# ON THE CONSISTENCY OF A LEAST SQUARES IDENTIFICATION PROCEDURE* 

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Conditions for the convergence of parameter estimates to the true value applicable in selftuning control models are presented. Persistent excitation property is proved by control theory methods.

## 1. INTRODUCTION

The paper deals with random processes the trajectory of which fulfills

$$
\begin{equation*}
\mathrm{d} X_{t}=f(\alpha) X_{t} \mathrm{~d} t+U_{t} \mathrm{~d} t+\mathrm{d} W_{t}, \quad t \geqq 0 \tag{1}
\end{equation*}
$$

$\operatorname{In}(1) W=\left\{W_{t}, t \geqq 0\right\}$ is the $n$-dimensional Wiener process with incremental variance matrix $h$,

$$
\mathrm{d} W_{t} \mathrm{~d} W_{t}^{\prime}=h \mathrm{~d} t
$$

Prime denotes the transposition. $U=\left\{U_{t}, t \geqq 0\right\}$ is a random process nonanticipative with respect to $W . f(\alpha)$ denotes an $n \times n$-matrix of the form

$$
f(\alpha)=f_{0}+\alpha^{1} f_{1}+\ldots+\alpha^{m} f_{m}, \quad \alpha=\left(\alpha^{1}, \ldots, \alpha^{m}\right)^{\prime} \in \mathbb{R}^{m}
$$

$f_{0}, f_{1}, \ldots, f_{m}$ are given matrices, $\alpha$ is a parameter the true value $\alpha_{0}$ of which is to be estimated from the observation of $X$ and $U$.

The paper continues the research of parameter estimation in linear systems initiated in [2], [5], and shows that the applications of control theory methods to the consistency problems presented in [4] can be developed to obtain explicit results. The methods were extended in [1] to embrace the estimates of the drift parameters.

The least squares estimate of $\alpha_{0}$ on the basis of $\left\{X_{t}, t \leqq T_{j},\left\{U_{t}, t \leqq T\right\}\right.$ is denoted by $\alpha_{T}^{*}$. It is defined as follows. Let $l$ be a nonnegative definite symmetric matrix. Heuristically $\alpha_{T}^{*}$ is the minimizer of the quadratic functional

$$
\begin{equation*}
\int_{0}^{T}\left(\dot{X}_{t}-f(\alpha) X_{t}-U_{t}\right)^{\prime} l\left(\dot{X}_{t}-f(\alpha) X_{t}-U_{t}\right) \mathrm{d} t \tag{2}
\end{equation*}
$$

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where $\dot{X}_{t}$ denotes the derivative of $X_{t}$ which in fact does not exist. To improve this we substract from (2)

$$
\int_{0}^{T} \dot{X}_{t}^{\prime} l \dot{X}_{t} \mathrm{~d} t
$$

which does not depend on $\alpha$ and rewrite the remaining terms as

$$
\begin{equation*}
\int_{0}^{T}\left(f(\alpha) X_{t}+U_{t}\right)^{\prime} l\left(f(\alpha) X_{t}+U_{t}\right) \mathrm{d} t-2 \int_{0}^{T}\left(f(\alpha) X_{t}+U_{t}\right)^{\prime} l \mathrm{~d} X_{t} . \tag{3}
\end{equation*}
$$

Equating the derivatives of (3) with respect to $\alpha^{i}$ to 0 one obtains the linear system of equations
(4) $\quad \sum_{j} \int_{0}^{T} X^{\prime} f_{i}^{\prime} l f_{j} X \mathrm{~d} t \alpha_{T}^{* j}=\int_{0}^{T} X^{\prime} f_{i}^{\prime} l\left(\mathrm{~d} X-f_{0} X \mathrm{~d} t-U \mathrm{~d} t\right), \quad i=1, \ldots, m$,
for $\alpha_{T}^{* 1}, \ldots, \alpha_{T}^{* m}$. We remark that (4) is a recursive estimation procedure (see [1]).
The estimator $\alpha_{T}^{*}$ is consistent if $\alpha_{T}^{*} \rightarrow \alpha_{0}$ in probability. It is strongly consistent if $\alpha_{T}^{*} \rightarrow \alpha_{0}$ almost surely (abbreviated a.s.).

