[Proceeding] External condition removal in bearing diagnostics through EMD and One-Class SVM

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External condition removal in bearing diagnostics through EMD and One-Class SVM

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Abstract

The removal of the running conditions influencing data acquisitions in rotating machinery is a very important task because it could avoid some misunderstandings when diagnostic techniques are applied. This paper introduces a new parameter that could be able to identify damage in a rotating element of a roller bearing removing the effect of speed and external load. The parameter proposed in this paper is evaluated through Empirical Mode Decomposition (EMD). Our algorithm proposes firstly the decomposition of the acceleration vibration signals into a finite number of Intrinsic Mode Functions (IMFs) and then the evaluation of the energy for each one of these. Data are acquired both for a healthy bearing and for one with a 450 μm large indentation on a rolling element. Three different speeds and three radial loads are monitored for both cases, so nine conditions can be evaluated for each type of bearing overall. The parameters obtained, namely energy evaluated for a certain number of IMFs, are then used to train a One-Class Support Vector Machine (OCSVM). Healthy data belonging to the nine different conditions are taken into account and OCSVM is trained while other acquisitions are given to the classifier as test object. Since the real class membership is known, we consider how many errors the labelling produces. We compare these results with those obtained by considering a wavelet decomposition. Energies are evaluated for each level of decomposition and the previous approach is then applied to these parameters.

Keywords: Empirical Mode Decomposition; One Class SVM; fault diagnosis; speed and load effect removal.

1. Introduction

One of the most widely used components in machinery are surely rolling bearings and their condition monitoring had become more and more important in order to prevent the occurrence of breakdowns. Between the wide range of methods proposed since the Seventies, signal analysis has certainly been an important topic in mechanical fault diagnosis research and applications thanks to its ability to identify the fault patterns. For example, methods such as time-domain and Fourier analysis take into account the signal acquired, but their limit is that they are based on the assumption of stationarity and linearity of the process generating the signal itself. The main drawback for fault detection is that, however, the faults are time localised transient events, so this kind of techniques could give a wrong information.

Randall and Antoni develop some possible ways to overcome these aspects in [1]. According to them, in this tutorial they want to show various aspect related to the diagnostic analysis of acceleration signals from rolling element bearings, especially when strong masking signals from other machine components such as gears are present.

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The purpose of the authors is the explanation of a powerful procedure and its validation through some industrial applications that confirm the reliability of their methods.

Other interesting and useful tools to analyse non-stationary signals such as those related to bearing vibrations are time-frequency analysis techniques such as the Short Time Fourier Transform (STFT), Wavelet Transform (WT) and Wigner-Ville distribution (WVD). In particular, the wavelet transform provides powerful multi-resolution analysis in both time and frequency domain and thereby becomes a rather useful tool to extract the transitory features of non-stationary vibration signals produced by the faulty bearing. In general, this analysis results in a series of wavelet coefficients indicating how close the signal is to the particular wavelet itself. In order to extract the fault feature of signals more effectively, an appropriate wavelet base function should be selected. It is clear that the power of this method comes from the simultaneous interpretation of the signal in both time and frequency domain that allows local, transient or intermittent components to be exposed. One of the main drawback, however, is its dependence on wavelet basis function choice. An example is the Morlet wavelet, which is mostly applied to extract the rolling element bearing fault feature because of its large similarity with the impulse generated by the damaged bearing. Li shows an application in [2], where an approach for the detection of localized faults in the outer or the inner races of a rolling element bearing using the time scale spectrum of complex Morlet wavelet is investigated. The experimental results obtained on a gearbox with a rolling element bearing under simulated crack on the inner race or the outer race show that this method can effectively diagnose the faults. Other examples of wavelet-based analysis technique for damage identification in rotating machinery from the vibrating signature are [3],[4],[5].

