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EDITORIAL

Reduced-Order, Data-Driven, and Decomposition Methods for Modelling, Identification, and Estimation

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ABSTRACT

The focus of this special issue is on research applying reduced-order, data-driven, and decomposition paradigms within the control community. The issue includes six papers that address two main types of models: black-box ones, such as neural networks and multivariate splines, and classical white-box ones. Regardless of the specific modeling framework, the proposed solutions demonstrate how to leverage the available data from the plant of interest. This aspect, which is shared among the various approaches, aims to enhance experimental performance in identification, estimation, and control, while aligning with the underlying theoretical foundations.

We are proud to present this special issue dedicated to the latest advancements in reduced-order, data-driven, and decomposition methods for modelling, identification, and estimation. In fact, the integration of data-driven techniques is revolutioning the way we approach system modeling and estimation, enabling for more accurate and efficient solutions. These methodologies are at the forefront of research, offering innovative solutions to the complex challenges in adaptive control and signal processing for the coming years.

In the paper by Alessandri et al. [1], the effectiveness of data-driven neural learning is addressed in terms of local minima trapping and convergence rate. The study investigates the training of one-hidden-layer feedforward neural networks using the extended Kalman filter. This approach transforms the search for optimal network parameters into a state estimation problem, offering a significant advantage over traditional descent-based methods. The performance of the training is evaluated using the Cramér-Rao bound and a novel metric based on an empirical criterion, which assesses robustness against local minima trapping. This research highlights the potential of neural learning to enhance the accuracy and efficiency in the identification of black-box models.

The article by Aumann and Gosea [2] deals with interpolation-based data-driven methods, which are crucial for model reduction and widely applicable in systems and control communities. The study analyzes frequency-response data, derived from samples of the transfer function of the underlying unknown model. It proposes novel approaches that combine attributes of established methods to address specific issues, such as placing poles to enforce stability in reduced-order models, ensuring robustness to noisy or perturbed data, and switching between different rational function representations. The classical state-space format and various barycentric representations of fitted rational interpolants are discussed, offering a comprehensive view of the strengths and limitations of these methods.

Data-driven forecasting of ship motions in waves using feedforward and recurrent neural networks, as well as dynamic mode decomposition, is the topic of the work of Diez et al. [3]. The goal is to predict future ship motion variables based on past data collected in the field, employing equation-free approaches. Numerical results from two case studies involving the course-keeping of a naval destroyer in a high sea state using simulation data at model scale are presented. The proposed methods demonstrate success in predicting ship motions both in short-term and medium-term perspectives, with high accuracy and reduced computational effort. This research underscores the potential of data-driven techniques to enhance the reliability and efficiency of maritime operations.

In the realm of optimal control for continuous nonlinear systems, function approximation methods are often employed to overcome the curse of dimensionality. In the paper by Feng et al. [4], a multivariate spline-based reinforcement learning strategy is proposed for solving continuous-time nonlinear control problems. By integrating multivariate splines into reinforcement learning algorithms, this study approximates continuous value functions and policy functions from discrete action and value samples. The performance of this approach is evaluated in controlling an under-actuated inverted pendulum, demonstrating improved function approximation efficiency with less computation time compared to neural network optimization.

Addressing a major challenge in online data-driven control methods, Heydari et al. [5] propose a solution to reduce the sensitivity of the model-free adaptive control method to initial conditions and control parameters. The new control cost function incorporates the output error rate and integral along with an anti-wind up strategy for multi-input multi-output systems. Simulation findings on a nonlinear auto-regressive moving average model with exogenous inputs system demonstrate that the proposed control rule outperforms conventional model-free adaptive control and proportional–integral–derivative controllers, highlighting its robustness and efficiency.

Finally, tracking a moving target using only angle measurements in the presence of uncertainties in the target initial range and speed, as well as measurement outliers, is the challenging problem faced in the work of Urooj and Radhakrishnan [6]. Two new estimation frameworks are proposed to address these challenges, using a range and speed parametrization approach and employing maximum correntropy and centered error entropy criteria. The performance of these frameworks is evaluated against traditional unscented Kalman filter methods, demonstrating their robustness and accuracy in dealing with measurement and observer motion uncertainties.

In conclusion, the articles in this special issue provide valuable insights into the application of reduced-order, data-driven, and decomposition methods for modelling, identification, and estimation trough a review of many different case studies. These innovative approaches pave the way for more robust and efficient adaptive control systems, addressing critical challenges and opening new avenues for research and development.

Data Availability Statement

Research data are not shared.

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