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System Identification of a Linear Series Elastic Actuator using a Recursive Taguchi-based Algorithm

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***Abstract*—This paper addressed a new system identification method which is simply applicable to identify both of the linear and nonlinear models. Having a rough and initial range of values for the parameters of the system, the Taguchi method is used to identify the model of the purposed system. The purposed method is implemented on a custom made linear series elastic actuator. Five parameters of the system are identified through 75 iterations and within three steps of system identification process. To use this model, first a rough estimation for the values of the parameters are estimated, using the Taguchi method and Signal to Noise Ratios (SNRs), the previous attempts are modified and a new range of the values for each parameter is offered. The changes of signal to noise ratio diagrams are used as the stop criteria for the process. Also, SNRs are used to determine the next level of values for the parameters. The presented method significantly reduced the system identification time process, and the model is identified using just 75 iterations. In addition, utilizing the capability of the Taguchi method, the purposed method robustly estimates the system model. In this paper, based on the physical laws, the structure of the model was known and only the parameter estimation was required; however, using the presented method, estimation of both of the structure and the model is possible. The method is simply applicable and the computational complexity is very low in comparison to the alternative methods.**

Keywords—System identification; Taguchi method; Series elastic actuators; Signal to noise ratio;

I. INTRODUCTION

Finding a fast and low cost method of system identification is an important issue in system identification which receives a great amount of attention among researchers.

In general, system identification methods are divided into two major categories, data-driven methods in which there is no previous knowledge of the system [1], and the methods dealing with model estimation of a system with known structure [2,3]. Identification of a system includes two phases, structure detection and model estimation. The prediction error method (PEM) and the maximum likelihood are the standard approaches to estimate the system model; however, these techniques sometimes fail to accurately and robustly estimate the system model because of the short and noisy records [4,5].

Ref. [6] utilizes multiple kernel-based regularization method to both robustly identify the system model and reduce the cost of the computation. In order to reduce the computational complexity, Yantao [7] addresses the system identification using an adaptive algorithm with the sparse property and a partial updating method. In [8] the usage of a variable forgetting factor is studied to improve the robustness of the RLS algorithm. Evolutionary techniques such as genetic algorithms (GAs) [9-11] and dissimilation particle swarm optimization (PSO) [12,13] are also used to identify the structure of given systems.

In this project, using the physical laws, the structure of the dynamical model is known, therefore, the model estimation is purposed. The Taguchi method is used to robustly estimate the system model.

Taguchi method is a statistical optimization technique, which has the benefit of finding the optimal parameters through significantly reduced number of experiments. Unique features of the Taguchi method nominate it as a powerful practical gain tuning tool. Norouzi et al. [14,15], studied gain-tuning for a Fractional PID control systems using the Taguchi method. Yuce et al. [16] used a combination of the Taguchi method and neural network to optimize the control quality of a wood manufacturing firm; however, in this project, Taguchi method is used as a system identification tool.

In previous studies which used the Taguchi method as an optimization technique, a number of experiments suggested by the Taguchi method [17] were required to experimentally find the best level of the parameters. The presented method needs only one experiment and the Taguchi method adjusts the parameters of the simulated model. The identification process estimates the values of the five parameters of the dynamic model using L25 orthogonal array through three identification steps; then using only 75 simple recursive iterations, the system parameters are estimated. Therefore, the identification process time is reduced significantly.

A white Gaussian noise is added to the input signal and the values of the cost function are recorded two times for each parameter's levels to make the identification method robust.

As an experimental set-up, a linear Series Elastic Actuator (SEA) is selected to implement the purposed controller. SEAs are adjustable compliant actuators which today are intensively used in human assistive robots [18]. In the actuator, a spring is used to elastically decouple the electric motor from the load and improves tolerance to mechanical shocks. If proper stiffness is selected according to the target task, the spring can also protect the motor in the case of unwanted collisions of the output link [19].

