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ENSEMBLE EMPIRICAL MODE DECOMPOSITION (EEMD) AND TEAGER-KAISER ENERGY OPERATOR (TKEO) BASED DAMAGE IDENTIFICATION OF ROLLER BEARINGS USING ONE-CLASS SUPPORT VECTOR MACHINE

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ABSTRACT

Ensemble empirical mode decomposition (EEMD) is a newly developed noise assisted method aimed to solve mode mixing problem exists in empirical mode decomposition (EMD) method. Although EEMD has been utilized in various applications successfully, small defects of bearings are not able to be detected, especially in automatic defect detection, when only healthy samples are available for training. Teager-Kaiser energy operator (TKEO) technique is a non-linear operator that can track the energy and identify the instantaneous frequencies and instantaneous amplitudes of signals at any instant. As Teager-Kaiser energy operator (TKEO) technique detects a sudden change of the energy stream without any priori assumption of the data structure, it can be utilized for vibration based condition monitoring (non-stationary signals).

In this study it is investigated whether an automatic method is able to diagnose a small defect level of roller bearings through processing of the acquired signals. After applying TKEO on IMFs decomposed by means of EEMD, the extracted informative feature vectors of the healthy bearing are used to construct the separating hyperplane using one-class support vector machine (SVM). Then, success rates of state identification of both samples (healthy and faulty) are examined by labelling the samples. The data were generated by means of a test rig assembled in the labs of the Dynamics & Identification Research Group (DIRG) at mechanical and aerospace engineering department, Politecnico di Torino. Various operating conditions (three shaft speeds, three external loads and one small size damage on a roller) were considered to obtain reliable results.

KEYWORDS : *Roller bearing, Fault diagnosis, Ensemble empirical mode decomposition (EEMD), Teager-Kaiser energy operator (TKEO), One-class SVM*

INTRODUCTION

Early fault diagnosis of roller bearings is extremely important for rotating machines, especially for high speed, automatic and precise machines. Vibration based condition monitoring is the most experienced method to extract some important information to identify defective bearings. Empirical mode decomposition (EMD), a recently introduced technique, decomposes a signal into several intrinsic mode functions (IMFs) [1] 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 aimed to solve mode mixing problem which is a consequence of applying EMD [2]. Although EEMD has been utilized in various fault diagnosis applications successfully, there are still some cases that it is not able to reveal informative features such as detecting health condition of a rotating machine based on just previous healthy conditions.

Teager-Kaiser energy operator (TKEO) technique is a non-linear operator that can track the energy and identify the instantaneous frequencies and instantaneous amplitudes of signals at any instant. Teager [3] proposed TEKO first for modeling nonlinear speech production. Kaiser [4] applied it to

single time varying signals, for simultaneous modulation of amplitude and frequency. As it detects a sudden change of the energy stream without any priori assumption of the data structure, it can be utilized for vibration based condition monitoring (non-stationary signals).

Junsheng et al. [5] applied TKEO to each IMFs decomposed by EMD to extract the instantaneous amplitudes and frequencies. Then envelope spectra were obtained using the spectrum analysis to look for characteristic frequencies of damaged roller bearings. Li et al. [6] applied TKEO to the original vibration signals, instead of decomposed IMFs, and characteristic frequencies were extracted from envelope spectra. They also implemented a novel method to recognize faults of roller bearing based on Teager-Huang transform (THT) [7]. This method is based on empirical mode decomposition (EMD) and Teager-Kaiser energy operator (TKEO) technique. In all those studies, it was investigated to identify a kind of big damage size (1mm in depth 1.5mm width of the groove). Feng et al. [8] utilized the Fourier spectrum of Teager energy to identify the characteristic frequency of faulty bearings with very big defect sizes (2mm diameter and 1mm depth). Liu et al. [9] presented an approach to bearing fault diagnosis based on TKEO and Elman neural network. Wavelet packet was used to reduce noise existing in the Teager energy signal, and then feature vectors were extracted from the Teager spectrum. Rodriguez et al. [10] transformed the vibration signal to the Teager-Kaiser domain and featured it with statistical and energy-based measures. The diagnosis was performed with neural network and least square support vector machine (LS-SVM). Kwak et al. [11] applied TEKO in a combination with minimum entropy deconvolution (MED) to detect a defective roller bearing in terms of Kurtosis.