An innovative technique developed by Huang et al. in 90s and related to the time-frequency domain is the Empirical Mode Decomposition (EMD) [6]. This method allows the decomposition of any complicated signal into a collection of Intrinsic Mode Functions (IMFs) based on the local characteristic time scale of the signal. Its strength is the self-adaptiveness, due to the fact that each IMFs, working as a basis functions, is determined by the signal itself rather than being pre-determined. This allows the EMD to be highly efficient in non-stationary data analysis. Many applications to a wide range of problems have been proposed so far, from geophysics to structural health monitoring as presented in [7]. Lots of authors apply EMD to rotating machines and bearing with diagnostic intents, usually in association with other techniques. Some examples are in [8], where combined mode functions are introduced and with also a comparison with wavelet decomposition, in [9], where EMD is used jointly with an Auto Regressive model and [10], where an Artificial Neural Network (ANN) classifier is trained with the EMD energy entropies.

An aspect that is rather important in the diagnostic framework is the search for methods able to remove the effects produced in vibrations by external factors, such as temperature or test rig assemblies. An example is presented in [11], where the multi-variate statistical technique named Principal Component Analysis (PCA) is successfully used in bearing and rotating shaft fault detection. Varying load and speed are other factors influencing vibrations related to rotating elements: a changing in these parameters could produce biased results in the fault detection. Bartelmus and Zimroz show in [12] how the condition monitoring of planetary gearboxes is related to the identification of the external varying load condition. They analyse in detail how many factors influence the vibration signals generated by a system which presents a planetary gearbox and they show how the load has a consistent contribution. As regards bearings, some works are presented by Cocconcelli et al. in [13] and [14]. Here, they inspect the continuous change of rotational speed of the motor, that represent a substantial drawback in terms of diagnostics of the ball bearing. Almost all the algorithms proposed in the literature, in fact, need a constant rotation frequency of the motor to identify fault frequencies in the spectrum. They tackle this problem with encouraging results aided by ANN and Support Vector Machine (SVM).

These last two are Machine Learning techniques often used in the field of mechanical systems research. SVM in particular, is widely applied in relation with condition monitoring and damage classification, as shown in [15] and [16]. It is based on the concept of separation into different classes of data with the knowledge of all different type of instances since the beginning of the analysis. A specific case of SVM is the One-Class SVM (OCSVM), particularly well suited for diagnostic technique purpose. In fact, it requires the knowledge of only one class of data, that is what usually happens in damage detection, i.e only healthy data are available in the starting phases of the analysis. An example of this application is in [17], where OCSVM is adopted for machine fault detection and classification in electro-mechanical machinery from vibration measurements.

With our work we want to find a parameter able to remove the various conditions influence in order to detect properly a damage in a roller bearing. The paper is organised as follows. Section 2 shows the EMD method while Section 3 present SVM and the particular application in One Class case. Our algorithm is explained in Section 4 and then its application on a test rig is developed in Section 5, with a wavelet decomposition results comparison too.

