Parameter Identification for Electromechanical Servo Systems Using a High-gain Observer

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Abstract: In this paper, a High-gain Observer (HGO)-based identification technique is used to identify the parameters for electromechanical servo systems. The HGO is used for estimating the system states, disturbances due to uncertainty or parameter changing, and output noise. Then, a new model is presented using QR factorization. The estimated observer states show good agreement with the system actual states for noise free and bounded noisy input/output systems. Using model simulations and real-time input-output data gathered from a noisy electromechanical servo system, experimental study is made. It is shown that HGO-based parameters identification has better performance in bounded noise environment compared with the subspace algorithm.

1. INTRODUCTION

System identification is an established modelling tool in control engineering and numerous successful applications have been reported. The theory is well developed (Soderstrom, 1989, Ljung, 1999), and there are powerful software tools available, e.g., the System Identification Toolbox (SIT) (Ljung, 1997). According to the identified model, there are two kinds of identification techniques: polynomial model identification and state-space model identification. The polynomial identification technique is particularly suitable for a single-input-single output (SISO) systems as in (Abou-Zayed et al., 2008). State-space identification is considered instead of polynomial identification because of its ability to efficiently handle multiple inputs and/or outputs (Federico et al., 2007). It has been possible to apply advanced control techniques to these systems (Zhou et al., 1996, Apkarian and Adams, 1998, Lyantsev O. D. et al., 2004).

The subspace approach to state-space identification offers numerically reliable algorithms for computing state-space descriptions directly from data. This approach is competitive with respect to traditional prediction error or instrumental variable techniques, in particular for the high-order multi-input multi-output case (Viberg, 2002). The computations are based on QR-factorization and singular-value decomposition, for which numerically reliable algorithms are available. Subspace identification technique was adopted, and the resulting identification toolbox N4SID was developed (Ljung, 1997).

Given a state-space system, an observer is a system whose task is estimating, at least, the system states. The inputs of the observer are the system inputs and outputs. On the basis of different observers, several parameters estimation algorithms were developed based on noise free or Gaussian noise assumptions. Unfortunately, these kinds of noise assumptions can not meet some practical situations (Gao et al., 2008).

In this paper, a HGO-based identification technique is proposed as an extension for the work done in (Gao et al., 2007). The HGO is used for estimating the system states, disturbances due to uncertainty or parameter changing, and output noise. Then, a new model is presented using QR factorization. The estimated observer states show good agreement with the system actual states for noise free and bounded noisy input/output. The proposed technique is compared with the standard subspace algorithm in uncertainty parameters estimation using model simulation and real-time data.

The motivation of this work is to develop an identification technique suitable for MIMO state-space noisy systems to estimate system uncertainty. This technique assumed the existence of some bounded noise which is popular in many control issues.

The paper is organized as follows: In section 2, the design of the HGO is described briefly, and in section 3 the HGO is applied on the servo system. In Section 4, the comparison between the HGO technique and the subspace technique is discussed under four different conditions. Finally, Section 5 contains some conclusions.

2. PROBLEM STATEMENTS

2.1 High-gain Observer

The following dynamic system is considered (Gao et al., 2007):

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + d(t) + \omega_i(t) \\ y(t) = x(t) + \omega_o(t) \end{cases} \tag{1}$$

where $x(t) \in R^n$ is a state vector, $u(t) \in \Re^m$ represents a control input vector, $y(t) \in \Re^n$ is a measurement output vector, $\omega_i(t) \in \Re^n$, and $\omega_o(t) \in \Re^n$ are input and output noise vectors, respectively; A and B are known constant matrices, and $d(t)$ is unknown disturbance to be identified. Let:

$$d(t) = \Delta A x(t) + \Delta B u(t),$$

$$\bar{x}(t) = \begin{bmatrix} x(t) \\ d(t) \\ \omega_o(t) \end{bmatrix}_{3n\times 1},$$

