Model Reference Adaptive Control of a Gantry Crane Scale Model

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A new method of "reference model decomposition" as an extension of model reference adaptive control is presented. The decomposition method can be regarded as a way of including knowledge about the structure and parameters of "unmodeled" dynamics in the adaptive system, making it possible to choose a lower order controller which is only equipped for the "nominal" process part.

To illustrate the decomposition method, an adaptive controller for a scale model of a gantry crane is presented. Simplifying and linearizing the mathematical equations describing the crane yields a fourth order model, of which the dynamics of the load swing take two. A standard adaptive control algorithm needs eight parameters, which in practice yields unacceptable behavior. The decomposition method allows the use of only two adjustable parameters, and real-time experiments show practical results obtained with the method.

Introduction

Recently, control of flexible structures has been a subject of increasing interest in research and industry. The extra dynamic modes introduced by flexibility put heavy demands on the control algorithm, and particularly when adaptive control algorithms are applied the higher-order dynamics induce a robustness problem.

In model reference adaptive control (MRAC), the presence of unmodeled process dynamics may induce instability in the control loop. This effect is caused by violation of the perfect model matching condition, which states that a parameter setting must exist in the primary controller so that the process output equals the reference model output. This model matching violation also leads to a violation of the stability requirement that the linear part of the error equation should be strictly positive real (SPR).

If the unmodeled process dynamics are known to exist, it is possible to choose a higher-order controller, which has more parameters to be adjusted by the adaptive mechanism. The perfect model matching condition and the strictly positive real requirement of the error equation are then satisfied. However, this theoretical result is of limited use in a practical application, where a minimum number of adjustable parameters is favored. A system with many adjustable parameters is generally more sensitive to process nonlinearities, and the convergence problem may be significant.

Research on increasing the robustness of MRAC systems has focused on modifications of the adaptive law on one hand [1] and requirements of "persistent excitation" properties on the other [2]. However, neither approach considers the real source of occurring problems, mainly the fact that the reference model response is not achievable by the actual process.

A practical solution can be an adaptive adjustment of the reference model to the actual process capabilities, as demonstrated by the application of an adaptive controller on a direct-drive dc motor in [3]. The method of reference model decomposition to be presented here makes it possible to include rough knowledge of the unmodeled dynamics in the reference model. Because the parameters of these dynamics are not accurately known, the model output is continuously adjusted for occurring mismatch. Theoretically, model decomposition has positive effects on the error equation, and practically it allows the designer to use a lower-order controller while still obtaining good adaptation behavior. To illustrate this, the method is applied to a gantry crane scale model, in which the swing dynamics are considered as "unmodeled dynamics."

In the next section of this paper the adaptive controller is presented and the effects of unmodeled dynamics are described. In the following section the method of reference model decomposition is presented along with some theoretical results. Next, the experimental setup of the gantry crane scale model is described and a mathematical model is derived. The adaptive controller is designed using model decomposition and experimental results are shown. Finally, some conclusions are presented concerning the decomposition method.

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The Adaptive Controller

A model reference adaptive controller can be divided into three parts: the reference model, the primary controller, and the adaptation mechanism. The primary controller must have the capability to make the closed-loop response equal to the reference model response (the perfect model matching condition). This requirement puts demands on the controller complexity and the reference model, which must have the same relative degree as the process transfer function. After the primary controller is specified, the adaptive laws can be derived, usually by stability methods (Lyapunov or Hyperstability). Both methods demand determination of the error equation, which can be divided into a linear part (usually containing the reference model) and a nonlinear part (containing the adaptation mechanism). If the linear part of the error equation is strictly positive real (SPR) and the nonlinear part is passive, stability can be guaranteed [4].

