Applied Acoustics 89 (2015) 16–27

Contents lists available at ScienceDirect

Applied Acoustics

journal homepage: www.elsevier.com/locate/apacoust

Application of empirical mode decomposition and artificial neural network for automatic bearing fault diagnosis based on vibration signals

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ARTICLE INFO

Article history:
Received 9 January 2014
Received in revised form 1 August 2014
Accepted 23 August 2014
Available online 20 September 2014

Keywords:
Artificial neural network (ANN)
Bearing
Condition and health management (CHM)
Empirical mode decomposition (EMD)

ABSTRACT

Condition monitoring and fault diagnosis of rolling element bearings (REBs) are at present very important to ensure the steadiness of industrial and domestic machinery. According to the non-stationary and non-linear characteristics of REB vibration signals, feature extraction method is based on empirical mode decomposition (EMD) energy entropy in this paper. A mathematical analysis to select the most significant intrinsic mode functions (IMFs) is presented. Therefore, the chosen features are used to train an artificial neural network (ANN) to classify bearings defects. Experimental results indicated that the proposed method based on run-to-failure vibration signals can reliably categorize bearing defects. Using a proposed health index (HI), REB degradations are perfectly detected with different defect types and severities. Experimental results consist in continuously evaluating the condition of the monitored bearing and thereby detect online the severity of the defect successfully. This paper shows potential application of ANN as effective tool for automatic bearing performance degradation assessment without human intervention.

1. Introduction

Today, diagnosis is a very important research area in industry. Traditional concepts of preventive and corrective maintenance are gradually supplemented by diagnosis form. The main objective of this maintenance type is to ensure the dependability of industrial systems and increase their availability with lower cost. However, fault diagnosis is not an easy task; it is essentially a problem of pattern recognition. The most effective feature extraction and more accurate classifier are needed to obtain higher diagnostic accuracy [1].

Rolling element bearings (REBs) are widely used in industrial and domestic applications. REB is one of the most common components in modern rotating machinery and their failure is one of the most frequent reasons for machine breakdown. Approximately 45% of the failures are due to the bearing faults [2]. Failure surveys by the electric power research institute (EPRI) indicate that bearing-related faults are about 40% among the most frequent faults in induction motors [3].

Although the development of this critical component has progressed in a rapid manner, the development of an expert system for the diagnosis remains an important focus of research. One of the fundamental problems currently facing a wide range of industries is how to identify a bearing fault before it reaches a critical level and catastrophic failure.

Analyzing vibration signals is a quite common technique for mechanical system monitoring thanks to the great information that contain [4]. However, REB vibration signals are considered as non-stationary and non-linear [5]. Besides, noises present a serious trouble in the study of this type of signals [6]. Moreover, the relatively weak bearing signals are always affected by quite stronger signals (gears, bars...) [5]. All these constraints lead us to converge to a single question: What is the most effective method for bearing fault diagnosis?

To answer this question, many research lines have been developed and many techniques are being used. In [7], artificial neural networks (ANN) and principal components analysis (PCA) are used to diagnose the severity of bearing outer race faults. Four bearing classes were examined; the no-fault class and three different notches in the outer race (0.15, 0.50 and 1.00 mm wide).

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http://dx.doi.org/10.1016/j.apacoust.2014.08.016
0003-682X/

In [8], generalized empirical mode decomposition (GEMD), empirical envelope demodulation (EED) and Hilbert–Huang transform (HHT) were used to analyze REBs vibration signals. The simulation results are based on the data set of bearing data center of Case Western Reserve University (BDCWRU). An electro-discharge machine was used to introduce REBs faults with different fault diameters and depths.

In [9], the semi-supervised kernel Marginal Fisher analysis (SSKMFA) was used for bearing feature extraction and the K-nearest neighbor (KNN) classifier was added afterwards to distinguish different fault categories and severities. To validate the proposed method, bearings data set of BDCWRU was used. The classification results of the four classes (healthy, inner race failure, outer race failure, ball failure) were very important.

Although the results were very satisfactory in terms of classification in [7–9], like the majority of bearing diagnostic works, these works were based on synthetic bearing defects which were always introduced by the user (holes with different diameters and depths). In reality, this is not the case of a bearing defect in industrial environment. Many factors can cause deterioration of bearings such as

– Contamination and corrosion.
– Lack of lubrication causing heating and abrasion.
– Defect of bearing's mounting, by improperly forcing the bearing onto the shaft.
– Misalignment defects.

REBs degradation is a highly non-linear phenomenon; using the same type of bearing in the same experimental conditions never produces the same kind of failure in terms of time, type, and severity. This property is confirmed by Intelligent Maintenance Systems (IMS) bearing run-to-failure data set [10].

Relatively, only few papers discussed the bearing diagnosis based on run-to-failure vibration signals. This is due to the difficulties in processing these signals. The major problem is the noise; it is very difficult to detect degradation when it is smaller than the noise measurements. This form of degradation is often known as "degradation at early stage". Even though many researchers have performed fault bearing detection, they do not perform the diagnosis and identification of degradation at early stage.

In [11], the one class support vector machine (v-SVM) was used to detect characteristic changes of the monitored bearing vibration signals in order to detect REB defects. To validate the proposed non-destructive diagnostic method, the IMS bearing data set was exploited.

In [12], the combination of locality preserving projections (LPP) and exponential weighted moving average (EWMA) were presented. The non-monotonic EWMA performance quantification index shows undesirable results, in terms of false alarm creation. Motivated by the Gaussian mixture model (GMM) and the negative log likelihood probability (NLLP) advantages, experimental results were improved but they still have false alarms [13].

In this paper, to overcome the non-stationarity problem of REB vibration signals, we tend towards the application of the empirical mode decomposition (EMD) method. Based on the energy entropy of the different intrinsic mode functions (IMFs), a statistical analysis is detailed to determine the most appropriate IMFs for bearing fault diagnosis. The combination of EMD energy entropy, statistical features and ANN shows that it's very helpful for bearing state classification task. Thereby, the IMS run-to-failure vibration signals are used to detect seven bearing states (healthy, degraded inner race, degraded outer race, degraded roller, failure inner race, failure outer race and failure roller). The majority of the previous works defined just four bearing states however in this paper seven classes are defined to follow bearing degradation over time. To detect early stage bearing degradations in real time, this work proposes a health index (HI). This new approach is successfully applied and it identifies reliably early stage REB degradations base on vibration signals.

The paper is organized as follows: Section 2 presents in details the experimental setup and data recording. The different steps of the EMD method are also given in this section. Section 3 presents a mathematical analysis to select the most effective features for REBs diagnosis. Section 4 presents a good discussion and analysis of the experimental results by comparing the performances of the proposed method with previous methodologies in literature. Finally, our conclusions are provided in Section 5.

2. Materials and methods

2.1. Experimental setup

The used data set in this paper is generated by the NSF I/UCR Center for Intelligent Maintenance Systems (IMS) with support from Rexnord Corp.

Rexnord ZA-2115 double row bearings shown in Fig. 1 are installed on the shaft. Bearings contain 16 rollers in each row, a pitch diameter of 2.815 in., a roller diameter of 0.331 in. and a tapering contact angle of 15.17° [14].

PCB 353B33 High Sensitivity Quartz ICP accelerometers are installed on the bearing housing. All failures occurred after exceeding designed life time of the bearing which is more than 100 million revolutions. The test rig and sensors placement are shown in Fig. 2.

Four bearings are installed on a shaft. The rotation speed is kept constant at 2000 rpm by an alternative current motor coupled to the shaft via rub belts. A radial load of 6000 lbs is applied onto the shaft and bearings by a spring mechanism. All bearings are lubricated.

The test is carried out for 35 days until a significant amount of metal debris is found on the magnetic plug of the tested bearing [14]. In this way it is possible to obtain bearing run-to-failure data sets with known defects. Fig. 3 shows failure bearing components after test. It is clear that real bearing defects does not seem like holes with different diameters and depths.

