FAULT DETECTION FILTER BASED ON LUENBERGUER OBSERVER: AN GEOMETRIC APPROACH

FILTRO DE DETECION DE FALLAS CON OBSERVADOR DE LUENBERGUER: UNA APROXIMACION GEOMETRICA

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Abstract: This paper describes a methodology for designing Fault Detection Filters based on Luenberguer observer

Resumen: Este artículo describe una metodología para el diseño de un filtro de detección de fallas, basado en el observador de Luenberguer

Keywords: Luenberger Classic Observer, detection filter, fault detection, fault diagnosis.

I. INTRODUCTION

Together with the complexity of process development there is also a growing need to keep them reliable and available. Process availability requires efficient maintenance strategies.

Reliability is defined, as the probability that a system, unit or equipment under study will operate in a satisfactory way during a period of time under specific conditions. Probability, Satisfactory Performance, Time and Specific Operating Conditions, are key elements in defining a reliable system.

Fault detection and fault diagnosis are essential for highly reliable, secure and efficient process. Detection and Diagnosis, is achieved by supervising derived signs within a process, and continuously analyzing their behavior by means of proper tools developed for such purpose.

Therefore it was then considered appropriate to design a fault detection filter and apply it to the various instruments. The information obtained will allow maintenance and operations personnel to take corrective action well in advance by means of suitable Condition Based Preventive Maintenance (CBPM) strategies.

Designing fault detection filters based on the Classic Luenberger Observer and applying it to the instrumentation requires the use of the transmitter outputs to generate a residual vector, whenever deviations are registered in the field instrumentation.

2. THEORY

1. Detection Filter

Within this section the essential differences between designing an Observer as a Fault

Detection Filter or as a Fault Isolator will be stablished.

The behavior of a time invariant lineal system around the equilibrium coordinates is described by means of the following equations in the state space:

$$\dot{\mathbf{x}}(t) = \mathbf{Ax}(t) + \mathbf{Bu}(t), \tag{1}$$
$$\mathbf{y}(t) = \mathbf{Cx}(t). \tag{2}$$

With x (t) as the state vector, with n components as state variables, u (t) the control vector, with p components as input variables, y (t) the output vector, with q components as output variables, A the state matrix (dim. nxn), B the input matrix (dim. pxn) and C as the output matrix (dim. qxn).

1.1 Fault

It is a system internal action, auto-generated due to a bad behavior of one or more subsystems trying to drive it to a non desired state. For analyses purposes, each one of the possible system faults will be considered as the Livi (t) vector belonging to the system state space.

For k faults, the following expression applies:

$$faults = \sum_{i=1}^{K} \boldsymbol{Livi(t)}. \tag{3}$$

If a fault appears at time $t = to$, then:

$\boldsymbol{vi}(t) = 0$, $t < to$, (4)

$\boldsymbol{vi}(t) \neq 0$, $t \geq to$. (5)

The following assumptions will be made: (1) faults are considered additional terms within the process dynamics. (2) Faults are vectors in $\Re^n$, where n represents the system space dimension. (3) Faults are structured by *failure patterns* ***Li*** and failure modes ***vi*** (t). (4) Failure *patterns* ***Li***, are known or can be derived. (5) Failure modes ***vi*** (t) are arbitrary unknown functions time dependent. (6) Failure pattern components belonging to the observable sub-space are linearly independent. (7) The failure *pattern* vectors are located outside the observability nucleus of matrix ***Ker*** **(C, CA,..., CA^{n-1})**. (8) The system is detectable **(C, A** is detectable).

According to the previous paragraph, from now on it can be stated that a system in the presence of faults will have the following dynamics:

$$\dot{\mathbf{x}}(t) = \mathbf{Ax}(t) + \mathbf{Bu}(t) + \sum_{i=1}^{K} \boldsymbol{Livi}(t), \tag{6}$$
$$\mathbf{y}(t) = \mathbf{Cx}(t). \tag{7}$$

In equation (6), $\boldsymbol{Li} \in \Re^{nxpi}$, **u** (t) $\in \Re^p$, and **y** (t) $\in \Re^q$, ***vi*** *(t)* $\in$ to the space vector ***Vi,*** representing arbitrary fault functions, where dim. (***Vi***) = ***pi*** represents the unknown failure modes and the maps $\boldsymbol{Li}:\boldsymbol{Vi} \rightarrow \Re^n$ as the failure patterns. Failure modes and failure patterns will be used, together with the previous considerations, to model faults. If faults are non existing, then by definition it can be assumed that ***vi*** *(t)* is identically zero in equation (6).

