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Automatic bearing fault diagnosis based on one-class ν-SVM ☆

Diego Fernández-Francos *, David Martínez-Rego, Oscar Fontenla-Romero, Amparo Alonso-Betanzos

Department of Computer Science, Faculty of Informatics, University of A Coruña, Spain

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ABSTRACT

Rolling-element bearings are among the most used elements in industrial machinery, thus an early detection of a defect in these components is necessary to avoid major machine failures. Vibration analysis is a widely used condition monitoring technique for high-speed rotating machinery. Using the information contained in the vibration signals, an automatic method for bearing fault detection and diagnosis is presented in this work. Initially, a one-class ν-SVM is used to discriminate between normal and faulty conditions. In order to build a model of normal operation regime, only data extracted under normal conditions is used. Band-pass filters and Hilbert Transform are then used sequentially to obtain the envelope spectrum of the original raw signal that will finally be used to identify the location of the problem. In order to check the performance of the method, two different data sets are used: (a) real data from a laboratory test-to-failure experiment and (b) data obtained from a fault-seeded bearing test. The results showed that the method was able not only to detect the failure in an incipient stage but also to identify the location of the defect and qualitatively assess its evolution over time.

1. Introduction

Machine condition monitoring has emerged as a strategic area of concern in most companies since unanticipated faults in their production assets lead to losses that can affect their efficiency and productivity. Predictive maintenance is the most effective practice and, nowadays, is being implemented in many maintenance departments. It is based upon computer aided methods continuously monitoring the condition signals of a machine and periodically analysing its status.

Vibration analysis is the most popular technique in machine condition monitoring (Taylor, 2003; Scheffer and Girdhar, 2004). Existing principles that explain the signs that common failures leave behind in the raw vibration signal are well determined and thus can be used in the design of predictive maintenance systems. Many vibration phenomena can be interpreted as an amplitude modulation of the characteristic vibration frequency of the machine. Envelope analysis is a classical demodulation technique that emerged from the signal processing field already proven useful in the uncovering of early faults (Jones, 1996; McInerny and Dai, 2003; Yang et al., 2007b).

Bearing faults are among the most common problems encountered in the use of high-speed rotating machinery. The reason for this being that almost any industrial machine has at least one of these components and their fault can be the direct cause of subsequent problems in other vital components. Furthermore, because the time to catastrophic failure is different for inner race, outer race, rolling element and cage defects, it is very important to know the nature and severity of a bearing fault in order to select the most appropriate maintenance action.

Fault diagnosis in rolling-element bearings has been an important research topic in pattern recognition over the last decade. However, most studies have centred on fault type classification based on the availability of fault samples (Fang and Zijie, 2007; Yang et al., 2007a; Al-Raheem and Abdul-Karem, 2010; Kankar et al., 2010; Meng et al., 2010; Wang and Chen, 2011; Wu et al., 2012). But in real life applications it is extremely difficult to get data for all types of bearing problems because they do not occur frequently, and furthermore, failure vibration patterns are machine-specific. Some previous research have treated the problem as a novelty detection task (Mitoma et al., 2008; Pan et al., 2009; Alzghoul and Löfstrand, 2011; McBain and Timusk, 2011). Novelty detection is concerned with recognising inputs that differ in some way from those that are usual under normal conditions (Marsland, 2002). This paradigm overcomes one important limitation of competing methods in machinery fault detection problems i.e. the need for pre-collecting failure data. But these works are usually restricted to the detection of a fault.

The aim of this work is to develop a new automatic system for monitoring and diagnosing the condition of rolling-element bearings. The base of the system is an early detection of failures using a one-class ν-SVM (Schölkopf et al., 2000). This model treats fault uncovering as a novelty detection problem. Together with fault

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* Corresponding author. Address: Facultad de Informática, Campus Elviña s/n 15071, A Coruña, Spain. Tel.: +34 981 167 000; fax: +34 981 167 160.

E-mail address: dfernandezf@udc.es (D. Fernández-Francos).

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detection, an analysis of the envelope spectrum of faulty signals by means of a knowledge-based system, is proposed to diagnose whether the defect is in the inner race, outer race, rolling element or cage.

The contents of this paper are organised in the following way. In Section 2, background on rolling-element bearings is introduced. In Section 3, both the methodology proposed to detect and diagnose faults in bearings and the description of the techniques involved in the main steps of the method are presented. In Section 4, the proposed method is validated using data from two different real scenarios. Finally, the conclusions of this work are given in Section 5.

2. Rolling-element bearings

A rolling-element bearing is a mechanical device that reduces the friction between a rotating shaft and two or more pieces connected to it. The main components of a rolling bearing are: outer race, inner race, rolling elements and cage (see Fig. 1a). Each time a defect on one surface of a component strikes another surface, a force impact is produced. If the rotational speed of the races is constant, the impact repetition rates can be determined by the geometry of the bearing (McFadden and Smith, 1984). These repetition rates are called characteristic bearing frequencies.

When an angular contact ball bearing is mounted in such a way that the outer race is fixed in the housing and the inner race is rotating at the same speed as the shaft, the characteristic bearing frequencies are (Harris, 1991; Taylor, 2003; Scheffer and Girdhar, 2004; Taylor and Kirkland, 2004):

- BPFO, Ball Pass Frequency Outer Race

$$BPFO(\mathrm{Hz}) = F_s\left(\frac{N_b}{2}\right)\left(1-\frac{B_d}{P_d}\cos\Phi\right), \tag{1}$$

- BPFI, Ball Pass Frequency Inner Race

$$BPFI(\mathrm{Hz}) = F_s\left(\frac{N_b}{2}\right)\left(1+\frac{B_d}{P_d}\cos\Phi\right), \tag{2}$$

- FTF, Fundamental Train Frequency

$$FTF(\mathrm{Hz}) = F_s\left(\frac{1}{2}\right)\left(1-\frac{B_d}{P_d}\cos\Phi\right), \tag{3}$$

- BSF, Ball Spin Frequency

$$BSF(\mathrm{Hz}) = F_s\left(\frac{P_d}{2B_d}\right)\left(1-\frac{B_d^2}{P_d^2}\cos^2\Phi\right), \tag{4}$$

