DETERMINATION OF FAULT TOPOLOGY IN MECHANICAL SUBSYSTEMS OF AGRICULTURAL MACHINERY BASED ON FEATURE FUSION AND NEURAL NETWORKS

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Abstract
Bearings form an essential part of the mechanical subsystems of agricultural machinery and their failure is one of the most common causes of machine breakdowns. Accordingly, in order to increase reliability and reduce loss of production, condition monitoring of bearings has become more and more important in recent years. The use of vibration signals is quite common in the field of condition monitoring and fault diagnosis of bearings. Vibration analysis is based on the use of acceleration measurements from bearings in order to assess their health status. Advanced signal processing is used to construct a number of informative features that are sensitive to specific bearing faults and fault locations. The fusion of specific statistical features and the introduction of new features enable the accurate discrimination of faults based on their location. The capability of neural networks to visualize high-dimensional data is well known. They map nonlinear statistical relationships among variables of high dimensional input data on a low dimensional network, in a topology preserving fashion. The presented work concerns a neural network based diagnostic system architecture for monitoring the topology of extended faults in bearings. A Self-Organizing Map (SOM) based approach has been used to map time series of feature data produced by acceleration sensors in order to capture the process dynamics. The evolution of system states following the bearing health trend has been shown to successfully identify different bearing faults according to their location.

Introduction
Bearings are located at the heart of rotating machinery and play a very important role in industrial applications and are mainly used to support and fix the axle in rotating machinery. Their failure in practical operation can lead to the breakdown of the whole machine. Accordingly, to increase reliability and reduce loss of production condition monitoring of bearing gets more and more important in recent years. The use of vibration signals is quite common in the field of condition monitoring and fault diagnosis of bearings [1].
A machine vibration signal is composed of three parts, stationary vibration, random vibration, and noise. To inspect raw vibration signals, a wide variety of techniques have been introduced that may be categorized into two main groups: classic signal processing [2] and intelligent systems [3]. To make mention of a few, FFT, Wigner–Ville distribution [4], wavelets [5], blind source separation [6], statistical signal analysis [7], and their combinations [8] are classic signal processing methods. ANN-based, GA-based, FL-based, various similar

classifiers [9], expert systems [10], and hybrid algorithms [11] can be classified as intelligent systems. Currently, industrial applications of intelligent monitoring systems have increased due to the progress of intelligent systems.

The SOM algorithm

The Self-Organizing Map also called SOM [12] is a neural network that maps signals from a high-dimensional space to a one- or two-dimensional discrete lattice of neuron units. Each neuron stores a weight. The map preserves topological relationships between inputs in a way that neighbouring inputs in the input space are mapped to neighbouring neurons in the map space. SOM mimics the clustering behaviour observed in biological neural networks by grouping units that respond to similar stimuli together.

The learning rule of the SOM consists of two distinct phases: first phase starts when an input $\mathbf{x}$ is presented, search for the best matching unit or *bmu* through competition, and the second phase consists of the incremental update or learning of the codebook patterns of the *bmu* and its neighbours. In the basic SOM the activations of the units are inversely proportional to their Euclidean distances from the input pattern hence the *bmu* can therefore be defined as:

$$b(\mathbf{x}) = \arg\min_{i \in M} \left\| \mathbf{x} - \mathbf{m}_i \right\| \qquad (1)$$

where $b(\mathbf{x})$ is the index of the *bmu*, $\mathbf{m}_i$ is the codebook vector of unit i and $\mathbf{x}$ is the input pattern vector. The update part of the rule moves the *bmu* and its neighbours toward $\mathbf{x}$ to slightly enforce maps response to the pattern. The update rule can be written as follows:

$$\Delta \mathbf{m}_i = \gamma \cdot h(b(\mathbf{x}), i)(\mathbf{x} - \mathbf{m}_i) \qquad (2)$$

where γ is a learning rate parameter and $h(b(\mathbf{x}), i)$ captures the neighbourhood interaction between the *bmu* $b(\mathbf{x})$ and the unit i being updated.

Diagnosis of faults in rotating machinery

Today's industry uses increasingly complex rotating machines, some with extremely demanding performance criteria. Attempting to diagnose faults in these systems is often a difficult and daunting task for operators and plant maintainers. Machine failure can lead to economic loss and safety problems due to unexpected and sudden production stoppages. In rotating machinery, the root cause of faults is often faulty rolling element bearings. One way to increase operational reliability and thereby increase machine availability is to monitor incipient faults in these bearings.