The notation used here has subscript m for the reference model and subscript p for the process. The output is designated y and the transfer function designated W, as shown in (1) for the reference model and (2) for the process:

$$y_m = W_m r \tag{1}$$

$$y_p = W_p u. \tag{2}$$

The process input u is generated by the primary controller from the reference signal r and the process output y_p. In this paper only a first-order process and model will be considered, so only two controller parameters θ_1 and θ_2 are needed:

$$u = \theta_1 r + \theta_2 y_p \tag{3}$$

The desired controller parameters θ^*_1 and θ^*_2 are the values which allow the process output y_p to equal the model output y_m as shown:

$$0 = y_m - y_p = W_m r - W_p(\theta^*_1 r + \theta^*_2 y_p). \tag{4}$$

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Substituting (3) into (2) and then subtracting (1) and adding (4) gives the following expression for the output error:

$$e = y_p - y_m = W_m(\vec{\phi}^T\vec{\omega}) \tag{5}$$

where the two-dimensional parameter error vector $\vec{\phi}$ is the difference between vectors $\vec{\theta}$ and $\vec{\theta}^*$ and the two-dimensional signal vector $\vec{\omega}$ has components r and y_p. Because W_m is of order 1, the transfer function (5) is strictly positive real (SPR), and so the following yields a stable adaptive system, with Γ a constant adaption gain matrix:

$$\dot{\vec{\theta}} = -\Gamma\vec{\omega}e. \tag{6}$$

If W_m is of higher order, measures have to be taken to modify the error equation by using an error augmenting signal [5], or by a proper error compensation [4]. If there are unmodeled dynamics in the process, the error equation (5) changes to:

$$e = \tilde{W}_m(\vec{\phi}^T\vec{\omega}) + \nu(t) \tag{7}$$

In this equation the linear part of the error equation has changed to $\tilde{W}_m$ in which the unmodeled process dynamics are in some way incorporated [6]. This can violate the SPR property of the error equation because $\tilde{W}_m$ is not known. In addition, an output disturbance $\nu(t)$ has appeared in the error equation which depends on the relative importance of the unmodeled dynamics [6]. This output disturbance explains the non satisfaction of the perfect model matching condition because when $\vec{\theta}$ equals $\vec{\theta}^*$ and $\vec{\phi}$ equals 0, an output error still exists and y_p does not equal y_m.

In the literature two types of solutions can be found to deal with unmodeled dynamics. The output disturbance can be decreased by applying a modification of the adaptive law (e.g. a dead zone) [6], if this disturbance is not too large. The condition for SPR in the error equation can be allowed in some circumstances as can be shown using the averaging principle: if the error equation is positive real for "most" frequencies and the adaptive gain matrix Γ is "small", the system stability is maintained.

Reference Model Decomposition

The decomposition principle first appeared in predictive control [7], where an internal prediction model is used. If the process is unstable, a slight mismatch between process and prediction model causes an unbounded prediction error. This can partly be solved by adjusting the prediction model output to the process measurements in a decomposition-like manner. The use of decomposition in MRAC is, however, fundamentally different from that in predictive control.

If unmodeled dynamics exist, their effect is directly present in the output error $e = y_p - y_m$. Therefore, the adaptation reacts to these dynamics, although this reaction is not useful because model matching cannot be achieved. Reference model decomposition attempts inclusion of the unmodeled dynamics in the reference model output, thereby reducing the effect of the unmodeled dynamics on the output error.

This section first describes the decomposition principle and shows the way it can be applied in MRAC. Further, it is shown that decomposition improves the error equation, and the dilemma in the choice of the decomposition parameters is indicated. Finally, the decomposition design steps are summarized.

Basic Decomposition Idea

A system $H(s)$ to be decomposed is first separated into a nominal part $H_s(s)$ and an "unmodeled" part $H_u(s)$:

$$H(s) = H_s(s)\,H_u(s).$$

Next, $H_u(s)$ is decomposed into three polynomials $T_1(s)$, $T_2(s)$ and $N(s)$, such that:

$$H_u(s) = \frac{T_1(s)}{N(s) - T_2(s)}.$$

$H_u(s)$ can be visualized as a feedforward polynomial $T_1(s)$, followed by a transfer function $1/N(s)$ with a feedback $T_2(s)$. This leads to the observation that $T_1(s)$ and $N(s) - T_2(s)$ are determined by $H_u(s)$, but $N(s)$ may be chosen freely as long as the order of $N(s)$ is equal to the order of the denominator polynomial of $H_u(s)$. This decomposition is always possible.