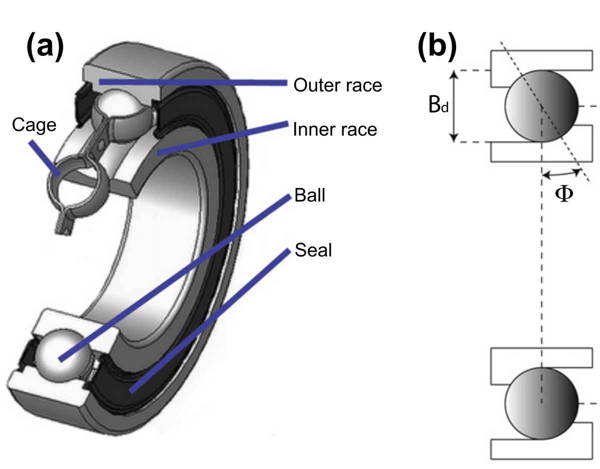

Fig. 1. Rolling bearing components.

where F_s is the shaft rotational frequency, B_d is the ball diameter, P_d is the pitch diameter, N_b is the number of rolling elements and Φ is the contact angle between the ball and the raceways (see Fig. 1b). These equations can be used with other kind of bearings such as roller bearings.

2.1. Vibration frequency characteristics of a bearing

The power spectrum of the raw vibrational signal measured on a machine containing a faulty bearing, will present one or more of the characteristic bearing frequencies above depending on the location of the fault. For defects on the inner race or the outer race, *BPFI* or *BPFO* is generated respectively. The presence of these frequencies along with harmonics will be an indication of the severity of the fault. For defects on a rolling element, usually, two times the ball spin frequency will be excited. This can be explained because the ball fault strikes both the inner and outer races each time it spins on its own axis. Moreover, this frequency will be modulated with other existing frequencies, such as BPFI and BPFO. Many publications have studied the use of these frequencies to diagnose faults in a bearing (Harris, 1991; Taylor, 2003; Taylor and Kirkland, 2004). Table 1 summarises the main relations between characteristic bearing vibration frequencies and fault diagnosis used in the traditional spectral analysis of vibrations (Li et al., 2000).

However, faults in a defective rolling bearing are difficult to diagnose through this simple frequency spectrum analysis, especially in early stages of the bearing failure, because the vibrations generated by the fault have very low amplitude and are obscured by noise and vibrations originated by other sources. Bearing frequencies will only be present in the conventional spectrum in the latter stages of the failure, when the bearing is really defective and should be changed as soon as possible. Alternatively, a signal processing technique exists called envelope analysis and this is useful to overcome this problem. In the early stages of a bearing fault, an amplitude modulating effect in the natural frequencies of the machinery is produced and envelope analysis can be used to extract this modulating frequency (characteristic fault frequency) and diagnose the defective element of the bearing, as will be shown in the next sections.

3. Model description

It is a common practice in machine monitoring to extract explanatory parameters from the raw vibrational data. The most frequently used methodology is first to extract some global statistics such as the root mean square (RMS) in order to detect a deviation, and subsequently to calculate its power spectrum (usually through Fast Fourier Transform) in order to analyse predetermined sub-bands and detect the location of the fault. If there is a fault, the spectrum will change in comparison to normal state spectrum in a determined way (Taylor, 2003; Taylor and Kirkland, 2004).

In this paper, a new automatic bearing fault detection and diagnosis method is proposed. Using the energy of different sub-bands of the normal state spectrum as training data, a novelty detection method (one-class ν-SVM) is used in order to detect a change of

Table 1
Bearing vibration frequency characteristics.

Bearing faults	Frequencies in power spectrum	Description
Rolling elements	$2 \times BSF$, *BPFO*, *BPFI*	Modulated by $2 \times BSF$ or *FTF*
Outer raceway	*BPFO*	Harmonics may be found
Inner raceway	*BPFI*	Harmonics may be found. Inner race faults are typically modulated by F_s

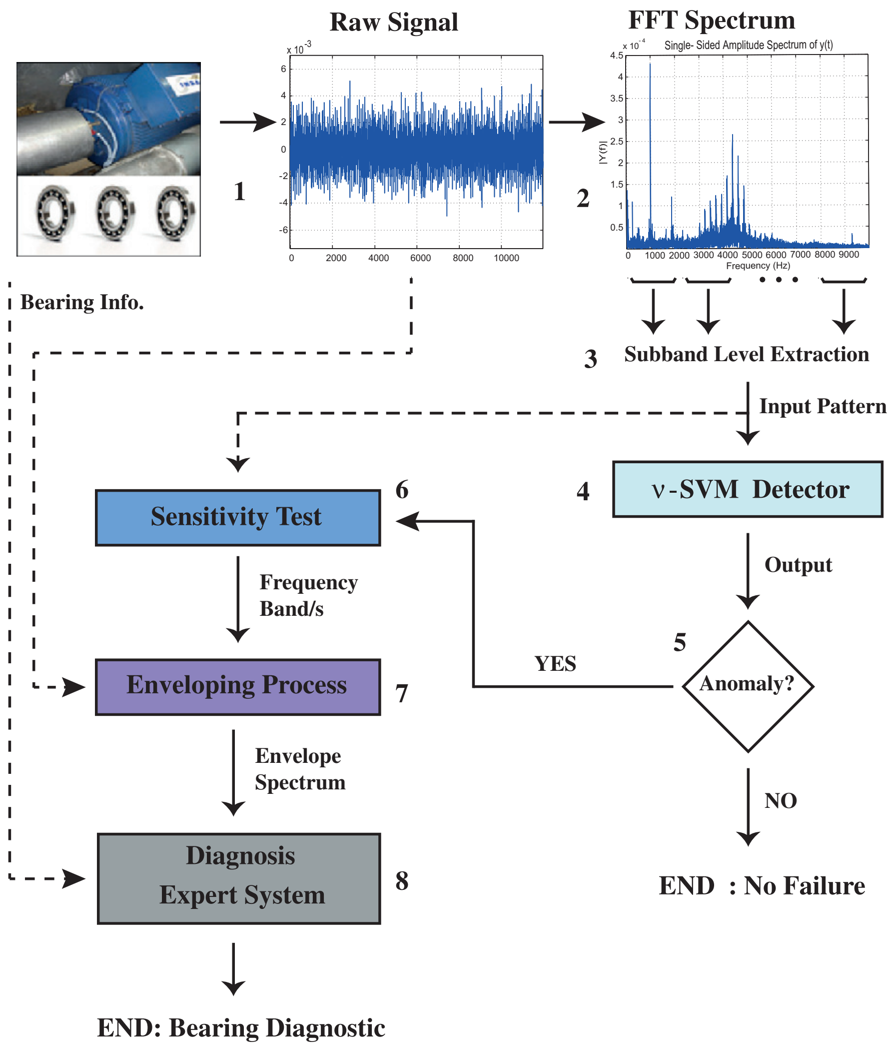

Fig. 2. Architecture of the automatic bearing diagnosis system.