$$\bar{A} = \begin{bmatrix} A & I_n & 0 \\ 0 & 0_{n\times n} & 0 \\ 0 & 0 & -I_n \end{bmatrix}_{3n\times 3n}, \bar{B} = \begin{bmatrix} B \\ 0_{n\times m} \\ 0_{n\times m} \end{bmatrix}_{3n\times m}, \tag{2}$$

$$\bar{C} = \begin{bmatrix} I_n & 0_{n\times n} & I_n \end{bmatrix}_{n\times 3n}, \bar{E} = \begin{bmatrix} I_n & 0 & 0 \\ 0 & I_n & 0 \\ 0 & 0 & 0_{n\times n} \end{bmatrix}_{3n\times 3n},$$

$$\bar{G} = \begin{bmatrix} I_n \\ 0 \\ 0 \end{bmatrix}_{3n\times n}, \bar{H} = \begin{bmatrix} 0 \\ I_n \\ 0 \end{bmatrix}_{3n\times n}, \bar{N} = \begin{bmatrix} 0 \\ 0 \\ I_n \end{bmatrix}_{3n\times n}$$

As a result, an augmented descriptor system can be obtained from (1), and (2) to give:

$$\begin{cases} \bar{E}\dot{\bar{x}}(t) = \bar{A}\bar{x}(t) + \bar{B}u(t) + \bar{G}\omega_i(t) + \bar{H}\dot{d}(t) + \bar{N}\omega_o(t) \\ y(t) = \bar{C}\bar{x}(t) \end{cases} \tag{3}$$

In this algorithm, $\dot{d}(t), \omega_i(t)$, and $\omega_o(t)$ are all assumed to be bounded. In this context, the observer can be constructed as follows:

$$\begin{cases} \bar{S}\dot{\zeta}(t) = (\bar{A} - \bar{K}\bar{C})\zeta(t) + \bar{B}u(t) - \bar{N}y(t) \\ \hat{\bar{x}}(t) = \zeta(t) + \bar{S}^{-1}\bar{L}y(t) \end{cases} \tag{4}$$

where $\zeta(t) \in \Re^{3n}$ is the state vector of the dynamic system (4), $\hat{\bar{x}}(t) \in \Re^{3n}$ is the estimate of $\bar{x}(t) \in \Re^{3n}$, $\bar{S} = \bar{E} + \bar{L}\bar{C}$, and $\bar{K}, \bar{L} \in \Re^{3n\times n}$ are the gain matrices to be designed. Choosing

$$\bar{L} = \begin{bmatrix} 0 & 0 & M \end{bmatrix}^T \tag{5}$$

where $M \in \Re^{n\times n}$ is a nonsingular matrix. Thus:

$$\bar{S} = \begin{bmatrix} I_n & 0 & 0 \\ 0 & I_n & 0 \\ M & 0 & M \end{bmatrix}_{3n\times 3n}, \bar{S}^{-1} = \begin{bmatrix} I_n & 0 & 0 \\ 0 & I_n & 0 \\ -I_n & 0 & M^{-1} \end{bmatrix} \tag{6}$$

In terms of (2) and (6), it is further derived that:

$$\bar{C}\bar{S}^{-1}\bar{L} = I_n, \bar{A}\bar{S}^{-1}\bar{L} = -\bar{N} \tag{7}$$

Using (7), the estimator (4) can be expressed as:

$$\bar{S}\dot{\hat{\bar{x}}}(t) = \bar{A}\hat{\bar{x}} + \bar{B}u(t) + \bar{K}(y(t) - \bar{C}\hat{\bar{x}}) + \bar{L}\dot{y}(t) \tag{8}$$

The dynamic equation of the plant (3) can be expressed as:

$$\bar{S}\dot{\bar{x}}(t) = \bar{A}\bar{x} + \bar{B}u(t) + \bar{G}\omega_i(t) + \bar{H}\dot{d}(t) + \bar{N}\omega_o(t) + \bar{L}\dot{y}(t) \tag{9}$$

