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CLASSIFIER BASED ON ARTIFICIAL NEURAL NETWORKS AND BEAMFORMING TECHNIQUE FOR BEARING FAULT DETECTION

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Abstract. *The importance of predictive maintenance optimization has been recognized over the past decades. A relevant aspect in the process of machinery noise control is the proper identification of noise sources. Microphone-array-based methods are known as alternatives for noise source identification in machines. In this work, the "Beamforming" technique is used to visualize the directionality pattern of the noise emitted by a rotating machine and a study is presented to compare the performance of machine condition detection using different architectures of classifiers based on Artificial Neural Networks. Sound maps from a rotating machine are used as inputs to classifiers for two-class (normal or fault) recognition. The classifier is trained with a subset of the experimental data for known machine conditions and is tested using the remaining data set. The procedure is illustrated using data from experimental sound maps of a rotating machine. The effectiveness of the classifiers and the network training is improved through the use of the Karhunen-Loève transform on the sound map data.*

Keywords: *Acoustics, Source Identification, Predictive Maintenance, Artificial Neural Network, Karhunen-Loève transform.*

1. INTRODUCTION

Condition monitoring and diagnostics are widely used in almost every field of industry with applications in automation, quality control and predictive maintenance. The use of vibration signals is quite common in the field of condition monitoring of rotating machinery and the use of acoustic measurements is a promising way of complementing predictive maintenance systems. In this work, the data analyzed are derived from monitoring of a experimental test rig. Sound maps have been generated in order to observe the operating conditions of rotating machinery through spatial patterns of sound emission. The conventional Beamforming technique in the frequency domain is used to generate the sound maps.

Artificial neural networks (ANNs) have been applied in problems of pattern recognition, dynamic system identification, problems of pattern classification, fitting function, process control, time series forecasting (Bishop, 2006). In the present work, it will be applied in diagnosis of machine conditions and automated detection treating these as classification problems based on learning pattern from empirical data modeling.

A study is presented to compare the performance of bearing fault detection using different architectures of classifiers based on Artificial Neural Networks, namely, Multilayer Perceptron Neural Networks (MLP). A microphone array with twelve elements acquires time-domain acoustical signals from a rotating machine with normal and defective bearings. These signals are processed in order to obtain sound maps. By comparing the sound maps of a machine running in normal and faulty conditions, detection of faults like bearing defects is possible.

2. SOUND MAP DATA

Figure 1 shows a rotating machine consisting of electric motor, mating gears, unbalanced disks and rolling bearings and an array circular with twelve microphones spaced by an angle of 30° at a radius r = 130 mm which was mounted 500 mm above from machine. Separate measurements were obtained for two conditions, one with normal bearings and the other with a defective bearing on the bearing block indicated in Fig. 1. The defect was introduced into the inner race and lubrication was removed.

The signals of twelve microphones in the circular array were acquired with a PXI-unit from National Instruments. The acquisition hardware can be seen in Fig. 2. The signals were obtained under laboratory conditions, with low background noise, although these conditions do not represent a limitation to use of the technique. Pacheco (2012) presents some results obtained with the signals acquired under industrial conditions.

Shaft revolution was sensed by an optical sensor giving one pulse for each turn of the shaft. This signal was also connected to the data acquisition system. The machine was set up to rotate at 1920 rpm. Measurements were obtained at a sampling rate of 20000 samples/s. In the present work, these time-domain data were processed to create the sound maps through a conventional Beamforming algorithm in the frequency domain, implemented in Labview.

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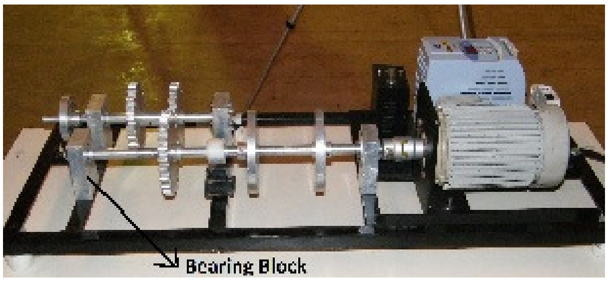

a) Test-rig.

b) Array circular with 12 microphones

Figure 1. Equipment and array used in the experiment.