Three tests were made. Each test is an experience of 4 bearings. In this way 12 bearings are used but only 4 bearings have reached failure with known defects. Each data set describes a run-to-failure experiment. It consists of individual files that are 1-s vibration signal snapshots recorded at specific intervals (every 10 min). Each file consists of 20,480 points with the sampling rate set at 20 kHz. Records (row) in the data file are data points. Data collection is provided by NI DAQ Card 6062E [14].

Three data sets are included in the data package. Each data set contains simultaneous testing of four bearings. The vibration bearing data set is provided by the Center on Intelligent Maintenance Systems (IMS), University of Cincinnati, USA [10].

Fig. 1. Rexnord ZA-2000 bearing series.

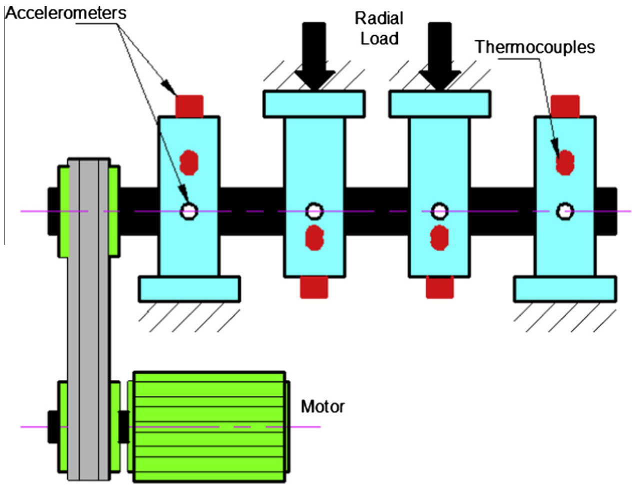

Fig. 2. Bearings test rig.

2.2. Empirical mode decomposition method

Empirical mode decomposition (EMD) method is developed from the simple assumption that any signal consists of different simple intrinsic modes of oscillations called intrinsic mode functions (IMFs). This adaptive decomposition method is especially applicable to the analysis of non-linear and non-stationary signals.

With the definition, any signal $x(t)$ can be decomposed as follows [15]:

1. Identify all the local maxima and then connect all of them by a cubic spline lines as the upper envelope.
2. Identify all the local minima and connect them by a cubic spline lines as the lower envelope. The upper and lower envelopes should cover all the data between them.
3. The mean of upper and lower envelope value is designated as $m_1(t)$, and the difference between the signal $x(t)$ and $m_1(t)$ is the first component $h_1(t)$. Ideally, if $h_1(t)$ is an IMF, then $h_1(t)$ is the first component of $x(t)$.
4. If $h_1(t)$ is not an IMF, it's treated as the original signal and repeat the steps 1, 2, 3 to find the fist IMF. After repeated up to k times, $h_{1k}(t)$ becomes an IMF, that is:

$$h_{1k}(t) = h_{(1(k-1))}(t) - m_{1k}(t) \tag{1}$$

Then, it is designated as $c_1(t) = h_1(t)$ which is the first IMF.

The first IMF $c_1(t)$ obtained from the original data should contains the finest scale or the shortest period component of the decomposed signal. IMF's accessing is known as "Sifting process". The sifting process is stopped by limiting the size of the standard deviation (S_D), calculated from the two consecutive results as [16]:

$$S_D = \sum_{t=0}^{T} \frac{[h_{k-1}(t) - h_k(t)]^2}{h_{k-1}^2(t)} \tag{2}$$

A typical value for S_D can be set between 0.2 and 0.3.

5. Separate $c_1(t)$ from $x(t)$ to get $r_1(t)$ which will be treated as the original data. By repeating the above processes, the second IMF component $c_2(t)$ of $x(t)$ could be obtained. Let us repeat the process as described above n times. Also n-IMFs of the original signal $x(t)$ can be obtained as:

$$\begin{cases} r_2(t) = r_1(t) - c_2(t) \\ \quad\vdots \\ r_n(t) = r_{(n-1)}(t) - c_n(t) \end{cases} \tag{3}$$

The decomposition process can be stopped when $r_n(t)$ becomes a monotonic function from which no more IMFs can be extracted. By summing up Eq. (3), we finally obtain:

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{4}$$

Thus, one can achieve a decomposition of the signal into n empirical modes and a residue $r_n(t)$, which is the mean trend of $x(t)$. More details about the EMD method are given in [17].

Figs. 4 and 5 show EMD results of bearing vibration signals extracted respectively from a healthy bearing and a roller defect one. Despite that the failed bearing is more rich than the healthy in term of information, the EMD results show 12 IMFs in the two cases. Theoretically, we should find more IMFs using a defect bearing but in practice this is not always the case. These findings are validated in [18] where EMD results shows 19 IMFs for a healthy REB and 18 IMFs for a defect REB. In industrial environment, informative accelerations are always affected, buried and masked by noises. Subsequently, the application of EMD for REB vibration signals processing produces some IMFs also strongly affected by noises. In other words, the number of the decomposed IMFs is dependent on the noise quantity. Besides, early stage signatures are easily submerged in noise [19]. Consequently, bearing damage detection at early stage is a very hard task and that is why a number of developed vibration diagnostic techniques are only effective at later stages of damage [18]. Moreover, many researchers have applied EMD combining with other techniques to bearing fault diagnosis in recent years and achieved better diagnosis results compared with the use of EMD alone [15]. The combination of EMD with other signal processing techniques or artificial intelligent techniques is an effective strategy to better EMD [15]. In this

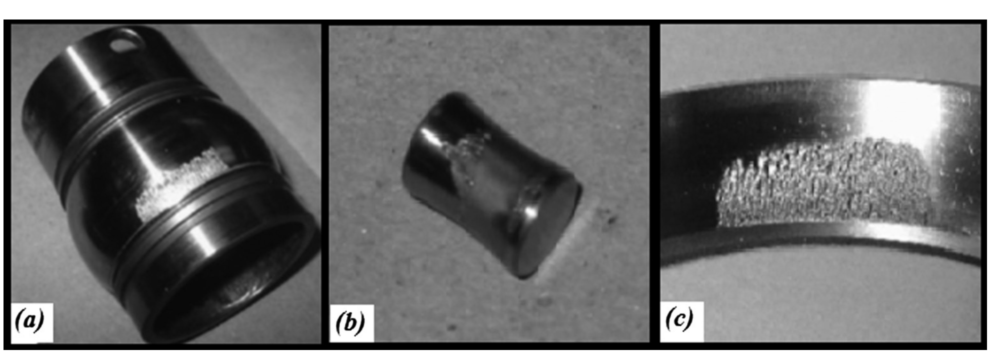

Fig. 3. Pictures of bearings components after test: (a) inner race failure, (b) roller element failure and (c) outer race failure [14].

