

Combining the best linear approximation and dimension reduction to identify the linear blocks of parallel Wiener systems

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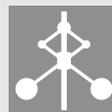
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Abstract

A Wiener model is a fairly simple, well known, and often used nonlinear block-oriented black-box model. A possible generalization of the class of Wiener models lies in the parallel Wiener model class. This paper presents a method to estimate the linear time-invariant blocks of such parallel Wiener models from input/output data only. The proposed estimation method combines the knowledge obtained by estimating the best linear approximation of a nonlinear system with a dimension reduction method to estimate the linear time-invariant blocks present in the model. The estimation of the static nonlinearity is fairly easy once the linear blocks are known.

Keywords: System identification, Parallel Wiener, Dimension reduction, Best Linear Approximation

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Abstract

A Wiener model is a fairly simple, well known, and often used nonlinear block-oriented black-box model. A possible generalization of the class of Wiener models lies in the parallel Wiener model class. This paper presents a method to estimate the linear time-invariant blocks of such parallel Wiener models from input/output data only. The proposed estimation method combines the knowledge obtained by estimating the best linear approximation of a nonlinear system with a dimension reduction method to estimate the linear time-invariant blocks present in the model. The estimation of the static nonlinearity is fairly easy once the linear blocks are known.

1 Introduction

The estimation of nonlinear models is mainly considered as an open topic in the system identification community [12]. Nevertheless nonlinear models are used to compensate for out of band distortion in communication channels, to improve the plant control of nonlinear systems, or to improve system design. To be practically useful, a nonlinear model needs to be simple to understand for the user, and flexible enough to model complex nonlinear systems. The class of block-oriented models obtains these properties by separating the static nonlinear and linear time-invariant (LTI) behavior into different building blocks.

Block-oriented models are already widely used and studied in literature [2, 7–9, 13, 14, 23, 25, 26]. Applications range from power amplifiers over physiological systems to chemical processes [7]. The most simple structure for block-oriented models are the so-called Hammerstein and Wiener models. A Hammerstein model consists of a static nonlinear block followed by a LTI block. The Wiener model consists of a LTI block followed by a static nonlinearity. These two basic type of models can be generalized using a series connection to, for instance, the Hammerstein-Wiener and the Wiener-Hammerstein models. Another way to expand these basic models consists in a parallel cascade.

A parallel cascade Wiener model connects different Wiener systems excited by the same input signal $u(t)$ in parallel. The static nonlinearity that is present in each of these Wiener branches can be generalized by one multiple-input-single-output nonlinearity. It has been shown that parallel Wiener models can approximate all fading memory systems arbitrary well [2] if the number of branches

is sufficiently high. A three-branch parallel Wiener system is shown in Figure 1. The identification of the LTI blocks in a parallel Wiener system is not trivial due to the static nonlinear combination of the outputs $z_i(t)$ of all the LTI subsystems that is present in the output $y(t)$ of the nonlinear system.

Previously proposed parallel Wiener estimation methods [8, 9, 13, 14, 23, 25, 26] suffer from some disadvantages. Some methods rely on an estimate of the Volterra kernel of the system under test [8]. This requires a very large amount of data for the identification. Other methods are limited to the use of finite impulse response models for the linear subsystems [9, 13, 14, 26], while others need to measure different linearized models of the system for different amplitudes of the input signal [23], or suffer from the presence of an abnormally high number of parallel branches in the estimated model [25].

The focus of this paper is put on the estimation of the LTI blocks in the parallel Wiener model, without the need for an estimation of the static nonlinearity. The proposed method combines the advantages of the best linear approximation (BLA) of a nonlinear system [4, 21] and dimension reduction techniques [11, 13, 27] to estimate a parallel Wiener model with a reasonable accuracy and an acceptable number of branches. The advantages of this approach are the low amount of data that are needed to estimate a good quality model, and the ability to estimate an infinite impulse response model for the LTI blocks. This is obtained for a low number of parallel branches in the model, as dimension reduction techniques are used to select a set of dominant branches.

The second section introduces the class of systems, and signals and the noise framework that are considered. Secondly, the best linear approximation of a parallel Wiener system is introduced in Section 3. Next, Section 4 discusses different dimension reduction methods. Section 5 explains the new estimation method for parallel Wiener models in some detail. Finally, a simulation example is given in Section 6 to show the efficiency of the method.

