[Proceeding] Fault diagnosis of roller bearings using ensemble empirical mode decomposition (EEMD) and support vector machine (SVM)

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Vibrations, Shocks and Noise

Fault diagnosis of roller bearings using ensemble empirical mode decomposition (EEMD) and support vector machine (SVM)

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Highlights

- The effects of amplitude of the added noise on early damage detection of roller bearing is investigated
- A new calculating algorithm for amplitude is introduced
- Various operating condition, two defect location and two acceleration direction is considered to obtain reliable results
- The proposed algorithm is achieved considerably higher success rate than predefined constant methods

Abstract

Rolling bearings are widely used in rotating machinery and their fault is one of the most common causes of industrial machinery failure. Damage identification of roller bearings has been deeply developed to detect faults using vibration-based signal processing. There exist different signal processing techniques to decompose a signal and extract informative features such as EMD and Wavelet transform. EMD is a method for decomposing a multi-component signal into several elementary Intrinsic Mode Functions (IMFs) and has been widely applied to fault diagnosis of rotating machines. However, there are some drawbacks such as stopping criterion for sifting process, mode mixing and border effect problem. Ensemble empirical mode decomposition (EEMD) is a newly developed noise assisted method to solve mode mixing problem exists in empirical mode decomposition (EMD) method. Since the white noise is added throughout the entire signal decomposition process, mode mixing is effectively eliminated. However, there is still a great challenge: identifying two effective parameters (the amplitude of added noise and the number of ensemble trials) which may affect the performance of EEMD. Using low amplitude (relative to the signal), mode mixing cannot be prevented. On the other hand, too large amplitude achieves some redundant IMFs. Although some algorithm or values have been proposed, there is no robust guide to select optimal amplitude yet, especially for early damage detection (very small defects). In this study a reliable method is investigated to determine suitable amplitude and numerous real vibration signals (various operating conditions and two damage locations) are analysed to verify effectiveness and robustness of the proposed method. Vibration signals for healthy and defective bearings were acquired using the test rig assembled by Dynamics & Identification Research Group (DIRG) at Department of Mechanical and Aerospace Engineering, Politecnico di Torino.

Keywords: Empirical mode decomposition, Ensemble empirical mode decomposition, Support vector machine, Roller bearing, fault diagnosis

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1. Introduction

Modern rotating machines become more precise and automatic and there is a demand to increase the reliability and detect any possible faults at an early stage. Through processing of collected vibration signals and extracting significant information, it is possible to detect even small defects on bearings. There are different signal processing techniques to decompose a signal and extract informative features such as EMD and Wavelet transform. EMD introduced by Huang et al. [1, 2] is a method for decomposing a multi-component signal into several elementary Intrinsic Mode Functions (IMFs) and has been widely applied to fault diagnosis of rotating machines. However, there are some drawbacks such as stopping criterion for sifting process, mode mixing and border effect problem.

The intermittency of the detected extrema which belong to the different components is the main reason for causing mode mixing. EEMD which is a noise assisted data analysis method has been recently proposed to eliminate mode mixing problem of EMD technique [3]. Essentially, EEMD repeatedly decomposes the original signal with added white noise into a series of IMFs, by applying the original EMD process. The means of the corresponding IMFs during is considered as the final EEMD decomposition result. Since the white noise is added throughout the entire signal decomposition process, mode mixing is effectively eliminated. EEMD has been used to detect rotating machines faults such as bearings and gears in the past few years [4]. However, there is still a great challenge: identifying two effective parameters (the amplitude of added noise and the number of ensemble trials) which may affect the performance of EEMD. If the amplitude of the added noise is too small relative to the original signal, a considerable mode mixing improvement cannot be achieved. On the other hand, if the amplitude of the added noise is too large, it will create some redundant IMF components which lead to misinterpretation of the analysis result. Although, an infinite number of ensemble trials is needed to completely cancel out the effect of the added white noise, too many trial numbers would increase the computational cost. Wu and Huang [2] suggested 0.2 of standard deviation of the original signal for the amplitude of the added white noise and a few hundred for trial number of ensemble. It has been shown in various cases that such an amplitude is not appropriate. Zhang et al. [4] suggested using a band-limited white noise to decrease the computational cost. Analyzing a simulated signal, it was concluded that appropriate range of SNR (signal to noise ratio which was defined based on power) is [50-60] dB. However, they used another range ([0.01-0.1]) which is outside of the suggested SNR. A non-stationary signal was constructed to mimics realistic vibration signals measured from rolling and the appropriate range of SNR was considered [49-58] dB for the vibration signals. Guo and Tse [5] investigated the influence of parameters setting on the results of reducing mode mixing problem using a simulated signal. The effects of frequency and amplitude ratio of two different parts of the simulated signal (the high frequency and low frequency components) were investigated as well. The investigated amplitudes were considered again coefficients of standard deviation of the original signal (0.01, 0.1, 0.2, and 0.3). As real data is noisy and the amplitudes and composition of frequency are unknown, lower amplitude of noise was added and more number of ensemble trials applied (0.1 of standard deviation of the original signal as the amplitude and 3000 for ensemble trial number). As only one specific operating condition with a single specific amplitude was investigated, it would not represent a reliable guideline on setting the parameters properly for real signals. Lin [6] tried to provide a guidance on choosing the appropriate amplitude and reduce the tremendous time waste occurring in the EEMD method. An optimal interval was suggested that lies between the square root of the average power of the weak sinusoid component and weak transient component. When the amplitude is selected from the mentioned interval, the Pearson's correlation coefficients (PCC) of the components reach their maximum value. Taking into consideration that only one specific gearbox vibration signal was investigated to verify the suggested procedure, its performance is not reliable to identify small defects. On the other hand, applying such a procedure is not easily practicable in damage identification, especially for automatic damage detection. Jiang et al. [7] applied multiwavelet packet as the pre-filter to enhance the weak multi-fault features in the narrow frequency bands. Then two ranges were suggested for the amplitude: [0-0.2] of the standard deviation of the original signal for high frequency components and [0.2-0.6] of the standard deviation of the original signal for the low frequency components. As some specific amplitudes were selected (0.04, 0.08 and 0.5) in this study with no discussion, it seems that there is no robust guide to choose the optimum amplitude from the wide suggested ranges. Tabrizi et al.