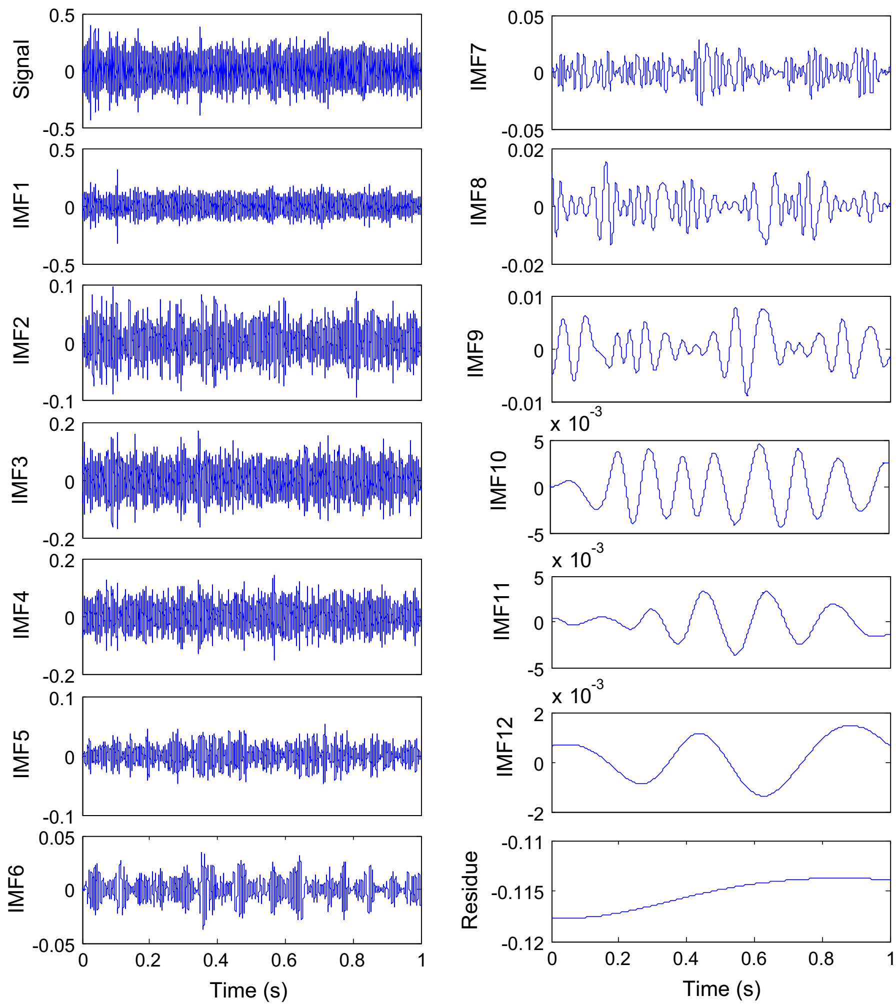

Fig. 4. EMD results of healthy bearing vibration signals.

work, we present an automatic bearing defect decision by combining EMD and artificial intelligence techniques where noise influences are reduced and bearing damage detection at early stage is achieved with good accuracy.

3. Feature extraction

3.1. Time domain feature extraction

The concept of feature extraction for accurately assessing bearing performance degradations is a critical task towards realizing an online bearing condition monitoring platform. Various original features that can be extracted from vibration signals of the roller bearing have been investigated.

Traditional statistic features are a powerful tool which characterizes the change of bearing vibration signals when faults occur. The benefits of these features are the simplicity of implementation and the low computational time. In order to characterize the time information within bearings data, this paper proposes to use statistical features shown in Table 1. In addition to these eight classic factors, two features are proposed as shown in the two last lines of Table 1.

Where *Init* is the average of all RMS for healthy bearings' state without defects. For this study *Init* = 0.078.

The main idea of these two added features is to have measurements that link several features together. For the application of bearings we are sure that the inner of the logarithm is positive, for other purposes absolute value should be added. A logarithmic scale is used to limit the amplitude of these two features to be compared to others. Fig. 6 shows bearing run-to-failure vibration signals ending with outer race failure and Fig. 7 shows the variation of the correspondent statistical features over time.

Theoretically, the magnitude of time domain features should increase when bearing degradations become more severe. This type of degradation is well known in the literature as ideal degradation where the evolution of time domain features is mainly monotonic increasing and represents an ideal case [20]. Consequently, bearing diagnosis can be done with some easy thresholds. However, sudden degradation is the most existing type of bearing defects in industrial environments. In most cases, the degradation appears suddenly and does not depict a slow monotonic behaviour. Thereby, it's very hard to define diagnosis thresholds. Besides, there are always some random slips of rolling elements because of the REB contact angle. Thus, rolling elements have different effective diameters and they try to roll with different speeds where the cage limits the deviation of the rolling elements from their mean position [5]. As a result, REB vibration signals are always affected random accelerations (which can be additive or subtractive) of the order 2% of recorded signals. Moreover, the strong noise present the main problem in processing REB vibration signals. In most situations, REB accelerations coincide with other excitations of rotating machine parts. In [11], authors showed that it would be very difficult to establish one feature based deterministic model

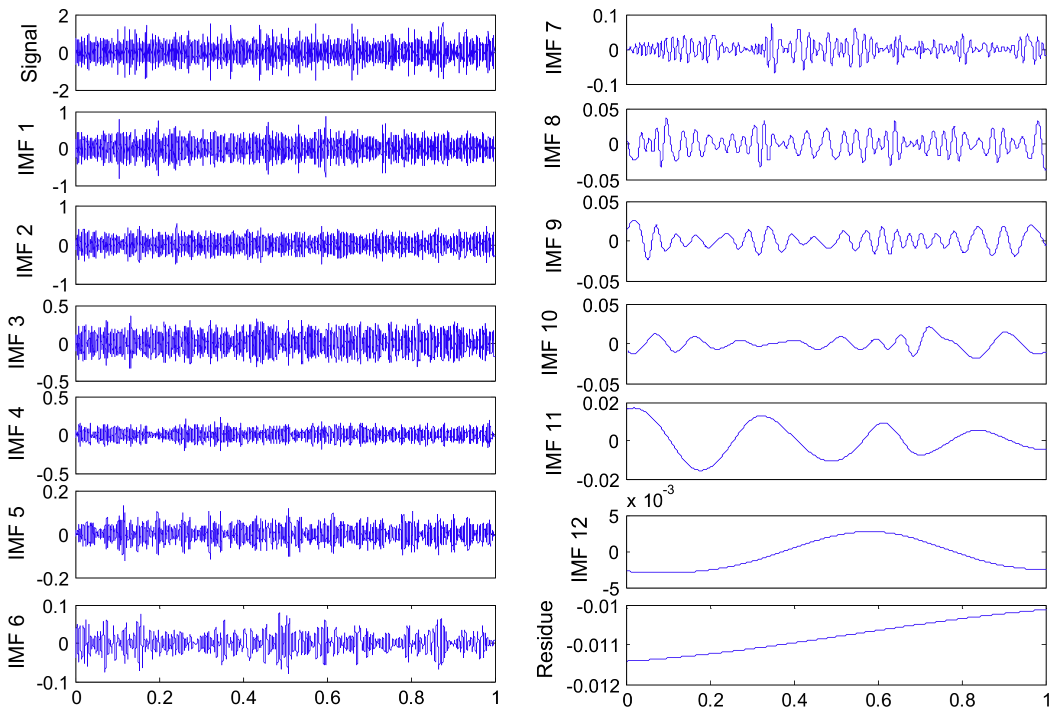

Fig. 5. EMD results of bearing vibration signals with roller failure.

Table 1
Time domain features.

RMS	$\left(\frac{1}{N}\sum_{i=1}^{N}x_i^2\right)^{\frac{1}{2}}$
Kurtosis	$\frac{1}{N}\sum_{i=1}^{N}\frac{(x_i-\overline{x})^4}{\sigma^4}$
Skewness	$\frac{1}{N}\sum_{i=1}^{N}\frac{(x_i-\overline{x})^3}{\sigma^3}$
Peak to peak (P_P)	$x_{\max}-x_{\min}$
Crest Factor	$\frac{max\lvert x_i\rvert}{RMS}$
Shape Factor	$\frac{RMS}{\frac{1}{N}\sum_{i=1}^{N}\lvert x_i\rvert}$
Impulse Factor	$\frac{max\lvert x_i\rvert}{\frac{1}{N}\sum_{i=1}^{N}\lvert x_i\rvert}$
Margin Factor	$\frac{max\lvert x_i\rvert}{\left(\frac{1}{N}\sum_{i=1}^{N}\lvert x_i\rvert^{\frac{1}{2}}\right)^2}$
Add Factor 1	$log(Kurtosis+\frac{RMS}{Init})$
Add Factor 2	$log\left(Kurtosis^{(CrestFactor)}+\left(\frac{RMS}{Init}\right)^{(P\_P)}\right)$

to accurately assess bearing performance degradations even using bearings under the same working condition. Finally, Fig. 7 confirms the conclusion of [21] that it is extremely difficult (or even impossible) to establish threshold value to separate healthy and faulty condition data based on simple statistical time domain features.

