Self-Organizing Map Neural Network for Transient Signal Classification in Mechanical Diagnostics*

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ABSTRACT

Acoustic Emissions (AE), generated by the formation and growth of micro-cracks in metal components, provide us with a promising mechanical fault detection technique in monitoring complex-shaped components in helicopters and aircraft. A major challenge for an AE-based fault detection algorithm is to distinguish crack related AE signals from other interfering transient signals, such as fretting related AE signals and electromagnetic transients. In this paper, we presents a classifier, which makes its decision based on the features extracted from joint time-frequency distribution data by Self-Organizing Map (SOM) neural network. In-flight data are used to test the performance of this classification system, with promising results.

1. INTRODUCTION

Acoustic Emissions (AEs) are ultrasonic waves emitted from material deformation process, such as micro crack generation and growth. These AEs can be detected by the piezoelectric transducers (PZT) placed close to the AE sources. Thus AE based nondestructive inspection technique provides an attractive automatic fault monitoring method in helicopter and other aircraft. The characteristics of AE signals due to crack generation and growth have been extensively studied in recent year [1]. Most of these studies have been done in isolated metal specimen under controlled laboratory environment. However, in practice, the crack-related AE signal has to be detected when the helicopter is in operation. In this case the crack related AEs are measured in the presence strong interference and noise. These interference and noise, caused by vibration, fretting, electromagnetic and many other factors are very complex and highly nonstationary. AEs from crack generation and growth have possible frequency components up to several MHz, whereas vibration signals occur below 100kHz [2]. Thus vibration noise can be removed by prefiltering. However other Interference such as fretting caused by rubbing of parts and electromagnetic noise are also transients and similar to crack related AE in both time and frequency domains. Then the discrimination of crack related AE from other interference transients becomes an important issue and needs considerable attention from a signal processing point of view.

This classification problem is further complicated by the fact that in complex metal component geometry the characteristics of AEs are not known *a prior*. Besides, the noise and interference are highly load and component dependent [3]. It is nearly impossible to use a conventional statistical classifier, to the extent it needs the accurate mathematical models of the signals, to distinguish the crack related AE from other interference transients. In contrast, the neural network classifier seems very suitable in this transient classification problem because it does not need the accurate model about the signals and it has strong non-linear mapping capability.

Previous research has shown that temporal information, i.e., time of arrival and rise time of the transients during a period of rotation cycles of the rotor, can be used to distinguish crack related AE and other interference [3][4]. However, the classification scheme based purely on temporal information is inadequate in a highly noisy environment such as the operating helicopter's rotor. Our investigations, over the past four years, suggest that the spectral components also bear valuable information for the discrimination of the crack-related AE from other interference. Thus, it is quite natural for us to design a classifier based on joint time-frequency distribution data.

In this paper, we present a direct transient signal classifier based on a Self-Organizing Map (SOM) neural network. In the proposed system, we do not need to add a detection stage before the classification. The basic idea is to use the SOM neural network to map high dimensional time-frequency distribution data into a low dimensional codebook. Then the output from the SOM is used to make the classification decision. In-flight helicopter data provided by Honeywell has been used to test the performance of this neural classifier. The paper is organized as follows. In Section 2, we present the in-flight transient signal acquisition system as well as the

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collected data. In Section 3 we give the classification system structure and how to use the SOM to do transient classification. The classification results are also given in Section 3. Section 4 summarizes the paper and proposes future research topics.

2. In-Flight Transient Signal Acquisition System

The Rotor Acoustic Monitoring System (RAMS) developed by Honeywell was flight-tested at Patuxent River Naval Base on CH-46 Sea Knight helicopter from August 28 to September 18, 1997 [8]. More than 16 hours of flight data was recorded from 8 piezoelectric sensors mounted on one of the rotor arms. The eight sensor positions are shown in the Fig. 1. Sensors 1, 2 and 3 are located on the connection link, sensors 4 and 5 on the pitch shaft, and sensors 6, 7, and 8 on the pitch housing. A piezoelectric pinger is mounted on the connection link of the rotor arm to simulate micro-crack generation. Whenever the pinger is ON, a small pressure proportional to the control voltage is added to the connection link. When the pressure is released, an acoustic transient signal is emitted from this area.

