ADAPTIVE AND NEURAL APPROACHES TO FAULT TOLERANT CONTROL

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Contents

Summary

This article is concerned with the design of fault tolerant control systems using adaptive and neural-network based approaches. Three types of techniques have been described and applied to case studies involving faults in actuator, sensor and process components, respectively. These have been selected to cover a collection of cases in terms of knowledge regarding process models, control design rules, location of faults etc.

The first technique is a purely adaptive one based on known model structures and a least squares estimator with on-line controller redesign and reconfiguration. It involves selection of one controller among a set of fixed controllers and an adaptive one. When a

fault takes place, the nominal controller is generally no longer the best one, and one of the others is selected. If none of the fixed controllers is adequate for the purpose, the adaptive controller is switched on, which attempts to improve the performance of the closed loop system based on an estimation of the plant parameters. A spacecraft autopilot operating under actuator failures is taken up as a case study to illustrate the technique.

The second technique is designed to accommodate sensor failures. An artificial neural network is trained to estimate the output of a sensor from the remaining measurements. When a sensor fails, the output of the estimator can be substituted in its place and fed back to the controller for continued performance. The simulation model of the Tennessee Eastman Challenge Process, which is a benchmark industrial case study in process control, is taken up to illustrate the proposed methodology.

The third technique describes an adaptive LQ control algorithm where a necessary optimisation parameter is estimated using a neural network. The problem of variations in process parameters is considered. A linear quadratic cost function is minimized using the adaptive algorithm, in which the system matrix is considered to be unknown. The method is illustrated using the auto-landing process of a re-entry vehicle and is found to work satisfactorily.

1. Introduction

Design of fault tolerant control systems (FTCS) is receiving increased attention to improve on the reliability, safety and autonomy of aerospace and industrial process control systems. Several approaches are possible for this purpose (see other articles under this topic, namely, Control Reconfiguration). In this article, three techniques employing adaptation and artificial neural-networks are described. Three different types of faults, namely, those in actuators, sensors and process components, have been treated. Cases of the model structures being known, partially known or completely unknown, have been considered. The solutions proposed involve sensor validation, sensor data estimation, controller switching, implicit as well as explicit adaptation, on-line and off-line learning using ANNs etc. The common characteristic of these techniques is that the control system is able to infer, on-line, the occurrence of changes in the dynamic characteristics due to faults from the process behavior and automatically adapts itself to the changes in the process.

An actuator fault tolerant control system essentially consists of two modules. The first module comprises a set of algorithms for detecting the onset of a fault and also for estimating various related quantities such as changes in model parameters or fault signals as defined in the fault model adopted. The second module comprises algorithms for reconfiguration of the control law to prevent system performance from degrading abruptly and significantly through switching in an appropriate controller. This controller may either be selected from a precomputed set of controllers based on some performance criterion, certainty equivalent redesign of an adaptive controller based on parameters estimated by the first module, or an adaptive controller with an adaptation law based an various errors signals computed by the first module. Based on the above structuring, we provide a brief review of some of these approaches reported in the literature.

The most natural approach for control reconfiguration that has appeared in the literature is the Multiple Model Switching and Adaptation (MMSA) approach, which is also adopted in the first part of this article. An early work is by Narendra and Balakrishnan in 1997, which presented an indirect adaptive control scheme based on a multiple model strategy, to improve the transient performance of the system. They also established the properties of the algorithm, including stability and convergence criteria. Narendra and Xiang (2000) analysed a similar scheme in the discrete-time domain. In the proposed scheme, there are a number of candidate controllers, one of which is to be selected based on an error criterion. Some of these controllers are fixed and some are adaptive. Further development along this approach has been carried out in Boskovic and coauthors [3-6], in the context of aerospace vehicles. In [3] an algorithm for stabilizing a linearised model of an aircraft is provided under assumptions of sensing (availability of the full state as measurements), plant dynamics (non-minimum phase nature) and actuators (sufficient degree of redundancy). This algorithm is further refined using a separate parameter estimator in [4]. In [5], an FTC algorithm for actuator failures is presented for the attitude control of a spacecraft using thrusters. It is based on an estimation of the unknown fault input using multiple FDI observers and the control switching is effected using a suitable criterion of estimation errors. In [6] the same problem is extended in case of control in the face of sensor bias.