2. Empirical Mode Decomposition method

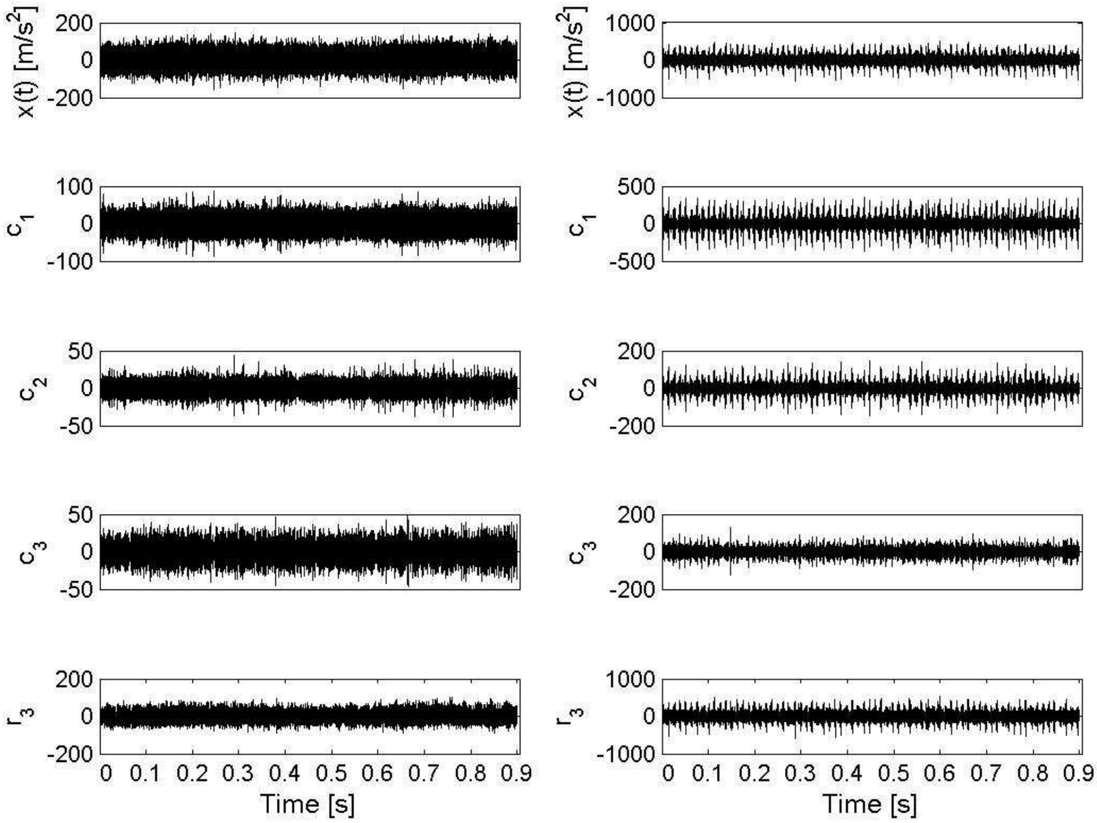


Fig. 1. Acceleration signal of a healthy roller bearing (left) and one with a fault on a rolling element (right) and their decomposition using EMD.

Huang et al. presented a new technique based on the local characteristic time scales of a signal named Empirical Mode Decomposition in [6]. This is a self-adaptive signal processing method that could be applied to non-linear and non-stationary process. It consists in the decomposition of a complex signal into a number of intrinsic mode functions (IMFs), where each one contains frequencies changing with the signal itself. Every IMF has to satisfy the following properties:

- In the entire data set, the number of extrema and the number of zero crossings must either be equal or differ at most by one.
- At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

In this way, each IMF represents the simple oscillation mode involved in the signal. Huang et al. developed a *sifting* process which goal is the extraction of the IMFs from a given signal $x(t)$ [6]. It consists of different steps:

1. Identify all the extrema of the signal, and connect all the local maxima by a cubic spline line as the upper

envelope. Use the same procedure to produce the lower envelope with the local minima.

2. Being m_1 the mean of the two envelopes, compute the difference between the signals $x(t)$ and m_1 as the first component, h_1, i.e.

$$x(t) - m_1 = h_1 \quad (1)$$

If h_1 is an IMF take h_1 as the first IMF component of $x(t)$. Otherwise, use h_1 as if it is the original signal and repeat the first two step. Obtain

$$h_1 - m_{11} = h_{11}. \quad (2)$$

Repeat the sifting process up to k times until when h_{1k}becomes an IMF:

$$h_{1(k-1)} - m_{1k} = h_{1k}. \quad (3)$$

The first IMF component is then named as

$$c_1 = h_{1k}. \quad (4)$$

3. Separate c_1 from the original signal $x(t)$ and obtain the residue r_1:

$$r_1 = x(t) - c_1. \quad (5)$$

4. Consider r_1 as the original signal and repeat the above process n times. The other IMFs $c_2, c_3, \ldots, c_n$are obtained and they satisfy

$$\begin{aligned} r_1 - c_2 &= r_2 \\ &\vdots \\ r_{n-1} - c_n &= r_n. \end{aligned} \quad (6)$$