There are various techniques for automatic fault diagnosis, such as artificial neural network (ANN) and SVM introduced by Vapnik [12]. SVM is a relatively new computational learning method based on statistical learning theory which has been applied successfully to numerous applications [13]. It can solve the learning problem with a smaller number of samples. Thus, taking into account the fact that acquiring sufficient faulty samples is not applicable in practice, SVM has been used in numerous fault diagnosis problems successfully [14]. As in many diagnostic applications, there is only one type of data (the healthy one), one-Class SVM proposed by Scholkopf et al. [15] can be adopted for anomaly detection [16].

In this study a new method is proposed to detect the state of roller bearings. TKEO is applied on IMFs of a healthy signal decomposed by means of EEMD and extracted features are used to construct the separating hyperplane using one-class support vector machine (SVM). Numerous healthy and faulty acceleration signals are analyzed to verify proposed algorithm in automatic fault diagnosis using one-class SVM.

1 ENSEMBLE EMPIRICAL MODE DECOMPOSITION (EEMD)

Decomposition using EEMD consists of following steps [2]:

- a) To add a random white noise signal to the acquired original signal:

$$\mathbf{x}_j(t) = \mathbf{x}(t) + \text{Amp} \cdot \mathbf{n}_j(t) \quad j = 1, 2, 3, \dots, M \quad (1)$$

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:

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

where \mathbf{c}_{ij} denotes the i -th IMF of the j th 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 $I = \min(N_1, N_2, \dots, N_M)$ and calculate the ensemble means of corresponding IMFs of

the decompositions as the final result (\mathbf{c}_i):

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

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

2 TEAGER-KAISER ENERGY OPERATOR (TKEO)

TKEO is a powerful nonlinear operator which is defined for a continuous time signal $x(t)$ as [17]:

$$\Psi[x(t)] = [\dot{x}(t)]^2 - x(t)\ddot{x}(t) \quad (4)$$

where $\dot{x}(t)$ and $\ddot{x}(t)$ are the first and the second time derivatives of $x(t)$, respectively.

For a discrete time signal $x(n)$ (where n is the discrete time index), using difference to approximate differential, TKEO can be proposed as [17]:

$$\Psi[x(n)] = x^2(n) - x(n+1).x(n-1) \quad (5)$$

As at any instant, only three consecutive samples are needed to estimate the instantaneous TKEO, it is adaptive to the instantaneous changes in signals and is able to resolve transient events.

The instantaneous frequency and instantaneous amplitude at any time instant of the signal $x(n)$ can be given as [18]:

$$f(n) = \frac{1}{2} \arccos \left(1 - \frac{\Psi[x(n+1) - x(n-1)]}{2\Psi[x(n)]} \right) \quad (6)$$

$$|a(n)| = \frac{2\Psi[x(n)]}{\sqrt{\Psi[x(n+1) - x(n-1)]}} \quad (7)$$

3 ONE-CLASS SUPPORT VECTOR MACHINE

One-class SVM tries to construct the separating hyperplane with only one class of data and label samples belong to any other possible classes as outliers [15]. It constructs a hyperplane around the data, such that its distance to the origin is maximal among all possible hyperplanes. A binary function is used that returns +1 in region containing the data and -1 elsewhere.

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 ($\mathbf{K}(x_i, x_j) = \Phi(x_i) \cdot \Phi(x_j)$) 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.