II. Modelng

In this paper, the FUM-LSEA is used as a test bed for implementation of the proposed Taguchi identification procedure. As shown in Fig. 1, the FUM-LSEA is a linear type SEA designed and manufactured by the FUM Robotics lab at the Ferdowsi University of Mashhad.

Simplified structure of the FUM-LSEA is shown in Fig. 2. A ball screw mechanism is actuated by a servo motor through a belt and pulleys connection and converts the rotational movement of the servo motor to a linear motion. The pulleys are indicated as P1 and P2 in Fig. 2. Actuation of the ball screw displaces the nut and deflects the elastic elements (springs) which in turn applies forces to the output link.

Fig. 3 illustrates the block diagram of the FUM-LSEA in which x_m is the displacement of the nut resulted from the motor rotatins, x_o is the displacement of the load and the output link and M_m represents the overall inertia of the motor attached parts including the motor shaft, the screw shaft and the nut.

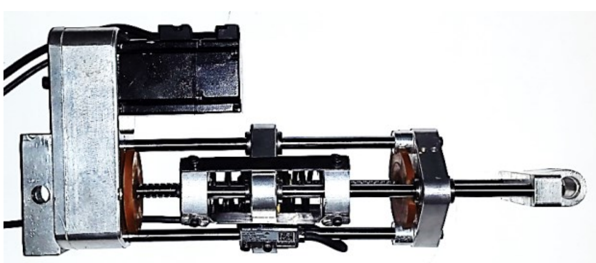


Fig. 1. FUM-LSEA.

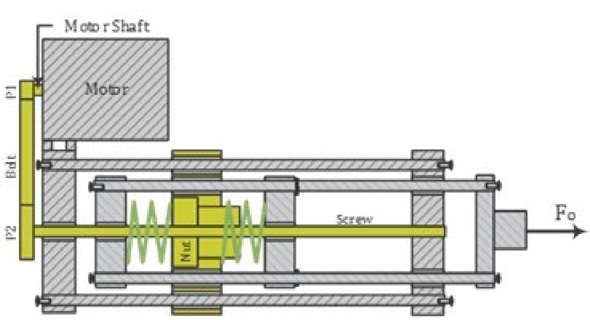


Fig. 2. Simplified structure of the FUM-LSEA.

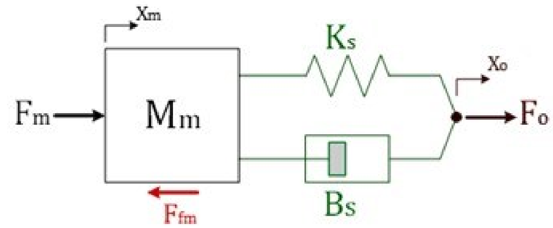


Fig. 3. Block diagram of the FUM-LSEA.

In Fig. 3, K_s and B_s are the stiffness and damping coefficients of the spring, respectively. F_o is the output force and F_m is the linear force of the motor which is related to the motor torque, τ_m, as,

$$F_m = \frac{2\pi n}{L_b} \tau_m \tag{1}$$

in which, n and $L_b$are respectively stand for the pulley ratio and the ball screw lead. Moreover F_{fm} in Fig. 3 represents the total friction of the motor and the ball screw shafts and the nut block including the viscous, F_{vm}, and dry effects, F_{dm}, as given in (2).

