TOWARDS A MULTIVARIABLE AUTO-TUNER

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Abstract: An MIMO auto-tuning method is develop that can be used by a layman of control. The method is based on MIMO identification and robust control design. The identification part delivers process model and model error bounds. The controller design block performs control synthesis, simulation and robust analysis. All steps can be done automatically. The parameters the user needs to enter are minimal and easy to understand and to obtain. The developed scheme is applied to a high-precision wafer stage motion control using simulations. The step tracking performance is optimized using the method and it is compared with a multi-loop PID controller.

Keywords: Multivariable systems, identification, error bound, robust control, servo systems.

1. INTRUDUCTION

Most controllers in industrial and engineering systems are still of the classical PID type. However, due to worldwide competition, control performance requirements become ever increasing and there is a growing need for advanced controllers. Often, the high cost of design and maintenance and the high technological skills necessary for MIMO control synthesis and implementation are viewed as main barriers for their applications.

The purpose of this work is to develop a MIMO tuning method that can be easily used by non-experts in control. The basic idea is to combine a MIMO identification method and a robust control design method so as to perform all tuning tasks and user choices in an automated way. In identification, nominal model and error bounds will be computed from the data. Based on the model and error bounds, a controller will be designed using robust control theory. Its performance and robustness will be evaluated by simulation studies and by a robustness analysis.

The outline of the paper is as follows. In Section 2 the identification method is presented. Section 3 discusses the controller design on the basis of identified models. A case study is given in Section 4 where the developed methodology is applied to a high-precision wafer stage motion control. Section 5 contains conclusions and perspectives.

2. AN ASYMPTOTIC METHOD OF IDENTIFICATION

An asymptotic method (ASYM) of identification was developed for the purpose of linear robust control; see Zhu (1990). In recent years, this method has been successfully applied in MPC control of refining and petrochemical processes (Zhu, 2001).

Given a multivariable process with m inputs and p outputs. Denote the data sequence that is collected from an identification test as

$$Z^N := \{u(1), y(1), u(2), y(2), ..., u(N), y(N)\} \qquad (1)$$

where $u(t)$ is an m-dimensional input vector, $y(t)$ is a p-dimensional output vector and N is the number of samples. We assume that the data is generated by a linear discrete-time process

$$y(t) = G^o(z^{-1})u(t) + H^o(z^{-1})e(t) \qquad (2)$$

where z^{-1} is the unit time delay operator. Here $H^o(z^{-1})e(t)$ represents the unmeasured disturbances acting on the outputs, and $e(t)$ is a p-dimensional white noise process.

The to-be-identified model is assumed to have the same structure as in (2):

$$y(t) = G(z^{-1})u(t) + H(z^{-1})e(t) \qquad (3)$$

Here, both $G(z^{-1})$ and $H(z^{-1})$ are parameterized in matrix fraction description (MFD) form with diagonal denominator matrices; see Zhu (2001) for details. The model parameters are obtained by minimizing the prediction error cost function; see Ljung (1985).

The frequency response of the process and of the model are denoted as

$$T^o(e^{i\omega}) := col[G^o(e^{i\omega}), H^o(e^{i\omega})]$$

$$\hat{T}^n(e^{i\omega}) := col[\hat{G}^n(e^{i\omega}), \hat{H}^n(e^{i\omega})]$$

where n is the degree of polynomials of the model, and $col(.)$ is the column stacking operator.

2.1 Asymptotic properties of the prediction error method

Under certain conditions of the test signal and model order, it can be shown that (Ljung, 1986 and Zhu, 1989)

- $\hat{T}^n(e^{i\omega}) \rightarrow T^o(e^{i\omega})$ as $N \rightarrow \infty$ (4)
- The errors of $\hat{T}^n(e^{i\omega})$ follow a Gaussian distribution, with covariance

$$\mathrm{cov}[\hat{T}^n(e^{iw}) \approx \frac{n}{N}\Phi^{-T}(\omega) \otimes \Phi_v(\omega) \qquad (5)$$

where $v = H(z^{-1})e$ and $\Phi(\omega)$ is the spectrum of inputs and prediction error residual $col[u^T(t), \xi^T(t)]$, $\Phi_v(\omega)$ is the spectrum matrix of unmeasured disturbances, $\otimes$ denotes the Kronecker product and T denotes transpose. The theory holds for the general case of closed-loop test.

