FAULT DIAGNOSIS IN ROTATING MECHANICAL SYSTEMS
USING SELF-ORGANIZING MAPS

ABHINAV SAXENA
School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, Georgia

ASHRAF SAAD
School of Electrical and Computer Engineering, Georgia Institute of Technology, Savannah, Georgia

ABSTRACT

The power of Self-Organizing Maps (SOM) for the visualization of high-dimensional data has been well recognized over the past decade. They map 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. This paper presents an SOM-based multi-sensor diagnostic system architecture for the condition monitoring of a bearing health. Bearings being an essential part of most of the rotating machinery their failure are one of the most common causes of machine breakdowns. Therefore a continuous monitoring of the bearing health is required and several sensors are often used for this purpose. Out of several sensors used, all do not respond to the fault in a similar fashion, and thus may or may not be indicative of a problem individually. A SOM based approach has been used to map the time series data produced by various sensors to map the process dynamics onto the network and a trajectory of system states showing the bearing health trend has been shown to warn of impending failure and/or shut down to prevent damage.

INTRODUCTION

One of the most effective descriptions for complex industrial plants or machines is the state space representation. Such systems are monitored by measurements from a variety of sensors to identify the current system states. The number of such measurements increases fast with the complexity of the system, and typically the number of state variables in such representations exceeds the number of measurements by an order of magnitude. Furthermore the fact, that the relationship among different variables may not be completely linear, makes the analysis fairly complex. Particularly in the process of fault diagnosis, it is very important to identify a smaller set of system states that are characteristic of the general behavior of the system, and can be assessed from the measurements. Therefore the application of SOM in system health monitoring can be a suitable choice to accomplish this goal. SOM has the ability to map a high dimensional signal manifold on a low dimensional topographic feature map, with most of the topological relationships of the signal domain preserved (Kohonen, 1996a, 1996b). It aggregates clusters of input information from the raw data, and projects them on a much simpler two or three
dimensional network, thereby contributing to relatively comprehensible visualizations.

The organization of the paper is as follows: Section I describes the basic SOM algorithm with a deeper insight of its capabilities, citing some applications. The roller bearing health monitoring context for fault diagnosis along with the methodology has been explained in section II. An approach based on SOM visualization has been suggested for health monitoring in section III. Section IV discusses the results thus obtained, followed by the conclusion from the study.

THE SOM ALGORITHM

Kohonen and Simula (1996) explain the SOM algorithm for engineering application context, and describe it as nonlinear, ordered and smooth mapping of high dimensional input data domain onto the elements of a regular, low-dimensional array. The algorithm can be implemented in the following manner.

An SOM array is defined in the final output dimension, usually 2-d or 3-d. The number of points/nodes in SOM array depends on the requirement to be able to best represent the input data vector set. For the original version of SOM algorithm, one needs to specify the size of the network in the beginning, however the Growing SOM implementation dynamically adjusts the array size at the time of training. Dittenbach et al (2000) discuss Growing Hierarchical SOM (GHSOM) architecture, where the training starts with an initial map size of 2x2 and further nodes are added/deleted until a predetermined criteria like the quantization error (QE) and the mean quantization error (MQE) have reached a predetermined threshold. However for simplicity the basic SOM algorithm has been presented here. Let the high dimensional input data be represented by a set \( \{X_i\} \) of real vectors \( x = [x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}]^T \in \mathbb{R}^n \). A parametric real vector \( m_i = [\mu_{i1}, \mu_{i2}, \ldots, \mu_{in}]^T \in \mathbb{R}^n \) is associated with each element of SOM array. A decoder function is defined on the basis of distance \( d(x,m_i) \) between the input vector and the nodes of SOM, to define the image of the input vector on the map. Definition of \( d(.) \) can be chosen based on the application, however the Euclidean distance measure is most widely used. The image is defined as the index of the node with minimum distance from the input vector.

\[
c = \arg\min_i d(x,m_i)
\]  
(1)

The task is to define \( m_i \) such that the mapping is ordered and descriptive of the order of \( x \) using vector quantization, optimized \( m_i \), can be obtained. As a result a set of values \( \{m_i\} \) is obtained as the limit of convergence of the following sequence (Kohonen, 1996b):

\[
m_{i}(t+1) = m_{i}(t) + \alpha(t) \delta_{ic} [x(t) - m_{i}(t)]
\]  
(2)

Where \( \alpha(t) \) is the monotonically decreasing learning rate and \( \delta_{ic} \) is the neighborhood function, which models elastic interconnections between the
adjacent nodes. The learning in such elastic environment is shown schematically in Fig. 1.

![Figure 1](image-url)

This elastic nature of the map helps it self organize it into a shape that best represents the data. For example a neighborhood function can be defined as $\delta_{ic} = 1$ if the distance between node $c$ and node $i$ is less than a specified radius, else $\delta_{ic} = 0$, and all such nodes for which the neighborhood function is non zero are said to be the neighbors of node $c$ and thus belong to $N_c$. Thus SOM equations reduce to:

$$m_i(t+1) = m_i(t) + \alpha(t)[x(t) - m_i(t)], i \in N_c(t)$$  \hspace{1cm} (3)

$$m_i(t+1) = m_i(t), i \not\in N_c(t)$$  \hspace{1cm} (4)

Several variants of the basic SOM have been used for different applications based on different distance and neighborhood functions. Also the learning rate $\alpha(t)$ can be defined specific to the problem. Other methods to find $m_i$ have been described in (Kohonen and Simula, 1996).

