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TUNING ISSUES IN LOOP MONITORING

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Abstract: The aim of this study is to develop an automatic control loop monitoring system. The first step includes the detection of changes and of oscillations in the control error and in the control signal. To determine the parameters of the statistical change detection test (a CUSUM test), the average run length (ARL) function is exploited. To detect oscillations, a modified version of Hägglund's approach is presented. Methods are proposed in order to help the operator in the choice of the parameters for both detection tests. The second step should consist in determining the origin of the oscillations or of the changes. Only the first step is presented in this work. *Copyright © 2002 IFAC*

Keywords: fault detection, fault diagnosis, control loop, monitoring loops, oscillation.

1. INTRODUCTION

In industrial plants, many control loops have poor performance which implies a decrease of the product quality, unnecessary high energy consumption, waste of raw material… These anomalies may have different causes such as hardware fault (friction in valve…), badly tuned controller, sensor fault…

The interest for automatic monitoring of control loop performance is growing. Several approaches have been proposed.

The minimum-variance based performance index introduced by Harris has stimulated numerous research works (Horch and Isaksson, 1999; Thornhill and Hägglund, 1997). It is based on the comparison between the actual output variance and the output variance as obtained using a minimum variance controller. The latter is deduced from a time-series model of the measured output. The form of the test depends on the zeros of the supervised process (presence of non-minimum phase zeros or not) and difficulties exist for its systematic tuning. Therefore, the emphasis here will be on simpler tests aimed at detecting changes from a predefined nominal performance characterised by the mean and the variance of the control error or of the control signal associated to a given set point.

Another important indication of deterioration of the control performance is the presence of oscillations in the control error especially due to friction in valve, oscillating load disturbances, or badly tuned controller. Several simple methods to detect these oscillations have been developed (Hägglund, 1995 ; Thornhill and Hägglund, 1997 ; Forsman and Stattin, 1999; Miao and Seborg, 1998). The problems encountered with the application of such methods to industrial data will be explained and an alternative method will be proposed.

Moreover, the determination of the source of deterioration is of particular importance. In

(Hägglund, 1999), a procedure for the automatic detection of sluggish control loops is described. The diagnosis of the causes of oscillations has received a large attention (Horch, 1999; Horch and Isaksson, 2000; Rengaswamy *et al.*, 2001, Thornhill *et al.*, 2001; Thornhill and Hägglund, 1997).

The aim of this study is to develop an automated monitoring system for the control loops usually encountered in the process industries, namely temperature, pressure and level control loops. The tuning of this monitoring system should require very limited process knowledge. It should be achievable from data recorded under normal condition for each loop. These data are the set point, the control error, the control signal and the measured output variable.
This control loop monitoring will be separated into two steps: the detection of performance degradation and the diagnosis of the cause of malfunction.
The first stage involves detecting

- changes in mean or in variance of the control error;
- changes in mean of the control signal (due to process change or sensor bias, without any change of the set point);
- oscillations.

The first two points are tackled by using statistical tests. The pre-processing of the data, the verification of the assumptions and the tuning of the test parameters are discussed. To detect oscillations, a modified version of Hägglund's approach is presented. For change detection as well as for oscillation detection, methods are proposed in order to help the operator in the choice of the design parameters.

In the second stage, we should concentrate on the determination of the origin of the oscillations, more precisely, we should aim at distinguishing oscillations due to valve stiction from oscillations due to other causes such as oscillating load disturbances. Moreover, diagnosis of the reason for changes in the mean or in the variance of the processed signals should be attempted. These issues will be studied in further work.

2. DETECTION OF DEGRADATION

2.1. Change detection

As seen in the introduction, performance degradation can imply change in mean and/or in variance of the control error and change in mean of the control signal (in the absence of set point modification) in comparison with the healthy state. In this section, the detection procedure is described.

Undersampling
In order to detect abrupt changes as well as slow changes in the mean of the signals, undersampling is performed on the original data. Several sampling periods that are multiple of the original one are considered. The undersampled signals are obtained by replacing the original data by their mean over the considered sampling period.

