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Developing an experiment to identify the dynamics of a DC servo motor based on a non-parametric model

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A B S T R A C T

System identification is one of the first tasks to address when solving an automatic control problem where the controlled object lacks parameters. The simple reason is that it is impossible to analyze or synthesize a system without a mathematical model to describe it. Therefore, the problem of kinematic identification has attracted significant attention from many scientists. These issues are studied in the course "System Dynamics Identification in Control Systems."

From this context, the research team proposes developing an experiment to identify the dynamics of a DC servo motor based on a non-parametric model. This paper applies a dynamics identification algorithm to develop a mathematical model for the controlled object, which is a small-power DC servo motor with missing parameters. The research product can be utilized in learning, research, and teaching the course "System Dynamics Identification in Control Systems."

Keywords: Identification, DC servo motor, experiment, mathematical model, Control Systems.

1. Introduction

Dynamic identification is the process of determining the mathematical model that represents the dynamics of a controlled object, based on experimental data of input and output signals from the actual system according to specific criteria.

Dynamic identification for a motor with missing parameters involves experimentally determining the mathematical model of the motor when certain parameters are absent by observing input and output signals. The identified mathematical model must have minimal error and ensure the highest accuracy compared to the actual motor.

To develop the mathematical model for the motor, two main methods can be employed: theoretical modeling and experimental modeling. Each method has its own advantages and limitations, and the choice of method depends on the specific requirements of the problem.

Theoretical modeling, also known as physical modeling, relies on fundamental physical and chemical laws to construct a mathematical model of the motor. This approach combines the motor's technical parameters to define differential or algebraic equations that describe its dynamics. Theoretical models are based on the physical and chemical relationships among the motor's internal quantities. However, theoretical modeling faces certain challenges: It often reflects only the dynamic characteristics of the motor, without accounting for factors such as the properties of measurement devices and actuators. It may fail to fully represent the motor's real-world operation. Determining accurate technical parameters from available device information can be difficult, reducing the precision and comprehensiveness of the model.

While theoretical modeling is useful for studying dynamic characteristics and designing control systems, it is less suitable for parameter identification when critical information about the motor is missing.

Experimental modeling, also known as the black-box or identification method, relies on experimental data to determine the mathematical model of a motor with missing parameters. This method begins with data collection on the motor's input and output signals through experiments. The mathematical model is then derived by analyzing the collected data to identify relationships between the input and output signals. The advantages of experimental modeling include: The ability to provide a relatively accurate mathematical model for the motor, especially when the model structure is known. Direct identification of model parameters based on experimental data, which enhances the model's ability to reflect the motor's real-world operation. However, the quality of the model depends heavily on the accuracy of the measuring equipment and the data collected. Noise during measurement can distort data and degrade the model's quality.

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In cases where the motor lacks critical parameters, experimental modeling becomes a valuable tool to compensate for missing information and improve the accuracy of the mathematical model. However, to achieve optimal results, it is essential to ensure precise measuring equipment and carefully process the data to minimize the effects of noise and measurement errors.

Dynamic identification of motors with missing parameters is essential because, in automatic control systems, the mathematical model of the object is the foundation for designing controllers. In many cases, theoretical models cannot fully describe the system's characteristics due to the complexity of industrial processes and the lack of information. Therefore, identification becomes a useful method to develop models for motors with missing parameters, which are then used for determining controller parameters.

Specifically, to determine the dynamic equations of a motor, the relationships between physical parameters such as the torque constant Km, back electromotive force constant Ke, armature inductance L, armature resistance R, moment of inertia J, and friction coefficient B must be considered. However, when a motor lacks information about parameters like Km, Ke, L, R, J, or B, experimental methods can be employed. This involves measuring the input voltage and the output angular displacement of the motor with missing parameters, and then using identification algorithms to derive the dynamic equations for the motor.

2. Dynamic Identification Process for Motors with Missing Parameters

The dynamic identification process for a controlled object is carried out in six steps, as illustrated in Figure 1.