1.2. Fault Conditions

The necessary conditions for fault detection and fault isolation in time invariant lineal systems are the Detection and Isolation Conditions.

1.2.1. Condition of Detection

Expression (8) specifies the necessary condition for fault detection.

Ker (CLi) = 0, i = 1, 2,..., I. (8)

1.2.2. Condition of Isolation

The condition of Fault Isolation is given by the possibility of geometrically decoupling each **C*Li*** image in the observable sub-space of $\Re^n$, considered as an orthogonal sum of two sub-spaces, the observable sub-space (**Ob**) (where non detected faults do hide), and the unobservable sub-space (**InOb**) (where faults to be detected exist), that is:

dim $\Re^n$ = (**Ob**) ⊕ (**InOb**). (9)

1.2.2.1. Necessary Conditions

A necessary, but not sufficient condition, to guarantee fault isolation is:

The space of images:
Im(**C*Li***), **Im**(**C*Li***),..., **Im**(**C*LI***), (10)

Should be lineal independent, that is:
Im(**C*Li***) ∩ (**Im**(**C*L*1**) + ... + **Im**(**C*L*i-1**) + **Im**(**C*l*i+1**) + ... + **Im**(**C*LI***)) = 0.” (11)

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1.3. Detectability Condition

The system described by means of equations (1) and (2) is detectable, if an observer as the one described by the following equation exists:

$$\dot{\tilde{\mathbf{x}}}(\mathbf{t}) = \mathbf{A}\tilde{\mathbf{x}}(\mathrm{t}) + \mathbf{Bu}(\mathrm{t}) + \mathbf{D}(\mathbf{C}\tilde{\mathbf{x}}(\mathrm{t}) - \mathbf{y}(\mathrm{t})), \qquad (12)$$

$$\tilde{\mathbf{y}}(\mathrm{t}) = \mathbf{C}\tilde{\mathbf{x}}(\mathrm{t}). \qquad (13)$$

In such a way that,

$Lim_{t \longrightarrow \infty}(\mathbf{x}(\mathrm{t}) - \tilde{\mathbf{x}}(\mathrm{t})) = \mathbf{e}(\mathrm{t}) = 0$, or being equivalent, if the error system is asymptotically stable.

If the error estimate is defined as the difference or as the residual existing among the space vectors $\mathbf{x}$(t) and $\tilde{\mathbf{x}}(\mathrm{t})$ or among the two systems described by (1) and (12), then an error dynamic can be expressed as:

$$\dot{\mathbf{e}}(\mathrm{t}) = \dot{\mathbf{x}}(\mathrm{t}) - \dot{\tilde{\mathbf{x}}}(\mathrm{t}) = (\mathbf{A} - \mathbf{DC})\mathbf{e}(\mathrm{t}), \mathbf{e}(\mathrm{t}) = \mathbf{e}_0. \qquad (14)$$

Where **eo**, is some unknown finite value.

The system error described by equation (14) will be asymptotically stable or $Lim_{t \longrightarrow \infty}\mathbf{e}(\mathrm{t}) = 0$, provided on the location of the auto-values of the map (**A-DC**), values that may be assigned arbitrarily in the absence of particular specifications, on the left side of plane s. This will ensure a state estimate vector $\tilde{\mathbf{x}}(\mathrm{t})$ being approximately or tending to the original state vector **x**(t) as *t* tends to infinite (∞).

1.4. Fault Detection Filter based on the Luenberger Classic Observer

Consider designing a complete system represented by equations (1) and (2), with an observer defined by equation (12).

Designing a fault Detection and Diagnosis Filter based on the Luenberger Classic Observer, requires a verification of compliance for the following:

a) *Availability of all outputs for the real system, on which fault detection and isolation is to be performed.*

This consideration implies a known system structure previously to the Filter design.

b) *The System model should be Observable.*

c) *The System model should be Detectable.*

The observer gain matrix (**D)** is designed by locating the characteristic values of the map (**A-DC**), for a system described by equation (14), to be asymptotically stable. In the absence of faults, the error equation approaches zero. If the fault appears at time $t \geq to$, then the error sign (**e**(t)) becomes different from zero, giving an indication of the presence of a fault.