2 Systems, signals and noise

This section describes the class of systems, the signal class and the noise framework that are considered in this paper. The considered class of systems is the class of parallel Wiener systems, the input signals are considered to be elliptically distributed, and the noise framework is colored additive output noise.

2.1 System

The considered class of systems is the class of parallel Wiener systems, as is shown in Figure 1. In a parallel Wiener system, the input $u(t)$ is applied to different LTI subsystems $H_i(q)$, where q^{-1} is the backwards shift operator. This produces the intermediate outputs $z_k(t)$. The final output $y(t)$ of the parallel Wiener system is obtained by applying a static nonlinear function $f(\mathbf{z}(t))$ on the intermediate outputs $\mathbf{z}(t)$, where $\mathbf{z}(t) = [z_1(t), z_2(t), \dots, z_{n_H}(t)]$. n_H is the number of parallel branches that are present in the parallel Wiener system. The LTI subblocks are modeled by a rational polynomial in q^{-1} .

$$H_i(q) = \frac{b_{0,i} + b_{1,i}q^{-1} + b_{2,i}q^{-2} + \dots + b_{n_b,i,i}q^{-n_b,i}}{a_{0,i} + a_{1,i}q^{-1} + a_{2,i}q^{-2} + \dots + a_{n_a,i,i}q^{-n_a,i}}, \quad (1)$$

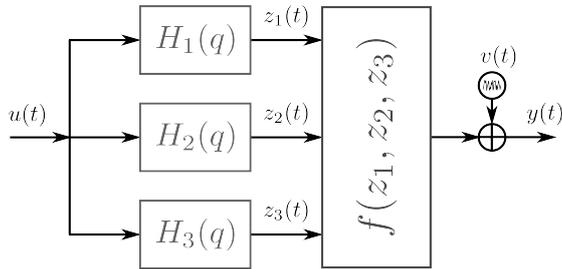


Figure 1: A 3-branch parallel Wiener system. The LTI blocks $H_i(q)$ are shown in light gray, the static nonlinearity $f(\mathbf{z})$ is shown in dark gray.

$$z_i(t) = H_i(q)u(t), \quad (2)$$

$$y_0(t) = f(\mathbf{z}(t)), \quad (3)$$

where $n_{b,i}$ and $n_{a,i}$ are the order of the numerator and the denominator of the frequency response function (FRF) model of the LTI block of the i -th branch respectively.

2.2 Signals

The input signal $u(t)$ is supposed to have an elliptical distribution [5], for instance a Gaussian distribution. This assumption is needed to estimate the best linear approximation used in Section 3, and to apply some of the dimension reduction techniques adopted in Section 4.

2.3 Noise

A Gaussian additive, colored noise source $v(t)$ is present at the output of the system:

$$y(t) = y_0(t) + v(t) \quad (4)$$

3 BLA of a parallel Wiener system

When elliptical distributed input excitation signals are used, Bussgang's theorem [3,5] can be applied on a parallel Wiener system. This means that all static nonlinear terms can be approximated by a constant. This shows that the BLA of a parallel Wiener system, as is shown in Figure 1, consists of a weighted sum of the linear subsystems that are present in the parallel Wiener system:

$$G_{BLA}(j\omega_k) = \sum_{i=1}^{n_H} \alpha_i H_i(j\omega_k). \quad (5)$$

Hence, when $G_{BLA}(j\omega_k)$ is estimated in a parametrized form, the estimated poles will be a consistent estimate for all the poles that are present in all the LTI blocks of the parallel Wiener system. The question that remains to be answered is how to find out which poles belong to which LTI block. This problem can be solved using dimension reduction techniques (Section 4).

