MASTER

Control relevant MIMO parametric identification of a 3DOF manipulator

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Abstract

This thesis addresses the problem of identification of a mechanical manipulator with the purpose of achieving a MIMO model for simulation as well as controller synthesis. In this thesis, first literature survey was carried out in order to find out what identification is most suitable for the project. The literature study concluded that the open loop state space methods are appropriate choice for this project. After choosing the appropriate identification method, the identification procedure was designed according to the specifications and limitations of the plant under study. In the next step the required software were implemented in order to connect the real plant to MATLAB and running the identification algorithms on MATLAB. Before performing the identification procedure for the real plant, the procedure was tested in simulation with a controlled and known model replacing the real plant. This way valuable insight on the identification procedure was obtained. This thesis was ended by achieving the model of the plant.

1 Introduction

Because of ever increasing controller performance specifications, there is always demand for increasing the performance of the controller of the mechanical modules. One way for improving the current design is to design a MIMO controller, as the cross talk between the three channels of the plant is one of the major contributors to controller error. Since for designing a MIMO controller an accurate MIMO model of the system is required, this thesis project is defined in order to achieve the MIMO model of the mechanical manipulator.

1.1 Problem statement

The problem addressed by this thesis can be formally stated as follows:

> *Achieve a MIMO parametric model of the plant, for the purpose of MIMO controller synthesis as well as simulation, and verification and quantifying the quality of the model*

This problem is addressed in the following steps:

Step 1: (Completion of) Design and implementation of a test setup for running experimental measurement on the plant.

Step 2: Literature study for the purpose of finding the best identification method for this project.

Step 3: Perform simulations.

Step 4: Perform experiments on the plant and estimate plant's model(s).

Step 5: Analyzing the model(s) quality generated by different methods and/or different settings and choosing a model as the final model of the system.

The rest of this document is structured as following: Section 2 reviews the time domain identification methods and establishes some criterion in order for choosing the suitable identification method. In addition, it covers the identification methodology and design decisions. Finally section 3 finishes this thesis by conclusion and recommendations.

2 System identification

This section presents the conventional system identification (SID) procedure (SID loop) and elaborates each step. Each step of the SIP loop requires some design decisions which shape the specific identification procedure designed for this project. This section addresses these design choices.

There are a few major steps in the identification procedure:

1. *Choosing the model structure*

   The model structure is the standard formulation of the state space models. These equations (the dimension of the matrices) represent a set of candidate models that the SID algorithm searches among them for the best fit.

2. *Experiment design in order to gather data*

   A set of input-output data is required as an input to the identification procedure. The data is often gathered by a specifically designed identification experiment. Since the data can potentially influence the quality of the model, the experiment design is an important factor for SID.

3. *Choosing a fitting criterion*

   The fitting criterion quantifies the quality of the model. It acts as a rule to determine the *best* model in the models set given by the model structure. The SID algorithm *tries* to optimize this criterion in order to achieve the best model.

4. *Calculating the model*

   Given the three aforementioned entities, one should calculate the model either using algebraic methods, or statistical methods.

5. *Validating the model*

   Regardless of how the model is generated, it is required to evaluate the quality of the resulted model. Although no model can represent the *true system*, yet it is possible to determine if the model is *good enough*.

6. *Repetition (if needed)*

   Depending on the validation result, the procedure may be repeated. At this point the designer should decide about the reason that caused the SID to fail. Whether the model structure was not close enough to the *true system*, the data set was not informative enough, or the fitting criterion was not appropriate, the designer should alter the SID procedure accordingly and repeat it.

These steps, as demonstrated in figure 1, are more or less the same for all identification methods described in previous chapter. As shown in figure 1, all these steps are initially influenced by the designer's knowledge about the system.

In the rest of this chapter each step of identification loop is elaborated considering that the state space is the method of choice for this project.