Reviewing the system error dynamic in the presence of a fault, as given by:

$$\dot{\mathbf{e}}(\mathrm{t}) = \dot{\mathbf{x}}(\mathrm{t}) - \dot{\tilde{\mathbf{x}}}(\mathrm{t}) = (\mathbf{A} - \mathbf{DC})\mathbf{e}(\mathrm{t}) + \sum \mathbf{Livi}(t), \mathbf{e}(\mathrm{t}) = \mathbf{e}_0. \qquad (15)$$

In absence of faults ($\sum \mathbf{Livi}(t) = 0$). The stability of the system error is conditioned by the characteristic values of the map (**A-DC**). The presence of a fault introduces an additional term $\sum \mathbf{Livi}(t)$, destabilizing the system error by setting it different from zero, and making it possible to detect faults at incipient stages within a dynamic system.

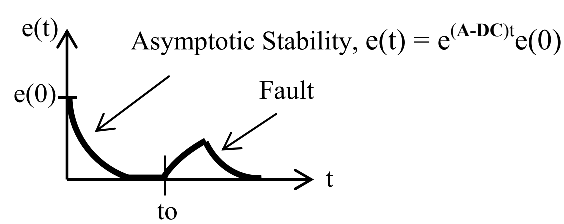

Fig. 1: Asymptotic Stability

a) *The Filter should be Sensitive and should have an error vector with a fast response.*

Selecting the characteristic values is a commitment between the speed response of the error vector and the system sensibility to interference and noise in the measured variables. A fault detection filter requires sensibility to detect deviations indicative of a possible fault. However, if the output signal of the plant is significantly contaminated with interference or noise in the measurements, the output will not be reliable and could generate false alarms. If the filter is set to avoid all possible false alarms due to interference or noise, there is a risk of not being able to detect true deviations and possible faults.

b) The Filter should allow as possible as it may be, decoupling faults within the dynamics of the real system.

The observer gain matrix (**D**) design should allow for maximum decoupling of faults, to enable geometrically identifying the initial perturbed coordinate. This will ensure that any destabilizing effects arising from perturbations while detecting this initial coordinate will not spread into others, making the fault isolation impossible. For this reason the map (**A-DC**) shall be as close as possible to the identity matrix *nxn*, or: (**A-DC**) ≈ - α**I**.

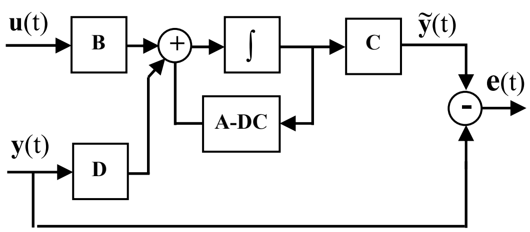

Fig. 2: Block Diagram of a Fault Detection Filter Based on a Classic Observer

2. MODELING

2.1. Modeling of a Dynamic System

Most dynamic models are developed by means of energy balances and/or mass balance, based on the laws governing them, such as Newton's for the mechanical ones. An approximate model may also be derived from a dynamic system response, whose equations can then be used to obtain those variables of interest. Obtaining a reasonable mathematical model is the most important part of the whole analysis.

2.2. Modeling Faults

In this section a formal fault definition for the sensor and actuator blocks will be provided as part of the representation of instrumentation for industrial dynamic systems.

2.2.1. Modeling Faults within Instruments (Sensors and Actuators)

For an ideal instrument, with no faults, the relationship between the real values of the variable, within the measuring range, and the instrument reading is a lineal one. See Figure 3.

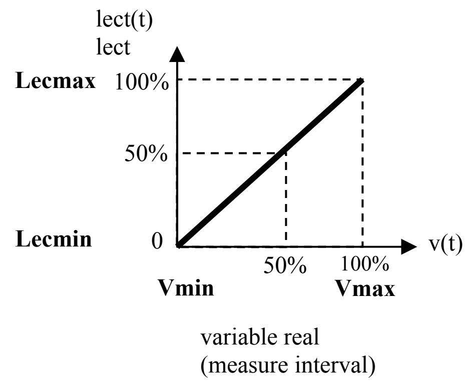

Fig. 3: Relation between measured variable and read out for any instrument

Fault models on instrumentation: valves, transmitters, sensor, etc., can be expressed as a function of a deterministic equation relating the dependent variable with the independent variable. This equation is obtained from a graphic analysis of figure 3, and it is not more than the equation of a straight-line, given by:

$$Lec(t) = \frac{(Lex\max - Lec\min)}{(V\max - V\min)}(V(t) - V\min) + Lec\min. \qquad (16)$$

To represent the instrument dynamic, we will convert this equation (16) into a first order dynamic equation:

$$\tau\frac{dLec\max(t)}{dt} + Lec(t) = \tau\frac{(Lec\max - Lec\min)}{(V\max - V\min)}(V(t) - V\min) + Lec\min \qquad (17)$$

Where τ is the time constant of the instrument function block.

