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SELF-TUNING CONTROL OF AN ELECTRO-HYDRAULIC ACTUATOR SYSTEM

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Abstract- Due to time-varying effects in electro-hydraulic actuator (EHA) system parameters, a self-tuning control algorithm using pole placement and recursive identification is presented. A discrete-time model is developed using system identification method to represent the EHA system and residual analysis is used for model validation. A recursive least square (RLS) method with covariance resetting technique is proposed to estimate parameters of the discrete-time model. The results show the proposed control algorithm can adapt the changes occur in model parameters compared with the fixed controller.

In conclusion, a self-tuning control is required in improving the EHS system performance in industrial positioning applications.

Index terms*:* System identification, pole placement, recursive least square, electro hydraulic actuator system, self tuning control

I. INTRODUCTION

Electro-hydraulic actuator (EHA) system are crucial in engineering field because it can provide very high forces, high control accuracies, high power to weight ratio and also have a compact structure [1]. For that reason, research in control of force, pressure and position of EHA system attract a great interest to both the researcher and engineer. Recently, EHA system has become increasingly popular in many types of industrial equipment and processes. Such applications include aircrafts [2], robot manipulators [3], hydraulic excavator [4] and all kinds of automation especially in automotive industry [5], where linear movements, fast response, and accurate positioning with heavy loads are needed.

In general, it is difficult to establish or identify an accurate dynamics model of EHA system. EHA system inherently have many uncertainties, high nonlinearities and time varying which makes the modeling and controller design are more complicated. Nonlinear flow/pressure characteristics, actuator friction, internal/external leakages and fluid compressibility are major sources of nonlinearity in the actuation system. These factors have caused a great difficulty in system modeling and control. To overcome the problem, system identification technique is often proposed in the modeling process of EHA system [6, 7].

System identification has gain much interest in many engineering applications where the parameter of the system can be estimate using recursive and non-recursive manner such as least squares (LS), recursive least squares (RLS), recursive instrumental variables (RIV) and recursive maximum likelihood (RML) methods. Many industrial applications have been reported from the literature in implementation of RLS algorithm. RLS algorithm has been realized in [8, 9] for identification of electromechanical system. Subsequently, the work has been extended in [10, 11] by implementing the RLS algorithm in the experimental study for linear and nonlinear cases. Followed by work published in [12], two mechatronics systems which are servo DC motor and

Gyroscope system have been tested to identify the input-output patterns with excellent accuracy. Recently, authors in [13] utilized the RLS estimator for pneumatic system where the best performance results obtained using one-step-ahead prediction.

It can be summarized from presented research studies that the RLS estimator is extensively used as the capability to reduce bias, simple numerical solution and fast parameter convergence. The combination of RLS with various control strategy also has been widely implemented for many years [6, 14, 15, 16, 17]. When combining with control scheme as an adaptive or self-tuning mechanism, the convergence speed of plant parameters is very important to make the controller responds with any changes in the system where in real application, the control and plant parameters are achieved simultaneously.

The objective of this paper is to develop a self-tuning algorithm for position tracking of an EHA system. First, an off-line identification is conducted to validate the discrete-time model using residual analysis. Then, RLS algorithm with covariance resetting approach is proposed which gives better estimations in terms of convergence speed and accuracy. Finally, pole placement controller is implemented for position tracking control and the controller parameters are determined based on the estimated parameters of EHA system.

II. ELECTRO-HYDRAULIC ACTUATOR SYSTEM

EHA system merges the high power of hydraulic actuation with electronic control. The schematic illustrated in figure 1 described the physical parameter consist of actuator and valve dynamics where P_s is defined as supply pressure and P_o is pressure return to the tank. The parameters q_{vi} and q_{vo} are known as oil flow for input and output of the cylinder respectively while A_i and A_o are defined as piston area for both ends. M_t is the mass attached at the top of cylinder rod where the displacement, y is measured. x_v is spool valve position that can be controlled by input voltage to the valve.

