



Brief paper

Computational complexity analysis of set membership identification of Hammerstein and Wiener systems[☆]

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a r t i c l e i n f o

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This paper analyzes the computational complexity of set membership identification of Hammerstein and Wiener systems. Its main results show that, even in cases where a portion of the plant is known, the problems are generically NP-hard both in the number of experimental data points and in the number of inputs (Wiener) or outputs (Hammerstein) of the nonlinearity. These results provide new insight into the reasons underlying the high computational complexity of several recently proposed algorithms and point out the need for developing computationally tractable relaxations.

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1. Introduction

Identification of systems consisting of the cascade of a memoryless, static nonlinearity and a Linear Time Invariant (LTI) plant has received considerable attention in the past decade, since this configuration arises in a wide range of domains, including control (Wigren, 1994), communications, (Cripps, 1999; Giunta, Jacoviti, & Neri, 1991), and biology, (Brinker, 1989; Celka & Colditz, 2002).

Roughly speaking, existing techniques can be classified into two broad categories: those based on a statistical approach (see for instance Bai (1998, 2002, 2003a,b, 2004), Chou, Haverkamp, and Verhaegen (1999), Greblicki (1992, 1997, 2000), Lia, Pengan, and Bai (2006) Raich, Zhou, and Viberg (2005), Westwick and Verhaegen (1996) and references therein), and those using a set membership framework (Belforte & Gay, 2001; Cerone & Regruto, 2003, 2007; Falugi, Giarre, & Zappa, 2005; Garulli, Giarre, & Zappa, 2002). The latter are attractive since they furnish hard bounds on the values of the unknown parameters of the plant, in a

form that can be directly used for instance by robust control synthesis techniques. However, a common feature of existing set membership approaches is the high computational complexity entailed in the resulting algorithms, requiring for instance solving an optimization over rank one matrices (Garulli et al., 2002), non-convex optimization problems (Falugi et al., 2005), or a combinatorial number of Linear Programs (Cerone & Regruto, 2003). In all cases, this necessitates the use of different relaxations in order to obtain computationally tractable problems.

The goal of this paper is to shed some insight into the reasons underlying this high computational complexity. As shown here, this is an intrinsic difficulty of the general framework, rather than a feature of specific approaches. Our main results shows that, contrary to the case of *linear identification*, the problems of set-membership identification of Hammerstein or Wiener systems are generically NP-hard in both the number of inputs (Wiener) or outputs (Hammerstein) of the nonlinearity, and in the number of experiments, *even* when a portion of the system is known. These results highlight the intrinsic difficulty of Hammerstein/Wiener (and by extension non-linear) systems identification and point out to the need to develop polynomial time relaxations, such as the ones in Cerone and Regruto (2003), Falugi et al. (2005) and Garulli et al. (2002) or the one recently proposed in Ma, Lim, Sznaier, and Camps (2006). In addition, our results also highlight a connection between high computational complexity and non-invertibility of the static nonlinearity.

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2. Preliminaries

In this section we introduce the notation used in the paper and some background results required to perform the computational complexity analysis.

2.1. Notation

Z, R, C set of integer, real, complex numbers, respectively

\mathcal{D} closed unit disk in C

$\bar{\sigma}(\mathbf{A})$ maximum singular value of the matrix \mathbf{A} .

ℓ^p Banach space of finite vector valued real sequences equipped with the norm:

$$\|x\|_p \doteq \left(\sum_{i=0}^N \|x_i\|_p^p \right)^{\frac{1}{p}},$$

$p \in [1, \infty)$ and $\|x\|_\infty \doteq \sup_i \|x_i\|_\infty$.

\mathcal{H}_∞ space of transfer functions analytic in $|z| \leq 1$, equipped with the norm $\|G\|_\infty \doteq \text{ess sup}_{|z| < \rho} \bar{\sigma}(G(z))$.

$\bar{\mathcal{B}}\mathcal{H}_\infty(\gamma)$ closed γ -ball in \mathcal{H}_∞ : $\{H \in \mathcal{H}_\infty : \|H\|_\infty \leq \gamma\}$.