$$F_{fm} = F_{dm} + F_{vm}\dot{x}_m \tag{2}$$

According to Erkorkmaz and Altintas [20], neglecting the Stribeck effect, the dry friction can be modeled as,

$$F_{dm} = \begin{cases} -F_{mt} & if\ |\dot{x}_m| \leq V_z \& |F_{mt}| \leq F_{cm} \\ -F_{cm} sign(F_{mt}) & if\ |\dot{x}_m| \leq V_z \& |F_{mt}| > F_{cm} \\ -F_{cm} sign(\dot{x}_m) & if\ |\dot{x}_m| > V_z \end{cases} \tag{3}$$

where, F_{cm} represents the static and kinetic friction forces, assumed to be identical, and V_z is a constant below which the calculated velocities are assumed to be zero. This constant is included in the model to eliminate the friction fluctuations when $\dot{x}_m$ approaches zero. $V_z = 0.001$ is considered throughout this paper. F_{mt} accounts for the total forces applied to M_m, except for the dry friction forces, and calculated as,

$$F_{mt} = F_m - F_{vm}\dot{x}_m - B_s(\dot{x}_m - \dot{x}_o) - K_s(x_m - x_o) \tag{4}$$

Note that the block diagram of Fig. 3 shows a general model of series elastic actuators which is readily applicable to all linear or even rotary type SEAs. However, for the rotary type SEAs, the force and displacement variables should be replaced by their equivalences for the rotary motions.

Applying the Newton's law, the dynamic equation of motion for the system of Fig. 3 can be easily obtained as,

$$\begin{cases} F_m = M_m \ddot{x}_m + (B_s + F_{vm})\dot{x}_m + K_s x_m \\ \qquad -B_s \dot{x}_o - K_s x_o + F_{dm} \\ F_o = B_s(\dot{x}_m - \dot{x}_o) + K_s(x_m - x_o) \end{cases} \tag{5}$$

If the output link is fixed, the dynamic equation of motion of the system simplifies to,

$$\begin{cases} F_m = M_m \ddot{x}_m + (B_s + F_{vm})\dot{x}_m + K_s x_m + F_{dm} \\ F_o = B_s \dot{x}_m + K_s x_m \end{cases} \tag{6}$$

Note that all the considered parameters for the actuator model appear in (6). Therefore, it is possible to estimate all the system parameters by identifying the actuator model while the output link is fixed.

III. Identification Procedure

In this paper the system identification method aims at identification of the model parameters. According to (6), there are five parameters in the actuator model which may take a wide range of values. Therefore, a huge number of combinations should be considered to find the model which fits best to the experimental data. In this paper, the Taguchi optimization method is used for identification of the system parameters. This method significantly reduces the number of identification iterations. This method predicts the best model by checking a small number of possible values for the parameters.

The proposed Taguchi procedure for identifying the model of the FUM-LSEA includes five steps as follows;

Step- I: Prepare a sufficiently exciting trajectory for $F_m(t)$, fix the output link of the SEA, apply $F_m(t)$ to the SEA motor and measure the resulting output force trajectory, $F_o(t)$.

Step- II: Set the number of levels for each parameter of the model and assign the initial parameter values for each level.

Step-III: Prepare a Taguchi table of orthogonal arrays according to the levels and values of the Step-II. Assign the values of each row of the orthogonal array to the corresponding parameters of the model. Simulate the model by applying the $F_m(t)$ trajectory of the Step-I and determine the calculated output force trajectory, $F_{oc}(t)$. Calculate the output column of the orthogonal array, Y_i, as the time integral of the absolute value of the error between calculated output force trajectory, $F_{oc}(t)$, and the measured one, $F_o(t)$. In the other words, $Y_i = \int |F_o(t) - F_{oc}(t)| dt$. Repeat this step for all rows of the orthogonal array.

Step-IV: Analyze the signal-to-noise ratio, SNR, diagrams. Three cases may occur:

Case 1: If the SNR values for some parameters change significantly across the different levels, determine the new levels for those parameters and go to the Step-III. Consider the parameter levels with the largest SNRs as the base levels for the next iteration. If the SNR diagram of a parameter achieves its maximum for an intermediate level, this level should be taken as the central level for the corresponding parameter in the next iteration and other levels should be chosen around this level. If the maximum SNR value for a parameter occurs at the boundary levels, spread the levels in the direction which the maximum SNR indicates.