The dynamics equations are derived in [18] is representing the EHA system for a symmetric actuator. In servo valve design, the dynamics of the valve can be approximated as a single gain where the spool valve structure is assumed as critical-center and symmetrical. The equation relates the control signal, u and the spool valve position as in Eq. (1).

$$x_v = K_v u \tag{1}$$

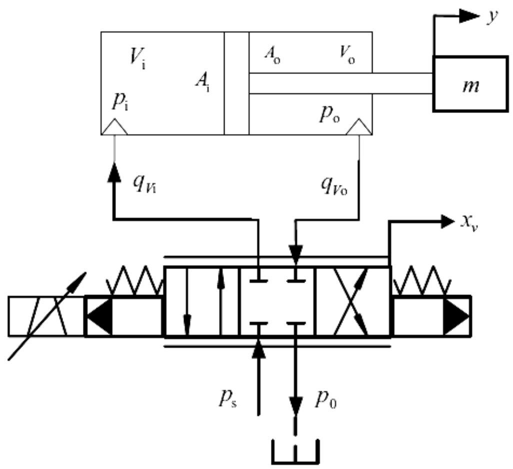

Figure 1. A schematic diagram of the electro-hydraulic system

With that, the dynamics of the electro-hydraulic system are derived from a Taylor series linearization by the following equation:

$$Q_L = K_q u - K_C P_L \tag{2}$$

Defining the load pressure, P_L as the pressure across the actuator piston, its derivative is given by Eq. (3) relates with total load flow, Q_L , bulk modulus, β_e , discharge coefficient, C_{tp} and total volume, V_t.

$$\dot{P}_L = \frac{4\beta_e}{V_t}(Q_L - C_{tp} - A_p \dot{y}) \tag{3}$$

The force of the actuator, F_a can be determined,

$$F_a = A_p P_L = M_t \ddot{y} \tag{4}$$

Substitute Eqs. (2) and (3) into (4) and Laplace transform the equation will give,

$$\frac{Y(s)}{U(s)} = \frac{K\omega_n^{\ 2}}{s(s^2 + 2\xi\omega_n s + \omega_n^{\ 2})} \tag{5}$$

where $K = \dfrac{K_q}{A_p}$, $\omega_n = A_p\sqrt{\dfrac{4\beta_e}{V_t M_t}}$, and $\xi = \dfrac{M_t(K_c + C_{tp})}{2A_p^{\ 2}}$.

Open loop transfer function of the EHS system relates between the control signal from the controller and displacement of the hydraulic actuator. The corresponding discrete-time model followed by transforming the continuous-time model in Eq. (5) with zero-order-hold as in Eq. (6).

$$G(z^{-1}) = \frac{y(k)}{u(k)} = \frac{b_1 z^{-1} + b_2 z^{-2} + b_3 z^{-3}}{1 + a_1 z^{-1} + a_2 z^{-2} + a_3 z^{-3}} \qquad (6)$$

III. SYSTEM IDENTIFICATION AND PARAMETER ESTIMATION

System identification is a field of modeling dynamic systems from measured data using mathematical algorithm. The identification process consists of estimating the unknown parameters of the systems dynamics. The recursive least square (RLS) method has been recommended by [7] for the identification process for ease of implementation and application to real systems. For the linear identification process, discrete-time model for the EHA system is given as follow:

$$A(z^{-1})y(k) = B(z^{-1})u(k) + e(t) \qquad (7)$$

where

$A(z^{-1}) = 1 + a_1 z^{-1} + a_2 z^{-2} + ... + a_n z^{-n}$,

$B(z^{-1}) = b_1 + b_2 z^{-1} + b_3 z^{-2} + ... + b_m z^{-m+1}$

and the symbol z^{-1} denotes the backward shift operator, $u(k)$ and $y(k)$ are the system input and output, respectively and $e(k)$ is the white noise of the system with zero mean. The parameter a_n and b_m are real coefficient while n and m are the orders of the polynomial $A(z^{-1})$ and $B(z^{-1})$.

Parameter estimation is the most important part of the self tuning control algorithm. A RLS parameter estimator is used with a covariance resetting approach and random walk operations to provide robust and quick convergence. The main idea is to update continuously (recursively) the unknown parameters of the plant model and used in the controller design. For the RLS algorithm to be able to update the parameters at each sample time, it is necessary to define an error from Eq. (7):

$$\varepsilon(k) = y(k) - \phi^T(k)\hat{\theta}(k-1) \qquad (8)$$

$$P(k) = \frac{1}{\lambda} P(k-1)\left[I_p - \frac{\phi(k)\phi^T(t)P(k-1)}{\lambda + \phi^T(k)P(k-1)\phi(t)} \right] \qquad (9)$$

$$\hat{\theta}(k) = \hat{\theta}(k-1) + P(k)\phi(k)\varepsilon(k) \tag{10}$$

where $\hat{\theta}(k)$ is the estimated parameter, $P(k)$ is the covariance matrix, the subscript *'p'* is the dimension of the identity matrix, $p = n_a + n_b$, and λ is the forgetting factor, $0 < \lambda \le 1$.