5. Stop the decomposition process when r_n becomes a monotonic function and no other IMFs can be extracted. Summing Eq. (5) and Eq. (6) we obtain

$$x(t) = \sum_{i=1}^{n} c_i + r_n. \quad (7)$$

Eq. (7) shows how the signal $x(t)$ could be decomposed into n empirical modes and a residue r_n, which could be seen as the mean trend of the signal. Each IMF c_j is considered stationary and in each one of these components various frequency bands are considered, ranging from high to low.

Fig. 1 presents the acceleration signal for a healthy and for a damaged roller bearing with their 5-IMFs decomposition.

3. One-class Support Vector Machine

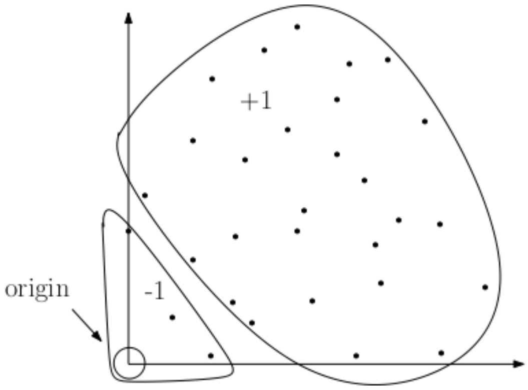


Fig. 2. One class SVM classifier with the origin as the only member of one class.

During the 80s Vapnik developed a computational learning method named Support vector machine (SVM) [18]. It is based on the statistical learning theory and it is well suited for classification: in fact, given some data points belonging to a certain class, it is able to state the class of a new data point. Given a n-dimensional input data with samples belonging to two different classes, positive or negative, this method is able to built a hyperplane separating the two classes. The particularity of this boundary is that its distance from the nearest data points in each class is maximal. In such a way, the optimal separating hyperplane named the maximum margin is created. Those points belonging to the different classes and nearest to this margin are called support vectors and they contain all the information necessary to define the classifier. When a new element appears, it is classified according to where it places with respect to the separating hyperplane.

In case of non-linear application SVM could be applied using a proper function $\Phi(x)$ that maps data onto a high-dimensional feature space, where the linear classification is then possible. If we want to avoid to evaluate explicitly $\Phi(x)$ in the feature space, we could apply a kernel function $K(x_i, x_j) = \Phi^{\mathrm{T}}(x_i) \cdot \Phi(x_j)$. Some examples of kernel functions that could be used are linear, polynomial or Gaussian ones. The use of kernel is rather outstanding because it enables SVM to be used in case of very large feature spaces since the dimension of classified vectors does not influence directly the classifier performance.

SVM could be applied also when more than two classes are present with the name of Multi-class SVM. In this case, two different approaches are considered: One-against-all (OAA) and One-against-one (OAO). In the first one the i-th SVM is trained with all the elements in the j-th class with positive labels and all the other with negative labels, while in the latter each classifier is trained on data from two classes.

Looking at the previous cases, it could be seen that two or more classes of data are given since the beginning of the analysis. If we think to more general diagnostic applications, usually only one type of element could be acquired at the early stage, that is the healthy one. This means we could refer to anomaly detection, i.e. the detection of patterns in data that do not conform to a well defined notion of normal behaviour. For SVM we can talk about One-Class SVM as presented by Schölkopf et al. in [19]. They construct a hyper-plane around the one-class data and it has to be maximally distant from the origin. Moreover, it must separate the region where there are data from those that do not contain any. To obtain this, they propose the use of a binary function that returns +1 in region containing data and -1 elsewhere. For a hyper-plane w which separates the data x_i from the origin with maximal margin ρ, the following quadratic program has to be solved:

$$\min_{w \in F, \epsilon \in \mathbb{R}^n, \rho \in \mathbb{R}} \quad \frac{1}{2}||w||^2 + \frac{1}{\nu n}\sum_i \epsilon_i - \rho \tag{8}$$

$$\text{subject to} \quad (w \cdot \Phi(x_i)) \geq \rho - \epsilon_i, \quad \epsilon_i \geq 0 \tag{9}$$

where ϵ represents the slack variable and ν is a variable taking values between 0 and 1 that monitors the effect of outliers (hardness and softness of the boundary around data).

