Int. J. Appl. Math. and Comp. Sci., 1999, Vol.9, No.4, 839–853

IDENTIFICATION OF LOW-ORDER CONTINUOS-TIME MODELS VIA DISCRETE-TIME TRENDS OF MEASUREMENTS

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The paper deals with the problem of continuous-time (CT) identification of parameters in transfer functions for low-order linear systems, based on recorded discrete-time (DT) data. Algorithms for direct estimation of CT parameters are developed from rules for transformation of a CT transfer function controlled via a zero-order sampling-and-hold unit into a DT representation. Two schemes are derived and tested: the first is based on the Goodwin transformation and the other is derived from the modified Tustin transformation. Both the approaches result in relations which can be used for direct estimation of CT parameters in a model of the investigated system. The numerical schemes contain some expressions that are reminiscent of DT differences and consequently they may magnify disturbances. Therefore the results of extensively testing both the schemes including different types of disturbances, measurement noise, slow varying drifts, measurement resolution errors together with changes in the sampling time are presented. A model of a pneumatic servomechanism system was used as a test plant.

Keywords: continuous time, transfer function, discrete-time model, identification

1. Introduction

An interest in identification of CT models via discrete-time data can be observed in recent trends in science and engineering practice (Bai, 1995; Kowalczuk, 1995; Kowalczuk and Kozłowski, 1998; Sagara and Zhao, 1990; Unbehauen and Rao, 1990). The reason behind this lies in the fact that modern measuring equipment records data in a discrete way. Various DCS or SCADA systems provide huge sets of data and raise a possibility of investigating dynamic models for supervision, control or fault detection and diagnosis. For all these applications CT models are usually suitable, since they easily account for basic dynamic properties of the identified plants and allow for a simple prediction of their behaviours. It is possible to extract a CT model from a properly estimated DT model via the frequency domain or inverse Z-transform, but these approaches are neither easy nor simple.

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The problem of parameter identification of CT models has been considered e.g. in (Bai, 1995; Ninness and Goodwin, 1991; Unbehauen and Rao, 1990; Young 1981). Different methods are used ranging from the frequency domain approach (Unbehauen and Rao, 1990), through fitting CT models, to some presentation of discrete-time models (Unbehauen and Rao, 1990), direct estimation of the terms corresponding to polynomial parameters of the transfer function (Bai, 1995) or the recent approach based on application of integrals (Kowalczuk, 1995; Kowalczuk and Kozłowski, 1998). Those methods are generally too complex for on-line applications. The methods presented in (Kowalczuk, 1995; Kowalczuk and Kozłowski, 1998) are adapted to an on-line procedure, but they sometimes involve problems when initial conditions are non-zero or unknown.

The momentum method (Isermann, 1977) which can be rated among most simple and direct approaches is based on estimation of time derivatives of input and output signals and their usage in a regression scheme. This method has not been used for CT data because of obvious problems which appear in time derivation of signals, especially in processing discontinuous input signals. This approach possesses, however, one important advantage: a vector of the inputs to the model consists of the values of different time derivatives which express consecutive phase states and are usually much less cross-correlated than the vectors of the models corresponding to difference or DT state equations. All the above-mentioned approaches have one common aspect: they measure the quality of the estimated model in terms of the error defined as the difference between the model output and the measured system output.

The approach presented in this paper is based on the following observation: a CT transfer function and the corresponding differential equation express properties of a linear dynamic system as a linear combination of the time derivatives of input and output signals. The time derivatives express trends of variations in the input or output. In DT domain we do not need time derivatives to express these trends but only differences calculated at subsequent DT instants to evaluate them, hence the problem with e.g. time derivation of a step signal will not appear. This approach may magnify the influence of noise or instant changes in signals e.g. due to finite-resolution measurements or a number representation, etc. These disturbances pose a problem for estimation schemes, because they usually exert an influence on the auto-regressive part of each model. Hence all estimation schemes reduce the auto-regressive coefficients in the case of a strong noise impact. This well-known effect will not be so vital in the case of a model without the auto-regressive part.

