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ROBUSTNESS ISSUES IN CONTINUOUS-TIME SYSTEM IDENTIFICATION FROM SAMPLED DATA

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Abstract: This paper explores the robustness issues that arise in the identification of continuous-time systems from sampled data. A key observation is that, in practice, one cannot rely upon the fidelity of the model at high frequencies. This implies that any result which implicitly or explicitly depends upon the folding of high frequency components down to lower frequencies will be inherently non-robust. We illustrate this point by referring to the identification of continuous-time auto-regressive stochastic models from sampled data. We argue that traditional approaches to this problem are sensitive to high frequency modelling errors. We also propose an alternative maximum likelihood procedure in the frequency domain, which is robust to high frequency modelling errors.
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Keywords: continuous-time systems, parameter estimation, stochastic systems, robust estimation, sampled data

1. INTRODUCTION

Identification of continuous-time systems is a problem of considerable importance in various disciplines such as economics, control, fault detection and signal processing. In recent years, there has been an increased interest in the problem of identifying continuous-time models (Rao and Garnier, 2002; Garnier *et al.*, 2003; Ljung, 2003). Even though it is theoretically possible to carry out system identification using continuous-time data (Young, 1981; Unbehauen and Rao, 1990), this will generally involve analogue operators to emulate time derivatives and will thus usually be impractical. Thus, one is usually forced to work with sampled data (Sinha and Rao, 1991; Pintelon and Schoukens, 2001). In this context, one might hope that if one samples quickly enough then the difference between discrete and continuous processing would be vanishing small. There are indeed many cases which support this hypothesis — see, for example, (Middleton and Goodwin, 1990; Feuer and Goodwin, 1996; Goodwin *et al.*, 2001).

The above discussion can, however, lead to a false sense of security when using sampled data. A well known instance where *naive* use of sampled data can lead to erroneous results is in the identification of continuous-time stochastic systems where

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the noise model has relative degree greater than zero. In the latter case, it has been shown in (Wahlberg, 1988) that the sampled data model will have *sampling zeros*. These are the stochastic equivalent of the well-known sampling zeros that occur in deterministic systems of relative degree greater than one (Åström *et al.*, 1984). The stochastic sampling zeros play a crucial role in obtaining unbiased parameter estimates in the identification of such systems from sampled data. The reason is that most identification procedures rely upon *whitening* of the noise, an operation which is sensitive to the sampling zeros of continuous-time systems of non zero relative degree.

A particular case of the above problem has been studied in detail in (Söderström *et al.*, 1997; Larsson and Söderström, 2002; Larsson, 2003). In particular, these papers deal with continuous-time auto-regressive (CAR) system identification from sampled data. Such systems have relative degree n, where n is the order of the auto-regressive process. It has been shown that if one ignores the stochastic sampling zeros, *e.g.*, by using ordinary least squares, a clear bias will appear in the parameter estimates, even when using fast sampling rates (Söderström *et al.*, 1997).

In the current paper we further explore the circle of ideas outlined above. We pay particular attention to the impact of high frequency modelling errors on continuous-time system identification when using sampled data. We show that high frequency modelling errors can be equally as catastrophic as ignoring sampling zeros. Thus we argue that one should always define a *bandwidth of fidelity* of a model and ensure that the model errors outside that bandwidth do not have a major impact on the identification results. This leads us to develop a frequency domain identification procedure which we show is insensitive to both relative degree and unmodelled high frequency poles.

2. BACKGROUND TO THE IDENTIFICATION OF CAR SYSTEMS

The ideas presented in this paper are equally applicable to all continuous-time identification problems. However, to be specific we will focus primarily on the case of CAR system identification from sampled data.

In (Larsson and Söderström, 2002), estimation of the parameters of a CAR system is performed by using a filtered least squares procedure. In fact, the prefilter applied to the data is closely related to the asymptotic sampling zeros described in (Wahlberg, 1988) (for stochastic models, and in (Åström *et al.*, 1984), for the deterministic case). This is an elegant and insightful solution to the problem. However, the asymptotic location of the sampling zeros depend on the relative degree of the continuous-time plant description. At this point our claim about a *bandwidth of validity* for this model becomes relevant since relative degree may be an ill-defined quantity for continuous-time systems.

This kind of issues has been previously illustrated, for example, by the same authors in the context of deterministic control (Yuz *et al.*, 2004). Here we extend these ideas to the identification problem.

