Identification of Linear Dynamic Systems in State Space

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Abstract

System identification has been growing in an engineering community over the last 60 years, and an intensive research has been published in this field. This study presents an identification method of a linear time-invariant continuous dynamic system directly from time series data. The considered system is represented in a state space form. All states are assumed to be measured. The proposed identification algorithm is demonstrated and investigated, with noise-free data and noisy data, on a MATLAB simulation environment. The results confirm that the simple procedures of the proposed algorithm give an effective and successful estimation of the system parameter matrices.

Keywords: System Identification; Linear system; State space model; Measurement noise; Parameter estimation.

1. Introduction

System identification is a methodology for finding out or improving mathematical system model from the measurement record of the system signals [1-2]. In a dynamic system, the values of the output signals depend on both the instantaneous values of the input signals and the past behavior of the system. The needs for system models arise from various requirements: system design, system control, system optimization, and fault detection [3].

There are many methods of the system identification. They can be classified in to two main categories; time-domain system identification and frequency-domain system identification [3]. In this research, the time-domain system identification is dealt with. Also, systems are divided into continuous-time systems and discrete-time systems. For continuous-time systems, many identification methods presented estimating the parameters of the transfer function models from the step response. Work including an integral equation approach [4], a
direct identification approach of continuous-time delay systems [5], robust identification problems of first-order plus a dead-time model [6], identification from step and pulse responses with consideration of the transient initial conditions [7-8]. The integral equation approach also expanded using sinusoidal inputs, included first, second and nth models of transfer function [9].

In the areas of a discrete-time system identification, an intensive research has been published over the last decades. The research focused on the least squares algorithms [10-12], the recursive least square Algorithms [13-14], the stochastic gradient algorithms [15-16], the multi-innovation algorithms [17-21], the auxiliary model based identification algorithms [22-23], the hierarchical least squares algorithms [24-25], and the iterative algorithms [26-27] which can be used to find the iterative solutions of matrix equations [28-30]. In system theory and control, a state-space model is a most obvious choice for the mathematical representation of the system [31], and many different identification methods have been proposed for model parameter identification of state space representation of LTI systems. If all states are assumed to be directly measured, then least squares methods may be used to estimate the matrices of the linear state-space model [32]. On other hand, if the states cannot be directly measured, subspace methods must be used instead [33-35] with least squares as a possible internal step.

In this paper, an identification algorithm of linear time invariant (LTI) continuous systems in state space form is presented. A simple number of input, output and state data are required for estimating the system matrices. The main step of this algorithm consists of the $S(T), P(T), S_s(T)$ and $P_s(T)$ matrices, constructed with integrated input, output and state data, and considerably reduced the measurement noise effect. The rest of the paper is organised as follows: Section 2 briefly describes the LTI dynamic system and the problem statement that presented in this work. The derivation, computational procedures and conditions of the proposed identification algorithm to find the system matrices are presented in details in section 3. Section 4 shows the overall simulation system and the results for both a noise-free data and noisy data. Finally, some conclusions are drawn in Section 5.

2. Dynamic System and Problem Formulation

Consider the following LTI state space system:

\[ \dot{x}(t) = Ax(t) + Bu(t) \]  

\[ y(t) = Cx(t) + Du(t) \]  

where $u \in \mathbb{R}^r$, $y \in \mathbb{R}^m$, and $x \in \mathbb{R}^n$ represent the inputs, noise-free outputs, and noise-free state vectors, respectively. $A \in \mathbb{R}^{n \times n}, B \in \mathbb{R}^{n \times m}, C \in \mathbb{R}^{m \times n}$, and $D \in \mathbb{R}^{r \times m}$ denote the system, input, output, and direct feedthrough constant matrices, respectively. The noise-free data are for theoretical interest only, since the measurements are always contaminating with noise. In such practical situations, the measured states and outputs can be written as following

\[ x_s(t) = x(t) + w(t) \]
\[ y_s(t) = y(t) + v(t) \]  

(4)

where the vectors \( w \in \mathbb{R}^n \) and \( v \in \mathbb{R}^m \) are the measurement noise, both assumed to be zero-mean white Gaussian noise. Note that all the states are assumed to be measured and all the state space matrices are unknown. From the input, output and state data, the proposed identification method aims to estimate \( \{A, B, \hat{C}, \hat{D}\} \) of the system. The problem can be stated as in Fig. 1.

