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ON NONPARAMETRIC IDENTIFICATION OF WIENER SYSTEMS WITH DETERMINISTIC INPUTS

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ABSTRACT

The identification of nonlinear Wiener models (NWMs) for deterministic inputs and Gaussian noise is studied. We show that the nonparametric kernel regression estimation of the nonlinearity of a NWM (based on the Nadaraya-Watson kernel estimator) can be formulated as a parametric estimation problem leading to a Gaussian conditional observation model. This property allows us to derive the maximum likelihood estimators of the unknown parameters of the NWM, as well as the associated Cramér-Rao (CR) bounds. We finally derive a CR-like bound on the global mean squared error (MSE) of the estimated nonlinearity of a NWM. Numerical results obtained for a pulse wave input are presented and compared to the ones based on the Nadaraya-Watson kernel estimator.

Index Terms— Wiener model, non-parametric identification, Cramér-Rao bound, Maximum Likelihood Estimator, Mean Square Error.

1. INTRODUCTION

Many nonlinear models such as Wiener and Hammerstein models are composed by a combination of a linear filter and a static nonlinearity (see Fig. 1) . The combination of these very simple structures is known to approximate a wide range of nonlinear processes [1, 2, 3, 4]. In particular, these models become particularly attractive if one considers a general class of nonlinearities that are not assumed to be parametric and smooth, providing better results than a simple polynomial of finite order [5]. It is possible to extend even more their applicability to nonlinear system identification if one assumes a nonparametric model for the static nonlinearity, as introduced in [3][6] for nonlinear Wiener models (NWMs) and extended in [3][7] for noninvertible nonlinearities. A nonparametric identification algorithm was proposed in [7] for NWMs. The convergence of this algorithm relies on the following assumptions: (i) the input signal $\{x_n\}$ is a sequence of i.i.d. random variables with known probability density function (pdf) and finite first and second order moments, (ii) the noise process $\{z_n\}$ is an i.i.d. sequence with zero mean and finite but unknown variance σ_z^2, (iii) the noise $\{z_n\}$ and the input signal $\{x_n\}$ are mutually independent. The above basic assumptions imply that both the interconnecting signal $\{\omega_n\}$[1] and the output signal $\{y_n\}$ are second-order stationary stochastic processes.

However in many applications, the input signal x_n is not a sequence of i.i.d. random variables, but rather a deterministic time series, and the noise sequence $\{z_n\}$ is simply an additive i.i.d. Gaussian noise with zero mean and finite but unknown variance σ_z^2. In this setting, we show that the nonparametric kernel regression estimation of the nonlinear function $g(.)$ proposed in [7], i.e., the Nadaraya-Watson kernel estimator [10], can also be regarded as a parametric estimation problem, which belongs to the Gaussian conditional observation model [8][9]. Indeed, it amounts to estimating a parameter vector $\boldsymbol{\gamma}$ associated with a given nonparametric kernel estimator of the nonlinearity $g(.)$, as well as the weights $\boldsymbol{\lambda}$ associated with the filter relating x_n and ω_n and the unknown noise variance σ_z^2. By using the well-known Slepian-Bangs formula [16], the first contribution of this paper is to derive the deterministic Cramér-Rao (CR) bound (CRB) for the NWM parameters, i.e., $\boldsymbol{\gamma}$, $\boldsymbol{\lambda}$ and σ_z^2. Furthermore, we also derive an asymptotic CR-like bound on the global mean squared error (MSE) of the estimated nonlinearity $g(.;\boldsymbol{\gamma})$ for consistent and locally unbiased estimators of $\boldsymbol{\gamma}$. An interesting property of this bound is its relation with the mean integrated squared error (MISE) criterion introduced in [7]. Since we consider a conditional signal model, the maximum likelihood estimators (MLEs) of the NWM parameters converge to their associated CRBs at high signal-to-noise-ratio (SNR) [17]. Therefore we derive the associated MLEs and compare their performance with the estimators proposed in [7] (based on the Nadaraya-Watson kernel estimator), which are shown to be sub-optimal when the input signal x_n is not stationary.

[1]System identification algorithms assume that the input and output sequences $\{x_n\}$ and $\{y_n\}$ are available. However, the so-called interconnecting signal $\{\omega_n\}$ is not observed.

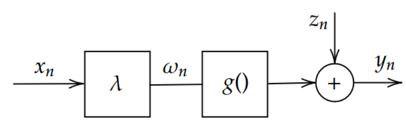

Fig. 1. Nonlinear Wiener model.