For monitoring the variance of a signal over different time horizons, a similar approach is used. New undersampled signals are obtained by computing the variance of the original data over windows corresponding to the different sampling periods. In this way a "variance signal" is obtained and changes in the mean of this signal are associated to changes in the variance of the original data.

Test
To detect changes in the mean of the undersampled signals, a statistical test, the CUSUM (cumulative sum) test is applied (Basseville and Nikiforov, 1993, pp. 41-47). This test is briefly reviewed before addressing specific implementation issues.

Consider a sequence of independent random variables y(k), k=1, 2,.. with probability density function $p_\mu(y)$ depending upon the mean μ. μ is equal to μ_0 before the unknown change time, while μ is equal to μ_1 ($\mu_1 = \mu_0+\nu$ or $\mu_1 = \mu_0-\nu$) after change. The problem is to decide between the following three hypotheses:
H_0: data have mean $\mu = \mu_0$
H_1: data have mean $\mu = \mu_0$ before time $k_0 \leq k$ and mean $\mu = \mu_0 + \nu$ after time k_0
H_2: data have mean $\mu = \mu_0$ before time $k_0 \leq k$ and mean $\mu = \mu_0 - \nu$ after time k_0
where k denotes the present time instant.
The CUSUM test is based on the cumulative sum, which is defined as

$$S_k = \sum_{i=1}^{k} \ln \frac{p_{\mu_1}(y(i))}{p_{\mu_0}(y(i))} \qquad (1)$$

If the observations are assumed to be normally distributed and their variance σ is supposed to be constant, the iterative two-sided CUSUM test amounts to computing the two decision functions:

$$g^+(k) = \max\left(0, g^+(k-1) + \frac{\mu_1-\mu_0}{\sigma^2}\left(y(k)-\mu_0-\frac{\nu}{2}\right)\right) \qquad (2),$$

$$g^-(k) = \max\left(0, g^-(k-1) + \frac{\mu_1-\mu_0}{\sigma^2}\left(-y(k)+\mu_0-\frac{\nu}{2}\right)\right) \qquad (3)$$

Upper index + (-) refers to positive (negative) changes in the mean. An alarm is generated when one of these functions crosses a fixed threshold h. The alarm time is thus given by: $t_a = \min\{k : (g^+(k) > h) U (g^-(k) > h)\}$.
An estimate of the change time is computed as follows

$$\hat{t}_0^{\,+} = t_a^{\,+} - N_{t_a^+}{}^{+} + 1 \text{ and } \hat{t}_0^{\,-} = t_a^{\,-} - N_{t_a^-}{}^{-} + 1 \qquad (4)$$

with $N_k^{\,+} = N_{k-1}^{\,+} 1_{\{g_{k-1}^{\,+}>0\}} + 1$ and $N_k^{\,-} = N_{k-1}^{\,-} 1_{\{g_{k-1}^{\,-}>0\}} + 1$
where $1_{\{x\}}$ is the indicator of the event x ($1_{\{x\}} = 1$ if x if true and $1_{\{x\}} = 0$ otherwise). N_k is the number of observations after the re-start of the test, namely after

the last time instant for which the decision function was null. t_a^+ (t_a^-) is equal to t_a when the alarms is issued by the test function (2) (test function (3)).

Discussion of the assumptions

This recursive test (Eq. (2) and (3)) is derived under the assumptions that the processed signal has Gaussian distribution and its samples are independent.

The latter hypothesis is never satisfied on the undersampled signals that were obtained from a set of industrial data corresponding to temperature, level, and pressure loops. In order to meet this requirement one should design an appropriate whitening filter for each signal. As our aim is to obtain a monitoring system with as few tuning knobs as possible, the design of this filter should be automated. Yet, from analysis of the data, it appears that the spectrum of a given signal may change under healthy working conditions. Hence one should resort to an adaptive whitening filter. This seriously increases design complexity and makes automated design for an arbitrary loop extremely difficult. Besides, a whitening filter can change significantly the fault profile as indicated in Fig. 1 and in Fig. 2 where the change in the mean of the original signal was strongly attenuated by the whitening operation. Moreover, upon occurrence of a change in the mean in the original signal, a transient is observed in the filtered signal which is thus not stationary. This should ideally be accounted for in the CUSUM change detection test, which makes its design more complex and yields a test for which no theoretical result exists on performance criteria such as mean time between false alarms.