![Fig. 1: Schematic of identification from the measurements of the inputs, outputs and states](image)

3. Derivation of Identification Algorithm

For the LTI continuous system in Eqs. (1) and (2), the values of the parameter matrices \( A, B, C \) and \( D \) can be estimated easily from the measurements of the inputs, outputs and states. In this algorithm, \( N \) data set for each input, output and state signal is required. This data are collected at \( N \) different instants of the dynamic system responses. The identification procedures are given below.

3.1 Parameter Estimation from Free-Noise Data

By integrating both sides of Eqs (1) and (2) from 0 to \( t \) and obtain:

\[
x(t) - x(0) = A \int_0^t x(t) dt + B \int_0^t u(t) dt
\]

(5)

\[
\int_0^t y(t) dt = C \int_0^t x(t) dt + D \int_0^t u(t) dt
\]

(6)

Eqs. (5) and (6) can be collected and expressed in a compact form as below

\[
\begin{bmatrix}
  x(t) - x(0) \\
  \int_0^t y(t) dt
\end{bmatrix} =
\begin{bmatrix}
  A & B \\
  C & D
\end{bmatrix}
\begin{bmatrix}
  \int_0^t x(t) dt \\
  \int_0^t u(t) dt
\end{bmatrix}
\]

(7)

With the following definition:

\[
s(t) =
\begin{bmatrix}
  x(t) - x(0) \\
  \int_0^t y(t) dt
\end{bmatrix}
\]

(8)
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\[ p(t) = \begin{bmatrix} \int_0^t x(t)dt \\ \int_0^t u(t)dt \end{bmatrix} \]  \hspace{1cm} (9)

\[ M = \begin{bmatrix} A & B \\ C & D \end{bmatrix} \]  \hspace{1cm} (10)

where \( s \in \mathbb{R}^{n+m} \) and \( p \in \mathbb{R}^{n+r} \) represent the state-output and state-input vectors, respectively. \( M \in \mathbb{R}^{(n+m)\times(n+r)} \) denote the parameter matrix. The Eq. (7) can be simplified and rewritten as

\[ s(t) = Mp(t) \]  \hspace{1cm} (11)

For measurement time \( t = kT \), where \( T \) is a measuring period time, Eq. (11) becomes

\[ s(kT) = Mp(kT) \]  \hspace{1cm} (12)

with \( k = 1, 2, ..., N \), Eq. (11) becomes

\[ S(T) = \bar{M}P(T) \]  \hspace{1cm} (13)

where the matrices \( S \in \mathbb{R}^{(n+m)\times N} \), \( P \in \mathbb{R}^{(n+r)\times N} \), and \( \bar{M} \in \mathbb{R}^{(n+m)\times(n+r)} \) represent the state-output, and state-input and identified parameters, respectively. \( S(T) \) and \( P(T) \) matrices are defined by

\[ S(T) = [s(T_1) \ s(2T_1) \ \cdots \ s(NT_1)] \]  \hspace{1cm} (14)

\[ P(T) = [p(T_1) \ p(2T_1) \ \cdots \ p(NT_1)] \]  \hspace{1cm} (15)

If \( P(T) \) is a square nonsingular matrix (\( N = n + r \) and \( |P(T)| \neq 0 \)), then the identified parameter matrix can be easily computed by

\[ \bar{M} = P^{-1}(t)S(T) \]  \hspace{1cm} (16)

The identified matrices \( \hat{A}, \hat{B}, \hat{C} \) and \( \hat{D} \) can be extracted directly from \( \bar{M} \) as following:

\[ \hat{A} = \bar{M}(1: n, 1: n) \]  \hspace{1cm} (17)

\[ \hat{B} = \bar{M}(1: n, n + 1: n + r) \]  \hspace{1cm} (18)

\[ \hat{C} = \bar{M}(n + 1: n + m, 1: n) \]  \hspace{1cm} (19)

\[ \hat{D} = \bar{M}(n + 1: n + m, n + 1: n + r) \]  \hspace{1cm} (20)

3.2 Parameter Estimation from Noisy Data

In this case, the measured data of the states \( x_s(t) \) and outputs \( y_s(t) \) contaminates with noises \( w(t) \) and \( v(t) \) as mentioned in section 2. These measurement noises assumed to be Gaussian, zero-mean and white. Therefore, \( x(t) \) and \( y(t) \) in Eq. (7) are replaced by \( x_s(t) \) and \( y_s(t) \) and obtain
\[
\begin{bmatrix}
    x_s(t) - x(0) \\
    \int_0^t y_s(t) \, dt
\end{bmatrix} =
\begin{bmatrix}
    A & B \\
    C & D
\end{bmatrix}
\begin{bmatrix}
    \int_0^t x_s(t) \, dt \\
    \int_0^t u(t) \, dt
\end{bmatrix} 
\]