Defining $\bar{e}(t) = \bar{x}(t) - \hat{\bar{x}}(t)$ and subtracting (8) from (9):

$$\dot{\bar{e}}(t) = \bar{S}^{-1}\left[(\bar{A} - \bar{K}\bar{C})\bar{e}(t) + \bar{G}\omega_i(t) + \bar{H}\dot{d}(t) + \bar{N}\omega_o(t)\right] \tag{10}$$

$$= \bar{S}^{-1}(\bar{A} - \bar{K}\bar{C})\bar{e}(t) + \bar{N}M^{-1}\omega_o(t) + \bar{H}\dot{d}(t) + (\bar{G} - \bar{N})\omega_i(t)$$

From (10), choosing a high gain M reduces the effect of $\omega_o(t)$ on the state error. According to (Gao et al., 2007), the high gain matrix $\bar{K}$ can be computed as:

$$\bar{K} = \bar{S}\bar{P}^{-1}\bar{C}^T \tag{11}$$

where $\bar{P}$ is the solution of the following Lyapunov equation

$$-(\mu I + \bar{S}^{-1}\bar{A})^T \bar{P} - \bar{P}(\mu I + \bar{S}^{-1}\bar{A}) = -\bar{C}^T\bar{C} \tag{12}$$

with $\mu > 0$ satisfying $\Re\left[\lambda_i(\bar{S}^{-1}\bar{A})\right] > -\mu, \forall i \in \{1, 2, ..., 3n\}$. Defining $d(t) = \Delta A x(t) + \Delta B u(t)$, the system in equation (3) is constructed. Therefore, the observer (8) (Gao et al., 2007), can be used to estimate the states, the uncertainty, and the output noise.

2.2 Electromechanical Servo System

A DC-servo system can be described by the following second-order model:

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) \\ y(t) = Cx(t) \end{cases} \tag{13}$$

where,

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}, \quad B = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix}, \quad C = I_2,$$
$$x(t) = \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} = \begin{bmatrix} \omega_{sh}(t) \\ \theta_L(t) \end{bmatrix} = y(t), \quad u(t) = \begin{bmatrix} v_a \end{bmatrix} \tag{14}$$

where $\omega_{sh}(t)$ is the shaft speed, and $\theta_L(t)$ is the load angular position. The parameters of A and B can be obtained primarily by using the subspace identification approach (Ljung, 1999, Abou-Zayed et al., 2008).

A view from the experimental setup is shown in Fig.1. The DC servo mechanism setup to be studied operates at ±10V input voltage with a permissible output motor shaft speed of ±!0V related to actual speed ±2200 r.p.m. The shaft is connected to an inertial load through a coupling gear with ratio (r=1/30).The load shaft carries an absolute position sensor with linear range ±10V related to actual position ±180° (mechanical degrees). A personal computer PC (Pentium III, 700 MHz, 256 MB RAM), running the

MATLAB software, is connected to the servo system setup through a data acquisition card. This PC is used as a signal generator and data logger for system identification.

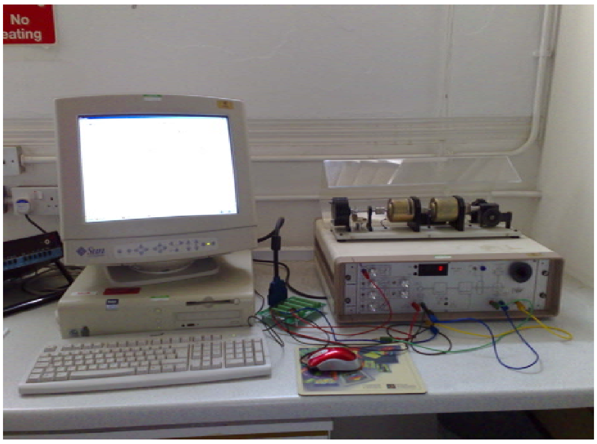

Fig. 1. Electromechanical servo system setup.