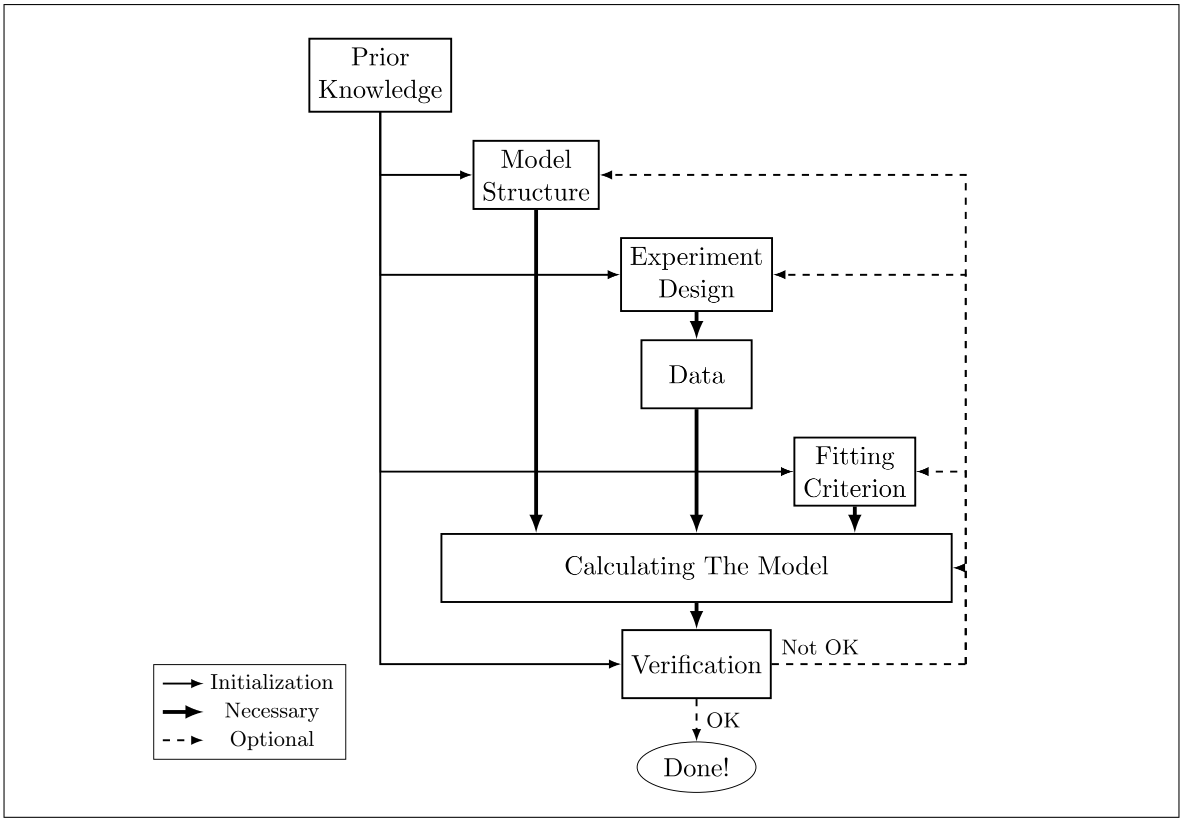

Figure 1: The system identification loop [1]

2.1 Model structure

The model structure greatly depends on the SID method. The following equation shows the general structure enforced by the state space based methods.

$$\begin{aligned} x(t+1) &= Ax(t) + Bu(t) + Kw_p(t) \\ y(t) &= Cx(t) + Du(t) + v_m(t) \end{aligned} \tag{1}$$

where $u(t) \in \mathbb{R}^m,\ x(t) \in \mathbb{R}^n,$ and $y(t) \in \mathbb{R}^l$ are the input, state, and output vectors respectively. The $w_p(t) \in \mathbb{R}^n,\ and\ v_m(t) \in \mathbb{R}^l$ are immeasurable input, process, and measurement noise. The matrices $A \in \mathbb{R}^{n\times n},\ B \in \mathbb{R}^{n\times m},\ C \in \mathbb{R}^{l\times n},$ and $D \in \mathbb{R}^{l\times m}$ are respectively, the system, input, output, and direct feedthrough matrices. They are together shaping the parameter matrix $\Theta = \left(\begin{smallmatrix} A & B \\ C & D \end{smallmatrix}\right)$.

The dimensions $n,\ m,$ and l represent the number of state variables, inputs, and outputs respectively. While the number of inputs and outputs are imposed by the system, the designer can change the number of state variables to influence the estimated model by the SID procedure. In other words, the order of the model can be modified. Prior knowledge about system plays a great role for specifying the model order.

It is know that for the plant under study the order of the system is in the scale 10^1 since there are limited (in order or 10^1) resonances in the transfer function of the plant. These observations suggest that it is possible to try different model orders (in range of $[10 \quad 100]$) to find the correct order of the model (by comparing the quality of generated model).

Table 1: Model structure decision

Comparison Criterion	**Educated guess**	**Dynamic model**
Effort required	$+$	$-$
Accuracy	$-/+$	$+$
overall	$+$	0

One other approach would be to build an accurate dynamic model of the plant and estimate the model order by linearizing the dynamic model. This method is not appropriate since (assuming that accurate methods exist) they require great deal of effort and time.

Table 1 summarizes the information presented in this section.