Case 2: If flat SNR diagrams are obtained for all parameters but the level differences for some parameters are large, chose different levels for those parameters and go to the Step-III.

Case 3: If flat SNR diagrams are obtained for all parameters and all the level differences are sufficiently small, optimum parameters are found. Go to the Step-V.

Step- V: Stop the procedure and form the best model using the identified parameters.

Note that the Step- I is the only experimental step of the procedure which has a single iteration. The overall structure of the described Taguchi procedure is depicted in Fig. 4.

IV. Experiment

Experimental step of the proposed procedure is performed by preparing a test bed as shown in Fig. 5. The test bed is a single axis stage actuated by direct coupling of a servo motor to a ball-screw mechanism. The stage is designed such that the FUM-SEA is easily placed on the top and its output link is fixed to movable block of the stage as shown in Fig. 5.

It can be seen that two CMM2 load cells, by DACELL Co., are placed at connection point of the actuator and the stage. These load cells are used to measure the output force of the SEA. A motion control card by tsPishro Co. is used to send force trajectories to drive of the SEA motor and also to read the output force from load cells amplifiers. The communication between the motion control board and MATLAB/Simulink Desktop Real-Time toolbox is stablished via an Ethernet connection and the real-time data transmission is performed at a sampling rate of 1 kHz.

According to the discussions provided in Section II, for identification purposes, it is sufficient to fix the output link of the FUM-LSEA and apply some force trajectories to the SEA motor. Therefore, although the test bed has the possibility of applying desired motion to the output link of the FUM-LSEA, in the present study the movable block of the test bed is fixed which in turn fixes the output link of the SEA.

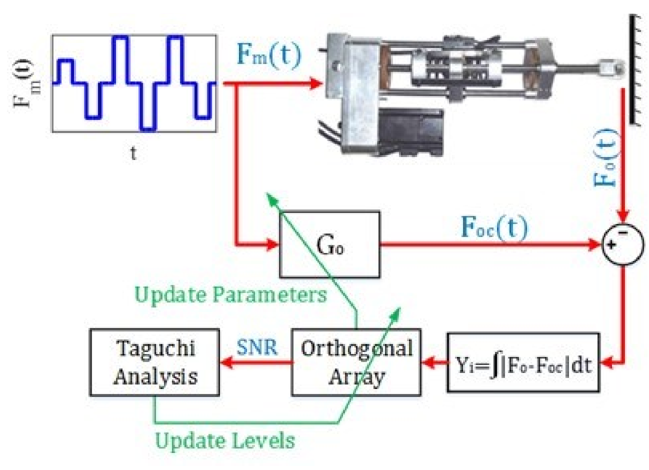
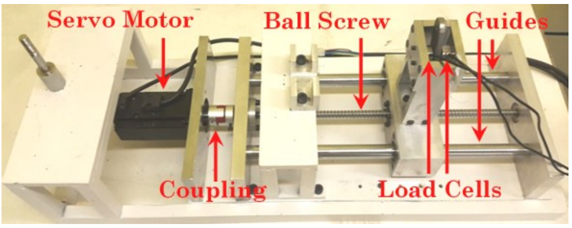
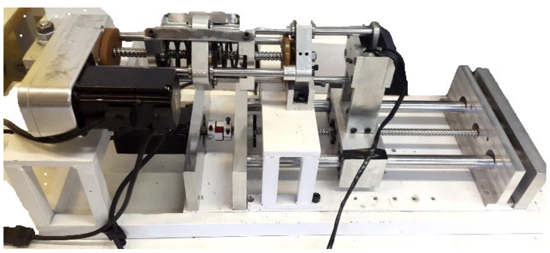


Fig. 4. Proposed Taguchi identification procedure.

As shown in Fig. 6(a), the motor force trajectory is considered as a sequence of square wave signals with different amplitudes. Such signal is known to be sufficiently exciting to excite all modes of the system. The output force trajectory of the FUM-LSEA, measured by the two load cells, is also depicted in Fig. 6(b).