Finally, given a Linear Time Invariant (LTI) system H , we will denote by \mathbf{h} its impulse response sequence (Markov parameters).

2.2. Background results on computational complexity

In order to establish that the problems of set membership identification of Hammerstein or Wiener systems are both NP-hard, we need the following preliminary results concerning the computational complexity of two optimization problems.

Lemma 1 (Martello & Toth, 1987). Given a vector $\mathbf{a} \in Z^n$, the problem of determining if there exists a vector $\mathbf{x} \in \{-1, 1\}^n$ such that $\mathbf{a}^T \mathbf{x} = 0$ (the knapsack problem) is NP-complete.

Lemma 2 (Chen & Gu, 2000, page 307). For a given vector $\mathbf{a} \in Z^n$, there exists a polynomial time computable $(2n + 1) \times (2n + 1)$ symmetric matrix \mathbf{A}_a and a polynomial time computable number $\epsilon_a \in (0, 1)$ such that $\max_{z_1, z_2 \in \mathcal{D}^{2n+1}} |z_1^T \mathbf{A}_a z_2| = 1$ if there exists a solution $\mathbf{x} \in \{-1, 1\}^n$ to $\mathbf{a}^T \mathbf{x} = 0$, and is less than or equal to $1 - \epsilon_a$ otherwise.

Corollary 1. The problem of checking whether

$$\max_{z_1, z_2 \in \mathcal{D}^{2n+1}} |z_1^T \mathbf{A}_a z_2| > 1 - \frac{\epsilon_a}{2}$$

is NP-hard, since the knapsack problem can be reduced to it in polynomial time.

In the sequel we will establish that the problems above can be reduced in polynomial time to a suitable Wiener or Hammerstein set membership identification problem. It follows that these identification problems are NP-hard.

3. Computational complexity analysis of set membership identification of Wiener systems

In this section we present a computational complexity analysis of the problem of set membership identification of Wiener systems using time-domain data. We begin by precisely stating the problem under consideration.

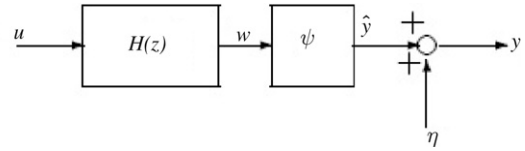


Fig. 1. Wiener system structure.

3.1. Statement of the problem

Consider the Wiener system shown in Fig. 1 consisting of the interconnection of a LTI system $H(z)$ and a memoryless nonlinearity $\psi(\cdot)$. The corresponding equations are given by:

$$\begin{aligned} \omega_k &= (\mathbf{h} * \mathbf{u})_k, & \hat{\mathbf{y}}_k &= \psi(\omega_k) \\ \mathbf{y}_k &= \hat{\mathbf{y}}_k + \eta_k \end{aligned} \quad (1)$$

where $*$ denotes convolution and the signals $\mathbf{u} \in R^{n_u}$ and $\mathbf{y} \in R^{n_y}$ represent the experimental data: a known input and its corresponding output, $\hat{\mathbf{y}}_k$, corrupted by unknown but norm-bounded measurement noise η . In this context, the set membership Wiener identification problem can be stated as:

Problem 1. Given (i) *a priori* information consisting of a set membership description of the admissible plants, non-linearities and noise, $\mathcal{S}, \mathcal{F}, \mathcal{N}$, respectively, and (ii) *a posteriori* experimental data $\{\mathbf{y}_k, \mathbf{u}_k\}_{k=0}^{N_m-1}$, determine:

1. if the *a priori* and *a posteriori* information are consistent, i.e., the consistency set

$$\begin{aligned} \mathcal{T}(\mathbf{y}, N_m, \mathcal{N}) &\doteq \{H \in \mathcal{S} : \mathbf{y}_k = \psi[(\mathbf{h} * \mathbf{u})_k] + \eta_k, \\ &k = 0, \dots, N_m - 1 \text{ for some } \psi \in \mathcal{F} \\ &\text{and some sequence } \eta_k \in \mathcal{N}\} \end{aligned}$$

is nonempty.