2.2 The ASYM procedure

1) Optimal test signal design

For an open loop test, the optimal test signal is designed to minimise the sum of the squares of the simulation error. The spectra of the test signals are based on an equation which can be derived from (2.6). For a closed-loop test, in a SISO case, an approximate optimal spectrum formula of the test signal at the setpoint r of the closed-loop system (see Figure 3.1) can be derived. See Zhu, (2001). The spectra of the test signals can be realised by GBN (generalised binary noise) signals or filtered white noises.

2) Parameter Estimation

a) Estimate a high order ARX model

$$\hat{A}^n(z^{-1})y(t) = \hat{B}^n(z^{-1})u(t) + \hat{e}(t) \qquad (6)$$

where $\hat{A}^n(z^{-1})$ and $\hat{B}^n(z^{-1})$ are polynomial matrices, of degree n polynomials.

b) Perform frequency weighted model reduction

The variance of model (6) is high due to its high order. One can reduce the variance by perform a model reduction. Using the asymptotic result of (4) and (5), one can show that the asymptotic negative log-likelihood function for the reduced process model is given by (Wahlberg, 1989).

$$\sum_{i=1}^{p}\sum_{j=1}^{m}\int_{\omega_1}^{\omega_2} |\{|\hat{G}_{ij}^n(\omega) - \hat{G}_{ij}(\omega)|^2 \frac{1}{[\Phi^{-1}(\omega)]_{jj}\Phi_{v_i}(\omega)}\}|\,\mathrm{d}\omega \qquad (7)$$

The reduced model $\hat{G}(z^{-1})$ is thus calculated by minimizing (2.7) for a fixed order. The reduced model is converted to diagonal Box-Jenkins form.

3) Order selection

The best order of the reduced model is determined using a frequency domain criterion ASYC. Let $[\omega_1, \omega_2]$ define the frequency band that is important for the control application, the asymptotic criterion (ASYC) is given by:

$$\sum_{i=1}^{p}\sum_{j=1}^{m}\int_{\omega_1}^{\omega_2} |[|\hat{G}_{ij}^n(\omega) - \hat{G}_{ij}(\omega)|^2 - \frac{n}{N}[\Phi^{-1}(\omega)]_{jj}\Phi_{v_i}(\omega)]|\,\mathrm{d}\omega \qquad (8)$$

4) Error bound matrix

According to the result (4) and (5), a 3σ bound can be derived for the high order model as follows:

$$\left|G_{ij}^o(e^{i\omega}) - \hat{G}_{ij}^n(e^{i\omega})\right| \le 3\sqrt{\frac{n}{N}[\Phi^{-1}(\omega)]_{jj}\Phi_{v_i}(\omega)} \quad \text{w.p. } 99.9\% \qquad (9)$$

We will also use this bound for the reduced model because the model reduction will in general improve model quality. If the controller is linear and time-invariant, the upper bound (9) can readily be used in robust stability and performance analysis. The ASYM method as described here can be automated (Zhu, 2000) and is therefore user friendly.

3. ROBUST CONTROL DESIGN BASED ON IDENTIFICATION

3.1. Robust stabilization of uncertain systems

Considering the additive error structure

$$G^o = G + \Delta \qquad (10)$$

where G is the nominal model, G^o is the true or perturbed model and Δ is the additive perturbation.
Consider the feedback configuration of Figure 1 and assume that the controller C stabilizes the system when $\Delta = 0$.

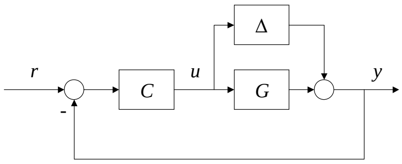

Figure 1. Feedback control of uncertain system

A robustness result of (Morari and Zafiriou, 1989) then states that

C stabilizes $G^o = G + \Delta$ if and only if

$$\left\| C(I+GC)^{-1} \right\|_\infty \|\Delta\|_\infty < 1 \cdot \qquad (11)$$

Let $\overline{\Delta}$ be the frequency dependent matrix whose *ij*th entry is the right hand side of (9). Then (Zhu, 1990) $\|\Delta\|_\infty \le \|\overline{\Delta}\|_\infty$.

