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Application of Fourier Descriptors & Artificial Neural Network to Bearing Vibration Signals for Fault Detection & Classification

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Abstract
Automatic fault detection and diagnosis has always been a challenge when monitoring rotating machinery. Specifically, bearing diagnostics have seen an extensive research in the field of fault detection and diagnosis. In this paper the time-frequency representations of vibration acceleration signals which were acquired from the bearing in different states were calculated and displayed in grey scale images. Artificial neural networks (ANN) were then used to classify the time–frequency images after the images were normalized. By this way, the fault diagnosis of the bearing was transformed to the classification the Fourier Descriptors of time–frequency images. As there is no need to extract further fault features such as eigenvalues or symptom parameters from the time–frequency distributions before classification, the fault diagnosis process is highly simplified. The challenge is not only to be capable of diagnosing automatically but also to generalize the process of classification of the measured signals. The analysis results show that this approach effectively improves the accuracy and reliability of fault diagnosis of the bearing.

Key Word and Phrases
Condition Monitoring, Fault Diagnosis and Classification, Time-frequency Analysis, Fourier Descriptors, Artificial Neural Network.

1. Introduction

Automatic fault detection and diagnosis has become an interesting added value as a result of incorporating intelligent procedures into machine control systems. The artificial intelligence techniques have been proposed for machine component predictive maintenance strategies. Bearing monitoring has seen an extensive research in the field of fault detection by vibration analysis techniques. Rolling bearings are bound to fail due to their continuous use in demanding situations. Their faults can provoke from safety problems to production loses. Therefore, the automatic and rapid detection of the fault is a peremptory requirement.

Machine condition monitoring, early fault detection, diagnosis and classification are extremely important topics in the engineering field. Proper machine monitoring and fault detection method will result in improved safety, improved reliability and reduction of the cost of different engineering system operation [1].

A traditional approach to prevent machine failure is based on planning, regular inspection, parts replacement and preventive maintenance. Although these methods are effective, they are all incapable of given early warning for the machine conditions under operation. For this reason automatic fault detection and diagnosis methods that monitor the machine while it operating is becoming popular.

In rotary machines bearings are crucial components and the majority of failures arise from defective bearing. The unprocessed vibration data collected from a rotary machines gives some information about the condition of the bearing, however to detect fault at early stages, further processing of the vibration signal is necessary. Several methods in different domains have been implemented for interpreting the vibration signals:

Time-domain analysis is a method of representing a waveform by plotting amplitude over time. In addition, time-domain analysis calculates characteristic features from time waveform signals as descriptive statistics. For example: mean, peak, peak-to-peak interval, crest factor, high order statistics: RMS (root mean square), kurtosis, etc.

Frequency-domain analysis is a method of representing a waveform by plotting its amplitude against frequency. The advantage of frequency-domain analysis over time-domain analysis is its ability to easily identify and isolate certain frequency components of interest. The Fourier transform transforms a time domain signal into a frequency domain representation of that signal.

This means that it generates a description of the distribution of the energy in the signal as a function of frequency. So, this is normally displayed as a plot of frequency (x-axis) against amplitude (y-axis) called a spectrum. The main idea of spectrum analysis is to either look at the whole spectrum or look closely at certain frequency components of interest and thus extract features from the signal.

In digital signal processing the Fourier transform is almost always performed using an algorithm called the Fast Fourier Transform or FFT. This is, as its name suggests, a quick way of performing this transform and it gives the same results as the slower Discrete Fourier Transform (DFT) would. The Fourier transform of third-order cumulant-generating function is called the bispectrum or bispectral density. Bispectrum analysis has been shown to have wide application in machinery diagnostics for various mechanical systems such as gears [2], bearings [3], rotating machines [4] and induction machines [5]. Li et al investigated the application of bispectrum diagonal slice to gear fault diagnostics. Yang et al used both bispectrum diagonal slice and bi-coherence diagonal slice, summed bispectrum, and summed bi-coherence for bearing fault diagnostics. A limitation of Frequency-domain analysis is its incapacity to handle the instantaneous signals, which are very common when the fault of machines occur. Thus, time-frequency analysis, which investigates waveform signals in both time and frequency domain, has been developed for non-stationary waveform signals.

The analysis of nonstationary signals generally consists of the description of temporal evolution of certain relevant properties of the analyzed signals. There are two major classes of approaches based on whether the spectral contents (time-frequency methods) are considered or if the behavior of the signal in various scales of observation (time-scale methods) is aimed. Time-frequency analysis uses time-frequency distributions, which represents the energy or power of waveform signals in two-dimensional functions of both time and frequency. Short-time Fourier transforms (STFT) [6]-[7] and Wigner-Ville distributions [8]-[9] are the most popular time-frequency distributions. Cohen reviewed a class of time-frequency distributions which include spectrogram, Wigner-Ville distribution, Choi-Williams and others.

The complicated theory of time-frequency analysis restricts engineers from using these methods in machine diagnosis. To implement all the above-mentioned methods an in- house software program (TF-Analysis) has been developed. This program has been developed especially for the diagnosis of defects in machinery and it allows the user to different distributions of Cohen’s class of time-frequency method and it provides different kinds of Wavelet transforms.

In most cases to identifying the deteriorations, the general method is to classify the images through a visual inspection made by a technician. This is clearly dependent on human experience and introduces many subjective factors and errors in fault diagnosis. Unsurprisingly, the recognition results are usually not very good, for this reason, it is necessary to develop automatic monitoring systems to detect faults more reliable and more effective.

There exists a great deal of diagnosis techniques that appear to be classified in the literature in diverse ways [10]; [11]; [12]; [13]. For the case of machinery diagnostics, signal-based Fault Detection and Identification techniques are the most convenient since vibration signals can provide a fault signature when diagnosing rotating machinery components. The stage of feature extraction implies preparing the signal so that its information is interpretable. This is generally achieved by means of signal processing techniques. On the other hand, the classification (to interpret the signal information to decide whether there is a fault and which is the element in fault) typically involves applying all techniques. Finally, due to the blooming of artificial intelligence, the fault diagnosis techniques have been increasingly developed with the use of learning algorithm [14], artificial neural networks [15], Fuzzy logic method [16] and genetic algorithms [17].

In this paper Time-frequency distributions are used to analyze vibration signals. The analyses of results are expressed in time–frequency images. An artificial neural network algorithm is then used to classify non-linearly separable data directly using the Fourier descriptors of these time–frequency images. As there is no need to extract further fault features, such as Eigenvalues or symptom parameters, the classification and fault diagnosis process becomes simple and easy to apply.

