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Embedded Model Control: Outline of the theory

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Abstract

Embedded Model Control allows one to proceed systematically from fine plant dynamics and control requirements to the Embedded Model (EM), which is the core of control design and algorithms. The model defines three interconnected parts: the controllable dynamics, the disturbance class to be rejected and the neglected dynamics. Controllable and disturbance dynamics must be observable from the plant measurements. Control algorithms are designed around the first two parts, while stability and performance are constrained by the third one. The key design issue is discriminating between driving noise and neglected dynamics, to guarantee updating disturbance in view of its rejection. To this end, concept and equations of the 'error loop' are outlined: it maps error sources to performance and shows how to discriminate destabilizing sources, while meeting performance requirements. An introductory example with analytical and simulated results illustrates the design steps.

Keywords: Digital control; Embedded Model; Error loop

1. Introduction

The paper explains the fundamentals of a model-based design called Embedded Model Control (EMC), which can be traced back to [1]. Since then, EMC has been fully developed and applied to different applications, the most recent being [2–6,19]. The present theory outline revises, simplifies [1] and prepares for a paper showing a standard application: web winding [17]. The core is a stylized model of the plant to be controlled, the Embedded Model (EM), written as a discrete-time state equation to be embedded in the control unit and real-time updated by command and noise in order to keep controllable and disturbance state variables active, as they are the main source of command synthesis.

Although model-based design is widely adopted by internal model control (IMC) [7,8], and model predictive control (MPC) [9,10,22], a subtle difference must be pointed out: the design model is not preserved by control algorithms but absorbed within autoregressive-moving-average (ARMA) models connecting measures and reference signals to commands. The extreme case occurs in PID control design [11], where models, if any, and control algorithms are completely separated. As the opposite occurs in the EMC, explicit feedback channels can be established between the model error, i.e. the difference between plant measures and their model counterpart, and the vector of unpredictable, arbitrary signals – the driving noise – capable of updating the EM disturbance state in real time.

Model error also becomes a feedback source in IMC, but in this case, the absence of explicit disturbance dynamics makes it impossible to go beyond a generic interpretation as the plant disturbance effect [8]. Model error occurs as a feedback source in state observers [12,13], but as their concern is how to ensure asymptotic stability and minimal variance, feedback channels are designed without any regard of their significance as disturbance. MPC essentially treats the problem of constrained regulators tracking some predictable reference [10]. The addition of disturbance dynamics appears to be more of an option than a must, as case studies reduce generic and complex formulation to 1st order dynamics [23].

Actually, extracting driving noise from plant measures must be kept as the central control problem closely entwined with robust closed-loop stability, as command-independent noise always becomes entangled with the command-dependent effects of neglected dynamics (vibrations in mechanical systems, transport delays in thermal and fluid systems). Several techniques have been designed for the purpose: among them,

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(1) disturbance state observers, usually in the form of steady-state Kalman filters [14],
(2) feedback filters, shaped from an assumed spectral densities of random disturbances [15].

Both methods assume disturbance is stationary and some knowledge of the statistics, which actually is seldom available, and if available is largely uncertain as pointed out in [23]. The present approach mimics state observers, but nonstationary disturbance dynamics is admitted and noise statistics may not explicitly enter the design, but just through plant simulation to derive a priori performance. Disturbance dynamics is synthesized by combining pure discrete-time integrators driven by arbitrary signals, which, in a statistical framework, lead to random drifts (a subclass of ARIMA processes in [26, 27]). They are nonstationary, but their finite-time realizations encompass those of stationary processes with (variable) time constants longer than the realization time-span. The advantage is to dispose of simple and parameter-free models, where only the number of integrators and their topology must be synthesized. By leaving noise statistics free, process realizations may be also interpreted as arbitrary piecewise polynomials as in [27]. In this framework, noise and disturbance may act at any point on the controllable dynamics or may be absent in some part, which in Kalman filters would imply singular covariance. The problem is solved by allowing the output-to-state feedback of state observers to be dynamic but of minimal order. The corresponding algorithm is called the Noise Estimator and when closed around EM takes the form of a state predictor.

The essential architecture of the EMC includes two main sets of feedback channels in agreement with classical LQG control [12]:

(1) the output-to-state feedback of the Noise Estimator in charge of estimating the current noise,
(2) the state-to-command feedback of the Control Law, in charge of providing commands one-step ahead.

In general, the Noise Estimator is accompanied by the reference generator, not treated here, in charge of computing the EM reference trajectories subject to command and state constraints and to real-time operator requests. Noise Estimator and reference generator constitute the Measurement Law acting as the interface from plant/operator measurements to EM state.

Since plant dynamics will never match the Embedded Model, because neither plants nor processes are mathematics, the separation theorem [12,16] cannot be invoked as in linear quadratic Gaussian (LQG) design to guarantee closed-loop stability. Stability recovery passes through EM and the Noise Estimator, asking them to disentangle noise and neglected dynamics from model error so as to provide a clean noise estimate. To this end, theorems in [1] are revised through the so-called error loop, showing the Noise Estimator to be committed to overall closed-loop stability. In this way, error loop concept and inequalities enable a weak separation principle to be recovered, in which Control Law and reference generator should be model-based and performance oriented, while the Noise Estimator should aim at robust stability. As the latter achievement necessarily constrains noise estimation and disturbance updating, disturbance modeling becomes a prominent issue in recovering performance, if it is degraded by stability.

The gain values of the Noise Estimator derive from the state-predictor eigenvalues, which have to guarantee error loop stability and performance. Two cases may occur.

(1) Driving noise estimate is entangled with neglected dynamics – in other terms it is command dependent – in which case eigenvalues must guarantee closed-loop stability inequality with some margin.
(2) Driving noise estimate is command independent in which case performance dominates, and steady-state Kalman or signal-to noise ratio design as in [23] can be applied upon knowledge of bounds to noise statistics. Highly variable noise statistics is not treated here, but would require real-time estimation of the noise statistics.

Owing to uncertainty about neglected dynamics and noise statistics, the designed eigenvalues must be refined versus plant simulation and in-field.

The paper concentrates on the results to be employed in the application paper [17], but an introductory example is treated throughout and accompanied with simulated results in Section 6. In Section 2, the Embedded Model focuses on disturbance and neglected dynamics. Although a time-varying EM arises in [17], linear-time invariance (LTI) is assumed by deferring extensions to [17]. Section 3 provides the basic theorem for designing a model-based Control Law capable of decoupling unstable disturbance dynamics from performance variables and bounding the effects of residual noise. Section 4 shows how to estimate driving noise from model error through static/dynamic feedback channels called Noise Estimators. EM corruption by neglected dynamics spilling through noise estimates is the source of plant instability. Section 5 demonstrates the error loop, i.e. a loop connecting neglected dynamics to control errors and showing how to recover plant stability and performance through Noise Estimator tuning.

2. Fine and Embedded Model

2.1. The extended plant, model error and fine model

The Embedded Model is a discrete-time (DT) state equation, which is the composition of two interconnected sub-models, the controllable and the disturbance dynamics. A linear, time-invariant model is assumed. Discrete times are denoted by $t_i = iT$, T being the time unit to be designed.

The EM describes the causal relation between the scalar, real-valued plant command $u(i)$ and the multivariate, real-valued plant measures $\mathbf{y}(i)$. Both of them are part of the digital control unit (DCU), which is assumed to process data with a numerical accuracy higher than digital-to-analogue converters (DAC) and analogue-to-digital converters (ADC). The overall plant from $u(i)$ to $\mathbf{y}(i)$, is referred to as the extended plant. In this way the extended plant and the EM share the same