Direct identification, indirect identification and joint input–output identification methods can be performed in the closed-loop identification problems [19]. The direct identification method in closed-loop system is used to identify the system unknown parameters since this method is simple and applicable without taking account of the presence of a feedback controller. This approach is especially suitable for systems with nonlinear or unknown feedback mechanisms. Indirect identification is based on the assumption that the feedback control law is known. Then, the closed-loop system is identified and the open-loop system is determined using the identified closed-loop system and the known feedback law. Joint input–output identification is carried out regarding the acquired input and output as outputs of a multivariable system in response to an external signal such as noise. Open-loop system parameters are obtained using the identified multivariable system.

IV. SELF-TUNING CONTROL DESIGN

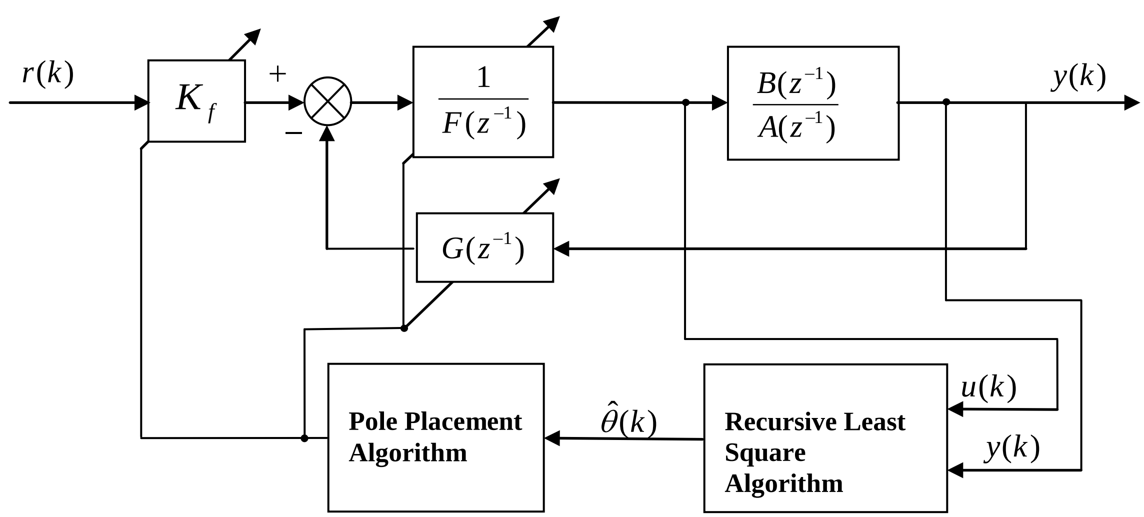

Figure 2. Self Tuning Control Strategy

The self-tuning scheme proposed in figure 2 is based on pole placement method and it is of indirect form since the controller parameters are re-updated at all time based on the estimated plant parameter by the recursive estimator. By integrating the recursive algorithm or on-line estimation of the time-varying system with the conventional model-based controller, self-tuning control scheme can be developed to encounter the EHA system characteristic that often vary due to its nonlinearities.

The model obtained from the offline identification technique will be used in designing the feedback control system design. The closed loop transfer function is given by:

$$\frac{y(k)}{r(k)} = \frac{K_f B(z^{-1})}{A(z^{-1})F(z^{-1}) + B(z^{-1})G(z^{-1})} \tag{11}$$

where

$$F(z^{-1}) = 1 + f_1 z^{-1} + f_2 z^{-2} + \ldots + f_m z^{-m-1}$$

$$G(z^{-1}) = g_0 + g_1 z^{-1} + g_2 z^{-2} + \ldots + g_m z^{-n-1}$$

A Diophantine equation can be derived from Eq. (11) is given as follows:

$$A(z^{-1})F(z^{-1}) + B(z^{-1})G(z^{-1}) = T(z^{-1}) \tag{12}$$

where

$$T(z^{-1}) = 1 + t_1 z^{-1} \quad \text{and} \quad K_f = \frac{1 + \sum_{i=1}^{p} t_i}{\sum_{i=0}^{m} b_i}$$