2. Signal Processing Procedure

The shapes we consider in this paper are outline shapes which can be described as single plane closed curves. The shapes in our database are obtained from time–frequency analysis images and they are presented in the form of gray level images. The purpose of pre-processing is to extract boundary information (coordinates of the boundary) from the shape. Figure 1 shows the structure of the pre-processing algorithm.

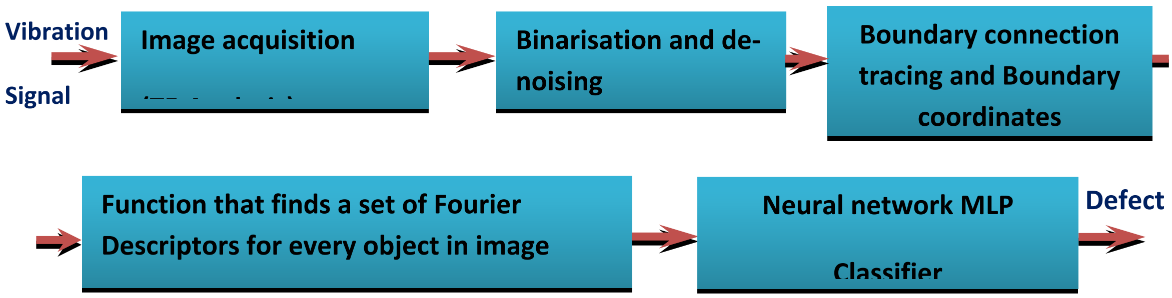

Fig.1 Image processing system.

The first step in pre-processing is to binarize the shape image; a simple thresholding function is applied to convert the gray level shape image into a binary image. In reality, shape images are often corrupted with noise, and as a result the shape obtained from the threshold usually has noise around its boundary. A de-noising process is therefore applied. This eliminates isolated pixels and small isolated regions or segments. For a non-silhouette shape, the shape boundary is not always connected, and therefore an m-connectivity connection technique is used to fill the gaps between boundary points. The shape is then traced using an 8-connectivity contour tracing technique to obtain the shape boundary coordinates.

3. Fourier Descriptors

Fourier descriptors are used to describe the shape of any object (input image). Their main advantage is that they are not affected by translation, rotation and scaling of the observed object. Also, they are easily computed and based on the well-developed theory of Fourier transformation.

In this paper the shape of the pattern is described by coordinates of its contour in a complex coordinate system, and then a Discrete Fourier Transformation is applied to this data to obtain the Fourier Descriptors of the shape.

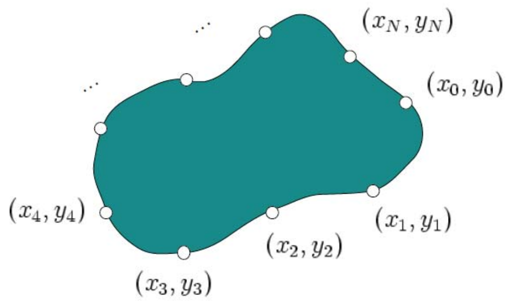

Fig.2 Representing a contour using Fourier descriptors [18].

3.1 Calculating the Fourier Descriptors

Before calculating the Fourier descriptors the input image must be segmented and the boundary of the object must be determined. The boundary will be presented as an array of complex numbers which correspond to the pixels of the object boundary if the image is placed in the complex plane. Fourier descriptors are calculated by combining Fourier transform coefficients of the complex array.

Let the complex array Z_0, Z_1, Z_2……Z_{N-1} represent the boundary belonging to the object whose shape needs to be described. The k-th Fourier transform coefficient is calculated as [19]:

$$Z_K = \sum_{n=0}^{N-1} Z_n e^{-2\pi ikn/N} \text{ , } k=0, 1\text{………………., } N\text{-}1. \tag{3.1}$$

The Fourier descriptors are obtained from the sequence Z_k as follows:

$$C_K = \left|\frac{Z_k}{Z_1}\right| \text{ , } k=2, 3\text{………………., } N\text{-}1. \tag{3.2}$$

To make Fourier Descriptors rotation- and shift- invariant, we must use only absolute values of coefficients Z_k, and in order to make them scale invariant, we normalize them by dividing each one by the first value.

4. Artificial Neural Network Classifier Designs

The multilayer perceptron is the most widely used paradigm among neural networks in various applications. It is biologically inspired, that is, it is designed to have a similar structure and behavior to a biological neural system. A first interest in neural networks emerged after the introducing of simplified neurons by McCulloch and Pitts in 1943. These neurons were presented as models of biological neurons and as conceptual components for circuits that could perform computational works.

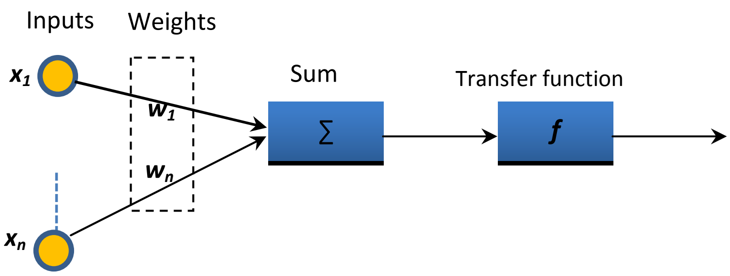

Fig.3 An Artificial neuron.

Even if it is far from the real biological neural system, it is a powerful signal processing algorithm for solving many practical problems. It is known to be a universal approximator in which it can approximate any function to any degree of accuracy given enough nodes in hidden layer. This capability makes the MLP a powerful classifier in pattern classification problem. An artificial network consists of a set of simple processing units (neurons) which communicate by sending signals to each other over a large number of weighted connections.

Every Neural Networks should be trained before usage, it can learn from examples through training. During the training process, neural network changes the values of weights and biases, to perform desired response. Besides its ability to approximate, MLPs have a good generalization. After successful training, it can give good results for unseen input data within the same input space. There are two categories of the learning rules:

- supervised learning: Associative learning in which the network is trained by providing it with input and matching output patterns. These input-output pairs can be provided by an external teacher, or by the system which contains the network (this category of Neural Network training is used in this paper).
- unsupervised learning: Self-organization in which an output unit is trained to respond to clusters of pattern within the input. In this paradigm the system is supposed to discover statistically salient features of the input population. Unlike the supervised learning paradigm, there is no feedback from the environment to indicate what the desired outputs of a network should be or whether they are correct; rather the system must develop its own representation of the input stimuli.