According to Brandstein and Ward (2001), Beamforming is a method of mapping noise sources by assessing sound pressure levels based upon the direction from which they originate. The idea behind the technique is that a coherent sound, in the form of a plane wave, coming from a specified direction and being received by different microphones will lead to similar signals that are delayed on time based on the different travel paths (Christensen and Hald, 2004). Beamforming allows a "real-time" analysis of the incident sound, since it can picture a snapshot of the waves reaching the array. Of course this snapshot is restricted by the amount of time necessary to acquire the samples needed for the FFT-algorithm being used.

Figure 2. Experimental setup and Acquisition hardware.

The sound maps generated by an array of microphones installed near the experimental test rig, are analyzed in the 1/3 octaves band centered about 1250 Hz, 1600 Hz, 2000 Hz, 2500 Hz, 3150 Hz, 4000 Hz, 5000 Hz, 6300 Hz and 8000 Hz. The different directionality patterns of the sound maps are related to machine running in normal and faulty conditions, this variation can be observed in Fig. 3 and Fig. 4 respectively, in the 1/3 octave band centered about 6300 Hz.

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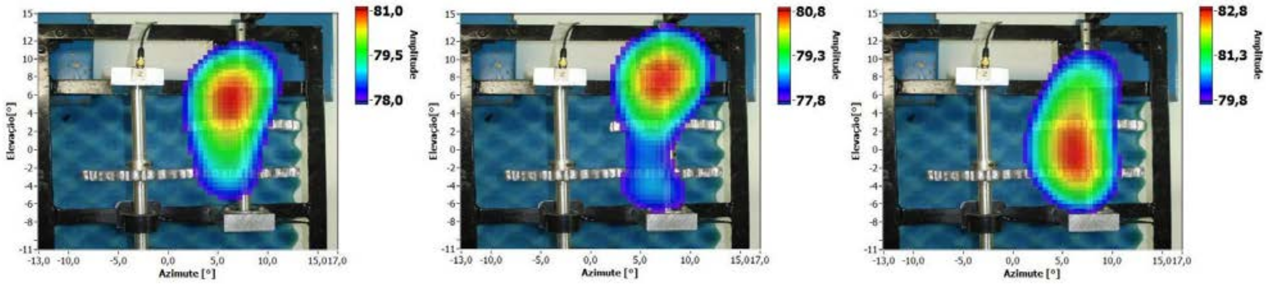

Figure 3. Sound maps at different instants of time to machine running in normal conditions at 6300 Hz.

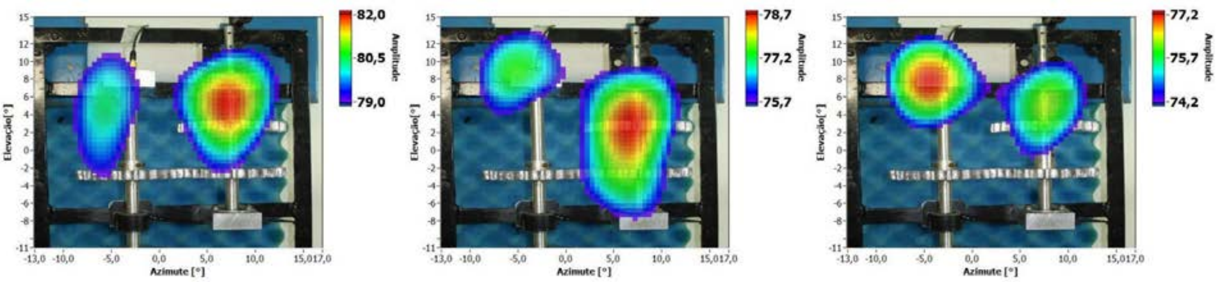

Figure 4. Sound maps at different instants of time to machine running in fault condition at 6300 Hz.

Two sets of experimental data, with normal and defective bearings, were considered. For each set, two signal groups consisting about 200000 samples were obtained using the microphones monitoring the machine condition. These samples were divided into 140 bins of 2500 samples each with 50% overlapping. These bins were further processed, in Labview, to create one set of sound maps for each 1/3 octave band.

The total set is a matrix 1080x140x2 consisting of 1080 sound pressure levels, 120 for each 1/3 octave band, associated with each direction of the sound map, i.e., each row of the matrix represents a sound map orientation, 10x12 pixels for a specific 1/3 octave band. The columns represent the time series of the sound maps, 140, and two bearing conditions, normal and defective. These data are used as inputs to the classifier. The classifier is trained with a subset of the experimental data for the known machine conditions and is tested using the remaining set of data.