3.1 Estimating the BLA

The BLA, is a best approximation in least-square sense. It is defined as in [4, 6, 17] by:

$$\hat{G}_{BLA}(j\omega_k) = \arg \min_{G(j\omega_k)} E \left\{ |Y(j\omega_k) - G(j\omega_k)U(j\omega_k)|^2 \right\}, \quad (6)$$

herein, the nonparametric $\hat{G}_{BLA}(j\omega_k)$ is obtained as [1]:

$$\hat{G}_{BLA}(j\omega_k) = \frac{S_{YU}(j\omega_k)}{S_{UU}(j\omega_k)}, \quad (7)$$

$$S_{YU}(j\omega_k) = E \{ Y(j\omega_k) \bar{U}(j\omega_k) \}, \quad (8)$$

$$S_{UU}(j\omega_k) = E \{ U(j\omega_k) \bar{U}(j\omega_k) \}. \quad (9)$$

Practically speaking, the frequency response function of the BLA, $\hat{G}_{BLA}(j\omega_k)$, is obtained using the local polynomial method [16–20]. Besides the frequency response function, the local polynomial method also estimates the sample variance $\hat{\sigma}_{\hat{G}_{BLA}}^2(j\omega_k)$ which will be used as prior knowledge in the parametrization step of the frequency response function. $\hat{G}_{BLA}(j\omega_k)$ can be parametrized using a rational polynomial function:

$$\hat{G}_{BLA}(j\omega_k, \theta) = \frac{b_0 + b_1 q^{-1} + \dots + b_{n_b} q^{-n_b}}{a_0 + a_1 q^{-1} + \dots + a_{n_a} q^{-n_a}} \quad (10)$$

A maximum likelihood estimation framework is chosen to identify the parametrized $\hat{G}_{BLA}(j\omega_k, \theta)$. As the estimator uses the previously estimated sample mean and sample variance of the prior estimated nonparametric BLA, a sample maximum likelihood estimator results [22, 24]:

$$V_{SML}(\theta, Z) = \sum_{k=1}^F \frac{|\hat{e}(j\omega_k, \theta, \hat{Z}(k))|^2}{\hat{\sigma}_{\hat{G}_{BLA}}^2(j\omega_k)}, \quad (11)$$

$$\hat{e}(j\omega_k, \theta, \hat{Z}(k)) = \hat{G}_{BLA}(j\omega_k) - \hat{G}_{BLA}(j\omega_k, \theta). \quad (12)$$

4 Dimension reduction

Many dimension reduction methods are available in the statistical community. One class of these methods is the class of inverse regression methods. Some of these approaches have already been applied in a system identification setting, such as the sliced inverse regression (SIR) [11], the directional regression (DR) [10], and the discretized directional regression (DDR) [28]. More information about using inverse regression for system identification can be found in [14, 15]. Another promising, but computationally more expensive, dimension reduction method is the minimum average variance estimation (MAVE) method [13, 27], which uses an iterative forward regression approach.

To apply these dimension reduction methods off the shelf, the problem should be reformulated as follows:

$$y(t) = f(B^T \varphi(t)) + e(t), \quad B \in \mathfrak{R}^{n_d \times n_{rd}}, \quad (13)$$

where $e(t)$ is an unknown disturbing noise source, $\varphi(t)$ contains the perfectly known regression variables, and the reduced dimension n_{rd} is smaller than the number of regressors n_d . $\varphi(t)$ should be elliptically distributed for the inverse regression approaches. For the inverse regression approaches, the noise can also be present inside the nonlinearity.

The different dimension reduction methods estimate the matrix B . The estimation depends on a good choice of the regressors $\varphi(t)$. A possible choice of these regressors can be made using the BLA of the parallel Wiener system under test.

4.1 Inverse regression

In contrast to the standard forward regression methods, inverse regression methods regress the multivariate input φ against the output y . An important difference with respect to normal regression problems is that here only the matrix B in (13) needs to be estimated. Actually, only a set of basis functions that span the same space as the original B matrix needs to be estimated to be able to obtain a model that describes the input-output behavior of the system. No prior information about the nonlinear function f is required to be known. Using a standardized distribution for the applied regressors φ , the inverse regression curve $E(\varphi|y)$ lies in the space spanned by the original matrix B . A principal component analysis on the covariance matrix of $E(\varphi|y)$ will yield the estimate of B [10, 11, 14, 15].

4.2 MAVE

MAVE is a forward regression approach that solves the problem formulated in (13). It was first proposed in [27]. A semiparametric approach is proposed here. A parametric model is estimated for the matrix B , while a nonparametric model approximates the nonlinearity by a local linear expansion of the nonlinearity. MAVE minimizes the following cost function:

$$\underset{B: B^T B = I}{\text{minimize}} \quad E (y(t) - E (y(t)|B^T \varphi(t)))^2, \quad (14)$$

where the inner expectation value is approximated by a local linear expansion:

$$E (y(t)|B^T \varphi(t)) \approx \alpha_\tau + \beta_\tau^T B^T (\varphi(t) - \varphi_\tau). \quad (15)$$

One of the issues is that this problem is nonconvex. In [13] a convex relaxation is proposed to solve this minimization problem.