4.1 Classifying the Time–Frequency Images with ANN

Minsky and *al* [20] showed that a two layer feed forward network can overcome many restrictions, but did not present a solution to the problem of how to adjust the weights from input to hidden units. An answer to this question was presented in [21]. The main idea behind this solution is that the errors for the units of the hidden layer are determined by back-propagating the errors of the units of the output layer. For this reason the method is called back-propagation learning algorithm. The back-propagation algorithm performs two steps. The first step is that the inputs are ordinarily propagated forward from input to output layer, and then it produces an actual output. The error from the difference between target values and actual values are propagated backward from output layer to the previous layers to update their weights. A back-propagation method is a non-parametric statistical model for extracting nonlinear relations in the data.

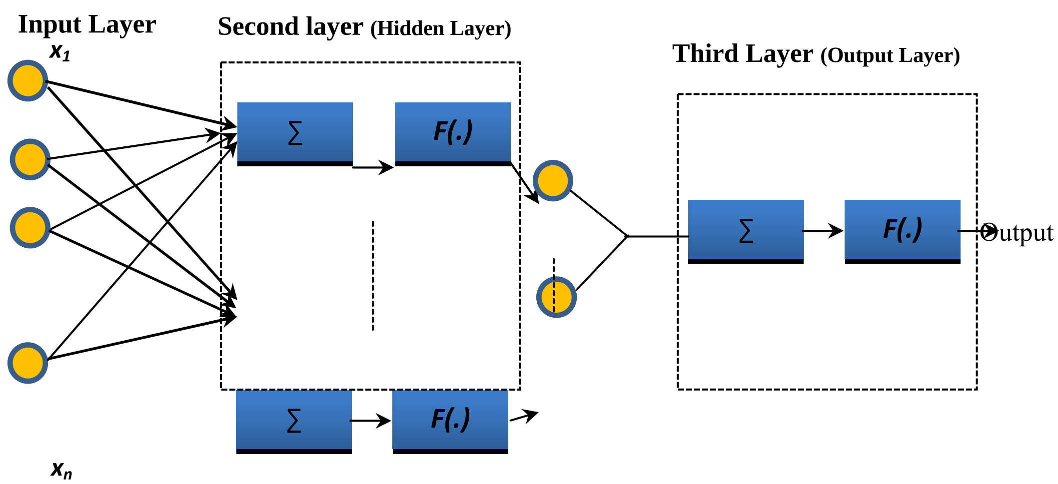

Fig.4 Block diagram of the Multi-layer perceptron network used in this paper.

By the current research, classification method based on artificial neural network was used. For this classification problem, this Multi-layer perceptron network consists of three layers: input layer, hidden layer and output layer as shown in Figure 4. The input layer unit does not perform any computation but simply distributes the input to the neurons in the pattern layer. Initial weights and biases were generated randomly in this algorithm and the output layer indicates what configuration was used at the input.

5. Bearing Fault Signatures

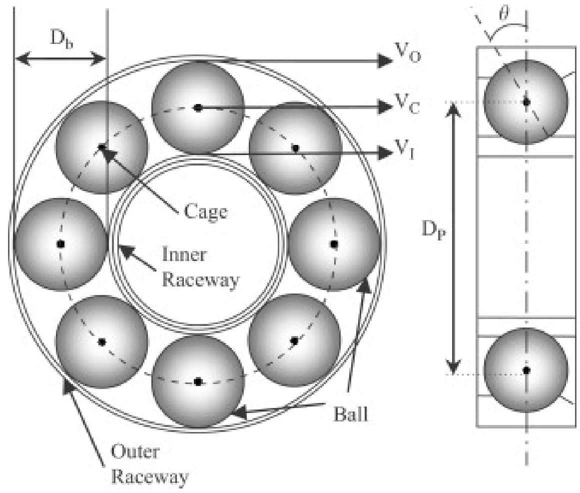

Fig.5 Dimension and frequencies related to bearing faults signatures.

The most typical faults in ball bearings are produced by a localized wear in the inner race, the outer race or the balls. Localized defects include cracks, pits and spalls on the rolling surface, although the dominant mode of fault is the spalling of the races. When the ball strikes the defect, a shock is produced, exciting high frequency resonances of the structure. The presence of such defect causes a significant increase in the vibration level. The frequency of the shocks can be calculated by the following formulas:

$$F_{CF} = \frac{1}{2} F_R (1 - \frac{D_B \cos\theta}{D_P}) \tag{5.1}$$

$$F_{ORF} = \frac{N_B}{2} F_R (1 - \frac{D_B \cos\theta}{D_P}) \tag{5.2}$$

$$F_{IRF} = \frac{N_B}{2} F_R (1 + \frac{D_B \cos\theta}{D_P}) \tag{5.3}$$

$$F_{BF} = \frac{D_P}{2D_B} F_R (1 - \frac{D^2{}_B \cos^2\theta}{D^2{}_P}) \tag{5.4}$$

where F_{CF}, F_{ORF} and F_{IRF} are the cage fault frequency, ball pass frequencies for outer and inner race respectively, and F_{BF} is the ball fault frequency. These fault frequencies are dependent on the number of balls (N_B), shaft speed (F_R) contact angle (θ) and ball (D_B) and pitch (D_P) diameters.

6. Experiments

6.1 Data acquisition

In order to verify the practicability of the proposed method, vibration signals were collected from a test rig '*Squeeze Film Damper* (SFD)' at École Polytechnique de Montréal. The original design of the SFD [22] has been modified to allow the testing of a defective bearing. The test setup is composed of a conical steel shaft, supported at its ends by two rolling bearings. The shaft is connected to the motor via a rigid coupling. Bearing near the coupling is auto-aligning and it is mounted freely (can keep the angular misalignment permitted by the rigid coupling). The opposite housing contains the tested bearing. Two accelerometers were used, one mounted on each bearing housing (Figure 6). Signals were gathered at a sampling frequency of 32.768 kHz for a period of 20 seconds while the shaft was running at different speed: 1800 rpm, 1500 rpm, 1200rpm, 900 rpm, and 600 rpm [23].