[8] applied wavelet packet decomposition with combination of EEMD to identify very small faults under various operating conditions. It was concluded that more appropriate amplitude was [0.4-0.6] of the standard deviation for noisy signals, and 0.5 for denoised signals.

In this study a new method is proposed to calculate an appropriate and effective amplitude. Numerous vibration signals are analyzed to verify proposed algorithm in automatic fault diagnosis using support vector machine (SVM).

2. EMD algorithm

EMD method decomposes a complex signal into a number of IMFs. Decomposition consists of following steps [1]:

1) Identify all the local extrema, and then connect all the local maxima by an interpolation method. Repeat the procedure for the local minima to produce the lower envelope.

2) Determine the difference between the signal x (t) and the mean of upper and lower envelope value to obtain the first component. If it is an IMF, then it would be the first component of x (t). Otherwise, it is treated as the original signal and step (1)–(2) are repeated. The sifting process can be stopped by any of the predetermined criteria which will be discussed in the next section.

3) Separate IMF from the original signal x (t) to obtain the residue and consider it as the new data and repeat the above described process.

4) Stop the decomposition process when the residue becomes a monotonic function from which no more IMF can be extracted.

3. Ensemble emprical mode decompositon (EEMD)

Decomposition using EEMD consists of following steps:

a) To add a random white noise signal to the acquired original signal [7]:

$$\mathbf{x}_j(t) = \mathbf{x}(t) + Amp \cdot \mathbf{n}_j(t) \qquad j = 1,2,3,...,M \tag{1}$$

where $\mathbf{x}_j(t)$ is the noise added signal, Amp is the amplitude of added white noise and M is the number of trial.

b) To decompose the obtained signal($\mathbf{x}_j(t)$)into IMFs using EMD:

$$\mathbf{x}_j(t) = \sum_{i=1}^{N_j} \mathbf{c}_{ij} + \mathbf{r}_{N_j} \tag{2}$$

where $\mathbf{c}_{ij}$ denotes the i-th IMF of the jth trial, $\mathbf{r}_{N_j}$ denotes the residue of j-th trial and N_j is the IMFs number of the j-th trial.

c) If $j < M$, then repeat steps a and b and add different random noise signals each time.

d) Obtain $I = \min(N_1, N_2, ..., N_M)$ and calculate the ensemble means of corresponding IMFs of the decompositions as the final result ($\mathbf{c}_i$):

$$\mathbf{c}_i(t) = (\sum_{j=1}^{M} \mathbf{c}_{ij}) / M \tag{3}$$

where $i = 1,2,3,...,I$.

As mentioned in section 1, the added noise must affect the extrema of the original signal so that the intermittency of the components will be removed or decreased as much as possible. However, in the predefined constant amplitude value, the extrema are being affected (and as a consequence decreasing the existed mode mixing) by a random noise which might not effectively change some exrema.

Instead of adding a predefined constant value, an adaptive method is proposed and its performance and applicability are evaluated utilizing several real vibration signals. After adding a random white noise, by applying the SNR definition (Eq.4), the Amplitude value for each data point of a sample is obtained from Eq.5. Considering an appropriate value for SNR, there would be a confidence that the extrema of the original signal are influenced adequately.

$$SNR_j(i) = 20Log\left(\mathbf{x}(t)\big/ Amp\cdot\mathbf{n}_j(t)\right) \tag{4}$$

$$Amp_j(i) = 10^{-\left(SNR/20\right)}\cdot\left(\mathbf{x}(t)\big/\mathbf{n}_j(t)\right) \tag{5}$$

where $j = 1,2,3,...,n$.