The use of vibration signals is quite common in the field of condition monitoring of rotating machinery. By comparing the signals of a machine running in normal and faulty conditions, detection of faults like mass unbalance, rotor rub, shaft misalignment, gear failures and bearing defects is possible. These signals can also be used to detect the incipient failures of the machine components, through the on-line monitoring system, reducing the possibility of catastrophic damage and the down time.

The procedure of fault diagnosis starts with data acquisition, followed by feature extraction, fault detection and identification. Feature extraction is critical for the success of the diagnostic procedure. Rolling element bearings often fail due to spall and extended defects in the inner and outer races (see an example in Fig. 1), and the rolling elements.

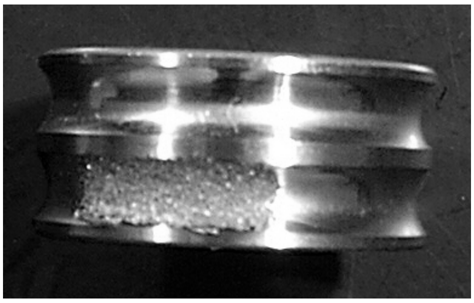

Fig. 1. Example of a extended fault in the inner race.

A gearbox test rig has been used in order to collect signals from different types of bearing faults. A photograph of the rig showing the position of the accelerometers and the encoder at the output shaft is shown in Fig. 2 [13]. Two types of faults (inner race and outer race crack) were tested under a 50 Nm load, while setting the output shaft speed to 10 Hz (600 rpm). Vibration signals were collected using two accelerometers positioned on the top of the gearbox casing above the defective bearing and sideways respectively. The 1.35 seconds (65536 samples) signals were sampled at 48 kHz. A photo-reflective switch was placed near the output shaft to measure its speed by providing a once per rev tacho signal. The torque for each case was measured at the input shaft.

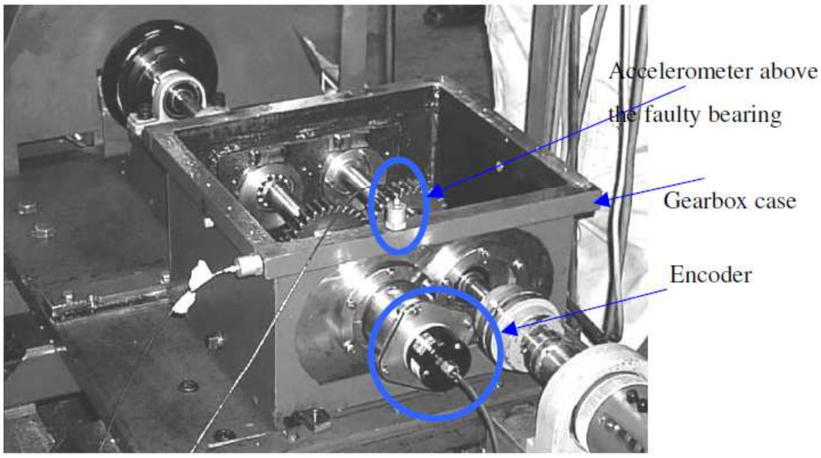

Fig. 2. The spur gear rig.

SOM approach for monitoring fault topography

The algorithm of Kohonen for training the SOM is a nonlinear projection method. It maps different characteristic features into the clusters on the map, without performing an explicit modeling of the system. The feature selection stage is one of the most important factors in the success of modeling. Using Kohonen's algorithm the feature data get mapped onto different regions on a 2D topographic map. Once the SOM network is trained, it is exposed to actual data from the system (in the form of the same type of features used for the training set) representing a yet 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. The current state SOM based estimation can be retrieved based on already stored labels representing fault classes.

Feature extraction was performed using two features, Kurtosis and a newly proposed feature consisting of the line integral of the acceleration signal. Both provide statistical information about the nature of data, and were found to be reasonably good features for bearing fault detection. The Kurtosis is the fourth moment about the mean normalized with variance and for a sliding window of N sampling points is given by Eq (3):

$$K = \frac{\sum_{i=1}^{N} (x_i - \mu_X)^4}{N\sigma_X^4} \quad (3)$$

The new line integral feature for a sliding window of N sampling points is given by Eq (4):

$$LI = \int_a^b ds \approx \sum_{i=1}^{N} \left\| \vec{r}(t_i + T_s) - \vec{r}(t_i) \right\| = \sum_{i=1}^{N} \sqrt{\left(x(t_i + T_s) - x(t_i) \right)^2 + T_s^2} \approx \sum_{i=1}^{N} \left| x(t_i + T_s) - x(t_i) \right| \quad (4)$$

Where N is the number of sample points (equal to 500) in the window used to calculate Kurtosis and the newly proposed line integral feature and Ts is the sampling period. Given the high sampling rate of 48 kHz and the domination of the signal from high frequencies (especially due to the presence of faults), the final approximation contains only acceleration values. The feature vectors are then fed to the SOM for training. To test the effectiveness of SOM, the 75% have been used for training while the 25% have been used in order to test the generalization of the SOM. The implementation used the SOM Matlab Toolbox [14].