As far as the Gaussian hypothesis is concerned, normality tests were applied to several data sets corresponding to different types of control loops. Table 1 summarises the results for tests performed on several data sets of the control error undersampled during healthy working conditions. It appears that the undersampled signals do not necessarily have a Gaussian distribution, and moreover, the distribution of a given signal changes from Gaussian to non Gaussian in healthy working conditions. Hence even though a CUSUM test could be designed for an arbitrary distribution, accounting for changes in distribution would make the design overly complicated.

In conclusion, the non-stationary character of the industrial signals in healthy working modes makes the pre-processing of the data by whitening filter and/or the introduction of a non-Gaussian signal distribution in the CUSUM test unrealistic. Besides, whitening filters might significantly reduce fault to noise ratio. For these reasons, it has been decided to process directly the undersampled data with the recursive equations (2) and (3) of the CUSUM test. This approach is also motivated by the known

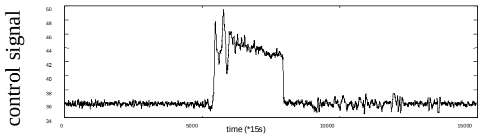


Fig. 1: Control signal.

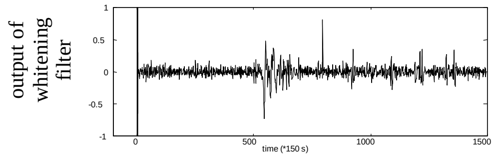


Fig. 2: Output of whitening filter for undersampled signal of Fig. 1.

Table 1: Results of normality tests on undersampled signal

loop	Number of Gaussian data sets	Number of non-Gaussian data sets
temperature	4	10
level	3	7

robustness of the CUSUM test w.r.t. the whiteness hypothesis (independent data samples) (Basseville *et al.*, 1981; Basseville, and Benveniste, (1983)), which will also be verified here (see following section).

Tuning of test parameters

μ_0 and σ are estimated from data sets corresponding to the healthy working mode of the considered closed-loop, or more precisely, from undersampled signals obtained from these sets.

Two tuning parameters are left in the CUSUM test: the change magnitude ν and the threshold h.

The first can be taken as the minimum value ν_{min} of the change one wishes to detect multiplied by 2. To justify this choice, consider Fig. 3 which represents $p_0(z)$, $p_1(z)$ and $p_2(z)$, the probability density functions of Gaussian distributions of a sample with mean μ_0, $\mu_0 + \nu_{min}$ and $\mu_0 + 2\nu_{min}$ respectively. If one considers a CUSUM test to detect a change between $p_0(z)$ and $p_1(z)$, it may issue an alarm as soon as the mean of the signal z is larger than $\mu_0 + \nu_{min}/2$. Indeed, the likelihood ratio $p_1(z)/p_0(z)$ is larger than 1 for values of z greater than $\mu_0 + \nu_{min}/2$ (take z_0 for instance). Hence, to ensure that the minimum detected change is ν_{min} one has to consider the ratio $p_2(z)/p_0(z)$ to design the CUSUM test.

The parameter h is more difficult to determine. It usually results from a compromise between the mean delay for detection and the mean time between false alarms. For a change in the mean μ, both quantities can be determined from the so-called average run length (ARL) function defined, as (Basseville and Nikiforov, 1993, pp. 176-177):

$$L(\mu) = E_\mu(t_a)$$

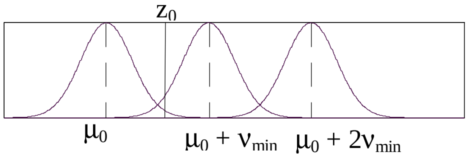


Fig. 3: Gaussian distribution with probability density function $p_0(z)$, $p_1(z)$ and $p_2(z)$, respectively with mean μ_0, $\mu_0 + \nu_{min}$ or $\mu_0 + 2\nu_{min}$

