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ABSTRACTING QUALITATIVE INFORMATION FOR PROCESS SUPERVISION

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Abstract

Supervisory Systems evolution makes the obtaining of significant information from processes more important, in the way that Supervision Systems particular tasks are being simplified. So, to have signal treatment tools capable of obtaining ellaborate information from the process' data is important. In this paper, a tool that obtains qualitative data about the trends and oscillation of signals is presented. An application of this tool is presented, as well. In this case the tool, implemented in a CACSD environment, is used in order to give to an ES for fault detection in a laboratory plant.

1. Introduction

According to bibliography, it seems that process supervision has had a great evolution in the last few years. So far, operator aid just consisted of process monitorization in several industrial projects. Nowadays, theory control has caused the work done by process engineers to be evolved from particular control tasks to supervision tasks [1]. Since a great deal of different parts of the process data are available for the operators and supervision engineers, it is difficult to get outstanding data and extract the most significant information. Application of Artificial Intelligence (AI) to supervision makes the qualitative idea (i.e. Error is positive) as well as models based on qualitative description of physical systems building useful and necessary for building supervisory systems.

Detection and fault diagnosis is one of the supervision's important tasks . At the beginning fault detection systems consisted of detecting unexpected changes in the bhaviour of process signals [2]. So far, the majority of fault detection systems are model based [3] [4] [5] [6], and faults are detected comparing the real system with the model. Uncertainties in the model and white noise make the fault detection problem more complicated. If a perfect system model is available and all the inputs can be measured, then relationships between inputs, real system outputs and model predictions are compared. Then if some divergences are found then deduction is that there is a fault in the system. If some of the noisy inputs are not available or the model is incomplete, the previous idea can not be applied.

In this case, a first step is to find out whether there is a difference between the model prediction and the real system data; and a second step, if there are divergences, then the supervisory system has to check whether these ones are due to either any fault, model uncertainty or noise.

In other cases fault detection is based on causal model building. Here system heuristic knowledge is represented by relating faults to possible causes [3] [4] [7]. Fault detection systems relate the system symptoms to possible malfunction causes.

At any rate, process knowledge will determine its representation and observation abstraction level. Consequently, a supervision module has been conceived according to this abstraction level and, therefore, this has to be related to the representation and information quality [8].

2. Need of abstractors

Sensitivity of fault detection systems to modelling errors and to other processes perturbations is an important problem, as mentioned before. False alarms are due, in a lot of cases, to noise that affects the supervised process.

Therefore, the point is to build systems capable of manipulating incomplete data, scarce information or uncertainties to undertake robustness to false alarms. On the other hand, to increase the qualitative reasoning power, advantage of all the available numerical information should be taken.

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So, to have tools for dealing with signals coming from the process is necessary in a way that the supervision, detection and diagnosis tasks have been made easier [9], [10]. These tools are called **abstractors** since their job is to abstract elaborated process data or information. This signal treatment will always depend on the kind of information desired.

Some abstractors

- *Qualification of filtered signals.*

A straight forward possible way of extracting useful information is the use of signal filtering. Filtering and its later qualification are the jobs done by the tool presented in section III. Sections IV and V present its application to a real process and the obtained results.

- *Trends triangular representation.* [11] [12]

Trends triangular representation is a signals qualitative description of their behaviour. First, singular points (maximums, minimums and inflexion points) of the signal to study are detected. Then, intervals between two singular points are represented by means of triangular episodes. These episodes are built up from each signal its value, its trend and its curvature. After this, the episodes can be grouped in trapezes in the way that a signal representation in different temporary scales is obtained .

- *Temporary windows, Histograms*

Using temporary windows for analysing the signal behaviour in a certain time interval is an interesting case [13] . It can be achieved by using and treating not only the signals in a certain instant but in its evolution in a whole time period. This last increases the obtained information quality.

Histograms [14] are based in the signal study during a period of time (temporary window) classifying the values that are taken in this time period in zones and intervals. Then, any temporary window indexes are calculated. These are the indexes that the supervisory system can use.

- *Wavelet transform [11] [15]*

Wavelet transform is a signal decomposition in the temporal and frequency domains with different resolutions. In this way, temporary and frequency representation at different scales can be achieved. This allows a description of general performances of the signals that contain quite different dynamics between them. These signals' decompositions could be very useful in supervising processes in order to study the most representative signal aspects and getting rid of the others without interest.