ANN based techniques have also been used for controller reconfiguration, especially in the presence of modeling uncertainty. A survey of ANN applications in adaptive flight control systems as well as a new algorithm for partial loss of actuators in presence of modeling uncertainty is available in [8]. An intelligent sliding mode control approach to stabilize the plant till an on-line leaning neuro-controller tunes itself is provided in [22]. On-line learning of ANNs has also been used in [18,21].

Sensor fault tolerant control essentially involves two steps, namely, first, detection of sensor failures followed by diagnosis (isolation) of the failed sensor, and second, estimation of the system variable measured by the failed sensor. The second step may be achieved by using the measurements of the remaining normal sensors in the system. It may be noted that no controller reconfiguration is needed for sensor fault tolerant control as long as the above two steps can be performed effectively. What is needed is only to switch the feedback input of the controller from the sensor to the estimator. Below we review some of the approaches adopted in the literature for performing the above two steps.

The problem of sensor failure detection and isolation has been investigated from as early as the seventies. Initial approaches proposed various kinds of observers such as the dedicated observer scheme or the generalised observer scheme [10]. System nonlinearity and unmodelled dynamics have also been treated [1,12]. A frequency domain approach is presented in [15].

Failure detection and tolerance using ANN-based and other learning approaches have been reported. An early work is by Guo and Nurre [13], where the authors train a neural network to identify the sensor whose measurement is not consistent with the other sensor outputs. To quote a few recent ones, we mention the following. Alessandri and co-authors [2] have proposed a recursive ANN-based state estimator for nonlinear

systems. Polycarpou and co-authors [16,17,23] have provided various schemes based on learning and provided analytical results on stability and detectability. Hierarchical structures of multiple feedforward ANNs have been used for fault isolation in process control [7] and robotics [19]. Chan and coworkers used a constrained Kohonen Network to detect faults from redundant sensors [9].

Beyond fault detection and isolation, approaches that attempt to estimate the signal corresponding to the faulty signal have been reported for linear systems in [11] and for nonlinear systems in [20]. Jiang and Coworkers [14,24,25] have used simultaneous state and parameter estimation using a two stage adaptive Kalman filter and certainty-equivalent eigenstructure assignment for reconfiguration.

The article is divided into three parts. The first part, presented in Section 2, describes an adaptive control formulation for the design of an FTCS. A number of controllers corresponding to certain fault modes are considered to be available based on off-line design. A logic based on the output prediction error is used to select the most suitable controller under a given condition. When the fault does not correspond to one of the pre-designed cases, an indirect adaptive controller is employed, which estimates the process parameters and tunes itself on line to achieve the desired performance. The methodology is applied to a numerical simulation example of a spacecraft autopilot and the design is carried out to make the system tolerant to actuator failures.

Section 3 describes another approach to the design of FTCS, which is based on artificial neural networks (ANN). In this case, numerical simulation of a complex non-linear chemical process, known as the Tennessee Eastman Challenge Process (TECP) is taken up to illustrate the technique of sensor data validation, estimation and sensor fault tolerant control. An ANN system is fed with the outputs of several sensors and trained to estimate the output of some other sensor under normal conditions. A number of such networks are trained corresponding to different outputs. In the event of a sensor being faulty, its correct value can be estimated from the remaining healthy ones using the trained network. Once a comparison of the estimated and the actual values detects the fault, failed sensor data is substituted with the estimated sensor value for feedback to the controller.

The third approach, a neuro-adaptive one, is described in Section 4. It considers the problem of accommodating faults in the process. It may be noted that generally one cannot afford to provide hardware redundancy in the process to achieve fault tolerance. Instead, fault diagnosis and controller reconfiguration needs to be attempted to maintain the desired level of performance. An alternative approach is to employ an adaptive controller that adapts based on an on-line computable performance index without explicit fault diagnosis. However, it is important to guarantee the closed loop stability of such an adaptive system, during adaptation. In this part, an adaptive mechanism is described which iteratively adapts the gain of the controller of an LQ regulator on-line while minimizing a quadratic cost function. This can be implemented using neural networks. The major advantage of using the LQ regulator theory during the process of adaptation is that the stability of the closed loop system during reconfiguration can be ensured. The methodology is applied to the auto-landing process of a re-entry vehicle.