If $H(s)$ is a reference model, the output of $H(s)$ is used to calculate an error signal between process and model. The decomposition effect is then achieved by feeding back not y_m via $T_2(s)$ but feeding back y_p, as shown in Fig. 1. Here, $W_m(s)$ is the "nominal" reference model, and the decomposition polynomials $T_1(s)$, $T_2(s)$, and $N(s)$ perform a correction of the reference model output y_m. The goal of this correction is to make the reference model output have a similar "unmodeled" part as the process output.

Intuitively, this is most clear if the polynomials $T_1(s)$, $T_2(s)$, and $N(s)$ are exactly the same as in a process decomposition (which, of course, is possible in the same way). The decomposition transfer $1/N(s)$, in which all "unmodeled" states of the reference model are present, then is controlled by two inputs. Suppose for a moment that the unmodeled dynamics consist of badly damped oscillations. The first input, $W_mT_1(s)r$, is similar to the corresponding input in the process decomposition in the sense that no oscillations are present and this input is "well behaved." The second input, $T_2(s)y_p$, represents the critical part due to the unmodeled dynamics. If the decomposition parameters are exact, this input is the same in the model and process decompositions and so forms a correction to the states in $1/N(s)$.

The decomposition polynomials are not considered part of the reference model but an addition to the existing structure. For an exact decomposition, the polynomials $T_1(s)$, $T_2(s)$, and $N(s)$ should be the same as those that would appear in a process decomposition. However, an exact process decomposition is not available, making the choice of the decomposition parameters an interesting topic.

Effects of Decomposition on the Error Equation

The decomposition has two effects on the error equation [8], which becomes:

$$e = \left[\frac{N - T_2}{N}\right]\tilde{W}_m(\vec{\phi^T\omega}) + \nu'(t). \tag{8}$$

First, the linear part $\tilde{W}_m$ has changed to $((N - T_2)/N)\tilde{W}_m$. By choosing the decomposition parameters the linear part of the error equation

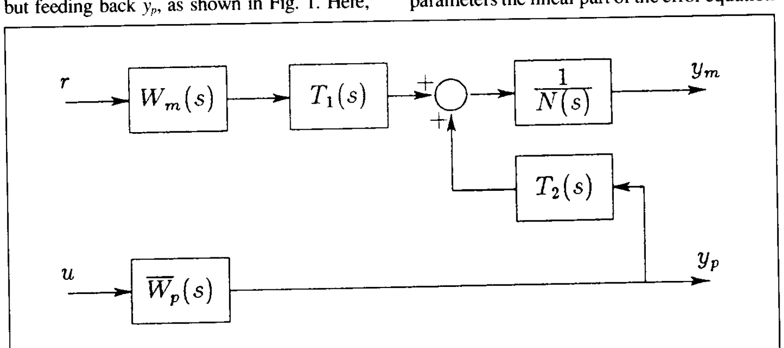

Fig. 1. Use of decomposition in MRAC.

can therefore be influenced, increasing the frequency range over which its real part is positive. This is advantageous because the averaging theory directly shows an increased robustness due to this effect.

Second, the output disturbance v has changed to v′, which can be derived to be [8]:

$$v'(t) = \left(\frac{N - T_2}{N} - \frac{N_p - T_{p2}}{N} \left[\frac{N - T_1 - T_2}{N_p - T_{p1} - T_{p2}} \right] \right) v(t). \quad (9)$$

In this equation, T_{p1}, T_{p2} and N_p are polynomials of a process decomposition.

It can be observed that the decomposition polynomials T_1, T_2 and N, in relation to their equivalents in a process decomposition, influence the output disturbance. In particular, if $T_1 = T_{p1}$, $T_2 = T_{p2}$ and $N = N_p$ the disturbance $v'(t)$ is zero, which implies that exact decomposition parameters restore the perfect model matching condition. However, this is achieved partly by adjusting the reference model output and so the resulting closed-loop response is not *a priori* known.

The Choice of the Decomposition Parameters

In the choice of the decomposition parameters the following dilemma exists.

First, the linear part of the error equation is changed to $((N - T_2)/N)W_m$, making it possible to achieve a more SPR error equation for increased stability.

