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An Investigation on the Wiener Approach for Nonlinear System Identification Benchmarks

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1 Introduction

We evaluate the effectiveness of the Wiener model structure in modeling of the given benchmark problems. Two different approaches are proposed for parameter estimation. The results are compared for three problems, i.e. Silver Box, Wiener-Hammerstein, and Wiener-Hammerstein with noise. The aim is to evaluate the capability of the algorithms on the other benchmark problems in future works as well.

2 The proposed Wiener Approaches

In the following two different algorithms for parameter estimation of the Winer model structure is proposed and they are applied to the benchmark problems.

A. Winere-Neural Nonlinear Identification [2]

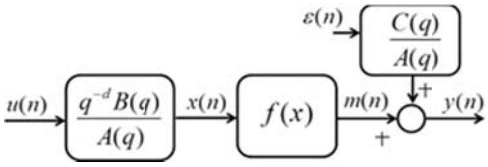
State-space representation of a Wiener model can be stated as follows:

$$\begin{aligned} x(k+1) &= \mathbf{A}x(k) + \mathbf{B}u(k) \\ z(k) &= \mathbf{C}x(k) + \mathbf{D}u(k) \\ y(k) &= f(z(k)) + v(k) \end{aligned} \tag{1}$$

where $x(k)$ is $n\times 1$ the state vector at time , $u(k)$ is $m\times 1$ the vector of control input, $y(k)$ is the $l\times 1$ vector of measured output, and $v(k)$ is a measurement noise assumed to be zero-mean and independent of $u(k)$ for all k's. The system matrices $\mathbf{A},\mathbf{B},\mathbf{C},\mathbf{D}$ are real with proper dimensions and $f(.)$ is a nonlinear vector function defined on $R^l \to R^l$. The first step is identification of linear part using state-space methods. So assuming the nonlinear mapping as an identity, the linear dynamics characterized by quadruple $(\mathbf{A},\mathbf{B},\mathbf{C},\mathbf{D})$ will be identified. Then using the identified matrices $(\mathbf{A},\mathbf{B},\mathbf{C},\mathbf{D})$, the output sequences of this LTI system $\{\hat{z}(k)\}_{k=1}^{N}$ will be computed. With this sequence a primary identification of the nonlinear part of the Wiener model can be estimated. Here the static nonlinear term is identified using a single layer neural network.

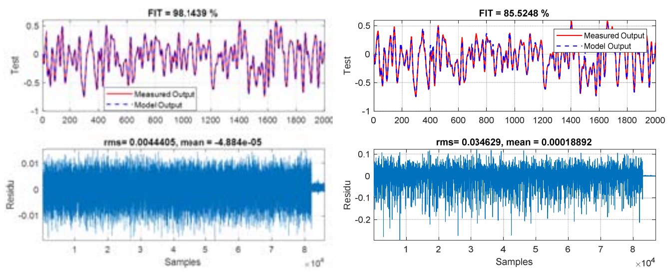
B. Iterative Recursive Least Square Wiener [3]

The model structure of the Wiener model is shown in the figure below. It consists of an unknown linear transfer function followed by a parametrised polynomial nonlinearity. The noise model is also added to the output $m(k)$. The parameters of the linear transfer function, static nonlinearity, and the noise model are estimated using an iterative recursive LS technique. Since in this formulation of the problem the intermediate signal $x(n)$ and the noise signal $\varepsilon(n)$ are not already known, they are estimated in the iterative phase of the algorithm.



3 Preliminary Results

The results show that both techniques perform well to identify the SilverBox example [4]. The identification is performed against various scenarios for estimation and test signals and both techniques show robustness in this sense, i.e. the best fit is achieved for the multi-sine signal. Figure below shows the identification results for the Wiener-Hammerstein example [3]. The results confirm that the Wiener model structure captures the properties of the cascades Winer-Hammerstein system when no process or measurement noise exist. Nevertheless, in case of noisy data the Wiener-Neural fails as it doesn't have any measure to model the system noise while IR-Wiener shows some degrees of fit if the noisy data are used for estimation. Better tuning of the noise model may result in a better fit.



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