(21)

The presence of integration in the last equation removes the noise from the terms \(x_s(t)\) and \(y_s(t)\) as below

\[
\int_0^t x_s(t) \, dt = \int_0^t [x(t) + w(t)] \, dt = \int_0^t x(t) \, dt 
\]

(22)

\[
\int_0^t y_s(t) \, dt = \int_0^t [y(t) + v(t)] \, dt = \int_0^t y(t) \, dt 
\]

(23)

where \(\int_0^t w(t) \, dt = \int_0^t v(t) \, dt = 0\) because they have zero-mean value. Although of this integration, there is some noise still remained in Eq. (21) in the term \(x_s(t) - x(0)\), which causes an error in the parameter estimation. In order to achieve the accurate estimation and decrease the error, the remained noise must be removed before the other procedures; this can be done by taking the 2\(^{nd}\) integration on both sides of Eq. (21), yields

\[
\begin{bmatrix}
    \int_0^t [x_s(t) - x(0)] \, dt \\
    \int_0^t y_s(t) \, dt
\end{bmatrix} =
\begin{bmatrix}
    A & B \\
    C & D
\end{bmatrix}
\begin{bmatrix}
    \int_0^t x_s(t) \, dt \\
    \int_0^t u(t) \, dt
\end{bmatrix}
\]

(24)

In similar manner as in Eqs. (8), (9) and (10), the following terms can be defined as following

\[
s_s(t) = \begin{bmatrix}
    \int_0^t [x_s(t) - x(0)] \, dt \\
    \int_0^t y_s(t) \, dt
\end{bmatrix} 
\]

(25)

\[
p_s(t) = \begin{bmatrix}
    \int_0^t x_s(t) \, dt \\
    \int_0^t u(t) \, dt
\end{bmatrix} 
\]

(26)

\[
M = \begin{bmatrix}
    A & B \\
    C & D
\end{bmatrix} 
\]

(27)

where \(s_s \in \mathbb{R}^{n+m}\) and \(p_s \in \mathbb{R}^{n+r}\) represent the noisy state-output and noisy state-input vectors, respectively. The Eq. (24) can be simplified and rewritten as

\[
s_s(t) = Mp_s(t) 
\]

(28)

This equation is similar to Eq. (11), and the identified parameter matrix can be computed by

\[
\tilde{M} = P_s^{-1}(t)S_s(T) 
\]

(29)

where \(S_s \in \mathbb{R}^{(n+m)\times N}\) and \(P_s \in \mathbb{R}^{(n+r)\times N}\) represent the noisy state-output and noisy state-input matrices, respectively. \(S_s(T)\) and \(P_s(T)\) matrices are defined by

\[
S_s(T) = [s_s(T) \quad s_s(2T) \quad \cdots \quad s_s(NT)] 
\]

(30)

\[
P_s(T) = [p_s(T) \quad p_s(2T) \quad \cdots \quad p_s(NT)] 
\]

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From the identified parameter matrix, the \( \hat{A}, \hat{B}, \hat{C} \) and \( \hat{D} \) matrices can be found as following:

\[
\hat{A} = \hat{M}(1:n, 1:n) \\
\hat{B} = \hat{M}(1:n, n+1:n+r) \\
\hat{C} = \hat{M}(n+1:n+m, 1:n) \\
\hat{D} = \hat{M}(n+1:n+m, n+1:n+r)
\]

From both sections 3.1 and 3.2, the computational steps of this algorithm can be summarized as follows:

1. From the number of the input and state signals, determine the required number of samples \( N \) as follows
   \[
   N = n + r
   \] (36)
2. Measure the inputs, outputs and states at \( t = kT \) where \( k = 1, 2, ..., N \)
3. Integrate these measurements from 0 to \( t = kT \) once for noise-free data, and twice for noisy data.
4. Construct the block matrices \( S(T) \) and \( P(T) \) for noise-free data, and \( S_s(T) \) and \( P_s(T) \) for noisy data.
5. Calculate the identified parameter matrix \( \hat{M} \), and then determine the system matrices \( \hat{A}, \hat{B}, \hat{C} \) and \( \hat{D} \).
6. Test the identified system by comparing its response with the true system response.