3. PARAMETER ESTIMATION OF THE SERVO SYSTEM

A DC-servo system can be described as second order model (13) and (14). Most of the existing parameter identification approaches are based on the Gaussian noise assumption. However, the bounded noise assumption is more popular in the analysis and design of systems and control applications. Here, the HGO with QR factorization technique will be used to identify the uncertainty or the disturbance for noisy servo system.

A servo system with uncertainty, input, and output noise can be described as in (1). The system uncertainty can be expressed as follows:

$$d(t)=\begin{bmatrix} d_1(t) \\ d_2(t) \end{bmatrix}=\begin{bmatrix} \Delta a_{11}x_1(t)+\Delta a_{12}x_2(t)+\Delta b_1 u(t) \\ \Delta a_{21}x_1(t)+\Delta a_{22}x_2(t)+\Delta b_2 u(t) \end{bmatrix} \tag{15}$$

Therefore, a HGO in the form of (8) can be designed to give the estimated signals $\hat{x}(t)$ and $\hat{d}(t)$. The predicted disturbance $\hat{d}(t)$ can be expressed as:

$$\begin{aligned}\hat{d}(t)=\begin{bmatrix} \hat{d}_1(t) \\ \hat{d}_2(t) \end{bmatrix}&=\begin{bmatrix} \Delta\hat{a}_{11}\hat{x}_1(t)+\Delta\hat{a}_{12}\hat{x}_2(t)+\Delta\hat{b}_1 u(t) \\ \Delta\hat{a}_{21}\hat{x}_1(t)+\Delta\hat{a}_{22}\hat{x}_2(t)+\Delta\hat{b}_2 u(t) \end{bmatrix} \\ &=\begin{bmatrix} \Delta\hat{a}_{11} & \Delta\hat{a}_{12} & \Delta\hat{b}_1 \\ \Delta\hat{a}_{21} & \Delta\hat{a}_{22} & \Delta\hat{b}_2 \end{bmatrix}\begin{bmatrix} \hat{x}_1(t) \\ \hat{x}_2(t) \\ u(t) \end{bmatrix}\end{aligned} \tag{16}$$

The QR factorization technique is suitable for solving the previous linear equation. The number of uncertainty parameters $\Delta\hat{A}$, and $\Delta\hat{B}$ is *n(n+m)* parameters (6 in our case). However, there are only *n* equations in (16). So, (16) can be extended over a certain time length of *N* samples, assuming there are no parameter changes during this period. The smallest number of samples *N* required for the solver is *(n+m)* to get a unique solution. Increasing number of samples *N* leads to over-determined equations, hence improves the solution, but slowing the solver and losing memory.

Finally, the identified parameters using the HGO-based approach should be as follow:

$$\begin{cases} \dot{\hat{x}}(t)=\hat{A}\hat{x}(t)+\hat{B}u(t)+\omega_i(t) \\ \hat{y}(t)=\hat{x}(t)+\hat{\omega}_o(t) \end{cases} \tag{17}$$

where,

$$\begin{aligned}\hat{A}&=A+\Delta\hat{A} \\ \hat{B}&=B+\Delta\hat{B}\end{aligned} \tag{18}$$

A and *B* are the initial system matrices that can be identified using the standard subspace technique.

4. IMPLEMENTATION OF THE HGO-BASED IDENTIFICATION ALGORITHM

The HGO and the QR solver are implemented together using SIMULINK. The proposed technique is applied on the servo system and then compared with the subspace algorithm for different cases.

Case 1: Noise free.