3. KARHUNEN-LOÈVE TRANSFORM

The Karhunen-Loève transform (KLT), also called Principal Component Analysis or Hotelling Transform, is a well-known statistical method for feature extraction, data compression and so far it has been broadly used in a large series of signal and image processing, pattern recognition and data analysis applications.

In this work, the KLT was adopted for dimensionality reduction. Using the KLT technique, basically a higher dimensional data space can be transformed onto a lower dimensional space (Pacheco and Pinto, 2011). The sound map data used for classification purpose consist of 280 vectors with 1080 dimensions, 140 vectors for each of the 2 classes (normal and faulty). Initially all 1080 dimensions were used for training. After that was successfully implemented, the KLT technique was used to reduce the number of dimensions from 1080 to 49, according the Broken Stick test (Jackson, 1993).

Essentially, the KLT uses the covariance matrix obtained from the input data vectors. By looking at the covariance matrix of the data vectors, one can determine which of the dimensions are highly variable across the data space. This leading to a standard Eigenvalue problem. The KLT technique thus transforms the existing data space into a new data space. The variance of the resulting, transformed data set can be controlled along with the reduction in the dimension of the set, i.e., the number of components in the data vector is reduced. At the same time, most of the information contained in the original data set is retained. With KLT, new features obtained are a linear combination of the original ones.

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4. ARTIFICIAL NEURAL NETWORK

Artificial Neural Networks (ANNs) were introduced as models of biological neural networks. An ANN is a system composed of interconnected processing elements, called neurons, which are arranged in layers. Each neuron is responsible for mapping linear and nonlinear data input and output, mainly determined by its activation function (Bishop, 2006).

Among different kinds of ANNs, multilayer perceptron (MLP) neural networks are quite popular and will be used in this work. MLPs consist of an input layer of source nodes, one or more hidden layers of computation nodes or ‘neurons’ and an output layer (Haikin, 1999). Figure 5 shows an example of a ANN architecture that is widely used in practical applications.

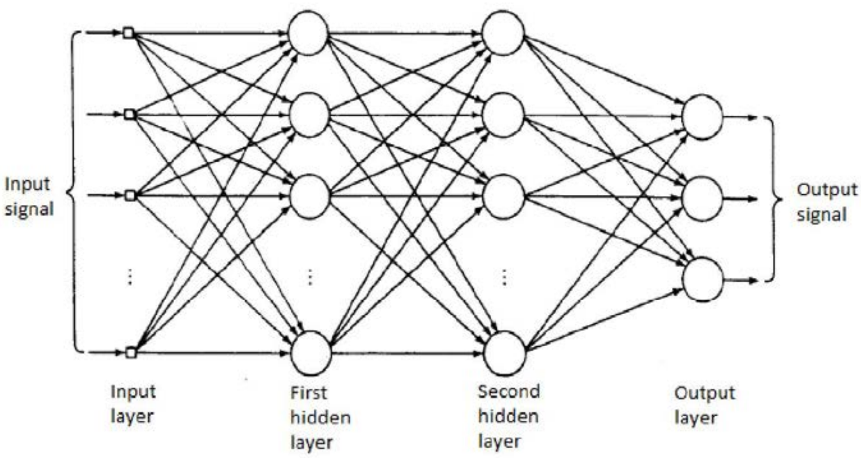

Figure 5. Architecture of a Multilayer Perceptron (MLP) Neural Networks (Haikin, 1999).

The neuron can be represented mathematically through the following expressions:

$$_k = \sum_{j=1}^{m} w_{kj} x_j \tag{1}$$

and

$$y_k = \ (\ _k + b_k) \tag{2}$$

where, $x_1, x_2, ..., x_m$ are the input signals; $w_{k1}, w_{k2}, ..., w_{km}$ are the synaptic weights; $_k$ is the output of linear combiner; $(.)$ is the activation function and y_k is the output signal of neuron. The model neuron also includes a bias externally applied, represented by b_k The bias has the effect of increasing or decreasing the net inflow of the activation function, depending on whether it is positive or negative, respectively. The parameters weights and biases together, constitute the adaptive parameters in the network.

The number of nodes in the input and the output layers depend on the number of input and output variables respectively. The number of hidden layers and the number of nodes in each hidden layer affect the generalization capability of the network.