We consider a CAR system described by:

$$A_c(\rho)y(t) = \dot{v}(t) \tag{1}$$

where $A_c(\rho)$ is a polynomial in the differential operator $\rho = \frac{d}{dt}$, *i.e.*

$$A_c(\rho) = \rho^n + a_{n-1}\rho^{n-1} + \ldots + a_0 \tag{2}$$

In equation (1) the term $\dot{v}(t)$ represents a continuous-time white noise process.

Remark 1. We already notice the source of some difficulties since the process $\dot{v}(t)$ does not exist in any meaningful sense. Indeed, equation (1) should actually be written as a stochastic differential equation driven by a process with independent increments, that is, *Brownian motion* or *Wiener* process (Øksendal, 2003). Indeed, a continuous-time *white noise* (CTWN) process is a mathematical abstraction and does not physically exist (Jazwinski, 1970), but it can be approximated to any desired degree of accuracy by conventional stochastic processes with broad band spectra (Kloeden and Platen, 1992). Note, however, that the difference between a *broad band* spectra and *white noise* is equivalent to a particular form of high frequency modelling error. This is the key issue of relevance in the current paper.

If we treat equation (1) appropriately then it is possible to derive an exact discrete-time system that describes the samples of $y(t)$ (Wahlberg, 1988). This model takes the following generic form:

$$A_d(q^{-1})y(k\Delta) = B_d(q^{-1})w_k \tag{3}$$

where w_k is a discrete-time white noise process, and A_d and B_d are polynomials in the backward shift operator q^{-1}.

It is readily shown that the polynomial $A_d(q^{-1})$ in equation (3) is *well behaved* in the sense that it converges naturally to its continuous-time counterpart. This relationship is most readily portrayed if the model is rewritten in the equivalent delta form (Middleton and Goodwin, 1990):

$$A_\delta(\delta) = \delta^n + \bar{a}_{n-1}\delta^{n-1} + \ldots + \bar{a}_0 \tag{4}$$

where $\delta = \frac{q-1}{\Delta}$ is the delta operator.

Using (4), it can be shown that, as the sampling period Δ goes to zero:

$$\lim_{\Delta \to 0} \bar{a}_i = a_i \quad ; i = n-1, \ldots, 0 \tag{5}$$

An interesting fact, in the current context, is that the polynomial $B_d(q^{-1})$ in equation (3) has no continuous-time counterpart. This is the stochastic sampling zero polynomial (Wahlberg, 1988; Larsson and Söderström, 2002) arising from the folding of high frequency components back onto the low frequency range.

Much is known about the polynomial $B_d(q^{-1})$ and its roots (Åström *et al.*, 1984; Wahlberg, 1988; Weller *et al.*, 2001). In particular, it has been shown that its coefficients converge asymptotically to specific values as the sampling period Δ goes to zero.

If we apply the prediction error method (PEM) (Ljung, 1999) to the model (3), then one needs to minimise the cost function:

$$J_{PEM} = \sum_{k=1}^{N} \left[\frac{A_d(q^{-1}) y(k\Delta)}{B_d(q^{-1})} \right]^2 \tag{6}$$

Notice the key role played by the sampling zeros in the above expression. A simplification can be used at high sampling rates by replacing the polynomial $B_d(q^{-1})$ by its asymptotic expression. However, this polynomial can never be ignored. Hence it is not surprising that the use of ordinary least squares, *i.e.*, a cost function of the form:

$$J_{LS} = \sum_{k=1}^{N} \left[A_d(q^{-1}) y(k\Delta) \right]^2 \tag{7}$$

leads to (asymptotically) biased results, even when using the delta formulation (4) (Söderström *et al.*, 1997). We illustrate these ideas by the following example.

Example 2. Consider the continuous-time system defined by the *nominal model*:

$$A_c(\rho) y(t) = \dot{v}(t) \tag{8}$$

where $\dot{v}(t)$ is a CTWN process with (constant) spectral density equal to 1, and

$$A_c(\rho) = \rho^2 + 3\rho + 2 \tag{9}$$

Following (Wahlberg, 1988), the exact discrete-time model has the form:

$$Y(z) = \frac{B_d(z)}{A_d(z)} W(z) = \frac{z(z - z_1)}{(z - e^{-\Delta})(z - e^{-2\Delta})} W(z) \tag{10}$$

As the sampling rate increases the sampled model converges to:

$$\frac{B_d(z)}{A_d(z)} \xrightarrow{\Delta \to 0} \frac{z(z - z_1^*)}{(z-1)^2} \tag{11}$$

where $z_1^* = -2 + \sqrt{3}$ is the asymptotic stochastic sampling zero, which corresponds to the stable root of the polynomial (Åström *et al.*, 1984; Wahlberg, 1988):

$$B_3(z) = z^2 + 4z + 1 \tag{12}$$

For simulation purposes we choose a sampling frequency $\omega_s = 250$[rad/s]. Note that this frequency is two decades above the fastest system pole, located at $s = -2$. We perform $N_{sim} = 250$ simulations, using $N = 10000$ data points in each run.