Based on the robust stability condition (11), we can derive the robust stability condition using this bound:

C stabilizes $G^o = G + \Delta$ with probability greater than 99.9% if

$$\left\| C(I+GC)^{-1} \right\|_\infty \|\overline{\Delta}\|_\infty < 1 \cdot \qquad (12)$$

This robust stability condition comes with a probability because the upper bound is a soft bound. From (12) it follows that one can improve the stability of the system by

1) Reducing the control sensitivity $C(I+GC)^{-1}$.

2) Reduce the norm of $\overline{\Delta}$ by modifying the identification test through changes of signal amplitudes, signal spectra and test time; see (9).

In order to obtain high control performance and robust stability, one should design the identification test so that the upper bound $\overline{\Delta}$ is sufficiently small. On the other hand, if it is too costly to further reduce this bound, one needs to detune the controller. The upper bound (9) and the robust stability condition (12) can be shown graphically so as to provide quantitative information for both the identification test design and the controller design.

3.2 General problem of robust control

For solving the robust control problem an augmented plant is constructed (see Figure 2) that contains not only the process model but also a number of dynamic filters whose frequency characteristics capture all a priori information on noise signals, uncertainties and performance specifications and trade-offs that are relevant for the synthesis of an H_∞ optimal controller.

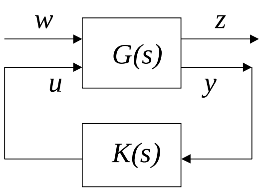

Figure 2 Augmented Plant

All exogenous inputs are collected in w which are arbitrary square integrable signals. Controlled outputs are collected in z. The output y contains the measured signals that can be used as inputs for the controller K. Its output u functions as the controller input, applied to the augmented system with transfer function $G(s)$. The augmented plant can be partitioned as:

$$\begin{pmatrix} z \\ y \end{pmatrix} = \begin{pmatrix} G_{11} & G_{12} \\ G_{21} & G_{22} \end{pmatrix} \begin{pmatrix} w \\ u \end{pmatrix} \qquad (13)$$

$$u = Ky \qquad (14)$$

where K denotes the controller. The closed loop system is obtained by eliminating u and y and is given by the linear fractional transformation (LFT) as

$$z = \left[G_{11} = G_{12} K (I - G_{22} K)^{-1} G_{21} \right] w = M(K) w \qquad (15)$$

The controller is designed so as to obtain a stable closed loop system for which

$$\sup_{w \in L_2} \frac{\|z\|_2}{\|w\|_2} = \|M(K)\|_\infty \qquad (16)$$

is minimal.

3.3 MIMO Auto-tuner: from identification to control

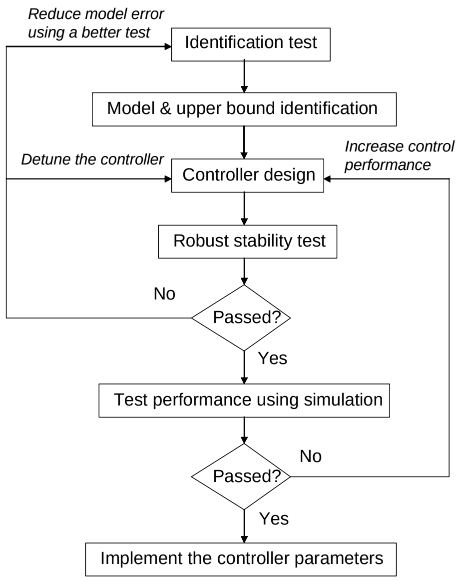

Figure 3. Procedures of the MIMO auto-tuner

The MIMO auto-tuner scheme amounts to combining the above identification and robust control algorithms. The design procedure is shown in Figure 3.