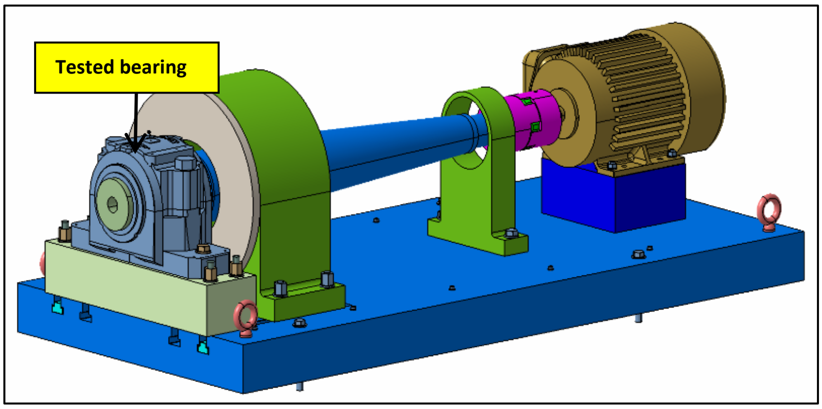

Fig.6 Test setup at École Polytechnique de Montréal.

Fig.6 Continued.

Table 1 Test Setup Characteristics.

Components	Technical Specifications
Motor	1 Hp 1750 rpm 60 Hz 1,2 amp
Coupling	7/8 *po* to 1 $^{1/4}$ *po*
Bearing near coupling	SKF 2310 E2RS1TN9
Tested bearing	SKF 1211 EKTN9

Table 2 Fault frequency (Hz).

Model	BPFO/FR	BPFI/FR	BSF/FR
SKF 2310 E2RS1TN9	5,36	7,64	5,47
SKF 1211 EKTN9	8,68	11,3	7,39

7. Artificial Neural Network Defect Classifier using Fourier Descriptors

Most of the rotating machine fault phenomena (outer, inner race and ball fault) behave in a nonlinear way meaning that the observed data describe a curve or curved subspace in the original data space. Identifying such nonlinear manifolds becomes more and more important in the field of diagnostic. Artificial Neural Networks (ANN) which used in this study can be used in numerous main tasks: function approximation and classification. Neural networks are nonlinear, multivariable models built from a set of input/output data. Generally there are 3 layers: input, hidden, and output. Each layer contains "neurons" that take a weighted sum of its inputs, and applies a function to introduce nonlinearity. For ANNs, that nonlinear function generally is "sigmoidal".

Four different synthetic classes are considered to test the performance of the proposed intelligent system: normal, inner race, outer race and ball fault (the size, shape and depth of the defects performed on bearing components could not be controlled adequately. The approach adopted for this purpose is by trial-error: the component is damaged until the theoretical frequency of fault can be clearly distinguished):

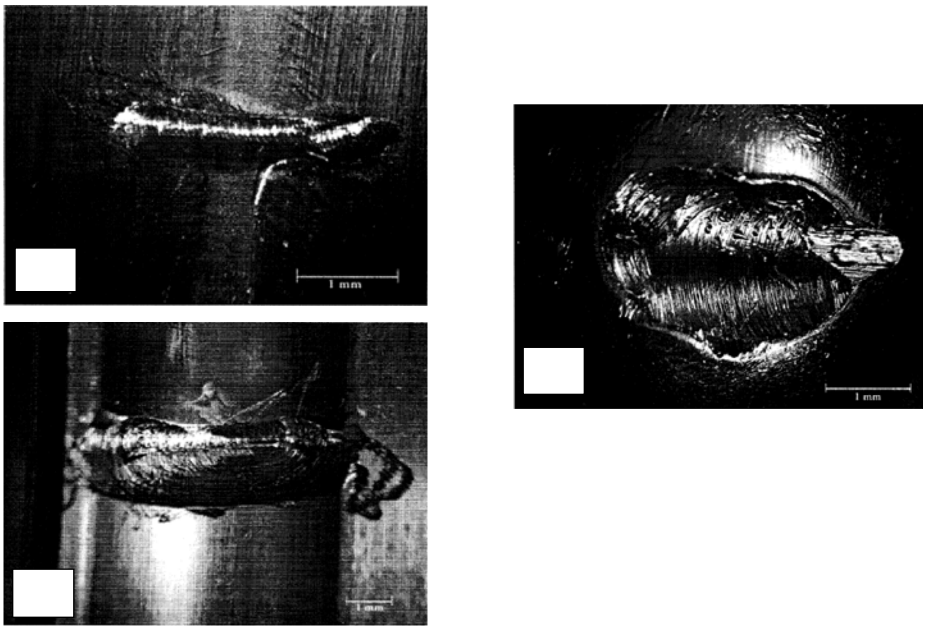

Fig.7 Fault simulations on SKF 1211bearing **a)** outer race fault, **b**) inner race fault and **c)** ball fault.

There are three main factors influencing the generalization of a network: the size efficiency of the training data and the physical complexity of the problem at hand and the architecture of the network used [24].

All factors are equally important to overall classification performance of a network. Learning of different classes due to the complexity of classification and/or an uneven number of training data from different classes is likely to be encountered in practice. In an ideal case the number of training data should be equal, with an ample and representative amount for each class.

MLP networks can be trained by several methods but the most popular method is the error backpropagation algorithm. This algorithm uses a gradient-descent to update the weights of the network. Although there are several methods to improve the rate of convergence of the error backpropagation, the standard error backpropagation is used throughout this research in order to classify input signals in four classes. To test the reliability of the learning process 100 signals per class (normal, inner race, outer race and ball fault) are fed to the training block, then the classifier uses these training data to provide decision.

8. Discussions and Results

The results of Time-Frequency Analysis are the Spectrogram (STFT) of the simulated normal and defective SKF 1211 bearing. The output of Time-Frequency Analysis for each signal is an $n \times n$ matrix and represent by an image. The Time-Frequency Analysis method provides a three dimensional representation of a signal. Figures 7, 8, 9 and 10 show time-frequency representations with normal and defects fault located at different speed of the simulated classes.

During classification, the most significant fifteen Fourier Descriptors (This selection is justifiable by simple property—most of the information about the object boundary will be located in the low frequency part of the discrete Fourier transform) representing objects found in the Time-Frequency image are sent to the trained Neural Network block.

Every training input vector is labeled with its corresponding feature class in binary representation as indicated in table. If a Pattern vector is classified as faulty or non-faulty bearing signal, then its corresponding feature class is copied to the output image. The remaining combinations can be considered are unknown or unclassified defect classes.