5 Combining the BLA with dimension reduction techniques

The BLA estimates the transfer function of the dynamics that are present in the nonlinear system. This transfer function can be represented using a rational

function of q . This rational form can be decomposed in a sum of rational forms of order 1 using the partial fraction expansion, which, in the absence of coinciding poles, is given by:

$$\begin{aligned} G_{BLA}(j\omega_k, \theta) &= \frac{b_0 + b_1 q^{-1} + \dots + b_{n_b} q^{-n_b}}{a_0 + a_1 q^{-1} + \dots + a_{n_a} q^{-n_a}}, \\ &= \frac{r_1}{p_1 - q^{-1}} + \frac{r_2}{p_2 - q^{-1}} + \dots + \frac{r_{n_a}}{p_{n_a} - q^{-1}} + k, \end{aligned} \quad (16)$$

where k is a constant in the case of proper systems and r_i is the residual associated to each pole. The terms of this partial fraction expansion can be used as a set of basis functions to reconstruct the original LTI blocks of the parallel Wiener system.

The terms of complex conjugate poles can be combined in order to have fewer terms:

$$\begin{aligned} G_{BLA}(j\omega_k, \theta) &= \frac{r_1}{p_1 - q^{-1}} + \dots + \frac{r_{n_r}}{p_{n_r} - q^{-1}} \\ &\quad + \frac{r_{n_r+1,0} + r_{n_r+1,1} q^{-1}}{p_{n_r+1,0} + p_{n_r+1,1} q^{-1} + q^{-2}} + \dots \\ &\quad + \frac{r_{n_d-1,0} + r_{n_d-1,1} q^{-1}}{p_{n_d-1,0} + p_{n_d-1,1} q^{-1} + q^{-2}} + k, \\ &= P_1(q) + P_2(q) + \dots + P_{n_d-1}(q) + k, \end{aligned} \quad (17)$$

where the terms 1 to n_r correspond to the basis functions associated to the real poles, and the terms $n_r + 1$ to $n_d - 1$ correspond to the basis functions associated to the complex conjugate poles, where n_d is previously defined in (13).

The regression matrix $\varphi(t)$ for the dimension reduction methods can be constructed starting from the partial fraction expansion of the frequency response function as a model for the system. Denote $P_i(z)$ as the i -th basis function of the partial fraction expansion. The associated regression matrix is:

$$\varphi(t) = [P_1(q)u(t) \quad P_2(q)u(t) \quad \dots \quad P_{n_d-1}(q)u(t) \quad u(t)]^T. \quad (18)$$

Next, a dimension reduction method of choice is applied to the constructed regression matrix $\varphi(t)$ and the measured output $y(t)$. This results in the matrix \hat{B} , an estimate of the true B matrix as defined in (13). Hence, the in dimension reduced set of basis functions is given by:

$$\hat{H} = P\hat{B} \quad (19)$$

$$[\hat{H}_1(q) \quad \hat{H}_2(q) \quad \dots \quad \hat{H}_{n_{rd}}(q)] = [P_1(q) \quad P_2(q) \quad \dots \quad P_{n_d-1}(q) \quad 1] \hat{B} \quad (20)$$

where $n_{rd} < n_d$, as defined in (13). This low rank set of basis functions \hat{H} acts as the estimate of the LTI blocks in the parallel Wiener model.

Note that the sub-blocks in a parallel Wiener structure cannot be uniquely identified from input-output data only. A full rank linear similarity transformation between the outputs of the dynamic systems and the inputs of the static nonlinearity can introduce infinitely many equivalent model descriptions [23].

A full rank similarity transform $T^{-1}T$ can be inserted in the output equation of a parallel Wiener model:

$$y(t) = f(T^{-1}T\mathbf{H}(q)u(t)), \quad (21)$$

$$y(t) = \bar{f}(\bar{\mathbf{H}}(q)u(t)), \quad (22)$$

where:

$$\bar{f}(x) = f(T^{-1}x), \quad (23)$$

$$\bar{\mathbf{H}}(q) = T\mathbf{H}(q), \quad (24)$$

and $\mathbf{H}(q)$ is given by:

$$\mathbf{H}(q) = [H_1(q) \quad H_2(q) \quad \dots \quad H_{n_H}(q)]^T \quad (25)$$

6 Simulation example

A simulation example is performed to illustrate the method. First the simulation setup is explained. Next, the simulation results are discussed.