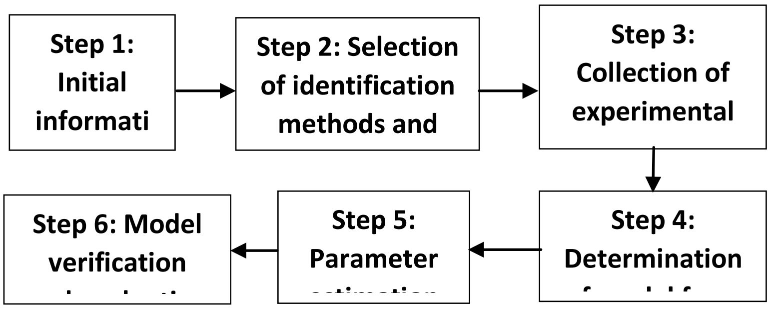

Fig.1. Dynamic Identification Process for a Controlled Object

The specific content of the steps in the identification process is as follows:

a) Step 1: Initial Information Extraction

In the first step of the dynamic identification process for a motor with missing parameters, collecting and analyzing initial information is crucial for preparing subsequent steps. This involves analyzing data to identify key input-output variables, boundary conditions, and related assumptions. Step 1 is a vital preparatory stage to gather the necessary data for constructing the mathematical model. Clearly defining the input-output variables, boundary conditions, and related assumptions provides a solid foundation for selecting the identification method, collecting experimental data, and determining the model structure in later steps.

In this study, the controlled object is assumed to be a small-power DC servo motor, specifically the Dynamixel XL-320 with missing parameters. The input variable is the applied voltage, and the output variable is the motor's angular displacement.

b) Step 2: Selection of Identification Methods and Algorithms

The choice of identification methods, estimation algorithms, and evaluation criteria is essential for building an accurate and appropriate dynamic model for a motor with missing parameters. In this study, a passive identification method and the least squares algorithm are selected to identify the dynamics of the small-power DC servo motor, Dynamixel XL-320, with missing parameters.

c) Step 3: Collection of Experimental Data for Each Input-Output Pair

In this step, experimental data is collected for the motor's input and output variables to construct the dynamic model. First, the input-output variable pairs to be measured, such as input voltage and output angular displacement, are determined. Experimental data is then collected, ensuring that the data accurately reflects the relationships between the variables. Additionally, data processing is conducted to eliminate inaccuracies or noise, ensuring the quality and reliability of the information used to construct the model.

In this study, experimental data for the input voltage and output angular displacement of the small-power DC servo motor, Dynamixel XL-320, with missing parameters, is collected.

d) Step 4: Determination of Model Form and Structure

In this step, the form and structure of the dynamic model are determined based on the intended application and the selected identification method. First, the decision is made whether the model should be linear or nonlinear, continuous or discrete, to ensure it meets specific application requirements. Next, hypotheses about the model structure are proposed, including factors such as the order of the numerator and denominator in the transfer function and whether the system has delays. This process helps accurately shape the model, facilitating parameter estimation and model performance evaluation.

In this study, the identification model is chosen to be a transfer function and state-space equation with an order less than 3 for the small-power DC servo motor, Dynamixel XL-320, with missing parameters. According to [5], the transfer function and state-space equation for a DC servo motor have the following form:

$$P(s) = \frac{K}{s((Js+b)(Ls+R)+K^2)} \quad (1)$$

$$\begin{cases} \dot{X} = A.X + B.U \\ Y = C.X \end{cases} \quad (2)$$

In which:

s is the Laplace operator

J is the moment of inertia of the rotor

b is the motor's viscous friction coefficient

K is the motor's torque constant

R is the armature resistance

L is the armature inductance

X is the state variable matrix

U is the control input matrix

Y is the output matrix

A is the system matrix

B is the control matrix

C is the output matrix

$$A = \begin{bmatrix} 0 & 1 & 0 \\ 0 & \frac{b}{J} & \frac{K}{J} \\ 0 & \frac{-K}{L} & \frac{-R}{L} \end{bmatrix}; \quad B = \begin{bmatrix} 0 \\ 0 \\ \frac{1}{L} \end{bmatrix}; \quad C = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}$$

e) Step 5: Parameter Estimation for the ModelIf the identification has been carried out for each sub-model, input-output channel, and stage of the process, the next step is to combine them into a comprehensive model. The tools used for this can be software such as Matlab, Maplc, or programming languages like C, Pascal, Delphi, etc.

In this study, the System Identification Toolbox (SIT) in Matlab is used to identify the dynamics of the small-power DC Servo motor, Dynamixel XL-320, with missing parameters.

g) Step 6: Model Verification and EvaluationAfter calculating the parameters and setting up the model, the next step is to verify the accuracy of the model. This is usually done by comparing the input-output data of the model with experimental input-output data. To ensure accurate verification, the real data used must be different from the data used for model identification. If the verification results do not meet the requirements, it is necessary to return to step 4 to adjust the model. If the results are unsatisfactory due to low-quality data, it is necessary to go back to step 3 to collect and process the data again.