## 2. STATEMENT AND PROOF OF RESULTS

Lemma 1. Let $g$ be an $n \times n$-matrix. If

$$
\begin{equation*}
\frac{1}{T} \int_{0}^{T}|X|^{2} \mathrm{~d} t, \quad T>0 \tag{5}
\end{equation*}
$$

is bounded in probability (respectively a.s.), then

$$
\begin{equation*}
\lim _{T \rightarrow \infty} \frac{1}{T} \int_{0}^{T} X_{t}^{\prime} g^{\prime} \mathrm{d} W_{t}=0 \quad \text { in prob. (respectively a.s.) } \tag{6}
\end{equation*}
$$

Proof. Introduce

$$
V_{T}=\int_{0}^{T} X^{\prime} g^{\prime} h g X \mathrm{~d} t .
$$

The following equation is satisfied

$$
\int_{0}^{T} X^{\prime} g^{\prime} \mathrm{d} W=\mathscr{W}_{V_{T}},
$$

where $\left\{\mathscr{W}_{s}, s \geqq 0\right\}$ is a Wiener process. Let (5) be bounded in probability. Choose $\varepsilon>0$ and find $K_{\varepsilon}$ such that

$$
\mathrm{P}\left(V_{T} / T \leqq K_{\varepsilon}\right)>1-\varepsilon, \quad T>0 .
$$

Then
(7) $\mathrm{P}\left(\left|\frac{1}{T} \mathscr{W}_{v_{T}}\right|>\varepsilon\right) \leqq \varepsilon+2 \mathrm{P}\left(\sup _{s \leq K_{t} T} \mathscr{H}_{s}>\varepsilon T\right)=\varepsilon+4 \Phi\left(-\varepsilon T / \sqrt{ }\left(K_{\varepsilon} T\right)\right)$,
where $\Phi(y)$ is the standardized normal distribution function. The last term in (7) tends to 0 as $T \rightarrow \infty$, which proves (6) in probability.

The alternative with a.s. converegence is proved directly using the strong law of large numbers for $\mathscr{W}$.

Proposition 1. Let the matrices
(8)

$$
\sqrt{ } l f_{i} \sqrt{ } h, \quad i=1, \ldots, m
$$

be linearly independent where $\sqrt{ } l, \sqrt{ } h$ is the symmetric square root of $l$ and of $h$, respectively. If

$$
\begin{equation*}
\frac{1}{T} \int_{0}^{T}\left(\left|X_{t}\right|^{2}+\left|U_{t}\right|^{2}\right) \mathrm{d} t, \quad T>0 \tag{9}
\end{equation*}
$$

is bounded in probability (respectively a.s.), and

$$
\begin{equation*}
\lim _{T \rightarrow \infty}\left|X_{T}\right|^{2} / T=0 \quad \text { in prob. (respectively a.s.) } \tag{10}
\end{equation*}
$$

then

$$
\begin{equation*}
\lim _{T \rightarrow \infty} \alpha_{T}^{*}=\alpha_{0} \quad \text { in prob. (respectively a.s.) } \tag{11}
\end{equation*}
$$

Proof. Inserting (1) with $\alpha=\alpha_{0}$ into (4) we get

$$
\sum_{j} \int_{0}^{T} X^{\prime} f_{i}^{\prime} l f_{j} X \mathrm{~d} t\left(\alpha_{T}^{* j}-\alpha_{0}^{j}\right)=\int_{0}^{T} X^{\prime} f_{i}^{\prime} l \mathrm{~d} W
$$

and hence
(12) $\sum_{i j} \frac{1}{T} \int_{0}^{T} X^{\prime} f_{i}^{\prime} l f_{j} X \mathrm{~d} t\left(\alpha_{T}^{* i}-\alpha_{0}^{i}\right)\left(\alpha_{T}^{* j}-\alpha_{0}^{j}\right)=\sum_{i} \frac{1}{T} \int_{0}^{T} X^{\prime} f_{i}^{\prime} l \mathrm{~d} W\left(\alpha_{T}^{* i}-\alpha_{0}^{i}\right)$.