2. OBSERVATION MODEL FOR NONPARAMETRIC WIENER SYSTEM

The nonlinear Wiener model shown in Fig. 1 is defined as

$$y_n = g(\omega_n) + z_n,\ \omega_n = \sum_{p=0}^{P} \lambda_p x_{n-p}, \quad 1 \le n \le N \qquad \text{(1a)}$$

where $g(.)$ is an unknown deterministic function of $\Omega \to \mathbb{R}$, $\Omega \subset \mathbb{R}$, and $\boldsymbol{\lambda} = (\lambda_0, \lambda_1, \ldots, \lambda_P) \in \mathbb{R}^{P+1}$ is an unknown deterministic vector. It is important to observe that the pairs $(g(\omega), \boldsymbol{\lambda})$ and $(g(\lambda_0\omega), \boldsymbol{\lambda}/\lambda_0)$ generate the same observations. Indeed, the pair

$(g(\omega), \boldsymbol{\lambda})$ can be identified up to an homothetic transformation affecting $g(.)$. This identifiability problem can be bypassed by assuming $\lambda_0 = 1$, leading to

$$y_n = g(\omega_n) + z_n,\ \omega_n = x_n + \sum_{p=1}^{P} \lambda_p x_{n-p}, \quad 1 \leq n \leq N \quad \text{(1b)}$$

where $\boldsymbol{\lambda} = (\lambda_1, \dots, \lambda_P) \in \mathbb{R}^P$. We introduce the following notations: $\mathbf{y} = (y_1, \dots, y_N)^T$, $\boldsymbol{\omega} = (\omega_1, \dots, \omega_N)^T$, $\mathbf{g}(\boldsymbol{\omega}) = (g(\omega_1), \dots, g(\omega_N))^T$, $\mathbf{z} = (z_1, \dots, z_N)^T$, $\mathbf{x} = (x_1, \dots, x_N)^T$, $\underline{\mathbf{x}} = \left((x_{1-P}, \dots, x_0), \mathbf{x}^T\right)^T$, and

$$\mathbf{T}_{\underline{\mathbf{x}}} = \begin{bmatrix} x_0 & \dots & x_{1-P} \\ \vdots & \vdots & \vdots \\ x_{N-1} & \dots & x_{N-P} \end{bmatrix}$$

where $\mathbf{y}, \boldsymbol{\omega}, \mathbf{g}(\boldsymbol{\omega}), \mathbf{z}, \mathbf{x} \in \mathbb{R}^N$, $\underline{\mathbf{x}} \in \mathbb{R}^{N+P}$, $\mathbf{T}_{\underline{\mathbf{x}}} \in \mathbb{R}^{N \times P}$. The nonparametric kernel regression estimation proposed in [7], based on the Nadaraya-Watson kernel estimator of the nonlinearity $g(.)$ [10], is defined as

$$\widehat{g}(\omega) = \widehat{g}\left(\omega; \widehat{\boldsymbol{\lambda}}\right), \quad \widehat{g}(\omega; \boldsymbol{\lambda}) = \frac{\sum_{i \in \mathcal{I}_1} y_i K_h(\omega - \omega_i(\boldsymbol{\lambda}))}{\sum_{i \in \mathcal{I}_1} K_h(\omega - \omega_i(\boldsymbol{\lambda}))}, \quad \text{(2a)}$$

$$K_h(\omega) = \frac{K(\frac{\omega}{h})}{h}, \widehat{\boldsymbol{\lambda}} = \arg\min_{\boldsymbol{\lambda}} \left\{ \sum_{n \in \mathcal{I}_2} (y_n - \widehat{g}(\omega_n(\boldsymbol{\lambda}); \boldsymbol{\lambda}))^2 \right\},$$

where $\omega_j(\boldsymbol{\lambda}) = x_j + \sum_{p=1}^{P} \lambda_p x_{j-p}$, $N = card(\mathcal{I}_1) + card(\mathcal{I}_2) + 2P$ and $K(\omega)$ is a positive symmetric function (kernel) such that

$$\int_{-\infty}^{\infty} K_h(\omega)\, d\omega = \int_{-\infty}^{\infty} K(u)\, du = 1. \quad \text{(2b)}$$

Let $\mathcal{G}_I(\boldsymbol{\gamma})$ be the set of parametric functions $g(.; \boldsymbol{\gamma})$ defined as

$$g(\omega; \boldsymbol{\gamma}) = \frac{\sum_{i=1}^{I} \alpha_i K_h(\omega - \beta_i)}{\sum_{i=1}^{I} K_h(\omega - \beta_i)}, \ \boldsymbol{\gamma} = \begin{pmatrix} \boldsymbol{\alpha} \\ \boldsymbol{\beta} \end{pmatrix} \in \mathbb{R}^{2I}. \quad \text{(3)}$$

From a broader perspective, (2a) can also be regarded as an estimator of $g(.; \boldsymbol{\gamma})$ defined in (3) where $I = card(\mathcal{I}_1)$, $\widehat{\alpha}_i = y_i$, $\widehat{\beta}_i = \omega_i\left(\widehat{\boldsymbol{\lambda}}\right)$. Therefore the nonparametric kernel regression estimation of the nonlinearity $g(.)$ defined in (2a) can be recast as a parametric estimation problem.