3.3 Conditions for Solution Existence

The proposed algorithm depends on the existence of the dynamic state and output responses of the system. With the measurements of the inputs, outputs and states at different instants of the system response, the system model can be identified. As pointed out by the previous sections, the solutions of Eqs. (16) and (29) require the inverse of \( P(T) \) and \( P_s(T) \), respectively, which means that all columns and rows of these matrices must be linearly independent.

4. Simulation and Results

The performance of the proposed identification algorithm has been evaluated on simulated data sets. A scalar example of a third order SISO system is chosen.

\[
\dot{x}(t) = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 2 \\ -26 & -11 & -6 \end{bmatrix} x(t) + \begin{bmatrix} 1 \\ 1 \\ 2 \end{bmatrix} u(t) \\
y(t) = [3 & 1 & 0] x(t)
\]

where \( u \in \mathbb{R}^1 \), \( y \in \mathbb{R}^1 \), and \( x \in \mathbb{R}^3 \). This system was used to generate the output and state data with the input excitation is \( u(t) = 1 \).
4.1 Noise Free Data

Fig. 2 shows the simulated time responses of the output and states, with the initial states $[0 \ 0 \ 0]^T$. It is clear that the settling time $t_s$ of the system responses is 4 sec. In order to apply the proposed algorithm and avoid the repeated rows or columns of $P(T)$, the system data are collected from the transient response region. The proposed algorithm used a data set of 20 samples (4 samples from each input, output and state) to estimate the system matrices $[\hat{A}, \hat{B}, \hat{C}, \hat{D}]$. The obtained results are illustrated in Table 1 for different values of the measuring period time. In each identification process, the used samples were collected at different instant times $[T, 2T, 3T, 4T]$ of the system response.

By comparing the simulation results with the true system matrices, it can be observed that the proposed algorithm, with noise free-data gives excellent identification accuracy for $\hat{A}$, $\hat{B}$, $\hat{C}$ and $\hat{D}$ matrices for all values of $T$.

![Fig. 2: System step responses](image-url)
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Table 1: Identified system matrices from noise-free data

<table>
<thead>
<tr>
<th>$T$</th>
<th>$\hat{A}$</th>
<th>$\hat{B}$</th>
<th>$\hat{C}$</th>
<th>$\hat{D}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1sec</td>
<td>$\begin{bmatrix} 0.000 &amp; 1.000 &amp; 0.000 \ 1.000 &amp; 0.000 &amp; 2.000 \ -26.000 &amp; -11.000 &amp; -6.000 \end{bmatrix}$</td>
<td>$\begin{bmatrix} 1.000 \ 1.000 \ 2.000 \end{bmatrix}$</td>
<td>$\begin{bmatrix} 3.000 &amp; 1.000 &amp; 0.000 \end{bmatrix}$</td>
<td>$\begin{bmatrix} 0.000 \end{bmatrix}$</td>
</tr>
<tr>
<td>0.5sec</td>
<td>$\begin{bmatrix} 0.000 &amp; 1.000 &amp; 0.000 \ 1.000 &amp; 0.000 &amp; 2.000 \ -26.000 &amp; -11.000 &amp; -6.000 \end{bmatrix}$</td>
<td>$\begin{bmatrix} 1.000 \ 1.000 \ 2.000 \end{bmatrix}$</td>
<td>$\begin{bmatrix} 3.000 &amp; 1.000 &amp; 0.000 \end{bmatrix}$</td>
<td>$\begin{bmatrix} 0.000 \end{bmatrix}$</td>
</tr>
<tr>
<td>1.0sec</td>
<td>$\begin{bmatrix} 0.000 &amp; 1.000 &amp; 0.000 \ 1.000 &amp; 0.000 &amp; 2.000 \ -26.000 &amp; -11.000 &amp; -6.000 \end{bmatrix}$</td>
<td>$\begin{bmatrix} 1.000 \ 1.000 \ 2.000 \end{bmatrix}$</td>
<td>$\begin{bmatrix} 3.000 &amp; 1.000 &amp; 0.000 \end{bmatrix}$</td>
<td>$\begin{bmatrix} 0.000 \end{bmatrix}$</td>
</tr>
<tr>
<td>2.0sec</td>
<td>$\begin{bmatrix} 0.000 &amp; 1.000 &amp; 0.000 \ 1.000 &amp; 0.000 &amp; 2.000 \ -26.000 &amp; -11.000 &amp; -6.000 \end{bmatrix}$</td>
<td>$\begin{bmatrix} 1.000 \ 1.000 \ 2.000 \end{bmatrix}$</td>
<td>$\begin{bmatrix} 3.000 &amp; 1.000 &amp; 0.000 \end{bmatrix}$</td>
<td>$\begin{bmatrix} 0.000 \end{bmatrix}$</td>
</tr>
</tbody>
</table>

To study the effect of initial conditions on the performance of the identification algorithm, $x(0)$ is changed into $[0.7 \ -1.0 \ -0.8]^T$ and several simulation identification tests are carried out. The simulated step responses are shown Fig. 3, and they illustrated that:

- No dynamic responses of the output and states.
- $x_1(t), x_2(t), x_3(t)$ and $u(t)$ are linearly dependents.