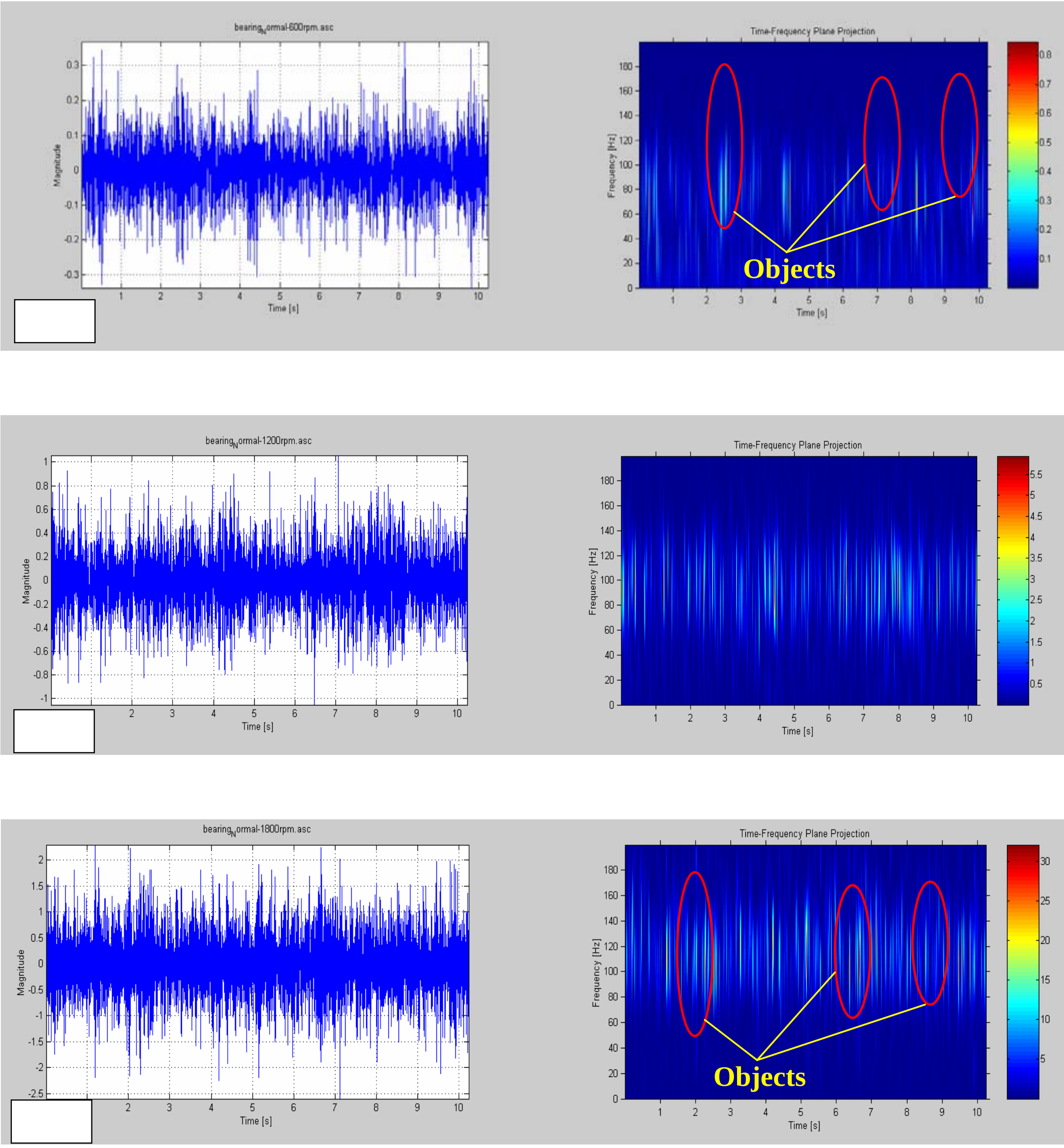

Fig.8 STFT image of the simulated Normal class at a) 600 rpm, b) 1200 rpm and 1800 rpm.

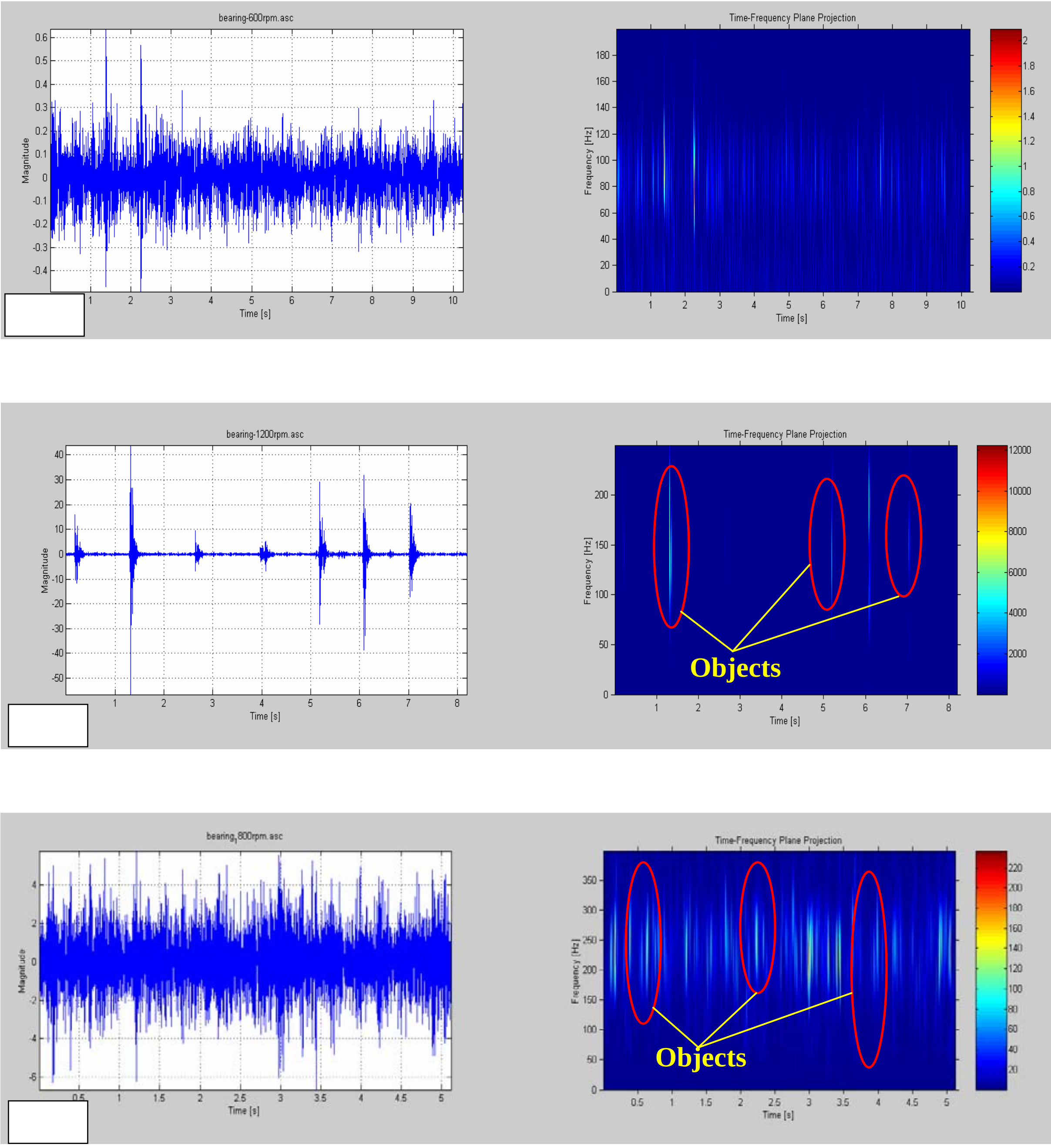

Fig.9 STFT image of the simulated Ball fault class at a) 600 rpm, b) 1200 rpm and 1800 rpm.