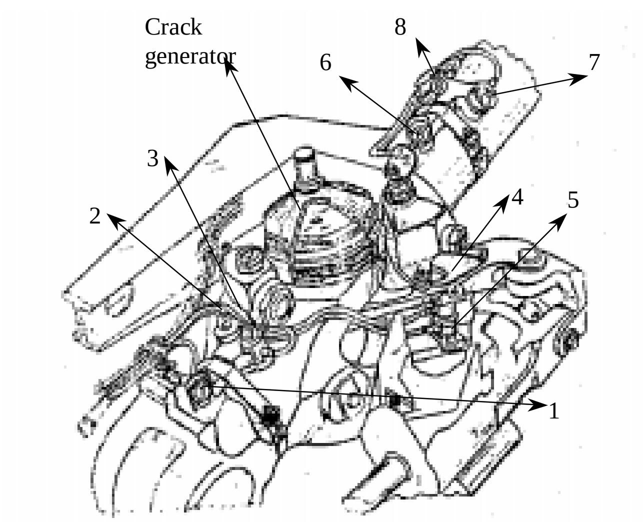

Fig. 1 Sensor position at in-flight data acquisition system

Honeywell provided us with a digitized set of data from the level flight. The data includes the recordings at all eight sensors for all eight permutations of pinger ON/OFF and pinger control voltages of 100V, 48V, 20V and 10V case. Different pinger excitation voltages simulate the different micro crack sizes, from a small crack (voltage 10V) to a large crack (voltage 100V). However the digitization of the data for the different channels of observation was not synchronized, i. e., the data digitized at different channels were all from different time segments. The duration of each digitized segment of data was about 2 seconds at a sampling frequency of 2MHz (12 bit A/D accuracy).

In this paper, we use the data collected from sensor 2 at excitation voltage of 100V only since sensor 2 is located at the same connection link as the pinger. Sensor 3 is also located at the same component. However, its data was corrupted at the time of data recording and could not be used. Although sensor 1 is also mounted at the connection link, it is further away from the pinger than sensor 2 and 3. The signal energy drops quickly in sensor 1. Thus we will only use the data from sensor 2 in this paper to test the performance of our neural classifier. All the other sensors are mounted on different components from the pinger. A more sophisticated method is needed to detect acoustics emission signal before any classification methods can be used.

3. Transient Signal Classification System Based on the SOM

Previous work conducted by our group has verified that time-frequency decomposition is well-suited for the detection and classification of AE signals [5] [6]. The responses of sensors to a crack related AE signal and extraneous interference have different arrival times and different frequency contents. These differences are due to propagation effects in mechanical parts. We propose our transient classification system structure as shown in Fig. 2.

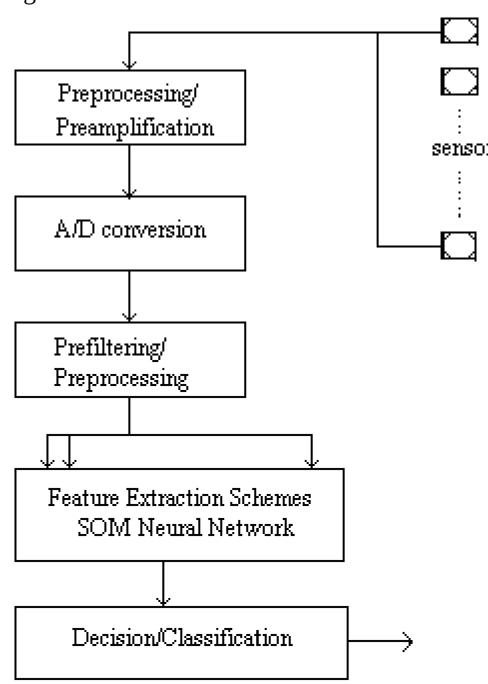

Fig. 2 Transient Classification System Block Diagram

During the prefiltering/preprocessing stage, after A/D conversion, we conduct bandpass filtering to remove most of low frequency vibration noise (lower than 50 kHz) and high frequency components (higher than 300KHz), which carry no useful information in the Honeywell data. Then we apply