When w and ρ solve the minimisation problem presented in Eq. (8) and Eq. (9), the decision function

$$f(x) = \operatorname{sign}((w \cdot \Phi(x_i)) - \rho) \tag{10}$$

is positive for most instances representing the majority of data.

Figure 2 shows graphically the idea presented here, with the origin that becomes one of the few elements in the class labelled -1.

4. Methodology

In the previous sections the background and the theoretical aspects of the two methods that now we want to use together have been presented. In our study we want to the search for a parameter able to identify a damage in a rotating element of a roller bearing by removing the effect of external conditions that influences vibrations.

Our diagnosis method is developed through different steps:

1. Collect vibration signals considering various condition of speed and radial load applied, for both a healthy and a damaged bearing.
2. Apply EMD to decompose the original signal into some IMFs. The first n are chosen to create the feature vector used during the analysis.
3. Evaluate the total energy for the n selected IMFs as:

$$E_j = \int_{-\infty}^{+\infty} |c_j(t)|^2 dt \qquad j = 1, \ldots, n \tag{11}$$

4. Create a feature vector with the energies of the n selected IMFs:

$$F = [E_1, \ldots, E_n] \tag{12}$$

5. Normalise the feature vector dividing F for E_N:

$$E_N = \left(\sum_{j=1}^{n} |E_j|^2 \right)^{\frac{1}{2}} \tag{13}$$

6. Obtain the n-dimension feature vector after the normalisation:

$$F' = [E_1/E_N, \dots, E_n/E_N] \tag{14}$$

7. Divide the healthy data in two groups: 75% are considered as training, the remaining 25% and the damaged data as test. $Analyse all loads and speeds together.
8. Train the One-Class SVM classifier on training data and use the classifier to label the test data. Since the real class of any data is known, errors in labelling could be computed.
9. To give statistical significance to the analysis repeat point 6. and 7. 30 times changing healthy data order and evaluate the error percentage in labels assignment.