To investigate the left-hand side of (12) take $\mu \in \mathbb{R}^{m},|\mu|=1$, and denote

$$
\begin{equation*}
p(\mu)=\sum_{i} \mu^{i} \sqrt{l} f_{i}, \quad q(\mu)=p(\mu)^{\prime} p(\mu) \tag{13}
\end{equation*}
$$

Consequently,

$$
\sum_{i j} \frac{1}{T} \int_{0}^{T} X^{\prime} f_{i}^{\prime} I f_{j} X \mathrm{~d} t \mu^{i} \mu^{j}=\frac{1}{T} \int_{0}^{T} X^{\prime} q(\mu) X \mathrm{~d} t
$$

Set $f=f\left(\alpha_{0}\right)$. It can be assumed that $f$ is a stable matrix because without loss of generality it can be replaced by $f-a I$ where $I$ is the unit matrix. Introduce the quadratic functional

$$
\begin{equation*}
Q_{T}(\mu)=\int_{0}^{T} X^{\prime} q(\mu) X \mathrm{~d} t+c \int_{0}^{T}|U|^{2} \mathrm{~d} t \tag{14}
\end{equation*}
$$

where $c>0$. Consider $U$ as a control process and $Q_{T}(\mu)$ as a cost functional. The minimum of $\mathrm{E} Q_{T}$ over all $U$ nonanticipative is obtained by solving a Riccati equation whose limiting form as $T \rightarrow \infty$ is

$$
\begin{equation*}
w f+f^{\prime} w-c^{-1} w^{2}+q(\mu)=0 \tag{15}
\end{equation*}
$$

where $w$ is nonnegative definite. It follows then

$$
\begin{equation*}
\inf _{u}\left\{2 x^{\prime} w(f x+u)+x^{\prime} q(\mu) x+c|u|^{2}\right\}=0, \quad x \in \mathbb{R}^{n} \tag{16}
\end{equation*}
$$

From (1) and (16) applying the Ito formula to $\int_{0}^{T} \mathrm{~d}\left(X^{\prime} w X\right)$ it follows that

$$
\begin{equation*}
Q_{T}(\mu)-T \operatorname{trace}(h w)+X_{T}^{\prime} w X_{T} \geqq 2 \int_{0}^{T} X^{\prime} w \mathrm{~d} W \tag{17}
\end{equation*}
$$

Setting $v=c^{-1} w$ we get from (15)

$$
v f+f^{\prime} v-v^{2}+c^{-1} q(\mu)=0
$$

From here it follows that

$$
\begin{equation*}
v \sim c^{-1 / 2} \sqrt{ } q(\mu), \quad c \rightarrow 0+ \tag{18}
\end{equation*}
$$

Because of the linear independence of (8), $\sqrt{h} q(\mu) \sqrt{h}$ is nonzero, and hence $\sqrt{ } h q(\mu)^{1 / 4}$ is nonzero. Consequently,

$$
\inf _{|\mu|=1} \operatorname{trace}(h \sqrt{ } q(\mu))=\inf _{|\mu|=1} \operatorname{trace}(\sqrt{ } h \sqrt{ } q(\mu) \sqrt{ } h\rangle>0
$$