Test 1: If one uses ordinary least squares as in (7), then one finds that the parameters are (asymptotically) biased, as discussed in detail in (Söderström *et al.*, 1997). The continuous-time parameters are extracted by converting to the delta form and then using (5). We obtain the following (mean) parameter estimates:

$$\begin{bmatrix} \hat{a}_1 \\ \hat{a}_0 \end{bmatrix} = \begin{bmatrix} 1.9834 \\ 1.9238 \end{bmatrix} \tag{13}$$

We observe that $\hat{a}_1$ is clearly biased, but close to the asymptotic biased value theoretically predicted $\hat{a}_1 \to \frac{2}{3} a_1$ (Söderström *et al.*, 1997).

Test 2: We next perform least squares estimation of the parameters, but with prefiltering of the data by the asymptotic sampling zero polynomial, *i.e.*, we use the sequence of filtered samples $\{y_F(k\Delta)\}$ given by:

$$y_F(k\Delta) = \frac{1}{1 + (2 - \sqrt{3}) q^{-1}} y(k\Delta) \tag{14}$$

Note that this strategy is essentially as in (Larsson and Söderström, 2002; Larsson, 2003).

Again, we extract the continuous-time parameters by converting to the delta form and using (5). We obtain the following estimates for the coefficients of the polynomial (9):

$$\begin{bmatrix} \hat{a}_1 \\ \hat{a}_0 \end{bmatrix} = \begin{bmatrix} 2.9297 \\ 1.9520 \end{bmatrix} \tag{15}$$

The residual small bias in this case can be explained by the use of the asymptotic sampling zero in (11), while the sampling period Δ is finite.

Up to this point, we have not introduced any high frequency under-modelling. In the following section, we will see the consequences of an unmodelled fast pole or, equivalently, *wide-band* (*i.e.*, non-white) noise, in the filtered least squares estimation.

3. REAPPRAISAL OF CAR SYSTEM IDENTIFICATION

The solution of the CAR identification problem for sampled data would seem to be straightforward given the discussion in Section 2. Apparently, one only needs to include the *sampling zeros* to get asymptotically unbiased parameter estimates using least squares. However, this ignores the issue of fidelity of the high frequency components of the model. Indeed, as pointed out before, relative degree cannot be robustly defined for continuous-time systems due to the presence of (possibly time-varying and ill-defined) high frequency poles or zeros. If one accepts this claim, then one cannot rely upon the integrity of the extra polynomial $B_d(q^{-1})$. In particular, the error caused by ignoring this polynomial (as suggested by the cost function (7)) might be as catastrophic as using a sampling zero polynomial arising from some hypothetical assumption about the relative degree. Thus, this class of identification procedures seems to be inherently non-robust. We illustrate this by continuing Example 2.

Example 3. (Example 2 continued). Let us now assume that the *true model* for the system (8) is given by the polynomial:

$$A_c(\rho) = A_c^o(\rho)(0.02\rho + 1) \tag{16}$$

where we have renamed the polynomial (9) in the original model as $A_c^o(\rho)$. The *true* system has an unmodelled pole at $s = -50$, which is more than one decade above the fastest nominal pole in (8)–(9), but almost one decade below the sampling frequency, $\omega_s = 250$[rad/s].

We repeat the estimation procedure described in *Test 2*, in Section 2, using the filtered least squares procedure. We obtain the following estimates:

$$\begin{bmatrix} \hat{a}_1 \\ \hat{a}_0 \end{bmatrix} = \begin{bmatrix} 1.4238 \\ 1.8914 \end{bmatrix} \tag{17}$$

These are clearly biased!