Short-time Fast Fourier Transform (SFFT) to the time-domain signal to obtain the signal. This results in a sequence of frequency decomposition vectors extending along the time axis. This high dimensional spectrogram matrix is then fed into the SOM neural network and the low dimensional SOM codebook matrix is obtained. The final stage is to make classification decision based on the SOM outputs.

We applied the above classification system to the in-flight data acquired from the system described at Section 2. A sample segment of data after bandpass filtering from sensor 2 at pinger excitation voltage level of 100V is shown in Fig. 3, and its spectrogram representation is shown in Fig. 4.

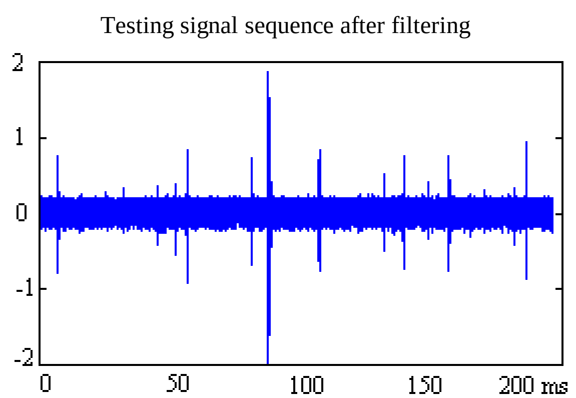

Fig. 3 A segment of time domain signal from sensor 2

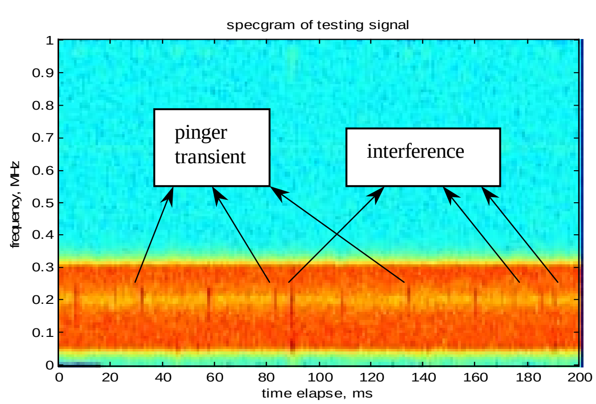

Fig. 4 Spectrogram of a segment of data from sensor 2

3.1 Feature Extraction by SOM

The concept of Self-Organizing Map (SOM) neural network was introduced by Kohonen in early 1981 [7]. The SOM is a sheet like neural network with M×N neurons. Each neuron or a neighboring group of neurons responds to a specific kind of input pattern. After the competitive learning process, the locations of the active neurons to different input pattern tend to become ordered. Thus the spatial location of a neuron in the neural network can represent a particular input signal domain.

As shown in the Fig. 5, the SOM network takes the form of grid structure. The grid vertices are called neurons, whose weight vectors have the same dimension as the input training vector. When the training process starts, the SOM takes the neuron with the minimum distance or most similar to the input vector as the winner. Then the SOM updates the weight vector adaptively in the neighborhood of the winner neuron. When the training process ends, all the input vectors are mapped onto different neurons' weight vectors called a codebook.

