Intelligent Sensor Fault Detection and Identification for Temperature Control

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Abstract: This paper addresses artificial intelligence and signal processing based online fault detection and identification. Fuzzy logic controller has been utilized for temperature control. Faults often cause undesired reactions, so to keep the system stable and to obtain an acceptable control performance is an important problem for control system design. In this paper, a multiplicative, an additive and a disturbance type of Termocouple sensor faults have been examined for temperature control. Feature vector of the sensor faults has been constructed using a statistical analysis. For classifier of the feature vector the Self Organizing Map (SOM) has been used. So sensor fault can be detected and identified using feature vector.

Key-Words: sensor fault, fault detection and identification, temperature control

1 Introduction

In automatic processes, faults will often cause undesired reactions and shut-down of a controlled plant and the consequences could be damage to technical parts of the plant, to personnel or the environment [1]. To keep the system stable and acceptable control performance is an important problem for control system design. Control system stability and reliability are critical for nuclear stations, passenger airplanes, power large-scale productions. Most of modern industrial plants are complex and often include a number of subsystems which may compensate for the effects of sensor faults [2]. Ideally, when faults happen, the closed-loop system should be capable of maintain its present operation. This leads to the recently studied area of fault tolerant control

FTC combines fault detection and identification with control methods to handle faults in an intelligent way. It is essential that such systems are reliable with respect to performance, robustness, failure modes, etc [3].

Fault detection consists of decision as to whether a fault occurred or not. Fault identification imposes a stronger condition. When one or more faults occur, this method identify, which faults have occurred. [4]. In this paper online fault detection and identification has been examined for temperature control. Sensor faults which are multiplicative and additive types have been examined on theoven.

2 Design of Fault Detection and Identification

The monitoring of faults in feedback control system components has come to be known as fault detection and identification (FDI) [5]. The FDI methods can he classified into two major groups: model-free methods and model-based methods [6]. In this study model – free method has been used.

The analytical approaches based on quantitative models are used mainly. The main idea is the generation of residuals which is the difference between nominal and faulty system. The residuals are usually generated using analytical approaches, such as observers, parity equations or parameter estimation, based on analytical redundancy. Since most of the real processes are nonlinear, the FDI model-based methods require a precise and accurate model. The traditional model-based FDI methods cannot guarantee satisfactory performance. For this reason, knowledge-based methods have been developed combination of the analytical approaches with the artificial intelligence methods e.g. neural networks, fuzzy logic, evolutionary programming, etc. [6]. Knowledge-based methods are sometimes called modelfree or qualitative methods.

In this study model-free method has been used with artificial intelligence and signal processing techniques. Figure 1 shows the scheme of artificial intelligence and signal processing based FDI [9].



2.1 Wavelet analysis

Faults cause certain changes in the response of measured signals, changes in time response and in frequency response. These changes would result in transient behavior of system variables and transient analysis becomes critical for fast and accurate fault detection. Wavelet analysis is capable of detecting the change or transition in the signal [7]. For this reason wavelet analysis has been used in this study.

In signal processing stage of FDI, decomposition for discrete signal is computed using a series of low-pass and high-pass filters. Filters computation has shown below equations [7].

$$y_{high}[k] = \sum_{n} x[n].g[2k-n]$$
(1)
$$y_{low}[k] = \sum_{n} x[n].h[2k-n]$$
(2)
$$x[n] = \sum_{k} \frac{(y_{high}[k].g[2k-n]) + }{(y_{low}[k].h[2k-n])}$$
(3)

n being the total number of samples in x[n]. As shown in equations (4)- (5), c[k] are called approximation coefficients and dj[k] are called detail coefficients. Parameter j determines the scale or the frequency range of each wavelet basis function^{Ψ}. Parameter k determines the time translations.

$$c[k] = \int_{-\infty}^{\infty} f(t)\phi(t-k)dt$$
(4)
$$d_{j}[k] = \int_{-\infty}^{\infty} f(t)2^{j/2}\psi(2^{j}t-k)dt$$
(5)

Discrete wavelet transform (DWT) is a linear transform that is very suitable to represent the non-stationary events in signals. DWT has good localization properties of high frequency components. In this study db6 wavelet has been used for FDI stage. Fig. 2 shows the db6.