3.2. Time–frequency domain feature extraction

Added to these ten-time domain features, EMD is used to extract some other features to form robust and reliable database features. Every 10 min, IMS bearing signals are extracted with recording duration of one second from bearing run-to-failure accelerations. Each second consists of 20,480 points with the sampling rate 20 kHz. We consider only the first part of signals with 0.1 s duration and 2048 points to limit the time of computation. The EMD feature extraction method is given as the following:

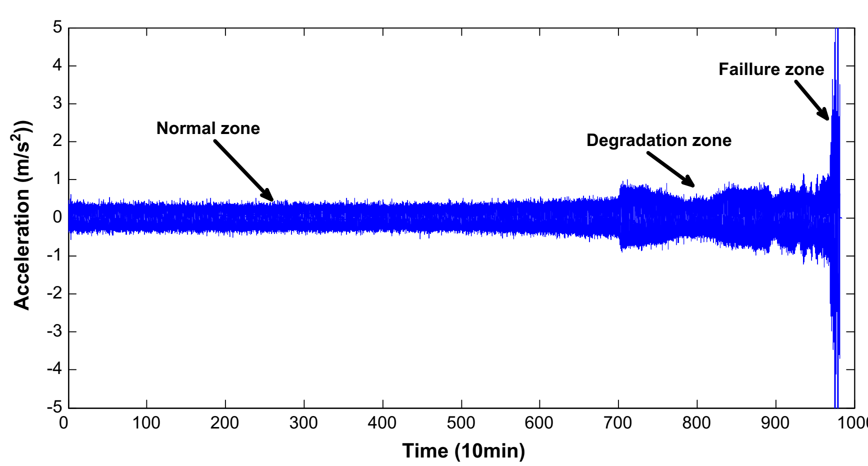

Fig. 6. Bearing run-to-failure vibration signals ending with outer race failure.

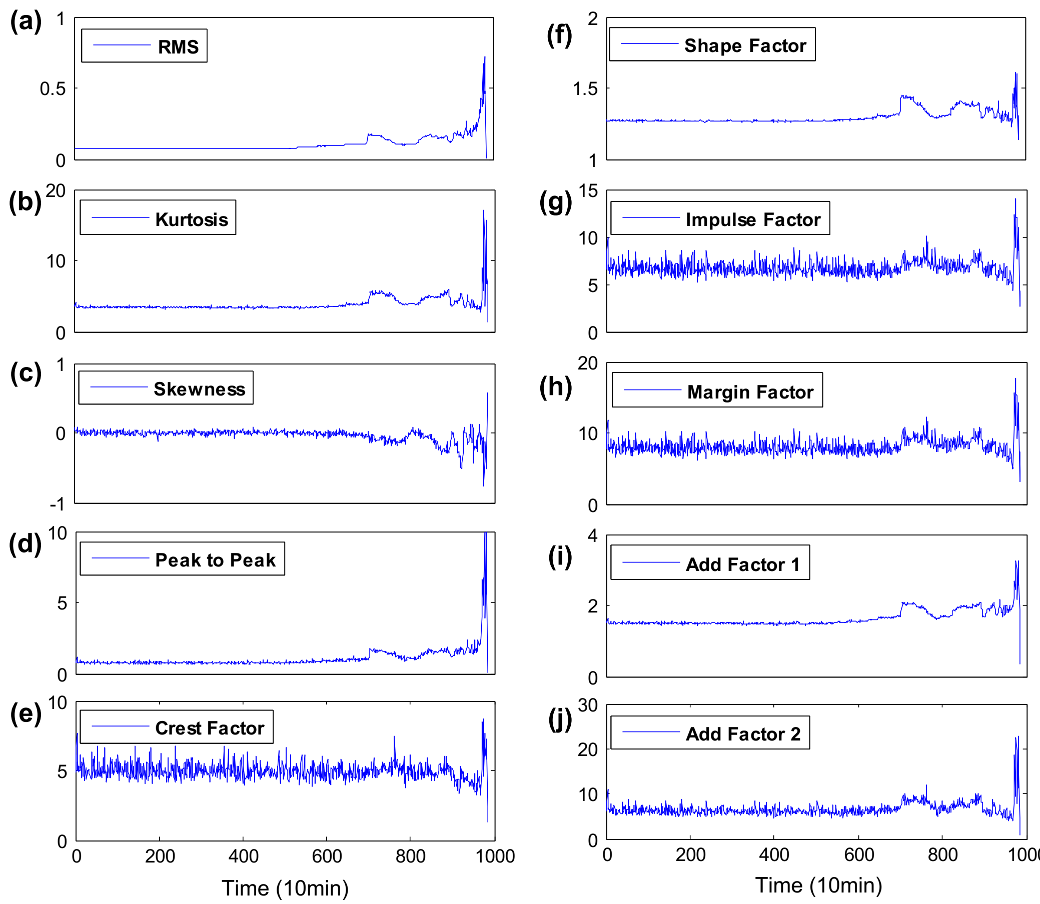

Fig. 7. Variation of statistical features: (a) RMS, (b) Kurtosis, (c) Skewness, (d) P_P, (e) Crest Factor, (f) Shape Factor, (g) Impulse Factor, (h) Margin Factor, (i) Add_Factor1, (j) Add_Factor2.

1. Decompose bearing signals into some IMFs.
2. Calculate the total energy all IMFs.

$$E_i = \sum_{j=1}^{2048} |c_{ij}|^2 \tag{5}$$

3. Calculate the total energy of all IMFs.

$$E = \sum_{i=1}^{n} E_i \tag{6}$$

4. Construct the feature vector.

$$\left[H_{en}, \frac{E_1}{E}, \frac{E_2}{E}, \ldots, \frac{E_n}{E}\right] = [H_{en}, H_{en}IMF1, H_{en}IMF2, \ldots, H_{en}IMFn] \tag{7}$$

where H_{en} is the EMD energy entropy in the whole of the original signal, *HenIMFi* is EMD energy entropy in the whole of the IMF number i and n is the number of IMFs found during the decomposition. EMD energy entropy is calculated as [22]:

$$H_{en} = -\sum_{i=1}^{n} p_i log(p_i) \tag{8}$$

where $p_i = E_i/E$ is the percentage of the energy entropy of the IMF number i relative to the total energy entropy.

In previous studies, most works were based on EMD extract the energy entropy of IMFs as features. In [22], authors have shown that the EMD energy entropy changes with the energy variation of vibration signals. When the bearing operates with different faults, it includes the most dominant fault energy. Fig. 8 shows the variation of the energy entropy of the bearing vibration signals presented in Fig 6. Also, the energy entropy of the first eight IMFs of this signal are shown in Fig. 8.

In most studies, there is no much scientific explanation for the choice of most effective features for bearing diagnosis. For this purpose, RMS and the kurtosis have been mostly applied. ISO IS 7919 suggests the threshold peak-to-peak levels of vibration displacement. ISO 10816/2372, ISO IS 3945 and VDI 2056 suggest the threshold RMS values of vibration velocity [23]. In this paper, we have applied a statistic criterion to decide the most effective IMFs for bearing diagnosis. This degree is based on the report of the inter-class variance by the intra-class variance [24]. The greater this degree called "*J*" gets the more the classification based on the correspondent attributes is accurate [24].