2. If $\mathcal{T}(\mathbf{y}, N_m, \mathcal{N}) \neq \emptyset$, find a nominal model $\{H, \psi(\cdot)\}$ that interpolates the experimental data.

In particular, in its simplest form the set description of the admissible set of linear plants and noise are (see for instance Ma et al. (2006)) $\mathcal{S} \doteq \bar{\mathcal{B}}\mathcal{H}_\infty(K)$ and $\mathcal{N} \doteq \{\eta : \|\eta_k\|_p \leq \epsilon\}$ for some known constants K, ϵ .

3.2. Computational complexity analysis

In this section we show that the problem of set membership Wiener systems identification from time-domain data is generically NP-hard both in the number of inputs of the nonlinearity and in the number of experimental data points, even when the nonlinearity ψ is completely known.

Theorem 1. The problem of identifying the linear portion of a Wiener system is generically NP-hard in the number of inputs to the static nonlinearity.

Proof. The proof proceeds by showing that the Knapsack problem can be reduced in polynomial time to the problem of worst case identification of the linear portion of a Wiener system cascaded with a known nonlinearity. To this effect, given a vector $\mathbf{a} \in Z^n$, consider a Wiener system of the form shown in Fig. 2, with an input $\mathbf{u} = [(\mathbf{u}^1)^T, (\mathbf{u}^2)^T]^T$, $\mathbf{u}^1 \in R^{2n+1}$, an (unknown) linear portion of the form $H(z) = \begin{pmatrix} H_1(z) & 0 \\ 0 & H_2(z) \end{pmatrix} \in \bar{\mathcal{B}}\mathcal{H}_\infty$, where each block H_i is diagonal, e.g. $H_i = \text{diag}\{H_i^j\}$, $j = 1, 2, \dots, 2n + 1$, and a (known) static nonlinearity $\psi(\cdot) = \mathbf{w}_1^T \mathbf{A}_a \mathbf{w}_2$, where $\mathbf{w}_1 = (\omega_{0,1} \dots \omega_{0,2n+1})^T$ and $\mathbf{w}_2 = (\omega_{0,2n+2} \dots \omega_{0,4n+2})^T$, and

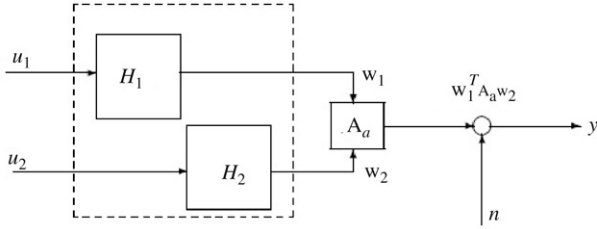


Fig. 2. Reducing the knapsack problem to a Wiener identification.

where $\omega_{0,i}$ denotes the i th output of $H(\cdot)$ at time $k = 0$. Further, assume the following *a priori* information:

$$\eta \in \ell^p, \|\eta\|_p \leq \frac{\epsilon_a}{2}, \quad p \in [1, \infty)$$

and *a posteriori* experimental data $\mathbf{u}_0^1 = \mathbf{u}_0^2 = [1, 1, \dots, 1]^T$, $y_0 = 1$. Let $\mathbf{h}_{0,1}$ and $\mathbf{h}_{0,2}$ denote the first Markov parameter of $H_1(z)$ and $H_2(z)$, respectively. From Carathéodory–Fejér Theorem (see for instance Theorem 2.3.6 in Chen and Gu (2000)) it follows that there exists $H_1(z), H_2(z) \in \bar{\mathcal{B}}\mathcal{H}_\infty$ such that $H_i = \mathbf{h}_{0,i} + \dots$, $i = \{1, 2\}$ if and only if $\mathbf{h}_{0,i} \in \mathcal{D}^{2n+1}$. Thus, the *a priori* assumptions are consistent with the *a posteriori* experimental data if and only if there exists a pair $\{\mathbf{h}_{0,1}, \mathbf{h}_{0,2}\} \in \mathcal{D}^{2n+1}$ such that

$$|1 - \mathbf{h}_{0,1}^T \mathbf{A}_a \mathbf{h}_{0,2}| \leq \frac{\epsilon_a}{2}. \quad (2)$$