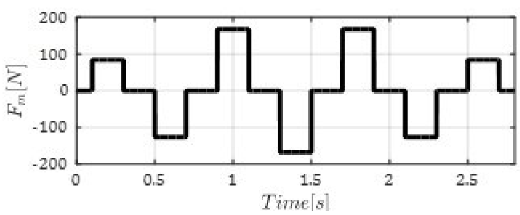


(a)

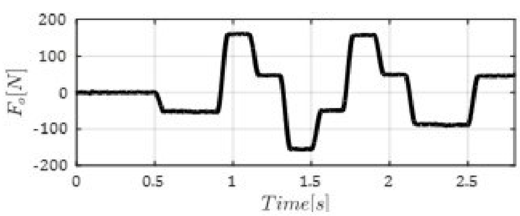


(b)

Fig. 5. Test bed for identification of FUM-LSEA parameters; (a): The single axis stage, (b): The FUM-LSEA placed on the test bed.



(a)



(b)

Fig. 6. Force Trajectories; (a): Applied motor force trajectory, (b): Measured output force trajectory.

Note that the load cells can only measure the compression forces. Therefore, the output forces trajectory is obtained as $F_o = F_{of} - F_{or}$, where F_{of} and F_{or} refer to the forces measured by front and rear load cells, respectively.

Since the parameters may take a wide range of values, five levels are considered for each factor. Considering five factors with five levels, an L25 Taguchi orthogonal array is designed and used for all identification iterations. The levels of parameters for the first iteration of identification are given in Table I. Using the parameter values corresponding to the levels of each row of the orthogonal array and applying the motor force trajectory of Fig. 6 to the SEA model of (6), the calculated output force trajectory, $F_{oc}(t)$, is obtained. Then the output variables, Y_i, for the first iteration are calculated and the SNR diagrams are obtained as depicted in Fig. 7.

TABLE I. FACTOR LEVELS FOR THE 1ST ITERATION

Factors	Levels				
	1	*2*	*3*	*4*	*5*
$F_{cm}[N]$	10	50	80	100	110
$F_{vm}[Ns/m]$	1	5	10	50	80
$M_m[kg]$	4	6	8	10	12
$K_s[kN/m]$	1	4	6	8	10
$B_s[Ns/m]$	0.1	2	5	10	20

According to the SNR diagrams of Fig. 7, the values of the 4th level for F_{cm}, the 4th level for F_{vm}, the 1st level for M_m, the 4th level for K_s and the 2nd level for B_s are considered as the base values for the levels of the 2nd iteration of identification as given in Table II. Fig. 8 depicts the SNR diagrams for the 2nd iteration.

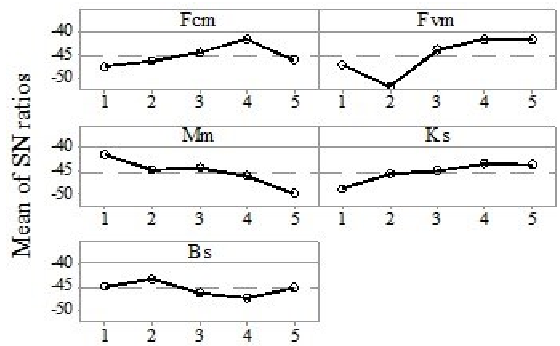


Fig. 7. SNR diagrams for the 1st iteration.

The SNR diagrams of Fig. 8 indicate that the values of the 2nd level for F_{cm}, the 2nd level for F_{vm}, the 4th level for M_m, the 3rd level for K_s and the 4th level for B_s should be considered as the base values for the levels of the 3rd iteration as given in Table III. The SNR diagrams for the 3rd iteration are shown in Fig. 9.