In this study, the SIT toolbox automatically verifies and evaluates the model's suitability using the FIT (Fitting) criterion.

3. Practical Experiment: System Identification for a DC Servo Motor with Missing Parameters

3.1. Collecting Input and Output Data for the DC Servo Motor

Figure 2 illustrates the process of collecting data and identifying the system dynamics.

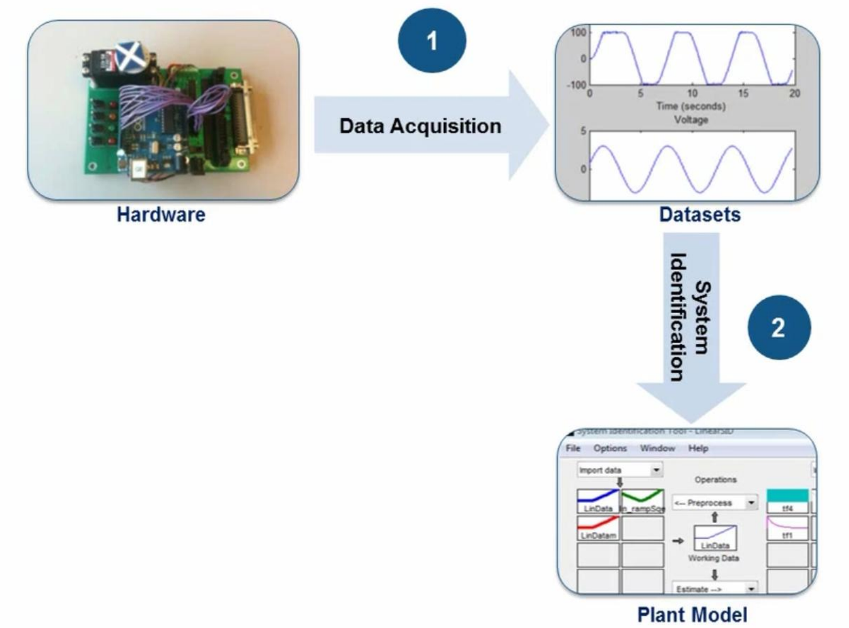

Fig.2. Data collection and system dynamics identification process

The process of collecting input and output data for the DC servo motor is carried out through the following steps:

Step 1: Write the Data Collection Program

The data collection program is designed to record the input and output parameters of the Dynamixel XL-320 DC Servo motor.

Input Data: This is the applied voltage value Uv, which is adjusted via a potentiometer. The voltage is proportional to the desired angle θv and is sent from the potentiometer to the Arduino Uno R3 board. The Arduino converts the voltage value into a PWM signal to control the DC servo motor to rotate to the desired angle.

Output Data: Measured by the integrated encoder in the Dynamixel XL-320 motor, it provides the actual angular displacement θr. This value is sent back to the Arduino via TTL communication.

The Arduino receives both the input signal θv and output signal θr, then converts them into proportional voltage values and sends them to the computer through the COM port.

Step 2: Connect the DC Servo Motor to the Arduino Board

Connect the power wire (red) to the 5V pin.

Connect the ground wire (black) to the GND pin.

Connect the signal wire (orange) to the digital pin D4.

Step 3: Connect the Arduino Board to the Computer

Use a USB cable to connect the Arduino to the computer. This acts as a communication channel between the Arduino and the computer, allowing data transmission via COM6 (or another port if configured).

Step 4: Connect the Potentiometer to the Arduino Board

The potentiometer is connected to one of the Arduino's analog input pins (e.g., A0). When the potentiometer's value is changed, the input voltage will vary, and the Arduino will record this value to adjust the motor's rotational angle.

Step 5: Run the Data Collection Program

After completing the hardware setup, run the data collection program written in Matlab. This program will begin collecting the input angle θv and the actual rotational angle θr of the motor from the COM port over a 10-second period.

Step 6: Convert Data into iddata Format

After collecting the data, the program will convert the input and output signals into the iddata format in Matlab. This data is then used for system identification.