behaviour due to the presence of a fault. Then, using well known signal processing techniques, the proposed system will be capable of highlighting the source of the fault and returning a diagnosis.

The architecture of the proposed system is shown in Fig. 2. The system performs periodically the following steps:

1. A new raw vibration signal is captured from the bearing.
2. The raw vibrational signal is pre-processed. The energy of each sub-band is extracted from the power spectrum of the vibration signal. In this step, a decision about the size of the sub-band has to be made. This size is a compromise between two requirements: (a) it should not be sensitive to noise and (b) it should be able to accurately concentrate the diagnosis in the band where the fault is significant. If the size of the sub-band is too narrow, the method will be very sensitive to noise. On the other hand, too wide sub-bands would not allow us to accurately localise the exact band where the fault is evident. In this work, we use 200 Hz sub-bands as a compromise of these two goals.
3. The sub-band energy pattern is analysed.
4. In the event that this analysis detects a fault, it is signalled to the maintenance practitioner.

The main analysis steps carried out by the one-class ν-SVM-based fault diagnosis system are the following:

1. Detection of changes in the conditions of the machine under monitoring. Bearing vibrational data captures are used for this purpose. The novelty detection algorithm one-class ν-SVM is used in this stage. This model has been previously trained using historical data under normal conditions. If an anomaly is present, the system goes to step 2.
2. Selection of the frequency band where the defect appears evident in the power spectrum of the signal. This is done by selecting the most deviated sub-bands of the input pattern and concatenating them to find the deviated band of the spectrum. This Sensitivity Test is thoroughly explained in Section 3.2.
3. Envelope analysis (see Section 3.3) is utilised to highlight the characteristics of the abnormal signal based on the band obtained in the previous step. These will be analysed by a knowledge-based system in order to diagnose the defective element of the bearing.

The advantages of the proposed method stem from the combination of the three analysis steps. Each step fulfils the requirements of the subsequent step (covering the necessary processing from raw vibrational signals to diagnosis). The knowledge-based system utilices simple rules extracted from the bearing vibration characteristics presented in Table 1. The knowledge base needs to know which frequency is provoking the anomalous behaviour in the vibration of the machine in order to discern the failure mode. Envelope analysis is able to extract this frequency, but it needs to know whether there is a deviation and in which sub-band it is present. These two fundamental requirements are fulfilled by the combination of the one-class ν-SVM and the Sensitivity Test.

In the next sections, techniques used in the main steps of the model are discussed.

3.1. One-class SVM for bearing fault detection

One class ν-Support Vector Machines (Schölkopf et al., 2000, 2001) are intended to solve the following problem: try to obtain a function that captures regions in input space where a probability density support lives. In doing so, the obtained function f complies with the following condition: given a probability density function P, if a previously unseen data point $\mathbf{x}$ is generated using P, with a predefined probability level α, f takes a positive value, otherwise a negative one. In order to adjust f, we are given a set of normal data points $X = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_l\}$ which have been i.i.d. generated from the normal state probability distribution P which we want to characterise. In this case, each input vector $\mathbf{x}_i$ contains the energy of the different sub-bands in which the power spectrum of a vibration signal has been partitioned. Mathematically, one-class ν-SVMs can be formulated as a convex optimisation problem as follows:

$$\begin{aligned} \min_{\mathbf{w},\xi_i,\rho} \quad & \frac{1}{2}\|\mathbf{w}\|^2 + \frac{1}{\nu l}\sum_{i=1}^{l}\xi_i - \rho \\ \text{s.t.} \quad & \mathbf{w}\cdot\phi(\mathbf{x}_i) \geqslant \rho - \xi_i \\ & \xi_i \geqslant 0; \end{aligned} \tag{5}$$

where $\mathbf{w} \in F,\ \xi_i \in \mathbb{R},\ \rho \in \mathbb{R}, \phi(\mathbf{x}_i) : \mathbb{R}^n \mapsto F$ represents a nonlinear function that maps vectors in input space to a feature space F usually with a greater dimension and $\nu \in (0,1]$ is a hyperparameter that represents the estimation of spurious data that is expected to appear in the base set. This hyperparameter should be set by the practitioner. The criteria for setting it is detailed at the end of this section. The pair $\mathbf{w}$ and ρ that solve the problem will give a decision function

$$f(\mathbf{x}) = sgn(\mathbf{w}\cdot\phi(\mathbf{x}) - \rho) \tag{6}$$

that will be positive only for data points similar to the examples in the training set which represent the 'normal' support. The argument of the *sgn* function in Eq. (6) will be called *SVM Output* throughout this paper. In the event that this argument becomes negative, the data point is considered anomalous.