From (18) we deduce that

$$
\operatorname{trace}(h v) \geqq r / \sqrt{c}
$$

or

$$
\begin{equation*}
\operatorname{trace}(h w) \geqq r \sqrt{c} \tag{19}
\end{equation*}
$$

where $r>0$ is independent of $\mu$ and $c,|\mu|=1, c<1$.
Let $(9)$ be bounded in probability and let (10) hold in probability. Applying Lemma 1 to the integral in (17) we obtain using (10) and (19) that for $\delta>0$

$$
\begin{equation*}
\lim _{T \rightarrow \infty} \mathrm{P}\left(\frac{1}{T} Q_{T}(\mu) \geqq r \sqrt{ } c-\delta\right)=1 \tag{20}
\end{equation*}
$$

Using (20) we shall estimate the left-hand side of (12).
Let $\varepsilon>0$. Find $K_{\varepsilon}$ such that

$$
\begin{equation*}
\mathrm{P}\left(\frac{1}{T} \int_{0}^{T}\left(|X|^{2}+|U|^{2}\right) \mathrm{d} t \leqq K_{\varepsilon}\right) \geqq 1-\varepsilon, \quad T>0 \tag{21}
\end{equation*}
$$

Then
(22) $\mathrm{P}\left(\left|\frac{1}{T} \int_{0}^{T} X^{\prime}(q(\mu)-q(v)) X \mathrm{~d} t\right| \leqq|q(\mu)-q(v)| K_{\varepsilon}, \mu, v \in \mathbb{R}^{m}\right) \geqq 1-\varepsilon$.

Further fix $c>0$ such that

$$
\begin{equation*}
r \sqrt{ } c-c K_{\varepsilon}-3 \delta>0 \tag{23}
\end{equation*}
$$

Next choose a finite set $\mu_{k}, k=1, \ldots, N,\left|\mu_{k}\right|=1$, such that

$$
\begin{equation*}
\inf _{k}\left|q(\mu)-q\left(\mu_{k}\right)\right| K_{\varepsilon} \leqq \delta \quad \text { whenever } \quad|\mu|=1 \tag{24}
\end{equation*}
$$

By virtue of (20) for $T>T_{0}$

$$
\mathrm{P}\left(\frac{1}{T} Q_{T}\left(\mu_{i}\right) \geqq r \sqrt{c}-\delta, i=1, \ldots, N\right) \geqq 1-\varepsilon
$$

and hence from (14), (21) (23)

$$
\mathrm{P}\left(\frac{1}{T} \int_{0}^{T} X^{\prime} q\left(\mu_{i}\right) X \mathrm{~d} t \geqq 2 \delta, i=1, \ldots, N\right) \geqq 1-2 \varepsilon
$$

(22) and (24) imply the persistent excitation condition (see [3])

$$
\begin{equation*}
\mathrm{P}\left(\frac{1}{T} \int_{0}^{T} X^{\prime} q(\mu) X \mathrm{~d} t \geqq \delta|\mu|^{2}, \mu \in \mathbb{R}^{m}\right) \geqq 1-2 \varepsilon \tag{25}
\end{equation*}
$$

Consequently,
(26) $\mathrm{P}\left(\sum_{i j} \frac{1}{T} \int_{0}^{T} X^{\prime} f_{i}^{\prime} l_{j} X \mathrm{~d} t\left(\alpha_{T}^{* i}-\alpha_{0}^{i}\right)\left(\alpha_{T}^{* j}-\alpha_{0}^{j}\right) \geqq \delta\left|\alpha_{T}^{*}-\alpha_{0}\right|^{2}\right) \geqq 1-2 \varepsilon$.

