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Epistemological decision making for fault diagnosis in process control system using self organizng maps

Tarun Chopra

Department of Electrical Engineering, Govt. Engineering College, Bikaner, India- 334001.

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ABSTRACT

Self-Organizing Map (SOM) can be used to quickly create a qualitative overview of the data. It maps nonlinear statistical relationships among different variables of a high dimensional input data on a low dimensional network, preserving most of the topographic relationships from the input space. Hence, for dealing the complex problem of separation of incipient faults of highly overlapping nature, an epistemological decision making approach using SOM is proposed in this paper.

Introduction

Advanced computational techniques based on Statistical, Machine learning and Neural Network based techniques are found to be fairly effective for abrupt faults. However, it has been found that the application of these techniques to the datasets representing the entire spectrum of possible faults produces limited success. The two groups of incipient faults of highly overlapping in nature are not separable with the selected computational techniques. Hence, further research is required to be focused on developing a suitable methodology based on an epistemological tool for acquiring an understanding of the semantics of data and for generating hypothesis about the associated faults.

Epistemological theories emphasize that Constructive learning involves qualitative restructuring and modification of internal knowledge representations, rather than just accumulation of new information in memory. The Self-Organizing Map (SOM) can be considered as a good example of constructive learning [1]. It is not a behavioristic model. On the contrary, the internal state of the system influences the behavior and changes during learning.

State of Art

Marcin Mrugalski et al [2], has adopted Outer Bounding Ellipsoid (OBE) algorithm for MLP based fault diagnosis of incipient faults in DAMADICS benchmark. The feasible parameter set obtained with this approach is only an approximation of the original one. The approximation of the original feasible parameter set by the ellipsoid leads to determination of too wide system output uncertainty interval. Due to this, some small incipient faults are difficult to detect. The authors of the cited paper have accepted this shortcoming and expressed need for future work for incipient fault separation.

In the research work carried out by Marcin Witczak et al [3], only four faults were considered out of which two were incipient faults. They have used bounded-error approach for GMDH networks. However, the obtained results show that incipient and small faults can not be detected by the approach adopted in cited paper. The authors have suggested at the end of cited paper that a technique that enables a further increase in the fault sensitivity should be developed for dealing with incipient faults.

Dilek Dustegor et al [4], has adopted Structural analysis for the DAMADICS valve model, but two of the fault are not detectable at all without extra sensors for extensive fault modelling and four of the incipient faults not separable within the group.

If the above reported results are compared with the proposed approach in the paper which deals with whole set of incipient faults with reasonable accuracy, the proposed approach seems to be superior.

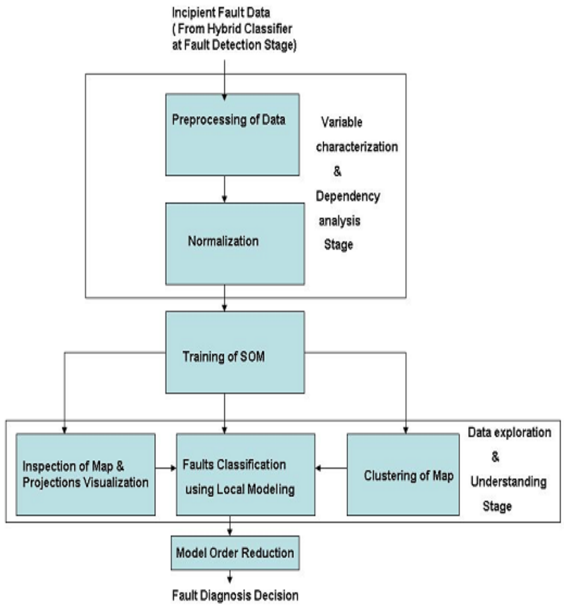

Figure 1: Generalized Block Diagram of Computational Decision Making System for Diagnosis of Incipient Faults

Proposed Methodology

As depicted in Figure 1, methodology employing SOM based fault diagnosis is proposed in this paper for the incipient fault data received from the output stage of hybrid classifier in Secondary Decision Making System. The proposed SOM based

Tele:
E-mail addresses: tarun_ecb@rediffmail.com

approach is attractive, due to its unsupervised learning and topology preserving properties. As dataset under consideration being multidimensional and of highly overlapping nature, includes two categories of incipient fault sets:-

In the first stage of proposed methodology, the original raw data is cleaned in the preprocessing phase and transformed (normalized) so that:-

- The dataset presents interesting data properties more clearly,
- It has no or at least fewer erroneous values, and
- It is in a form suitable for the subsequent analysis methods.

In training phase, the SOM algorithm implements a nonlinear topology preserving mapping from a high-dimensional input data space onto a low dimension discrete space (usually two-dimensional), called the topological map.

The goal of Map inspection and visualization of projections is to convey large amounts of detailed information about the data to the operator/user. Clustering of Map is done to partition the data into natural groups. In order to provide insight to the data, it is also important to describe these groups in terms of properties that are typical for the objects in the groups that makes them different from objects in the other groups. The understanding gained through these stages helps in diagnosing the incipient faults by applying SOM in the supervised mode.