Using Lagrange multipliers $\alpha_i,\ \beta_i \geqslant 0$ and the so called Wolfe dual of convex constrained problems (Fletcher, 1987), the optimisation problem (5) can be rewritten as

$$\begin{aligned} \max_{\alpha} \quad & -\frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}\alpha_i\alpha_j k(\mathbf{x}_i,\mathbf{x}_j) \\ \text{s.t.} \quad & 0 \leqslant \alpha_i \leqslant \frac{1}{\nu l} \\ & \sum_i \alpha_i = 1 \end{aligned} \tag{7}$$

Due to the fact that normal data points in feature space $\phi(\mathbf{x}_i)$ are involved in (7) only in terms of their dot products, we can approximate their dot product $\phi(\mathbf{x}_i)\cdot\phi(\mathbf{x}_j)$ by a kernel function $k(\mathbf{x}_i, \mathbf{x}_j)$. This so-called 'kernel trick' property of support vector machines methods allows us to obtain functions that approximate nonlinear probability density supports in input space without the need to map input normal patterns into feature space. Common choices for $k(\mathbf{x}_i, \mathbf{x}_j)$ are RBF, polynomial, sigmoid, etc. (Schölkopf and Smola, 2001). In this work the Gaussian RBF kernel was used:

$$k(\mathbf{x}_i,\mathbf{x}_j) = e^{-\gamma\|\mathbf{x}_i-\mathbf{x}_j\|} \tag{8}$$

where γ controls the width of the distribution. It can be proved that, using this kernel function, one-class ν-SVM is equivalent to the Support Vector Data Description (SVDD) presented in Tax and Duin, 1999 (see details in Schölkopf et al. (2001) and Tax and Duin (2004)), which has been explored in other past works (Pan et al., 2009).

Using the Karush–Kuhn–Tucker conditions in the optimum, the following identities are fulfilled

$$\begin{aligned} & \alpha_i((\mathbf{w}\cdot\phi(\mathbf{x}_i)) - \rho + \xi_i) = 0, \forall i \\ & \beta_i\xi_i = 0, \forall i \\ & \beta_i = \frac{1}{\nu l} - \alpha_i \end{aligned} \tag{9}$$

where α_i and β_i are the Lagrange multipliers of the restrictions in Eq. (5). Using the fact that $\xi_i = 0$ and $\mathbf{w}\cdot\phi(\mathbf{x}_i) = \rho$ only when $\alpha_i \neq 0$ and $\beta_i \neq 0$, we can obtain ρ from any data point whose $\alpha_i \in (0, \frac{1}{\nu l})$:

$$\rho = \mathbf{w}\cdot\phi_i(\mathbf{x}_i) = \sum_{j\in SV}\alpha_j k(\mathbf{x}_j,\mathbf{x}_i) \tag{10}$$

where SV is the set of data points whose corresponding $\alpha_j > 0$, which are called Support Vectors. In the optimum, only a small fraction of the input data points will have a $\alpha_j > 0$, which gives a sparse definition of the final function f. This is an advantage over other methods like Parzen Density Estimators as we define the support of the 'normal' distribution only in terms of a small portion of the input data set.

There are additional properties of one-class ν-SVMs that play an important role in its application to fault detection problems.

Proposition 1. *Assume the solution of (5) satisfies $\rho \neq 0$. The following statements hold:*

1. *ν is an upper bound on the fraction of outliers.*
2. *ν is an lower bound on the fraction of SVs.*
3. *Suppose the normal data were generated i.i.d. from a distribution P(x) which does not contain discrete components. Suppose, moreover, that the kernel is analytic and non-constant. With probability 1, asymptotically, ν equals both the fraction of SVs and outliers.*

The formal proof of this statement can be consulted in (Schölkopf et al., 2001). Here we analyse its implications for fault detection applications. The parameter ν that we have to adjust in order to estimate the 'normal' model represents the estimation of spurious or abnormal vibration captures that are expected to appear in the base set, which we can estimate from experimental and past data captures. This proposition gives us a practical criteria for setting ν. Furthermore, there is an additional property that holds.

Proposition 2. *Suppose we are given a set of l examples $X \in X^l$ generated i.i.d. from the normal unknown distribution P which does not have discrete components and we solve (5) for data set X also generated by P. Let $R_{\{w,\rho\}} = \{\mathbf{x}{:}f(\mathbf{x}) \geqslant \rho\}$ denote the induced decision region. With probability $1-\sigma$ over the draw of the random sample $X \in X^l$, for any $\delta > 0$,*

$$\text{P}\{\mathbf{x} : \mathbf{x} \notin R_{w,\rho-\delta}\} \leqslant \frac{2}{l}\left(k + log\frac{l^2}{2\sigma}\right) \tag{11}$$

where the constant k depends on the trade off given by δ.

Based on these propositions, it can be concluded that one-class ν-SVM can generate a decision criteria from normal data. Once trained, the method is able to detect anomalies in real time and finally it can give a qualitative measure of the evolution of the fail-

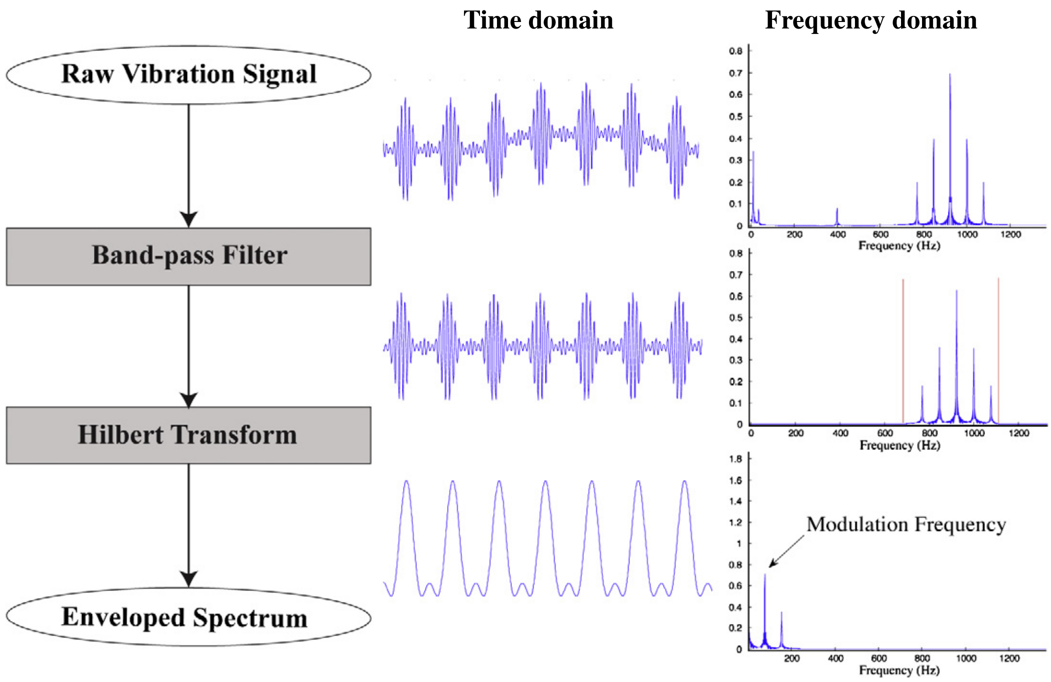

Fig. 3. Signal processing steps for envelope analysis.

