An Approach for Fault Localization based upon Unsupervised Neural Networks

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Abstract: Nowadays classical strategies for fault detection and isolation present the lack of availability in order to tackle unknown scenarios. In here, fault localization based upon unsupervised neural networks is presented as an alternative approach in order to determine abnormal situations under certain conditions. This proposal uses two well known techniques in order to classify patterns and clusters of patterns. This approach is followed in order to enhance the capability of fault localization by avoiding noise ratio and time variant behaviour. These two cluster techniques are trained off-line in order to response to on-line time constraints based upon case study.

Keywords: Fault Localization, Neural Networks.

1.- Introduction

Nowadays, fault classification and localization presents the advantage over fault detection and isolation in order to determine abnormal scenarios on-line. In this respect fault localization, lacks of fault isolation in terms of a formal declaration of this last scenario. In fact, this proposal enhance the availability of the system rather than its safety. Different approaches have been followed by the use of neural networks, Principal Component Analysis (PCA), and statistical approaches. The emergence of embedded fault classification into peripheral units opens a new area for on-line reconfiguration, self-calibration and self-health evaluation (Masten, 1997). In recent years, approaches for fault classification have been based on Neural PCA techniques such as that proposed by Moya et al., (2001).

Neural networks (Patan, et al., 2002; Ge et al., 2002; Wang et al., 2002; Ma et al., 2002; Benitez-Perez et al., 2001) have been used in different methods in order to achieve the goal of classification of abnormal situations. The proposal approach does not pretend to overcome the use of model-based classical fault detection and isolation (FDI) techniques. It is an alternative for an on-line response in order to isolate unknown scenarios (Patton et al., 2000).

Based upon this brief review it has been found that there is a necessity to determine abnormal behaviour on-line in order to enhance safety requirements. Fault localization is defined as the identification of current scenario with respect to the closest cluster.

A suitable approach is the use of unsupervised neural networks, specifically Self Organizing Maps (SOM) due to their inherent capacity of noise rejection. Furthermore, when the system is time variant, it becomes a challenge for these types of Unsupervised networks to de-couple abnormal behaviour from that of inherent behaviour of external modifications from a particular operating point (Mendes et al., 2002). Furthermore, SOM may couple with this characteristic for boundary (local) time variations.

The goal of this paper is to propose a technique of fault localization based upon the combination of two strategies in order to overcome noise presence and time

variant behaviour by the use of two classification approaches.
This paper is divided into six sections, current section presents a brief introduction of this topic. The second section shows a background of the unsupervised neural networks that have been used. The third section presents the fault localization approach pursued in this work. The fourth section described the case study used. Fifth section shows several results and finally the sixth section presents some concluding remarks related to this approach.

2.- Unsupervised Neural Networks Background

A brief explanation of two neural networks used in the case study is presented. The purpose of Kohonen self-organizing feature maps is to capture the topology and probability distribution of input data (Kohonen, 1989 and Hassoum, 1995) (Fig. 2.1). Firstly, a topology of self-organizing map is defined as a rectangular grid (Nelles, 2000) (Fig. 2.2). Different types of grid may be used, although Fig. 2.2 presents a homogenous response suitable for noise cancellation. The neighbourhood function with respect to a rectangular grid is based upon bi-dimensional Gaussian functions in eqn. 2.1.

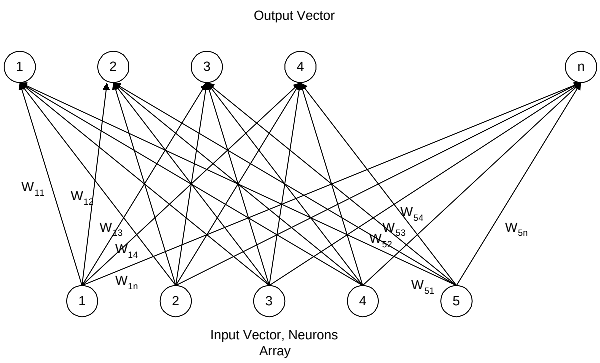

Fig. 2.1 Topology Network

$$h(i_1,i_2)=\exp\left(-0.5*\frac{\left(i_1^{win}-i_1\right)^2+\left(i_2^{win}-i_2\right)^2}{\sigma^2}\right) \tag{2.1}$$

where i_1 and i_2 are the index of each neuron. σ is the standard deviation from each Gaussian distribution. This distribution determines how the neurons next to winner neuron are modified. Each neuron has a weight vector (c_i^l) that represents how this is modified by an input updating. $h(i_1,i_2)$ is the Gaussian representation that permits the modification of neighbour neurons.