Brief description of basic working principle of SOM is illustrated in Figure 2.

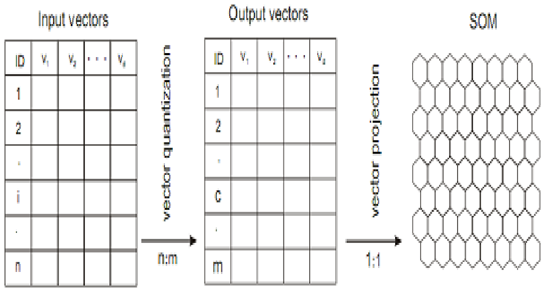

Figure 2: Illustration of SOM Principles [6]

Application of Proposed Methodology

The efficacy of proposed methodology has been demonstrated for the set of incipient fault groups considering all measured parameters.

The performance of SOM based fault classifier has been tested for demonstrating its visualization abilities for the sample fault data set pertaining to the fault classes F3,F4,F5,F6 and F9 of DAMADICS Problem [5] briefly discussed in Table 1.

Table 1: Overlapping Fault category { F3,F4,F5,F6,F9 }

S. No.	Fault	Location	Description	Physical interpretation
1	F3	Control Valve	Valve plug or valve	Mechanical wear (friction, cavity, aging,
			seat erosion	fatigue) or chemical treatment (corrosion)
				of valve seat and plug
2	F4	Control Valve	Increased of valve or	Mechanical wear, air pollution, corrosion
			bushing friction	products, sedimentation
3	F5	Control Valve	External leakage	Mechanical wear, material or erosion fault
				or valve assembly mounting fault causing
				leakage from the control valve body by
				leaky bushing , valve covers or terminals
4	F6	Control Valve	Internal leakage	Valve seat – plug assembly tightness
				caused by mechanical wear, erosion,
				corrosion
5	F9	Servo-motor	Servo-motor's	Due to actuator mechanical vibrations
			housing or terminals	installed in harsh industrial environment
			tightness	

The analysis has been made using SOM Toolbox [6] in MATLAB environment. The screen shot of program is shown in Figure 3.

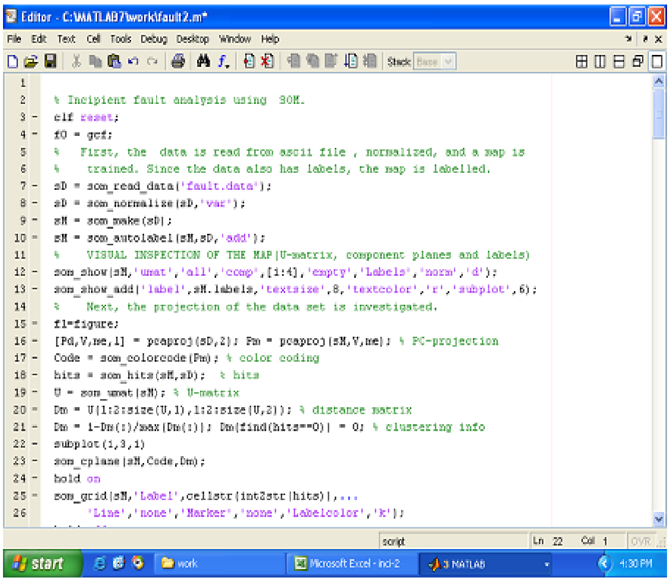

Figure 3: Screen shot of MATLAB Program

Preprocessing of Dataset

The data set consisting of 50 representative samples from each of five types of faults (a total of 250 samples), is read from ASCII file. The measured variables are CV (process control external signal), P1 (pressure on valve inlet), P2 (pressure on valve outlet), T (Temperature) X (valve plug displacement), F (main pipeline flow rate). The label associated with each sample is the fault type information viz 'F3' (Valve plug or valve seat erosion), 'F4' (Increased of valve or bushing friction) etc.

Since SOM algorithm is based on Euclidian distances, the scale of the variables is very important in determining the nature of map. If the range of values of some variable is much bigger than of the other variables, that variable will probably dominate the map organization completely. For this reason, the different components of the data set are usually normalized in the Pre-processing of Dataset, as shown in Figure 4.

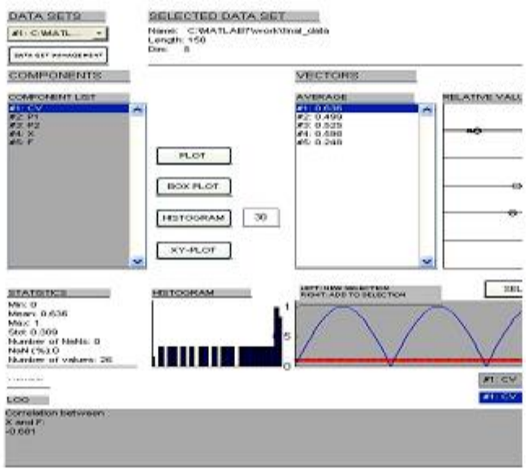

Figure 4: Preprocessing of Data Set

The results of preprocessing and normalization of dataset have been shown in Table 2.