Results and discussion

For the experiments a map size of 7x32 was used. Following a voting procedure for allocation of labels on the SOM in Fig. 3(a) shows clusters formed on the SOM with their fault classes. For the case of the fusion vector of features, the component maps in Figs. 3(b) and 3(c) show the distribution of Kurtosis and the component maps in Figs. 3(d) and 3(e) show the distribution of line integral values respectively for the units of the SOM. The fusion (by direct concatenation) of features from both the vertical and the horizontal accelerometer, due to their complementary nature, results in more accurate separation of classes regarding fault position as one can deduce from the results presented in Table 1 which indicates the superiority of the fusion based classification result.

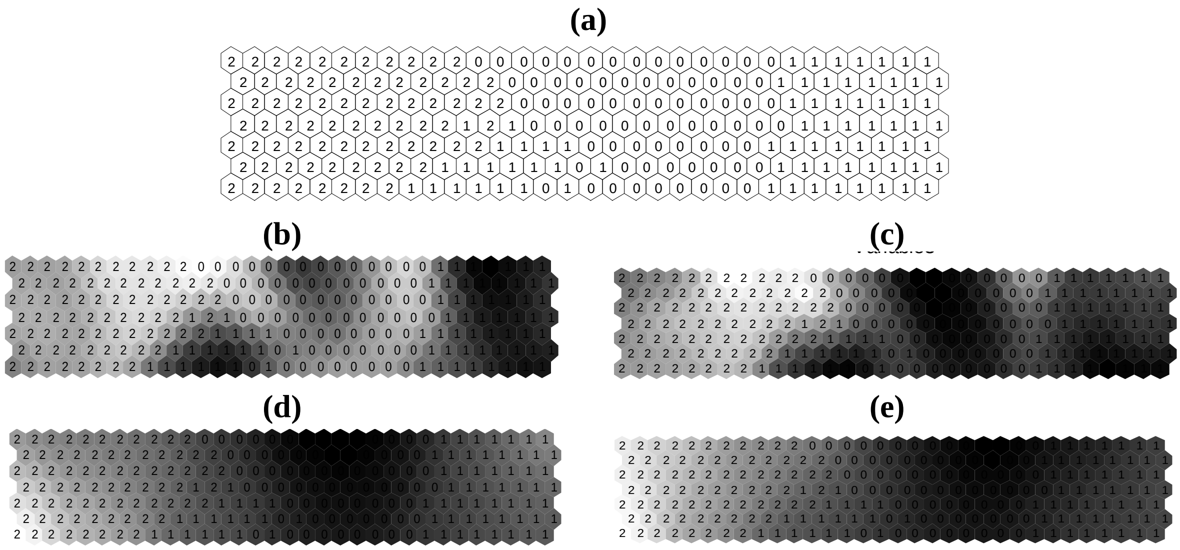

Fig. 3. Different manifestations of the features are shown for the fusion vector:
(a) Labels correspond to extended fault types (0:intact, 1:inner race fault, 2:outer race fault).
(b) Component map corresponding to Kurtosis (vertical accelerometer).
(c) Component map corresponding to Kurtosis (horizontal accelerometer).
(d) Component map corresponding to Line integral (vertical accelerometer).
(e) Component map corresponding to Line integral (horizontal accelerometer).