To separate the data set from the origin, the following quadratic program must be solved [15]:

$$\min \left(\frac{1}{2} \|\mathbf{w}\|^2 + \frac{1}{\nu \ell} \sum_{i=1}^N \xi_i - \rho \right) \quad (8)$$

$$\text{Subject to } y_i \langle \mathbf{w}, \Phi(x_i) \rangle \geq \rho - \xi_i, \quad \xi_i \geq 0$$

where ξ_i is slack variable and measuring the distance between the hyperplane and the examples that laying in the wrong side of the hyperplane, ν is a variable taking values between 0 and 1 that monitors the effect of outliers (hardness and softness of the boundary around data). It is upper bound on the fraction of training errors and a lower bound on the fraction of support vectors relative to the

total number of training samples. w and ρ are the weight vector and offset parameterizing the hyperplane.

Introducing Lagrange multipliers and solving the dual optimization problem, non-linear decision function will be [15]:

$$f(x) = \text{sign}\left(\sum_{i=1}^N \alpha_i \mathbf{K}(x, x_i) - \rho\right) \quad (9)$$

There are different kinds of kernel functions such as radial basis function:

$$\mathbf{K}(x, x_i) = \exp(-\gamma \|x - x_i\|^2) \quad (10)$$

where γ is the kernel parameter to be set for a specific problem.

4 METHODOLOGY

The goal of this study is to evaluate performance of the proposed algorithm in condition detection for various operating conditions of a roller bearing.

The fault diagnosis method is given as the following:

- 1) To collect acceleration signals of healthy and defective bearings at three different external loads and three shaft speeds.
- 2) To apply EEMD 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 apply TKEO to decomposed the first m IMFs.
- 4) To calculate sum of each TKEO.

$$\text{TKE}_i = \sum_{i=1}^m \Psi(\text{IMF}_i) \quad (11)$$

- 5) To create a feature vector with the sum of the calculated TKEO:

$$\mathbf{FV} = [\text{TKE}_1, \text{TKE}_2, \dots, \text{TKE}_m] \quad (12)$$

- 6) To normalize the feature:

$$\mathbf{FV}_n = [\text{TKE}_1 / \text{TKE}, \text{TKE}_2 / \text{TKE}, \dots, \text{TKE}_m / \text{TKE}] \quad (13)$$

where $\text{TKE} = (\sum_{i=1}^m \text{TKE}_i)$.

- 7) To carry out the training procedure of one-class SVM by utilizing the normalized feature vectors. The 80% of healthy samples are used for training and the rest (remaining healthy samples and all faulty data) are taken as the test samples.
- 8) After training procedure successfully, it would be ready to test samples to identify the different work conditions and fault patterns.

5 EXPERIMENT

The bearing data set (acceleration signals) were collected under various operating conditions using the test rig (Figure 1) 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. The small artificial defect severity over one roller was 450 microns in diameter. Three different shaft speeds (100, 200, 300 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 Figure 1 so that x , y and z axis corresponds to the axial, radial and tangential direction, respectively.

The original acquired healthy signals were divided into 30 segments (20 segments for defective bearing) including 10000 data points each, to extract required informative feature vectors. Thus,

each healthy signal includes 30 segments which create 30 feature vectors (20 feature vectors for defective bearing) 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 1- DIRG test rig, the triaxial accelerometers (X, Y, Z) and the damaged roller used in the tests

6 ANALYSIS

An acquired acceleration signal, its three first IMFs (decomposed using EEMD) and TKEO of those IMFs are shown in Figure 2. Implementing the methodology described in section 4, feature vectors for each algorithm are obtained: normalized energy of IMFs for EMD and EEMD methods (just using only first three elements of the feature vectors [19]) and normalized TKEO for the proposed method. 0.3 of standard deviation of each original signal is used as appropriate amplitude of added noise in EEMD method [19].

As it can be seen in in Figure 3, there is confusion among healthy and faulty samples. Although EEMD achieves more reliable separation, the best results are obtained using the proposed method. In Table 1-3, it is shown the results of classification (for shaft speed=100, 200 and 300 Hz) using one-class SVM. The best values of parameters (γ and ν) are presented for each methods.