Regarding the right-hand side of (12) we have by Lemma 1 for $T>T_{0}$

$$
\mathrm{P}\left(\left(\sum_{i}\left(\frac{1}{T} \int_{0}^{T} X^{\prime} f_{i}^{\prime} / \mathrm{d} W\right)^{2}\right)^{1 / 2} \leqq \delta^{2}\right) \geqq 1-\varepsilon,
$$

and hence

$$
\begin{equation*}
\mathrm{P}\left(\sum_{i} \frac{1}{T} \int_{0}^{T} X^{\prime} f_{i}^{\prime} l \mathrm{~d} W\left(\alpha_{T}^{* i}-\alpha_{0}^{i}\right) \leqq \delta^{2}\left|\alpha_{T}^{*}-\alpha_{0}\right|\right) \geqq 1-\varepsilon . \tag{27}
\end{equation*}
$$

From (12), (26), (27) it follows that

$$
\mathrm{P}\left(\left|\alpha_{T}^{*}-\alpha_{0}\right|<\delta\right) \geqq 1-3_{\varepsilon}, \quad T>T_{0} .
$$

Note that $\delta$ in (23) can be chosen arbitrarily small. The validity of (11) in probability is thus established.

The boundedness of (9) and the validity of (10) almost surely implies

$$
\mathrm{P}\left(\liminf _{T \rightarrow \infty} \frac{1}{T} Q_{r}(\mu) \geqq r \sqrt{ } c\right)=1 .
$$

Moreover $T>T_{0}$ can be added to the events whose probabilities are computed starting with (21) and ending with

$$
\mathrm{P}\left(\left|\alpha_{T}^{*}-\alpha_{0}\right|<\delta, \quad T>T_{0}\right) \geqq 1-3 \varepsilon,
$$

which proves the validity of (11) almost surely.
Assume next that $h$ is singular, $0<\operatorname{rank} h=s<n$. Renumbering the coordinates if necessary $h$ can be expressed as

$$
h=\binom{h^{00}, h^{01}}{h^{10}, h^{11}}=\left(h^{0}, h^{1}\right),
$$

where rank $h^{00}=s$. The same partitioning will be used also for the blocks of other matrices. Recall the definition (13) of $p(\mu), q(\mu)$.

Proposition 2. The implication of Proposition 1 remains valid if

$$
\begin{equation*}
\operatorname{rank} p^{1}(\mu)<\operatorname{rank} p(\mu), \quad \mu \in \mathbb{R}^{m} . \tag{28}
\end{equation*}
$$

Proof. Write $X_{t}^{0}=\left(X_{t}^{1}, \ldots, X_{t}^{s}\right)^{\prime}$, similarly for $U_{t}^{0}, W_{t}^{0}$, and set $V_{t}=$ $=\left(X_{t}^{s+1}, \ldots, X_{t}^{n}\right)^{\prime}$. From (1) it follows

$$
\mathrm{d} X_{t}^{0}=f^{00} X_{t}^{0} \mathrm{~d} t+f^{01} V_{t} \mathrm{~d} t+U_{t}^{0} \mathrm{~d} t+\mathrm{d} W_{\mathrm{t}}^{0}, \quad t \geqq 0
$$

Consider $U^{0}$ and $V$ as control processes and proceed as in the proof of Proposition 1.
It holds

$$
X^{\prime} q(\mu) X=X^{0 \prime} q^{00}(\mu) X^{0}+2 V^{\prime} q(\mu)^{10} X^{0}+V^{\prime} q^{11}(\mu) V
$$

Note that

$$
q^{00}=\left(p^{0}\right)^{\prime} p^{0}, \quad q^{10}=\left(p^{1}\right)^{\prime} p^{0}, \quad q^{11}=\left(p^{1}\right)^{\prime} p^{1}
$$

Without loss of generality it can be assumed that $q^{11}$ is nonsingular, i.e., $p^{1}$ has linearly independent columns. Otherwise the dimension of $V$ could be reduced. Moreover, let $h^{00}=I$, and let $f^{00}$ be a stable matrix.