5. Application to bearing data

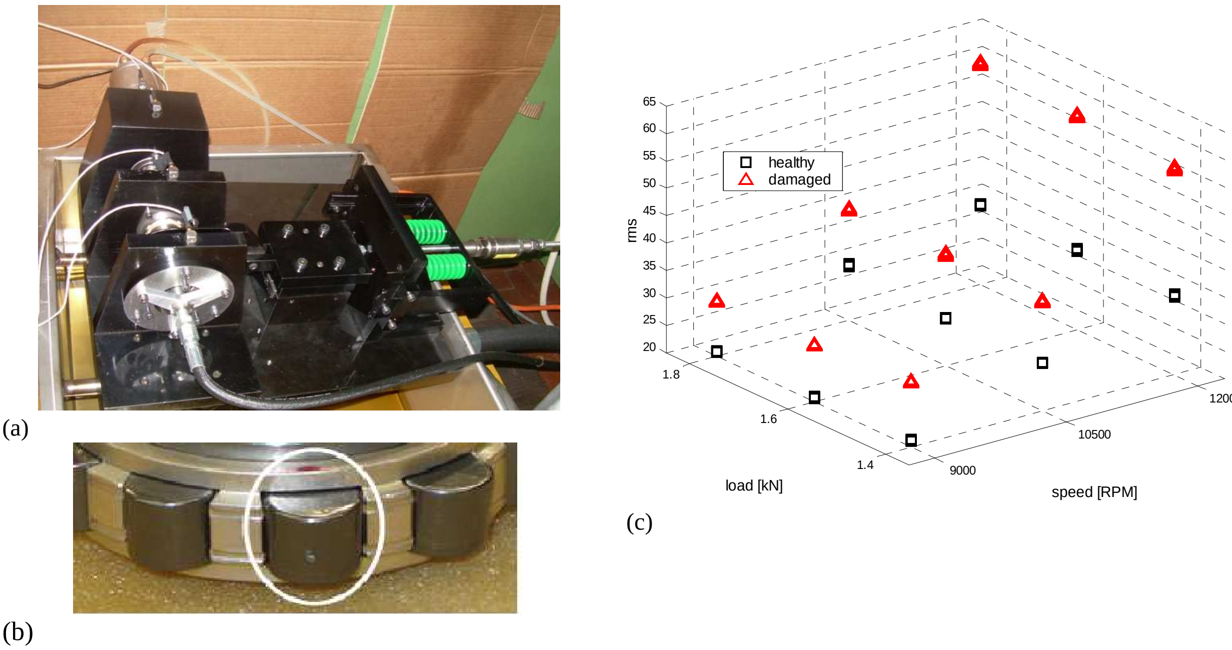
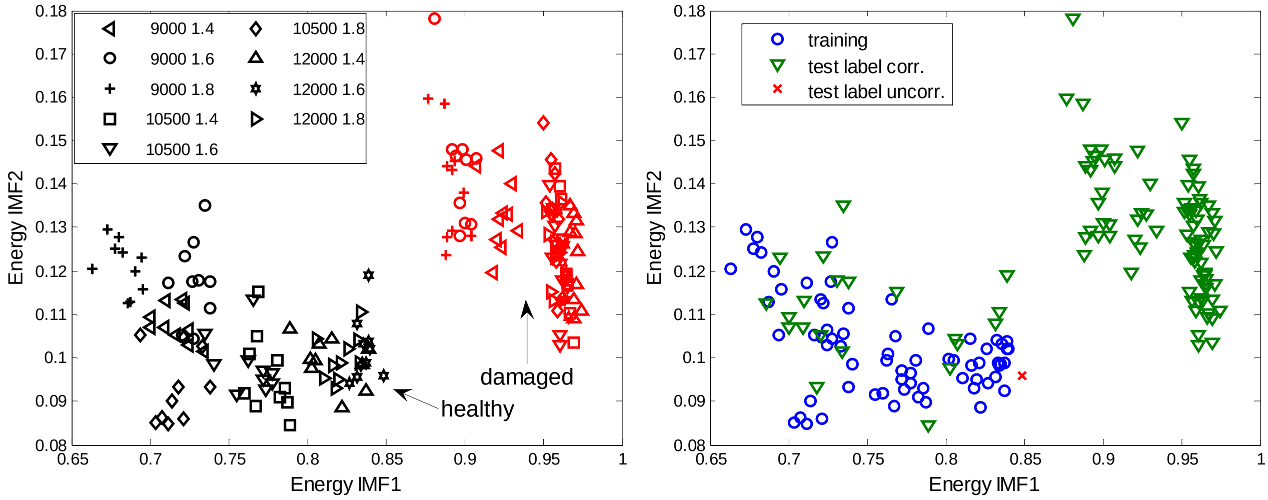


Fig. 3. The test rig (a) and the roller bearing used during the tests, with the damaged roller in the white circle (b). RMS value for healthy and damaged bearing (c).

Data acquisition on our test rig are influenced by various conditions such as rig speed, externally applied load on a bearing, temperature variations. The detection and the removal of these factors is important to avoid any bias during the application of diagnostic techniques. Small changing in speed or in the temperature of the oil circulating in a system gives rise, in fact, to variations that a diagnostic algorithm may erroneously detect as a damage, producing a false alarm. In this paper we want to introduce a parameter that would help in identifying a damage in a rotating element of a roller bearing with the removal of speed and external load influences.