This bi-dimensional function allows the weight matrix to be updated in a global way rather than just to update the weight vector related to the winner neuron.

Similar to other types of non-supervised neural networks such as ART2-A (Frank et al., 1998), the input vector performs an inner product with each weight vector. Having calculated every product, these are compared between each other in order to determine the largest value. This value is declared as winner. The related bi-dimensional index based upon Fig. 2.2 is calculated in order to determine how the weight matrix is modified.

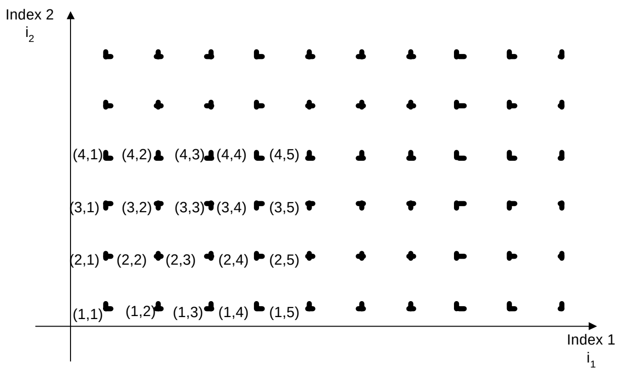

Fig. 2.2 Index Grid

The process of updating the weight matrix is based upon the equation 2.2.

$$c_j^{new}=c_j^{old}+\eta*h(i_1,i_2)*\left(u-c_j^{old}\right) \tag{2.2}$$

where η represents a constant value equals to 0.7. Finally, u represents the current input vector.

A similar network named ART2-A (Adaptive Resonance Theory) network is presented (Baraldi et al., 1999a, 1999b). The objective of this technique is to define certain groups (from actual data) around specific data points named as cluster centres. For the purpose of classification, these clusters are named in further sections as scenarios. When a new group appear its centre is identified in order for it to be defined as cluster.

Each processed sample either generates a new pattern or identifies an already known pattern.

There are two parameters to be tuned for ART2-A network(η and ρ). This is based upon the following equations. Firstly, data normalization is needed:

$$I=\frac{A}{\|A\|} \tag{2.3}$$

Where I is the normalized input vector, A is the input vector and $\|.\|$ is the eucledian norm. The bottom-up net activities are determined by

$$t_j = \begin{cases} I * W_j & if \quad j \quad is \quad chosen \quad prototype \\ \alpha = \sum_{i=1}^{M} i_j & otherwise \end{cases} \quad (2.4)$$
$$0 \le \alpha \le \frac{1}{\sqrt{M}}$$

Where W is the weight matrix, M is the number of data elements, α is vigilance parameter, i_j is the j's element of I and t_j is a comparison matrix. η defines the maximum depth of search for a fitting cluster. Adaptation occurs either J is the searching index for an winning prototype or if ρ is bounded as follows.

$$\rho \le I * W_J = t_J \quad (2.5)$$

Adaptation of the final winning prototype requires a shift toward the current input pattern.

$$W_J^{(new)} = \eta * I + (1-\eta) * W_J^{old} \quad (2.6)$$
$$0 \le \eta \le 1$$

where *old* means the last value of this vector and new is the update value of the same vector. This network has been implemented following the approach presented by Frank et, al. (1998).

Alternative techniques for pattern classification such as fuzzy c-Means (Abe, 2001) allow the classification of data by the use of self-definition of cluster centres.

3.- Fault Localization Approach

This technique is base upon the use of feature extraction (Abe, 2001) by the combination of two techniques, SOM and ART2 Network. This strategy is depicted in Fig. 3.1.

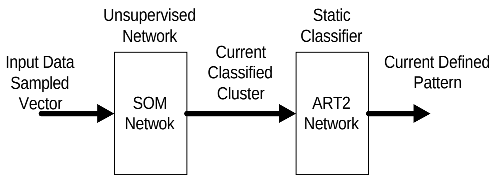

Fig. 3.1 Proposed Approach

Here the SOM classifies, on-line, a sampled vector of normalized input and output data. These classified clusters are localized with respect to different scenarios by the use of the ART2 network.