4. APPLICATION TO A WAFER STAGE MOTION CONTROL

4.1. Introduction

This system has been studied in van de Wal et.al. (2001). Wafer scanners are opto-mechanical machines for producing integrated circuits (ICs) on a silicon wafer, using a photolithographic process. The wafer stage is one of the main components of a wafer scanner. This is an electromechanical servo system that positions the wafer (200-300mm diameter) with respect to the imaging optics. The wafer stage largely determines the throughput (80-100 wafers/h; 80-200 ICs/wafer) and the accuracy of the products and is subject to strict performance requirements. Normal scan speeds and accelerations are 0.5 m/s and 10 m/s^2, respectively. The positioning accuracy is in terms of nanometers and micro radians.

In today's industrial motion control applications, multi-loop SISO (diagonal) controllers are still the most widespread for controlling MIMO plants. But the performance requirements for wafer stages are ever becoming tighter, due to Moore's Law. Thereby the performance of conventional controllers may one day become insufficient and MIMO controller will become necessary. Wafer stages are controlled in multiple motion degrees-of–freedom (DOFs), but one cannot avoid the interaction of the various DOFs. This becomes a major performance-limiting factor with multi-loop SISO PID controllers. MIMO control can be used to deal with plant interaction.

The wafer stage has six motion DOFs (Degrees of Freedom): Three translations (x,y and z) and three rotations (Rx, Ry and Rz where the subscript refers to the rotation axis). See Figure 4. Among the six DOFs to be controlled, only y/Rx/z are subject to MIMO controller design. These DOFs are especially critical for performance, since in normal operation mode the scans are in the y-direction and the disturbances in the Rx- and z- directions are the dominant ones. The other DOFs (x/Rz/Ry) are controlled by PID controllers with a low bandwidth. In this case the interaction between x/Rz/Ry on the one hand and y/Rx/z on the other hand can be neglected and y/Rx/z can be considered as an isolated subsystem. So, y/Rx/z can be considered as a 3×3 isolated subsystem for which an independent MIMO controller design is justified.

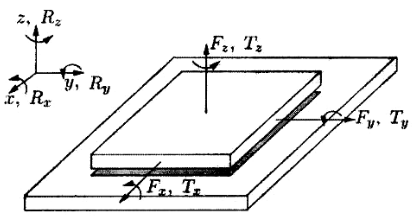

Figure 4 Schematic view of a wafer stage

The wafer stage must follow reference trajectories for y/ Rx/z (starting and ending at standstill), while x/Rz/Ry must be kept at zero. The y-motion is in the order of 10^{-1}m, while the Rx- and z-displacements are in the order of 10^{-4} rad and 10^{-6} m.

In this section we will present a MIMO tuning method based on H_∞ control that can be easily used by a non-control expert and we will demonstrate the practical feasibility of the design procedure by applying it to an identified model of the wafer stage.

It is known that the given servo system has double integrators which is unstable. This kind of unstable dynamics is difficult to identify due to numerical instability. While leaving the identification of double integrator for future research, we will solve, or more precisely, avoid the problem using a two loop control scheme as explained in the next section.

4.2 A two-loop scheme for identification and control

For an unstable or nearly unstable process, an open loop identification test is not permitted and closed-loop test will be used. Normal approach is to identify the original open loop process and design a new controller. Here we will use a so called two-loop scheme that can avoid the identification of the original unstable model.

Step 1, perform a closed-loop test using a stabilizing controller C_1; see Figure 5. Identify a model of the closed-loop system $PC_1/(1+PC_1)$.

Step 2, design the second loop controller C_2 for the closed loop system $PC_1/(1+PC_1)$ based on its model, in order to improve or to optimize the performance of the system. See Figure 6.

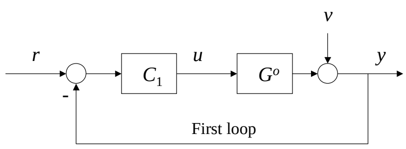

Figure 5. Identification of the first loop system

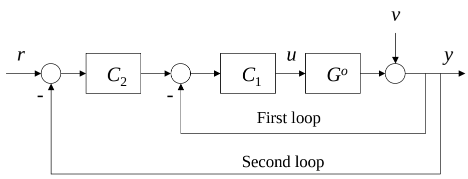

Figure 6. Design of the second loop controller for the closed loop

The scheme was proposed in Zhu (1990). However, an important question needs to be answered: Does the system loose the optimality, in other words, can the optimal controller for the process be realized by the two-loop structure? The answer is that if the first loop controller C_1 is proper and stable, then the optimal controller can be realised using the two-loop scheme; see Vidyasagar (1985). Note that the MIMO auto-tuner is not dependent on the two-loop scheme. We use it here in order to avoid the identification of the double integrator system.