In Fig.1 a vibration signal of a roller bearing and a created random noise are shown. A suggested fixed value (eg. 0.3) multiplied by standard deviation of the original signal, creates a predefined constant value along whole of the signal (Fig.2). Thus, affecting on the extrema depends on value of random noise at the location of the extrema.

Instead, using proposed algorithm (Eq.5), prepares an adaptive value (Fig.2) to preserve the SNR ratio. It means that for any randomly created noise, the amplitude will be high enough to affect the extrema. Investigating the result of adding noise to the vibration signal shows the proposed amplitude acts more effective on the extrema (Fig.3).

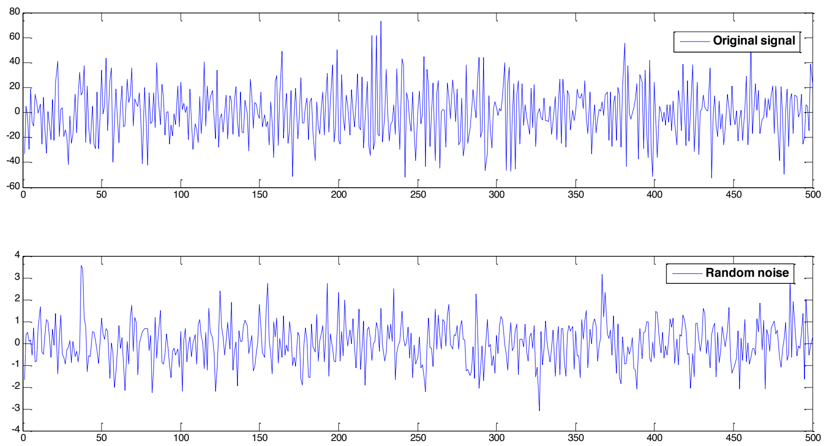

Figure 1- A real vibration signal of a roller bearing and a created random white noise

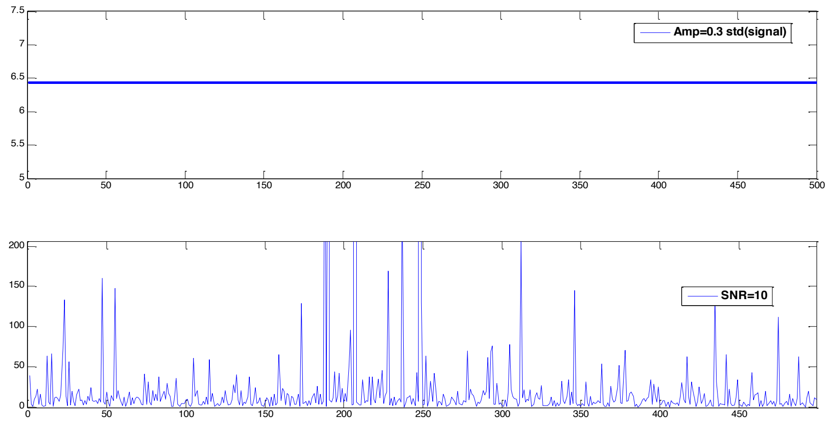

Figure 2- The redefind constant amplitude (0.3 std(signal)) and proposed amplitude algorithm (SNR=10)

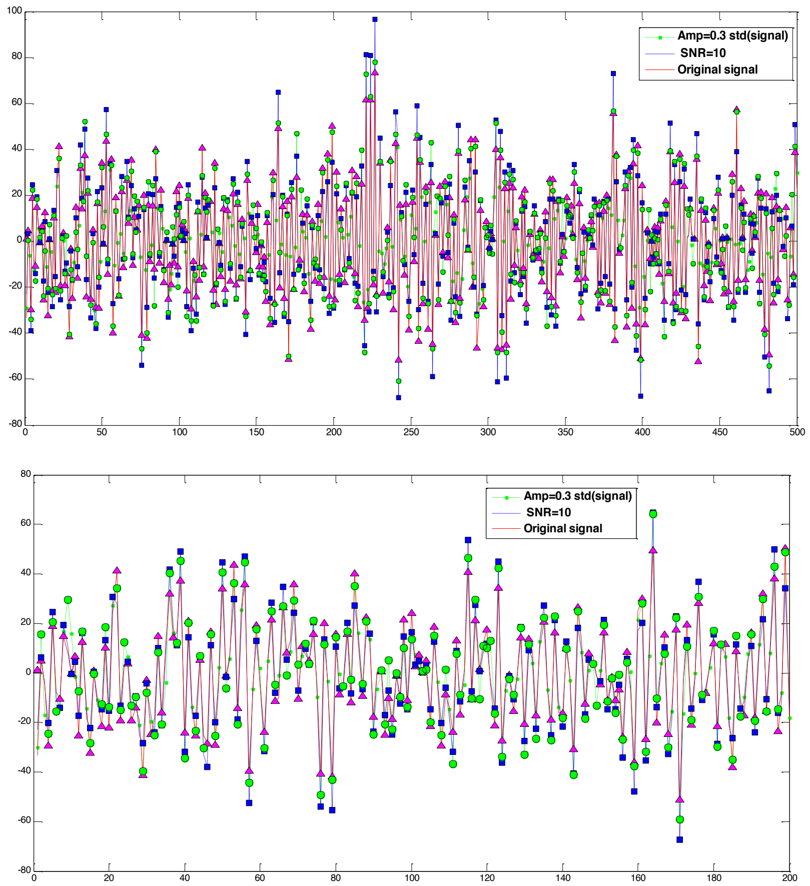

Figure 3- Influence of using constant amplitude (0.3 std(signal)) and proposed amplitude algorithm (SNR=10) on extrema