2.1. Gaussian Conditional Observation Model

The observation model (1b) can be rewritten as follows

$$z_n = y_n - g\left(x_n + \sum_{p=1}^{P} \lambda_p x_{n-p}\right), \quad 1 \leq n \leq N.$$

If $\underline{\mathbf{x}}$ is a known deterministic vector, the pdf of $\mathbf{y}$ conditionally on $\underline{\mathbf{x}}$ with parameters $\boldsymbol{\lambda} \in \mathbb{R}^P$ is

$$p(\mathbf{y}|\underline{\mathbf{x}}; \boldsymbol{\lambda}) = p_{\mathbf{z}}(\mathbf{y} - \mathbf{g}(\mathbf{x} + \mathbf{T}_{\underline{\mathbf{x}}}\boldsymbol{\lambda})). \quad \text{(4a)}$$

If $p_{\mathbf{z}}(\mathbf{z})$ depends on a vector of unknown deterministic parameters $\boldsymbol{\mu}$, then $p_{\mathbf{z}}(\mathbf{z}) \triangleq p_{\mathbf{z}}(\mathbf{z}; \boldsymbol{\mu})$ and (4a) becomes

$$p(\mathbf{y}|\underline{\mathbf{x}}; \boldsymbol{\lambda}, \boldsymbol{\mu}) = p_{\mathbf{z}}(\mathbf{y} - \mathbf{g}(\mathbf{x} + \mathbf{T}_{\underline{\mathbf{x}}}\boldsymbol{\lambda}); \boldsymbol{\mu}). \quad \text{(4b)}$$

At this point, if $g(.) \triangleq g(.; \boldsymbol{\gamma}) \in \mathcal{G}_I(\boldsymbol{\gamma})$ and if we consider $\boldsymbol{\theta}^T = \left(\boldsymbol{\mu}^T, \boldsymbol{\lambda}^T, \boldsymbol{\gamma}^T\right)$, then (4b) becomes

$$p(\mathbf{y}|\underline{\mathbf{x}}; \boldsymbol{\theta}) = p_{\mathbf{z}}(\mathbf{y} - \mathbf{g}(\mathbf{x} + \mathbf{T}_{\underline{\mathbf{x}}}\boldsymbol{\lambda}; \boldsymbol{\gamma}); \boldsymbol{\mu}) \quad \text{(4c)}$$

where $g(.; \boldsymbol{\gamma})$ is an unknown parametric deterministic function. Finally, if $\mathbf{z} \sim \mathcal{N}\left(\mathbf{0}, \sigma_z^2 \mathbf{I}_N\right)$ then (4c) is a Gaussian pdf as well and thus (1b) defines a Gaussian conditional observation model.

3. DETERMINISTIC CRAMÉR-RAO BOUNDS FOR A NONPARAMETRIC WIENER SYSTEM

The general theory about lower bounds on the MSE of estimators of deterministic parameters is detailed in [12, Section II & III][13] (and summarized in [14, Section II]). In particular, if $\underline{\mathbf{x}}$ is a known deterministic vector, the inverse CRB of $\boldsymbol{\theta}$ is [16]

$$\mathbf{CRB}_{\boldsymbol{\theta}}^{-1}(\underline{\mathbf{x}}) = \mathbf{F}_{\boldsymbol{\theta}}(\underline{\mathbf{x}}) = -E_{\mathbf{y}|\underline{\mathbf{x}};\boldsymbol{\theta}}\left[\frac{\partial^2 \ln p(\mathbf{y}|\underline{\mathbf{x}}; \boldsymbol{\theta})}{\partial \boldsymbol{\theta} \partial \boldsymbol{\theta}^T}\right] \quad \text{(5a)}$$

where $\mathbf{F}_{\boldsymbol{\theta}}(\underline{\mathbf{x}})$ is the Fisher information matrix (FIM). Under the hypothesis that $\mathbf{y} \triangleq \mathbf{y}|\underline{\mathbf{x}} \sim \mathcal{N}(\mathbf{m}(\boldsymbol{\theta}), \mathbf{C}(\boldsymbol{\theta}))$, the FIM (5a) is obtained from the Slepian-Bangs formula [16, (3.31)]

$$(\mathbf{F}_{\boldsymbol{\theta}})_{i,j} = \frac{\partial \mathbf{m}(\boldsymbol{\theta})^T}{\partial \theta_i} \mathbf{C}(\boldsymbol{\theta})^{-1} \frac{\partial \mathbf{m}(\boldsymbol{\theta})}{\partial \theta_j} + \frac{1}{2} tr\left(\mathbf{C}(\boldsymbol{\theta})^{-1} \frac{\partial \mathbf{C}(\boldsymbol{\theta})}{\partial \theta_i} \mathbf{C}(\boldsymbol{\theta})^{-1} \frac{\partial \mathbf{C}(\boldsymbol{\theta})}{\partial \theta_j}\right). \quad \text{(6)}$$

In the Gaussian case considered in this work, $\boldsymbol{\theta}^T = \left(\sigma_z^2, \boldsymbol{\lambda}^T, \boldsymbol{\gamma}^T\right)$, $\mathbf{C}(\boldsymbol{\theta}) = \sigma_z^2 \mathbf{I}_N$ and $\mathbf{m}(\boldsymbol{\theta}) = \mathbf{g}(\mathbf{x} + \mathbf{T}_{\underline{\mathbf{x}}}\boldsymbol{\lambda}; \boldsymbol{\gamma})$. As a consequence, the FIM of $\boldsymbol{\theta}$ is