First, a noise free simulation study is carried out using industrial input and the measured output from servo system model. The initial system matrices, constructed using off-line subspace identification at different operating condition, are:

$$A=\begin{bmatrix} -1.0830 & -0.0453 \\ 0.1004 & 0.0014 \end{bmatrix}, B=\begin{bmatrix} 0.9540 \\ 0.0140 \end{bmatrix}, C=\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{19}$$

Due to uncertainties or system ageing, the system matrices become:

$$\begin{aligned}\tilde{A}&=\begin{bmatrix} 1.5 & 0 \\ 0 & 0.5 \end{bmatrix}A=\begin{bmatrix} -1.6245 & -0.0680 \\ 0.0502 & 0.0007 \end{bmatrix}, \\ \tilde{B}&=\begin{bmatrix} 0.8 & 0 \\ 0 & 1.2 \end{bmatrix}B=\begin{bmatrix} 0.7632 \\ 0.0168 \end{bmatrix}\end{aligned} \tag{20}$$

Table 1, gives the estimated parameters using subspace and HGO algorithms. Both algorithms give a good estimation for the new model parameters. For comparison, the Fit quantity (Ljung, 1997, Ljung, 1999) is used for both outputs:

$$\text{Fit}=\left(1-\left(\sqrt{\sum_{t=1}^{N}\left(y(t)-\hat{y}(t)\right)^2 \Big/ \sum_{t=1}^{N}\left(y(t)-\bar{y}\right)^2}\right)\right)\times 100\% \tag{21}$$

Where $y(t)$, and $\hat{y}(t)$ are the measured and predicted output respectively. $\bar{y}$ is the mean value of the measured output and defined as:

$$\bar{y}=\frac{1}{N}\sum_{t=1}^{N} y(t)$$

Table 1. Comparison between both algorithms for case 1

Parameters	Perturbed model	Subspace	HGO
a_{11}	1.6245	-1.627	-1.6245
a_{12}	0.0680	-0.06812	-0.068014
a_{21}	0.0502	0.05011	0.05021
a_{22}	0.0007	0.0007137	0.00071993
b_1	0.7632	0.7643	0.76307
b_2	0.0168	0.01685	0.01681
Fit % (y1/y2)		99.91/99.94	99.93/99.95

Case 2: Input noise.

The uncertainty is assumed as before, but an input noise is imposed during the simulation. The noise is assumed a sine signal with amplitude 0.025 and frequency 80 Hz, corrupted by a random signal with variance 0.0005. Both algorithms are still giving a good estimation performance. Therefore, in the next test, the input noise is amplified to sine wave amplitude 0.25 and random signal variance of 0.001. Figure 2 shows the noisy input signal and both algorithms outputs, which are in good agreement with the measured output.

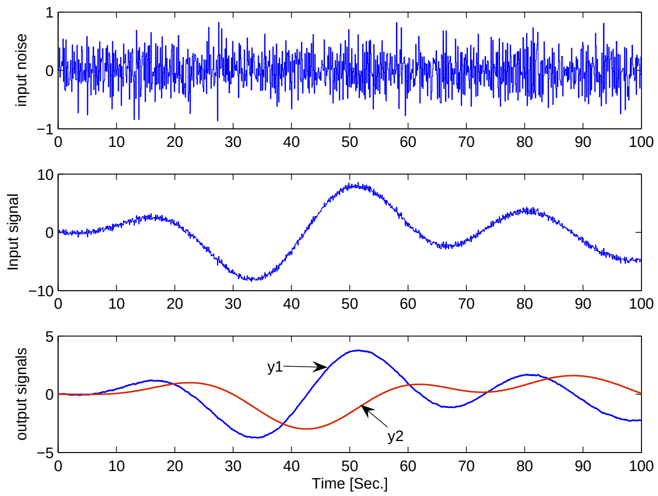

Fig. 2. **Case 2:** Input and output signals for both algorithms.

Table 2. Comparison between both algorithms for case 2

Parameters	Perturbed model	Subspace	HGO
a_{11}	-1.6245	-1.63	-1.6245
a_{12}	-0.0680	-0.06783	-0.070685
a_{21}	0.0502	0.05019	0.05021
a_{22}	0.0007	0.00076	0.00066152
b_1	0.7632	0.766	0.7632
b_2	0.0168	0.01683	0.0168
Fit % (y1/y2)		99.93/99.86	99.94/99.95

The identified parameters using both algorithms are shown in table 2. It is clear that the input noise has a minor effect on both algorithms because the servo system model is working as a Law Pass Filter. Hence, the model output is not affected by the input noise.