Table 2: Preprocessing information

Measured Parameter	Minimum	Maximum	Mean	Std. Deviation
CV	0.5157	0.7378	0.6434	0.0697
P1	0.8323	0.9187	0.875	0.031
P2	0.6428	0.6573	0.6498	0.005
F	0.2118	0.2171	0.2147	0.0012
T	0.5005	0.7434	0.6464	0.0774
X	0.1995	0.7883	0.3867	0.1748

Map Training

The function SOM_MAKE is used to train the SOM. It first determines the map size, then initializes the map using linear initialization, and finally uses batch algorithm to train the map in following steps:-

- Determination of map size
- Initialization
- Training using batch algorithm
- Rough training phase
- Fine tuning phase

The qualitative and quantitative analysis of results obtained by using the proposed methodology is presented in following Subsections.

Results

The results for the chosen data set after Map training step are obtained as follows:-

Map size = [10, 5] i.e., A two-dimensional SOM of 50 neurons (10 by 5), organized in a hexagonal neighborhood lattice.

Following results are obtained for the data set, after fine tuning phase:-

- Quantization error: 0.683
- Topographic error: 0.000

Map Analysis by Visual Inspection

The first step in the analysis of the map is visual inspection. The U-matrix and component planes obtained for the dataset are shown in Figure 5 (A).

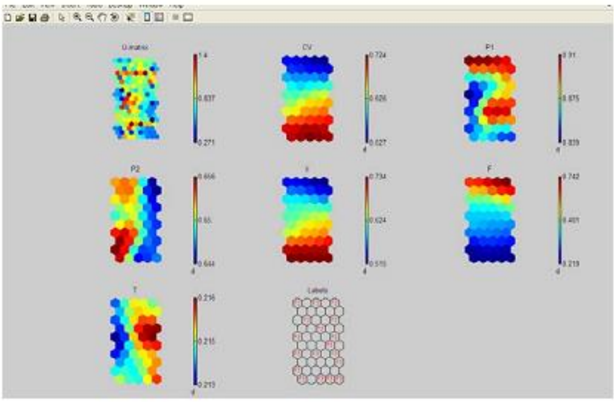

Figure 5 (A): Visualization of U-matrix and Component Planes

The Unified distance matrix (U-matrix) is useful for detection of cluster borders and especially suitable for estimation of inter cluster distances. The U-matrix shows distances between neighbouring map units using color levels. Red color represents long distances and blue short ones. High values on the U-matrix mean large distance between neighboring map units, and thus indicate cluster borders. The U-matrix visualization has many more hexagons that the component planes. This is because distances between map units are shown and not only the distance values at the map units.

The component planes ('CV', 'P1', 'P2', 'X' 'F' and 'T') show values possessed by the prototype vectors of the map units. The value is indicated with color, and the color bar on the right shows what the colors mean. The component plane is used to find pairs and groups of related variables. The technique is very useful when dealing with a large number of variables. The SOM does not utilize class information during the training phase. Figure 5 (B) clearly identifies the fault labels associated with each map unit (F3, F4, F5, F6 and F9). From the labels it can be seen that unlabeled units indicate cluster borders and the map unit in the Upper half corresponds to the F3 and F4. The remaining three fault conditions form the other clusters. The U-matrix shows no clear separation between them, but from the labels it seems that they correspond to two sub clusters.

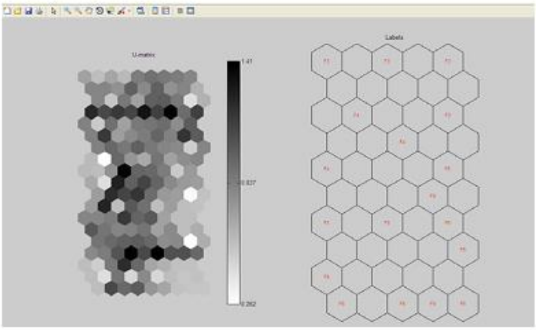

Figure 5 (B): Visualization of U –Matrix and Class Labels

Inference

The nature of data pertaining to incipient faults is generally overlapping with normal operating condition on one hand and abrupt fault condition on the other hand. Hence, it is essential to first understand the data that is being processed for obtaining better and meaningful results. The central task for gaining the necessary understanding is data exploration, which has been attempted by using SOM. This has resulted in the classification of incipient faults in both the benchmark and real industrial problem with reasonable success.

The SOM plays a versatile role in providing an initial organization of the data which is useful both in visualization and as a way to keep the projection and clustering methods used in the analysis computationally feasible. An important aspect of the SOM based architecture is that it helps the designer to get rid of the difficulty and cost of the design of the hidden layers. The advantages of the supervised SOM architecture are based on both the accuracy and the faster learning.

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