3. Created abstractors

This work shows two abstractors which are very useful to show the qualitative process perception that expert operators could have. In process control there are a lot of cases where signal variations from processes go together with damped oscillations. First, a separation of each signal variation from the proper oscillations due to these variations has been tried. Then, a qualification of the variations as well as the oscillations has been done to obtain two symbolic features as a final result: the **trend** and the **oscillation level.** They reflect the variables behaviour from the previous mentioned point of view. Qualitative data, as well as quantitative data, will be used later by the supervision system. An important abstractors feature is that they can give process information on line.

In the following paragraphs, a description of how the abstractors work and the information they give to the expert system is detailed.

Qualitative trends

The most important and useful feature that could be extracted from signals is their trends to go up, down or maintain level. An algorithm that makes an estimation of this abstraction has been done with the following structure:

1. Noise filtering
2. Extremes detection
3. Adaptive filtering
4. Gradient
5. Gradient qualification

Further detailed, the described algorithm is:

- *Step 1: Noise filtering*

First a low-pass filtering is done in order to remove the noise added to the signal. This will allow the next steps to be executed under guarantee.

- *Step 2: Extremes detection and period estimation*

Second step consists of a signal oscillation period estimation. In order to make an estimation of the period, a relative extremes (maximums, minimums, and inflection points) detection is done and period estimation is calculated from the time interval between two consecutive extremes. This calculation is done every time an extreme is detected. The estimated period is useful for finding the adaptive filtering cut-off frequency. So this cut-off frequency is changed every time that an extreme is detected.

- *Step 3: Adaptive filtering*

A low-pass filtering of the original signal is done at each sampling time by using a IIR filter (for example a 2nd order Butterworth filter); the cut-off frequency will depend on natural frequencies of the process (contained in the measured signal and obtained in step 2). This action smoothes the signal, its oscillations, and overshoots.

An important feature to keep in mind is that previous information of the signal behaviour is needed to filter it correctly without loosing useful information for the following steps And, moreover, eliminates the natural oscillations of the signal.

- *Step 4: Gradient*

The goal is to obtain the signal trend, and because of this, after the filtering process mentioned in the previous paragraph, the slope of the signal is obtained. This slope

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will tell us if the signal is going up, down or maintaining its level. The constraint is that signals evolution is only available up to the calculation time to obtain this slope, but future values are unknown. The most simple way to calculate it will be by subtracting the previous value and the present value.

- *Step 5: Obtained gradient qualification*

In order to use this qualitative trends abstractor by an ES the obtained slope will be classified into different levels. For example the trend can be divided into five levels as follows:

2 greatly rising
1 rising
0 keeps on level
-1 descending
-2 greatly descending

This classification is done according to the maximum and minimum values of the gradient obtained in the previous step and takes advantage of the knowledge of the process engineer. So, it will be necessary to know the previous behaviour of the signal as well.

Qualitative oscillation

Another important feature that could be extracted from the process is signals amplitude oscillation. This qualitative oscillation could be obtained by subtracting the filtered signal (without oscillation) from the original. Once done, only the oscillation remains. The following algorithm was created to do this:

1. Take the absolute value of the original signal subtracted by filtered signal.
2. Filter
3. Qualify

Further detailed:

- *Step 6:*

The filtered signal (obtained in step 2) is subtracted from the original signal and the absolute value is calculated. This gives an idea of the oscillation amplitude at each instant.

- *Step 7: Filtering*

The result of step 1 is filtered. The resulting signal is smoother than the original one. This signal with less rough changes is easier to qualify.

- *Step 8: Qualification*

The obtained oscillation grade is qualified into different levels, for example:

2 Large oscillation
1 Small oscillation
0 No oscillation

Figure 1 shows an operation scheme of this algorithm. The final result is two outputs that draw the trend and signal oscillation in a qualitative way. These outputs can be used by the supervision system.

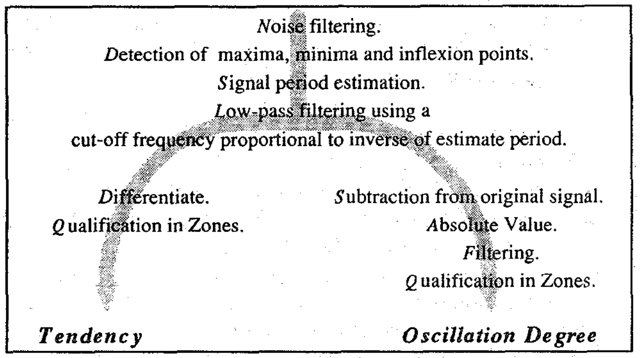

Fig. 1: Algorithm operation scheme

The present process regime can be another useful data to use in the supervision. Next, the way to calculate qualitatively the regime from the trend and oscillation parameters is shown.