Section 2 presents models for a linear continuous-time system derived from Goodwin's representation of linear CT transfer functions (Ninness and Goodwin, 1991) and for a modified Tustin approximation derived in (Janiszowski, 1993). These models will express relations between the parameters of the CT transfer functions and trends expressed by linear combinations of DT values of input and output signals. In Section 3 some results of direct parameter estimation for a model of a third-order, linear system with oscillatory and integral actions will be presented.

2. DT Representations of CT Linear Dynamic Systems and Derivation of Trend Structures

Consider a linear CT system represented by the following transfer function:

$$G(s) = \frac{B(s)}{A(s)} = \frac{b_0 + b_1 s + \cdots + b_{m-1}s^{m-1}}{a_0 + a_1 s + \cdots + a_{m-1}s^{m-1} + s^m} e^{-sT} = \frac{y(s)}{u(s)}, \tag{1}$$

where u is an input signal, y is an output signal, $b_0, b_1, \ldots, b_{m-1}, a_0, a_1, \ldots, a_{m-1}$ are the parameters of a SISO CT transfer function, m denotes the order of system (1) and T is a delay in the input action. The operator $\delta = (q-1)/\Delta$ (where q is a shift operator and Δ denotes the sampling interval) introduced by Goodwin (Ninness and Goodwin, 1991) to express the dynamics of a linear CT system, controlled by a zero-order sample-and-hold unit, results in the following relation between the sampled values of input $y(k)$ and output $u(k)$:

$$\begin{aligned} y(k)\left[\frac{(q-1)^m}{\Delta^m} + a_{m-1}\frac{(q-1)^{m-1}}{\Delta^{m-1}} + \cdots + a_1\frac{(q-1)}{\Delta} + a_0\right] \\ = u(k)\left[b_{m-1}\frac{(q-1)^{m-1}}{\Delta^{m-1}} + \cdots + b_1\frac{(q-1)}{\Delta} + b_0\right] q^{-d} \end{aligned} \tag{2}$$

recorded at time instants $t = k\Delta$, where d is a discrete value of delay $T = d\Delta$. Introducing the back-shift operator q^{-1} and multiplying (2) by Δ^m, we get

$$\begin{aligned} y(k)(1-q^{-1})^m &= -\sum_{i=0}^{m-1} a_i \Delta^{m-i}(1-q^{-1})q^{i-m}y(k) \\ &\quad + \sum_{i=0}^{m-1} b_i \Delta^{m-i}(1-q^{-1})^i q^{i-m-d}u(k). \end{aligned} \tag{3}$$

The left-hand side presents a trend in the output signal of the highest-order m. The terms on the right-hand side will be called the trends of $y(k)$ (or $u(k)$) of order p determined for the model of order m. These trends are defined as time operators $R(q^{-1})$ and $P(q^{-1})$ by the following definitions:

$$\begin{aligned} R_m^i(g^{-1}) &\triangleq \Delta^{m-i}(1-q^{-1})^i q^{i-m} \\ &= r_0^i + r_1^i q^{-1} + \cdots + r_m^i q^{-m}, \quad l = 0, 1, \ldots, m-1, \\ P_m^i(g^{-1}) &\triangleq \Delta^{m-i}(1-q^{-1})^i q^{i-m-d} \\ &= p_d^i q^{-d} + p_{d+1}^i q^{-1-d} + \cdots + p_{d+m}^i q^{-m-d}. \end{aligned} \tag{4}$$

Hence we introduce a model of the higest-order trend for $y(k)$ as a linear combination of trends $y_m^p(k)$, $u_m^p(k)$, and parameters a_i, b_i, i.e.

$$\begin{aligned} y_m^m(k) &= -\sum_{i=0}^{m-1} a_i y_m^i(k) + \sum_{i=0}^{m-1} b_i u_m^i(k) \equiv R_m^m(q^{-1})y(k) \\ &= -\sum_{i=0}^{m-1} a_i R_m^i(k)(q^{-1})y(k) + \sum_{i=0}^{m-1} b_i P_m^i(q^{-1})u(k), \end{aligned} \tag{5}$$

where the trends $y_m^i(k)$ and $u_m^i(k)$ are the inputs of the model structure and a_i, b_i are unknown parameters that have to be estimated.