Because W_m is unknown, the decomposition parameters cannot be chosen accurately to achieve this SPRness. In general, however, the poles determined by N must have a proper damping and the transfer $((N - T_2)/N)$ should have as large as possible a phase lead in order to obtain the best results in this respect.

The second decomposition effect is a decrease in the output disturbance. To achieve a zero disturbance the model decomposition parameters should be as close as possible to the process parameters. This requirement differs from the one above, and so simulation studies are required in order to find a proper compromise.

Decomposition Design Steps

The design steps that have to be taken to apply the decomposition method are as follows.

• The first step in the design is to decide which part of the process dynamics is to be regarded as "nominal," and which part is to be considered "unmodeled." The controller order can then be chosen such that the nominal part can be controlled properly and the controller design can take place. The decision can be based on the desired system specifications, and the feasibility of a higher-order controller.

• In the next step, the structure of the "unmodeled" process dynamics is analyzed. This structure is modified in the sense that it represents an acceptable output disturbance. For example, to an oscillatory part a damping ratio is added.

• The modified structure is finally transformed into polynomials $T_1(s)$ and $N(s) - T_2(s)$. In the decomposition structure, the polynomial $N(s)$ can be chosen freely (therewith determining $T_2(s)$). As shown in the above paragraph, the two decomposition effects put different requirements on the choice of these polynomials.

Application to a Gantry Crane

This section describes inclusion of the decomposition method in a model reference adaptive controller for a scale model of a gantry crane. After a description of the experimental setup and the accompanying mathematical model, the adaptive controller with model decomposition is presented. Practical results are shown which illustrate the useability of the method.

Process Description

The experimental setup consists of a scale model of a gantry crane (Fig. 2), whose larger cousin is often seen in harbors where it is used in shipping for loading and unloading containers to and from ships. The crane as shown in Fig. 2 is placed on rails parallel to the harbor, so that load movement in three directions is possible. The crane operator is seated inside the trolley, which moves over the rails spanning the working area. He is responsible for moving the load so that it arrives at the desired spot as fast as possible, under the constraint that only a very limited overshoot of the load in a horizontal direction is allowed. Violating this requirement may easily result in damaging the load or the truck being loaded on to. A real crane may allow a trolley movement of 80 to 90 m, demanding a position accuracy of 0.2 to 0.8 m, depending on the desired load location [9]. After proper training and much practical experience the crane operator has gained enough expertise to handle this task. Even the varying swing frequency of the load due to the varying cord length is no problem to an experienced operator.

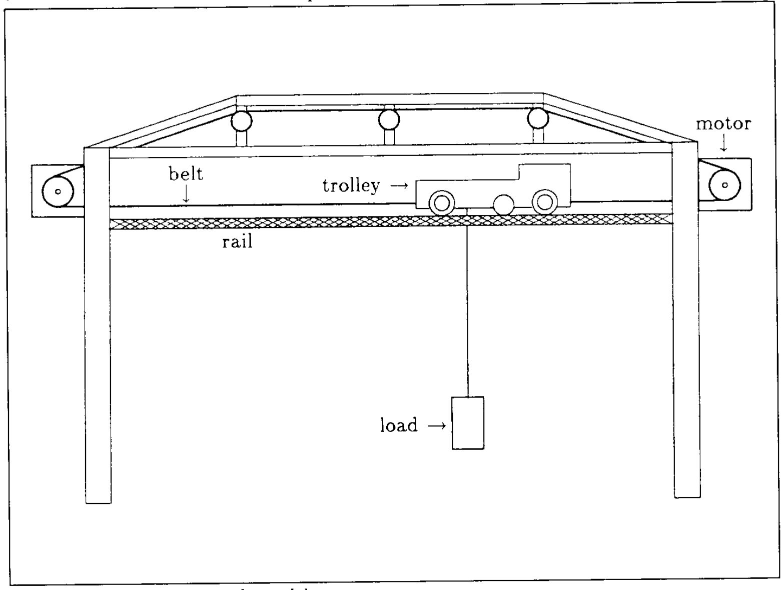

Fig. 2. The gantry crane scale model.

The laboratory scale model has two basic limitations with respect to a real gantry crane. First, all physical dimensions are scaled down dramatically, to make the experimental setup fit within a laboratory environment. Second, a movement is only possible in two directions: the trolley can move horizontally over the spanning rails, and a motor in the crab can lift the load vertically.