4. Support vector machine (SVM)

Support vector machine (SVM) is a useful technique for data classification. In machine condition monitoring and damage detection problems, SVM is adopted to label a new sample whether it is healthy or faulty. Based on available acquired data (which are mentioned as the training data), SVM attempts to construct a hyperplane that separates two different classes of samples and orients it to maximize the "Margin" which is the distance from the hyperplane to the closest data points in either class. An example of the optimal hyperplane of two data sets is shown in Fig.4 [9]. Every time a new element appears, it could be classified according to where it places with respect to the separating hyperplane.

SVM could also be applied in a case of non-linear classification by mapping the data onto a high dimensional feature space, where the linear classification is then possible. By applying Kernel function as the inner product of mapping functions $(\mathbf{K}(x_i,x_j)=\boldsymbol{\varphi}(x_i).\boldsymbol{\varphi}(x_j))$ it is not necessary to explicitly evaluate mapping in the feature space. Various kernel functions could be used, such as linear, polynomial or Gaussian RBF (Radial basis function).

In real world problem it is not likely to get an exactly separate line dividing the data and we might have a curved decision boundary. Ignoring few outlier data points will create smooth boundary. This is handled here by using slack variable ξ_i and the error penalty C and is called soft margin-SVM.

The Margin is defined as [10]:

$$\text{Margin} = 2/\|\mathbf{w}\|^2 \qquad (6)$$

And the optimization problem will be [10]:

$$\min\left(\frac{1}{2}\|\mathbf{w}\|^2 + c\sum_{i=1}^{N}\xi_i\right) \qquad (7)$$

Subject to $y_i\langle \mathbf{w}.\mathbf{X}\rangle + b \geq 1-\xi_i$, $\xi_i \geq 0$

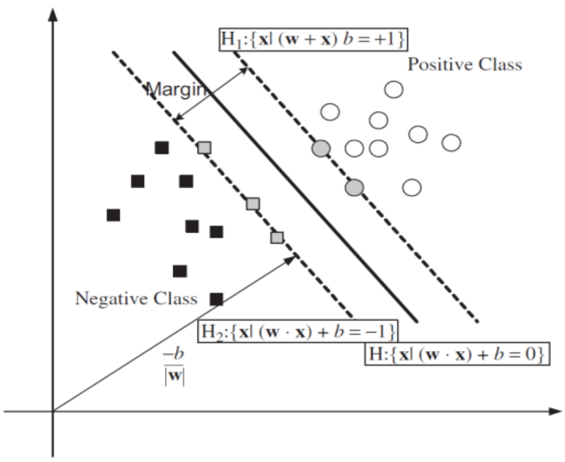

Figure 4. Classification of two classes of data using SVM

where **w** and b are the vector and scalar that are used to define the position of the hyperplane, ξ_i is measuring the distance between the hyperplane and the examples that laying in the wrong side of the hyperplane. Introducing Lagrange multipliers and solving the dual optimization problem, non-linear decision function will be [9]:

$$f(x) = sign(\sum_{i=1}^{N} \alpha_i y_i \mathbf{K}(x, x_i) + b) \tag{8}$$

5. Methodology

The goal of this study is to evaluate performance of the proposed amplitude calculating algorithm in EEMD method for various operating conditions of a roller bearing. Normalized energy of IMFs is used as the feature vector [11].

The fault diagnosis method is given as the following:

1) To collect vibration signals both for a healthy and defective bearings at three different external loads and four shaft speeds.
2) To apply EEMD with different amplitude of added white to decompose the vibration signals into some IMFs. The first m IMFs including the most dominant fault information are chosen to extract the feature.
3) To calculate the total energy $\mathbf{E}_i$ of the first m IMFs:

$$\mathbf{E}_i = \int_{-\infty}^{+\infty} \left|\mathbf{c}_i(t)\right|^2 dt \tag{9}$$

4) To create a feature vector with the energies of the m selected IMFs:

$$\mathbf{FV} = \left[\mathbf{E}_1, \mathbf{E}_2, \ldots, \mathbf{E}_m\right] \tag{10}$$

5) To normalize the feature:

$$\mathbf{FV}_n = \left[\mathbf{E}_1/\mathbf{E}, \mathbf{E}_2/\mathbf{E}, \ldots, \mathbf{E}_m/\mathbf{E}\right] \tag{11}$$

where $E = (\sum_{i=1}^{m} \left|\mathbf{E}_i\right|^2)^{1/2}$.