**BEARING FAULT DIAGNOSIS**

Rolling element bearings are common components to almost all forms of rotating machinery. Bearing failure is one of the foremost causes of breakdowns in such machinery. This breakdown, when unexpected, can be catastrophic, as in a helicopter main rotor bearing, or result in costly downtime, as in a process plant machine. Critical machines are therefore subjected to continuous condition monitoring for bearing health trending, to warn of impending failure, and/or to shut down a machine to prevent further damage. Several sensors can be used to obtain the signatures of the fault, but the vibration and acoustic sensors have been shown to be the most effective in most of the rotating machine parts. This study shows how the measurements obtained for a faulty bearing can be mapped to a two dimensional pictorial representation and state trajectory can be plotted to observe the system heading.

Eight channels of data corresponding to 8 different sensors (2 acoustic emission sensors (AE), and 6 accelerometers) were obtained for a faulty tapered
SOM APPROACH FOR BEARING HEALTH MONITORING

As SOM algorithm is a nonlinear projection method, it efficiently maps different characteristic features into the clusters on the map, without any explicit modeling of the system. The feature selection is however very critical, and one of the most important factors in the success of modeling. In practical situations some measurement values may be missing, due to any of the many possible reasons, but such deficiencies in the data can be handled very well by SOM (Samad and Harp, 1992). Two approaches have been proposed in the literature for the application of SOM for fault diagnosis (Kohonen and Simula, 1996). First, as a supervised case when data corresponding to almost all the states, including faults, is available, secondly as the unsupervised case where only the non-faulty data is available. Whatever may be the choice of applicability, SOM shows its strengths. This paper presents the case of a supervised SOM, where the data corresponding to a particular fault in several stages has been used to train the SOM. This data gets mapped onto different regions on a 2D topographic map. Once the SOM network is ready, it is exposed to the actual data from the system under unknown state. The data points are mapped onto the network as they are sequentially fed to the map describing the current state of the system. A trajectory is drawn joining all the points to show, how and to which state the system is approaching next. This information can be used for fault diagnosis, and with few enhancements, also for making prognostic assessments towards the remaining useful life of system. Feature extraction was done using mainly two features, Kurtosis and the Curve length. Both provide statistical information about the nature of data, and were found to be reasonably good features for single shaft bearings. Kurtosis is the fourth moment about the mean normalized with variance as given by Eq (5):
\[ K = \frac{\sum (x - \mu)^4}{N\sigma^4} \]  
(5)

Where \( N \) is the number of sample points in the window used to calculate Kurtosis. The feature vectors are then fed to the SOM for training. To test the effectiveness of SOM, several snapshots of data corresponding to a fault evolution in a similar bearing were used. The points map to the nodes representing the similar state as the current input, and when plotted give trajectories showing the system advancement during fault evolution. All the implementation was done using SOM Matlab Toolbox (URL toolbox, 2003).

RESULTS AND DISCUSSIONS

As shown in Fig. 3, a 2D topographic map for each sensor was created, and nodes corresponding to different features mapped at different points. It can be seen that these sensors form about 3-4 different groups. Sensors number 1, 2 and 3 fall in one category, as they show similar behavior at similar positions. Sensors number 5, 6 and 7 fall in one group. However both acoustic sensors namely number 4 and number 8 do not match in response to any of the accelerometer groups. U-matrix (Fig. 5) shows a comprehensive mapping taking into account the feature values from all sensors collectively. Three groups can be easily identified. Group 1 consists of very closely scattered data points in the input space, and group 3 consists of relatively sparse data. Furthermore, Fig. 4 shows the system trajectory for data from sensor number 3. It can be clearly seen that the system started (marked as blue star) from a low feature value and approached towards high feature value suggesting the fault evolution. The shape of the trajectory remains the same on all maps. Since the data from different sensors map differently, depending upon how they perceive the change in the vibration signal, not all sensors are able to detect the fault in a similar fashion. Some sensors that did not detect fault can be recognized by the fact that even for small fault levels they show high feature values and for large faults they do not necessarily approach towards the high values. Moreover this idea can also be extended to the cases where the a priori information about the faults is not available. A suitable measure like quantization error can be defined, and if it increases beyond a certain bound for the new input vectors, an alarm can be raised to indicate that the system is approaching a faulty state. The SOM toolbox itself implements the growing SOM, and hence determines the number of nodes on the map based on the input vectors. It was observed that up to an extent increasing the size of network decreased both the quantization error and the topographic error, but beyond that both errors did not change much. For the illustrations in this paper a map size of 9x9 was used. An area of future research is to use hierarchical SOM models to discover if the data contains any inherent hierarchy.

CONCLUSIONS

It has been shown that SOMs can be used to detect faults in roller bearings, and can therefore prove to be a powerful tool for bearing health monitoring. This approach can be used for both supervised and unsupervised learning. User-
friendly and fairly comprehensible visualizations are easy to monitor and also indicate which sensors respond to what faults, and under what conditions. A fault may be indicated by a collective response of several sensors, which may not be obvious just looking at the data using other diagnostic techniques.

ACKNOWLEDGEMENTS

Authors would like to thank Woodroof School of Mechanical Engineering, and Intelligent Control Systems Laboratory at the School of Electrical and Computer Engineering, Georgia Institute of Technology for the experimental data sets provided for the work.

REFERENCES


Kohonen, T., Self-Organizing Maps, 2nd ed. Springer Series in Information Sciences.


Figure 3. Shown above are the eight different SOM planes corresponding to eight sensors. Different sensors perceive vibrations differently, and therefore for the same evolving defect, they organize themselves differently in the topographic plane.

Figure 4. Detailed view of accelerometer (z-axis) response (mounted on the top of the housing). This accelerometer nicely captures most of the states in the evolution of the fault, and thus the trajectory clearly seems to approach lighter (faulty) region, as time progresses.

Figure 5. U-Matrix shows overall dispersion of data, taking into account the information from all sensors. Three different clusters can be very clearly seen.