6.1 Setup

A 2-branch parallel Wiener system is simulated. The linear block consists of two low-pass Chebychev filters of order 4, with a cut-off frequency of respectively $0.30f_s$ and $0.175f_s$, and a ripple of 5 and 3 dB. The frequency response functions of the filters are shown in Figure 2. The static nonlinearity is given by:

$$y(t) = z_1(t) + 0.7z_2(t) + 0.1 \arctan(3z_1(t)) \operatorname{sign}(z_2(t)) \quad (26)$$

The input signal $u(t)$ is a random phase multisine [17] containing $N = 512$ samples with a flat amplitude spectrum, and the excited band ranges from $\frac{f_s}{N}$ to $\frac{f_s}{2}$:

$$u(t) = A \sum_{k=1}^{N/2} \cos(2\pi k \frac{f_s}{N} t + \phi_k), \quad (27)$$

where the phases ϕ_k are independent uniformly distributed random variables between 0 and 2π . Two simulations are performed, one with 4 and another with 8 different phase realizations of a random phase multisine. Gaussian noise with a standard deviation of 0.001 is added to the output, and this results in a signal to noise ratio at the output of approximately 60 dB.

6.2 Estimation results

The estimation is performed using the SIR, DR, DDR and MAVE algorithms and the local polynomial FRF estimation algorithm. 40 slices are used in the dimension reduction algorithms SIR and DR. The estimated basis functions reconstruct the true LTI blocks quite well, as can be seen in Figures 2 and 3.

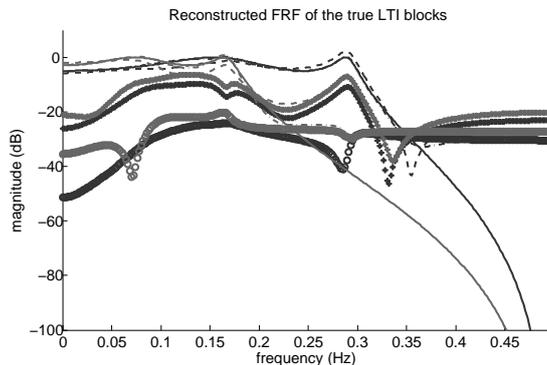


Figure 2: True LTI blocks (full lines), reconstructed LTI blocks using inverse regression (dashed lines), and reconstructed LTI blocks using MAVE (dash-dotted lines) of the parallel Wiener system. The errors are shown by the stars (inverse regression, DDR), and circles (MAVE). 4 input realizations are used during the estimation.

	basis	MAVE	SIR	DR	DDR
relative error H_1	0.0589	0.0597	0.2423	0.2717	0.2758
relative error H_2	0.0972	0.0981	0.4053	0.4556	0.4623
subspace angle	6.6364	6.7058	29.016	33.000	33.575

Table 1: Error of the reconstruction of the underlying true LTI blocks of the simulated system with 4 realizations of the input signal. The first column shows the result for the basis functions before the dimension reduction step, the second to fourth column show the results for the MAVE, SIR, DR and DDR algorithms respectively.

Tables 1 and 2 show the relative error between the true and reconstructed FRF's of the linear subsystems at the excited frequency lines:

$$\frac{\text{rms}(H_i(j\omega) - H_{i,r}(j\omega))}{\text{rms}(H_i(j\omega))}, \quad (28)$$

where rms denotes the root mean square operator, and $H_{i,r}(j\omega)$ is the reconstructed i -th LTI-block starting from the estimated basis functions.

Also, the difference in space spanned by the true and estimated LTI blocks is shown in Tables 1 and 2 using the angle between subspaces:

$$\text{angle}(A, B) = \arcsin(\|\Pi_A - \Pi_B\|_2), \quad (29)$$

where Π_A is the orthogonal projection on the column space of A. This is a generalization of the angle between vectors.

