Disturbance Observer for Estimating Coupled Disturbances

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I. Related Work

In this section, we review key areas related to this work. We begin by discussing recent research in the well-studied area of disturbance observers. As our proposed method falls into the realm of the scheme combining control and data-driven learning, the related advanced research is also reviewed. The connections between existing approaches and our contribution are emphasized.

A. Analytical Disturbance Estimation

The basic idea of the disturbance estimation approach is to design an ad-hoc observer to estimate the disturbance by utilizing its influence on the system [1]. The estimation method is a two-degree-of-freedom control framework [2], [3], which can achieve tracking and anti-disturbance performances simultaneously. For most disturbance observers, like Frequency Domain Disturbance Observer (FDDO) [4], ESO [5], Unknown Input Observer (UIO) [6], Generalized Proportional Integral Observer (GPIO) [7], and Time Domain Nonlinear Disturbance Observer (TDNDO) [8], zero-error estimation can be usually achieved in the event of constant disturbances. For more complicated time-varying disturbances, accurate estimation usually requires *a priori* knowledge of disturbance features. For example, UIO [6] and TDNDO [9] can accurately estimate the harmonic disturbance if its frequency is known. GPIO [7] and higher-order TDNDO [10] can achieve an asymptotic estimation of the disturbance represented by a high-order polynomial of time series. More recently, for multi-disturbance with limited *a priori* information, the simultaneous attenuation and compensation approach appears to be a nascent solution [2].

Most disturbance observers are limited to external disturbances and show unsatisfactory performance for inner model uncertainty. Some researchers attempt to estimate a coupled disturbance with a bounded derivative assumption, such as ESO [5] and NDO [11]. This bounded derivative assumption has limitations from a theoretical perspective because it demands that the system state is bounded in advance [12]. Moreover, a large derivative bound can result in a large estimation error.

A two-stage Active Disturbance Rejection Control (ADRC) strategy [12] is designed in order to avoid the requirement of bounded derivative assumption on system states. The controller in the first stage guarantees the boundness of the system state by a special auxiliary function, and a linear ESO in the second stage is employed to estimate the total disturbance. However, the existence of the auxiliary function is not discussed. Another solution is to utilize *a priori* disturbance structure. Focusing on wind disturbance, a refined disturbance observer is proposed in [13] to directly estimate the wind speed instead of the whole wind disturbance. By this means, not only the bounded derivative assumption of the coupled disturbance is avoided, but also the bound of estimation error is reduced. However, this scheme is limited to the case with an explicitly known disturbance coupling structure.

B. Combining Analytical Control and Data-Driven Learning

Nowadays, the interest in combining control-theoretic approaches with data-driven learning techniques is thriving for achieving stable, high-precision control. In [14], DNNs are utilized to synthesize control certificates such as *Lyapunov* functions and barrier functions to guarantee the safety and stability of the learned control system. In [15], DNNs are employed to learn the mass matrix and the potential energy in *Lagrangian* mechanics and *Hamiltonian* mechanics. Compared to naive black-box model learning, a more interpretable and plausible model that conserves energy can be obtained. With respect to the uncertainty satisfying *Gaussian* distribution, a *Gaussian* belief propagation method is designed in [16] to compute the uncertainty, which is finally utilized to tighten constraints of Model Predictive Control (MPC). [17] finds that a higher-order nonlinear system controller by the Reinforcement Learning (RL) policy behaves like a linear system. The stability of the RL policy can be analyzed by the identified linear closed-loop system with the pole-zero method. [18] combines a robust control and Echo State Networks (ESN) to control nonlinear systems, where ESN is employed to learn the inverse dynamics and to help mitigate disturbance. However, the bounds of disturbance and learning output need to be known.

Even with these advances, for nonlinear systems perturbed by external time-varying disturbances that cannot be accurately sampled, data-driven supervised learning methods would no longer be applicable. Several works are proposed to handle the coupled disturbance by establishing a bi-level optimization problem [19], [20]. Within the framework of adaptive control, the nonlinear features depending on the system state are learned via meta-learning offline in [19]. This work breaks through the assumption that the unknown dynamics are linearly parameterizable in the traditional adaptive control method. [20] develops a control-oriented meta-learning framework, which uses the adaptive controller as the base learner to attune learning to the downstream control objective. Both methods attribute the effect of external disturbance in the last layer of the neural networks, which is estimated adaptively online. However, the above scheme ensures zero-error convergence only when the external disturbance is constant. Moreover, laborious offline training is needed.

In this work, the coupled disturbance can be accurately estimated by merging the data-driven learning with an analytical disturbance observer. Not only the bounded derivative assumption in estimation methods [5] can be avoided, but also the requirement of the external disturbance being a constant in learning methods [19], [20] can be relaxed.

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