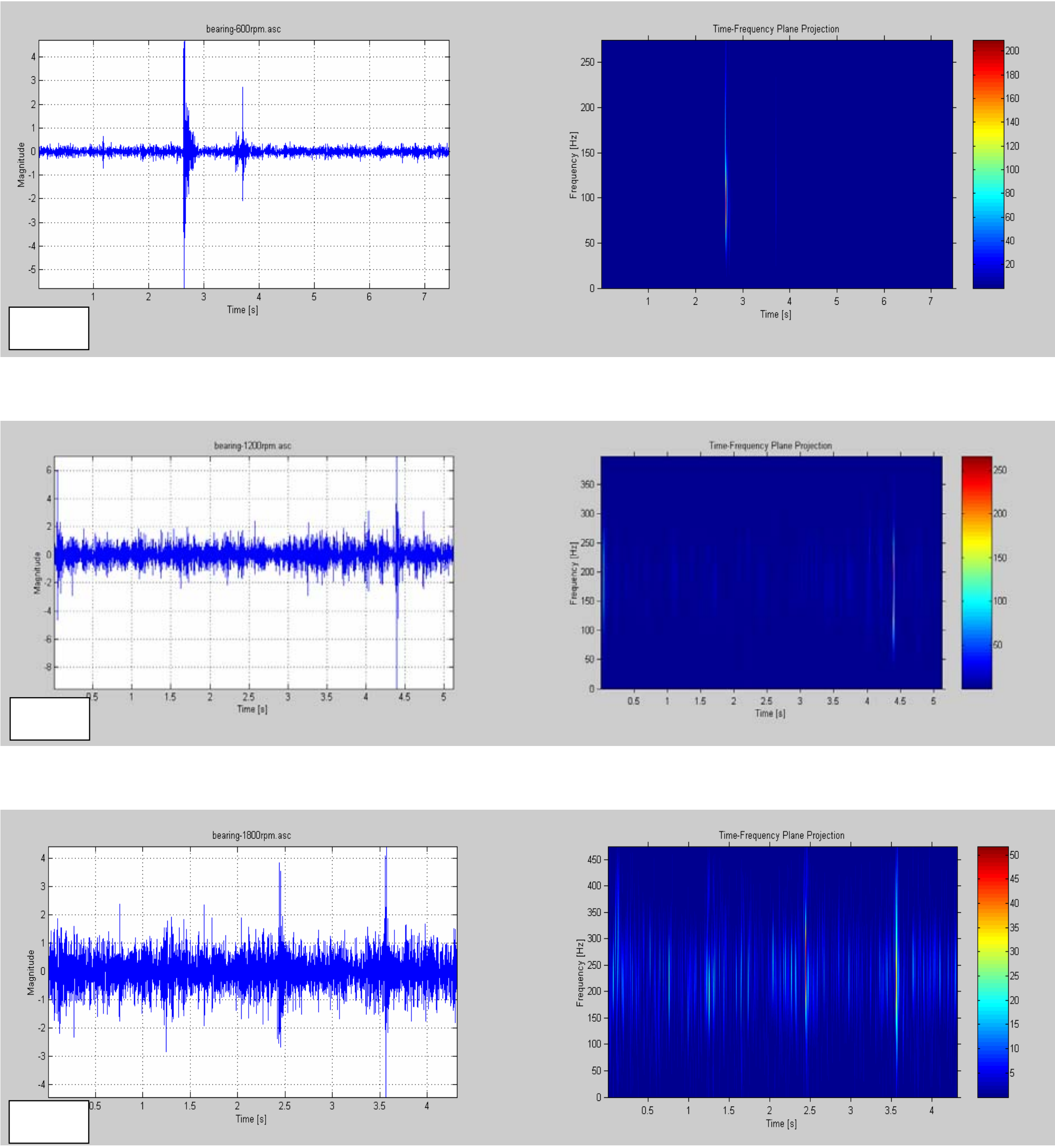

Fig.10 STFT image of the simulated Inner fault class at a) 600 rpm, b) 1200 rpm and 1800 rpm.