Another DT representation for (1), which is more accurate especially for small sampling time intervals, was derived in (Janiszowski, 1993) as a modification of the well-known Tustin approximation. This way of transformation of a CT system with a zero-order sample-and-hold unit is defined by the rule

$$G^*(q^{-1}) = \left\{ \left. \frac{B(s)}{A(s)} \right|_{s=\frac{2(1-q^{-1})}{\Delta(1+q^{-1})}} \right\} \frac{2q^{-1}}{1+q^{-1}}, \tag{6}$$

where $G^*(q^{-1})$ denotes a DT transfer function. The above transformation yields the following relation between the sampled data of the input and output:

$$\begin{aligned} 2^m(1-q^{-1})^m y(k) &= -\sum_{i=0}^{m-1} a_i 2^i \Delta^{m-i}(1-q^{-1})^i(1+q^{-1})^{m-i}y(k) \\ &\quad + \sum_{i=0}^{m-1} b_i 2^{i+1}\Delta^{m-i}q^{-1-d}(1-q^{-1})^i(1+q^{-1})^{m-i-1}u(k). \end{aligned} \tag{7}$$

The operators of the trends for the input and output signals are defined as follows:

$$\begin{aligned} R_m^i(g^{-1}) &\triangleq 2^i\Delta^{m-i}(1-q^{-1})^i(1+q^{-1})^{m-i} \\ &= r_0^i + r_1^i q^{-1} + \cdots + r_m^i q^{-m} r_m^i, \\ P_m^i(g^{-1}) &\triangleq 2^{i+1}\Delta^{m-i}q^{-1-d}(1-q^{-1})^i(1+q^{-1})^{m-i-1} \\ &= p_d^i q^{-d} + p_{d+1}^i q^{-1-d} + \cdots + p_{d-m}^i q^{-m-d}. \end{aligned} \tag{8}$$

With the above definitions, model (5) describes the highest-order trend of the output $y_m^m(k)$. Representation (5) determined for (4) or (8) can now be used for identification, where the coefficients of the model vector are equal to the corresponding parameters of the CT transfer function. After determination of trends (4) or (8) many schemes can be used to estimate parameters a_i, b_i.

Let us notice that the output to model (5) is not a measurable signal, hence there is no possibility of comparison with any reference and hence there is no direct way to evaluate the quality of the estimated model. The only measurable signal is the output of the investigated process and the determined estimates have to be coherent with values of $y(k)$. The estimates $\hat{a}_i$, $\hat{b}_i$ can now be used to evaluate the values $\hat{y}(k)$ of the measured output $y(k)$. This will be determined by the truncated trend operators for the output signal that contain only past values of the output signal

$$\widetilde{R}^i_m(q^{-1}) \triangleq r^i_1 q^{-1} + \cdots + r^i_m q^{-m}. \tag{9}$$

The evaluation $\hat{y}(k)$ of the output, based on the estimated parameters $\hat{a}_i$, $\hat{b}_i$, can be determined by

$$\begin{aligned} \hat{y}(k) &= \alpha^{-1}\left[-\sum_{i=0}^{m} \hat{a}_i \widetilde{R}^i_m(q^{-1})y(k) + \sum_{i=0}^{m-1} \hat{b}_i P^i_m(q^{-1})u(k)\right], \\ \alpha &= \sum_{i=0}^{m} r^i_0 \hat{a}_i, \quad \hat{a}_m \triangleq 1. \end{aligned} \tag{10}$$

A measure of the distance between the recorded values of $y(k)$ and its evaluation $\hat{y}(k)$

$$\mathrm{IQ} = \sum_{k=0}^{N} (y(k) - \hat{y}(k))^2 \quad \text{or} \quad \mathrm{IV} = \sum_{k=0}^{N} |y(k) - \hat{y}(k)|, \tag{11}$$

where N is the number of investigated measurements, can be an indicator of proper determination of parameters in the assumed model structure, e.g. the delay T, the model order, or the number of parameters in polynomials $A(s)$ or $B(s)$.