6) To carry out the training procedure of SVM by utilizing the normalized feature vectors. The 60% of data are used for training and the rest are taken as the test samples.
7) After training the SVM successfully, it would be ready to test samples to identify the different work conditions and fault patterns.

6. Experiment

The bearing data set (acceleration signals) were collected under various operating conditions using the test rig (Fig. 5) developed and assembled by the Dynamics & Identification Research Group (DIRG) at the Department of Mechanical and Aerospace Engineering of Politecnico di Torino. The signals were acquired at 102.4 kHz sampling frequency for both healthy and defective roller bearings. Two defective bearings were utilized during the test, one with the very small artificial defect severity over one roller (150 microns in diameter) and another with the same fault level on the inner ring. Four different shaft speeds (100, 200, 300 and 400 Hz) and three different external radial loads (1.0, 1.4 and 1.8 kN) were considered to acquire the signals in different operating conditions in controlled laboratory conditions, allowing speed, load and oil temperature control. The axes orientation of the triaxial accelerometers are shown in Fig.5 so that x, y and z axis corresponds to the axial, radial and tangential direction, respectively.

The original acquired signals were divided into 20 segments including 10000 data points each, to extract required informative feature vectors. Thus, each signal includes 20 segments which create 20 feature vectors as inputs for the SVM. Selecting samples as the training ones includes all the possible random selections to obtain the maximum classification accuracy rate for training.

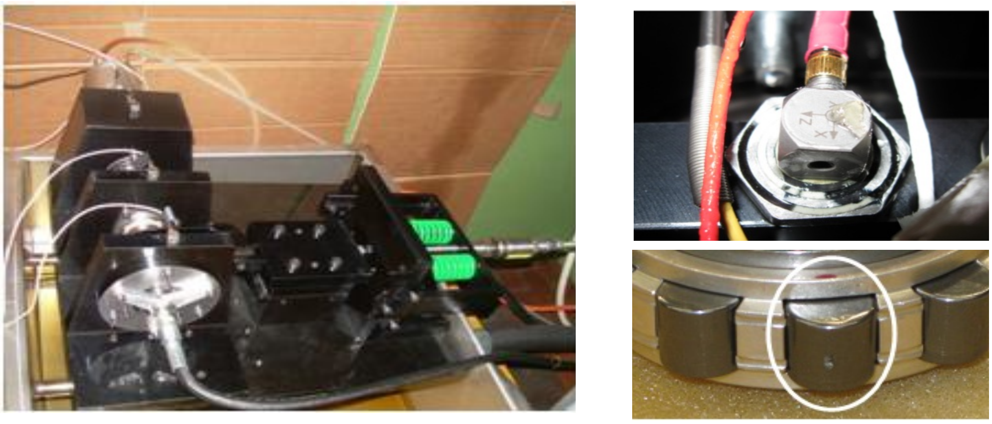

Figure 5- DIRG test rig, the axes orientation of the triaxial accelerometers (X, Y, Z) and the damaged roller used in the tests

7. Analysis

Implementing the methodology described in section 5, feature vectors for each algorithm, damage location and signal direction are obtained. Normalized energy of IMFs introduced as an efficient feature vector in fault diagnosis of roller bearing, has been adopted just using only first three elements of the feature vectors [8].

In Table 1, it is shown that very small defect size (150 microns on a roller) is not recognized using EMD for signals collected through the accelerometer in Y direction. Although applying EEMD improves the success rate, there is no correct classification and fault diagnosis for some operating conditions. It seems that amplitudes with 0.3, 0.5 and 0.6 lead to less misclassification (three operating conditions).

Table 1- Results of classification for different operating conditions (signals collected in Y direction)

Method	Amplitude of added noise	100 Hz 1.0 kN	100 Hz 1.4 kN	100 Hz 1.8 kN	200 Hz 1.0 kN	200 Hz 1.4 kN	200 Hz 1.8 kN	300 Hz 1.0 kN	300 Hz 1.4 kN	300 Hz 1.8 kN	400 Hz 1.0 kN	400 Hz 1.4 kN	400 Hz 1.8 kN
EMD	**-**	100	100	**75.0**	100	100	**81.3**	100	**81.3**	100	100	**93.8**	**62.5**
EEMD	**0.2**	100	100	**81.3**	100	**93.8**	**87.5**	100	**87.5**	100	100	100	100
EEMD	**0.3**	100	100	**93.8**	100	100	**87.5**	100	**93.8**	100	100	100	100
EEMD	**0.4**	100	100	**87.5**	100	**93.8**	**81.3**	100	100	100	100	100	100
EEMD	**0.5**	100	100	**87.5**	100	**87.5**	**87.5**	100	100	100	100	100	100
EEMD	**0.6**	100	100	**87.5**	100	**87.5**	**87.5**	100	100	100	100	100	100