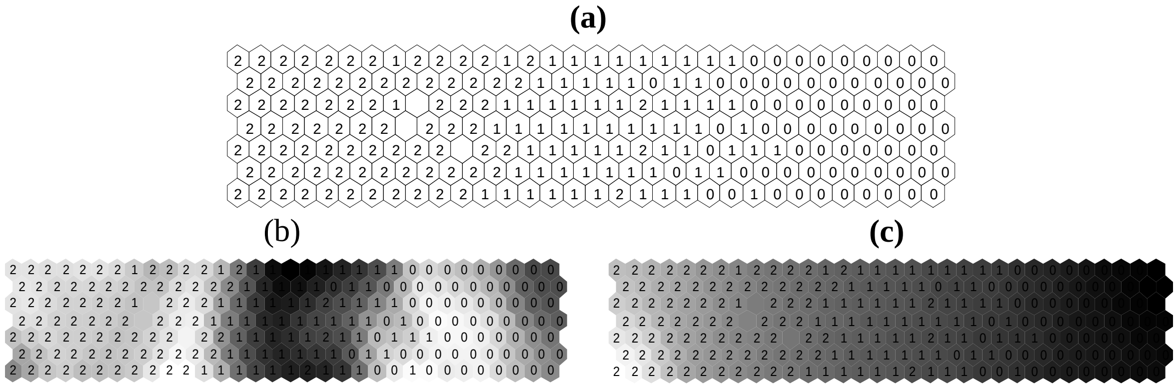

Fig. 4. Different manifestations of the features are shown for the vertical accelerometer:
(a) Assigned labels corresponding to different extended faults (0: no fault, 1: inner race fault, 2: outer race fault).
(b) Component map corresponding to Kurtosis (vertical accelerometer).
(c) Component map corresponding to Line integral (vertical accelerometer).

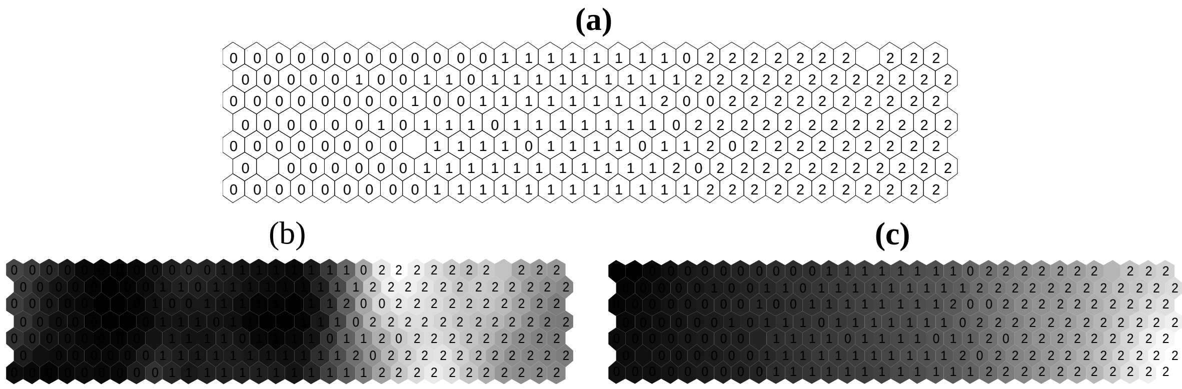

Fig. 5. Different manifestations of the features are shown for the horizontal accelerometer:
(a) Assigned labels corresponding to different extended faults (0: no fault, 1: inner race fault, 2: outer race fault).
(b) Component map corresponding to Kurtosis (horizontal accelerometer).
(c) Component map corresponding to Line integral (horizontal accelerometer).

Table 1. Results of classification of faults depending on their position by using a vertical accelerometer, a horizontal accelerometer and the fusion features from both. The testing set has been used consisting of the 25% of the data.

Fusion (% correct class estimate for healthy-inner race fault-outer race fault)			*Vertical (% correct class estimate similar to fusion)*			*Horizontal (% correct class estimate similar to fusion)*		
91.4504	7.1756	1.3740	91.4504	8.2443	0.3053	76.4885	20.4580	3.0534
6.2595	92.0611	1.6794	11.6031	75.8779	12.5191	17.0992	81.8321	1.0687
1.5267	3.5115	94.9618	1.3740	18.4733	80.1527	1.0687	5.4962	92.8244

Conclusions

It has been shown that the SOM can be used to detect faults in roller bearings and discover the position of the faults, and can therefore prove to be a powerful tool for bearing health monitoring. Different bearing faults can be detected with high accuracy by using the collective response of several features and the fusion of different sensors, which may not be obvious by just looking at the data using other diagnostic techniques. The use of kurtosis and a newly introduced feature, the line integral of the acceleration signal has given promising results in detecting the position of bearing faults. The feature based fusion of the vertical and horizontal acceleration signals has increased the accuracy of fault detection to 92-95% for different fault types. This result represented a substantial increase in discrimination performance of at least 10% for certain types of fault. It is planned that this work be extended to include more real data, different features and spall sizes for bearings in gearboxes or other machines.

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