Section 5 concludes the article with an assessment of the strengths and the weaknesses of the methodologies presented here in comparison with other approaches to fault tolerant control.

2. An Adaptive Approach to Actuator Fault Tolerant Control

In this section an adaptive approach to fault tolerant control is described. The effectiveness of the scheme is demonstrated in actuator fault tolerant control. Adaptive control became an area of extensive research work during the seventies (see Adaptive Control). In the so-called indirect adaptive control approach, there are two stages in the adaptation process. In the first stage, the system parameters are estimated by minimizing an 'identification error' and in the second stage the controller gain matrices are computed based on the estimated parameters. Although extensive analysis of these adaptive control algorithms was made and stability and convergence results established, these control schemes did not become popular in the industrial control environments due to their complexity, uncertain transient behavior and often large convergence time.

In 1997, Narendra and Balakrishnan presented an indirect adaptive control scheme based on a multiple model strategy, to improve the transient performance of the system. They also established the properties of the algorithm, including stability and convergence criteria. Narendra and Xiang (2000) analysed a similar scheme in the discrete-time domain. In the proposed scheme, there are a number of candidate controllers, one of which is to be selected based on an error criterion. Some of these controllers are fixed and some are adaptive. Initially the plant is controlled by a fixed controller which has been designed based on a nominal plant model. An identification error is defined which is the difference between the plant output and the output of the nominal plant model, fed with the same input signal. When this error goes above a limit, it indicates that the nominal plant model no longer adequately reflects the plant behavior, and one of the remaining controllers is to be selected. A switching scheme is necessary to select one of them depending on which of them corresponds to the minimum identification error. When none of the fixed controllers seems adequate, the adaptation mechanism is activated. The parameters being estimated are initialized to those of the fixed model that gives the minimum identification error. This ensures a better transient performance of the system and reduces the convergence time.

This scheme appears quite suitable for fault tolerant control. One can design a few fixed controllers corresponding to different fault models. Naturally, all types of faults cannot be considered a-priori. Therefore, an adaptive controller needs to be included to handle fault conditions other than those associated with the fixed controllers. Such a scheme for fault tolerant control using the above principle is shown in Figure 1. In this approach, we have a plant, which is normally controlled by a nominal controller (say, Controller 1) designed off-line, using the parameters of the nominal model of the process (Model 1). In addition, there are a finite number of fixed controllers (say, Controllers 2,…*N*-1), which may correspond to different extreme fault conditions, like complete loss of an actuator. Each fixed controller is designed *a-priori* based on the corresponding faulty models (Models 2,…*N*-1) of the plant. The difference between the outputs of the *j-th* model and the measured output of the plant is the identification error e_I^j. Finally, there is an adaptive controller consisting of a model (Model *N*), updated recursively by

minimizing the identification error e_I^N. The parameters of the corresponding controller (Controller *N*) are computed on-line based on the estimated model parameters. The design of the control system can be divided into the following 5 steps.

Step 1. Modelling of the plant under normal and faulty conditions and the study of the behavior of the plant under different faults. This may involve the determination of stability, controllability and other important properties of the system under fault. This step would determine the types of fault that can be tolerated by the control system.

Step 2. Design of the nominal control system and fixed controllers corresponding to each fault mode assumed a-priori. Usually a few of them should be designed corresponding to the important faults.

Step 3. Design of a scheme for on-line estimation of the parameters of the adaptive model and the computation of the corresponding controller parameters.

Step 4. Design of the decision logic. The 'identification error' corresponding to each of the controllers is to be fed to this logic. A suitable measure of this error is to be evaluated. The switching of controllers has to be done based on this measure.

Step 5. Evaluation of the performance of the FTCS.