To understand how a fault may be modeled as part of an instrument system (sensors and actuators) we will see an example.

Let us assume that a variation exists in Lecmax, with ΔLecmax as the quantity representing the deviation. Now the dynamic equation of an instrument with a deviation in Lecmax, is given by:

$$\tau\frac{dLec\max(t)}{dt} + Lec(t) = \tau\frac{((Lec\max \pm \Delta Lec\max) - Lec\min)}{(V\max - V\min)}(V(t) - V\min) + Lec\min \qquad (18)$$

If we separate the deviation effect ΔLecmax, while maintaining the original equation structure, will result on:

$$\tau \frac{dLec\max(t)}{dt} + Lec(t) = \tau \frac{((Lec\max - Lec\min)}{(V\max - V\min)}(V(t) - V\min) + Lec\min \pm \frac{(v(t) - V\min)}{(V\max - V\min)}(\Delta Lec\max(t)) \quad (19)$$

With the last equation representing the instrument behavior with an additional component being a fault, and given by:

$$fault = \pm \frac{(v(t) - V\min)}{(V\max - V\min)}(\Delta Lec\max(t)). \quad (20)$$

Out of this equation we can differentiate, a fault *pattern* ***Li*** and a *failure mode* ***vi***:

$$\mathbf{Li} = \pm \frac{(v(t) - V\min)}{(V\max - V\min)}. \quad (21)$$

$$\mathbf{vi}(t) = (\Delta Lec\max(t)). \quad (22)$$

As for modeling sensor faults, we make reference exclusively to the transmitter. A faulty sensor may be modeled as a deviation on the model of the sensor (matrix C). For generic purposes we will consider this deviation as a model or generic pattern, denominated **ΔC**.

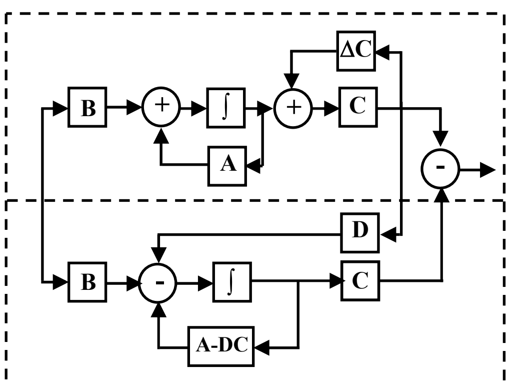

Fig. 4: Block diagram representing faulty sensors

In general, an instrument may generate any number of failures. However, we will only consider the common ones: span, span dead zone, zero dead zone, zero calibration, and hysteresis.

Figure 5, represents the various characteristics that instruments may exhibit, we will define in a general way, the parameters involved in this figure.

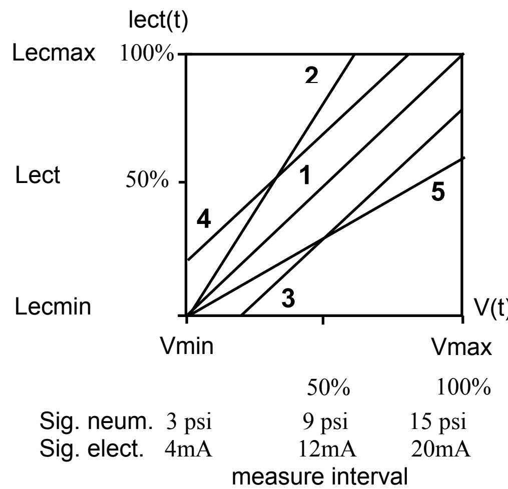

Fig. 5: Most common instrument failures

2.2.1.1. Span and dead zone failures

These types of faults imply that all readings increase or diminish progressively with respect to a straight-line representing normal operating conditions, line 1 (see figure 5). These type of failures do not cause a base point change, but do change the meter "reading" progressively as the measuring interval increases. These deviations can be positive or negative. On positive ones (Span failure, line 2), the related failure parameter is Lecmax. On negative deviations (span dead zone, straight-line 5), the related failure parameter is Vmax.

2.2.1.2. Zero dead zone and zero calibration failures

These failures imply that all readings have been displaced with respect to the corresponding straight-line of the instrument as noted in figure 5. As it can be observed such displacement may be positive or negative. The starting point or base of the representative straight-line varies without modifying the slope or the shape of the curve. For a positive displacement drift (zero calibration failure, straight-line 4), the related failure parameter is Lecmin. In case of a negative displacement (zero dead zone, straight-line 3), the parameter involved is Vmin.