The test rig used for the acceleration acquisitions was assembled by the Dynamics & Identification Research Group (DIRG) at Department of Mechanical and Aerospace Engineering and is shown in Fig. 3a. This is a test rig designed to perform accurate testing of bearings with different levels of damage in controlled laboratory conditions. It regards especially the reduction of spurious signals coming from the mechanical sounds of other bearings, rotating



(a) (b)

Fig. 4. Empirical Mode Decomposition: (a) 2-dimension feature vector representation with various conditions: in the legend the first number is the speed expressed in RPM, the second is the load expressed in kN. (b) 2-dimension feature vector after OCSVM classification.

shafts, gear wheels meshing and other vibrating elements. In this way, we are sure that the only variations in accelerations are caused by speed and load, elements that can be properly monitored.

In our analysis we consider three different speed values (9000, 10500 and 12000 RPM) and three radial loads (1.4, 1.6 and 1.8 × 10^3 N) and we acquire data for each combination. We register 1 second of vibrating signal with sampling frequency 102.4 kHz for 10 times and for each of the 9 different cases. These acquisitions are repeated both for a healthy bearing and for a damaged one. Fig. 3b shows this last one, characterized by a 450 μm damage on a rolling element. The temperature of the oil circulating is almost constant between the different acquisitions, so that the only variations detected through vibrations are caused by load and speed changing.

Figure 3c presents the Root Mean Square values evaluated for the 10 acquisitions with the dependence on speed and load. It is clear from this plot that there is no particular variation among the 10 measures given a certain speed/load combination, while the speed influences the values rather than the load. In particular, the difference in RMS between healthy and undamaged case increases when the speed is higher. If we observe the values for damaged data at 9000 Hz in Fig. 3c (triangles) we notice that they are very similar to those for a healthy bearing (square) but at 12000 Hz. In this way, if we consider all the nine conditions together, the exact bearing identification may be strongly biased. So, it is necessary to use a parameter that could avoid these kind of errors.

Following the technique developed in Section 4, we evaluate a normalised feature vector considering the first 8 IMFs. In [20] we consider different vector dimension and also various SVM kernel. We analyse the error percentage in the labels given by the OCSVM classifier and we check the number of dimensions necessary to have a better damage identification. We obtain that when the classifier uses a Gaussian kernel on a feature vector made up of the first two IMFs as dimensions the error percentage is very low. The ability in the identification could be observed from Figure 4a in the fact that damaged and healthy data composes two different groups of data. Moreover any dependence on different loads and speeds seems to be removed: each symbol corresponds to a combination and no particular agglomeration related to the nine different conditions is noticed.

If we apply OCSVM as explained in points 7 and 8 in Section 4 to the data in this 2-dimension space we obtain Figure 4b. The circles are the training data, i.e. the 75% of healthy measures with all load and speed conditions considered together. The testing data, composed by the 25% of healthy and all damaged instances, are marked with triangles if correctly labelled by the classifier and with crosses when there is some mistake. In this case, only one cross is present, so the error percentage amounts to 0.89%. Following point 9 in Section 4 we obtain that 0.42% of label are wrongly assigned by the OCSVM classifier, so this could be considered a proper identification technique. Moreover, the various load and speed do not seem to have any influence in the results, so this method seems to be