The electrical drives responsible for the trolley movement are fitted in the gantry and move the trolley by means of a flexible steel belt transmission. The belt must be kept tensed, for which special provisions have been made. Despite the small elasticity of the belt, the remaining flexibility induces some oscillating behavior, which depends on the actual trolley position. To measure this position accurately and independent of this effect, a potentiometer is fitted in the trolley. This position sensor is connected to a wheel riding over the rails, which has no other function. Slip between this wheel and the rail induces measurement offset when the crane has been in operation for a long time.

The maximum trolley range is 2.40 m. In the vertical direction, the lift motor in the trolley can move the load over a range of 0.66 m (the cord length can be varied between 0.63 m and 1.29 m). The maximum load mass is 10 kg, and to keep the cord straightened a minimum load of 0.5 kg is required.

The control goal is a fast and accurate movement of the load in the horizontal direction, independent of the cord length. During the movement, the cord length is assumed to be fixed, which corresponds with the situation in practice: all load lifting and lowering is done when the trolley is in a fixed position. The swing frequency ω of the load depends only on the actual cord length l:

$$\omega = \sqrt{(g/l)}; \quad g = 9.81 \text{ Nm/kg}.$$

Therefore, ω varies between 2.76 and 3.95 rad/s. Besides, as will be shown below, the swing amplitude depends on the cord length. The control signal is the input voltage u at the trolley motor. For the controller to be designed, three sensors are available. First, the position sensor at the trolley as mentioned above provides the trolley position x_t. Other potentiometers in the trolley measure the angle α of the cord with respect to the vertical axis and the cord length l (Fig. 3).

Combining the information of these sensors, the actual horizontal load position x_l can be calculated:

$$x_l = x_t + l \sin(\alpha). \tag{10}$$

The position x_l is used as feedback information for the controller, so that the crane is considered as a single-input, single-output system. The next paragraph derives the mathematical model of the crane.

Mathematical Model of the Crane

In this paragraph the transfer x_l/u is derived. Neglecting the electrical time constant in the motor, the voltage u on the trolley motor results in a trolley position x_t given by

$$x_t = \frac{k}{s(s\tau + 1)} u.$$

Here, flexibility in the transmission belt is neglected because its influence is small with respect to the load swing. This flexibility has a frequency of 35 rad/s, which is about ten times higher than the swing frequency. The oscillation amplitude depends on the trolley position and has a value of about 2% of a trolley position change (at nominal speed), which is negligible compared to the swing amplitude. However, for accurate control of the trolley only this flexibility must be included.

The time constant τ depends on the motor parameters (back-EMF constant), and on viscous friction between the trolley and the rail it moves on. Measurements have yielded values of $k = 0.19$ and $\tau = 0.065$ s.

Due to Coulomb friction the motor does not come into movement if the voltage is below a certain threshold. This effect does not depend on the trolley position, but is asymmetric: the negative and positive thresholds are -1.6 V and +1.2 V, respectively. Because these values are more or less constant, a direct compensation is implemented (with a small safety margin, so that a zero controller output never results in a trolley movement).

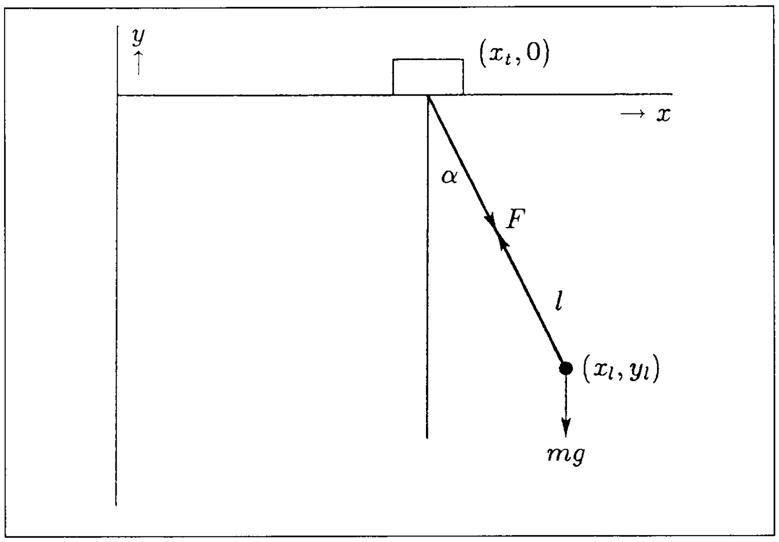

Fig. 3. Definition of some of the variables.