This network does not modify its own centres. These centres are the reflection of several scenarios such as fault free and fault scenarios.

The use of two classification methodologies allows noise cancellation ratio inherent to the system response. Any variation from a particular fault-free scenario would be kept inside the related classified cluster from first neural network. However, this *classified cluster* can presents several mismatching between patterns that may be overcome by on-line adjusting vigilance and learning variables. Alternatively, a second neural network is used in order to produce a second classification of current *classified clusters*. The idea is to separate fault and fault-free scenarios even in the presence of inherent variations. In terms of pattern classification Fig. 3.2 shows the method pursued. In fact, the *defined patterns* are the representation of several scenarios whereas those *classified clusters* are the representation of the local behaviour of the system.

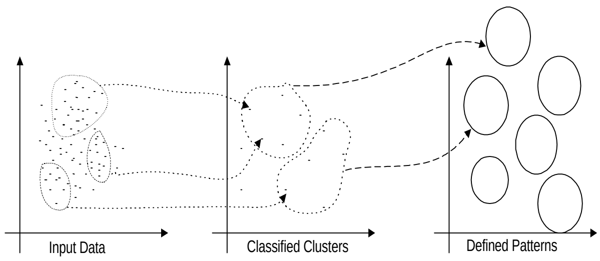

Fig. 3.2 Method Proposed in Terms of Patterns

The number of *classified clusters* can be increased by modification of current learning variables of SOM network. *Classified clusters*, which are near between each other represent common scenarios. Variations between *defined patterns* are due to time behaviour for fault and fault free scenarios. Moreover, ART2 algorithm group similar patterns in terms of pre-defined centres based upon off-line information. Therefore, *defined patterns* are a unified vector representation of several similar *classified clusters* determined by previous networks.

The updating procedure using both techniques does overcome the misclassification of fault-free variations. Those unknown scenarios that are declared on-line by second neural network correspond to non-studied catastrophic situations.

4.- Case Study

The presented case study is related to a pressure sensor integrated by the use of a local control law and the proposed approach (Fig. 4.1). It has been simulated based upon MATLAB ver 6.0 (Mathworks, 1998).

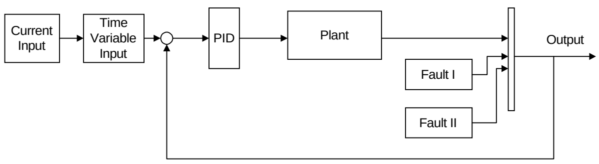

Fig. 4.1 Case Study

The dynamics of this example are:

$$\begin{aligned} \dot{x} &= Ax + bu \\ y &= cx \\ A &= \begin{bmatrix} 1.1 & 0 \\ 0 & 2.1 \end{bmatrix} \\ b &= \begin{bmatrix} 1.8 & -2.1 \\ 0.9 & 0.86 \end{bmatrix} \\ c &= \begin{bmatrix} 0 & 1 \end{bmatrix} \end{aligned} \tag{4.1}$$

The current input is a square signal with 2 hz frequency and amplitude of 0.5 volts. This measure represents current pressure. Output measure represents an electric signal. Where the response of this linear system is presented in following section.

5.- Results

These results are based upon several scenarios, which are listed below:

- Fault Free Scenario, square input, freq 10 hz.
- First Fault Scenario, saturation at output system.
- Second Fault Scenario, backlash behaviour.

One particular *defined pattern* represents each scenario. The current value, which is represented by a star, belongs to the *classified cluster*.

For the Fault Free Scenario (Fig. 5.1) the time variance is presented as 0.001 rad/secs. First module (those *classified clusters)* presents a common pattern numbered as 41 and second module (*defined patterns)* presents a total number of 8 clusters for the whole scenario.

In Fig. 5.1, horizontal axe represents time in terms of seconds and vertical axes represent current amplitude in terms of volts. Although, for pattern, cluster and fault level cases, these represent the a-dimensional number of patterns and conditions, respectively.