The reason is that all states of the system have initial values equal to the steady state values. As a result, the $P(T)$ matrix is singular and its inverse cannot be found, and therefore the algorithm will be unable to estimate the system matrices.

![Fig. 3: System step responses with $x(0) = [0.7 \ -1.0 \ -0.8]^T$](image-url)
4.2 Noise Free Data

In this case, both the system states and output in Eqs. (37) and (38) are distorted with observation noises; a zero-mean white Gaussian each. For initial conditions $[0 \ 0 \ 0]^T$, several simulation tests were carried out to investigate the algorithm for signal to noise ratio $snr_w = 20dB$ and $snr_v = 15dB$. The resulted system responses are shown in Fig. 4.

![Fig. 4: Noisy system step responses](image)

From the system response in Fig. 4, the data was collected and both matrices $S_s(T)$ and $P_s(T)$ were constructed and the calculated $\hat{A}$, $\hat{B}$, $\hat{C}$ and $\hat{D}$ matrices are presented in Table 2. It can be observed that the identification process achieved at $T = 0.5sec$ and $1.0sec$ provide the best $\hat{A}$, $\hat{B}$, $\hat{C}$ and $\hat{D}$ matrices and show a good agreement with the true system matrices, compared with the estimated results at $T = 0.1sec$ and $2.0sec$. This is because the data points, used for identification, collected at $0.5sec$ and $1.0sec$ cover most the required information of the transient response. Meanwhile, the use of $0.1sec$ and $2.0sec$ lead to loss these information. With noise and missing information from the transient response, the system will be misidentified. In order to validate the identified matrices for $T = 0.5sec$ and $1.0sec$ in Table 2, these systems are reconstructed and other simulation tests were executed with zero initial conditions and the resulted step responses are presented in Fig. 5.
Table 2: Identified system matrices from noisy data

<table>
<thead>
<tr>
<th>$T$</th>
<th>$\hat{A}$</th>
<th>$\hat{B}$</th>
<th>$\hat{C}$</th>
<th>$\hat{D}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1sec</td>
<td>$\begin{bmatrix} -6.916 &amp; 2.428 &amp; -0.032  \ 3.018 &amp; 0.671 &amp; 1.526  \ -18.736 &amp; -11.512 &amp; -6.249 \end{bmatrix}$</td>
<td>$\begin{bmatrix} 0.015 \ 1.044 \end{bmatrix}$</td>
<td>$\begin{bmatrix} 3.078 &amp; 1.321 &amp; 0.022 \end{bmatrix}$</td>
<td>$\begin{bmatrix} 0.008 \end{bmatrix}$</td>
</tr>
<tr>
<td>0.5sec</td>
<td>$\begin{bmatrix} -0.002 &amp; 1.001 &amp; 0.002  \ 1.002 &amp; -0.001 &amp; 2.001  \ -25.991 &amp; -10.993 &amp; -6.001 \end{bmatrix}$</td>
<td>$\begin{bmatrix} 0.999 \ 0.997 \end{bmatrix}$</td>
<td>$\begin{bmatrix} 2.995 &amp; 0.999 &amp; 0.001 \end{bmatrix}$</td>
<td>$\begin{bmatrix} 0.001 \end{bmatrix}$</td>
</tr>
<tr>
<td>1.0sec</td>
<td>$\begin{bmatrix} 0.002 &amp; 1.002 &amp; 0.002  \ 0.999 &amp; -0.001 &amp; 1.994  \ -25.994 &amp; -10.999 &amp; -5.999 \end{bmatrix}$</td>
<td>$\begin{bmatrix} 1.000 \ 1.001 \end{bmatrix}$</td>
<td>$\begin{bmatrix} 3.001 &amp; 1.000 &amp; 0.000 \end{bmatrix}$</td>
<td>$\begin{bmatrix} 0.000 \end{bmatrix}$</td>
</tr>
<tr>
<td>2.0sec</td>
<td>$\begin{bmatrix} 0.080 &amp; 1.033 &amp; 0.019  \ 1.215 &amp; 0.098 &amp; 2.063  \ -26.657 &amp; -11.234 &amp; -6.089 \end{bmatrix}$</td>
<td>$\begin{bmatrix} 1.061 \ 1.011 \end{bmatrix}$</td>
<td>$\begin{bmatrix} 3.321 &amp; 1.086 &amp; 0.049 \end{bmatrix}$</td>
<td>$\begin{bmatrix} 0.011 \end{bmatrix}$</td>
</tr>
</tbody>
</table>