From Lemma 2 it follows that if the knapsack problem has a solution, then

$$\max_{\mathbf{h}_{0,1}, \mathbf{h}_{0,2} \in \mathcal{D}^{2n+1}} |\mathbf{h}_{0,1}^T \mathbf{A}_a \mathbf{h}_{0,2}| = 1.$$

Furthermore, $\mathbf{h}_{0,1}, \mathbf{h}_{0,2}$ can be chosen such that $\mathbf{h}_{0,1}^T \mathbf{A}_a \mathbf{h}_{0,2} = 1$, and thus (2) is satisfied. On the other hand, if the knapsack problem is infeasible, then

$$|1 - \mathbf{h}_{0,1}^T \mathbf{A}_a \mathbf{h}_{0,2}| \geq 1 - \max_{\mathbf{h}_{0,1}, \mathbf{h}_{0,2} \in \mathcal{D}^{2n+1}} |\mathbf{h}_{0,1}^T \mathbf{A}_a \mathbf{h}_{0,2}| \geq \epsilon_a \quad (3)$$

and thus (2) is violated. Since the reasoning above (polynomially) reduces the NP-complete knapsack problem to a Wiener identification one, it follows that the later is generically NP-hard. \square

Remark 1. Recent research (Sznaier & Camps, 2007) has shown that the problem of nonlinear dimensionality reduction via manifold embeddings can be formalized as a Wiener system identification problem. Since in this case the dimension of the output (the raw data to be reduced) is very high (typically at least $\mathcal{O}(10^3)$ in image processing applications), the result above points out to an intrinsic difficulty in nonlinear manifold embedding and highlights the need for developing computationally tractable relaxations of the underlying identification problem.

The next result complements the results above by showing that the problem is also NP-hard in the number of experimental data points used in the identification.

Theorem 2. *The problem of set membership identification of the linear portion of a Wiener system is generically NP-hard in the number of experimental data points*

Proof. As before, the proof proceeds by showing that the knapsack problem can be reduced in polynomial time to the problem of worst case identification of the linear portion of a Wiener system. In this case, consider a Wiener system consisting of the cascade of a SISO linear plant $H \in \bar{\mathcal{B}}\mathcal{H}_\infty(n)$ and the nonlinearity $\psi(w) = w^2$. Further assume that $\mathcal{N} = \{\eta; |\eta_k| \leq 0.5\}$ and, given an arbitrary vector $\mathbf{a} \in \mathcal{Z}^n$, consider the following three experiments:

- (1) $u_k^1 = \delta(0)$ and $y_k^1 = 1.5$, $k = 0, 1, \dots, n-1$
- (2) $u_k^2 = \delta(0)$ and $y_k^2 = 0.5$, $k = 0, 1, \dots, n-1$
- (3) $u_k^3 = \alpha \cdot a_{k+1}$, $k = 0, 1, \dots, n-1$ where $\alpha \doteq \frac{1}{\sqrt{2 \sum_{i=1}^{n-1} |a_i|}}$ with corresponding measurements $y_k^3 = 0$, $k = 0, 1, \dots, n-2$ and $y_{n-1}^3 = -0.5$.

Clearly, the consistency sets of the first two experiments are given by

$$\begin{aligned} \mathcal{T}_1 &= \{H \in \bar{\mathcal{B}}\mathcal{H}_\infty(n): 1 \leq h_i^2 \leq 2, i = 0, 1, \dots, n-1\} \\ \mathcal{T}_2 &= \{H \in \bar{\mathcal{B}}\mathcal{H}_\infty(n): 0 \leq h_i^2 \leq 1, i = 0, 1, \dots, n-1\}. \end{aligned} \quad (4)$$