This is the expected value of the alarm time instant. When $\mu = \mu_0$, the ARL is equal to the mean time between false alarms, and when $\mu = \mu_1$, the ARL yields the mean delay for detection.
In the case of a change in the mean μ of a Gaussian sequence, the ARL function for a two-sided CUSUM test is computed as:

$$L^T(\mu) = \frac{L^+(\mu)L^-(\mu)}{L^+(\mu) + L^-(\mu)} \quad (5)$$

with L^+, the ARL function for the one-sided CUSUM test corresponding to (μ_0, $\mu_0 + \nu$) and L^-, the ARL function for the one-sided CUSUM test corresponding to (μ_0, $\mu_0 - \nu$).

As control loop monitoring is essentially aimed at predictive maintenance in the process industries, it is usually important to avoid false alarms. So, the operator will be allowed to choose the minimum acceptable value for the mean time between false alarm, T_{min}. The threshold will be calculated to meet this requirement.

Exact computation of the ARL function is involved, and hence one resorts to bounds on this function (Basseville and Nikiforov, 1993, pp. 205 - 206). Here the threshold of the test will be computed from the expression of a lower bound for the mean time between false alarms. Setting this lower bound to T_{min} should ensure that the actual mean time between false alarms is larger than T_{min}.
Several lower bounds for the ARL exist in the literature, and, as our actual signals do not meet all the hypotheses linked to the considered ARL function, one has chosen to work with the most conservative lower bound among the bounds described in (Basseville and Nikiforov, 1993, pp. 205 - 206). The bound used has been selected after analysis of comparisons given in (Basseville and Nikiforov, 1993, pp. 220 - 221) and our own simulation study. As the signals processed by the CUSUM test are undersampled, some terms are negligible in the formula for the bound. Using equation (5) for the ARL function of the two-sided CUSUM test, the mean time between false alarm will be given by:

$$T_{min} = \frac{\exp\left(-2\left(\mu_s h / \sigma_s^{\,2}\right)\right) - 1 + 2\left(\mu_s h / \sigma_s^{\,2}\right)}{4\mu_s^{\,2} / \sigma_s^{\,2}} \quad (6)$$

with μ_s and σ_s, respectively, the mean and the variance of the increments of the cumulative sum. Their values are respectively $-\nu^2/2\sigma^2$ and ν^2/σ^2.

The threshold, h, is obtained from equation (6).

Although expressions (5) and (6) for the ARL and for T_{min} are theoretically only valid under the hypothesis of independent signal samples with normal distribution, they turn out to be quite useful for tuning the test threshold even when such hypotheses are not met. This is illustrated by the results of tests performed on several types of industrial signals given in Table 2 and 3.

To build Table 2, signals from 5 loops were selected during healthy condition. N is the length of the chosen data set. For each loop, undersampling and calculation of the “variance signals” were performed with three windows of respectively 10, 100 and 1000 original sampling periods. Table 2 indicates the parameters of the CUSUM test applied to the undersampled signals (first 5 lines) and to the “variance signals” (last 5 lines). Each line gives the parameters for the three undersampled signals or “variance signals” of a loop, z_i, with i, the length of the sampling window. The subscripts in Table 2 refer to the length of the sampling windows. μ_i and σ_i^2 are respectively the mean and the variance of the signals z_i corresponding to the first 20000 samples of the original data set. ν is defined as: $\nu = \max\left(\left|\max(z_i) - \mu_i\right|, \left|\min(z_i) - \mu_i\right|, \quad i = 10,100,1000\right)$.
The lower bound for the mean time between false alarms is chosen equal to 1 week or 40320 original sampling periods. Finally, h is the threshold obtained from equation (6). The tests performed on the 10 signals with parameters defined in Table 2 give no false alarm.

Table 3 shows the effectiveness of the detection test. The data are obtained from control loops 1, 2 and 5. The tuning parameters of the tests are those deduced from healthy data as indicated in Table 2. The estimated detection delay (deduced from equation (4)), expressed here in the undersampling period, is short. The advantage of the use of different window lengths is verified: a short window is suitable to detect large faults with short duration, and a larger window should allow detection of faults with small magnitude but long duration.