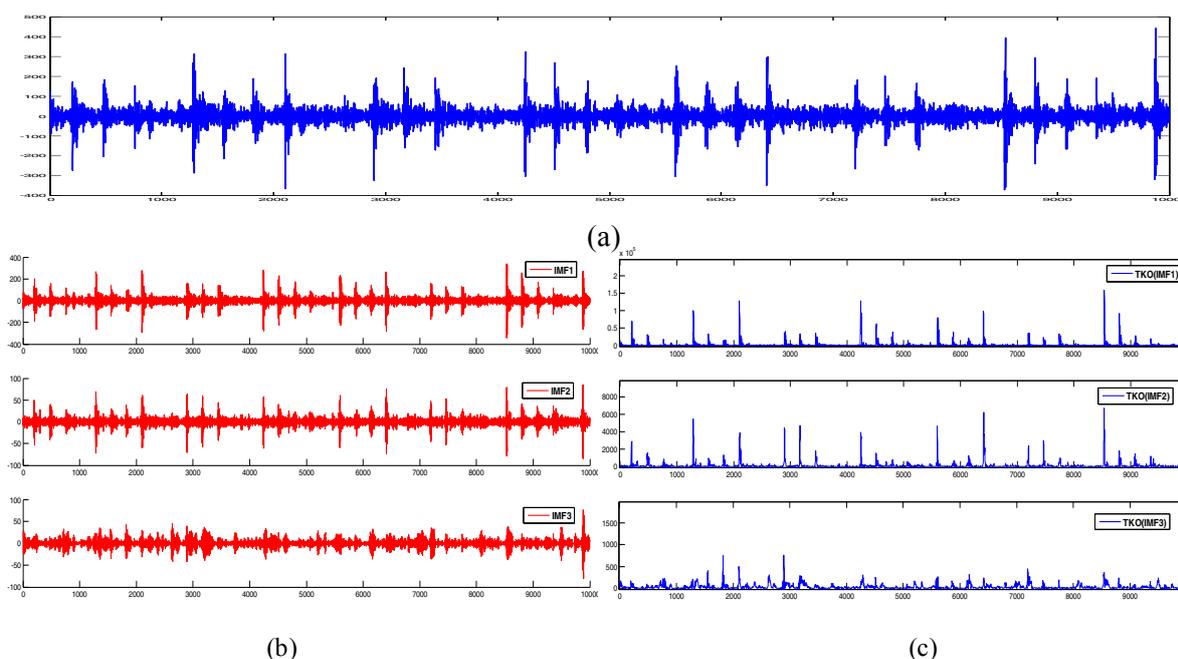
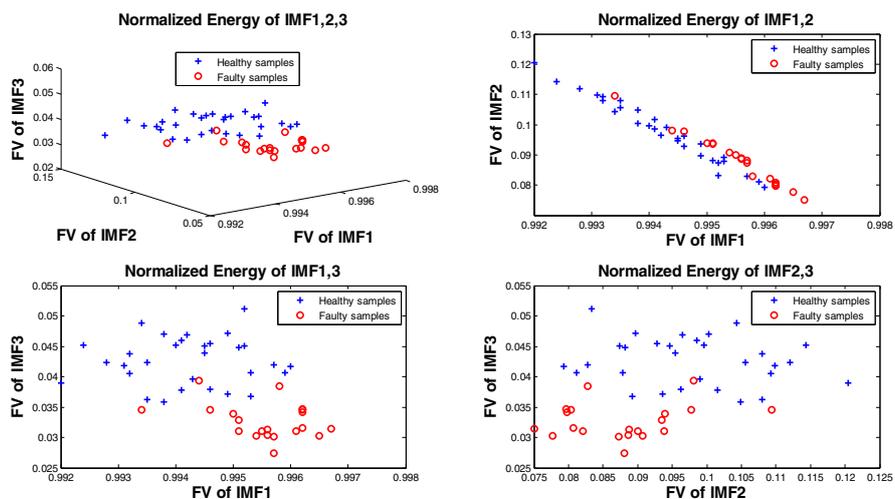
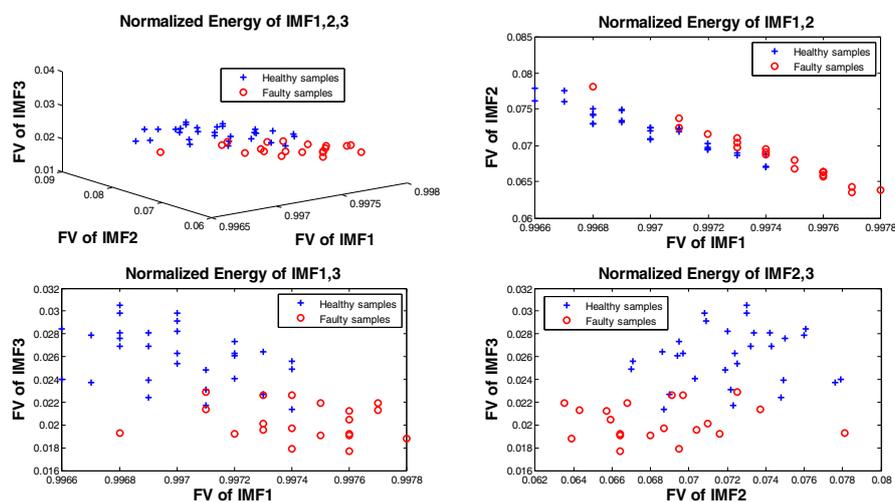