In the above derivation, it is assumed that the swinging load does not influence the trolley position. It will be shown below that this assumption is valid and that this disturbance need not be incorporated in the model.

Now, the equations of movement of the load will be derived. Taking the x, y-plane as in Fig. 3, the load position (x_l, y_l) is

$$x_l = x_t + l \sin(\alpha)$$
$$y_l = -l \cos(\alpha). \tag{11}$$

Applying Newton's law yields

$$m\ddot{x}_l = -F \sin(\alpha)$$
$$m\ddot{y}_l = F \cos(\alpha) - mg \tag{12}$$

in which m is the mass of the load, F is the tension in the cord, and g is the gravity constant. Eliminating F from (12) gives

$$\ddot{x}_l \cos(\alpha) + \ddot{y}_l \sin(\alpha) = -g \sin(\alpha). \tag{13}$$

Differentiating (11) twice, assuming that l is constant, yields

$$\ddot{x}_l = \ddot{x}_t - l\dot{\alpha}^2 \sin(\alpha) + l\ddot{\alpha} \cos(\alpha)$$
$$\ddot{y}_l = l\dot{\alpha}^2 \cos(\alpha) + l\ddot{\alpha} \sin(\alpha). \tag{14}$$

Substituting (14) in (13) gives

$$\ddot{x}_t \cos(\alpha) + l\ddot{\alpha} = -g \sin(\alpha) \tag{15}$$

or

$$\ddot{\alpha} = -\frac{g \sin(\alpha) + \ddot{x}_t \cos(\alpha)}{l} \tag{16}$$

which gives a relation between the trolley acceleration $\ddot{x}_t$ and the angular acceleration $\ddot{\alpha}$. Assuming that α has a small enough value to allow an approximation $\sin(\alpha) \approx \alpha$ and $\cos(\alpha) \approx 1$, the transfer from $\ddot{x}$ to α becomes

$$\alpha = \frac{1/l}{s^2 + g/l} \ddot{x}_t \tag{17}$$

Combining this equation with (10) yields

$$\frac{x_l}{u} = \frac{k}{s(s\tau + 1)} \left(1 + \frac{s^2}{s^2 + g/l} \right) \tag{18}$$

The open-loop response of the crane has a pure integrating factor and undamped oscillations with a period of about 8 s. Equation (18) describes the simplified transfer from the input voltage u to the horizontal load position x_l. Coulomb friction, belt flexibility, and the goniometric relations have all be neglected, as has the influence of the load swing on the trolley. This latter effect will now be analyzed to show the validity of this simplification.

For the trolley, which weighs 9.7 kg, a "virtual mass" can be defined as the relation between an externally applied force on the trolley and the resulting acceleration. Because of the trolley motor, which acts as a "dynamic brake," the virtual mass is much larger than the actual mass. By applying a force on the trolley and studying the occurring trolley movement, the virtual mass can be determined. This approach has lead to a virtual mass of M = 170 kg, which is large with respect to the load mass. The ratio m/M expresses the influence the load has on the trolley movement. The allowed range of the load mass results in a value of m/M between 0.003 and 0.06, which is sufficiently small to allow the neglect of this disturbance on the trolley.