For this purpose, three bearings have been used; bearing 4 and 3 of testing 1 and bearing 1 of testing 2. Vibration signals of these REBs are shown respectively in Fig. 9.

Thanks to the three presented REBs, seven bearing states are defined (healthy (H), degraded roller (DR), failure roller (FR), degraded inner race (DIR), failure inner race (FIR), degraded outer race (DOR), failure outer race (FOR)). For each class, 50 extracts have been used to be evaluated. In this way seven classes have been used ($K = 7$) and 50 extracts are evaluated ($N = 50$). The procedure of the J criterion can be summarized as follow:

1. Calculate the average feature vectors of the kth class.

$$\underline{\mu}_k = \frac{1}{N}\sum_{n=1}^{N} \underline{x}_{k,n} \tag{9}$$

where $x_{k,n}$ the nth extract of the kth class.

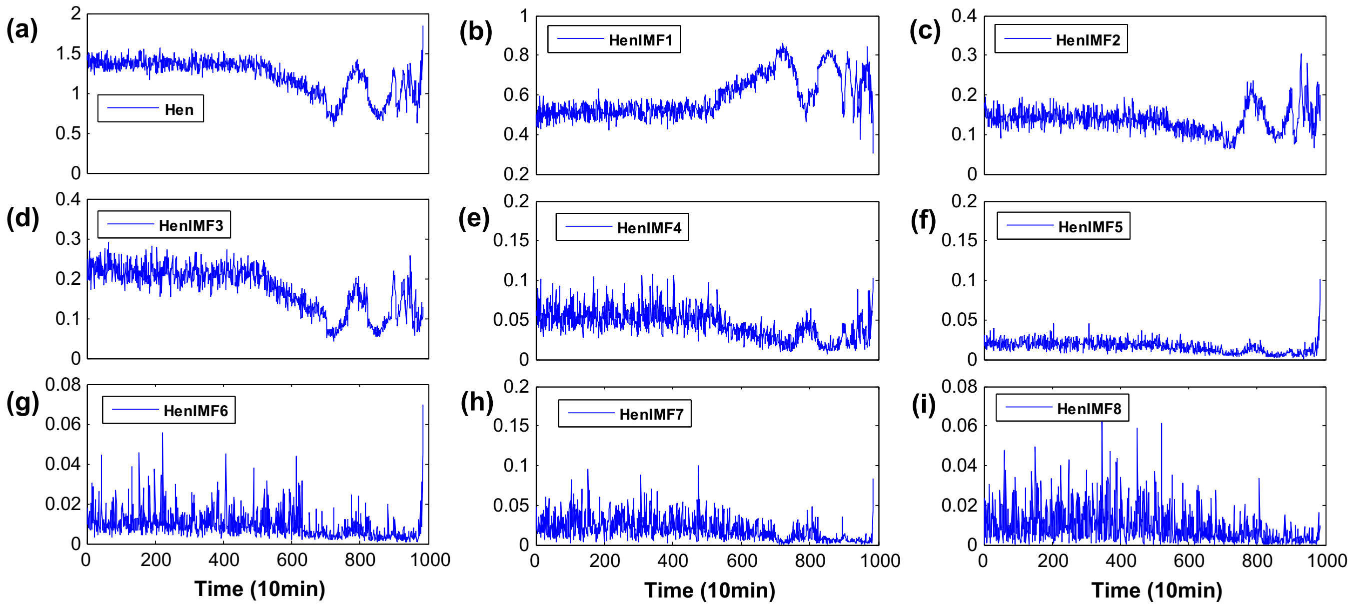

Fig. 8. Variation of features based on EMD: (a) H_{en}, (b) H_{en}IMF1, (c) H_{en}IMF2, (d) H_{en}IMF3, (e) H_{en}IMF4, (f) H_{en}IMF5, (g) H_{en}IMF6, (h) H_{en}IMF7 and (i) H_{en}IMF8.

2. Calculate the total average feature vectors of all classes.

$$\underline{\mu}_c = \frac{1}{K}\sum_{k=1}^{K}\underline{\mu}_k \tag{10}$$

3. Calculate the intra-class variance matrix of average dispersion coefficients.

$$S_{\text{intra}} = \frac{1}{KN}\sum_{k=1}^{K}\sum_{n=1}^{N}(\underline{x}_{k,n} - \underline{\mu}_k)(\underline{x}_{k,n} - \underline{\mu}_k)^t \tag{11}$$

4. Calculate the inter-class variance of average dispersion between different classes.

$$S_{\text{inter}} = \frac{1}{K}\sum_{k=1}^{K}(\underline{\mu}_k - \underline{\mu}_c)(\underline{\mu}_k - \underline{\mu}_c)^t \tag{12}$$

5. Finally, the J degree is given by:

$$J = trace\left(S_{\text{intra}}^{-1}.S_{\text{inter}}\right) \tag{13}$$

Note that a phase of standardization is necessary before applying this criterion. The used technique in this work is the normalization with zero average and constant variance as:

$$x_{k,n} = \frac{x_{k,n} - mean(x_{1:K,n})}{\sqrt{var(x_{1:K,n})}} \tag{14}$$

Compared to the most features used in other studies for REBs diagnosis (RMS and kurtosis), Table 2 shows that the first seven IMFs are the most effective for bearing diagnosis. All IMFs of an order higher seven will not be considered in this study. This result is very important to the advancement of diagnosis research.

For more evaluation of the J criterion, Fig. 10 shows a three-dimensional repartition of the best and the worst IMFs energy entropy. Feature distribution confirms that the best features are most appropriate for bearing states separation. This result probably improves the classification results of any classifier based on this study.

4. Experimental results

This section presents the experimental results of our proposed method. Classification descriptions of bearing defects are given in Section 4.1. Results of the real time damage detection at early stage are analyzed in Section 4.2. Discussion and comparison with some previous works are detailed in Section 4.3.

4.1. Application of ANN for life cycle vibration classification

For this application, three bearings are used. Each bearing is a run- to-failure experience. The first experience ended with roller failure, the second with an inner race failure and the third with an outer race failure as shown in Fig. 9. Every 10 min, an individual file is recorded during one-second vibration signal with the sampling rate 20 kHz. The record number of the used bearings is presented in Table 3.

The total number of records is 5394. Each record is formed by 20,480 samples. Because of the overlap between normal-degradation zones and degradation-faulting zones; the number of records is reduced to 3911. This reduction is made with a very great caution to ensure the reliability of measures. Each experience is divided into three zones as shown in Fig. 6 (Normal, degraded and failure). In this way, seven states of bearings are obtained (H, DR, FR, DIR, FIR, DOR, FOR).

After determining the feature vector for each record, ANN is adopted to identify the various patterns. The used ANN has four layers: an input layer includes 18 nodes according to the number of components of feature vectors, a first hidden layer with 20 nodes, a second hidden layer with 18 nodes and an output layer with 4 nodes. Each subsequent layer has a weight coming from the previous layer. Weight adaptations are done with hyperbolic tangent sigmoid transfer function. Typically, testing is made with a threshold equal to 0.5. All layers have biases. After 140 epochs of training, the error decreases to 4×10^{-4} and convergence is reached. The cross-validation method is used to select the optimum proposed ANN structure. The training-bearing data set is divided into five equally-sized sub-data sets (five folds). Then, five iterations of training and validation are performed. Each iteration presents four folds for the training and one fold for the validation. Also, five folds cross-validation experiments are done to select the optimal number of hidden layers and nodes number in each layer.

By applying the back-propagation (BP) algorithm and 2728 learning records, trained ANN is able to identify all training data sets and the overall average classification rate 93% is achieved.