The MLP Neural Network, used in this work, consists of input layer, hidden layer and output layer. The input layer has 1080 nodes representing the sound maps in the original way. Through the application of the KLT the number of input nodes is decreased to only 49. Representing the two classes, “normal” and “failed” bearings the 2 binary output nodes are always complementary. The inputs were normalized in the range of 0.0 – 1.0. In the ANN, sigmoid activation functions were used in the hidden and in the output layers. The ANN was created, trained and implemented using Matlab neural network toolbox with back-propagation and the Levenberg-Marquardt training algorithm. The ANN was

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trained iteratively to minimize the mean square error (MSE) between the network outputs and the corresponding target values. At each iteration, the gradient of the performance function (MSE) was used to adjust the network weights and biases. In this work, a minimum gradient of 10^{-10}, a mean square error of 10^{-6} and maximum iteration number (epoch) of 100 were used. The training process would stop if any of these conditions were met. The initial weights and biases of the network were generated automatically by the program.

5. RESULTS

The original data set, consisting of 1080 sound pressure levels associated to each direction of the sound maps, in nine different 1/3 octave bands, split in form of 140 bins, for each bearing condition, were divided into two subsets. The first 84 bins of each signal, or 60% of bins, were used for training the ANNs and the rest were used for validation. The target value of output node was set 1 and 0 for normal and failed bearings, respectively.

The KLT technique was used to reduce the number of dimensions from 1080 to 49, drastically reducing the number of input nodes.

The classification results are presented to see the effects of the Karhunen-Loève transform for the diagnosis of machine condition using MLPs. To evaluate the effect of the architecture of the neural network on the performance of classifiers, neural networks of different architectures with one or two hidden layers were tested for each classifier. These architectures were chosen on the basis of training trials. Table 1 and 2 show a summary of the best results obtained with the training of six types of architectures of MLP.

Table 1. Results of success rate of different MLP architectures without dimension reduction.

Architecture	Training time (s)	Success rate (%)
1080x3x2	28.7	97.86
1080x5x2	80.1	98.93
1080x9x2	413.5	95
1080x4x3x2	59.8	98.93
1080x3x6x2	18.35	93.21
1080x6x5x2	187.6	98.57

Table 2. Results of success rate of different MLP architectures with dimension reduction.

Architecture	Training time (s)	Success rate (%)
49x6x2	0.64	98.57
49x18x2	2.24	95.36
49x19x2	2.98	98.93
49x3x3x2	0.88	98.57
49x4x4x2	0.78	91.43
49x7x3x2	0.93	98.21

The neural network architecture 49x4x4x2 (49 neurons in the input layer, 4 neurons in the first hidden layer, 4 neurons in the second hidden layer and 2 neurons in output layer) showed the lowest success rate of the patterns presented to it, i.e., the network has recognized only 91.43%. The architecture with better ability to generalize the network was 49x19x2 with success rate of 98.93%. In general, it is noted in Tab. 1 and 2 that the other architectures were also able to classify with efficiency above 91.43%. It should be noted that the increase in the number of layers or neurons does not necessary leads to improved performance.

The training time needed for the different architectures depends on the amount of neurons used. With the dimension reduction achieved by the KLT the corresponding times are much lower than those for the original set. For the same highest success rate, of 98.93%, the training time is reduced from 80.1 s to 2.98 s. The smallest time of only 0.64 s still allows a success rate of 98.57%.

Even with data with dimension reduced by KLT the failure introduced in the experimental test rig could be recognized. The results show that the MLP can be used satisfactorily as an alternative technique for fault diagnosis and classification, using maps sound in conjunction with KLT.

6. CONCLUSIONS

In this work the performance of a bearing fault detection system is investigated. The use of sound maps is proposed in order to correlate possible failures with their spatial locations. The great amount of data from these maps, in different frequency ranges, poses a difficulty for the training of ANN based classifiers.

The application of the KLT allowed the use of an approximation with fewer dimensions than the original data set. It simplifies the database of the sound maps and greatly improves the training of the ANN.

The technique has advantages over the conventional spectral analysis by allowing the spatial location of the failed bearing.

The recognition of patterns on the sound maps 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 machine down time.

This work is an introduction to the application of the classifiers in a real gas turbine to the failure prediction in the framework of its maintenance system. The results, problems and limitations are discussed in Pacheco (2012).

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