$$\mathbf{F}_{\boldsymbol{\theta}}(\underline{\mathbf{x}}) = \begin{bmatrix} \frac{1}{2}\frac{N}{\sigma_z^4} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{F}_{\boldsymbol{\lambda}}(\underline{\mathbf{x}}) & \mathbf{F}_{\boldsymbol{\lambda},\boldsymbol{\gamma}}(\underline{\mathbf{x}}) \\ \mathbf{0} & \mathbf{F}_{\boldsymbol{\lambda},\boldsymbol{\gamma}}^T(\underline{\mathbf{x}}) & \mathbf{F}_{\boldsymbol{\gamma}}(\underline{\mathbf{x}}) \end{bmatrix}$$

$$\mathbf{F}_{\boldsymbol{\lambda}}(\underline{\mathbf{x}}) = \frac{1}{\sigma_z^2}\left(\frac{\partial \mathbf{g}(\mathbf{x} + \mathbf{T}_{\underline{\mathbf{x}}}\boldsymbol{\lambda}; \boldsymbol{\gamma})}{\partial \boldsymbol{\lambda}^T}\right)^T \frac{\partial \mathbf{g}(\mathbf{x} + \mathbf{T}_{\underline{\mathbf{x}}}\boldsymbol{\lambda}; \boldsymbol{\gamma})}{\partial \boldsymbol{\lambda}^T}$$

$$\mathbf{F}_{\boldsymbol{\gamma}}(\underline{\mathbf{x}}) = \frac{1}{\sigma_z^2}\left(\frac{\partial \mathbf{g}(\mathbf{x} + \mathbf{T}_{\underline{\mathbf{x}}}\boldsymbol{\lambda}; \boldsymbol{\gamma})}{\partial \boldsymbol{\gamma}^T}\right)^T \frac{\partial \mathbf{g}(\mathbf{x} + \mathbf{T}_{\underline{\mathbf{x}}}\boldsymbol{\lambda}; \boldsymbol{\gamma})}{\partial \boldsymbol{\gamma}^T}$$

$$\mathbf{F}_{\boldsymbol{\lambda},\boldsymbol{\gamma}}(\underline{\mathbf{x}}) = \frac{1}{\sigma_z^2}\left(\frac{\partial \mathbf{g}(\mathbf{x} + \mathbf{T}_{\underline{\mathbf{x}}}\boldsymbol{\lambda}; \boldsymbol{\gamma})}{\partial \boldsymbol{\lambda}^T}\right)^T \frac{\partial \mathbf{g}(\mathbf{x} + \mathbf{T}_{\underline{\mathbf{x}}}\boldsymbol{\lambda}; \boldsymbol{\gamma})}{\partial \boldsymbol{\gamma}^T}$$

which leads to

$$\begin{aligned} \mathbf{CRB}_{\boldsymbol{\lambda}}^{-1}(\underline{\mathbf{x}}) &= \mathbf{F}_{\boldsymbol{\lambda}}(\underline{\mathbf{x}}) - \mathbf{F}_{\boldsymbol{\lambda},\boldsymbol{\gamma}}(\underline{\mathbf{x}})\mathbf{F}_{\boldsymbol{\gamma}}^{-1}(\underline{\mathbf{x}})\mathbf{F}_{\boldsymbol{\lambda},\boldsymbol{\gamma}}^T(\underline{\mathbf{x}}) \\ \mathbf{CRB}_{\boldsymbol{\gamma}}^{-1}(\underline{\mathbf{x}}) &= \mathbf{F}_{\boldsymbol{\gamma}}(\underline{\mathbf{x}}) - \mathbf{F}_{\boldsymbol{\lambda},\boldsymbol{\gamma}}^T(\underline{\mathbf{x}})\mathbf{F}_{\boldsymbol{\lambda}}^{-1}(\underline{\mathbf{x}})\mathbf{F}_{\boldsymbol{\lambda},\boldsymbol{\gamma}}(\underline{\mathbf{x}}). \end{aligned} \quad \text{(7)}$$

With a few additional computations, it is easy to show that

$$\frac{\partial \mathbf{g}(\mathbf{x} + \mathbf{T}_{\underline{\mathbf{x}}}\boldsymbol{\lambda}; \boldsymbol{\gamma})}{\partial \boldsymbol{\lambda}^T} = \left(\frac{\partial \mathbf{g}(\mathbf{x} + \mathbf{T}_{\underline{\mathbf{x}}}\boldsymbol{\lambda}; \boldsymbol{\gamma})}{\partial \omega}\mathbf{1}_P^T\right) \odot \mathbf{T}_{\underline{\mathbf{x}}}$$

$$\frac{\partial g(\omega; \boldsymbol{\gamma})}{\partial \alpha_{i'}} = \frac{K_h(\omega - \beta_{i'})}{\sum_{i=1}^{I} K_h(\omega - \beta_i)}$$

$$\frac{\partial g(\omega; \boldsymbol{\gamma})}{\partial \beta_{i'}} = K_h^{(1)}(\omega - \beta_{i'}) \frac{\sum_{i=1}^{I} (\alpha_i - \alpha_{i'}) K_h(\omega - \beta_i)}{\left(\sum_{i=1}^{I} K_h(\omega - \beta_i)\right)^2}$$

where $\odot$ denotes the Hadamard product, $\mathbf{1}_P^T = (1,\ldots,1) \in \mathbb{R}^P$, $K_h^{(1)}(\omega) = \partial K_h(\omega)/\partial\omega$ and

$$\frac{\partial g(\omega;\boldsymbol{\gamma})}{\partial\omega} = \left(\sum_{i=1}^I \alpha_i K_h^{(1)}(\omega-\beta_i)\right) / \left(\sum_{i=1}^I K_h(\omega-\beta_i)\right) - \left(\sum_{i=1}^I K_h^{(1)}(\omega-\beta_i)\right) / \left(\sum_{i=1}^I K_h(\omega-\beta_i)\right) g(\omega;\boldsymbol{\gamma}).$$