From Eq. (12), the following equation can be obtained for the third order system,

$$\begin{aligned}&(1 + a_1 z^{-1} + a_2 z^{-2} + a_3 z^{-3})(1 + f_1 z^{-1} + f_2 z^{-2}) + \\ &(b_1 z^{-1} + b_2 z^{-2} + b_3 z^{-3})(g_0 + g_1 z^{-1} + g_2 z^{-2}) = 1 + t_1 z^{-1}\end{aligned} \tag{13}$$

Expanding the equation and comparing the coefficient, the equation can be expressed in matrix form as follows:

$$\begin{bmatrix} 1 & 0 & b_1 & 0 & 0 \\ a_1 & 1 & b_2 & b_1 & 0 \\ a_2 & a_1 & b_3 & b_2 & 0 \\ a_3 & a_2 & 0 & b_3 & b_2 \\ 0 & a_3 & 0 & 0 & b_3 \end{bmatrix} \begin{bmatrix} f_1 \\ f_2 \\ g_0 \\ g_1 \\ g_2 \end{bmatrix} = \begin{bmatrix} t_1 - a_1 \\ -a_2 \\ -a_3 \\ 0 \\ 0 \end{bmatrix} \tag{14}$$

Since the parameters of the discrete time model are estimated recursively, the matrix equation from the pole placement algorithm can be obtained and the control parameters can be determined. The integration system identification technique with pole placement control with covariance resetting technique process is shown in figure 3. The components of RLS algorithm is relocate to its initial conditions if any changes occur during the position tracking control.

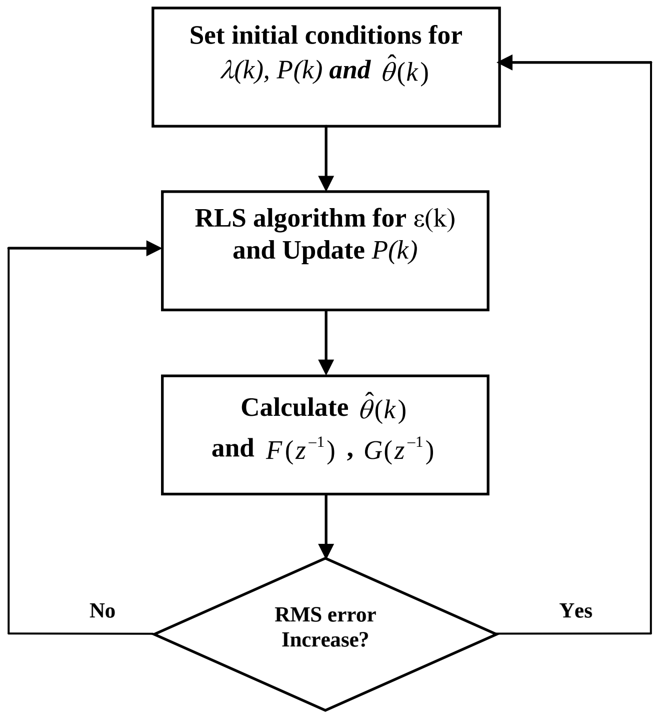

Figure 3. Recursive algorithm with covariance resetting approach

V. RESULTS AND DISCUSSION

The EHA system in this study consists of single-ended cylinder type of actuator and the pressurized fluid flow is control by a proportional valve. The double acting cylinder has 150 millimeter stroke length, 40 millimeter bore size and 25 millimeter rod size. The displacement sensor is mounted at the top of cylinder rod and both input-output signals are acquired using data acquisition system. Figure 4 shows the experimental workbench where the input-output measurement was acquired for identification process.