Hence, these two experiments are consistent if and only if $h_i \in \{-1, 1\}$. Note that these values do not invalidate the *a priori* assumptions since $\|H\|_\infty \leq \sum_{i=0}^{n-1} |h_i| \leq n$. Next, note that the first $n-1$ experimental data points from the third experiment do not provide additional information, since ω_k , the intermediate signal corresponding to the input sequence u_k^3 satisfies:

$$\begin{aligned} |\omega_k^3| &= \left| \sum_{i=0}^k h_i u_{k-i}^3 \right| \leq \alpha \sum_{i=0}^k |h_i| |a_{k-i+1}| \\ &\leq \frac{\sum_{i=0}^k |a_{k-i+1}|}{\sqrt{2} \sum_{i=1}^{n-1} |a_i|} \leq \frac{1}{\sqrt{2}} \end{aligned}$$

which is consistent with information already available, since the difference between the actual and observed output: $|y_k^3 - \hat{y}_k^3| = |0 - (\omega_k^3)^2| \leq 0.5$, the noise level. Finally, since $\hat{y}_k \geq 0$, the last data pair in experiment 3 is equivalent to:

$$\hat{y}_{n-1} = 0 \Rightarrow \sum_{i=0}^{n-1} h_i a_{k-i} = 0. \quad (5)$$

Thus, establishing consistency of the *a priori* information and the *a posteriori* experimental data is equivalent to finding a vector $\mathbf{h} \in \{-1, 1\}^n$ such that (5) hold, e.g. solving a knapsack problem with \mathcal{O} (number of experimental data points) variables. \square

4. The Hammerstein systems case

In this section we analyze the computational complexity of set membership identification of Hammerstein systems, consisting of the cascade of a static nonlinearity followed by an LTI plant (see Fig. 3).

In this case the corresponding equations are given by:

$$\omega_k = \psi(\mathbf{u}_k), \mathbf{y}_k = (\mathbf{h} * \omega)_k + \eta_k \quad (6)$$

and the identification problem can be stated as

Problem 2. Given (i) *a priori* information consisting of a set membership description of the admissible plants, non-linearities and noise, $\mathcal{S}, \mathcal{F}, \mathcal{N}$, respectively, and (ii) *a posteriori* experimental data $\{\mathbf{y}_k, \mathbf{u}_k\}_{k=0}^{N_m-1}$, determine:

- (1) if the *a priori* and *a posteriori* information are consistent, i.e., the consistency set

$$\begin{aligned} \mathcal{T}(\mathbf{y}, N_m, \mathcal{N}) &\doteq \{H \in \mathcal{S}: \mathbf{y}_k = [\mathbf{h} * \psi(\mathbf{u})]_k + \eta_k, \\ &k = 0, \dots, N_m - 1 \\ &\text{for some } \psi \in \mathcal{F} \\ &\text{and some sequence } \eta_k \in \mathcal{N}\} \end{aligned}$$

is nonempty.

- (2) If $\mathcal{T}(\mathbf{y}, N_m, \mathcal{N}) \neq \emptyset$, find a nominal model $\{H, \psi(\cdot)\}$ that interpolates the experimental data.

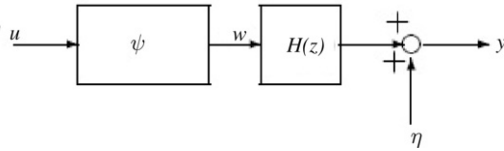


Fig. 3. Hammerstein system structure.

4.1. Computational complexity analysis

In this section we show that the problem of set membership identification of Hammerstein systems is also NP-hard both in the number of outputs of the nonlinearity (inputs to the linear portion of the system) and in the number of experimental data pairs.

Theorem 3. *The problem of identifying the static nonlinearity of a Hammerstein system in a set membership framework is generically NP-hard in the number of experimental data pairs, even when the linear portion of the plant is known.*

Proof. Given an arbitrary vector $\mathbf{a} \in Z^n$, consider the following *a priori* information:

$$H(z) = a_1 + a_2z + \dots + a_nz^{n-1} + \dots$$

$$\mathcal{F} = \left\{ \psi: \psi = \sum_{i=1}^n x_i \psi_i(u), x_i \in \{-1, 1\} \right\}$$

where: $\psi_i(u) = \begin{cases} 1 & i-1 \leq u < i \\ 0 & \text{otherwise} \end{cases}$ (7)

$$\mathcal{N} = \left\{ \eta: |\eta_k| \leq \epsilon \doteq \sum_{i=1}^{n-1} |a_i| \right\}$$

and *a posteriori* experimental data:

- (1) *Experiment 1:* Input $\{u^*\}$: $u_k = k, k = 0, 1, \dots, n-1$ and corresponding output $y_k = 0, k = 0, 1, \dots, n-2; y_{n-1} = \epsilon$.
- (2) *Experiment 2:* Input $\{u^*\}$ and corresponding output $y_k = 0, k = 0, 1, \dots, n-2; y_{n-1} = -\epsilon$.