4. A LOWER BOUND ON THE GLOBAL ESTIMATION ERROR

The quality of the estimation of $g(.;\boldsymbol{\gamma}) \in \mathcal{G}_I(\boldsymbol{\gamma})$ based on the estimator $g(.;\widehat{\boldsymbol{\gamma}})$ can be measured via the global estimation error

$$\|g(.;\boldsymbol{\gamma}) - g(.;\widehat{\boldsymbol{\gamma}})\|^2 = \int_\Omega (g(\omega;\boldsymbol{\gamma}) - g(\omega;\widehat{\boldsymbol{\gamma}}))^2 \, d\omega. \quad (8)$$

From a theoretical point of view, (8) is a random variable whose distribution is difficult to determine in the general case. As a consequence, we consider a simpler performance criterion, i.e., its mean value which equals the global MSE defined as

$$\begin{aligned}\mathcal{C}(\boldsymbol{\gamma},\widehat{\boldsymbol{\gamma}}) &= E_{\mathbf{y}|\underline{\mathbf{x}};\boldsymbol{\theta}}\left[\|g(.;\boldsymbol{\gamma}) - g(.;\widehat{\boldsymbol{\gamma}})\|^2\right] \\ &= \int_\Omega E_{\mathbf{y}|\underline{\mathbf{x}};\boldsymbol{\theta}}\left[(g(\omega;\boldsymbol{\gamma}) - g(\omega;\widehat{\boldsymbol{\gamma}}))^2\right] d\omega. \quad (9)\end{aligned}$$

It is interesting to note that $\mathcal{C}(\boldsymbol{\gamma},\widehat{\boldsymbol{\gamma}})$ in (9) is the limiting value for $T, L \to \infty$ of the MISE performance criterion [7, (28)] (weak law of large numbers)

$$MISE(\widehat{g}(.)) = \frac{1}{LT}\sum_{l=1}^{L} \|\mathbf{g}(\boldsymbol{\omega}_T;\boldsymbol{\gamma}) - \mathbf{g}(\boldsymbol{\omega}_T;\widehat{\boldsymbol{\gamma}}_l)\|^2 \quad (10)$$

where L is the number of independent observations, $\Omega = [a,b]$, $\omega_t = a + \frac{b-a}{T}(t-1)$ is the compact interval containing the possible values of ω, and $\mathbf{g}(\boldsymbol{\omega}_T;\boldsymbol{\gamma}') = (g(\omega_1;\boldsymbol{\gamma}'),\ldots,g(\omega_T;\boldsymbol{\gamma}'))^T$. Under the assumption that $\widehat{\boldsymbol{\gamma}} \triangleq \widehat{\boldsymbol{\gamma}}(\mathbf{y}|\underline{\mathbf{x}})$ is a consistent estimator of $\boldsymbol{\gamma}$, i.e., provided that $\widehat{\boldsymbol{\gamma}} = \boldsymbol{\gamma} + d\widehat{\boldsymbol{\gamma}}$ with $d\widehat{\boldsymbol{\gamma}}^T d\widehat{\boldsymbol{\gamma}} \to 0$ when $\sigma_{\mathbf{z}}^2 \to 0$, then $g(\omega;\widehat{\boldsymbol{\gamma}}) - g(\omega;\boldsymbol{\gamma}) \to \frac{\partial g(\omega;\boldsymbol{\gamma})}{\partial\boldsymbol{\gamma}^T} d\widehat{\boldsymbol{\gamma}}$ when $\sigma_{\mathbf{z}}^2 \to 0$ leading to:

$$\begin{aligned}\mathcal{C}(\boldsymbol{\gamma},\widehat{\boldsymbol{\gamma}}) &\underset{\sigma_{\mathbf{z}}^2\to 0}{\longrightarrow} \int_\Omega \frac{\partial g(\omega;\boldsymbol{\gamma})}{\partial\boldsymbol{\gamma}^T} \mathbf{C}_{d\widehat{\boldsymbol{\gamma}}}(\underline{\mathbf{x}}) \frac{\partial g(\omega;\boldsymbol{\gamma})}{\partial\boldsymbol{\gamma}} d\omega \\ &= tr\left(\mathbf{C}_{d\widehat{\boldsymbol{\gamma}}}(\underline{\mathbf{x}}) \int_\Omega \frac{\partial g(\omega;\boldsymbol{\gamma})}{\partial\boldsymbol{\gamma}} \frac{\partial g(\omega;\boldsymbol{\gamma})}{\partial\boldsymbol{\gamma}^T} d\omega\right).\end{aligned}$$