Figure 3 and Table 2 show that the dimension reduced basis functions are good estimates of the linear blocks of the parallel Wiener system. Using 8 realizations of the input signal, a reconstruction error of -10 to -30 dB is obtained using DDR, and an error between -30 to -60 dB is obtained using MAVE. A fairly good estimate is obtained when only 4 realizations of the input signal are used (Figure 2 and Table 1), a reconstruction error of -5 to -30 dB is obtained using

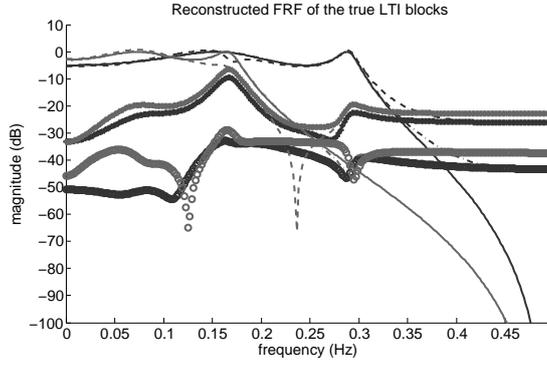


Figure 3: True LTI blocks (full lines), reconstructed LTI blocks using inverse regression (dashed lines), and reconstructed LTI blocks using MAVE (dash-dotted lines) of the parallel Wiener system. The errors are shown by the stars (inverse regression, DDR), and circles (MAVE). 8 input realizations are used during the estimation.

	basis	MAVE	SIR	DR	DDR
relative error H_1	0.0177	0.0180	0.1483	0.2285	0.1606
relative error H_2	0.0307	0.0314	0.2443	0.3435	0.2592
subspace angle	2.0386	2.0843	17.083	25.119	18.266

Table 2: Error of the reconstruction of the underlying true LTI blocks of the simulated system with 8 realizations of the input signal. The first column shows the result for the basis functions before the dimension reduction step, the second to fourth column show the results for the MAVE, SIR, DR and DDR algorithms respectively.

DDR, and an error between -20 to -50 dB is obtained using MAVE. This worse performance with only 4 input signal realizations is due to a worse estimate of the poles that are present in the system. This can be seen because the dimension reduction step does not decrease the quality of the reconstruction. So, it is clear from the difference between the 4 and 8 input signal realizations case that high quality basis functions are needed. For this a good estimate of the BLA is needed, which is in this case obtained by averaging over different signal realizations. In both cases the MAVE estimate obtains results which come very close to the result obtained with the non-reduced set of basis functions coming from the BLA. Significantly better results are obtained using the MAVE algorithm compared to the inverse regression algorithms in the case of 8 signal realizations, but this comes at the cost of an increased computational complexity. The computational complexity of MAVE grows quadratically with the number of regressors n_d , while the computational cost of the inverse regression methods grow only linearly with the number of regressors n_d .

The simulations show that the method can give good estimates of the linear blocks of a parallel Wiener model. A high quality estimate of the BLA combined with the MAVE method to perform the dimension reduction step seems to give the best results.

7 Discussion

The combination of the BLA and the dimension reduction gives promising results. The BLA estimates the poles and zeros present in the overall system dynamics, and the dimension reduction method selects which poles and zeros belong to which branch. A simulation example shows the ability of the method to retrieve an accurate estimate of the linear subsystems in the system under test. The proposed approach needs high-quality estimates of the poles present in the parallel Wiener system. Further work could involve extending the basis functions to obtain good results even when the basis functions are constructed starting from a poor estimate of the poles that are present in the system.

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Titel Combining the best linear approximation and dimension reduction to identify the linear Title blocks of parallel Wiener systems Författare Maarten Schoukens, Christian Lyzell, Martin Enqvist Author		
Sammanfattning Abstract <p>A Wiener model is a fairly simple, well known, and often used nonlinear block-oriented black-box model. A possible generalization of the class of Wiener models lies in the parallel Wiener model class. This paper presents a method to estimate the linear time-invariant blocks of such parallel Wiener models from input/output data only. The proposed estimation method combines the knowledge obtained by estimating the best linear approximation of a nonlinear system with a dimension reduction method to estimate the linear time-invariant blocks present in the model. The estimation of the static nonlinearity is fairly easy once the linear blocks are known.</p>		
Nyckelord Keywords System identification, Parallel Wiener, Dimension reduction, Best Linear Approximation		