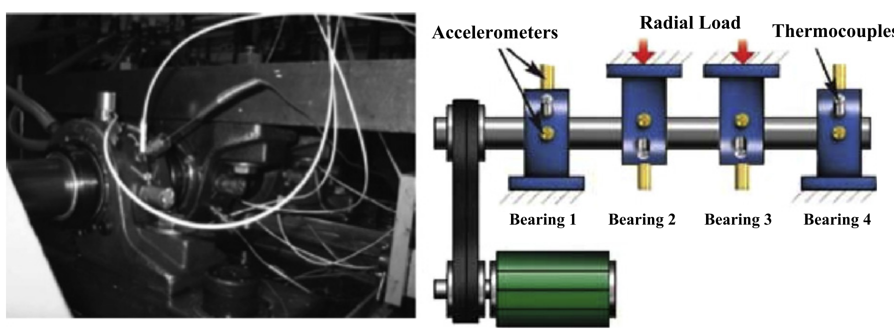

Fig. 4. Bearing test rig for the test-to-failure experiment.

ure. The rationale behind this fact is that the argument of *sgn* function in (6) gives a measure of the normality of the new pattern under *P*. Once normal criteria are trespassed, this argument gives us a qualitative indicator of the evolution of the failure. This is a useful property that allows us to generate a more subtle behaviour than a binary decision system. In the experimental results section, we present the response of this model with real vibrational data that supports this statement.

3.2. Sensitivity test

If the ν-SVM classifies an input pattern as an anomaly, it would be interesting to obtain some information about the characteristics or parameters of the input pattern that are more deflected with respect to the normality represented by the support vectors of the model. In this work, a simple approximation to obtain these characteristics is devised.

Together with Eq. (8), the argument of *sgn* function in (6) transformed by the SV expansion is the following:

$$g(\mathbf{x}) = \sum_{j \in SV} \alpha_j k(\mathbf{x}_j, \mathbf{x}) - \rho \tag{12}$$

Taking the derivative of (12) with respect to each component (i) of $\mathbf{x}$,

$$\mathbf{sens}^{(i)} = \frac{\partial f(\mathbf{x})}{\partial \mathbf{x}^{(i)}} = 2\gamma \sum_{j \in SV} \alpha_j k(\mathbf{x}_j, \mathbf{x}) \left| \mathbf{x}_j^{(i)} - \mathbf{x}^{(i)} \right| \tag{13}$$

a measure (**sens**), that indicates the components or parameters of the input vector which are more separated from the components of the support vectors can be obtained. A ranking of the most influential parameters of the input pattern can be constructed with this measure. This process will be referred to, in this work, as the Sensitivity Test.

As we have already mentioned during the model description, this simple method allows us to select the most relevant sub-bands of the input pattern and obtain the frequency band of the vibration signal that will be employed for the enveloping process. This band is extracted following the next principle: select the widest band that results from concatenating the *M* most relevant sub-bands. This process discards spurious nonconsecutive sub-bands that can appear. In this paper, we used $M = 15$ giving a maximum band length of 3000 Hz.

3.3. Envelope analysis for bearing fault diagnosis

Each time a defect on a component strikes another part of the bearing, a series of force impacts are produced. These impacts may excite resonances in the bearing and in the machine. The nat-

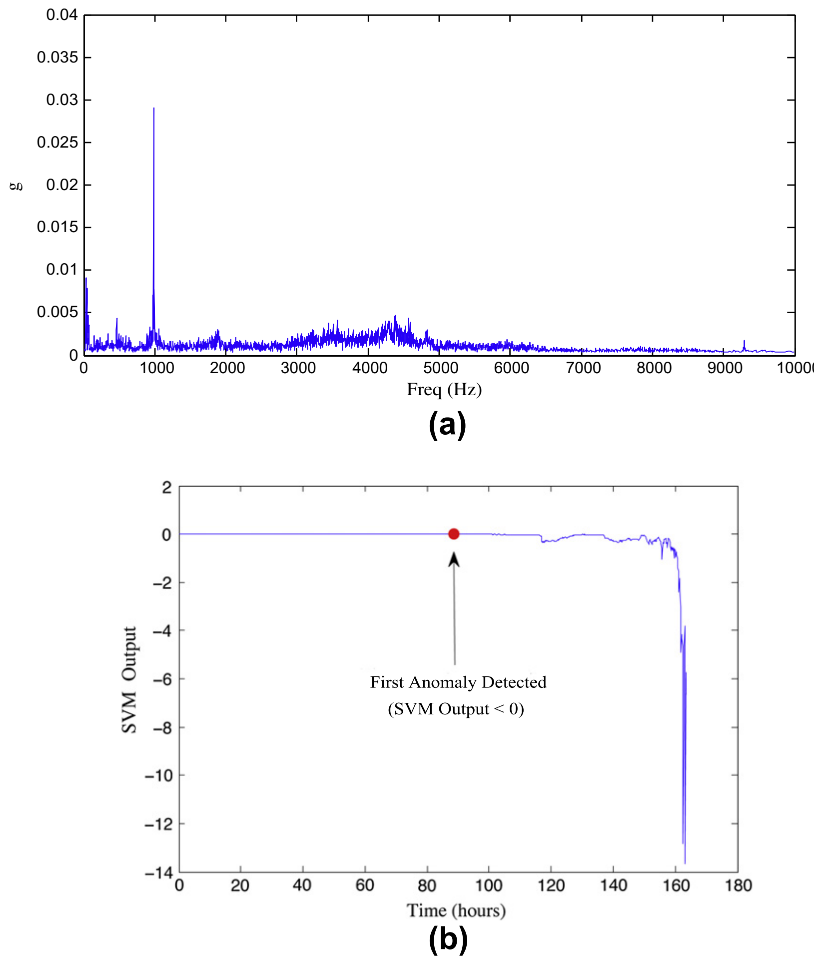

Fig. 5. (a) Normal state power spectrum. (b) ν-SVM detection on IMS experiment.