The Adaptive Controller

In applying a standard adaptive method without modification, eight adjustment parameters would be required. In practice, such a system shows unacceptably non-converging behavior, which is caused by the simplifications discussed in the preceding paragraph. The controller will therefore be designed only for the "nominal" part, which is chosen as:

$$W_p(s) = \frac{k}{s(s\tau + 1)} \quad . \tag{19}$$

The reference model is of second order:

$$W_m = \frac{b_0}{s^2 + a_1 s + a_2} \quad . \tag{20}$$

Now, the time constant $\tau = 0.065$ s is small enough to be neglected in the primary controller, and so the control signal is made up of only two elements:

$$u = \theta_1 r + \theta_2 x_l . \tag{21}$$

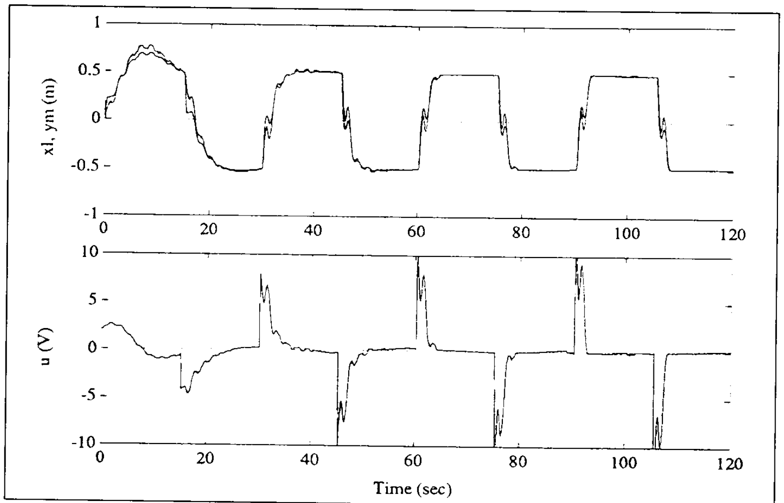

Fig. 4. Crane response with decomposition, l = 1 m.

The reference model parameters are selected $b_0 = 20$, $a_1 = 9$, and $a_2 = 20$, yielding poles at $s = -4$ and $s = -5$. To be able to deal with the "unmodeled" oscillations, the decomposition method is applied. For the decomposition polynomials, a form is chosen which resembles the "unmodeled" part of the process, however including a damping ratio z_m:

$$\frac{T_1}{N - T_2} = \left(\frac{s^2}{s^2 + 2z_m\omega_m s + \omega_m^2} + 1 \right)$$

$$= \frac{2s^2 + 2z_m\omega_m s + \omega_m^2}{s^2 + 2z_m\omega_m s + \omega_m^2} \quad . \tag{22}$$

The polynomials $T_1(s)$ and $N(s) - T_2(s)$ are determined by parameters z_m and ω_m. The polynomial $N(s)$ can be chosen arbitrarily, although its order is assumed to be 2. Writing $N(s)$ as:

$$N(s) = s^2 + 2z_n\omega_n s + \omega_n^2 \tag{23}$$

we find that:

$$T_2(s) = 2(z_n\omega_n - z_m\omega_m)s + (\omega_n^2 - \omega_m^2). \tag{24}$$

Imposing an arbitrary frequency on the oscillating system is not useful and would take much control effort. Therefore, our intention is to make the error equation insensitive to the oscillation *frequency*, and so ω_m is chosen equal to the nominal value of ω_p. In this case, ω_m^2 is chosen equal to the minimum occurring value of g/l, which is 7.6. Practical experiments showed the best results with this setting, because the decomposition is then tuned for the largest occurring amplitude of the swing. To ensure a proper model damping, z_m is chosen 1. The parameters z_n and ω_n^2 are chosen 1 and 30, respectively. The value of $\omega_n^2 = 30$ is large enough to provide a considerable phase lead, and small enough to allow a computer implementation at a sample time of 30 ms (see the next paragraph).

Practical Results

The gantry crane sensors and motors are connected to a hardware interface, which conditions all signals to voltages between −10 and +10 V. The hardware interface is connected, via A/D and D/A converters, to a µVAXII minicomputer, which is equipped with the real-time shell MUSIC (MUlti-purpose SImulation and Control). The controller is written in FORTRAN and interfaces to a software module which operates the A/D and D/A converters. Further, this module calculates the actual load position x_l from the measurements, and removes the sensor offsets. The computing effort needed for the complete system, including the adaptive controller, allows a sample time of 30 ms.