2.2 Experiment design

Experiment is the procedure of providing the input-output data set. The experiment design is the combinations of input signal design as well as determining the test setup topology, i.e. in input injection point, the measurement point, sampling time etc. The test setup topology is previously addressed and set to be an open loop design. The input design is associated with various properties, e.g. the spectrum $\Phi_u(\omega)$ of the input, the shape of the signal, etc. Different input signals trigger different dynamics of the system, hence result in different models. The output measurement is done with a fixed sample time T_s which is important for SID procedure. The available test setup has an upper limit of 2.5kHz for measured signals. Furthermore, the first resonance of the plant is at 250Hz, thus in order to have accurate model it is logical to measure upto 10 times the frequency, i.e. 2.5kHz. As a result, all the frequency range upto the limit imposed by the RCP setup is interesting for the identification.

2.2.1 Excitation signal design considerations

For designing the experiment there are a few objectives to consider. Namely the signal's Crest Factor (CF), persistence of excitation, and meeting the plant constraints.

Crest Factor It is possible to show that the covariance of the model is reversely proportional to the input signals power [2]:

$$\mathrm{Var}\big(G(\hat{\theta}_N)\big) \approx \frac{n}{N}\frac{\Phi_\delta(\omega)}{\Phi_u(\omega)} \tag{2}$$

where n is the model order, N is the number of data samples, and $\Phi_\delta(\omega)$ and $\Phi_u(\omega)$ are the output noise and input signal power spectrum. Here, output noise is the effect of all the noises present in the systems added to the output.

It suggests that, regardless of the identification method, the higher the power spectrum of the input signal is, the better the variance of the model would be. In practice, as will be elaborated later, the amplitude of the signal is limited. Thus, in order to indicate the quality of the input power it is possible to use the crest factor with the following definition [3]:

$$CF(u) = \frac{\|u\|_\infty}{\mathrm{RMS}(u)} \tag{3}$$

The closer the CF to one, the closest the signal power to its theoretical maximum, and thus the better the signal.

Persistence of excitation Thinking about the transfer function of the plant, intuitively, the model cannot be trusted in the regions that there do not exist any frequency component in the input signal. In other worlds, the excitation signal should be informative in all frequencies. Formally stating, the signal $u(t)$ is persistently exciting of order of n if, for all proper and rational filters $M_n(q)$ of order n the following holds [1]

$$\left|M_n(e^{i\omega})\right|^2 \Phi_u(\omega) = 0 \Rightarrow M_n(e^{i\omega}) = 0 \tag{4}$$

This equation states that if, the output signal's spectrum is zero at a certain frequency, then it implies that the filter equals zero at that frequency. The input signal should be persistently exciting in order to achieve a correct model. Otherwise, the input will result to a biased model (w.r.t. the *true* model).

Meeting constraints of the plant In practice there are always limitations to the actuators range which constraints the input amplitude. Furthermore, there are security considerations to regard. The exist constraints not only on the input signal, but also on the position of the plant, velocity and acceleration. The following equations formally define the input design constraints:

$$\begin{array}{rcl} T_a\ u(t) & \leq & L^u_{amp} \\ T_a\ \dot{u}(t) & \leq & L^u_{vel} \\ T_a\ \ddot{u}(t) & \leq & L^u_{acc} \end{array} \tag{5}$$

$$\begin{array}{rcl} T_s\ y(t) & \leq & L^y_{amp} \\ T_s\ \dot{y}(t) & \leq & L^y_{vel} \\ T_s\ \ddot{y}(t) & \leq & L^y_{acc} \end{array} \Rightarrow \begin{array}{rcl} T_s\ G(q)u(t) & \leq & L^y_{amp} \\ T_s\ \frac{d}{dt}(G(q)u(t)) & \leq & L^y_{vel} \\ T_s\ \frac{d^2}{dt^2}(G(q)u(t)) & \leq & L^y_{acc} \end{array} \tag{6}$$

where T_a and T_s are constant transmission matrices, and $L^{\mathrm{x}}_{\mathrm{xxx}}$ is the limitations on either input or output's amplitude, velocity, or acceleration. The designed input must be such that these constraints are not violated.

2.2.2 Excitation signal shape

There are a few signals commonly used for identification purposes. Namely, noise signal, PRBS*, and multisine. In this subsection the properties of these three signals is compared w.r.t. the criteria introduced in previous subsection, and the best fitting signal for this project is chosen.

Noise One possible input signal is White noise. The advantage of using noise is that is an easy way to make sure that all possible frequencies are excited. In other worlds, the noise signal is persistently exciting for all orders. Noise has a draw back specific for this project. Since noise signal is randomly distributed, there is no way to guaranty the safety requirements of velocity and acceleration.