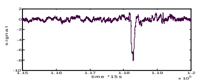
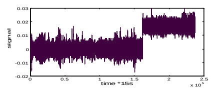
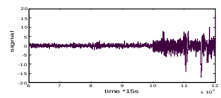
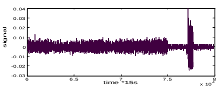
2.2. Oscillations

In the literature, several methods have been developed in order to detect oscillations. Most of them are based on the study of the integrated absolute error (IAE) between successive zero crossings of the control error. Some methods (Forsman and Stattin, 1999, Thornhill and Hägglund, 1997) may be fooled by oscillations of very small amplitude. In (Hägglund, 1995), the amplitude of the oscillations is taken into account. Another method is based on the analysis of the autocorrelation function (Miao and Seborg, 1999). The choice of the test parameters of the last two methods may be inappropriate. Indeed, it

Table 2 : parameters of the CUSUM test for change in mean and in variance

loop	N	ν	μ_{10}	σ^2_{10}	h_{10}	μ_{100}	σ^2_{100}	h_{100}	μ_{1000}	σ^2_{1000}	h_{1000}
1	161545	0.0242	-4e-6	7.05^{e}-6	12.7	-7.9^{e}-6	2.2^{e}-7	13.9	-1.1^{e}-5	1.8^{e}-8	14
2	75000	0.019	1.43^{e}-5	1.87^{e}-6	13.5	1.6^{e}-5	1.9^{e}-7	13.5	1.1^{e}-5	2.6^{e}-9	15.5
3	107000	0.013	$-4^{e}6$	1.12^{e}-6	13.4	$-1.9^{e-}6$	6.4^{e}-8	13.9	-7.7^{e}-7	1.99^{e}-9	15.1
4	107890	24.7	0.23	9.58	12.45	0.24	2.45	11.51	0.23	0.26	11.46
5	100000	4.9	-6.8^{e}-4	0.1108	13.7	-0.0016	0.0566	12.05	-0.0073	0.0045	12.3
1	161545	1.8^{e}-4	4.15^{e}-6	1.8^{e}-11	15.8	1.1^{e}-5	6.8^{e}-11	12.1	3^{e}-6	6.1^{e}-11	9.9
2	75000	4.4^{e}-5	2.8^{e}-6	3^{e}-12	14.8	4.3^{e}-6	3.4^{e}-12	12.3	4.5^{e}-6	1.4^{e}-12	10.9
3	107000	2^{e}-5	1.9^{e}-6	1.3^{e}-12	14	2.8^{e}-6	5.2^{e}-13	12.6	2.8^{e}-6	4.9^{e}-14	12.7
4	107890	142.5	7.08	76.37	13.88	13.7	19.43	12.9	15.8	3.26	10.85
5	100000	2.36	0.0134	1.5^{e}-4	18.8	0.0676	0.0056	12.9	0.1236	0.0035	11.1

Table 3: results of detection test

	Undersampled signal tested	Loop (table 2)	Window length 10	Window length 100	Window length 1000
	mean	5	Change detected. Detection delay : 1	Change detected. Detection delay : 1	Change detected. Detection delay : 1
	mean	1	Change detected. Detection delay : 3	Change detected. Detection delay : 1	Change detected Detection Delay : 1
	variance	5	Change detected. Detection delay : 1	Change detected. Detection delay : 1	Change detected Detection Delay : 1
	variance	2	Change detected Detection Delay : 1	Change detected Detection Delay : 1	Change not detected : window too large

is based on the ultimate frequency or, if the latter is not known, on the integral time of the controller, assuming that it is of the same magnitude as the period corresponding to the ultimate frequency. But the latter assumption is not always satisfied.
Here new guidelines for parameter tuning of Hägglund's method are proposed.