Fig. 2. Daubechies 6

2.2 Feature extraction

For real time processing, a moving time window technique has been used. In moving time window, the latest several samples carry the most up to date information on any changes in the signal. Sliding window is needed technique to track dynamic data and detect the transient state of faults [8, 9].

Detecting the variations along with the time using wavelet analysis, equation 6-7 have been used to calculate the information of the signal. Absolute maximum value changing ratio and variance changing ratio has been used for feature extraction of the signal. Feature vector contains the changing ratio values for more than one system measurements.

$$r_{1} = \frac{var(Current window) - var(Past window)}{var(Past window)}$$
(6)
$$r_{2} = \frac{max(|Current data zone|) - max(|Past window|)}{max(|Past window|)}$$
(7)

3. Temperature Process

For temperature process, mathematical description of the oven has been used. Fig.3 shows the oven. In this study, Ziegler-Nichols Step Response is used. Ziegler-Nichols Step Response method is based on transient response experiments. Many industrial processes have step responses of the type shown in Fig. 4, in which the step response is monotonous after an initial time. A system with step response of the type shown in Fig. 4 can be approximated by the transfer function as in equation 8. where k is the static gain, τ is the apparent time delay, and T is the apparent time constant. The parameter a is given in equation 9 [10].



Fig. 3. The oven

Table 1: Units for The System.				
1	Oven			
2	Termocouple (Temperature sensor)			
3	Fan			
	Disturbances (Two holes on the top of			
4	the oven)			



Fig 4. Unit step response of a typical industrial process [4].

The oven used in this study is a First Order Plus Dead Time (FOPDT) plant. An FOPDT system has a transfer function as in equation 8. In this equation, the parameters should be known are k, τ and T. These parameters are k=106, τ =64.14s and T = 1494.7s [11]. Transfer function of the oven is given as in equation 10.

$$G(s) = \frac{106}{1495s+1}e^{-64,14s} \tag{10}$$

4. Sensor Fault

Sensor faults represent incorrect reading from the sensors that the system is equipped with. Sensor faults can also be subdivided into partial and total types. Total sensor faults produce information that is not related to value of the measured physical parameter. They can be due to broken wires, lost contact with the surface, etc. Partial sensor faults produce reading that is related to the measured signal in such a way that useful information could still be retrieved. For example, be a gain reduction, a biased measurement resulting in a offset in the reading or increased noise [12]. In this paper partial sensor faults which are additive, multiplicative and disturbance types were taken into consideration. Sensor faults are shown in

Table 2.

Table 2. Sensor faults

Status No	Status
0	Normal operating condition
1	Additive fault
2	Multiplicative fault
3	Additive fault
4	Disturbance
5	Multiplicative fault

5. Simulation Results

Detection and identification of different sensor fault types are presented for the oven. Figure 5 shows the feature vectors of the sensor faults which have been applied on the mathematical model of the oven. Feature vectors have been constructed using wavelet analysis, absolute maximum value changing ratio and variance changing ratio.



Fig. 5. feature vector

Figure 6 shows the classification of the feature vector by SOM.



Fig. 6. Classification of the feature vectors

Sensor faults have been detected and identified at 1502 second. When fault has been detected and identified, the

system stop. If the faults were not detected, the system would not stop. As a result the system's sum square error has been shown in Table 3.

Table 3. Sum square error of faults

Status number	Sum square error
1	464.3593
2	366.9509
3	77.8999
4	0.3148
5	163.8772

As shown in Table 3 sum square error is low for status number 4. Because this fault has been applied as a disturbance during 20 seconds. At the end of this duration, system has been kept on working normal situation.

6. Conclusions

This paper addresses intelligent online fault detection and identification for temperature control. Faults often cause undesired reactions, so to keep the system stable and to obtain acceptable control performance is an important problem for control system design. In this paper, thermocouple sensor faults as a multiplicative, an additive and a disturbance type have been examined on the oven. Feature vector of the sensor faults has been constructed using wavelet analysis, sliding window and a statistical analysis. The Self Organizing Map (SOM) has been applied as a classifier of the feature vector.

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