To analyse the effect of different types of undermodelling, we now consider the *true* denominator polynomial (16) to be:

$$A_c(\rho) = A_c^o(\rho)\left(\frac{\rho}{\omega_u} + 1\right) \tag{18}$$

We consider different values of the parameter ω_u in (18), using the same simulation conditions as in the previous examples (*i.e.*, 250 Monte Carlo runs using 10000 data points each). Figure 1 clearly shows the effect of the unmodelled dynamics, even beyond the sampling frequency due to the folding effect inherent to the sampling process.

Figure 2 shows similar simulations results using an instrumental variable (IV) estimator. The IV-

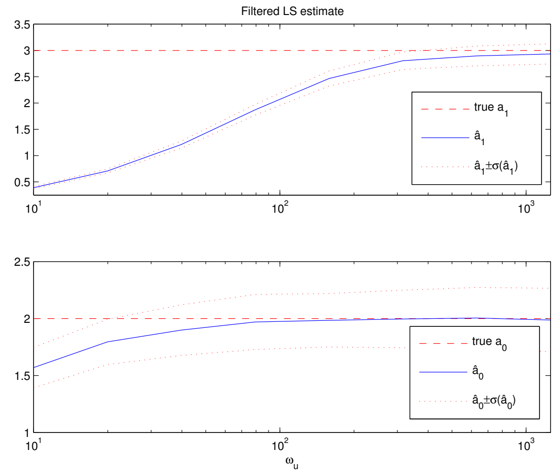

Fig. 1. Mean of the parameter estimates as a function of the unmodelled dynamics, using filtered LS.

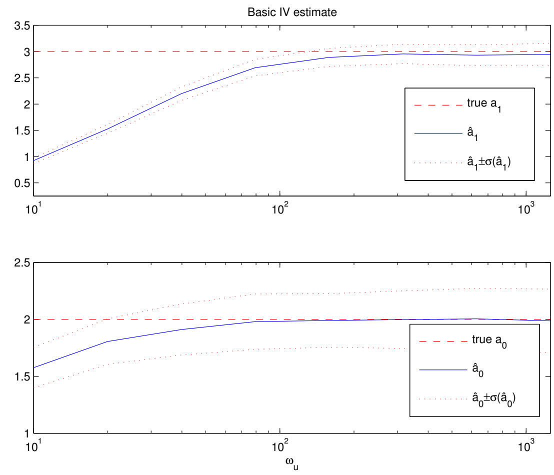

Fig. 2. Mean of the parameter estimates as a function of the unmodelled dynamics, using simple delayed IV.

estimator is a basic IV method where the IV vector consists of observations of $y(t)$ delayed one sampling period (Bigi *et al.*, 1994).

4. FREQUENCY DOMAIN ESTIMATION

The difficulties raised above are due to the fact that the high frequency model is not exactly as hypothesised in the algorithm. Thus, the folding that occurs is **not** governed by the anticipated sampling zero polynomial that is used to prefilter the data.

This raises the question as to how this problem might be avoided, or at least reduced by using an identification procedure more robust to high frequency under-modelling. Our proposal to deal with this problem is to suggest that one must designate a *bandwidth of validity* for the model assumed and then develop an algorithm which is insensitive to errors outside that range. This is most easily done in the frequency domain.

If one converts the data to the frequency domain, then one can carry out the identification over a limited range of frequencies. Note, however, that one needs to carefully define the likelihood function in this case. We use the following result.

Lemma 4. Let us consider the (approximate) discrete-time model:

$$A_d(q)y(k\Delta) = w_k \tag{19}$$

where w_k is a discrete-time stationary Gaussian white-noise sequence with variance σ_w^2. Given N data points of the output sequence $y(k\Delta)$ sampled at ω_s[rad/s], the appropriate likelihood function, in the frequency domain, takes the form:

$$L = \sum_{\ell=0}^{n_{max}} \frac{|A_d(e^{j\omega_\ell\Delta})Y(e^{j\omega_\ell\Delta})|^2}{N\sigma_w^2} - \log\frac{|A_d(e^{j\omega_\ell\Delta})|^2}{\sigma_w^2} \tag{20}$$

where $\omega_\ell = \frac{\omega_s \ell}{N}$ and n_{max} corresponds to the bandwidth to be considered, *i.e.*, $\omega_{max} = \frac{\omega_s n_{max}}{N}$.