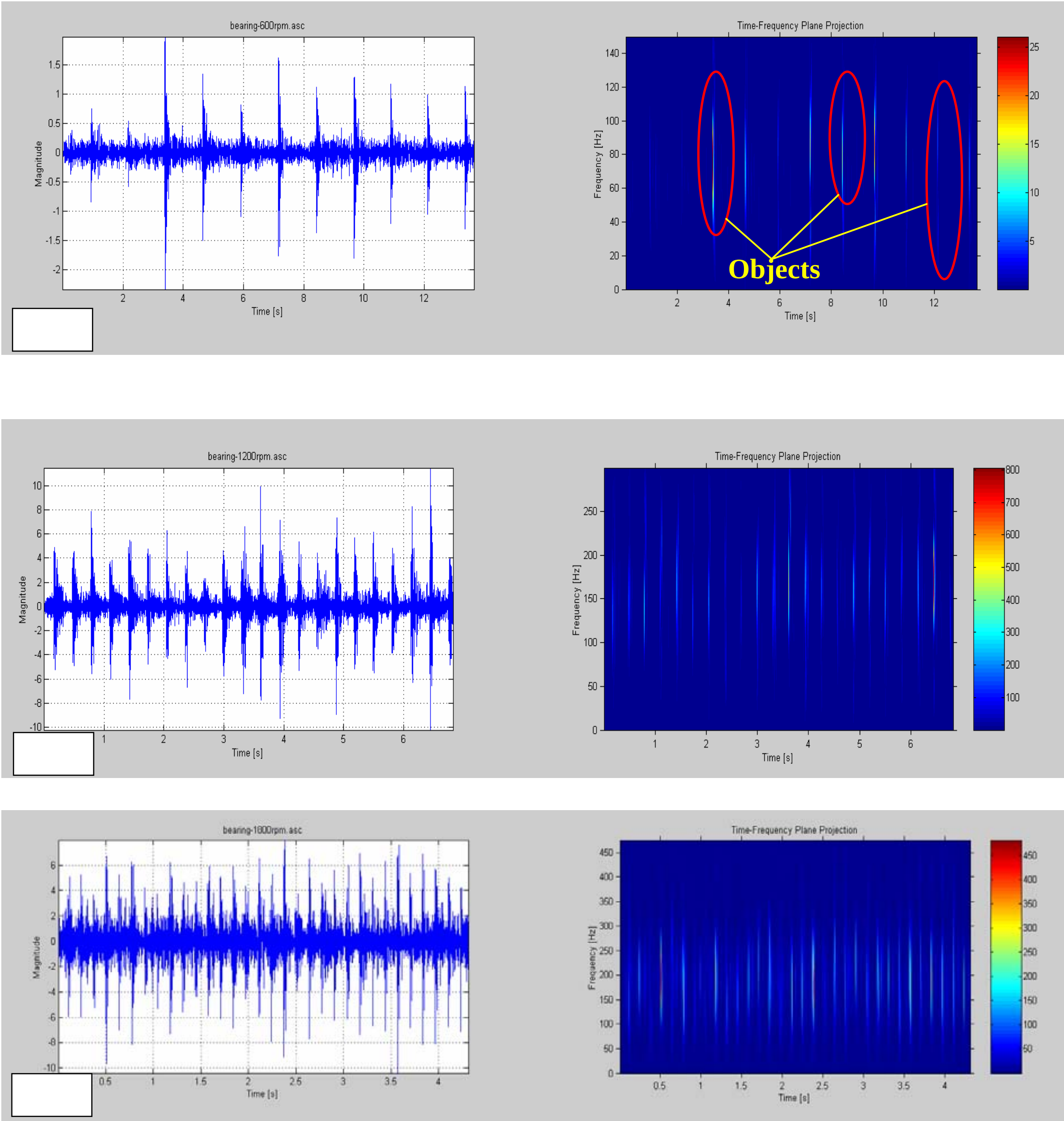

Fig.11 STFT image of the simulated Outer fault class at a) 600 rpm, b) 1200 rpm and 1800 rpm.

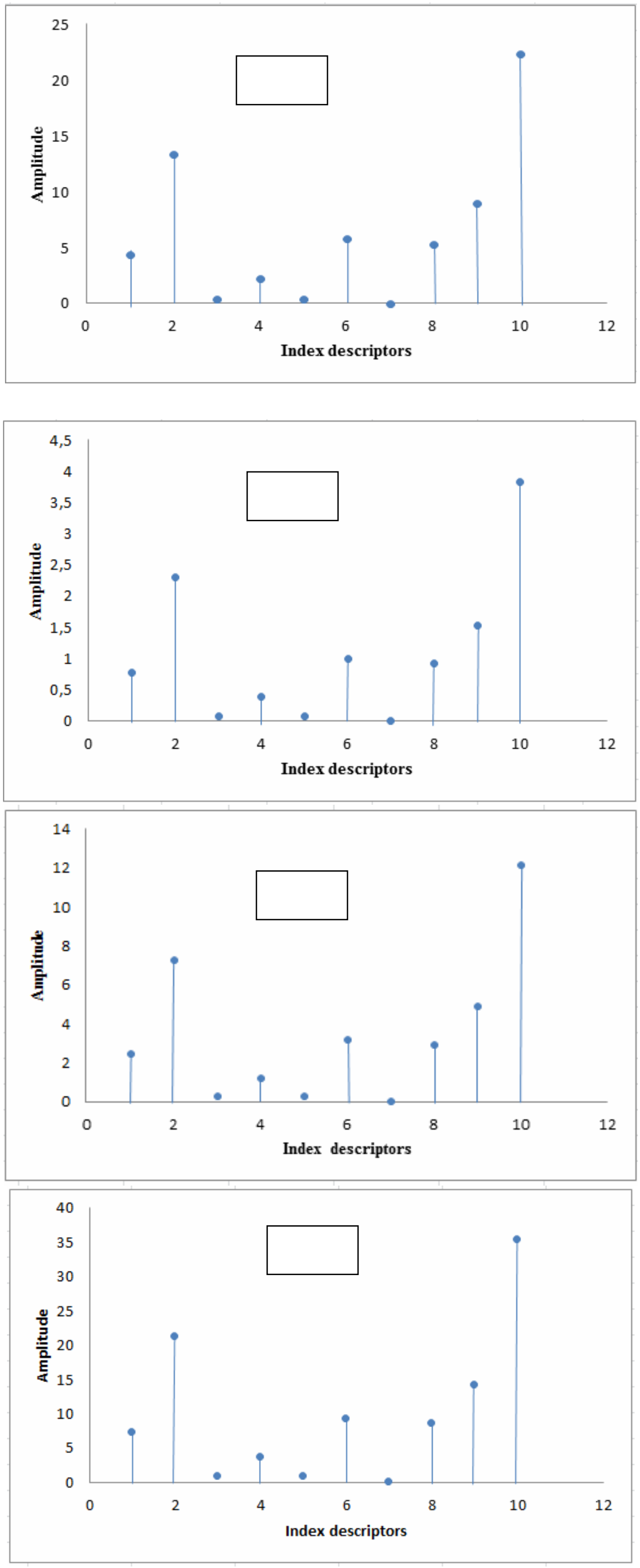

Fig.12 Fourier descriptors of one object of STFT image at 600 rpm of : **a)** Normal class **b)** Defect ball **c)** Inner race defect **d)** Outer race defect.

As it was mentioned earlier, the classifier uses the trained data to provide decision, for this reason when the training is complete; the network performance is checked to determine if any changes need to be made to the training process, the network architecture or the data sets Figure 12.