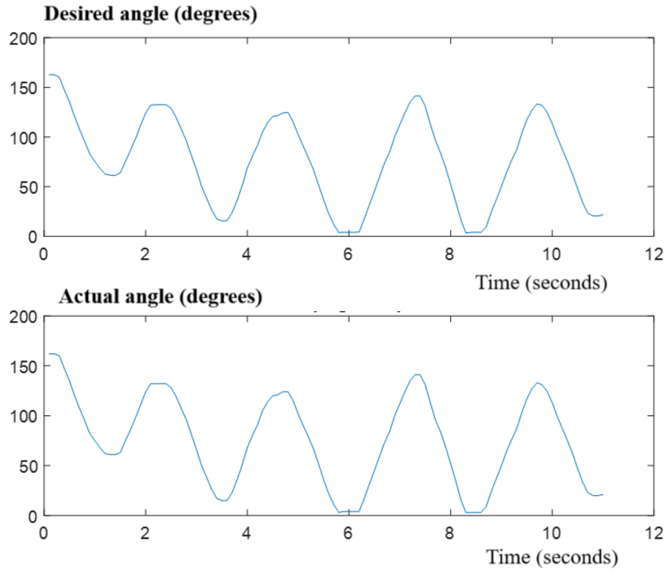

Fig.3. Input angle and actual rotational angle signals of the motor

3.2. System Identification for DC Servo Motor

After the data collection process, the result is the acquisition of data sets in the iddata format. These datasets are selected to be provided to the System Identification Toolbox to determine a model that is simple yet sufficient to accurately describe the system's dynamics. Below are two types of models chosen for the identification process: the transfer function model and the state-space model.

a) Identification using Transfer Function Model

Identification using the transfer function model involves estimating a linear dynamic model for the system in the form of a continuous transfer function. To perform this estimation, the number of poles and zeros needs to be determined. The System Identification Toolbox will automatically determine the poles and zeros to maximize the fit with the selected data sets.

Launch the system identification tool by running the command: >> ident

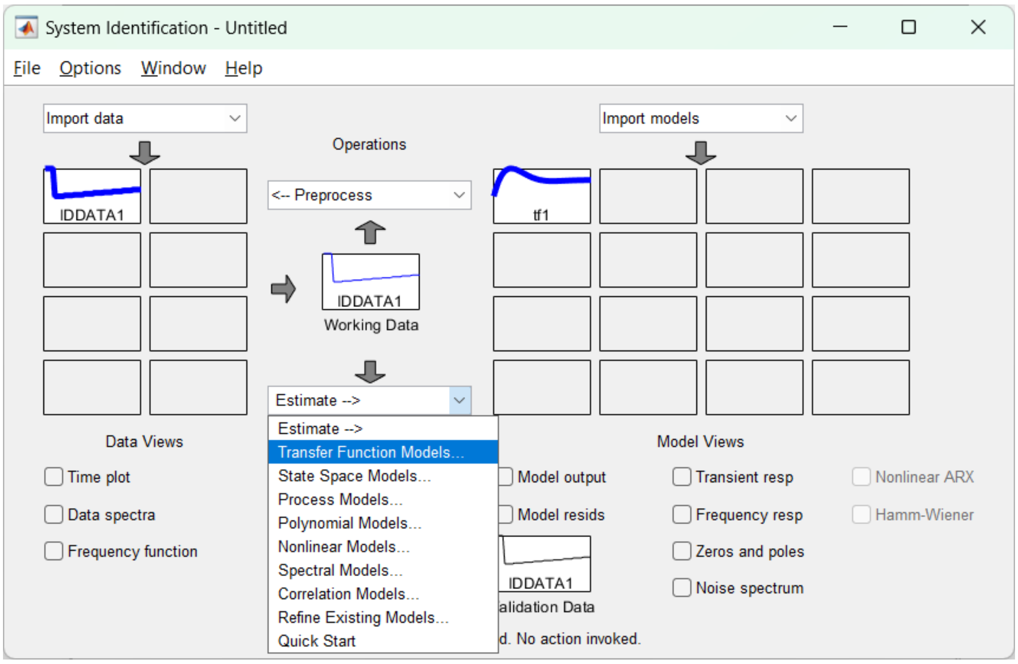

Fig.4. Selecting the transfer function model for identification

Import the datasets into the tool from the Workspace by using the "Import Data" dropdown menu. Figure 4 shows the system identification tool with the IDDATA1 dataset already imported.