The numerical task of the estimation of CT transfer-function parameters amounts to estimating the coefficients of the linear model

$$\begin{aligned} y^m_m(k) &= v(k)\theta, \\ v(k) &= \left[y^{m-1}_m(k), \ldots, y^0_m(k), u^{m-1}_m(k), \ldots, u^0_m(k)\right], \\ \theta &= \left[-a_{m-1}, \ldots, -a_0, b_{m-1}, \ldots, b_0\right]', \end{aligned} \tag{12}$$

where $v(k)$ is the vector of model inputs and θ is the vector of unknown model coefficients. This form of the model will be used if all parameters a_i, b_i, $i = 0, \ldots, m-1$ are investigated. When some of the coefficients a_i or b_i are not expected in the CT transfer function, the corresponding trends y^i_m or u^i_m will not appear in the vector $v(k)$.

Vector $v(k)$ contains variables of different physical meanings, different units and, consequently, of a different magnitude. To improve the numerical conditioning of calculations, all the variables in $v(k)$ have to be of the same level of magnitude. The normalised highest-order trend expressed by normalised model inputs is the final

Table 1. Errors in estimation of model parameters in different simulation conditions, Part I.

Variable factor	Method	Simulation parameter	N/S factor [%]	Error in σC [%]	Error in $\sigma\omega_0$ [%]	Error in $\sigma\xi$ [%]	CONV $\times 10^{-3}$	T_{ss} [ms]
drift $w=$		$\Delta = 1$ ms, $\eta = 1\,\mu$m, $\varepsilon = 2\,\mu$m						
$100\,\mu$m			0.63					
	Goodwin			5.9	0.42	0.75	0.166	93
	Tustin			0.23	0.17	0.49	0.100	89
1 mm			4.46					
	Goodwin			6.1	0.42	0.77	0.216	97
	Tustin			0.24	0.19	0.51	0.179	97
2 mm			8.79					
	Goodwin			8.1	0.34	0.35	1.47	132
	Tustin			0.1	0.59	0.69	1.53	133
5 mm			21.75					
	Goodwin			59.2	2.49	11.1	6.17	324
	Tustin			6.6	10.4	3.5	8.16	308
10 mm			43.48					
	Goodwin			184.5	2.55	39.4	9.10	356
	Tustin			22.9	40.3	10.7	18.2	409
noise $\eta=$		$\Delta = 1$ ms, $d = 100\,\mu$m, $\varepsilon = 2\,\mu$m						
$10\,\mu$m			1.04					
	Goodwin			6.3	0.39	0.70	0.48	101
	Tustin			0.19	0.23	0.54	0.47	106
$100\,\mu$m			8.35					
	Goodwin			40.1	4.22	7.53	3.95	228
	Tustin			2.01	3.27	1.53	4.62	171
$200\,\mu$m			16.72					
	Goodwin			138.1	16.3	30.8	6.29	317
	Tustin			8.1	12.2	4.11	9.56	299
$500\,\mu$m			41.78					
	Goodwin			591.2	55.3	137.7	12.56	422
	Tustin			37.6	72.2	17.6	28.46	466

Magneto-strictive measurement systems, usually used in the servomechanisms under consideration, gained the resolution of appr. 10–50 μm with additive noise of the level of 10 μm. For this noise level the estimation of the system parameters was robust and fast enough.

Very poor, low-cost, potentiometer measurement systems of accuracy 0.1–0.5 mm with noise corresponding to η of the 100–200 μm range, could be used too, but the estimation time T_{ss} was long. Fortunately, the low values of convergence for CONV indicate fast convergence to final estimates. The comparison of effects of the different types of noise suggests that fast noise η had more impact (at the same N/S ratio) than drifts w.

In an adaptive control system the estimated parameters have to be stationary. In the case of estimation algorithms of fast convergence but with significant fluctuations an effective design of a control algorithm will be a hazardous task. In Fig. 1 transients of normalised model coefficients are presented for the following simulation conditions: $w = 200\,\mu\text{m}$, $\eta = 20\,\mu\text{m}$, $\varepsilon = 10\,\mu\text{m}$ and sampling interval $\Delta = 1\,\text{ms}$. After appr. 90 ms the estimated parameters were very close to the nominal values and after 150 ms they were practically constant and equal to the final values.