4.3 Identification of the plant (first loop)

An identified model of the wafer stage is used as the "real process". The local dynamics of the wafer stage strongly depends upon the position with respect to the imaging optics. The identified plant model at the center position is used as the “real plant” in the study. There exists a controller C_1 that consists of three PID controllers. The PID controllers have been designed independently, based on the three diagonal entries of the identified models. This controller was designed for disturbance rejection.

In the previous section we have mentioned that the controller C_1 must be stable and proper for the optimality of the two-loop scheme. A PID controller is not stable because of its integrator. In order to meet the optimality condition we will replace the integrator by a first order transfer function with a pole near zero. Then the closed-loop system using the stable “PID” is tested (simulated) using a test signal at the setpoint of the system. Three low-pass filtered GBN (generalized binary noise) signals are used as test signals. To make the simulation more realistic, 3% unmeasured noise signals are added at the outputs.

The simulation is done in continuous time, and the sample frequency for model identification is 8Khz. The identification test time is 1.5 second. The whole identification process is automatic. The time needed for model identification is 1 to 2 seconds for using a modern PC. The results of identified model are shown in Figures 7 and 8. The identified model of the first loop system is stable and it has 61 states. Model reduction is used to reduce the order to 25.

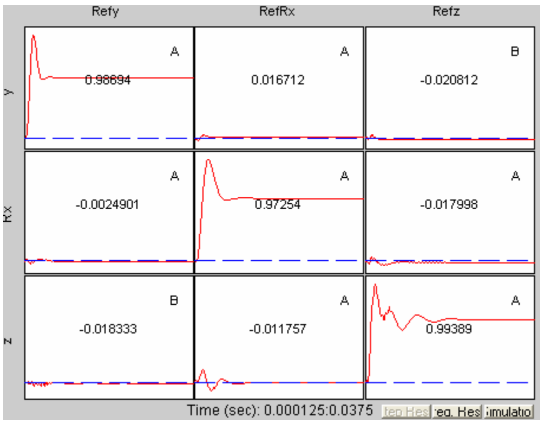

Figure 7. Step response of the model

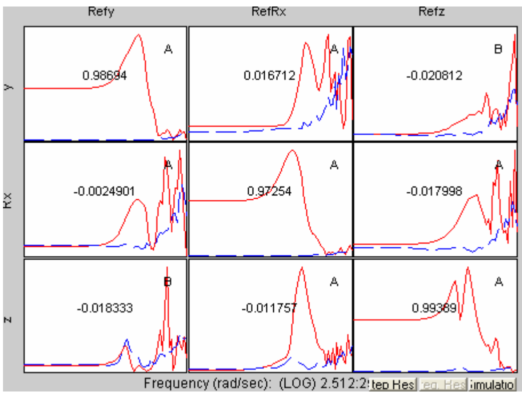

Figure 8. Frequency response of the model. Red/solid line is the frequency response, blue/dashed line is the upper bound

4.4 Controller design (second loop)

Control Objective

Normal motion control requirements are setpoint tracking and/or disturbance reduction. To demonstrate the MIMO auto-tuner, the control goal is set as good step tracking. It should be clear that if the MIMO auto-tuner can work for step tracking, it could also work for disturbance reduction or tracking/disturbance reduction by modify weighting functions.

Using three first order filters with unit gain specifies the step tracking property of the controlled system. Filter time constants τ_1, τ_2 and τ_3 are used to specify the tracking speeds of y, R_x and z respectively. The interaction between the three coordinates should be minimized. These specifications can be realised by defining the so-called reference matrix D_{ref} :

$$D_{ref} = \begin{bmatrix} \frac{1}{\tau_1 s+1} & 0 & 0 \\ 0 & \frac{1}{\tau_2 s+1} & 0 \\ 0 & 0 & \frac{1}{\tau_3 s+1} \end{bmatrix} \tag{17}$$

and design a controller C such that closed loop system behaves like Dref in some sense. Mathematically, one can minimizes the H_∞ norm of the error between the closed loop system and D_{ref} :

$$\left\| PC(I+PC)^{-1} - D_{ref} \right\|_\infty \tag{18}$$

This is also called model-matching problem in control theory. The entries of the controller design program are the three time constants τ_1, τ_2 and τ_3 which are easy to understand by the non-expert user. Matlab’s LMI toolbox is used for the H_∞ controller synthesis. The augmented plant is a system with 31 states, 3 inputs and 3 outputs.