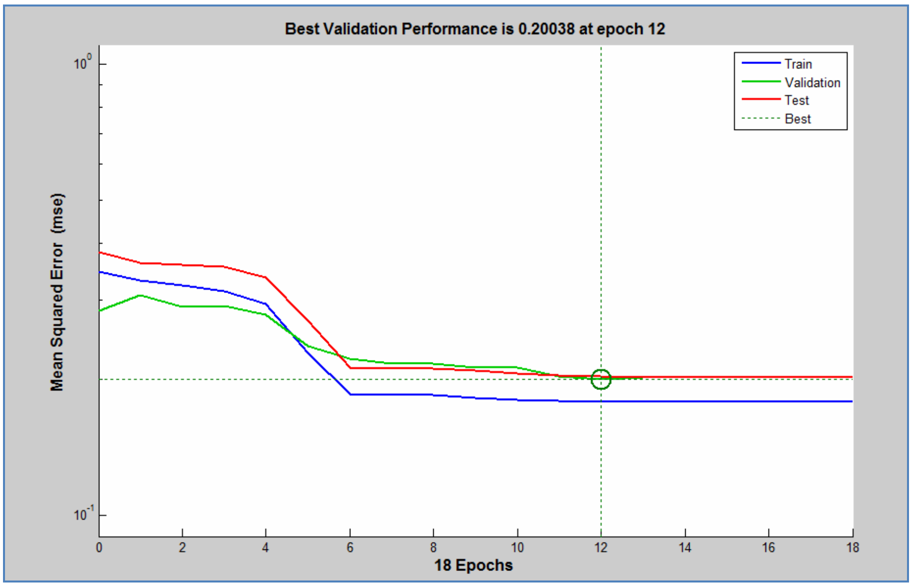

Fig.13 Training curve of the Neural Network Classifier.

This figure doesn't indicate any major problems with the training. The validation and test curves are very similar. After the network training and validation, the network object is used to calculate the network response to input Fourier Descriptors vector of the simulated classes.
In this work, Pattern recognition networks used are feedforward networks that can be trained to classify inputs according to target classes. The target data for pattern recognition networks should consist of vectors of all zero values except for a 1 in element *i*, where *i* is the class they are to represent.

Defect Targets is an $n \times n$ matrix of associated class vectors defining which of four classes each input is assigned to. Classes are represented by a 1 in row 1, 2, 3 or 4:
1) Normal class #1
2) Defect class #2
3) Defect class #3
4) Defect class #4

Table 3 Binary representation of defect classes.

Defect class	Class Binary Representation			
Normal class	1	0	0	0
Ball Defect	0	1	0	0
Inner race Defect	0	0	1	0
Outer race Defect	0	0	0	1

The objective at this stage is to use this dictionary to classify the signals derived from distributions that give the best results for our case. Based on the fact that the best distribution is the one that has the largest peak, the image of the top three time-frequency distributions will be selected for this component and hence the dictionary is created.

For a new product, to verify whether or not the signal has a fault, the process of detection is as follows: first, the signal is processed by the top three distributions retained. In the second step, a series of twelve Fourier descriptors should be found for every object in the time-frequency image. These significant Fourier descriptors will be chosen as the elements of the pattern vector for description of the object and a comparison procedure will be implemented between the latter and the dictionary (only signals that correspond to the state of the bearing) to identify its state.

Figure 14 indicates the successful classification of new added points used to evaluate the classifier. The classification performance result using neural network and Fourier Descriptors is reported in Table 4. It is obvious that the classifier response correctly to all of the test and training data. This appears to be an over-training problem. However, the goal was to create a system able to perform efficient classification with limited input cases, in attempt to achieve the neural network training with a reduced number of case patterns.

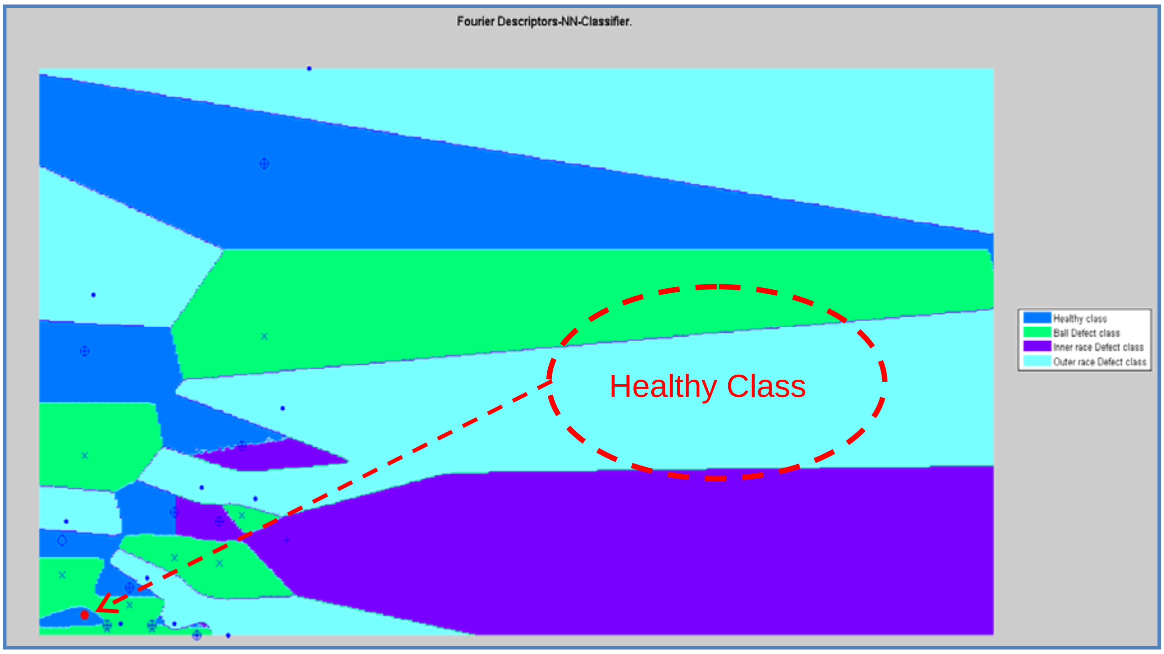

Fig. 14 Classification of new added points (●).

Table 4 Classification performance result.

Procedure	**Classification results**
Normal class	Correct decision
Ball Defect	Correct decision
Inner race Defect	Correct decision
Outer race Defect	Correct decision

9. Conclusions

In this paper, we proposed an automatic detection and diagnosis methods. The results were displayed in grey images, an important application of artificial neural network and Fourier Descriptors of Time-Frequency image for automatic defect classification using defect bearing signatures. This method does not require extract further fault features such as eigenvalues or symptom parameters from time–frequency distributions before classification, the fault diagnosis process is highly simplified. The superior performance of the proposed method has been demonstrated using experimental setups. The results obtained for this approach show that the classification of Fourier Descriptors of time–frequency images has been proved to have a high sensitivity as well as accuracy in detection, localization and assessment of the faulty conditions of ball bearings.

10. Acknowledgement

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