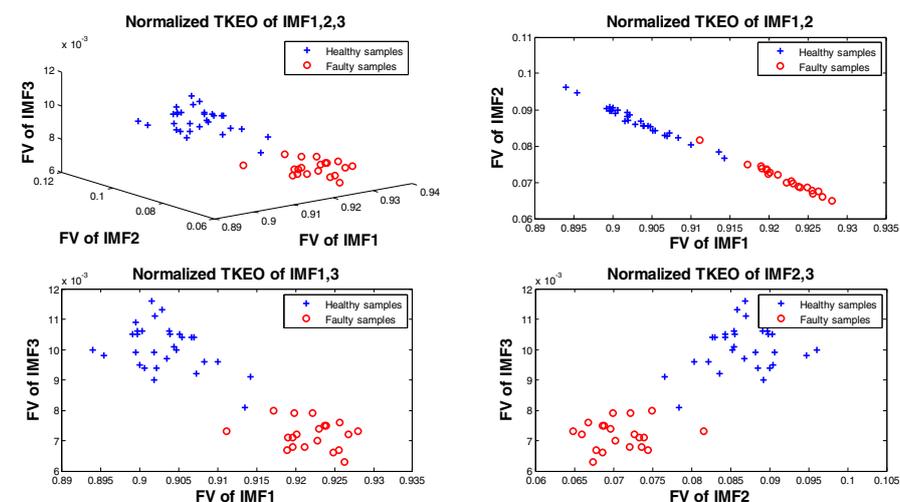
Figure 2- Acceleration signal (a), first three IMFs (b) and TKEO of those IMFs (c)



(a)



(b)



(c)

Figure 3- Normalized energy of IMFs decomposed (a) using EMD and (b) EEMD and (c) normalized TKEO feature (speed: 300Hz and load: 1.0 kN).

The classification results obtained using the proposed method, are higher in most cases so that in some cases there is a great changes. For example, in 300 Hz speed and 1.0 kN load, it improves the test success rate 15.4% and the training success rate 4.2% in comparison with EEMD method. The significant improvements are achieved in lower speed and higher load (100 Hz and 1.8 kN) and in higher speed and lower load (300 Hz and 1.0 kN). There is just one condition that the test results is a bit lower that EEMD technique (200 Hz speed and 1.4 kN load).