Moreover, if $\widehat{\boldsymbol{\gamma}}$ is a locally unbiased estimator of $\boldsymbol{\gamma}$, then $\mathbf{C}_{d\widehat{\boldsymbol{\gamma}}}(\underline{\mathbf{x}}) \geq \mathbf{CRB}_{\boldsymbol{\gamma}}(\underline{\mathbf{x}})$ [16] (in the sense that the difference between the two matrices is positive) and

$$\frac{\partial g(\omega;\boldsymbol{\gamma})}{\partial\boldsymbol{\gamma}^T} \mathbf{C}_{d\widehat{\boldsymbol{\gamma}}}(\underline{\mathbf{x}}) \frac{\partial g(\omega;\boldsymbol{\gamma})}{\partial\boldsymbol{\gamma}} \geq \frac{\partial g(\omega;\boldsymbol{\gamma})}{\partial\boldsymbol{\gamma}^T} \mathbf{CRB}_{\boldsymbol{\gamma}}(\underline{\mathbf{x}}) \frac{\partial g(\omega;\boldsymbol{\gamma})}{\partial\boldsymbol{\gamma}}$$

which allows us to define the following CR-like bound

$$\mathcal{C}(\boldsymbol{\gamma},\widehat{\boldsymbol{\gamma}}) \geq tr\left(\mathbf{CRB}_{\boldsymbol{\gamma}}(\underline{\mathbf{x}}) \int_\Omega \frac{\partial g(\omega;\boldsymbol{\gamma})}{\partial\boldsymbol{\gamma}} \frac{\partial g(\omega;\boldsymbol{\gamma})}{\partial\boldsymbol{\gamma}^T} d\omega\right). \quad (11)$$

5. AN MLE FOR NONPARAMETRIC WIENER SYSTEMS

When $g(.)$ is an unknown parametric deterministic function, i.e., $g(.) \triangleq g(.;\boldsymbol{\gamma}) \in \mathcal{G}_I(\boldsymbol{\gamma})$, the analysis can be conducted by rewriting (1b) as

$$y_n = \sum_{i'=1}^{I} \frac{K_h(\omega_n(\boldsymbol{\lambda}) - \beta_{i'})}{\sum_{i=1}^{I} K_h(\omega_n(\boldsymbol{\lambda}) - \beta_i)} \alpha_{i'} + z_n$$

which leads to the well known conditional Gaussian linear model [8][9][16]

$$\mathbf{y} = \mathbf{H}_{\underline{\mathbf{x}}}(\boldsymbol{\beta},\boldsymbol{\lambda})\boldsymbol{\alpha} + \mathbf{z}, \quad \mathbf{H}_{\underline{\mathbf{x}}}(\boldsymbol{\beta},\boldsymbol{\lambda}) = \frac{\partial \mathbf{g}(\mathbf{x} + \mathbf{T}_{\underline{\mathbf{x}}}\boldsymbol{\lambda};\boldsymbol{\gamma})}{\partial\boldsymbol{\alpha}^T}, \quad (12)$$

for which the MLE of $\boldsymbol{\theta}^T = (\sigma_z^2, \boldsymbol{\lambda}^T, \boldsymbol{\gamma}^T)$ is

$$\begin{aligned}\widehat{\sigma_z^2}(\mathbf{y}|\underline{\mathbf{x}}) &= \frac{1}{N}\left\|\mathbf{y} - \mathbf{H}_{\underline{\mathbf{x}}}\left(\widehat{\boldsymbol{\beta}},\widehat{\boldsymbol{\lambda}}\right)\widehat{\boldsymbol{\alpha}}\right\|^2 \\ \left(\widehat{\boldsymbol{\alpha}},\widehat{\boldsymbol{\beta}},\widehat{\boldsymbol{\lambda}}\right)(\mathbf{y}|\underline{\mathbf{x}}) &= \arg\min_{\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{\lambda}}\left\{\frac{1}{N}\|\mathbf{y} - \mathbf{H}_{\underline{\mathbf{x}}}(\boldsymbol{\beta},\boldsymbol{\lambda})\boldsymbol{\alpha}\|^2\right\}.\end{aligned}$$

Straightforward computations lead to [8][9][16]:

$$\widehat{\boldsymbol{\alpha}}(\mathbf{y}|\underline{\mathbf{x}}) = \left(\mathbf{H}_{\underline{\mathbf{x}}}(\boldsymbol{\beta},\boldsymbol{\lambda})^T \mathbf{H}_{\underline{\mathbf{x}}}(\boldsymbol{\beta},\boldsymbol{\lambda})\right)^{-1} \mathbf{H}_{\underline{\mathbf{x}}}(\boldsymbol{\beta},\boldsymbol{\lambda})^T \mathbf{y} \quad (13a)$$

$$\left(\widehat{\boldsymbol{\beta}},\widehat{\boldsymbol{\lambda}}\right)(\mathbf{y}|\underline{\mathbf{x}}) = \arg\max_{\boldsymbol{\beta},\boldsymbol{\lambda}}\left\{\mathbf{y}^T \boldsymbol{\Pi}_{\mathbf{H}_{\underline{\mathbf{x}}}(\boldsymbol{\beta},\boldsymbol{\lambda})}\mathbf{y}\right\} \quad (13b)$$