Now, by applying the proposed amplitude calculating algorithm, the accuracy of damage detection is investigated. The success rate of defect detection is shown in Table 2 for various preselected SNR values. Obviously, a considerable improved rates are achieved for some SNR values, especially, for SNR=10 which there exist only one working condition (speed = 200 Hz and load = 1.8 kN) that the state of bearing is not perfectly identified. However, none of SNR values leads to a perfect labeling for all conditions. Increasing the SNR (to SNR = 20), increases the success rate for the mentioned operating condition which means such a signal needs weaker noise to affect the extrema and decrease the mode mixing. Whereas for some signals (such as speed = 100 Hz and load = 1.8 kN and speed = 300 Hz and load = 1.4 kN) the smaller value (SNR = 10) seems to be more appropriate. It means that those signals require some stronger noises.

Table 2- The results of damage detection using EEMD with new proposed amplitude calculating algorithm (Y direction)

SNR	100 Hz 1.0 kN	100 Hz 1.4 kN	100 Hz 1.8 kN	200 Hz 1.0 kN	200 Hz 1.4 kN	200 Hz 1.8 kN	300 Hz 1.0 kN	300 Hz 1.4 kN	300 Hz 1.8 kN	400 Hz 1.0 kN	400 Hz 1.4 kN	400 Hz 1.8 kN
5	100	100	**81.3**	100	**87.5**	**73.3**	100	100	100	100	100	100
10	100	100	100	100	100	**87.5**	100	100	100	100	100	100
15	100	100	**93.8**	100	100	**93.8**	100	**87.5**	100	100	100	100
20	100	100	**87.5**	100	100	100	100	**87.5**	100	100	100	100
25	100	100	**81.3**	100	100	**93.8**	100	**87.5**	100	100	100	**93.8**
30	100	100	**81.3**	100	100	**93.8**	100	**87.5**	100	100	100	**93.8**

Table 3- The Margin calculated in EEMD with new proposed amplitude (Y direction)

SNR	100 Hz 1.0 kN	100 Hz 1.4 kN	100 Hz 1.8 kN	200 Hz 1.0 kN	200 Hz 1.4 kN	200 Hz 1.8 kN	300 Hz 1.0 kN	300 Hz 1.4 kN	300 Hz 1.8 kN	400 Hz 1.0 kN	400 Hz 1.4 kN	400 Hz 1.8 kN
5	1.1553	1.0479	**0.7044**	1.2654	**0.7560**	**0.7179**	1.2676	1.0039	0.9007	0.8362	1.0402	0.9647
10	1.1627	1.0881	0.8863	1.2660	0.8095	**0.6854**	1.1806	0.8123	0.8628	0.9342	0.8768	0.9274
15	1.2295	1.1278	**0.7577**	1.2779	0.8885	**0.7732**	1.1139	**0.7493**	0.8810	0.9128	0.8454	0.8652
20	1.2519	1.1192	**0.7303**	1.2750	0.9342	0.7749	1.0344	**0.6806**	0.8959	0.8668	0.8547	0.7864
25	1.2066	1.1015	**0.6819**	1.3166	0.9003	**0.7793**	1.0172	**0.7014**	0.9039	0.8631	0.8189	**0.7514**
30	1.1962	1.0799	**0.7069**	1.2634	0.8601	**0.7705**	0.9985	**0.7425**	0.9084	0.8292	0.7611	**0.7108**

Exploring reliability of the obtained success rate, Margin (Eq.6 and Fig.4) of each SVM classification is calculated and presented in Table 3. It is obvious from the definition of Margin that higher Margin means more reliable hyperplane and classification. As it can be seen, some Margins are much smaller than others such as 0.6806 (SNR=20, speed = 300 Hz and load = 1.4 kN). It means there might be new misclassified samples (like the result shown in Table 2). On the other hand, it is reasonable to expect that higher Margins have more reliable results (a correct classification and defect detection for any new investigated sample). The most important conditions are those achieving a perfect classification rate (100%), whereas the calculated Margin is not high enough such as 0.7749 (SNR=20, speed = 200 Hz and load = 1.8 kN). There might not be a reliable state and the constructed SVM may not recognize the state of new samples and leads to misclassification. It worth to mention that there is no a determined value for reliable Margin. The Margin of those amplitude calculating algorithms have better results are shown in Table 4.

To test reliability of the constructed SVM, 20 new samples (10 healthy and 10 damaged samples) for each operating condition were classified with previously constructed SVM (Table 2). The results are proposed in Table 5. Obviously, as it might be expected, the new samples are not classified perfectly for a low mentioned Margin

(SNR=20, speed = 200 Hz and load = 1.8 kN). Although the previous success rate was 100% and it seemed to be a reliable constructed SVM, its low Margin (in comparison with those showing a perfect damage detection) declares that it might not be a confident SVM. On the other hand, for all other conditions which have higher Margin, the states of new samples are identified correctly. As it can be seen in Fig.7, all faulty and healthy samples are completely separable.

