes distance between two surfaces

URL: View paper

Brief Assessment

Continuous Procrustes Distance[60] focuses on comparing 2D surfaces embedded in 3D space using Procrustes alignment for shape similarity, not on dynamical systems or recurrent neural networks. The optimization techniques are applied to different problem domains (geometric shape matching vs. dynamical similarity analysis).

Appendix: Text Similarity Detection

No high-similarity text segments were detected across any compared papers.

References

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