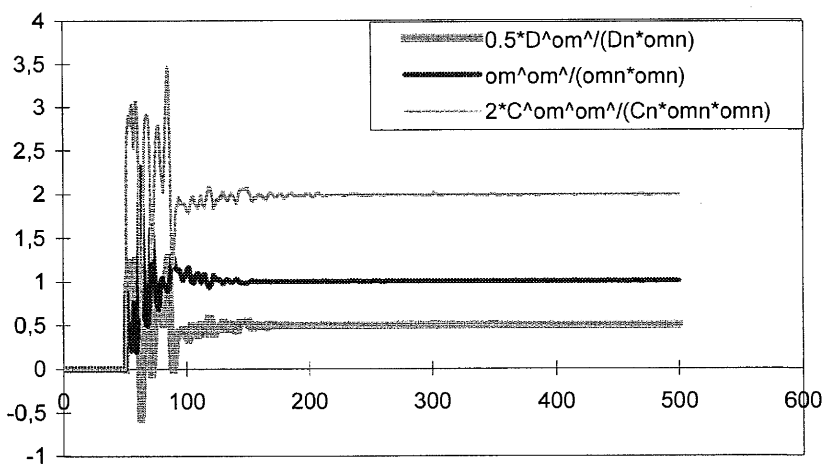

Fig. 1. Transients of model coefficients for: $w = 200\,\mu\text{m}$, $\eta = 20\,\mu\text{m}$, $\varepsilon = 10\,\mu\text{m}$ and $\Delta = 1\,\text{ms}$.

Part II of Table 1 presents the effect of the resolution of the measurement system on the estimation quality. The results were very optimistic, since the resolution errors within the range of $\langle 2\,\mu\text{m}, 200\,\mu\text{m}\rangle$ had little influence, even less than the drift signal of a comparable N/S ratio.

The lower part of this table shows the influence of the sampling interval Δ. This comparison was performed for other parameters corresponding to the good quality magneto-strictive measurement system. The optimum value of the sampling interval at 1 ms can be observed. Lower values of Δ, however, increased the size of the data set (and a numerical effort) but did not improve the quality and convergence of estimates. Very low sampling interval values for the trends defined by the Goodwin scheme were completely not advisable, but the trends defined by the Tustin scheme could cope with this case, too. For our system, an optimal sampling interval can be found and clearly established.

The previous results have revealed the quality of the estimates based on the assumption of the known model structure. The efficiency of the presented method in determination of the parameters of the CT transfer function in the case of an unknown or ill-defined structure has been examined. The tests were performed in the same

Table 1. Errors in estimation of model parameters in different simulation conditions, Part II.

Variable factor	Method	Simulation parameter	N/S factor [%]	Error in C [%]	Error in ω_0 [%]	Error in ξ [%]	CONV $\times 10^{-3}$	T_{ss} [ms]
measurem. resolution $\varepsilon =$		$\Delta = 1$ ms $w = 100\ \mu$m $\eta = 10\ \mu$m						
5 μm			1.22					
	Goodwin			6.3	0.39	0.70	0.58	105
	Tustin			0.19	0.24	0.54	0.52	109
10 μm			1.97					
	Goodwin			6.6	0.34	0.61	0.64	107
	Tustin			0.18	0.25	0.53	0.64	113
20 μm			3.49					
	Goodwin			7.73	0.21	0.34	1.03	125
	Tustin			0.12	0.36	0.56	1.06	127
50 μm			8.73					
	Goodwin			15.55	0.88	1.63	2.04	144
	Tustin			0.43	1.16	0.81	2.28	144
100 μm			17.03					
	Goodwin			42.2	4.11	7.71	4.02	234
	Tustin			2.33	3.83	1.88	4.90	183
sampling interval $\Delta =$		$w = 100\ \mu$m $\eta = 10\ \mu$m $\varepsilon = 10\ \mu$m						
0.25 ms			2.06					
	Goodwin			110.6	25.3	22.1	15.8	164
	Tustin			1.88	3.63	0.62	18.9	172
0.5 ms			2.05					
	Goodwin			31.1	11.3	7.61	6.64	133
	Tustin			0.2	1.63	0.25	6.95	134
1 ms			1.97					
	Goodwin			6.62	0.34	0.61	0.64	107
	Tustin			0.18	0.25	0.53	0.64	113
2 ms			1.98					
	Goodwin			10.2	1.0	2.53	1.07	147
	Tustin			0.36	0.80	1.98	0.67	144
5 ms			1.97					
	Goodwin			38.6	2.90	12.46	0.14	280
	Tustin			15.25	1.73	8.65	0.15	179