For new method (SNR=10, except for the only misclassified condition (Table 2)) and EEMD with the predefined constant amplitudes (except for those three misclassified conditions (Table 1)), all other conditions seems to be reliable and fault detections with constructed SVMs are successful. As it was expected because of their high Margins. In EMD method, it seems the Margin of all working conditions that classified correctly are high enough to expect a correct state recognition for the new samples. The results are shown in Table 5 confirm such an expectation.

To investigate more, the collected signals of another defective bearing (small defect on the inner ring) in two directions (Y and Z) are analyzed. The results of classification are shown in Table 6. As all constructed SVMs have high margins, are reliable and leads to perfect success rates for both Y and Z directions, except for one condition (speed = 200 Hz and load = 1.8 kN) in Z axis which achieved 81.3% success rate.

Table 4- The Margin calculated in EEMD with different amplitude (Y direction)

Method	Ampitude of added noise	100 Hz 1.0 kN	100 Hz 1.4 kN	100 Hz 1.8 kN	200 Hz 1.0 kN	200 Hz 1.4 kN	200 Hz 1.8 kN	300 Hz 1.0 kN	300 Hz 1.4 kN	300 Hz 1.8 kN	400 Hz 1.0 kN	400 Hz 1.4 kN	400 Hz 1.8 kN
EMD		1.1684	1.0417	**0.6961**	1.2276	0.8157	**0.7156**	0.9656	**0.7523**	0.8620	0.8438	**0.7013**	**0.7109**
EEMD	0.3	1.2248	1.1168	**0.8136**	1.3011	0.8000	**0.6922**	1.2131	**0.8100**	0.9289	1.0498	0.8895	0.9143
EEMD	0.5	1.2162	1.1324	**0.8112**	1.3009	**0.7000**	**0.6372**	1.2868	1.0633	0.9100	0.8995	0.8779	0.9069
EEMD	0.6	1.2388	1.1706	**0.7633**	1.3019	**0.7693**	**0.7099**	1.2880	1.0276	0.9312	0.9056	0.8980	0.9543
SNR	10	1.1627	1.0881	0.8863	1.2660	0.8095	**0.6854**	1.1806	0.8123	0.8628	0.9342	0.8768	0.9274
SNR	20	1.2519	1.1192	**0.7303**	1.2750	0.9342	0.7749	1.0344	**0.6806**	0.8959	0.8668	0.8547	0.7864

Table 5- Reliability test of constructed SVM with 20 new samples (Y direction)

Method	Ampitude of added noise	100 Hz 1.0 kN	100 Hz 1.4 kN	100 Hz 1.8 kN	200 Hz 1.0 kN	200 Hz 1.4 kN	200 Hz 1.8 kN	300 Hz 1.0 kN	300 Hz 1.4 kN	300 Hz 1.8 kN	400 Hz 1.0 kN	400 Hz 1.4 kN	400 Hz 1.8 kN
EMD		100	100	**75**	100	100	**80**	100	**85**	100	100	**85**	**65**
EEMD	0.3	100	100	**90**	100	100	**80**	100	**90**	100	100	100	100
EEMD	0.5	100	100	**90**	100	**85**	**75**	100	100	100	100	100	100
EEMD	0.6	100	100	**85**	100	**85**	**80**	100	100	100	100	100	100
SNR	10	100	100	100	100	100	**80**	100	100	100	100	100	100
SNR	20	100	100	**80**	100	100	**90**	100	**80**	100	100	100	100

Table 6- The Margin calculated in EEMD with new proposed amplitude, SNR=10 (defective inner ring)

Direction	100 Hz 1.0 kN	100 Hz 1.4 kN	100 Hz 1.8 kN	200 Hz 1.0 kN	200 Hz 1.4 kN	200 Hz 1.8 kN	300 Hz 1.0 kN	300 Hz 1.4 kN	300 Hz 1.8 kN	400 Hz 1.0 kN	400 Hz 1.4 kN	400 Hz 1.8 kN
Y	1.2186	0.8674	1.4268	1.3744	1.2852	1.0538	1.3522	1.1211	0.8542	1.2552	1.2583	0.8326
Z	1.2603	0.8788	1.3713	1.3391	0.9743	**0.7350**	1.2272	1.0937	1.1128	1.1918	1.1989	1.3516