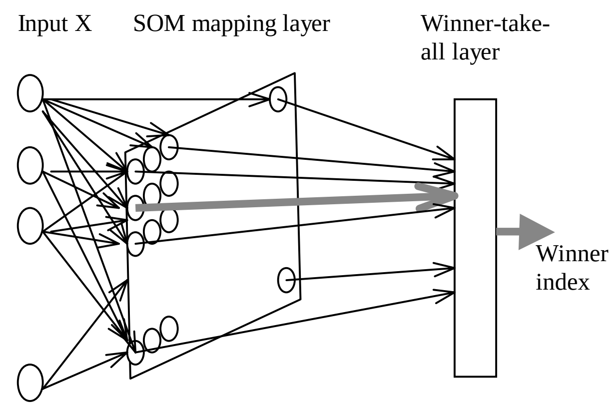

Fig. 5 Self-Organizing Map neural network

with time frequency vector as input

There are several ways to define the distance measure between the input vector and neurons' weight vectors such as Euclidean distance and inner product. Here we have used a simple Euclidean distance. The training steps of the SOM network are:

1. Initialize the SOM. Randomly assign small values to the weight vector of each neuron:

   $$W_i = [m_1, m_2, \cdots, m_n], i = 1, 2, \cdots, M \times N$$

   Here the input signal is a series of n×1 spectrogram vectors as shown in the Fig. 4.

2. Provide a new input vector $X = [x_1, x_2, \cdots, x_n]$, then calculate the distance between each neuron and the new input vector:

   $$D_j = \left\| X - W_j \right\| = \sum_{i=1}^{n} (x_i - w_{ji})^2,\ j = 1, 2, \cdots, M \times N$$

3. Select the neuron j* as winner so that the D_{j*} is the minimum among D_j, i.e.,

$$j^* = \arg\min_{j} D_j,\ j = 1,2,\cdots, M \times N$$

4. Update the weight vectors of the winner neuron j* and its neighboring neurons adaptively:

$$W_i(n+1) = W_i(n) + \eta(n)[X(n) - W_i(n)],\ i \in S_j(n) \quad or$$
$$W_i(n+1) = W_i(n), \qquad\qquad i \notin S_j(n)$$

where $S_j(n)$ is the neighborhood of the winner neuron j* at time instance n. The initial $S_j(n)$ can be large enough to include all the neurons in the SOM. After hundreds of training steps neurons show an ordered pattern, and $S_j(n)$ can eventually shrink linearly to include only one winner neuron j*. $\eta(n)$ $(0<\eta(n)<1)$ is the learning rate, which can be either a constant or a monotonically decreasing function.

Repeat the above steps 2 – 4 until the network reaches its pre-specified total training steps, which should be at least 500 times larger than the neuron number in the SOM [7]. At the end of training process the weight vectors of the SOM become ordered as shown in Fig. 6. The raw feature of the input signal, namely the time-frequency distribution data, has been encoded into the weight vectors of the SOM. Each weight vector represents a particular kind of input pattern. Thus different locations of the neurons in the SOM reflect different input spaces, which provide us with the basis to make a classification decision.

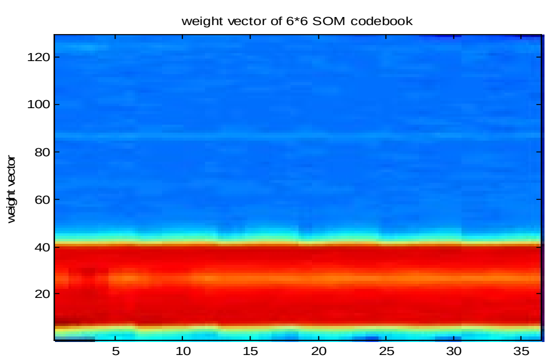

Fig. 6 Weight vectors of SOM after 20,000 training steps

3.2 Classification Decision Making Based on the Output of SOM

After the competitive learning process, each neuron or a group of neighboring neurons in the SOM responds to a particular kind of input pattern. Thus we can expect that different types of transient input signals will activate neurons (winning neuron) in different locations within the same codebook. Consequently, we can use the index sequence of active neurons to each input data set to discriminate between crack-related AE and other interference transients.