Case 3: Output noise.

In the next test, the uncertainty is assumed as before, but an output noise is imposed during the simulation. The noise is characterized as a sine signal with amplitude 0.025 and frequency 80 Hz, corrupted by a random signal with variance 0.00005. Figure 3 shows both algorithms output errors, which are nearly zero for HGO algorithm. Subspace algorithm shows bad tracking, especially for the shaft speed. The estimated and real disturbances and output noises for both outputs are shown in Fig. 4.

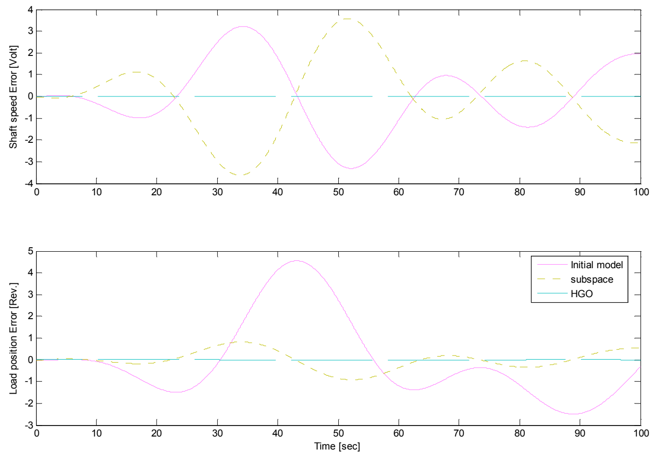

Fig. 3: **Case 3:** Output errors for initial model and both algorithms.

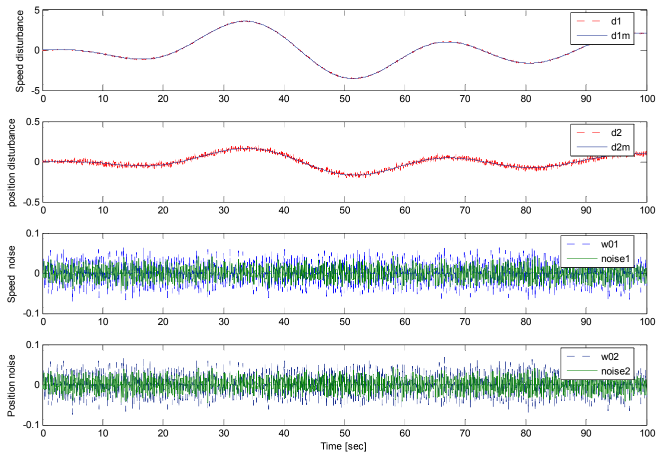

Fig. 4: **Case 3:** The estimated (HGO) and actual disturbances (15, 16) and output noises.

The estimation performance of the identified parameters is given for HGO in Fig.5. Table 3 shows the estimated model parameters for both algorithms. It is clear that the subspace algorithm give a bad performance when the system output is subject to noise.

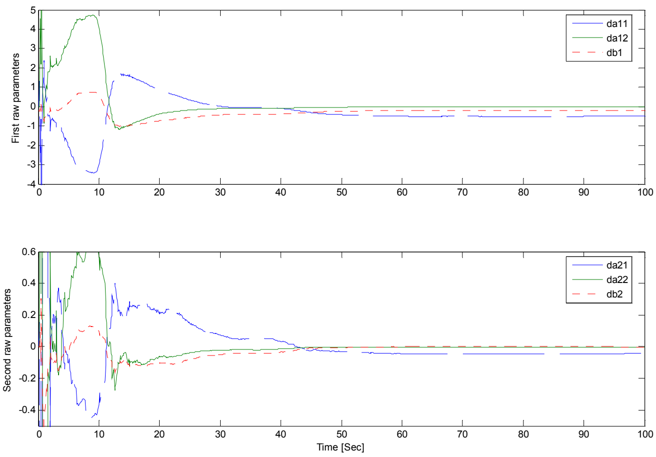

Fig. 5: **Case 3:** The estimated uncertainty parameters using HGO.