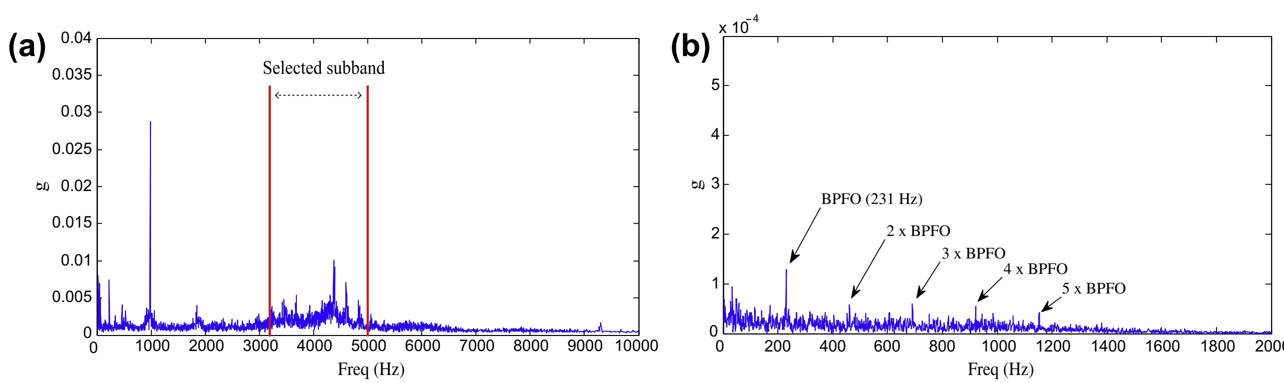

Fig. 6. (a) Incipient fault power spectrum and selected band. (b) Incipient fault envelope spectrum.

ural resonant frequency acts as a high-frequency carrier signal that is modulated in amplitude by a low-frequency signal (i.e., the bearing defect frequency), resulting in high frequency components around the carrier frequency. Envelope analysis or demodulation is the technique for extracting the modulating signal from an amplitude modulated signal (Harris, 1991; McFadden and Smith, 1984; Scheffer and Girdhar, 2004). This technique provides an important alternative to the traditional spectral analysis. The overall process is shown in Fig. 3.

The first step in the envelope analysis process consists of using a band-pass filter on the raw signal, with the aim of isolating the band where the natural resonant frequency excited by the impact frequency appears. Thus, the effects of the high amplitude, low frequency vibrations and the random noise outside the band are eliminated. The Sensitivity Test explained in the previous section is responsible for selecting this frequency band.

The next step is the rectification of the filtered signal to calculate its envelope. This can be done through Hilbert Transform (McInerny and Dai, 2003; Randall, 1986).

In the last step, Fast Fourier Transform of the rectified signal is calculated in order to obtain the envelope power spectrum. This spectrum will contain peaks at the bearing characteristic frequencies and harmonics of these if a fault is present. Furthermore, the amplitude of these peaks will increase as the fault evolves. In the

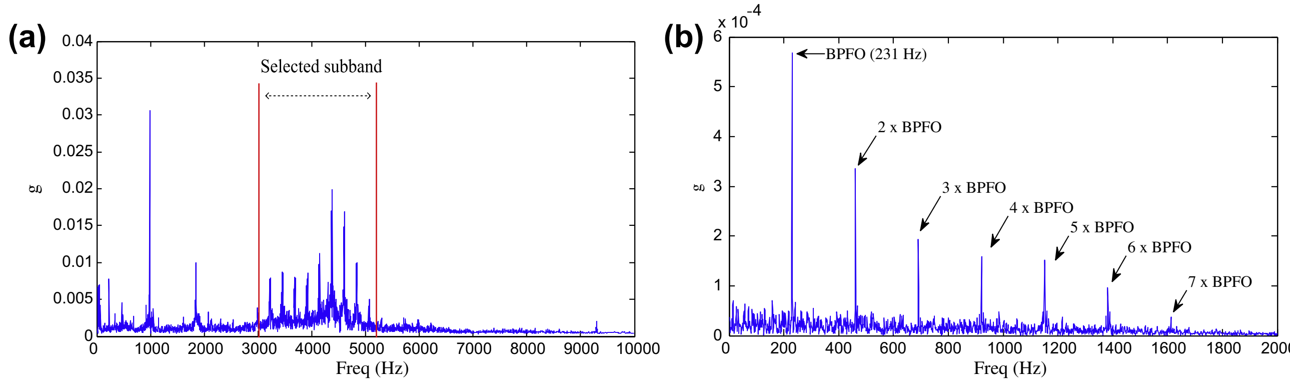

Fig. 7. (a) Advanced fault power spectrum and selected band. (b) Advanced fault envelope spectrum.

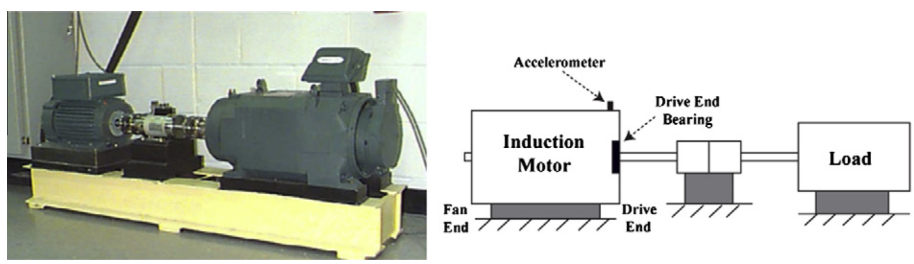

Fig. 8. Photography and schematic description of the experimental system.

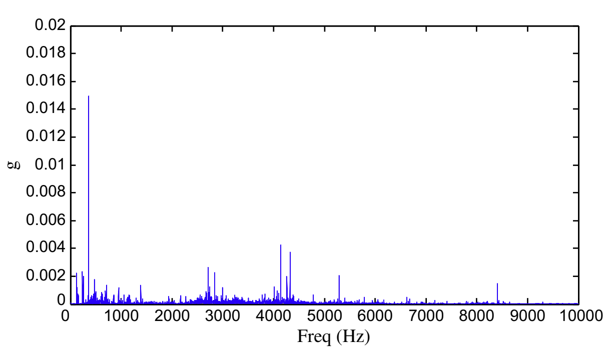

Fig. 9. Normal state power spectrum.