2.2.1.3. Hysteresis Failure

Hysteresis is the maximum difference that may be observed on recorded values for the same measurement, once the variable travels through the whole scale in two directions, upwards and downwards.

2.3. Modeling by Expanding the State Space

The interest of orienting Detection Filter design, towards fault detection and diagnosis for industrial dynamic systems, has resulted in the addition to the process dynamic model, of all the elements that conform the closed curl of control systems, including the actuator and sensor blocks. Including the actuator and sensor blocks into the process model, while designing fault detection filters based on observers, is denominated *modeling by expanding the state space*.

This expansion will allow discriminating against a larger number of causes of failures in a control curl. Due to the nature of the control curl being conformed by a series of function blocks: sensor, actuator, process and controller, any incipient faults originated in anyone of these blocks will propagate into the other blocks of the curl.

3. METHODOLOGY

To detect faults on the instrumentation of a compressor, the compressor dynamics and its related instrumentation dynamics need to be modeled transmitters and valves. To simulate the operation of the modeled system it is necessary to give some dynamics to the processes. Mathematical models are then built to fit the processes and instrumentation behavior. Once these are ready a simulation of the industrial model is performed, to closely fit the dynamic of the mathematical model to those of the real plant. Afterwards both a Classic Luenberger Observer and the Fault Detection Filter are designed. Once the filter design has been completed, its industrial model is simulated with the purpose of verifying the filter behavior as it responds to various simulated faults on the instrumentation.

4. CONCLUSIONS

The possibility of choosing an Observer gain matrix and arbitrary locating the characteristic values of map (**A-DC**), will allow a set of closed loop error equations to work as a fault detector, making it possible to geometrically isolate the faults.

A fault detection and diagnostic filter robustness is highly committed with the quality of the various field signals. Upon high noise signals and measuring dead times a fault detection and diagnostic filter may generate false signals.

The ability to decouple different failures is only possible when the isolation condition is satisfied. Being always possible to detect failures.

Information on fault detection with no diagnostics is useful data that may be used to determine the overall system reliability.

5. RECOMMENDATIONS

It is recommended to combine the results of a detection filter with other theories to allow for improved fault decoupling. E.g. Neural Nets and Artificial Intelligence.

The use of signal conditioners is recommended, for cases where the noise level may be harmful to a proper filter operation.

The Fault Detection and Diagnosis filter may interact with the control systems, as a supplement to more traditional control approaches, providing higher robustness on critical applications.

REFERENCES

[1].- Gertler J., Fault Detection and Diagnosis in Engineering Systems. Marcel Dekker, Inc. Printed USA, 1998.

[2].- Chen P., Robust Model-Based Fault Diagnosis for Dinamic Systems. Kluwer Academic Publishers, 1999.

[3].- Basseville M., Nikiforov I. Detection of Abrupt Changes: Theory and Application. Prentice-Hall, INC. 1998

[4].- Lieberman N., Lieberman E. A Working Guide to Process Equipment. Edición McGraw Hill. 1997.

[5].- Basseville M., Nikiforov I. Detection of Abrupt Changes: Theory and Application. Prentice-Hall, INC. 1998.

[6].- Moubray John. Reliability-Centred Maintenance. Second Edition. Editorial Planta Tree. 1997.

[7].- Ebeling Charles. An Introduction to Reliability and Maintainability Engineering. Edition McGraw Hill. 1997.

[8].- Pouliezos, Stavrakakis. Real Time Fault Monitoring of Industrial Processes. Kluwer Academic Publishers. (1994).

[9].- Jhon S. Oakland. Statistical Process Control. Jhon Wiley & Sons, Inc., New York, 1986.

[10].-Kailath, T. Linear Systems, Prentice-Hall. Englewood Cliffs. New Jersey. 1980.

[11].-Lang Serge, (1993). Algebra. Addison-Wesley Publishing Company. Third Edition.

[12].-Abraham,R., Marsden,J.E., Ratiu T. Manifolds, Tensor Analysis, and Applications. Springer-Verlag. 1983.

[13].-Wonham, W .M. (1985). Linear Mulivariable Control: A Geometric Approach. Springer-Verlag, New York.

[14].-Tarantino, R. (1999). *Fault Detection on Dynamic Time Variant Lineal Systems*. Work Doctoral, University of the Andes, Mérida.

[15].-Tarantino, R., Cabezas, K., Rivas, F. and Colina, E. (1999). *Detection and Diagnosis of Faults based on a Hybrid Method*. Mérida. University of the Andes.