Table 3. Comparison between both algorithms for case 3

Parameters	Perturbed model	Subspace	HGO
a_{11}	-1.6245	-0.4466	-1.586
a_{12}	-0.0680	-0.016742	-0.07097
a_{21}	0.0502	-1.8409	0.05554
a_{22}	0.0007	-0.07456	0.0001303
b_1	0.7632	0.010054	0.7453
b_2	0.0168	0.86606	0.014
Fit % (y1/y2)		4.14/65.7	99.77/98.8

The HGO algorithm shows a good estimation performance due to choosing a high gain (M=10), that reduces the effect of the output noise $\omega_o(t)$ on the state error (10).

Case 4: Output noise with different initial models.

This test is same as the previous test, but two different initial models will be used with the HGO-based identification technique. The first initial model is an unstable initial model defined as:

$$A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, B = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{22}$$

The second is the model obtained from the subspace algorithm in case 3 with Fits 4.14% and 65.7% for both system outputs. From Table 3 (column 3), system matrices are defined as:

$$A = \begin{bmatrix} -0.4466 & -0.016742 \\ -1.8409 & -0.07456 \end{bmatrix}, B = \begin{bmatrix} 0.010054 \\ 0.86606 \end{bmatrix}, C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{23}$$

Table 4 shows the estimated parameters using HGO-based identification algorithm using both initial models. HGO1 (column 3) and HGO2 (column 4) indicate the models estimated using initial models (22) and (23) respectively. It is clear, from table 4, that the HGO-based identification technique is insensitive to the initial model selection. HGO-based identification technique can be used to refine subspace models estimated in noisy environment as in HGO2 model.

Figure 6 shows the error signals of both system outputs, shaft speed and load position. Both models obtained by HGO-based identification algorithm show good agreement with the perturbed model outputs.

Table 4. Identified parameters for different initial models

Parameters	Perturbed model	HGO1	HGO2
a_{11}	-1.6245	-1.5873	-1.5822
a_{12}	-0.0680	-0.0715	-0.0713
a_{21}	0.0502	0.0454	0.0542
a_{22}	0.0007	0.0009	0.0004
b_1	0.7632	0.7457	0.7423
b_2	0.0168	0.0207	0.0155
Fit % (y1/y2)		98.92/95.65	98.91/97.91

Figure 6 shows the error signals of both system outputs, shaft speed and load position. Both models obtained by HGO-based identification algorithm show good agreement with the perturbed model outputs.

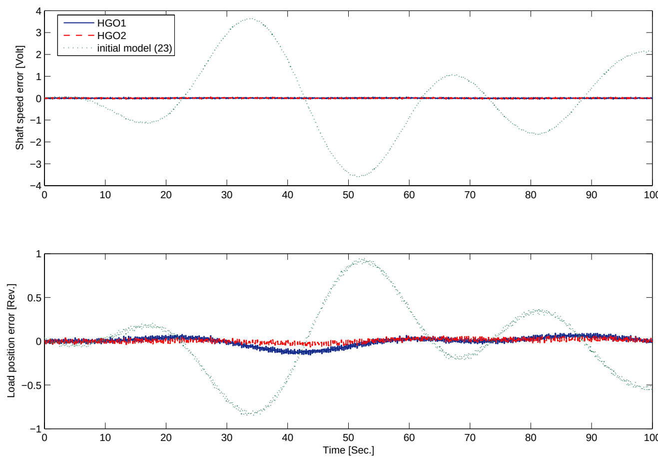

Fig. 6: **Case 4:** Output signals error of HGO for different initial models.

Case 5: Real input-output data.

This test is carried out using real input-output data collected from the servo system. Here, the uncertainty parameters are unknown. So, the comparison will be carried out using the Fit (21) of both algorithms models. The same input will be used for different servo system conditions.