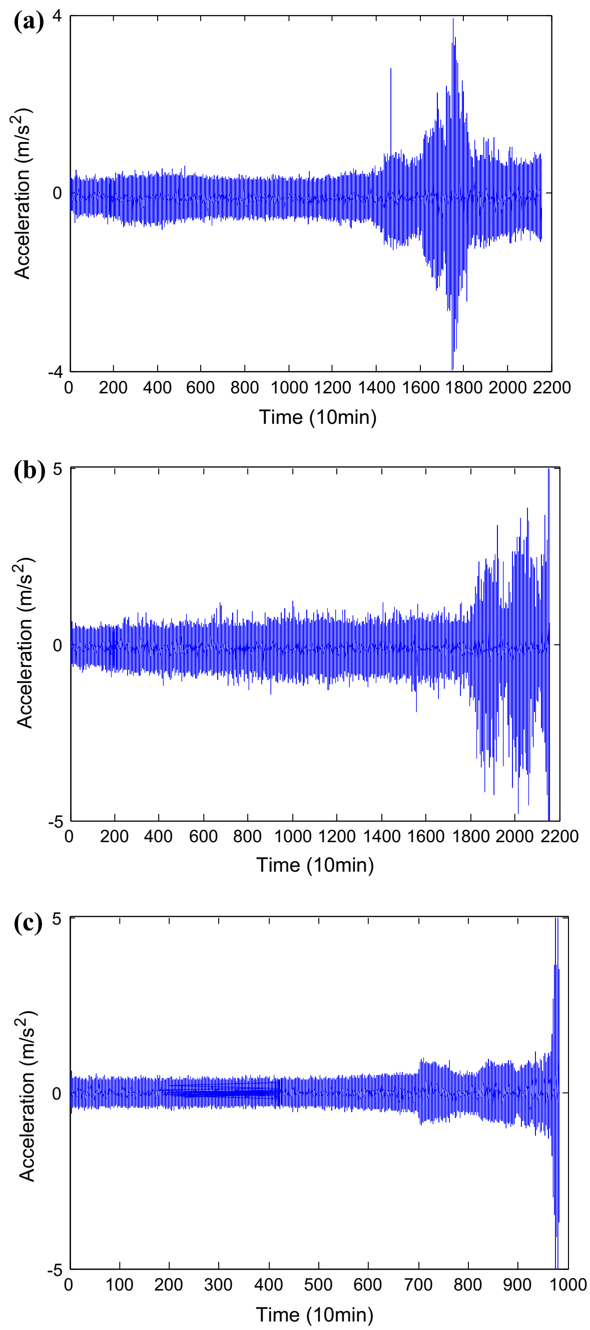

Fig. 9. (a) Acceleration of bearing 4 of testing 1 ending with failure roller. (b) Acceleration of bearing 3 of testing 1 ending with failure inner race. (c) Acceleration of bearing 1 of testing 2 ending with failure outer race.

Table 2
Evaluation of IMFs for bearing diagnosis.

Feature	J criterion's value
RMS	1.8193
HenIMF4	1.7111
HenIMF5	1.3875
Hen	0.9127
HenIMF6	0.5992
HenIMF1	0.5788
HenIMF3	0.4816
HenIMF7	0.4131
HenIMF2	0.4034
Kurtosis	0.3389
HenIMFi ($i > 7$)	<0.02

Numbers of records per class and ANN outputs are summarized in Table 4. Note that the classification accuracy (CA) is the ratio between the total numbers of correctly classified test samples to the total number of test samples.

$$CA[\%] = \frac{(\text{number of correctly classified samples})}{(\text{total number of samples in testing dataset})}100 \qquad (15)$$

The classification accuracy is very acceptable considering the large processed database. Moreover, the number of classes is important compared to previous works. Consequently, the classification is relatively harder than previous researches. That's why this work is considered exceptional comparing the number of treated measurements with previous works.

4.2. Online bearing damage detection at early stage

Real time damage detection of rolling bearing at early stage is a challenge for scientific researches.

To monitor the degradation of defects in bearings, a health index (HI) is proposed in this paper. The goal of a HI is to follow the degradation of a complex asset and provide an idea about the health state of this asset. The following algorithm shows the different calculation steps of the proposed HI:

- Step 1: Extract online a record of the used bearing.
- Step 2: Extract features.
- Step 3: Identify the REB state based on the trained ANN.
- Step 4: If ANN decision does not match any class of six types of fault, we conclude that it is a healthy bearing condition (no defect has appeared) and then $HI(i) = 0$. Otherwise, $HI(i) = HI(i) + 1$.

where i is the index of the treated record. The last step in the algorithm is a clever step: instead of incrementing the HI when the healthy state case is detected, incrementing is done when any defect is not found. This step allows ANN to reduce the effect of the 7% error in the classification phase. Fig. 11 shows the evolution of the HI for the three studied bearings.

For further evaluation, a new bearing run-to-failure acceleration vibration signals are tested. It's the bearing 3 of testing 3 ending with FOR. This test contains 4448 records never used in the learning phase. Despite that, the proposed ANN was able to detect early stage degradations perfectly. This experience really judges the effectiveness of the approach developed in this paper. Simulation results shown in Fig. 12 affirm the robustness of the proposed method.

Fig. 13 shows another bearing test ending with small degradation. The degradations are so slight; no fault is identified on the bearing by eye sight. Using the trained ANN, the proposed approach is able to detect this degradation perfectly. The proposed methodology is a sound approach for detecting REB degradations even at early stage.

In conclusion, the validation phase of our approach shows that our feature selection and the ANN classifier have good potential for improving bearing diagnosis. The combination of the proposed features and ANN classifier is promising for high-accuracy early anomaly detection.

4.3. Discussion and comparison with some previous works

In the open literature, two directions for bearing fault diagnosis have been widely demonstrating their effectiveness:

- Advanced signal processing techniques: Despite that these methods can be used as a simple diagnosis decision scheme, they do not fulfill expectations in real life, especially under time

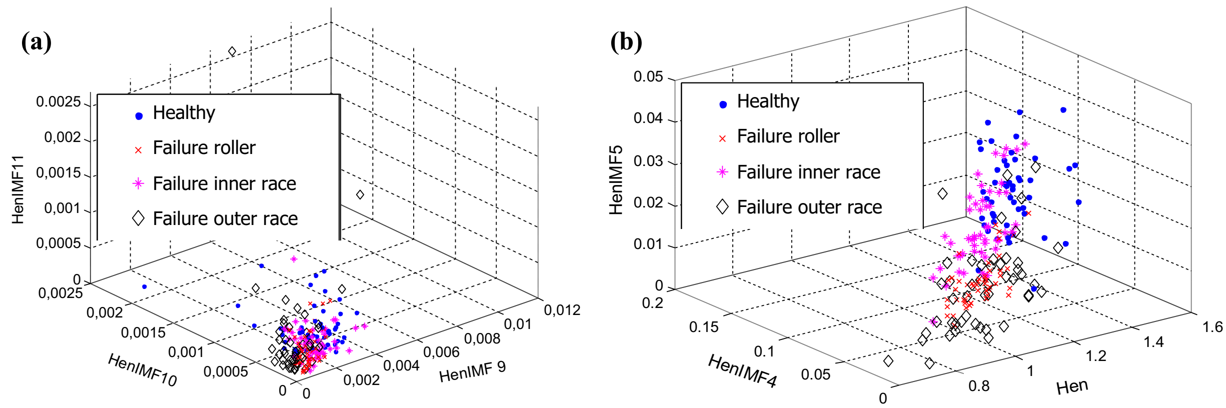

Fig. 10. (a) Spatial EMD energy entropy organization in the three-dimensional repair (H_{en}IMF9, H_{en}IMF10, H_{en}IMF11) and (b) Spatial energy entropy organization in the three-dimensional repair (Hen, H_{en}IMF4, H_{en}IMF5).

Table 3
Number of records per experience.

Type of experience	Experience ending with FR	Experience ending with FIR	Experience ending with FOR
Number of records	2155	2155	984

Table 4
Numbers of records per class and ANN outputs.