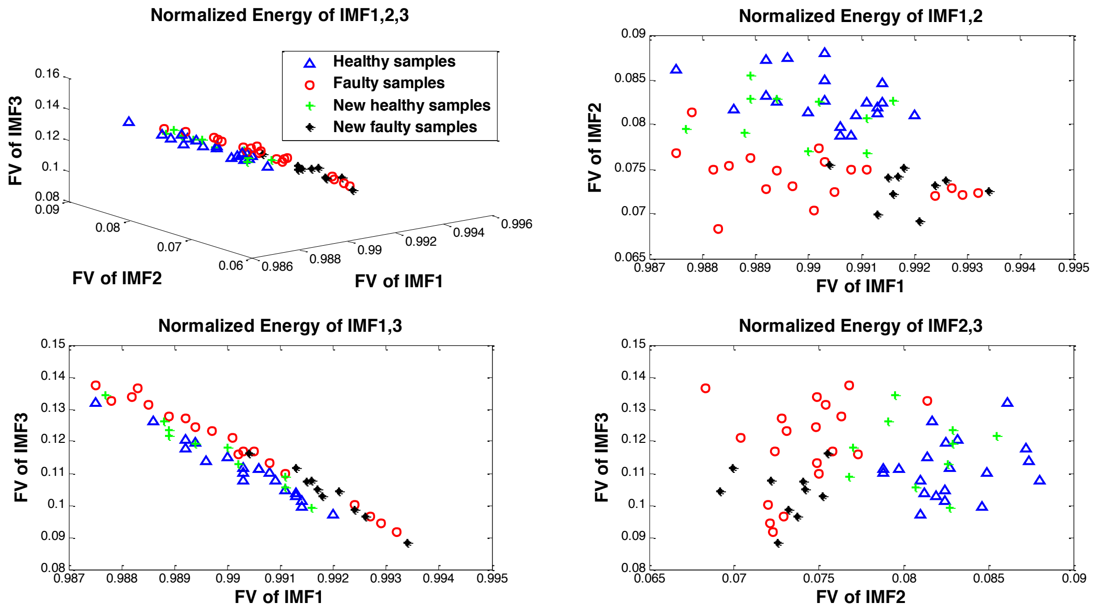

Figure 6- Normalized energy of IMFs with new samples, SNR=20 (speed: 200Hz and load: 1.8 kN)

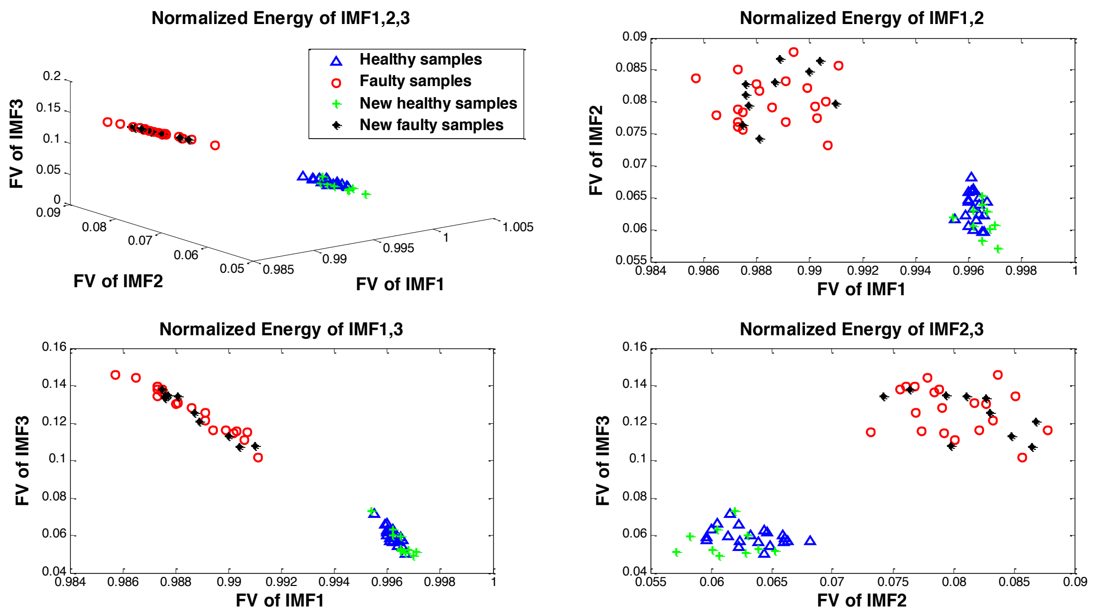

Figure 7- Normalized energy of IMFs with new samples, SNR=10 (speed: 200Hz and load: 1.0 kN)

8. Conclusion

Obviously, for EEMD (which is a noise assisted method to solve mode mixing problem exists in EMD), there is no robust guide to select an optimal amplitude for the added noise, which is very important, especially for early damage detection (very small defects). In this study instead of using previously suggested amplitudes which are predefined and constant, a reliable method is investigated to determine a suitable amplitude. Vibration signals of various operating conditions are analyzed for three bearings with different states: healthy, with very small fault on a roller and small defect on inner ring.

It is shown that by applying the proposed amplitude calculating algorithm (especially with SNR=10), there are considerable improves in accuracy of damage detection for both defective bearings, in comparison with predefined constant amplitudes. Exploring reliability of the obtained success rates, Margin of each SVM classification is calculated and it is confirmed that for those conditions whose Margin is relatively high, the results are more reliable.

For the defective inner ring, the acceleration signals of two radial directions are investigated to achieve more confidant results and it is validated that the proposed algorithm looks reliable and can be favorably applied instead of the previous pre-determined approach.

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