Output weighting

The designed controller without using a proper output weighting had steady-state errors for step references. An output weighting filter is used to introduce integral actions in the controller. After several experiments the output filter is determined as following:

$$W = \begin{bmatrix} \frac{10}{s+0.001} & 0 & 0 \\ 0 & \frac{10}{s+0.001} & 0 \\ 0 & 0 & \frac{10}{s+0.001} \end{bmatrix}$$

A controller has been designed for the following tracking speed: τ_1 = 0.0003 sec, τ_2 = 0.0007 sec, τ_3 = 0.0007 sec.

Robust stability test

The left hand side of robust stability criterion (12) is computed using the identified model of the first loop, the upper bound and the obtained controller. The maximum value is about 0.1, which means the designed system is robustly stable. See Figure 9.

Controller performance: step tracking

Then the controller is applied to the “real plant” (the first loop system) and its tracking performance is compared to that of a “best” multiple PID controller. The system outputs are shown in Figures 10. One can see that the H∞ controller performs much better than the multi-loop PID controller: the overshoot of the H∞ controller is over 50% smaller; its response time 20 to 30% shorter; and there is less interaction between the three coordinates. The control action with the H∞ controller is a little bit stronger (not shown), which is not a problem for servo control.

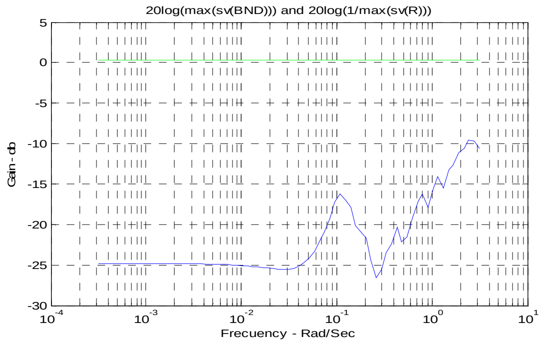

Figure 9. Robust stability test

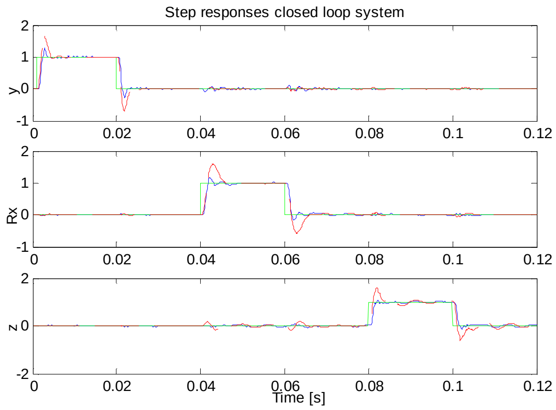

Figure 10. Step response, blue/solid: H_∞ controller, red/dashed: the best PID controller

The same design can be used if the control requirements are tracking and/or noise reduction. The MIMO auto-tuner is a very low cost solution for the wafer stage control: The identification test can be completed in 1 to 2 seconds; the model and error bound are obtained in another 1 or 2 seconds, while the controller is synthesized in a few minutes, including a robustness test and the simulations.

5. CONCLUSIONS AND PERSPECTIVES

There is a growing need for advanced MIMO controllers. The main problem in applying MIMO controllers is the difficulty in model building and controller development/maintenance. A possible solution to the problem is an MIMO auto-tuner that can be used by a layman of control. The MIMO auto-tuner developed in this work is based on automated identification and automated robust controller design/analysis. We have demonstrated the use of the MIMO auto-tuner on an industrial wafer stage (model). A MIMO robust controller can be developed in a matter of minutes and the control performance is increased considerably when compared to the popular multi-loop PID controllers.

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