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Risk-based fault detection using Self-Organizing Map

Hongyang Yu [a], Faisal Khan [a,b,*], Vikram Garaniya [a]

[a] National Centre for Maritime Engineering and Hydrodynamics, Australian Maritime College, University of Tasmania, Launceston, TAS 7250, Australia
[b] Faculty of Engineering & Applied Science, Memorial University, St. John's, NL, Canada A1B 3X5

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ABSTRACT

The complexity of modern systems is increasing rapidly and the dominating relationships among system variables have become highly non-linear. This results in difficulty in the identification of a system's operating states. In turn, this difficulty affects the sensitivity of fault detection and imposes a challenge on ensuring the safety of operation. In recent years, Self-Organizing Maps has gained popularity in system monitoring as a robust non-linear dimensionality reduction tool. Self-Organizing Map is able to capture non-linear variations of the system. Therefore, it is sensitive to the change of a system's states leading to early detection of fault. In this paper, a new approach based on Self-Organizing Map is proposed to detect and assess the risk of fault. In addition, probabilistic analysis is applied to characterize the risk of fault into different levels according to the hazard potential to enable a refined monitoring of the system. The proposed approach is applied on two experimental systems. The results from both systems have shown high sensitivity of the proposed approach in detecting and identifying the root cause of faults. The refined monitoring facilitates the determination of the risk of fault and early deployment of remedial actions and safety measures to minimize the potential impact of fault.

1. Introduction

The rapid increase in complexity of modern systems imposes a challenge towards ensuring the safety of operations. This increase in complexity is directly related to the number of variables a system comprises. Each variable represents an individual dimension. To ensure the safety of a system, multiple variables have to be monitored simultaneously. This requires a tool with reliable high dimensionality handling capabilities. In addition, as the dimensionality increases, the relationships among system variables become highly non-linear. The identification of these non-linear relationships enables precise monitoring of behaviors of variables which is another key aspect concerning the safety of systems [1]. The disruptions of the relationships among system variables can cause abnormal behaviors which are considered as faults. The potential impact on the safety of system increases with the progression of fault. To minimize the impact, it is best to detect the fault at its early stage; this requires the development of a fault detection approach with high sensitivity. Also, the progression of fault needs to be traced to facilitate the efficient determination of safety measures and remedial actions to minimize the impact.

In many cases, the monitoring of complex systems is achieved through a technique known as dimensionality reduction. In general, variables that represent the most variances of system are combined to form a new set of variables and the variables representing less variance are disregarded. The system is then monitored based on the new set of variables which has less dimensionality.

In recent years, Self-Organizing Maps (SOMs) have gained popularity in fault detection and identification of complex systems as an efficient dimensionality reduction technique [2]. SOM has the ability of capturing nonlinear relationships of high dimensional data and visualizing them on a low-dimensional display in a topologically ordered fashion known as feature clusters [2–5]. This feature of SOM makes it sensitive to the change of state of complex, nonlinear systems, therefore makes it an efficient tool for early fault detection [2]. Kohonen et al. [2] have given a comprehensive review of the applications of SOM in engineering applications. In particular, they have summarized two fault identification techniques by using the quantization errors and visualization power of SOM. These two techniques have been adapted by many others to detect and identify faults for different systems.

Gonçalves et al. [4] have utilized both techniques to detect and identify faults of electrical valves. The SOM was trained to form five feature clusters with five data sets comprising the normal condition and four fault conditions. A fault was detected when the quantization error exceeded a certain threshold. For fault identification, the dynamic behaviors of the monitored system were visualized as

* Corresponding author at: Safety and Risk Engineering Group, Faculty of Engineering & Applied Science, Memorial University. Tel.: +179 864 8939.
E-mail address: fikhan@mun.ca (F. Khan).

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trajectories on SOM. The fault type was identified when the trajectory moved in one of the four fault clusters. Similar techniques for fault identification can also be found in references [3,6–8].

Although the above research studies demonstrated the capability of SOM in dynamic monitoring and fault identification of complex systems, they are limited by the availability of data and they failed to address the potential impact of fault on the system. In fact, the visualization power of SOM also has the capability of indicating the magnitude of fault which can be used to determine the potential impact.

One important feature of SOM is that data with high similarity are mapped closer to each other; otherwise, they are mapped further apart [9]. This provides a means of measuring the progression of fault; that is, as the fault condition deteriorates, the process system generates data with less similarity to the normal data and is mapped further away from the normal cluster. In this regard, the exceedance of fault data from normal cluster corresponds to the degree of fault and the trajectory representing the dynamic behavior of system indicates the progression of fault.