In our study, a segment of spectrogram data of pure pinger ON transient from sensor 2 was fed into a 6×6 SOM to conduct the training. After 20,000 training steps, the weight vectors of the SOM became ordered as shown in the Fig. 6. Because of the limited number of available training vectors (about 3000 vectors), we used them repeatedly during the 20,000 training steps. The test signal consists of both a pinger ON transient and other interference transients from sensor 2. Fig. 4 shows a small portion of the test signals and Fig. 3 is the time domain waveform of the corresponding test signal. The index of the active neuron corresponding to each input vector has been recorded as output from the SOM.

As we expected, we found that only transients due to the pinger ON activated neuron 3 and only neuron 3 responded to transients due to the pinger ON, as shown in Fig 7 and 8 respectively. Fig 7 is the active neuron index of the transient due to the pinger ON. Fig. 8 is the active neuron index of interference transients. Thus, we designed our classifier using the following rules: whenever the active neuron is 3, we count the number of times that neuron 3 is active in the following 20 successive outputs. If the number exceeds 10, the classifier declares that the event is a pinger ON transient; otherwise it is a non-pinger interference transient.

Based on this classification decision rule, we tested all the data from sensor 2 at the excitation voltage 100V. The result showed that the SOM network successfully differentiated the pinger ON signal from other interference transients. There is no missed pinger ON transient and the false error rate is lower than 5%. The relatively high false error rate may be due to the limited data available for training in the current study. The simplicity of the final decision process may also contribute to the relatively high false alarm rate.

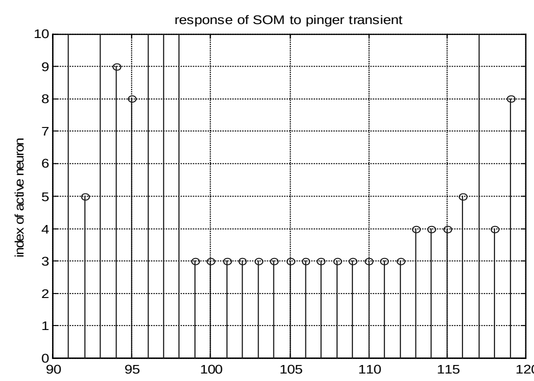

Fig. 7 Index of winner neuron corresponding to pinger ON transient

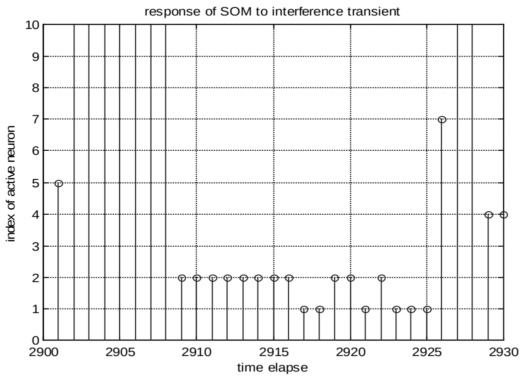

Fig. 8 Index of active neuron corresponding to interference transients

4. SUMMARY

In this paper, we proposed a neural network classifier and used it successfully to differentiate transients due to the pinger ON from other interference transients. These interference transients are very similar to the transients created by the pinger ON in both the frequency and time domains. A 6*6 SOM network was trained and tested on the in flight data provided by Honeywell Inc. We believe that the proposed methods can also be used in other applications such as tool-wear monitoring system. For example, L. Owsley, et. al. [9][10] found that the location of active neurons showed an ordered pattern when the tool condition is good and inharmonic and sudden changes when tool condition reaches its "break" point in a tool-maintaining application.

In the future we will include multi-sensor data in our classification. Since multiple sensors provide more information about the differences between crack related AE and other interference transients, we expect an enhanced classification performance. We have conducted some preliminary studies on this problem using simulated data. Spectrogram data from two sensors were cascaded to form the input vectors of an SOM to capture differences in arrival time and frequency content at the two sensors. Based on the classification system described above, a well trained 4*4 SOM correctly labeled all simulated crack related AE's and interference fretting transients. This confirmed that the proposed SOM based classification method is a promising transient signal classifier.

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