The output sequence corresponding to the input sequence $\{u^*\}$ is given by

$$\hat{y}_k = \sum_{i=1}^k a_i \omega_{k-i} = \sum_{i=1}^k a_i x_{k-i}. \quad (8)$$

Thus, the *a priori* information and *a posteriori* experimental data are consistent if and only if there exists $\mathbf{x} \in \{-1, 1\}^n$ such that: $|\hat{y}_k - y_k| \leq \epsilon$, or equivalently:

$$\left| \sum_{i=1}^k a_i x_{k-i} \right| \leq \epsilon, \quad k = 1, 2, \dots, n-1 \quad (9)$$

$$0 \leq \sum_{i=1}^n a_i x_{n-i} \leq 2\epsilon \quad (10)$$

$$-2\epsilon \leq \sum_{i=1}^n a_i x_{n-i} \leq 0 \quad (11)$$

where the two last equations originate from the last data pairs in experiments one and two respectively. Since condition Eq. (9) is trivially satisfied by our choice of the noise level ϵ , it follows that establishing consistency is equivalent to finding $\mathbf{x} \in \{-1, 1\}^n$ such that (10) and (11) are satisfied, or, equivalently, such that $\sum_{i=1}^n a_i x_{n-i} = 0$, e.g. solving a Knapsack problem with n variables. \square

Finally, we show that, as in the Wiener system case, the problem of set membership identification is generically NP-hard in the number of outputs of the nonlinearity.

Theorem 4. *The problem of identifying the static nonlinearity in a Hammerstein system is generically NP-hard in the number of outputs of the nonlinearity, even if the linear portion of the plant is known.*

Proof. Given an arbitrary vector $\mathbf{a} \in Z^n$, consider the following *a priori* information:

$$H(z) = \mathbf{a} + \dots; \quad \mathcal{S} = \mathcal{BH}_{\infty}(\|\mathbf{a}\|)$$

$$\mathcal{F} = \{ \psi: \psi = [\psi_1(\cdot), \dots, \psi_n(\cdot)]^T, \quad (12)$$

$$\psi_i = x_i \text{sign}(u), x_i \in \{-1, 1\} \}$$

$$\mathcal{N} = \{ \eta: |\eta_k| \leq \epsilon < 1 \}$$

and *a posteriori* experimental data $u_0 = 1, y_0 = 0$. In this case, the *a priori* information and the *a posteriori* experimental data are consistent if and only if there exists $\mathbf{x} \in \{-1, 1\}^n$ such that $|\mathbf{a}^T \mathbf{x}| \leq \epsilon$. Since $\mathbf{a} \in Z^n$ and $\epsilon < 1$ this last condition is equivalent to $\mathbf{a}^T \mathbf{x} = 0$. It follows then that the Knapsack problem can be reduced to a Hammerstein identification of the form above. Hence the latter problem is NP-hard. \square

5. Conclusions

This paper shows that the problems of set membership identification of two classes of nonlinear systems, Hammerstein and Wiener systems, are generically NP-hard, even in cases where a portion of the plant is known exactly. These results highlight the fact that, as opposed to the case of *linear identification*, these problems are intrinsically difficult, shedding some insight into the high computational cost of existing approaches and pointing out to the need to search for computationally tractable relaxations. An interesting feature borne out by the analysis presented here is the key role played by the non-invertibility of the nonlinearity in reducing the knapsack problem to a either a Wiener or a Hammerstein system identification and thus establishing that these problems are NP-hard. Thus, the issue of whether these problem are NP-hard in the case of *invertible* nonlinearities is still open.

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