End-to-End Learning for State Estimation in Nonlinear Dynamical Systems

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Abstract

This paper explores an end-to-end learning framework for state estimation that leverages deep learning techniques to directly infer latent system states from observational data. State estimation in nonlinear dynamical systems is a critical task across numerous scientific and engineering domains. Reliable state estimation in nonlinear dynamical systems is critical for defense applications such as missile guidance, UAV navigation, and real-time control of hypersonic vehicles—where classical filters often fall short due to nonlinearity, unmodeled dynamics, and sensor noise. This paper presents an end-to-end learning framework that combines Physics-Informed Neural Networks (PINNs) and Deep Koopman Operators for accurate and robust state estimation without relying on explicit system models. PINNs incorporate known physical laws—such as conservation of momentum and energy—into the loss function, while Koopman-based models learn interpretable linear embeddings of nonlinear systems. It demonstrate our approach on simulated high-speed flight dynamics and benchmark systems like the Lorenz attractor and Van der Pol oscillator, under both ideal and noisy conditions. Results show that our method outperforms traditional approaches like the Extended Kalman Filter in both accuracy and stability, highlighting its potential for deployment in mission- critical DRDO systems requiring real-time, data-driven control and decision-making. Experimental results demonstrate that our hybrid learning approach achieves higher accuracy and greater robustness compared to classical filtering techniques. These results indicate strong potential for real-time deployment in sensor fusion, UAV navigation, and adaptive control of nonlinear systems.