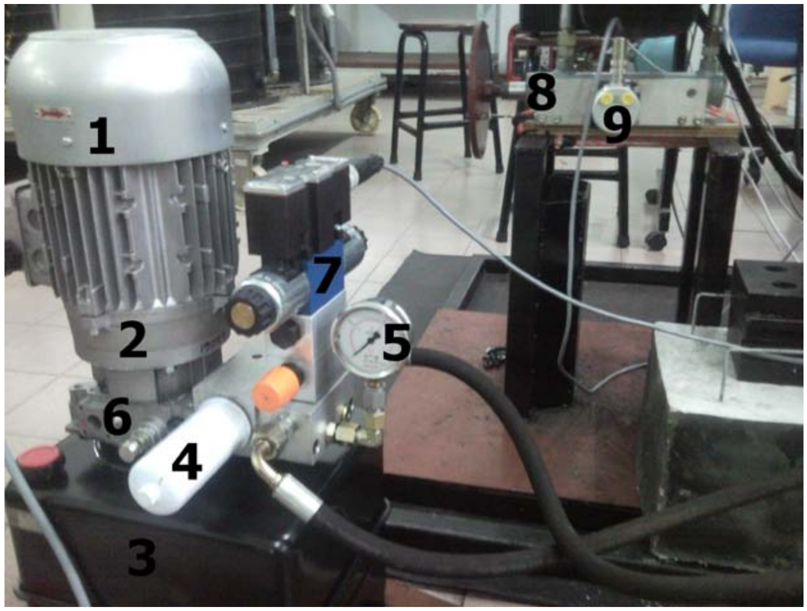

Figure 4. Experimental workbench for electro-hydraulic system. 1-electric motor; 2-pump; 3-tank; 4-filter; 5-pressure gauge; 6-relief valve; 7-proportional valve; 8-hydraulic actuator; 9-wire displacement sensor

There are some difficulties to examine the model using non-parametric method such as stability, feedback in data and noise model are exists. Since there is feedback from the output to the input in this experiment, due to some regulator in EHA system, then the spectral and correlation analysis estimates are not reliable [15]. For model estimation and validation, several parametric models can be developed based on Akaike's Final Prediction Error (FPE), Akaike's Information Criterion (AIC), Minimum Description Length (MDL) and Best Fitting Criterion. These criterions show the preciseness of the approximate model as compared to the true model. For parametric model estimation methods, the discrete-time model has been developed based on best fitting, minimum loss function and FPE criterion.

The choice of input signal determines the quality of the final parametric model and has a very significant influence on the observed data. The obtained parametric model is more accurate in frequency region where the input signal contains much energy and has to be rich enough to excite all interesting modes of the system. For software implementation, Simulink and Real Time Windows Target (RTWT) in MATLAB® have been used for analysis and communicate with the hardware. The choice of sampling time is important as to ensure the accuracy of the system response. In practice, the sampling time must be a bit higher than the Nyquist sampling theorem to ensure the resulting data will be useful in further analysis. It is established that, 50 milliseconds sampling time for the EHS system is sufficient to avoid folding and aliasing problem occur during the sampling process [20]. A set of data that consists of the input voltage and actuator displacement as shown in figure 5 was observed for a 50 seconds experiment under the off-line model identification.