where $\boldsymbol{\Pi}_{\mathbf{A}} = \mathbf{A}\left(\mathbf{A}^T\mathbf{A}\right)^{-1}\mathbf{A}^T$. We can observe that the MLE of $\boldsymbol{\alpha}$ (13a) is different from the "Nadaraya-Watson kernel estimator" (2a) [7, (11)]. In [17] it is shown that when $\sigma_{\mathbf{z}}^2 \to 0$, the MLEs $\left(\widehat{\boldsymbol{\alpha}},\widehat{\boldsymbol{\beta}},\widehat{\boldsymbol{\lambda}}\right)(\mathbf{y}|\underline{\mathbf{x}})$ (13a-13b) are consistent, Gaussian, locally unbiased and efficient (minimum variance). As a consequence, when $\sigma_{\mathbf{z}}^2 \to 0$, for a given pair $\left(\widehat{\boldsymbol{\beta}},\widehat{\boldsymbol{\lambda}}\right)(\mathbf{y}|\underline{\mathbf{x}})$, (2a)[7, (11)] leads likely to a biased estimator and sub-optimal (in the MSE sense) compared to the MLE (13a). In a nutshell, the following results can be obtained asymptotically (when $\sigma_{\mathbf{z}}^2 \to 0$): (i) the proposed MLEs $\left(\widehat{\boldsymbol{\alpha}},\widehat{\boldsymbol{\beta}},\widehat{\boldsymbol{\lambda}}\right)(\mathbf{y}|\underline{\mathbf{x}})$ are efficient; (ii) $g(.;\widehat{\boldsymbol{\gamma}}(\mathbf{y}|\underline{\mathbf{x}}))$ reaches (11).

6. RESULTS

We consider a synthetic scenario based on a pulse wave input $\mathbf{x}$ as displayed in Fig. 2 ($N = 100$), and a dynamical system defined by $\boldsymbol{\lambda} = (1/2, 1/2)^T$, $\boldsymbol{\alpha} = (6, -2)^T$, $\boldsymbol{\beta} = (-1/4, 1/4)^T$. A Gaussian kernel with bandwidth $h = 1$ is considered. The nonlinearity $g(.)$ resulting from this choice is shown in Fig. 2, where $\Omega = [a,b] = [-20, 20]$ and $T = 800$. Note that all the results presented in this paper have been obtained by averaging $L = 5000$ Monte Carlo runs. In Fig. 3 and 4 we compare the MSE of the MLEs (13a-13b) to the CRBs (7) as a function of the SNR defined as $SNR = \left(\frac{1}{N}\|\mathbf{g}(\mathbf{x} + \mathbf{T}_{\underline{\mathbf{x}}}\boldsymbol{\lambda};\boldsymbol{\gamma})\|^2\right)/\sigma_z^2$. Fig. 3 also compares the performance of two estimators of $\boldsymbol{\lambda}$, i.e., the MLE defined in (13b) and Pawlak's estimator defined in (2a) where $card(\mathcal{I}_1) = 51$ and $card(\mathcal{I}_2) = 47$. We can observe that the MLEs (13a-13b) converge to the CRBs (7) when the SNR increases, as expected [17]. Moreover, we can note that the MLE outperforms the kernel estimator of $g(.)$ proposed in [7]. Fig. 5 displays the estimated global estimation error, i.e. $MISE(\widehat{g}(.))$, of the two estimators versus SNR, which is compared with the proposed CR-like bound (11). As already mentioned for the estimation of $\boldsymbol{\lambda}$, the global estimation error of the MLE converges to the bound and outperforms the kernel estimator(2a)[7], which can also be observed in Fig. 6 showing the estimator of the nonlinearity $g(.)$ in both cases (for a given SNR), with a biased kernel estimator, as anticipated.

7. CONCLUSIONS

This paper addressed the nonlinear system identification problem for nonparametric Wiener models. The deterministic CRBs, the MLE

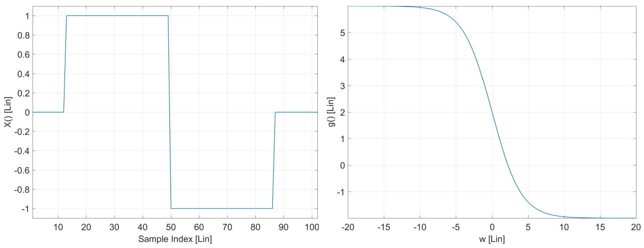

Fig. 2. Input signal x (left) and non linearity $g(.)$ (right)

