Parameter Estimation for Linear Time-Varying (LTV) Uncertain System Using Physics-Informed Machine Learning

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Abstract. This paper proposes a Physics-Informed Machine Learning (PIML) based parameter estimation method for Linear Time-Varying (LTV) uncertain systems. The proposed method is first to obtain the training data from the PIML-based Observer and second to estimate the time-varying uncertain parameters. The LTV system can be represented by the polytopic uncertain model, and the model can be accurately estimated from the PIML by finding the parameters for it in the proposed method. It will be applied to the parameter-dependent controller for systems with uncertain parameters.

Introduction

In several decades, many robust control studies have been conducted to design controllers to control systems with polytopic model uncertainty [1]. While the Linear Parameter-Varying (LPV) system is useful to design a controller because a parameter is measurable, the LTV uncertain systems have difficulties in controller synthesis where parameters over time are not available [2]. Therefore, it is very important to find parameters for the analysis and synthesis of systems with time-varying uncertainty and nonlinear dynamics.

Recently, PIML, a neural network structure capable of learning the Ordinary Differential Equation (ODE) or Partial Differential Equation (PDE), has been studied to obtain new physical information in the case of not being measurable with sensors. Therefore, the parameter can be estimated by combining the PIML structure and polytopic state-observer model. When the parameter values are fully estimated, the parameter-dependent control feedback gain can be designed to enhance the system's performance.

The methods of updating the neural network were researched by defining the loss function as an error between the actual state and the estimated state. However, in the PIML, the loss function includes the ODE, the exact solution for training data, and boundary conditions [3]. From the learned PIML, we can find the parameters through the convex combination of the estimated states from the low and upper bound model. After the parameters are computed through the above process, the parameters can be utilized as if they were measured and can be used in the gain scheduling process. Therefore, it is possible to ensure the performance and robustness of the system. The proposed system is described in Figure 1.

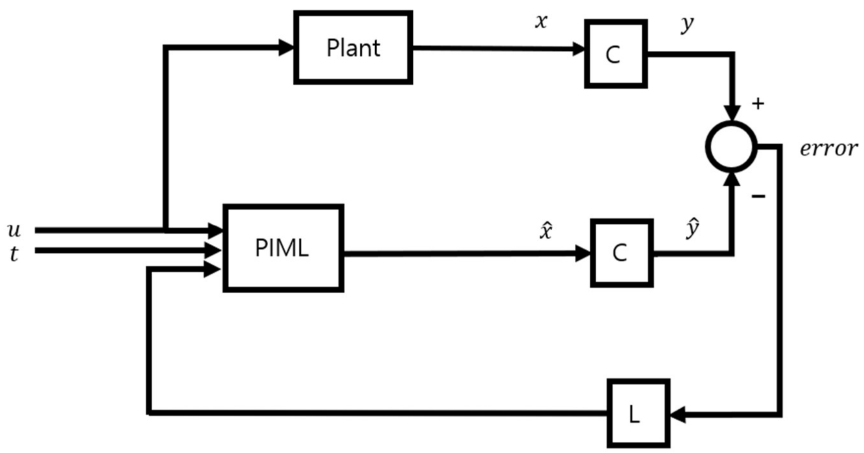

Figure 1: Block Diagram of the proposed method

References

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