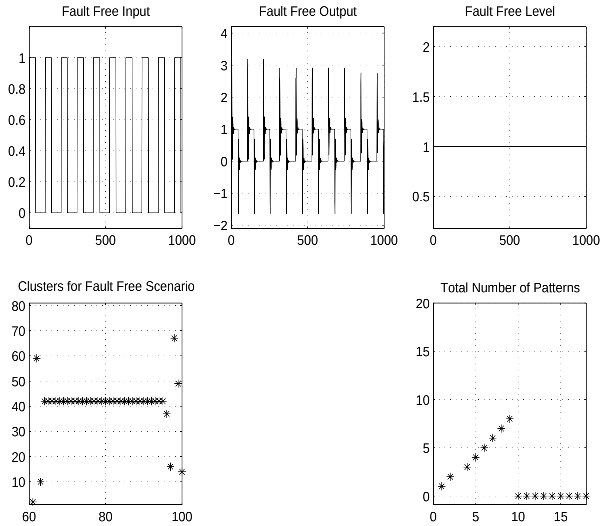

Fig. 5.1 Fault Free Scenario

In order to show the response of this proposal within fault conditions, second fault scenario is depicted as result.

For the Second Fault Scenario (Fig. 5.2) case (Backlash of 0.01 and Time delay of 0.01) with similar time variance there is a different response in the number of patterns. First module (*classified clusters*) has selected different clusters from 9 to 68, although, this total number is 9. Whereas for the case of the number of *defined patterns* this has not suffered an increment due to just one scenario has been evaluated.

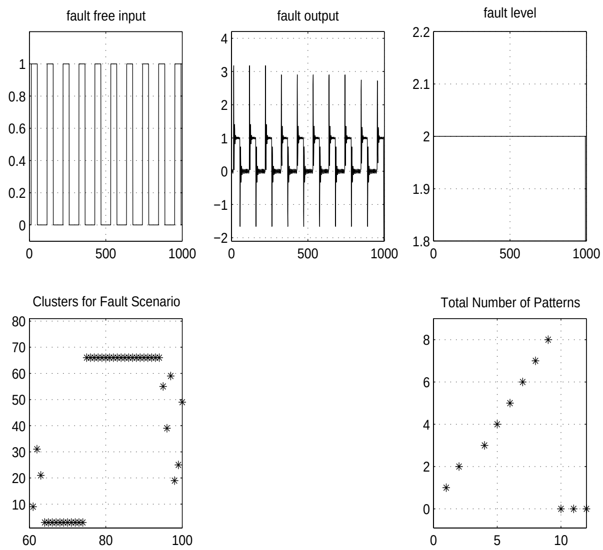

Fig. 5.2 Second Fault Scenario with Time Variance of 0.001 rad/sec.

Having explored second scenario in those conditions, this is modified with an increment of time variance of 0.05 rad/secs. As a result of this variation there is an increment of patterns rather than clusters. The number of clusters is still within the bounded number of 70. However, the number of patterns has suffered an increment of 25 due to the presence of both scenarios and the modification of time variance input.

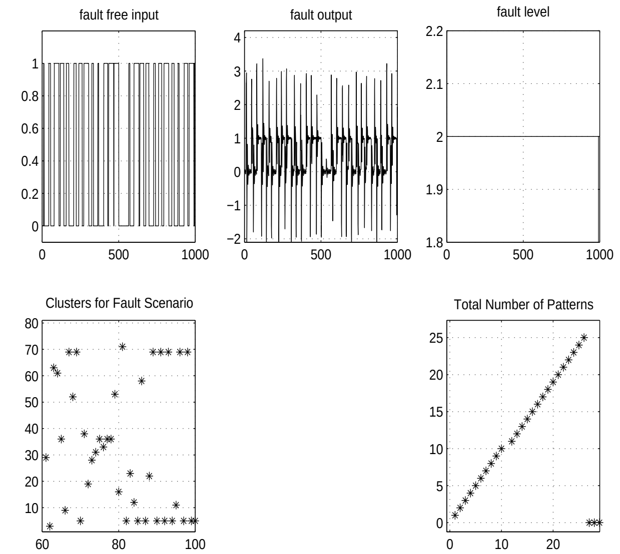

Fig. 5.3 Second Fault Scenario with Time Variance of 0.05 rad/sec.

6.- Conclusions

The use of these two techniques has shown the enhancement of fault localization with regard to unknown scenarios and time variance conditions.

The proposed method has attempted to address issues related to time variance, glitches and several other unknown scenarios that makes fault localization a difficult approach.

Several values may be defined off-line such as learning values as well as initial conditions of predetermined patterns.

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