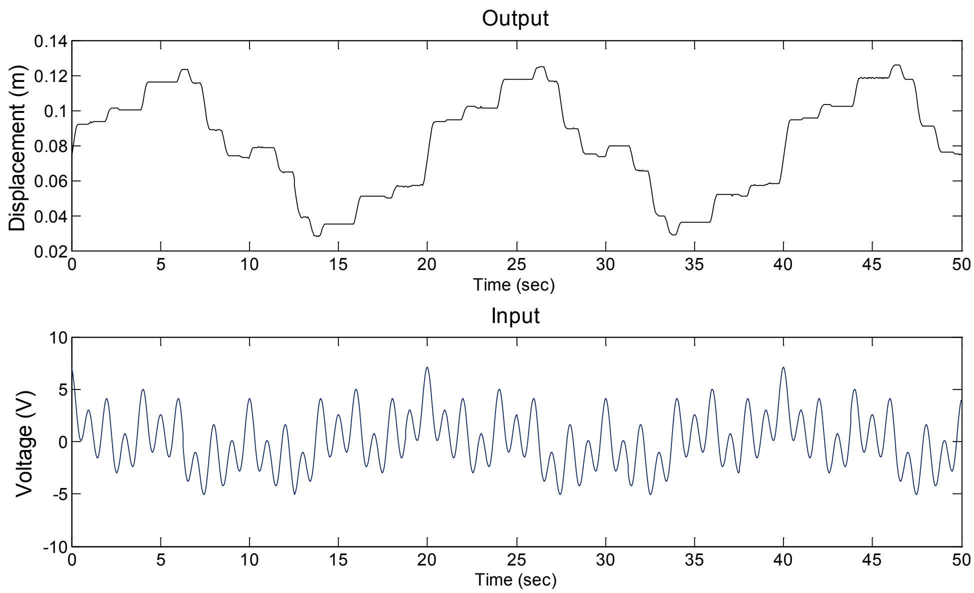

Figure 5. Input-output Measurement

Table 1: Model order analysis

Model Order	**Off-line System Identification**			
	2nd order	***3rd order***	***4th order***	***5th order***
Loss function	$1.3376\text{x}10^{-7}$	$1.0324\ \text{x}10^{-7}$	$0.9572\ \text{x}10^{-8}$	$0.9430\ \text{x}10^{-8}$
% of fit	79.36	84.63	84.15	83.90
FPE	$1.3596\text{x}10^{-7}$	$1.0575\text{x}10^{-7}$	$0.9882\ \text{x}10^{-8}$	$0.9814\ \text{x}10^{-8}$

Direct identification method in closed-loop system is considered in this paper as shown in figure 6. The plant input, *u(k)* and the output, *y(k)* are used for recursive identification by the recursive least square algorithm in exactly the same way as the open-loop system where the knowledge of the controller or the nature of the feedback is not a certain requirement. Widely known modeling of the discrete-time system and adaptive control of EHA system used a linear third-order difference equation [7, 14, 15]. Table 1 shows the off-line identification of several model order of discrete-time model. A third order model appears to be suitable for the system since there is no significant improvement in the model order increment. The analysis of model order based on the loss function, FPE and percentage of best fit in validation process. Various authors are used root-mean-square (RMS) [9], mean-square-error (MSE) [10] and prediction error [13] for model validation.

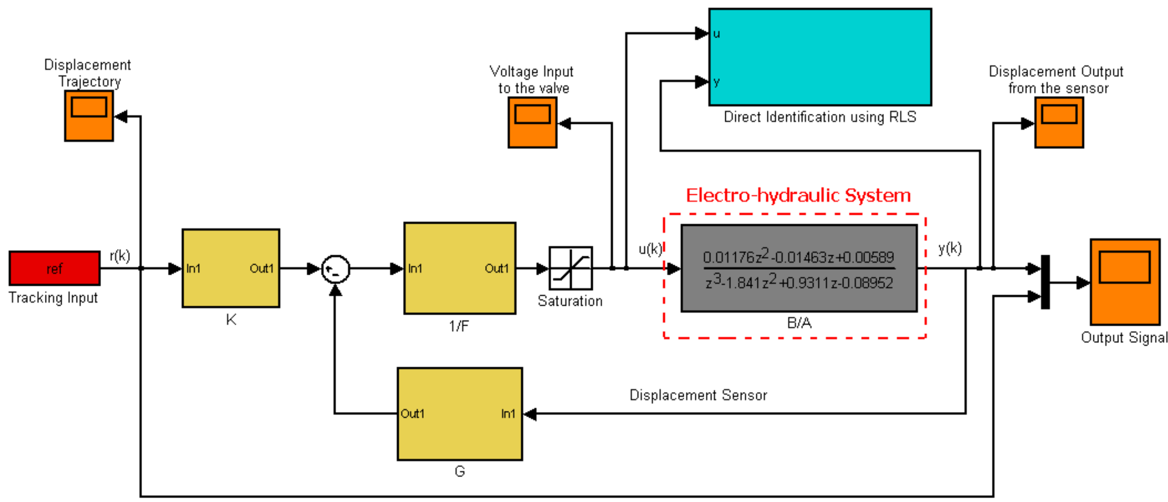

Figure 6. Direct identification for closed-loop system

For the recursive identification experiments, the third order model based on batch analysis is selected to represent the EHA system. It shown that off-line identification can be used in initial identification study in order to determine the best model structure before performing the recursive identification process. Figures 7 and 8 show the estimated parameters $A(z^{-1})$ and $B(z^{-1})$ for open-loop configuration and their values are tabulated in Table 2. Estimated parameters converge after a certain sample. Thus, the following discrete-time model was identified for third order system:

$$H(z^{-1}) = \frac{y(k)}{u(k)} = \frac{0.01176z^{-1} - 0.01463z^{-2} + 0.00589z^{-3}}{1 - 1.841z^{-1} + 0.9311z^{-2} + 0.08952z^{-3}} \tag{15}$$