Table 2
Characteristic fault frequencies of 6205-2RS SKF bearing.

BPFI	BPFO	FTF	BSF
157 Hz	104 Hz	11.6 Hz	68.5 Hz

last stage of the bearing failure, the noise floor will also increase blurring the peaks. Then, as can be seen, the same bearing vibration diagnosis principles of Table 1 are fulfilled for the analysis of the envelope spectrum with the advantage that bearing fault frequencies can be identified in early stages of the failure (Jones, 1996).

Although this analysis technique works very well for bearings, it also can be used for diagnostics of machinery where faults have an amplitude modulating effect on the characteristic frequencies of the machine such as gearboxes, turbines and induction motors.

4. Experimental results

Two different data sets have been used to check the performance of the fault diagnosis method proposed in the previous section: one with data obtained from a laboratory test-to-failure experiment and another with data from a fault-seeded bearing test. In every experiment, accurate fault detection has been achieved using the following parameters for the ν-SVM: $\nu = 0.01$ and a Gaussian kernel with $\gamma = 0.05$ (see Eq. (8)). The first parameter represents the estimation of spurious data (1%) in the normal state registry. The second one controls the width of the distribution and has been obtained empirically.

4.1. IMS bearing data

The methodology discussed in Section 3 has been applied to the vibrational data from the bearing data set provided by the Center on Intelligent Maintenance Systems (IMS), University of Cincinnati (Lee et al., 2007). As can be seen in Fig. 4, four bearings were installed on one shaft and two accelerometers were placed in each of them to register the vibration signals in two different spatial axes. The shaft was driven by an AC motor and coupled by rub belts. The rotation speed was kept constant at 2000 rpm and a 6000 lb. radial load was added to the shaft and bearings by a spring mechanism. Vibration data was collected every 10 min for 164 h with a sampling rate of 20 kHz. At the end of the test-to-failure experiment, an outer race defect occurred on bearing 1. Due to this, captures obtained by the horizontal accelerometer of bearing 1 have been used in the experiments.

In this case, the bearings contain 16 rollers in each row, a pitch diameter of 2.815 in., a roller diameter of 0.331 in., and a tapered contact angle of 15.17° (Qiu et al., 2006). With this data and the Eq. (1), we are able to calculate the characteristic fault frequency of the outer race (BPFO), i.e. 236.4 Hz. In this experiment, the BPFO is the only frequency that we need to know because the defect is in the outer race of bearing 1.

Most bearing diagnostics research involves studying bearings with simulated or "seeded" damage. However, experiments using these kinds of bearings are unable to discover the natural defect propagation in early stages. As we want to prove that our method

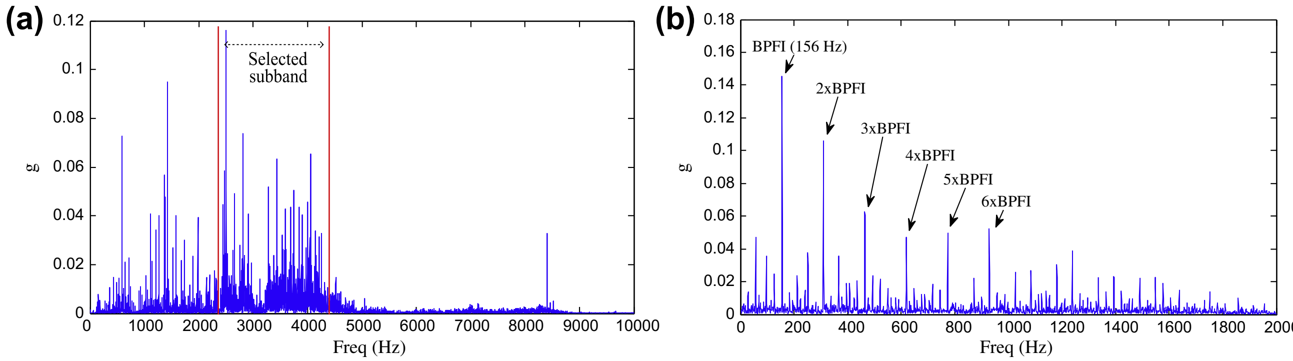

Fig. 10. (a) Power spectrum and selected band of an inner race defect. (b) Envelope spectrum of the inner race defect.

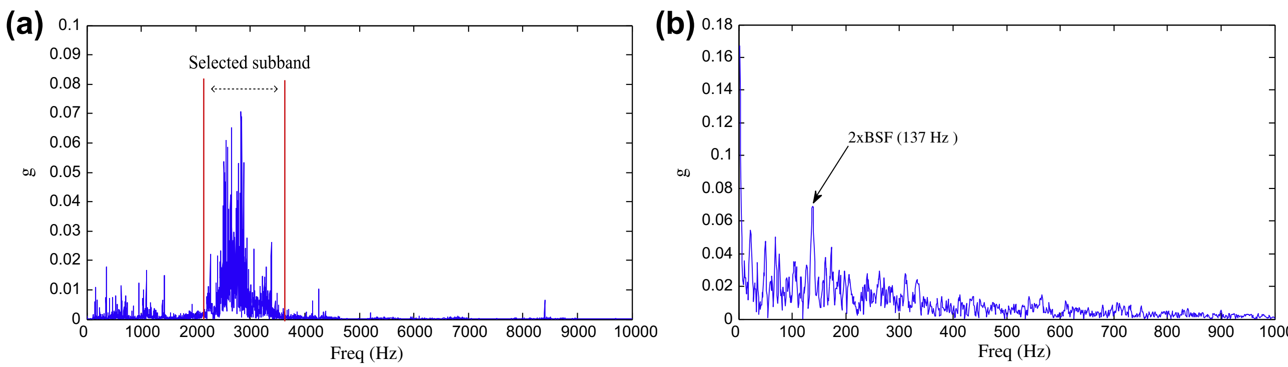

Fig. 11. (a) Power spectrum and selected band of a ball defect. (b) Envelope spectrum of the ball defect.

