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Model Order Selection Based on Robust Akaike's Criterion

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Abstract: This paper considers the model order selection due to process of identification of OE (output error) models with constant parameters in the presence of measurements with non-Gaussian noise distributions. In practical conditions, in measurements there are rare, inconsistent observations with the largest part of population of observations. Therefore, synthesis of robust algorithms is of primary interest. The presence of outliers can considerably degrade the performance of linearly recursive algorithms based on the assumptions that measurements have Gaussian distributions. In this paper, the robust parameter estimation algorithm is proposed which is based on Huber's theory of robust statistics. On the other side, ad hoc selection of model orders leads to overparametrization or parsimony problem. The natural frame to avoid these problems is AIC (Akaike's information criterion) for model order selection, which is obtained by minimization of the Kullback-Leibler information distance. The originally proposed Akaike's criterion cannot be applied since stochastic disturbance in the model belongs to the class of ε-contaminated distributions. By determining the least favourable probability density for a given class of probability distribution represents a base for design of the RAIC (robust version of Akaike's information criterion). The benefits of RAIC for robust parameter estimation procedure is illustrated through intensive simulations which demonstrate the superiority of the proposed robust procedure in relation to the linear algorithms (derived under the assumption that the stochastic disturbance has a Gaussian distribution).

Keywords: Model order selection, output error model, ε-contaminated distributions, robust Akaike's criterion.

Nomenclature

ε	Degree of contamination
$\Psi(\cdot)$	Vector influence function
$\varphi(k)$	Regression vector
$\theta(k)$	Vector of true parameters
$\hat{\theta}(k)$	Vector of parameter estimates
a_j, b_j	System parameters
$E(\cdot)$	Mathematical expectation
$J(\theta)$	Identification criterion
$\Phi(\cdot)$	Robust loss function
$p^*(.)$	The least favourable distribution of probability
$\mathcal{P}_\varepsilon$	Approximately normal distribution class
$p(e)$	Probability density function
σ^2	Variance
$P(k\|k)$	A posteriori covariance matrix
$P(k\|k-1)$	A priori covariance matrix
$e(k)$	Stochastic disturbance
$u(k)$	Input signal
$y(k)$	Output signal
$\varepsilon(k)$	Prediction error
$y_M(k)$	Output of an auxiliary model

1. Introduction

It is well known that obtaining models of physical systems based on the fundamental laws of physics is a difficult problem. The system identification is an alternative approach, which ensures obtaining the mathematical models based on input/output measurements [1, 2]. Most identification algorithms assume that the model structure is a priori known. As is well known, a fundamental difficulty in statistical