Table 2: RMS values of estimated parameters

Parameter value (RMS)	On-line System Identification					
	a_1	a_2	a_3	b_1	b_2	b_3
	-1.841	0.9311	-0.08952	0.01176	-0.01463	0.00589

Based on off-line identification, position tracking for EHA system can be performed by using conventional and self-tuning controller . In the simulation study, two different discrete-time models will be used as a plant for designing the self-tuning controller. Then, the parameter of conventional pole placement controller is implemented in fixed control as initial value for the recursive estimation process. To demonstrate the effectiveness of the self-tuning controller, the estimated discrete time discrete-time model $H(z^{-1})$ is changed to $H'(z^{-1})$ as parameter varying in EHA system after 25 seconds. The discrete-time model $H'(z^{-1})$ has been estimated using similar recursive estimation under different experiment environment and it shows the some significant changes in $H'(z^{-1})$ parameters. Therefore, the following identified discrete time model :

$$H^{'}(z^{-1}) = \frac{y(k)}{u(k)} = \frac{0.01176z^{-1} - 0.01463z^{-2} + 0.00589z^{-3}}{1 - 1.952z^{-1} + 0.9821z^{-2} + 0.10952z^{-3}} \tag{16}$$

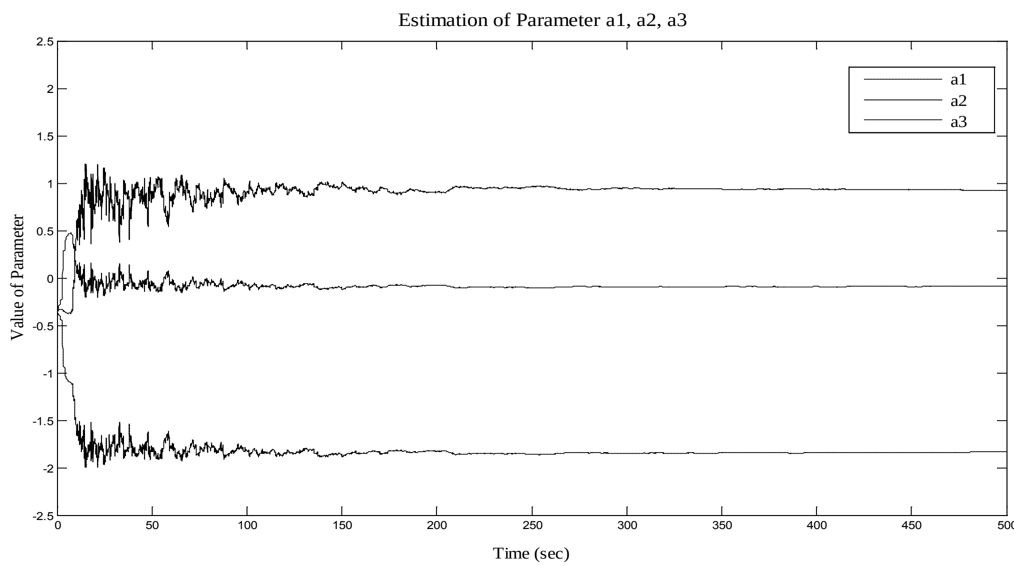

Figure 7. Estimated Parameters a_1,a_2,a_3

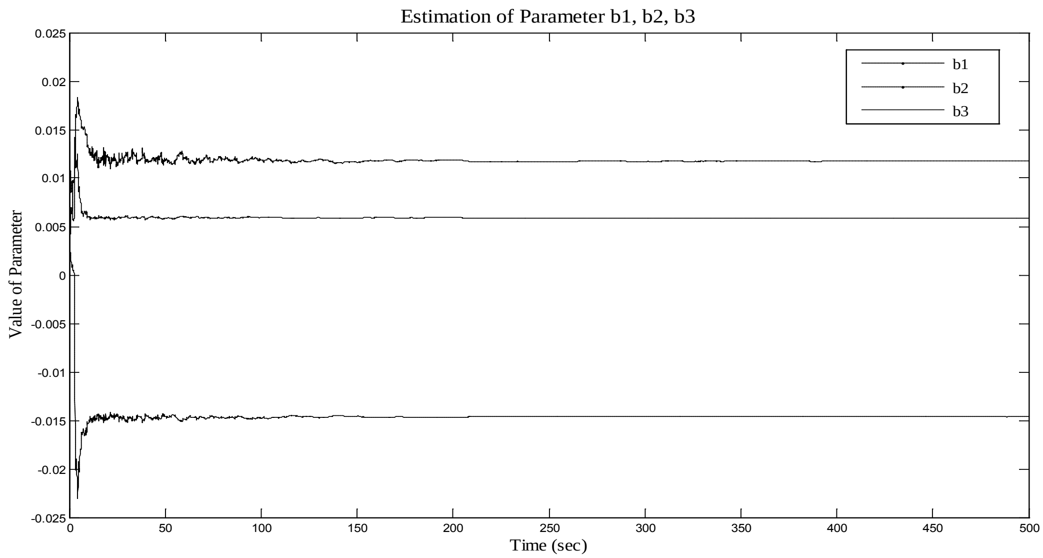

Figure 8. Estimated Parameters b_1,b_2,b_3