Regime

In general, a first regime division can be made, between transient and steady state or permanent. To determine in which regime the signal is, the trends and the oscillation degree will be used (there will be steady state when the signal will tend to maintain the state without oscillations). It will be obtained by the ES by using rules that extract the 'degree of transitory state' at the same time; so a regime qualification could be done.

For example:

0 Permanent
1 Almost-permanent
2 Transient

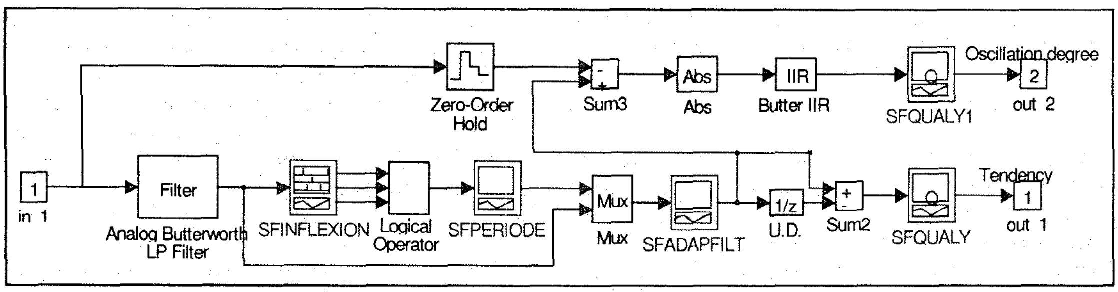

Fig. 2: Simulink implementation

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4. Application to a real process

This paragraph shows the application of abstractors in order to give information to a fault detection Expert System (ES). This ES has been developed in the G2 environment and is entrusted with detecting faults provoked in the laboratory plant.

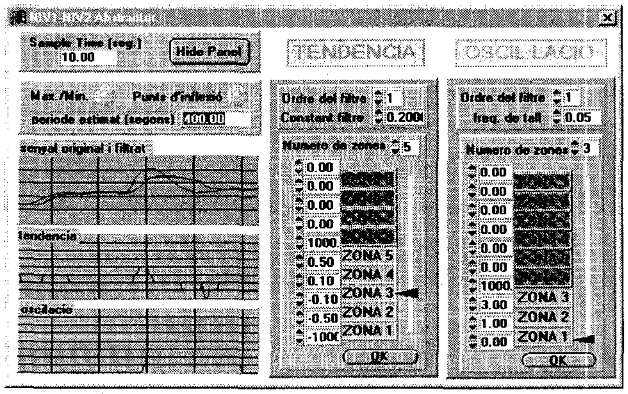

Fig. 3: LabWindows implementation

First abstractors implementation was fulfilled in Matlab-Simulink (Fig. 2) . The reasons for using this tool were to test with fulfilled simulations in this environment as well as the facilities offered to create and develop signals analysis tools. Then the tools were implemented in Labwindows (Fig. 3), permiting them to apply to the real process by means of a data acquisition board. Communication between abstractors (implemented in a PC) and Expert System (running in a SUN workstation) has been done using the serial port RS-232.

Laboratory Plant description

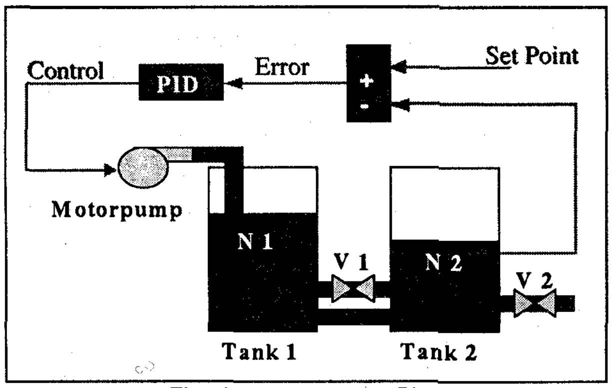

Fig. 4: The Laboratory Plant

The laboratory plant where fault situations are caused is composed by two coupled tanks with two pipes doing the connection between them as depicted in Fig. 4.
The goal is to control the level in the second tank by pumping the fluid to the first tank while the liquid flows through valve 2 (V2). The control signal of this process is the pump voltage and measures from the tank levels are also available. Correct operations are defined as follows: valves (V1 and V2) are open and the process is correctly controlled (good PID tuning and pump working). When failures are introduced then the expert diagnostic system has to be able to detect and identify them. Therefore, the goal of the supervisory system is to track the process and detect situations that incite failures or process malfunctions, as well as to know when the process works in the normal operating conditions.