Table 5 shows a comparison between the two algorithms for real data parameter estimation. The HGO model gives a higher Fit than the subspace model. Figure 7 shows a good agreement for model obtained using HGO-based identification technique with the real system outputs. The estimated disturbance and output noise using HGO when using real input-output data which contains, naturally, output noise and uncertainties are shown in Fig. 8.

Table 5. Comparison between both algorithms for case 5

Parameters	Initial model (19)	Subspace	HGO
a_{11}	-1.083	-0.077067	-0.5813
a_{12}	-0.0453	0.0037864	-0.104
a_{21}	0.1004	-0.045568	0.0806
a_{22}	0.0014	0.00025712	0.0078
b_1	0.954	0.031042	0.4037
b_2	0.014	0.082583	0.0228
Fit %	70.30/70.82	9.96/80.83	86.19/93.45

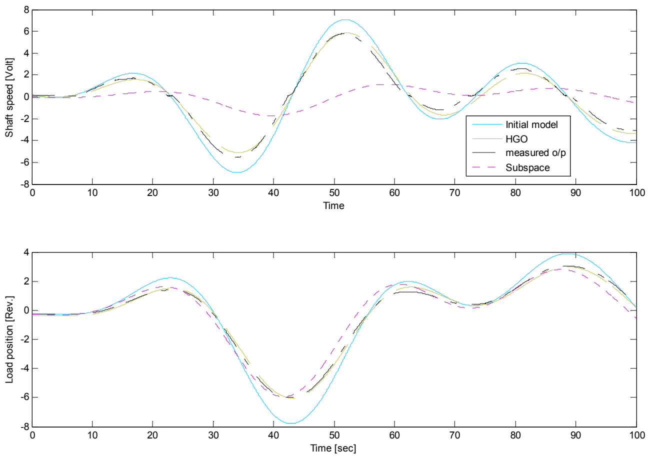

Fig. 7: **Case 5:** The signals of real, initial model and both algorithms outputs.

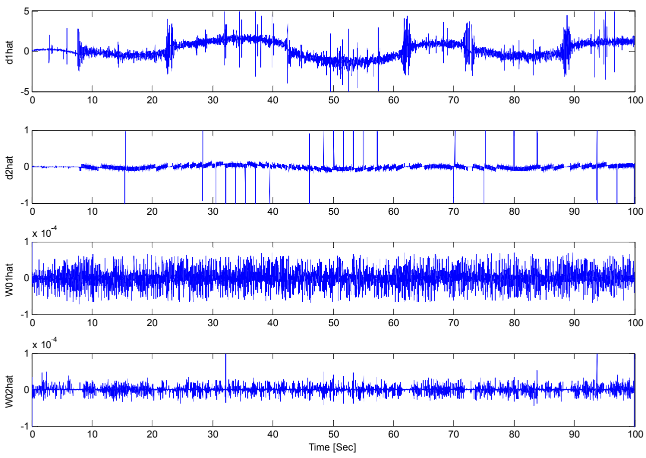

Fig. 8: **Case 5:** The estimated (HGO) disturbances and output noise.

5. CONCLUSIONS

In this paper, a HGO-based identification technique is discussed as an extension to (Gao et al., 2007, Gao et al., 2008). The HGO is used for estimating system uncertainties or parameters changing. Then, a new model is presented using QR factorization approach. A particular multi-output case has been considered. This technique is compared with the standard subspace algorithm in parameter estimation using model simulations and real-time data gathered from a servo system.

Both algorithms show a good estimation performance without output noise as shown in case1 and case 2. However, in the existence of output noise, the subspace algorithm shows a bad estimation for the model parameters as in case 3. While, the HGO-based identification technique gives a good agreement with the perturbed system output for the same case. This technique shows insensitivity to the selected initial model as in case 4. An acceptable Fit is obtained, in case 5, using the HGO model. This model is estimated using the servo system real input-output data.

Finally, the HGO-based identification technique shows a better performance than the subspace algorithm, especially with output noise or when using real input-output data.

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