Pole placement design was performed on the EHA system using single closed loop pole at t_1 = -0.8. Figure 9 illustrates the tracking signal using conventional and self-tuning control strategy when the discrete-time model varies after 25 seconds. It shows that the self-tuning control strategy can easily adapt the changes occur in model parameter while fixed controller unable to follow the trajectory when the parameter in the system change. By using the discrete plant model estimated by recursive least square, the coefficients of $F(z^{-1})$ and $G(z^{-1})$ were calculated recursively for particular closed-poles by solving the Diaphontine equation. The resetting technique for forgetting factor and covariance matrix in recursive least square algorithm is implemented. By resetting its value when parameter changes occur enables the estimator to estimate again the variance of the previous estimates until the estimator reach the new parameter values.

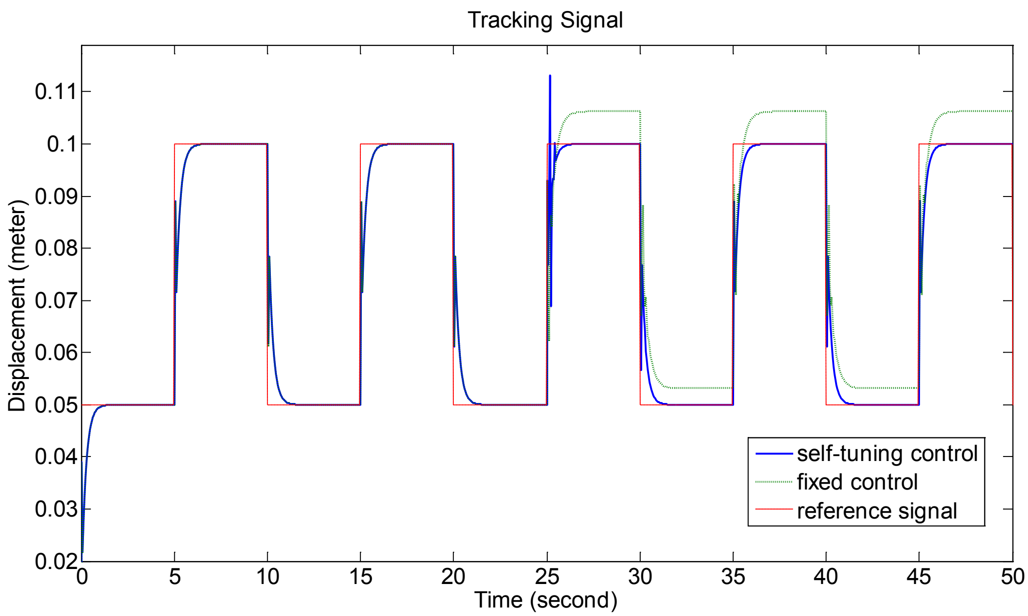

Figure 9. Tracking signal of self-tuning control

VI. CONCLUSIONS

In this paper, a complete study has been performed in the modeling using RLS method and designing the self-tuning controller. The self-tuning control strategy with covariance resetting technique has been utilized for position tracking control by integrating RLS with pole placement. As a conclusion, the proposed identification method and self-tuning controller are capable to handle wide range of system dynamics without knowledge of the actual system physics, thereby reducing the engineering effort required to develop the system's model.

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