Type of class	H	DR	FR	DIR	FIR	DOR	FOR
Number of records	2900	151	451	151	56	151	51
ANN outputs	1100	0010	0001	1010	1001	0110	0101

varying operational conditions [21]. Also, expert intervention is necessary for decision making.

– Artificial intelligence tools and patter recognition approaches: Despite the complexity of these methods, they show automatic bearing fault diagnosis expert systems (without human intervention) and they can be extended to predict the REB remaining useful life.

In [25], adaptive Schur filter was used to monitor belt conveyor bearings in mining machine. The computational cost was very important to derivate reflection coefficients. Besides, the method requires an initial processing based on certain assumptions. Subsequently, authors mentioned that they aimed to develop new algorithms for automatic defect detections. In [18], results were improved using a method based on EMD to aggregate IMFs into three combined mode functions. So, REB raw vibrations are divided into three parts of signal: noise, signal and trend parts. The limitation of this work that is validated only using an outer race defect. We note that this type of defect was chosen because it's relatively simple to monitor; shock-pulses are generated each time rolling elements strike the defected surface of the bearing outer race and consequently, excite resonances of the structure between the fault location and the vibration sensor [5].

In [6], the kurtogram analysis was used to detect bearing defects. However, filter centre frequency and bandwidth cannot be chosen entirely independently. That is why, it was necessary to add another smart tool for an automatic selection. So, kurtogram was combined with genetic algorithm to provide good results. As drawback, bearing damage detection at early stage was not treated: only the healthy case and sever degradations were considered.

In this paper, we have chosen to combine EMD (as advanced signal processing technique) and artificial neural network (as artificial intelligent approach) for automatic bearing fault diagnosis methodology which can be extended for prognostic tasks by prediction REB remaining useful life. The remainder of this section is dedicated to compare our proposed methodology with previous works based on artificial intelligent approaches which are highlighted compared to the direct use of advance signal processing techniques. Artificial intelligent techniques have been increasingly applied to machine diagnosis and have shown improved performance over conventional approaches [4].

Classification accuracy is much improved for all bearing diagnosis conditions by the use of methodologies based on feature extraction, feature selection and classification tools. The classification accuracy results are all greater than 92%. To get a good classification, the majority of scientific researches in the previous works have used four bearing states (H, FIR, FOR and FR). The superiority of this work is highlighted in the introduction of the default severity which was not held before. Severity consists of three types: normal, degraded and faulty. Thereby, seven bearing states have been used in our work. These added modifications allow the real time monitoring degradation. Table 5 summarizes previous works on automated identification of bearing faults.

The basic concept and major disadvantage of the methods summarized in the Table 5, is that training is performed using simulation data; they create bearing holes of different diameters and depths to have bearing with FIR, FOR or FR. In an industrial environment it is not always the case, most bearing degradation cases are the generalized roughness [27]. It is a type of fault where the condition of a bearing surface has degraded considerably over a large area and become rough, irregular, or deformed [28]. The importance of our work over others is the use of real data which result from real time vibrations describing the dynamic response of defective REBs. Moreover, the proposed method allows online bearings degradation following and detect the occurrence time of incipient faults which was not treated in the previous works. The proposed approach produces acceptable classification accuracy despite the important number of classes. For valuable industrial comparison, our method is compared with some existing methods using the same real data from IMS bearing data set. This comparison is cleared up in the Table 6.

IMS bearings data set confirms that the life of REB is a highly non-linear phenomenon. The 12 used bearings in the experimental setup were tested in the same conditions of speed and load. Despite that, only four bearings were broken and one bearing was slightly degraded. Moreover, the failure time and the failure nature of the four broken bearings were not the same. All these confirm that bearing fault assessment is a very hard task. Table 6 shows that the proposed method is very adequate in terms of fault

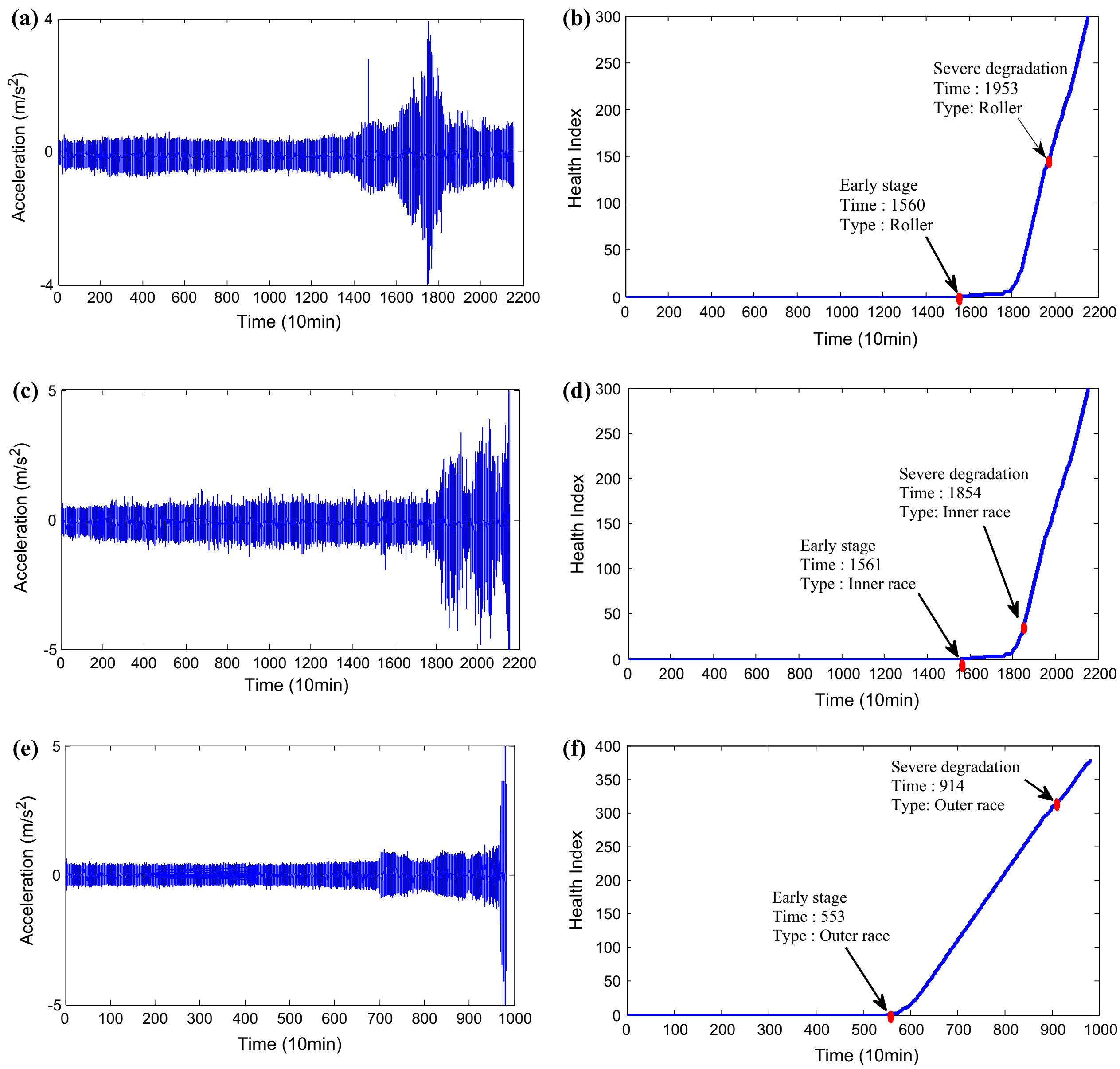

Fig. 11. (a) Bearing accelerations ending with RF. (b) Correspondent HI. (c) Bearing accelerations ending with FIR. (d) Correspondent HI. (e) Bearing accelerations ending with FOR. (f) Correspondent HI.