In the following, a case study of a spacecraft autopilot using the methodology described above is presented. The objective is to design a control system that would be tolerant to the failure of the actuators in the system.
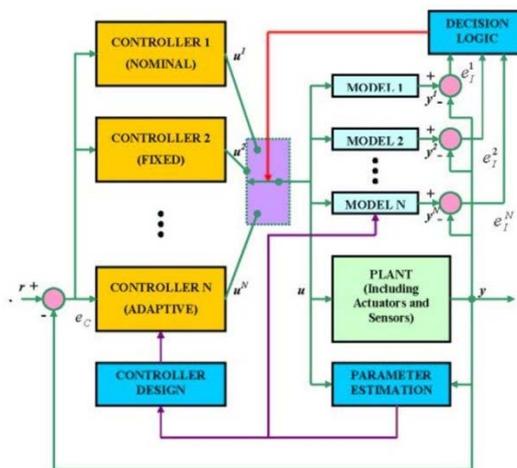

Fig. 1. Architecture of FTCS using multiple-model adaptive control

2.1 Model of a Space-craft Autopilot

In this section, the rigid-body mathematical model of a spacecraft for its angular motion dynamics is described. There are three subsystems, namely those governing the pitch (ξ), the angular motion in the vertical plane, the yaw (ζ), the motion in the horizontal plane and the roll (ϕ), the motion with respect to its longitudinal body axis. The nominal

model is given by a state space representation:

$$\dot{x} = Ax + Bu$$
$$y = Cx \tag{1}$$

where, x is the state vector of dimension $n=6$, whose elements are given as, $x_1 = \xi$, $x_3 = \zeta$ and $x_5 = \phi$ and x_2, x_4 and x_6 are the derivatives of x_1, x_3 and x_5 respectively. u is an $m=4$-dimensional input vector and y is a $p=3$ dimensional output vector. The matrices A, B and C are given in Table 1. Under state variable feedback, the input signal generated by the *l-th* controller is given by:

$$u^l = -F^l x + G^l r \tag{2}$$

Here r is the reference vector of dimension p corresponding to the outputs ξ, ζ and ϕ. The nominal gain matrices F^1 and G^1 are given in Table 2. The closed-loop poles of the system using the above controller are presented in Table 3 under normal condition and for two types of actuator failures.

$$
A = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0.6 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0.6 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad
B = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0.349 & -0.349 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0.349 & -0.349 \\ 0 & 0 & 0 & 0 \\ 1.7972 & 1.7972 & 1.7972 & 1.7972 \end{bmatrix} \quad
C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}
$$

Table 1: System Matrices under Normal Conditions

$$
F^1 = \begin{bmatrix} 8.16 & 7.344 & 0 & 0 & 0.2622 & 0.2998 \\ -8.16 & -7.344 & 0 & 0 & 0.2622 & 0.2998 \\ 0 & 0 & 8.16 & 7.344 & 0.2622 & 0.2998 \\ 0 & 0 & -8.16 & -7.3444 & 0.2622 & 0.2998 \end{bmatrix} \quad
G^1 = \begin{bmatrix} 8.16 & 0 & 0.2622 \\ -8.16 & 0 & 0.2622 \\ 0 & 8.16 & 0.2622 \\ 0 & -8.16 & 0.2622 \end{bmatrix}
$$

Table 2: Nominal Controller Gain Matrices

Pole Index	Condition		
	Normal	Complete failure in u_1	Complete failure in u_2 and u_3
1	-1.35	-1.35	+0.41
2	-1.35	-3.78	-0.40

3	-3.78	-1.68+0.51j	-1.83+0.25j
4	-3.78	-1.68-0.51j	-1.83-0.25j
5	-1.08+0.85j	-0.41+0.65j	-1.28+7.8j
6	-1.08-0.85j	-0.41-0.65j	-1.28-0.78j

Table 3: Closed loop pole locations for various conditions

It can be observed that, under multiple actuator failure, one of the closed loop poles crosses over to the right half of *s*-plane. Further, the system remains controllable for failure in a single actuator, while this property is lost under the occurrence of simultaneous failure of u_1 and u_2 or u_3 and u_4. However, the system remains controllable for other types of multiple failures, such as in u_2 and u_3. This is due to the fact that the system has redundant actuators, and a loss of one (and sometimes two of them) can be tolerated and one can design an FTCS which will be able to stabilize the plant for all cases of single actuator failures and some cases of double actuator failures. Under this circumstance, the closed loop poles can be placed at the location of original closed loop poles for the normal case. This would be illustrated with the results presented here.