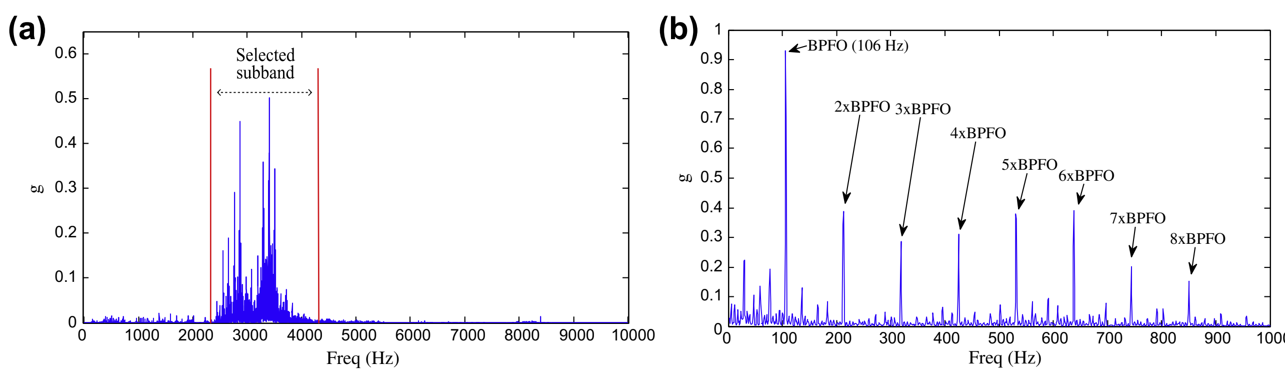

Fig. 12. (a) Power spectrum and selected band of an outer defect. (b) Envelope spectrum of the outer race defect.

is capable of detecting and diagnosing a bearing fault in early stages of the failure, this data set is in line with our goal.

In the experiments, 200 captures of normal state were used as the training set (33 h) and hereafter the method described above was applied in order to detect and diagnose possible deviations. Fig. 5a shows the power spectrum of one capture from the training set and Fig. 5b depicts the *SVM Output* (argument of Eq. (6)) of the ν-SVM during this test. The dot shows the point where the system detects a change of the behaviour for the first time, 75 h before the crack forced the machine to stop working. This figure also shows the qualitative indication of the exponential evolution of the failure.

Fig. 6a and Fig. 7a depict respectively an incipient fault power spectrum (89 h after the beginning of the experiment) and an advanced fault power spectrum (120 h) along with their corresponding frequency bands selected by the Sensitivity Test. The two corresponding envelope spectrums are shown in Fig. 6b and Fig. 7b to demonstrate how the diagnosis system works in real-time. In both figures, the characteristic fault frequency of the outer race can be seen (BPFO = 231 Hz, which is very close to the value previously calculated) along with harmonics. As the failure progresses, the amplitudes of the peaks increase, thus making the diagnosis easier and accurate.

4.2. CWRU bearings vibration data

The second example was carried out with data obtained from the data set of rolling-element bearings provided by the Case Western Reserve University (Loparo, 2003). The experimental setup, shown in Fig. 8, consisted of a Reliance Electric 2HP IQPreAlert induction motor connected to a dynamometer. Single point faults of 0.007, 0.014 and 0.021 in. in size were “seeded” into the drive-end bearing of the motor using an electrical discharge machine. An accelerometer was placed at the drive end of the motor housing

(12 o'clock position) to acquire the vibration signals from the bearing. All signals were recorded for motor loads of 0 to 3 horsepower at a sampling frequency of 48 kHz.

The bearings have 9 balls, a pitch diameter of 1.537 in., a ball diameter of 0.3126 in. and a contact angle of 0. With this information and the equations presented in Section 2, we are able to calculate the characteristic fault frequencies (shown in Table 2).

In order to test the diagnosis methodology proposed, four sets of data from this experimental system were used: under good conditions, with a fault on the outer race (aligned with the load at 6 o'clock position), with a fault on the inner race and with a ball fault. The experimental rotating frequency is approximately 29 Hz (1740 rpm). Data under good conditions was used as a training set (see Fig. 9) and hereafter the system was applied to the other data sets in order to detect and diagnose the possible faults. A 100% accurate detection was obtained.

Fig. 10a and b depict respectively an inner race fault power spectrum (load 1 and 0.007 in.) along with its selected frequency band and the corresponding envelope spectrum. The inner race fault frequency is clearly identifiable (peak at 156 Hz) as well as its harmonics modulated by the shaft frequency (29 Hz). In Fig. 11a, a power spectrum of a ball fault (load 2 and 0.021 in.) and the selected frequency band are shown. The corresponding envelope spectrum is depicted in Fig. 11b. In this case, there is a peak at 2 times ball spin frequency (137 Hz), which means that there is a fault in a rolling element. Finally, Fig. 12a depicts an outer race fault power spectrum (load 1 and 0.007 in.) along with its selected frequency band and Fig. 12b shows the corresponding envelope spectrum with peaks at the outer race fault frequency (peak at 106 Hz) and its harmonics. Once again, these examples demonstrate that the system can detect anomalies that do not correspond to normal behaviour and diagnose the possible sources of the failure.

5. Conclusions

In this paper, a new automatic method to diagnose faults in bearings based on pattern recognition and signal processing techniques is presented. The main contribution of this work lies in the combination of ν-SVM, envelope analysis and a rule-based expert system in order to early detect and diagnose the defective component of the bearing. An important stage of the method is the proposed Sensitivity Test which is able to automatically select the zone of the vibration spectrum where the fault is more evident. Another interesting feature in our design is that fault detection is accomplished only utilising normal functioning data to train the ν-SVM, thus making its use appropriate for real life applications.

In the test cases, the system was able not only to detect the bearing fault but also to qualitatively assess its evolution over time and to identify the location of the failure in its very early stages. These experimental results verify the adequacy and effectiveness of the proposed method. In the near future, this methodology can be extended to the diagnosis of other machinery, where faults have an amplitude modulating effect on the characteristic frequencies of the machine such as gearboxes, turbines and induction motors.

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