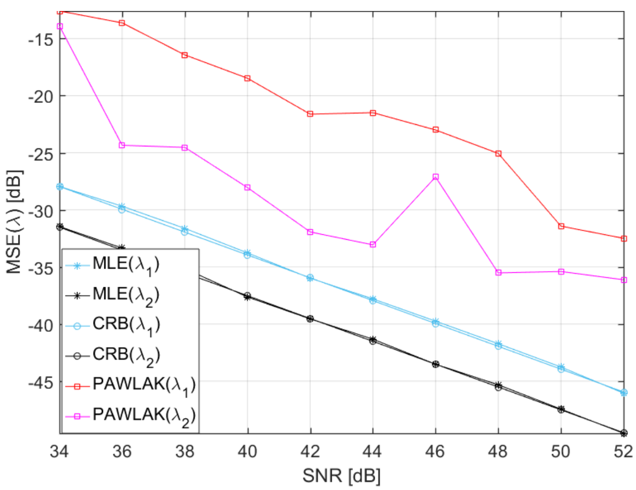

Fig. 3. MSEs of the MLE (13b) and of Pawlak's estimator (2a) for $\boldsymbol{\lambda}$ versus SNR, and the corresponding $\mathbf{CRB}(\boldsymbol{\lambda})$ (7).

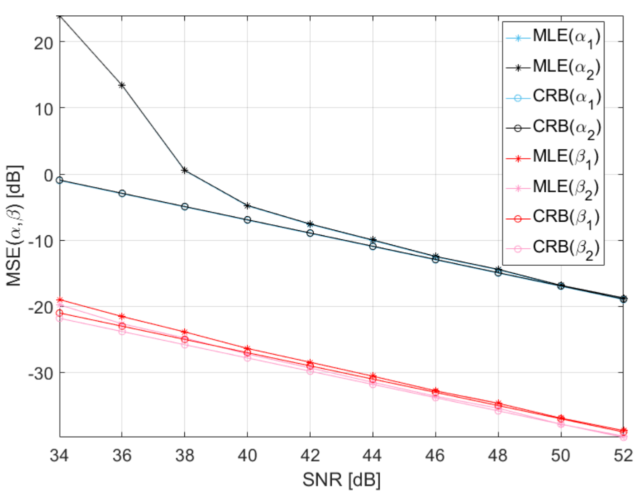

Fig. 4. MSE of the MLEs of $(\boldsymbol{\alpha}, \boldsymbol{\beta})$ (13a-13b) versus SNR, and the corresponding $\mathbf{CRB}\,(\boldsymbol{\alpha}, \boldsymbol{\beta})$ (7).

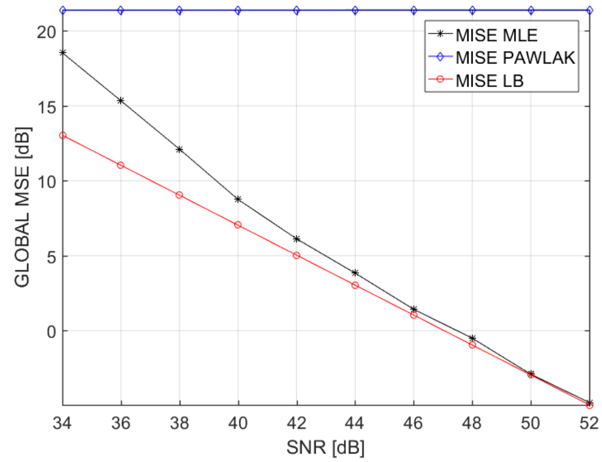

Fig. 5. $MISE(\widehat{g}\,(.))$ (10) of the MLE (13a-13b) and of Pawlak's estimator (2a) versus SNR, compared with the lower bound (11).

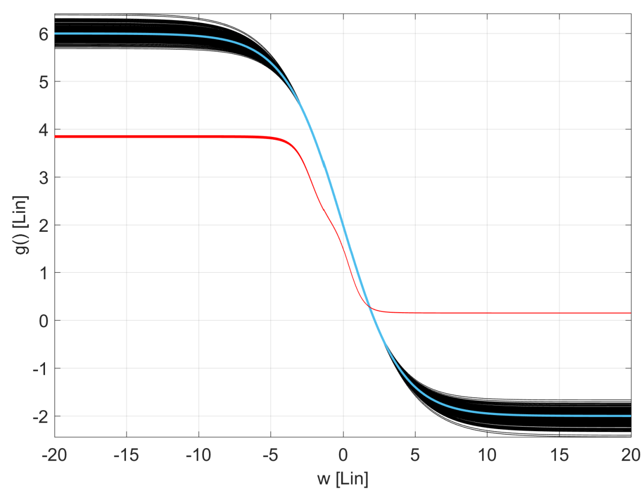

Fig. 6. Estimated nonlinearity $\widehat{g}\,(.)$ obtained with the MLEs (13a-13b, in black) and Pawlak's estimators (2a, in red) of $(\boldsymbol{\lambda}, \boldsymbol{\alpha}, \boldsymbol{\beta})$, compared to the ground truth $g\,(.)$ (in blue) at $SNR = 52dB$.

and an asymptotic CR-like bound for the global estimation error of the estimated nonlinearity were derived for this problem. Some simulation results confirmed that the maximum likelihood estimator of the nonlinearity has a global estimation error closer to the corresponding Cramér-Rao bound than an existing kernel estimator, which was designed for i.i.d. random input signals [7]. Based on the obtained results, further studies can be carried out to evaluate the optimal input signal for Wiener system identification and the influence of the bandwidth parameter h and/or the kernel type on the MLE performance.

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