The IAE is defined as

$$\mathrm{IAE} = \int_{t_{i-1}}^{t_i} |e(t)| dt \qquad (7)$$

with t_{i-1} and t_i, two successive instances of zero crossings. It is suggested to work with e(t) computed as the difference between the control error and its average value.
As proposed in (Hägglund, 1995), the method requires two steps.

Detection of large IAE

If the IAE exceeds the limit IAE_{lim}, it is considered to be large. This limit is computed from a user-defined sine wave characterising the smallest oscillation to be detected. Assume this sine wave has amplitude a and period T_{min}. Then IAE_{lim} is computed as:

$$IAE_{\lim} = \int_0^{T_{\min}/2} |a \sin(2\pi t / T_{\min})| dt = a T_{\min} / \pi \qquad (8)$$

The two parameters, a, the minimum amplitude and T_{min}, the minimum oscillation period, must be chosen by the operator.

Oscillation detection

If the number of detected large IAE exceeds a certain limit n_{lim} during a supervision time T_{sup}, it can be concluded that an oscillation is present. n_{lim} must be chosen by the operator and T_{sup} is defined as

$$T_{sup} = n_{lim} T_{max}/2 \qquad (9)$$

where T_{max}, the maximum period of oscillations, must be chosen by the operator.

In practice, Hägglund proposes to make the following test:

$$x(k) = \gamma x(k-1) + \mathrm{load}(k) > n \qquad (10)$$

where load(k) is equal to 1 if a large IAE has been detected at time k and to 0 otherwise, and $\gamma = 1 - T / T_{sup}$, with T, the sampling period. The limit n can be determined by simulation: it corresponds to the value of x calculated for an oscillation with a period equal to T_{max} and characterised by a number n_{lim} of IAE larger than IAE_{lim}.

In order to detect appearance of oscillations as well as disappearance, it is proposed to apply the test on a moving window of length T_{sup}.

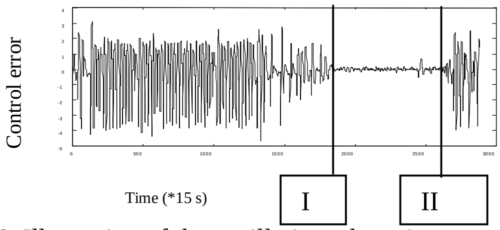


Fig. 6: Illustration of the oscillations detection test ($a = 1$, $T_{min} = 150$ s, $T_{max} = 1500$ s, $n_{lim} = 10$) I: detection of the disappearance of the oscillations; II: detection of the appearance of the oscillations.

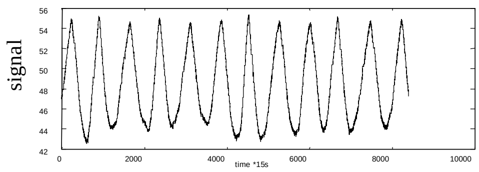


Fig. 7: oscillating signal

In Fig. 6, results obtained for an industrial data set show the effectiveness of the method and the advantage of the use of a moving window. Note that the oscillations of Fig. 7 can not be detected by Hägglund's nor by Miao's method. Indeed, in the latter methods, 5 oscillations periods should appear in a time window of 50 T_i or 250 T_i which is not verified in this case, since T_i is equal to 60s. On the contrary, the parameter tuning proposed here allows one to detect the oscillations (with $a = 1$; $n_{lim} = 10$; $T_{min} = 1500$ s; $T_{max} = 15000$ s).

In conclusion, this modified version of Hägglund's method has only 4 concrete parameters defined without any assumptions and depending on what the operator wishes to detect.

4. CONCLUSIONS

The problem of control loop monitoring has been separated into two steps: detection of performance degradation and diagnosis. Some guidelines have been presented to help the operator in the choice of the test parameters for the first step. The detection step includes change detection and oscillation detection. To determine the parameters of the statistical change detection test (namely the CUSUM test), a bound for the mean delay between false alarms obtained from the average run length (ARL) function for independent signal samples with Gaussian distribution is used. The efficiency of the parameter tuning is shown by application of the method to industrial data. To detect oscillations, Hägglund's method is modified by defining new thresholds using more concrete parameters.

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