Introduce the functional

$$
Q_{T}=\int_{0}^{T}\left(X^{0 \prime} q^{00} X^{0}+2 V^{\prime} q^{10} X^{0}+V^{\prime} q^{11} V\right) \mathrm{d} t+c \int_{0}^{T}\left(|U|^{2}+|V|^{2}\right) \mathrm{d} t
$$

We shall demonstrate the analogues of (17) and (19). The rest of the proof follows that of Proposition 1. Writing $x, u$ instead if $x^{0} u^{0}$ we replace (16) by

$$
\begin{align*}
& \inf _{(u, v)}\left\{2 x^{\prime} w\left(f^{00} x+f^{01} v+u\right)+x^{\prime} q^{00} x+\right.  \tag{29}\\
& \left.+2 v^{\prime} q^{10} x+v^{\prime} q^{11} v+c\left(|u|^{2}+|v|^{2}\right)\right\}=0
\end{align*}
$$

The minimum of the expression in braces is attained for

$$
u=-c^{-1} w x, \quad v=-\left(c I+q^{11}\right)^{-1}\left(\left(f^{01}\right)^{\prime} w+q^{10}\right) x
$$

Inserting these values into (29) we obtain

$$
\begin{gather*}
x^{\prime}\left(2 w f^{00}-c^{-1} w^{2}+q^{00}-w f^{01}\left(c I+q^{11}\right)^{-1}\left(f^{01}\right)^{\prime} w-\right.  \tag{30}\\
-2 w f^{01}\left(c I+q^{11}\right)^{-1} q^{10}-q^{01}\left(c I+q^{11}\right)^{-1} q^{10}- \\
\left.-c q^{01}\left(c I+q^{11}\right)^{-2}\left(q^{10}+2\left(f^{01}\right)^{\prime} w\right)\right) x=0
\end{gather*}
$$

From here we conclude that the asymptotic behaviour of $c^{-1} w$ as $c \rightarrow 0+$ depends on the matrix

$$
\begin{equation*}
q^{00}-q^{01}\left(q^{11}\right)^{-1} q^{10} \tag{31}
\end{equation*}
$$

From

$$
\inf _{v}\left|p^{0} x+p^{1} v\right|^{2}=x^{\prime}\left(q^{00}-q^{01}\left(q^{11}\right)^{-1} q^{10}\right) x
$$

it is seen that (28) implies that (31) is a nonzero matrix. Consequently,

$$
\inf _{|\mu|=1} \operatorname{trace}\left(q^{00}(\mu)-q^{01}(\mu) q^{11}(\mu)^{-1} q^{10}(\mu t)\right)>0
$$

From this inequality and from (30) it follows that

$$
\operatorname{trace}(w) \geqq r \sqrt{c}
$$

with $r>0$. This inequality with the inequality

$$
Q_{T}(\mu)-T \operatorname{trace}(w)+X_{T}^{0 \prime} w X_{T}^{0} \geqq 2 \int_{0}^{T} X^{0 \prime} w \mathrm{~d} W
$$

enables us to continue as in the proof of Proposition 1.

Example. A self-tuning control model is described by the equation

$$
\mathrm{d} X_{t}=f\left(\alpha_{0}\right) X_{t} \mathrm{~d} t+k\left(\alpha_{t}^{*}\right) X_{t} \mathrm{~d} t+\mathrm{d} W_{t}, \quad t \geqq 0,
$$

where $k(\alpha)$ are given feedback gain matrices. Assume that

$$
\mathscr{K}=\left\{k(\alpha), \alpha \in \mathbb{R}^{m}\right\}
$$

is a bounded set and that the following Liapunov type assumption (see [5]) is fulfilled. There exists a symmetric matrix $z>0$ such that

$$
\begin{equation*}
z(f+g k)+(f+g k)^{\prime} z+I \leqq 0, \quad k \in \mathscr{K} . \tag{32}
\end{equation*}
$$

The inequalities denote positive definiteness and negative semidefiniteness, respectively. (32) implies (9), (10) and Propositions 1,2 give sufficient condition for the self-tuning property.
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