PROOF. In the frequency domain, for every frequency ω_ℓ, we have that:

$$A_\ell Y_\ell = W_\ell \tag{21}$$

where $Y_\ell \triangleq Y(e^{j\omega_\ell\Delta})$ and $W_\ell \triangleq W(e^{j\omega_\ell\Delta})$ are the discrete Fourier transforms (DFTs) of the (finite) sequences $y(k\Delta)$ and w_k, respectively, and:

$$A_\ell \triangleq A_d(e^{j\omega_\ell\Delta}) \tag{22}$$

We note that the process W_ℓ has a (complex) Gaussian distribution such that:

$$E\{W_\ell W_m^*\} = N\sigma_w^2\delta_K[\ell - m] \tag{23}$$

where * denotes complex conjugation. The process Y_ℓ is also Gaussian and, from (21):

$$E\{Y_\ell Y_m^*\} = \frac{N\sigma_w^2}{A_\ell A_m^*}\delta_K[\ell - m] \tag{24}$$

Thus, its probability density function is given by:

$$p(Y_\ell) = \frac{|A_\ell|^2}{\pi N\sigma_w^2}\exp\left\{-\frac{|A_\ell|^2|Y_\ell|^2}{N\sigma_w^2}\right\} \tag{25}$$

We can now maximise the joint probability of the frequency components Y_0 up to $Y_{n_{max}}$, by minimising the function:

$$\begin{aligned} L &= -\log p(Y_0, \ldots, Y_{n_{max}}) = -\log\prod_{\ell=0}^{n_{max}} p(Y_\ell) \\ &= \sum_{\ell=0}^{n_{max}}\left[\frac{|A_\ell Y_\ell|^2}{N\sigma_w^2} - \log\frac{|A_\ell|^2}{\sigma_w^2}\right] + C \end{aligned} \tag{26}$$

where C is constant. Minimising (26) is equivalent to minimising (20).

Remark 5. In the full bandwidth case it can be readily shown that:

$$\frac{2\pi}{N}\sum_{\ell=0}^{N-1}\log\frac{|A_d(e^{j\omega_\ell\Delta})|^2}{\sigma_w^2} \to \int_0^{2\pi}\log\frac{|A_d(e^{j\omega})|^2}{\sigma_w^2}d\omega \tag{27}$$

as $N \to \infty$. The Jensen's formula for the unit disk (Goodwin *et al.*, 2001, Theorem C.11) guarantees that the last integral is equal to zero but **only** if one considers all frequencies components from 0 to π/Δ. Thus, with full bandwidth one can use ordinary least squares in the frequency domain for the model (19). However, with finite bandwidth, one must include the last term in (20). This logarithmic term is non-quadratic, however, this is the price one pays for using a restricted bandwidth. On the other hand, this ensures robustness to potential high frequency modelling errors.

Remark 6. Note that the likelihood function (20) is not scalable by σ_w^2 and hence one needs to also include this parameter in the set to be estimated. This is an important departure from the simple least squares case.

Remark 7. The result in Lemma 4 is independent of the discrete-time model representation. Both shift and delta model parameters can be estimated, using the discrete-time frequency responses relationship:

$$A_d(e^{j\omega_\ell\Delta}) = A_\delta\left(\frac{e^{j\omega_\ell\Delta} - 1}{\Delta}\right) \tag{28}$$

Example 8. We consider again the CAR system presented in 2. If we use the result in Lemma 4, using the full bandwidth $[0, \pi/\Delta]$ (or, equivalently, up to 125[rad/s]) we obtain the following (mean) value for the parameter estimates:

$$\begin{bmatrix}\hat{a}_1 \\ \hat{a}_0\end{bmatrix} = \begin{bmatrix}4.5584 \\ 1.9655\end{bmatrix} \tag{29}$$

As expected, these parameters are clearly biased because we are not taking into account the presence of the sampling zero polynomial in the true model.

On the other hand, we can reduce our estimation procedure to a certain *bandwidth of validity*. For example, the usual rule of thumb is to consider up to one decade above the fastest nominal system pole, in this case, 20[rad/s]. The obtained (mean of the) parameter estimates are then given by:

$$\begin{bmatrix}\hat{a}_1 \\ \hat{a}_0\end{bmatrix} = \begin{bmatrix}3.0143 \\ 1.9701\end{bmatrix} \tag{30}$$

Note that these estimates are essentially equal to the true values. Moreover, no prefiltering as in (6) or (14) has been used. Thus, one has achieved robustness to the relative degree at high frequencies since it plays no role in the suggested procedure.