If energy of each IMFs which are calculated based on instantaneous amplitude (Eq. 7) are used as the feature vectors, Instead of using the previously utilized feature vector (Eq. 11, 13), in some cases, higher success rates is achieved such as a perfect success rate in 200 Hz speed and 1.0 kN load. However, in the most cases very low and unacceptable success rates are obtained such as 83.3% for the training and 65.4% for the test in the operating condition that speed is 200 Hz and load is 1.0 kN load.

Table 1- Results of classification for best value of parameters (Shaft speed: 100Hz)

| Method | Load | | | | | | | | | | | |
|-----------|----------|-------|----------|------|----------|-------|------------|------------|----------|-------|------------|-------------|
| | 1.0 kN | | | | 1.4 kN | | | | 1.8 kN | | | |
| | γ | ν | training | test | γ | ν | training | test | γ | ν | training | test |
| EMD | 0.1 | 0.1 | 100 | 96.2 | 0.1 | 0.1 | 95.8 | 92.3 | 0.05 | 0.1 | 95.8 | 84.6 |
| EEMD | 0.1 | 0.1 | 100 | 96.2 | 0.05 | 0.1 | 100 | 100 | 0.3 | 0.05 | 100 | 76.9 |
| EEMD+TKEO | 0.1 | 0.3 | 100 | 96.2 | 0.5 | 0.1 | 100 | 96.2 | 0.5 | 0.05 | 100 | 92.3 |

Table 2- Results of classification for best value of parameters (Shaft speed: 200Hz)

| Method | Load | | | | | | | | | | | |
|-----------|----------|-------|------------|-------------|----------|-------|-------------|-------------|----------|-------|------------|------------|
| | 1.0 kN | | | | 1.4 kN | | | | 1.8 kN | | | |
| | γ | ν | training | test | γ | ν | training | test | γ | ν | training | test |
| EMD | 1.5 | 0.05 | 100 | 80.6 | 0.1 | 0.3 | 91.7 | 50.0 | 0.6 | 0.1 | 100 | 96.2 |
| EEMD | 0.05 | 0.3 | 100 | 84.6 | 0.3 | 0.5 | 91.7 | 57.7 | 0.9 | 0.1 | 100 | 100 |
| EEMD+TKEO | 0.001 | 0.1 | 100 | 88.5 | 0.001 | 0.5 | 91.7 | 65.4 | 0.3 | 0.1 | 100 | 100 |

Table 3- Results of classification for best value of parameters (Shaft speed: 300Hz)

| Method | Load | | | | | | | | | | | |
|-----------|----------|-------|------------|-------------|----------|-------|------------|-------------|----------|-------|------------|-------------|
| | 1.0 kN | | | | 1.4 kN | | | | 1.8 kN | | | |
| | γ | ν | training | test | γ | ν | training | test | γ | ν | training | test |
| EMD | 0.05 | 0.1 | 87.5 | 73.1 | 0.4 | 0.5 | 87.5 | 73.1 | 0.01 | 0.1 | 95.8 | 92.3 |
| EEMD | 0.05 | 0.3 | 95.8 | 80.8 | 0.05 | 0.5 | 87.5 | 92.3 | 0.1 | 0.3 | 100 | 92.3 |
| EEMD+TKEO | 0.05 | 0.3 | 100 | 96.2 | 0.05 | 0.1 | 100 | 96.2 | 0.01 | 0.3 | 100 | 92.3 |

CONCLUSION

It has been shown that using EMD and EEMD does not lead to a perfect condition detection when just healthy samples of a bearing are used to construct the separation hyperplane (one-class classification). There would be a noticeable improvement when informative features vectors defined based on TKE of three first IMFs are used as the input data of one-class SVM. The significant improvements are obtained in lower speed and higher load (100 Hz and 1.8 kN) and in higher speed and lower load (300 Hz and 1.0 kN).

Using feature vectors calculated based on energy of instantaneous amplitude obtained by TKEO of IMFs; do not achieve an appropriate change. The results of most cases are lower than the results of EEMD or even EMD.

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