In applying a block-type setpoint, using the original adaptive scheme of a low order (equipped for only a first order system), the crane response has a remaining overshoot of about 30%. It is observed that during the transient, the inevitable load swing causes a large error between the (second order) model and the process. This large error causes the feedforward gain θ_1 to become too large, which must be corrected after the transient, causing the overshoot. Fig. 4 shows results using the decomposition method implemented in the adaptive controller, with a block-type reference signal with an amplitude of 40 cm and a cord length of 1.00 m. It is seen that there is no overshoot of any importance left. Furthermore, experiments with varying cord lengths showed that the method is robust in this respect. Inspecting Fig. 4 it can be observed that the improvement is achieved by the changing reference model. During the transient, when the load swings, the reference model actually "observes" the swing and adjusts its output such that it actually can be followed. This corresponds with the philosophy of the decomposition method: the swing is inevitable and therefore it is of no use to try to eliminate it. By the direct model adjustment the plant-model error is made less sensitive to the load swing. Thus the practical useability of the decomposition method is demonstrated.

Conclusions

The primary decomposition goal is the improved robustness of adaptive systems with regard to unmodeled process dynamics with a known structure. Alternatively, decomposition can be regarded as a method that allows the use of a lower order controller than required for perfect model matching. Especially the last property is useful in a practical implementation. Application of the decomposition method requires knowledge about the structure of the unmodeled dynamics and "rough" knowledge about the parameters.

The decomposition principle is based on the observation that imposing an arbitrary behavior on a process is not wise unless one is constantly "in touch" with the process, determining the actual process capabilities. Decomposition is a way of adjusting the control goal as a reaction of these capabilities. Theoretically, this leads to an improvement of the error equations in the sense that the negative effects of unmodeled dynamics are relieved.

Application of the method to a gantry crane scale model showed the improvements model decomposition can achieve. The effects of the swing dynamics, which were regarded as being "unmodeled" were shown to be harmless.

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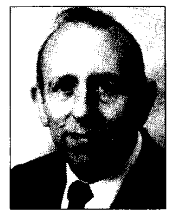
Hans Butler, photograph and biography not available at time of publication.



Ger Honderd was born in Amsterdam, The Netherlands, in 1933 and received the Ing degree in electrical engineering in 1954 from HTS, Amsterdam, and the IR degree in electrical engineering in 1961 from the Delft University of Technology, with a thesis on grafo-analytical synthesis of non-linear systems. In 1958 he joined the group on fundamental research of the Institute for Mechanical Constructions of the Organization for Applied Physics (TNO). In 1961 he became Member of the Scientific Staff of the Control Laboratory of the Department of Electrical Engineering of the Delft University of Technology. He was appointed Lector in 1968, and in 1980 Full Professor at that university. In his work at the university he has initiated several projects together with industrial co-workers on the application of control engineering. He has given special attention to the field of power generation; primary and secondary control as well as economic optimization of electric power production, actively promoting the development of especially adaptive control strategies and optimization methods. In the last few years he has paid special attention to the field of robotics. His main research interest is in the field of sensitivity analysis and adaptive control, especially model-reference adaptive control.

Job Van Amerongen, photograph and biography not available at time of publication.

DOCTORAL DISSERTATIONS

(Continued from page 51)

Dept., Univ. of Puerto Rico, Mayaguez, Puerto Rico 00709-5000.

Georgia Institute of Technology

G. N. Maliotis, "Adaptive Control of partially Known Robotic Manipulators."

Date: March 1990.

Supervisor: F. L. Lewis.

Current Address: Boeing Aerospace Operation, Inc., MS, FA 58, Kennedy Space Center, FL 32899.

Georgia Institute of Technology

D.M. Dawson, "Uncertainties in the Control of Robot Manipulators."

Date: March 1990.

Supervisor: F. L. Lewis.

Current Address: Dept. of Elect. and Comp. Eng., Riggs Hall, Clemson Univ., Clemson, SC 29634.

University of Roorkee

Mukherjee, Shaktidev, "Reduced Order Modelling and its Application in an Industrial Process."

Date: November 1989.

Supervisor: R. N. Mishra.

Current Address: University of Roorkee, Department of Electrical Engineering, Roorkee 247667 India.

University of Strathclyde, Glasgow, United Kingdom

Yun, Li, "ConcurrentArchitectures for Real-Time Control."

Date: September 1990.

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