The process will correctly work when the tank 2 level tracks the set point through a good regulation according to valves 1 and 2 are opened. In case one of these facts do not match, this will be considerated as a process failure. So, possible malfunction causes will be:

1. *Valve 1 closed*
2. *Valve 2 closed*
3. *The electrical pump does not work*
4. *Bad regulation*

Situations when more than one of these malfunctions happen simultaneously are not considered. To use an ES dealing with failures detection makes possible a study of the evolution process for each malfunction in order to obtain expert knowledge which allows the rules conception and construction.

In order to detect the failures, then abstractors have been applied to the most representative signals such as the *level difference* and the *error*.

In the Fig. 6-12 it can be seen the result of applying this ideas to extract the trend and oscillation grade from a level1-level2 signal.

5. Results

Together with the quantitative data, qualitative information from the abstractors is used by the Expert System in order to detect possible faults. The ES has been implemented using G2. This environment permits reasoning using symbolic information. This means that abstractors utilisation has facilitated the knowledge base development, since it would have been more difficult without abstractors. It would have implied the use of a lot more rules, and therefore more difficulties to build and validate.

if n1-n2>=15 and (sten_n1-n2 is keep_on_level or sten_n1-n2 is rising or sten_n1-n2 is greatly_rising) then conclude that V1 is closed

Fig. 5 :Rules operate with qualitative (*trend* and *oscillation degree*) and quantitative information.

In Fig. 13 temporal evolution of variables can be observed. *Trends* and *Oscillation degree* are represented as well as the filtered signal of *n1-n2* and *error* signals.
A table is added below each figure. This table shows the conclusion obtained for the ES regarding introduced failures.

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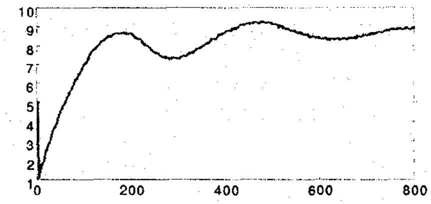


Fig. 6: Level1-Level2 Measure

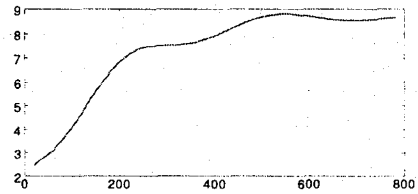


Fig. 7: Filtered Signal (*Step* 3)

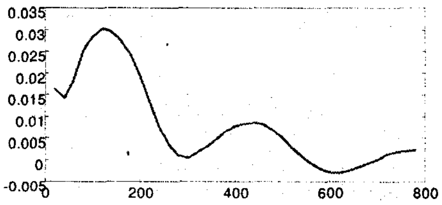


Fig. 8: Filtered Signal Gradient (*Step* 4)

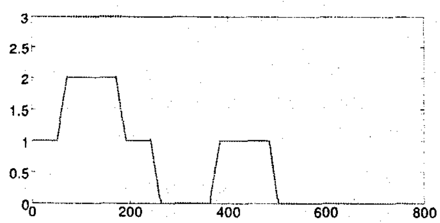


Fig. 9: Signal Trends (*Step* 5)

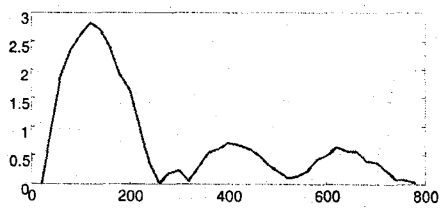


Fig. 10: Original Signal minus Filtered Signal (*Step* 6)

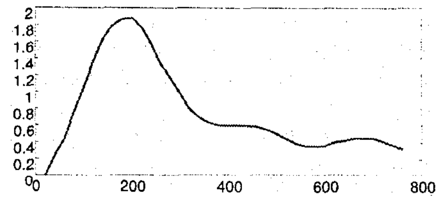


Fig. 11: Filtered Oscillation (*Step* 7)