- Case 1: Choosing 2 poles and 1 zero: The identified transfer function is tf1. This is a second-order continuous transfer function that represents the relationship between the input "Voltage" and the output "Angle." The transfer function has two poles and one zero.

$$tf1=\frac{-1389s+8,205\times10^4}{s^2+60,13s+2306}$$

Model Evaluation:

FIT = 80.7% is the goodness of fit between the experimental data and the output data from the identified model. This value does not meet the required criterion of FIT > 95%.

FPE = 47.34 is the error between the experimental data and the output data from the identified model. The smaller this value, the more accurate the model.

MSE = 46.22 is the mean squared error between the actual and predicted values from the model. The smaller the MSE value, the more accurate the model.

- Case 2: Choosing 2 poles and 0 zeros: The identified transfer function is tf2.

$$tf2=\frac{10}{0,01s^2+0,2s+1}$$

Model Evaluation:

FIT = 99.29% is the goodness of fit between the experimental data and the output data from the identified model. The larger this value, the more accurate the model. Therefore, the real model and the identified model have a better fit compared to the previous case.

FPE = 9.22 is the error between the experimental data and the output data from the identified model. The smaller this value, the more accurate the model. Hence, the identified model is more accurate than in the previous case.

MSE = 9.038 is the mean squared error between the actual and predicted values from the model. The smaller the MSE value, the more accurate the model. Thus, this identified model is more accurate than the previous case.

This result shows that the model has been optimized and fits the experimental data well.

b) State-Space Model Identification

The identified state-space model is ss1. This is a continuous-state model that represents the relationship between the input "Voltage" and the output "Angle."

dx/dt = A x(t) + B u(t) + K e(t)

y(t) = C x(t) + D u(t) + e(t)

A =

	x1	**x2**
x1	-17.89	-31.89
x2	14.24	6.093

B =

	Voltage
x1	-0.2034
x2	-0.992

C =

	x1	**x2**
Angle	406.6	46.94

D =

	Voltage
Angle	0

K =

	Angle
x1	0.301
x2	-0.4524

FIT = 98.58%. This value is very high, indicating that the model fits the experimental data very well.

FPE = 0.1661. This value is very small, indicating that the model is highly accurate.

MSE = 0.1621. This value is very small, indicating that the model has high accuracy.

This result shows that the continuous-state model has been optimized and fits the experimental data very well.

4. Conclusion

The paper presented the process of designing and constructing an experimental setup for dynamic modeling identification of a parameterless DC servo motor. The steps, from collecting the input and output data of the motor to performing dynamic identification based on transfer function and state-space models, were implemented in detail using Arduino Uno R3, Dynamixel XL-320 Servo Motor, and supporting tools like Arduino IDE and Matlab.

The process included Arduino programming, hardware connections, data collection, and dynamic identification, which were carried out systematically and efficiently. The results obtained were data sets in the iddata format, allowing system identification using two models: the transfer function model and the state-space model. Both models provided identification results with high FIT accuracy and small FPE and MSE errors, creating favorable conditions for designing controllers for the DC Servo motor.

The results have laid the foundation for conducting dynamic identification experiments for the DC servo motor, as well as advancing research for other types of parameterless motors.

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REFERENCES

Farzin Asadi, (2020), State-Space Control Systems: The Matlab/Simulink, Springer International Publishing.

Ogata, K., (2010), Modern Control Engineering, 5th Edition, Prentice Hall.

Khalil, H. K., (2002), Nonlinear Systems, 3rd Edition, Prentice Hall.

Franklin, G. F., Powell, J. D., & Emami-Naeini, A., (2015), Feedback Control of Dynamic Systems, 7th Edition, Pearson.

Nise, N. S., (2011), Control Systems Engineering, 6th Edition, Wiley.

Dorf, R. C., & Bishop, R. H., (2010), Modern Control Systems, 12th Edition, Pearson.

Ziegler, J. G., & Nichols, N. B., (1942), Optimum Settings for Automatic Controllers, Journal of Dynamic Systems, Measurement, and Control, 115(1), 220-222.

Seborg, D. E., Edgar, T. F., & Mellichamp, D. A., (2011), Process Dynamics and Control, 3rd Edition, Wiley.

Ljung, L., (1999), System Identification: Theory for the User, 2nd Edition, Prentice Hall.

Borraz-Sánchez, C., & Rodríguez, F. A., (2012), Matlab-based System Identification Toolbox for DC Motor Applications, Springer.