PRBS Pseudo-Random Binary Signal (PRBS) is a periodic sequence of a binary signal, meaning that it can only hold two values, namely the maximum and minimum input values. It is generated by the difference equation

$$u(t) = \mathrm{rem}(A(q)u(t), 2) = \mathrm{rem}(a_1 u(t-1) + \cdots + a_n u(t-n), 2), \tag{7}$$

*Pseudo-Random Binary Signal

Table 2: Excitation signals comparison

Comparison Criterion	**Noise**	**PRBS**	**Multisine**
CF	$+$	$+$	$+$
Persistence of excitation	$+$	$+$	$+$
Meeting the plant constraints	$-$	$-$	$+$
overall	$+$	$+$	$+++$

where $\mathrm{rem}(X, 2)$ is the remainder of X divided by 2 function. It is possible to show that PRBS signal with the period M is persistently exciting of order $M - 1$ [1]. Regarding the CF, theoretically, it is possible to make a PRBS signal with unity CF (when the signal only holds the maximum value). In practice, although it is not possible to reach unity for CF, it is possible to reach an acceptable CF. However, PRBS has a draw back considering the requirements of this project, i.e. the constraints of the plant. PRBS cannot meet the requirements of velocity and acceleration limits, since it has a pulse shape and thus its velocity is very large on the pulse edges.

Multisine A multisine (or multitone) signal is simply summation of multiple sinusoidal (or cosinusoidal) signals:

$$u(t) = \sum_{k=1}^{N} A_i \cos(2\pi f_i t + \varphi_i) \tag{8}$$

It is relatively straight forward to show that a multisine signal is persistently exciting of order of $2N$ [1]. By modifying the phase of each sinusoidal is is possible to change the CF and minimize it without changing the spectral properties of the signal. There also exist some efficient methods for minimizing CF of multisine signals [3, 4, 5]. As for the constrains of the plant, since the derivative of a sinusoidal is also a sinusoidal, it is possible to limit the velocity and acceleration of the signal by limiting the amplitude of each sinusoidal. Hence, it is possible to design a multisine signal that can satisfy the limitations of the plant.

Table 2 summarizes the information presented in this subsection.

2.3 Fitting criterion

The fitting criterion, indicates the optimality of the resulted model. Traditionally, in classical methods the model output error (prediction error) is chosen as the fitting criterion. Meaning that, the model which results in an output closer to the output of the plant would be considered a *better* model. As an alternative, the complexity of the model can be chosen as the criterion. The higher the model order, the longer it takes to compute the parameters. Furthermore, higher order models require more data samples. In case the order of the plant is too large (comparable with the number of samples), then it makes sense to look for models that can predict the plant with smaller number of parameters. Moreover, a model with a very large order is not suitable for controller synthesis.

As for the first fitting criteria, due to state space formulation of the problem, it is not as intuitive as in classical methods. Similarly to the classical methods the optimal prediction is targeted, though the formulation is not as straight forward as in classical methods.

Given the model in equation 1 with the block Hankel matrices of $U_{0|i}$ and $Y_{0|i}$ and the state vector of $X_i = \begin{pmatrix} x(i) & x(i+1) & \cdots & x(N+i-1) \end{pmatrix}$ the optimal parameter estimate would be the least square solution of [6]:

$$\hat{\Theta} = \arg\min_{\Theta} \left\| \begin{pmatrix} X_{i+1} \\ Y_{i|i} \end{pmatrix} - \Theta \begin{pmatrix} X_i \\ U_{i|i} \end{pmatrix} \right\|. \tag{9}$$

This equation states that the least square solution of the equality $\begin{pmatrix} X_{i+1} \\ Y_{i|i} \end{pmatrix} = \Theta \begin{pmatrix} X_i \\ U_{i|i} \end{pmatrix}$ is the estimated model. This equation, only indirectly, implies small prediction error.

3 Conclusions and recommendations

This thesis addressed the identification of a mechanical manipulator. After studying different time domain identifications, the open loop state space methods were chosen as the identification method for the project. For identification procedure a number of design choices were made, such as excitation input which was decided to be multisine signal, or the the validation criterion which was chosen to be both quality of the residuals and the model order, as to be able to use the model for both simulation purposes and control synthesis.

The designed identification procedure resulted into a model which was capable of capturing the dynamics of the plant in the whole available frequency bandwidth with an acceptable accuracy. The final model has an order of 100, and was generated by applying PEM algorithm to the output of MOESP method.

As a recommendation, for increasing the quality of the model specially in the low frequency range, one can increase the SNR even more, and run the experiments for a longer time span. Yet, the security of the plant should be considered if such approach is going to be used. The results of this thesis are appropriate for simulation purposes as they can estimate the output of the plant with an average error of a few tens of nm/nrad. It is also worth mentioning that the validation error is mostly due to error at the resonance frequencies, and the performance of the model is much better in the low frequency ranges.

Furthermore, the model can also effectively be used for controller synthesis as it has captured the dynamics of the plant in the whole available frequency range.

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