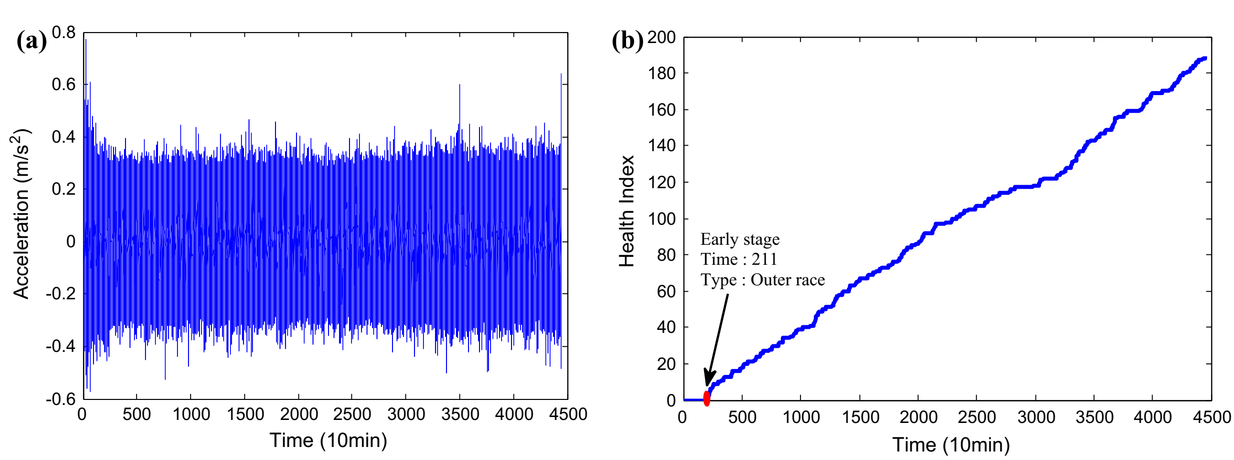

Fig. 12. Bearing 3 testing 3 ending with FOR.

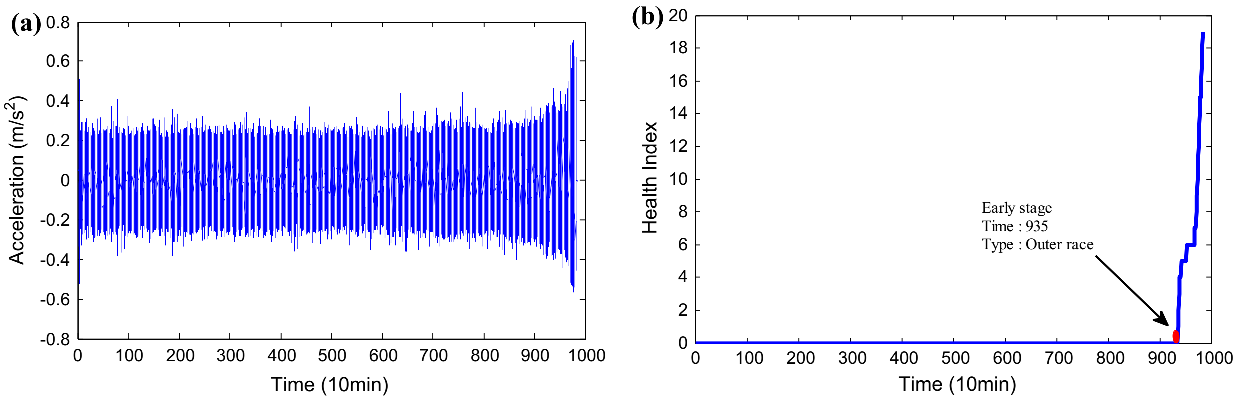

Fig. 13. (a) Bearing acceleration of bearing 4 testing 2 ending with unknown slight degradations. (b) Correspondent HI.

Table 5
Comparison of this work with some previous research.

Literature	Features	Classifier	# of Classes	Accuracy (%)	Real bearing degradation
[26]	Frequency domain based vibration energy features	SVM-OAA	3: H, FIR, FOR	100	No
[22]	Time–frequency domain based on EMD energy entropy of the first eight IMFs	ANN	3: H, FIR, FOR	93	No
[30]	Time domain and frequency domain	PSO-WSVM	4: H, FIR, FOR, FR	97.5	No
[31]	Time–frequency domain based on EMD energy entropy of the first six IMFs	IPSO-LSSVM	3: H, FIR, FOR	97	No
This work	Time–frequency domain features derived from EMD energy entropy of the first eight IMFs and statistical measurements	Propose methodology	7: H, DIR, DOR, DR, FIR, FOR, FR	93	Yes

Table 6
Comparison of this work with some previous research using IMS bearings data sat.

Literature	Classifier	Example of fault detection time (h)	Lifetime (h)	Presence of false alarms
[11]	v-SVM	⁎ V-SVM: 89 ⁎ Proposed methodology: 92.17	164	No
[12]	EWMA	⁎ EWMA: 298.33 ⁎ Proposed methodology: 260	359.16	Yes
[13]	NLLPEWMA	⁎ NLLPEWMA: 277.33 ⁎ Proposed methodology: 260.16	359.16	Yes

time detection and false alarm presence. We cannot judge which the most precise method is only if a real time implementation of all methods will be carried out with a non destructive control bearing test. The important issue is that all methods have shown the same evolution of the degradation curves.

The training set of the proposed method in [11] is based on the n first measures of healthy bearing which is not always the case. For example, the first 33 h of a bearing's life are used to train the v-SVM. In industries, it is not always true; if the tested bearing is mounted on a machine with important bad misalignment or sudden hit on the shaft, this yield to fast degradation and probably the bearing failure will occur in the first operating hours. Note that general REBs failures are due to manufacturing error, wrong installation or abrasive wear [29]. In our work, vibration measurements, resulting from the machine under condition monitoring, are extracted and processed directly by the already trained ANN, eliminating the need for training the SVM with experimental data of the specific defective bearing.

In [12,13], the complexity of calculation is important and it requires some seconds to detect the bearing state in each unit time. For the IMS bearing data set, the used techniques in [12,13] is applicable because each record is measured after 10 min, then the algorithm has 10 min to do the job. Using other data set for small bearings data set where the time between records is relatively low, used algorithms in [12,13] will be unable to detect anomalies because each small time interval a record is presented. Hence, the proposed ANN is able to perform the task in 0.8s CPU time (application with core i7 computer).

Consequently, results show that the proposed method is a suitable technique for online fault bearing diagnosis. Also, experimental results demonstrate its ability in online diagnosing bearing failures with reduced CPU time.

5. Conclusions and future works

In this work, an effort has been made to characterize and classify seven different bearing classes depending on statistical features, EMD energy entropy and artificial neural network (ANN). Two new statistical measurements are proposed to increase the number of features. Feature selection is done with a robust statistical criterion called J. Three bearing run-to-failure vibration signals ending with different defects (roller, inner race and outer race) are used at the same speed and torque conditions. A health index (HI) is proposed and compared with previous papers. The combination of the selected features and classifier is promising for a high-accuracy diagnosis of real bearing defects. Thereafter, experimental results demonstrate the ability of the proposed HI for degradation detections at early stage. This work can be developed for failure prognostic activities to anticipate the failure date by predicting the future health state of and its remaining useful life (RUL). Variable operating conditions (speed and torque) are the aspects of the ongoing works which may help generalizing the method. Finally, this work presents a solid foundation for the development of an automatic expert diagnosis and prognosis system.

Acknowledgments

The authors would like to thank Center on Intelligent Maintenance Systems (IMS) University of Cincinnati, USA, for providing on the web the bearing dataset. Also, we would like to thank Mr. Bennila Kamal, professor in Boudhina Hammamet Secondary School, Tunisia, for the grammar English look to the manuscript.

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