Fig. 5: Output responses of the true and reconstructed systems

As can be seen from Fig. 5, there are a great agreement between the identified and true output responses. The absolute error of output response $e(t)$ for each identified system can be calculated by:

$$|e(t)| = |y(t) - \hat{y}(t)|$$

(38)

where $y(t)$ and $\hat{y}(t)$ are true and identified output responses. The integrations of the absolute error over the range $[0, 10\text{sec}]$ of these systems are illustrated in Table 3.
Table 3: Integration of absolute error over range $[0, 10sec]$

<table>
<thead>
<tr>
<th>$T$</th>
<th>$0.5sec$</th>
<th>$1.0sec$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\int_{0}^{10}</td>
<td>e(t)</td>
<td>dt$</td>
</tr>
</tbody>
</table>

Although the obtained results show that the absolute error integrations are very small for both identified systems, but there is a little advantage to the system estimated at $T = 1.0sec$, due to the used data cover all information in the step transient response better than $T = 0.5sec$. Therefore, the selection of the measuring period time is a sensitive process and must be carefully selected to cover all information of the step transient response region. To ensure obtaining the best identification from noisy data with the step input function, the measuring period time can be determined as following:

$$T = \frac{t_s}{N}$$  \hspace{1cm} (39)

where $t_s$ and $N$ are the system settling time and the number of the samples.

From these results, it is evident that the proposed algorithm can successfully identify the parameter matrices of any LTI dynamic system using small amount of data.

This algorithm has also been extended to MIMO systems and further tests were also performed with several different input signals under different initial conditions. The results are similar to those presented here and showed the success of the algorithm in estimating the parameter matrices, but they have been omitted from this paper due to space constraints.

5. Conclusion

This paper has demonstrated the identification method of state space model for LTI dynamic system based on the measurements of the inputs, outputs and states.

- Derivation of the identification algorithm, computational steps, conditions and solution existence have been explained.
- Observation noise has been assumed to be Gaussian, zero-mean and white.
- A set of simulated results have been obtained from noise-free data and noisy data.
- It has been shown that the algorithm provides an excellent estimation parameters for $\hat{A}$, $\hat{B}$, $\hat{C}$ and $\hat{D}$ matrices with noise-free data and a good estimation with noisy data.
- The study has also clearly shown that the identified matrices $\hat{A}$, $\hat{B}$, $\hat{C}$ and $\hat{D}$ have the same form of $A$, $B$, $C$ and $D$ in the true system.
- The algorithm can be used for both SISO and MIMO systems.
This technique is simple, attractive and could easily be used for online or offline identification of LTI systems.

6. References


تعريف أنظمة التحكم الديناميكية الخطية في صورة فضاء الحالة

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قسم الهندسة الكهربائية والالكترونية، كلية الهندسة، جامعة مصراتة، ليبيا

ملخص البحث

تزايد الاهتمام بمجال تعريف الأنظمة في المجالات الهندسية على مدار السبعين عامًا الماضية، حيث شهدت نشر العديد من البحوث المكثفة حولها. تقدم هذه الدراسة طريقة تعريف للأنظمة الديناميكية الخطية ذات المعاملات الثابتة مباشرة من سلسلة بيانات زمنية. يتم تمثيل النظام الخطي في صورة فضاء الحالة، مع فرضية أن جميع متغيرات الحالة قابلة للقياس. أوضحت الدراسة عروضات من نظام في فضاء بيانات زمنية، حيث تم تمثيل النظام الخطي وقياسات الخروج من خلال استخدام نظام في فضاء بيانات زمنية. كما أوضحت الدراسة عروضات من نظام في فضاء بيانات زمنية، حيث تم تمثيل النظام الخطي وقياسات الخروج من خلال استخدام نظام في فضاء بيانات زمنية.

الكلمات المفتاحية: تعريف الأنظمة، الأنظمة الخطية، نموذج فضاء الحالة، تشويش قياس، تقدير المعاملات.