2.2 Design of Fixed Controllers

Five fixed controllers have been designed off-line, including the nominal controller described above. Each of the remaining four fixed controllers corresponds to complete failure of one of the actuators. Due to actuator failures, the matrices *A* and *C* do not change. However, the ith column of *B* becomes zero corresponding to complete loss of the ith actuator. Therefore, to maintain the same closed loop poles under such a fault, the corresponding gain matrices will have to be computed. This design is carried out for each case of single actuator failure and the results are shown in Table 4. The index *l* refers to the controller and *l*=2…5 correspond to the failure in actuators u_1 to u_4 respectively. F^l is obtained by using the conventional pole assignment technique for multivariable systems (see Pole Placement Control). The matrix G^l in each case is constructed as follows. Exploiting the special structures of the matrices *A* and *C* one can rewrite equation (2) as

$$u^l = -F_o^l y - F_e^l \dot{y} + G^l r \tag{3}$$

where F_o^l and F_e^l are constructed by combining the odd- and even-numbered columns of the matrix F^l respectively. By setting $G^l = F_o^l$, one obtains

$$u^l = F_o^l (r - y) - F_e^l \dot{y} \tag{4}$$

Defining

$$e_c = r - y \tag{5}$$

For a constant reference signal *r,*

$$\dot{e}_c = -\dot{y} \tag{6}$$

Thus equation (4) can be written as

$$u^l = F_o^l e_c + F_e^l \dot{e}_c \tag{7}$$

It is interesting to note from (7) that, with this choice of G^l, the above scheme can be viewed as a proportional plus derivative control. It may also be noted that this control would still guarantee zero steady state errors since there are integral terms in the open loop plant transfer functions.

l	F^l					
2	0	0	0	0	0	0
	-16.0368	-14.4262	-1.5873	-1.4692	-0.0081	-0.0075
	8.8135	7.9487	4.4908	3.9492	1.399	1.4089
	7.2249	6.4790	-2.9124	-2.4881	1.4443	1.4508
3	10.3091	9.1261	0	0	4.3782	4.0511
	0	0	0	0	0	0
	-4.7294	-4.1697	8.16	7.344	-1.0811	-0.8859
	-4.7294	-4.1697	-8.16	-7.344	-1.0811	-0.8859
4	1.8425	2.4801	7.5946	6.8533	3.0472	2.6777
	6.2225	-4.6085	7.5786	7.4276	0.8754	0.7114
	0	0	0	0	0	0
	4.7496	2.4893	-15.1865	-14.2563	-1.1853	0.6304
5	8.7850	7.9217	-4.4463	-3.9094	1.4626	1.4679
	-7.2824	-6.5327	-2.9487	-2.5205	1.4807	1.4848
	-1.5062	-1.3923	7.3736	6.4102	-0.1083	0.1006
	0	0	0	0	0	0

Table 4: System Gain matrices under failure in each actuator

2.3 Design of the Adaptive Controller

For ease of implementation the parameter estimator and the adaptive controller design is carried out in the discrete-time domain. Considering the discrete-time version of the system equation (1), the ith row may be written as

$$x_i(k+1) = \sum_{j=1}^{n} a_{ij} x_j(k) + \sum_{j=1}^{m} b_{ij} u_j(k) \tag{8}$$

where a_{ij} and b_{ij} are the *(i,j)-th* element of the discrete-time matrices corresponding to *A* and *B* respectively. In the present problem, since the actuator faults do not affect the system matrix *A*, the coefficients a_{ij} are assumed constant and known. Therefore one can write

$$x_i(k+1) - \sum_{j=1}^{n} a_{ij} x_j(k) = \sum_{j=1}^{m} b_{ij} u_j(k) \qquad (9)$$

In the above, the coefficients b_{ij} would have to be estimated in the event of a fault in any of the actuators. Equation (9) can be written in the form

$$z_i(k+1) = \psi_i^T(k)\,\beta_i \qquad (10)$$

where $z_i(k+1)$ is the expression on the l.h.s. of (9) and

$$\psi_i^T = \begin{bmatrix} u_1(k) & u_2(k) & \cdots & u_m(k) \end{bmatrix}$$

$$\beta_i^T = \begin{bmatrix} b_{i1} & b_{i2} & \cdots & b_{im} \end{bmatrix}$$

Equation (10) is in the standard linear-in-parameters form, and the vector β_i can be estimated using any recursive algorithm such as least squares (see Recursive Algorithms). Based on the estimated parameters the controller gains F^N and G^N can be computed in discrete-time domain by placing the closed loop poles at locations corresponding to those given in Table 3.

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Biographical Sketches

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