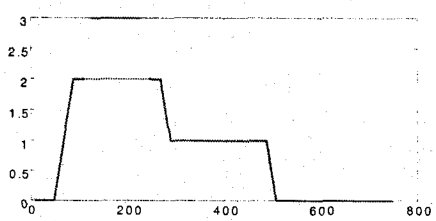
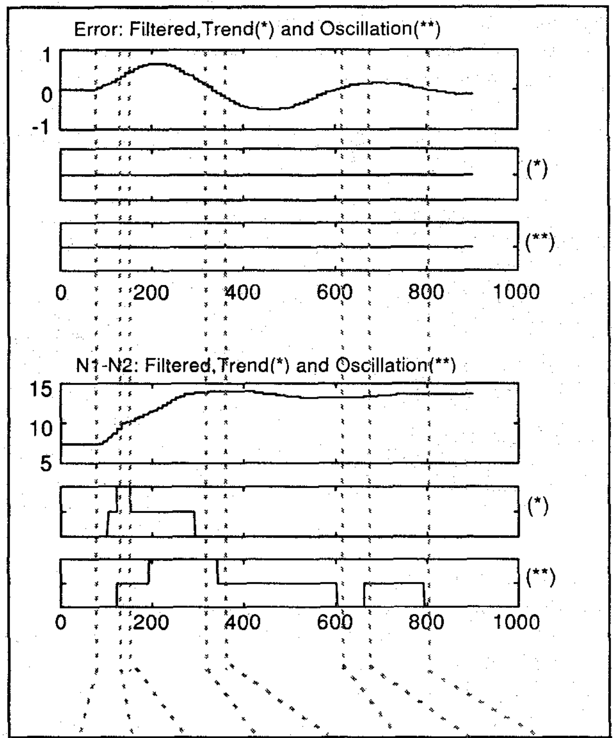


Fig. 12: Oscillation degree (*Step* 8)

The *n1-n2* gives significant information by means of the qualified signal processing *qualified trends* and *qualified oscillations*.



Set point Chang.	remote	remote	remote	remote	remote	remote	remote	remote
Regime	permanent	transient	transient	transient	Q-permanent	permanent	Q-permanent	permanent
V1	open	--	closed	--	closed	closed	closed	closed
V2	open	open	open	open	open	open	open	open
Pump	good	good	good	good	good	good	good	good
Control	good	good	good	good	good	good	good	good
General status	normal	normal	ab-normal	ab-normal	ab-normal	ab-normal	ab-normal	ab-normal

Fig. 13: V1 is closed at t= 50 sec.

For example, at t = 50 seconds a fault is introduced by switching off V1. 50 seconds later the abstractor of *n1-n2 trend* turns into *rising* which implies the effect of the failure is then detected. At that moment the ES could use this detection to infer the possible cause: the *regime* is *transient* but there is so far no *abnormal* situation. The *abnormal* situation is detected at t = 125 seconds when the qualified *tendency* is *greatly rising* and qualified *oscillation* is detected as *small*. Thus, the ES has the sufficient significant information to detect the *abnormal* situation and, moreover, to diagnose the failure *"V1 is close"*.

Time to detect and diagnosis was about 50 seconds (one third of the response time constant) after the failures were introduced into the process. In all cases, conclusions obtained from temporal evolution are satisfactory and

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causes of failures are fairly well diagnosed. Note, anyway, this KB is developed under the assumption that only one failure is introduced at a time.

6. Conclusions and future work

It has been proved that the signal treatment is very useful in order to extract significant information from the processes. A combination of AI tools and signal processing could give good results in process supervision.

The richer the information, the easier to carry out the correspondent supervision and therefore, the easier to build a supervision system, to make the detection and the diagnosis. As for the created abstractors, the following could be concluded that:

- They carry out with the goal: to give significant information to the fault detection system, making easier the expert system job.
- The use of filters produces some information loss and introduces some delays in the information given by the abstractors from process events.
- The intention was to make the abstractors completely general (adaptive filtering) but the consequence is that a lot of parameters have to be tuned before applying the abstractors to signals. This complexity must be overcome in the future work.

Once the utility of abstractors is shown, then more powerful alternative techniques, refered to in section II will be studied

7. Agreements

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