TABLE II. FACTOR LEVELS FOR THE 2ND ITERATION

Factors	Levels				
	1	*2*	*3*	*4*	*5*
$F_{cm}[N]$	85	90	95	100	105
$F_{vm}[Ns/m]$	45	50	55	60	65
$M_m[kg]$	3.5	3.75	4	4.25	4.5
$K_s[kN/m]$	7.5	8	8.5	9	9.5
$B_s[Ns/m]$	1	1.5	2	2.5	3

In this case, sufficiently small level differences and nearly flat SNR diagrams are obtained in the 3rd iteration. Therefore, the identification procedure stops in the 3rd iteration and the identified parameters are found as given in Table IV. However, one can continue the procedure if more accurate parameter values are required.

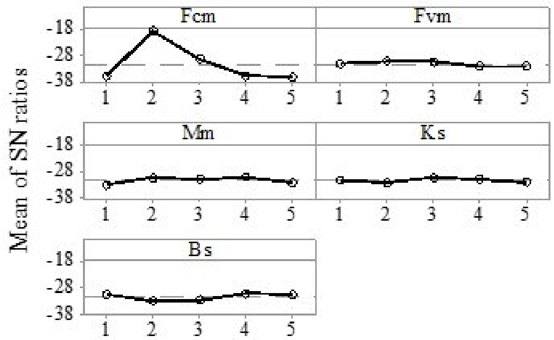


Fig. 8. SNR diagrams for the 2nd iteration.

TABLE III. FACTOR LEVELS FOR THE 3RD ITERATION

Factors	Levels				
	1	*2*	*3*	*4*	*5*
$F_{cm}[N]$	85.5	87	88.5	90	91.5
$F_{vm}[Ns/m]$	50	51.5	53	54.5	56
$M_m[kg]$	4.15	4.2	4.25	4.3	4.35
$K_s[kN/m]$	8.4	8.5	8.6	8.7	8.8
$B_s[Ns/m]$	2.3	2.4	2.5	2.6	2.7

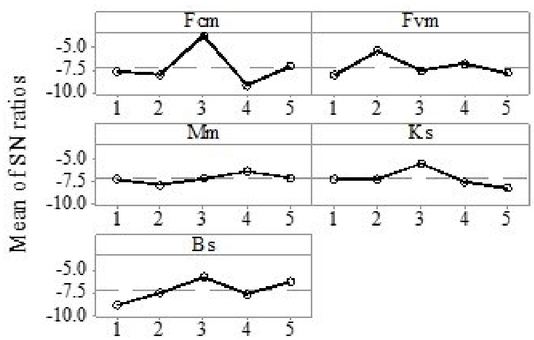


Fig. 9. SNR diagrams for the 3rd iteration.

TABLE IV. IDENTIFIED PARAMETERS VALUES FOR THE FUM-LSEA MODEL

Parameter	Value	Parameter	Value
$F_{cm}[N]$	88.5	$K_s[kN/m]$	8.6
$F_{vm}[Ns/m]$	51.5	$B_s[Ns/m]$	2.5
$M_m[kg]$	4.3		

V. CONCLUSION

In this paper, a Taguchi based procedure is proposed for identification of system parameters. The proposed procedure significantly reduces the number of parameter combinations to be checked for estimating the parameters values. The identification target may be either a linear or a non-linear model of a dynamical system. A single iteration of experimental test with a sufficiently exciting input is performed to obtain the system output. Then, the iterative steps of Taguchi identification procedure are repeated to obtain the system parameters with desired accuracy. The recursive steps include designing a Taguchi table of orthogonal arrays, computing the calculated system output for each row of the table, computing the output variable by integrating the absolute error between the actual and the calculated system output, obtaining the SNR diagrams and deciding to continue the procedure with new levels of parameters or to stop it. Therefore, the presented procedure also has the benefit of somehow involving the human intellect in the process of system identification. The proposed method is finally used to identify the parameters of a non-linear model of a custom made SEA, called FUM-LSEA. The results clearly indicate the effectiveness of the method.

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