Zadakbar et al. [10] described a way of measuring the impact of fault using a risk-based approach. They applied Principle Component Analysis (PCA) as the dimensionality reduction technique for fault detection. The normal data was projected into a subspace determined by PCA to form a normal cluster. The cluster was considered as a standard normal distribution and its boundary was defined by mean and standard deviation of the projected data. When monitored data was projected into the same subspace, the probability of fault and exceedance of process system operation were calculated based on the mean and standard deviation. The intensity of fault at a given exceedance was determined by summing the hazard potential of each system variable. Subsequently, the severity of fault was calculated based on the intensity and exceedance. Finally, the severity of fault was combined with the probability of fault to determine the risk of fault which provided a measure of potential impact on the system. However, due to the linear nature of PCA, the sensitivity of this approach for fault detection is limited.

In this work, SOM is combined with the risk-based approach developed by Zadakbar et al. [10]. The normal cluster on SOM is considered as a standard normal distribution. The probability, intensity and severity of fault are calculated and are combined to determine the risk of the fault. In addition, this new approach is also combined with probabilistic analysis to characterize the risk of fault into different levels. This allows a refined monitoring of the system as fault propagates. Proper safety measures and remedial actions can then efficiently be determined in correspondence to different risk levels to minimize the potential impact.

This paper is divided into the following sections: in Section 2, the methodology of the new approach based on SOM is explained. The verification of this new approach is then conducted in Section 3 on two experimental systems: a tank pressure control system in Section 3.1 and a flow control system in Section 3.2. The faults for verification are introduced as deviations into one variable of each system. The results from both systems are also discussed. Section 4 summarizes the major findings of the paper and conclusions are drawn.

2. Methodology

The overall methodology of risk-based fault detection approach is outlined by the following logical chart. (Fig. 1).

The real-time system data is projected onto a trained SOM map to form a trajectory representing the dynamic behavior of the system. Data filtering is then applied to the trajectory to filter out less significant variations of the system. Based on the trend of the filtered trajectory, the system behavior is predicted five-point forward using moving average trend prediction. Subsequently, the dynamic loading, severity and probability of fault are calculated. The dynamic loading is used to identify the root cause of fault. The risk of fault is determined by combining the severity and probability of fault. Meanwhile, the operation of the system is characterized into different states through probabilistic analysis. The prior probabilities and predicted probabilities of system operating in different states are calculated. The posterior probabilities of system operating in different states are determined by updating the prior probabilities with the predicted probabilities. Finally, the posterior probabilities and the risk of fault are used to determine the risk of system operating in different states. According to the risk level, proper remedial actions and safety measures are determined to minimize the potential impact of the fault.

2.1. Self-Organizing Map

The SOM was proposed by Kohonen [11] as a specific type of neural network. Its concept is originated from the functions of cerebral cortex of brain. The cerebral cortex is divided into different areas for processing signals such as sight, hearing and tactile sensation [12]. On receiving these signals, the cortex will first classify and then map them to the corresponding areas to be processed. In each area of the cortex, neurons with similar functionality are closely related, leading to fast and accurate processing of the signals. This form of classifying and mapping signals to the corresponding processing area is called topographic mapping which is also the fundamental concept of the SOM [11].

Self-Organizing Map is able to discover the nonlinear latent features from high dimensional data. These low-dimensional features are presented in the form of a layer of topologically ordered neurons on a 2D map. A typical two-dimensional SOM is shown in Fig. 2.

Training of SOM mainly composes of three phases; competition, cooperation and adaption [11]. In the phase of competition, neurons first compete with each other and the neuron having the weight vector closest to the input signal vector is declared as the winner neuron or the Best Matching Unit (BMU). It is assumed the input signal vector is represented by $\mathbf{I}=[I_1, I_2, I_3, \ldots, I_n]^T$ and the weight vector is represented by $\mathbf{W}=[W_1, W_2, W_3, \ldots, W_n]^T$. Mathematically, the difference between the weight vector and the input signal vector is computed as the Euclidean Distance between them.

$$E = \|\mathbf{I}-\mathbf{W}\| = \sqrt{\sum_{i=1}^{n} (I_i - W_i)^2} \tag{1}$$

The neuron that has the smallest **E** is the BMU. Next, in the cooperation phase, the direct neighborhood neurons of the BMU are identified. Finally, in the adaption phase, these neurons are selectively tuned to form a specific pattern on the lattice. This pattern corresponds to a specific feature of the input signal vector. The tuning function is expressed as;

$$\mathbf{W}(t+1) = \mathbf{W}(t) + \alpha(t)\theta(t)[\mathbf{I}(t) - \mathbf{W}(t)] \tag{2}$$

where $\alpha(t)$ is the tuning rate and $\theta(t)$ is the exponential neighborhood function. $\alpha(t)$ decreases exponentially over iteration resulting in a more refined tuning towards the end of training process.

$$\alpha(t) = \alpha_0 e^{(-t/\lambda)} \tag{3}$$

where α_0 is the initial learning rate and λ is the time constant which is determined as.

$$\lambda = \frac{N}{\sigma_0} \tag{4}$$