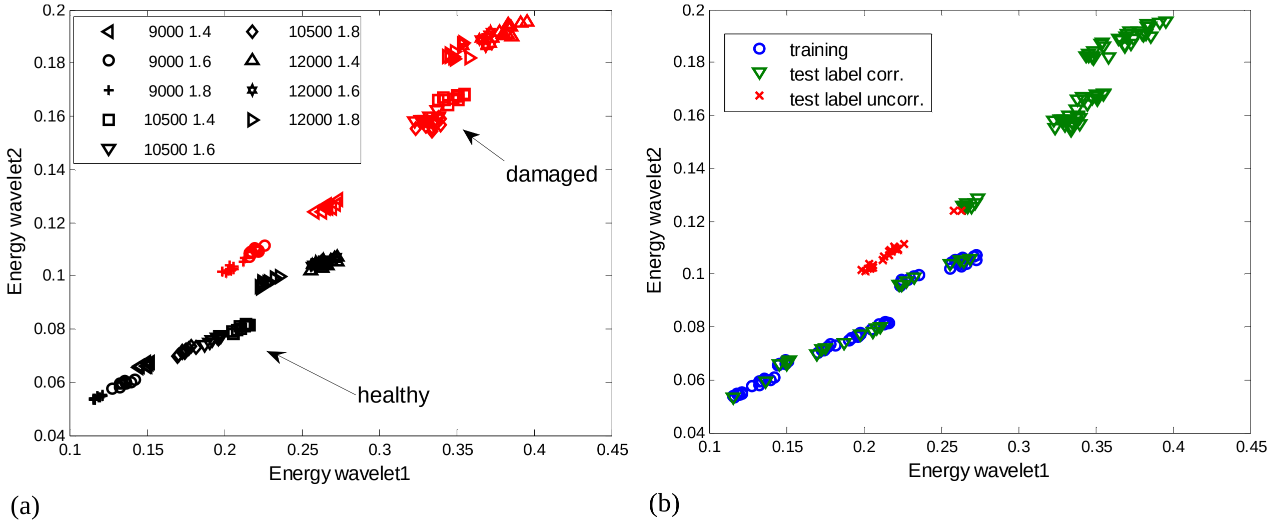


Fig. 5. Wavelet decomposition: (a) 2-dimension feature vector representation with various conditions: in the legend the first number is the speed expressed in RPM, the second is the load expressed in kN. (b) 2-dimension feature vector after OCSVM classification.

independent from these conditions in the proper damage detection.

5.1. Comparison with wavelet decomposition

The same approach described in Section 4 is adopted analysing another signal processing method, namely wavelet decomposition. We consider a Haar wavelet decomposition stopped at the 8th level, as for EMD. Then we follow points 3-9 in the methodology procedure and we evaluate the errors obtained during the detection problem by the classifier.

The first aspect to be noticed is clear from Figure 5a, where the 2-dimension vector of energies evaluated during the 10 acquisitions for each one of the 9 conditions of speed and load is plotted. The comparison between this picture with Figure 4b highlights the difference between these two methods. In fact, while in the case of EMD no particular division is due to the influence of these parameters (speed and load), the wavelet decomposition application leads to the creation of various groups according to the different condition. Furthermore, in Figure 5a it is clear that the separation between healthy and damaged elements is more difficult, mainly because of the dependence on the parameters. It is easy to foresee that the risk of error in the recognition of the real class membership is higher in this case.

In Figure 5b are presented the results obtained after the OCSVM classifier application to the data following the explained methodology. The kernel parameters are the same adopted for the EMD case to have better correspondence in the results that are however rather different. In fact, the error percentage amounts to 19.64% for this picture and to 20.18% after 30 permutation, according to point 9 of the methodology. This means that with this parameter the risk of labelling bias is higher, due to the influence that the speed and the load operate in its evaluation. We tried also other type of wavelets such as Daubechies and Symlets, but in general the results seem to be dependent on the effects of the speed/load conditions. A possible way to overcome this fact would be to use classification techniques able to create a narrower boundary around the known data.

6. Conclusions

In this paper we proposed a method for the detection of damages in roller bearings with the removal of speed and load dependence. Our technique considers the union between Empirical Mode Decomposition, exploited to produce the proper feature vector, and the One-Class Support Vector Machine, which classifies the data. If we apply the same methodology to obtain the feature vector through a wavelet decomposition instead of EMD, we obtain less precise results. Thus, we can state that EMD produces a feature able to remove speed and load dependence, so that any bias in data interpretation and identification is avoided. Further applications could deal with the influence removal of other factors conditioning vibrations, such as oil temperature.

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