

IDENTIFICATION IN H_∞ IN THE PRESENCE OF DETERMINISTIC AND STOCHASTIC NOISE

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Abstract

This paper considers two-stage nonlinear algorithm for the problem identification in H_∞ . The sufficiency of the conditions and necessity of the conditions is proved for robust convergence of the algorithm. The purpose of the present paper is to consider robust identification of systems, described by FIR model, in the presence of deterministic and stochastic disturbance. Stochastic noise can be unbounded. Proposed algorithm is analysed in terms of the Fourier transform of the convolution window function.

1 Introduction

It has long been understood that a key problem in control system design is to handle the uncertainties associated with the plant. Two main techniques for design a control systems in such situation are adaptive control [1] and robust control [2]. In the later control paradigm a controller is designed on the basis of a nominal model of the plant with the associated parametric and unstructured model uncertainties which are explicitly taken into account. Using combination of adaptive control and robust control design we have adaptive robust control. In that case key interest is robust identification (or control-relevant identification).

First step in the construction of robust identification algorithm in the presence of unmodeled dynamics is a variety of modification of the algorithms originally designed for the ideal case (σ and ε_1 modification, relative dead-zone, signal normalization and projection of parameter estimates) [3]. When the noise is stochastic, problem is considered in [4]. In reference [5] is considered algorithms possessing a low sensitivity to distribution noise changes. Robust estimation in the presence of noise uncertainty and unmodeled dynamic is presented in [6]. In above algorithms, under the standard conditions imposed on the modeled system part, it is shown that the estimation error converges to a limit which explicitly depends on the unmodeled dynamics in such a way that when the unmodeled dynamics decays the estimation error tends to zero.

Next step is estimation of nominal model and explicit bound on the plant uncertainty in a form compatible with a robust control design method. For the currently popular H_∞

robust control design is developed robust identification algorithm in H_∞ [7]-[10]. Above algorithms belongs to the problems of worst-case identification of linear system and general theory for such algorithms is presented in [11]-[13].

Key assumption in the identification in H_∞ is boundness of noise (except [8]). In the context of "classical" identification [14] disturbance is modeled as a stochastic process which can be unbounded. Such case for non-Gaussian disturbance in the field of identification in H_∞ is considered in [15]. The parallels between classical stochastic estimation (Kalman filtering) and the deterministic robust estimation is presented in [16].

The traditional description of noise (stochastic or bounded noise) is changed with the better picture (from physical reasons) which describe noise as the sum of stochastic noise and bounded component [17]. Such description of noise is considered in this paper in the context of identification in H_∞ of linear systems described as a FIR model.

In this paper we will consider problem of robust convergence of algorithm for identification in H_∞ in terms of the Fourier transform of the convolution window function.

2 Preliminary

In this section is defined the H_∞ identification problem when the traditional description of a noise is removed. Namely, if noise is modeled as bounded (for example, measurement errors of quantization) we have unknown-but-bounded approach to estimation and that is known as set membership identification [18]. When the noise model is stochastic we have the traditional identification methods of maximum likelihood/least squares [14]. The better approach for noise description is [17]

$$\hat{v}(i) = \hat{e}(i) + \hat{\eta}(i) \quad (2.1)$$

where

$$|\hat{\eta}(i)| \leq \varepsilon \quad (2.2)$$

and $\hat{e}(i)$ has conventional averaging properties

$$\bar{E}Z(i)\hat{e}(i) = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{i=1}^N EZ(i)\hat{e}(i) = 0$$