Finally, we show that the frequency domain procedure is also robust to the presence of unmodelled fast poles. We consider again the true system to be as in (16), restricting the estimation bandwidth up to 20[rad/s]. In this case, the mean of the parameter estimates is again very close to the nominal system coefficients:

$$\begin{bmatrix} \hat{a}_1 \\ \hat{a}_0 \end{bmatrix} = \begin{bmatrix} 2.9285 \\ 1.9409 \end{bmatrix} \tag{31}$$

5. CONCLUSIONS

This paper has considered the robustness implications of high frequency under-modelling on continuous-time system identification. It has been argued that any procedure that implicitly or explicitly relies upon high frequency folding is inherently non-robust. Examples illustrating this claim have been given, where it was shown the sensitivity to high frequency under-modelling. Finally, a maximum likelihood procedure in the frequency domain has been described. This approach is inherently robust to high frequency model errors, including both asymptotic relative degree and unmodelled poles. The robustness of this method has been illustrated by an example, obtaining very good estimates of the system parameters.

REFERENCES

Åström, K.J., P. Hagander and J. Sternby (1984). Zeros of sampled systems. *Automatica* **20**(1), 31–38.

Bigi, S., T. Söderström and B. Carlsson (1994). An IV scheme for estimating continuous-time models from sampled data. In: *10th IFAC Symposium on System Identification (SYSID'94)*. Copenhagen, Denmark.

Feuer, A. and G.C. Goodwin (1996). *Sampling in Digital Signal Processing and Control*. Birkhäuser. Boston.

Garnier, H., M. Mensler and A. Richard (2003). Continuous-time model identification from sampled data. Implementation issues and performance evaluation. *International Journal of Control* **76**(13), 1337–1357.

Goodwin, G.C., S.F. Graebe and M.E. Salgado (2001). *Control System Design*. Prentice Hall. New Jersey.

Jazwinski, A.H. (1970). *Stochastic Processes and Filtering Theory*. Academic Press. San Diego, California.

Kloeden, P.E. and E. Platen (1992). *Numerical Solution of Stochastic Differential Equations*. Springer-Verlag.

Larsson, E. K. (2003). Limiting properties of sampled stochastic systems. Technical Report 2003-028. Department of Information Technology, Uppsala University.

Larsson, E.K. and T. Söderström (2002). Continuous-time AR parameter estimation by using properties of sampled systems. In: *Proc. of the 15th IFAC World Congress*. Barcelona, Spain.

Ljung, L. (1999). *System Identification. Theory for the User*. 2nd. ed.. Prentice Hall. Englewood Cliffs, New Jersey.

Ljung, L. (2003). Initialisation aspects for subspace and output-error identification methods. In: *European Control Conference, ECC'03*. Cambridge, UK.

Middleton, R.H. and G.C. Goodwin (1990). *Digital Control and Estimation. A Unified Approach*. Prentice Hall. Englewood Cliffs, New Jersey.

Øksendal, B. (2003). *Stochastic Differential Equations. An Introduction with Applications*. 6th ed.. Springer.

Pintelon, R. and J. Schoukens (2001). *System Identification. A Frequency Domain Approach*. IEEE Press.

Rao, G.P and H. Garnier (2002). Numerical illustrations of the relevance of direct continuous-time model identification. In: *Proc. of the 15th IFAC World Congress*. Barcelona, Spain.

Sinha, N.K. and G.P. Rao (1991). *Identification of continuous-time systems. Methodology and computer implementation*. Kluwer Academic Publishers. Dordrecht.

Söderström, T., H. Fan, B. Carlsson and S. Bigi (1997). Least squares parameter estimation of continuous-time ARX models from discrete-time data. *IEEE Transactions on Automatic Control* **42**(5), 659–673.

Unbehauen, H. and G.P. Rao (1990). Continuous-time approaches to system identification – a survey. *Automatica* **26**(1), 23–35.

Wahlberg, B. (1988). Limit results for sampled systems. *International Journal of Control* **48**(3), 1267–1283.

Weller, S.R., W. Moran, B. Ninness and A.D. Pollington (2001). Sampling zeros and the Euler-Fröbenius polynomials. *IEEE Transactions on Automatic Control* **46**(2), 340–343.

Young, P. (1981). Parameter estimation for continuous-time models – A survey. *Automatica* **17**(1), 23–39.

Yuz, J.I., G.C. Goodwin and H. Garnier (2004). Generalised hold functions for fast sampling rates. In: *Proc. of the IEEE Conference on Decision and Control*. Nassau, Bahamas.

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