way as above with the following parameters: $w = 100\,\mu\text{m}$, $\eta = 10\,\mu\text{m}$, $\varepsilon = 10\,\mu\text{m}$ and sampling interval $\Delta = 1\,\text{ms}$. The system was investigated as a linear dynamic plant with integration action of order $m = 1, 2, 3$ and a different number of parameters $M = 2, \ldots, 6$ (excluding integral action). The parameters of the CT transfer function, corresponding to (16), were presented in Table 2 as values related to $b_0 = 10^6$ in the numerator and to $a_2 = 1.0$ in the denominator for an easy comparison of the results

$$G_{xu}(s) = \frac{b_0 + \cdots + b_{m-1}s^{m-1}}{s(s^m + a_{m-1}s^{m-1} + \cdots + a_1 s + a_0)} = \frac{b_0(1 + \cdots + b_{m-1}/b_0 s^{m-1})}{s(a_m/a_2 s^m + s^2 + \cdots + a_1/a_2 s + a_0/a_2)}.$$

As a measure of fitting of the determined parameters to the task of estimating the DT value of the velocity (10), the performance index IQ (11) was used.

Table 2. Estimated parameters of CT transfer functions for different structures of $G_{xs}(s)$.

Model structure parameters	$a_3 =$ 0.0	$a_2 =$ 1.0	$a_1 =$ 20.0	$a_0 =$ 400.0	$b_2 =$ 0.0×10^6	$b_1 =$ 0.0×10^6	$b_0 =$ 1.0×10^6	IQ
$m = 1,\ M = 2$								
Goodwin	—	—	1.0	−3.888	—	—	0.125	324.8
Tustin	—	—	1.0	−4.011	—	—	0.116	340.5
$m = 2,\ M = 3$								
Goodwin	—	1.0	21.24	400.6	—	—	0.9937	0.1042
Tustin	—	1.0	19.95	400.4	—	—	0.9941	0.1033
$m = 2,\ M = 4$								
Goodwin	—	1.0	20.29	395.7	—	0.00051	0.9861	0.1033
Tustin	—	1.0	19.95	400.1	—	0.000035	0.9935	0.1033
$m = 3,\ M = 5$								
Goodwin	0.00133	1.0	22.25	392.9	—	0.00087	0.9761	0.0995
Tustin	0.00102	1.0	19.61	396.7	—	0.000072	0.9821	0.1045
$m = 3,\ M = 6$								
Goodwin	0.00136	1.0	20.92	385.8	$0.65{\times}10^6$	0.00171	0.9639	0.0995
Tustin	0.00105	1.0	19.58	396.2	$0.13{\times}10^6$	0.00031	0.9822	0.1054

The presented results are not surprising: the terms absent in the original structure were determined with very low values, however this effect was not obvious. In the case of an order of the system model greater than $m = 2$ the estimates of all parameters were normalised with respect to $a_m \equiv 0.0$ and therefore some numerical problems could appear. Nevertheless, the estimates were stable and convergent and did not reveal any particular behaviour.

4. Conclusions

The estimation scheme is simple and directly delivers the demanded CT transfer function of the investigated system. The determination of trends increases the calculation effort only moderately. This approach does not involve complicated inverse calculations.

The results of testing were based on some special case (parameter estimation in a pneumatic servomechanism) and do not cover a wide range of dynamic systems. The example describes a real problem where the time efficiency was critical for successful application of adaptive control. The approach was successfully applied to adaptive position control.

The results have been compared with those obtained by the integration approach based on methods presented in (Kowalczuk, 1995; Kowalczuk and Kozłowski, 1998; Sagara and Zhao, 1990). This approach does not produce problems with bias due to non-zero mean values of the input and output signals and difficult-to-evaluate initial conditions for the integrals creating inputs to the model structure. The paper deals with a problem of identification of a SISO-plant, however the introduced approach can be directly used for MISO-plants.

Acknowledgements

The paper has been prepared within research partly sponsored by the PATIA program and the State Committee for Scientific Research under grant No. 1387/T11/99/16.

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Received: 8 March 1999
Revised: 10 September 1999