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# Clustering Optimized Analytic Vibration Signal of Rolling Bearing Faults Using K- Means Algorithm

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**Abstract:** This paper presents a new method for the classification of vibration signals of bearings faults of induction motor using the time-frequency dependent class signal "RTFDCS". First, we have normalized the analytical vibration signals of bearing faults by Hilbert transforms. The vectors form extraction realized by RTFDCS. The Fisher contrast is used to design the nonparametric kernel RTFDCS that is deliberately designed to maximize separability between classes and minimize the intra-class variance and the optimization of the size of these vectors by the particle swarm optimization PSO algorithm. These processing results give us a separation between the classes that is validated by k-means clustering algorithm. The vibration data that were used for analysis are obtained from the Case Western Reserve University Bearing Data Center.
**Keywords**: Classification, Time-frequency representation, Bearing faults, Vibration signals, Hilbert transform, K- means algorithm.

## Introduction

Fault diagnosis is often confronted with the problem of extracting vectors forms (Commonly known as a characteristics vector) that are relevant to the small size and best possible representation of the fault state. Several approaches have been discussed in the literature is the most a view pattern recognition [1-2], principal component analysis (PCA) and time-frequency representation [3]. In the traditional classification, data were often transformed into a Time-Frequency Representation (TFR) standard (eg the spectrogram or the Wigner-Ville TFR), then a projection was applied to the TFR for reach a reduced dimension of the space [4-5]. In diagnosis of rotating machinery, vibration analysis is widely known to be one of the most effective techniques. This stems from the fact that oscillation is an inherent characteristic of rotating machines and different components of these types of machinery such as shafts, bearings and gears produce vibration energy with different characteristics. Any deterioration in the condition of such components can affect their vibratory attributes and manifest itself in the vibration signature. This allows diagnosis of machine faults by analyzing the vibration signature of the system.

For improved and authentic fault diagnosis using vibration analysis techniques it is necessary that the acquired vibration signals be 'clean' enough that small changes in signal attributes due to an impending fault in any component can be detected. To tackle this problem, we have developed a method based on the cloud point's dispersion parameter.

In this article, we used the vibration analytical signals normalized by Hilbert transform of bearing fault of induction motor, then the extracting vibration vectors forms from RTFDCS. It is deliberately designed to maximize separability between classes and minimize the intra-class variance. Fisher contrast is used to design the kernel nonparametric RTFDCS, and recently the optimization of the size of these vectors by the PSO algorithm [7].

**Classification Procedure**

The procedure comprises three essential tasks, the first task consist in the Pretreatment data axial vibration for a machine bearing faults, the second part consists in the extraction of axial vibration signals of pertinent points classified into a vector known as forms, this Extraction is performed by TFR [5]. Because the whole points of the vector are not all interesting, we sum spread a optimized these vectors at the last spot optimized by the PSO algorithm [7-8].

**Vibratory Data Treatment by Hilbert Transform**

This representation is commonly used in image processing, where the phase of signal contains more relevant information as the module. Therefore on this principle and for the diagnostic necessary of the asynchronous machine [9] used a phase analysis of the spectrum, and concluded that the information by the phase may be relevant indicative a presence of a fault. in the time domain, The Hilbert transform is the convolution of the signal with $(1/t)$ and can underline local properties, as follows:

$$H[x(t)] = \frac{1}{\pi} \int_{-\infty}^{+\infty} \frac{x(t)}{t-\tau} d\tau = \frac{1}{\pi} x(t) \frac{1}{t} \qquad (1)$$

Where t is time, $x(t)$ is a signal in the time domain and $H[x(t)]$ is Hilbert transformed. From a signal $x(t)$ and its Hilbert transform $H[x(t)]$ is obtained the amplitude of signal:

$$A[x(t)] = x(t) + jH[x(t)] = a(t) \cdot e^{j\phi(t)} \qquad (2)$$

The amplitude of the analytical representing the instantaneous amplitude of signal (or envelope) of signal when the signal represents the instantaneous phase, which formulas are given their by:

$$a(t) = \sqrt{x^2(t) + H^2[x(t)]} \qquad (3)$$

$$\phi(t) = \arctan \frac{H[x(t)]}{x(t)} \qquad (4)$$

The use of the Hilbert transform for the phase analysis is applied to the modulus of the spectrum of the Fourier transform of the signal $x(t)$. Indeed, its analytical signal is given by:

$$A[x(f)] = x(f) + jH[x(f)] \qquad (5)$$

The phase of the analytic signal can be expressed by:

$$\phi(f) = \arctan \frac{H[x(f)]}{x(f)} \qquad (6)$$

**Vectors Forms Optimization by PSO**

The particle swarm optimization (PSO) algorithm is a search process based populations where individuals, referred to as particles, are grouped in a swarm. Each particle in the swarm represents a candidate solution to the optimization problem [10], [11-12]. In a PSO system, each particle is "controlled" in the multidimensional space search, adjusting its position in space according to its own experience and that of neighboring particles [13]. A particle is, therefore, produced by the best position itself and its neighbors to move towards an optimum solution. This shift occurs following a path defined by a fitness function (or objective function) which encapsulates the characteristics of the optimization problem.

## Results and Discussion

### *Data Acquisition*

The vibration data that were used for analysis are obtained from the Case Western Reserve University Bearing Data Center [14]. Reliance Electric's 2-hp motor, along with a torque transducer, a dynamometer, and control electronics, constitutes the test setup. With the help of electrostatic discharge machining, faults of sizes of 0.177 mm (0.07 in) and 0.533 mm (0.21 in) are made. The vibration data are collected using accelerometers placed at the three-o'clock position. The rotational frequency (Fr) is 29 Hz. The figures 2,3and 4 present respectively; Bearing vibration data for four signals (healthy bearing, inner race, ball and outer faults bearing), spectrumsand periodogram for each signals

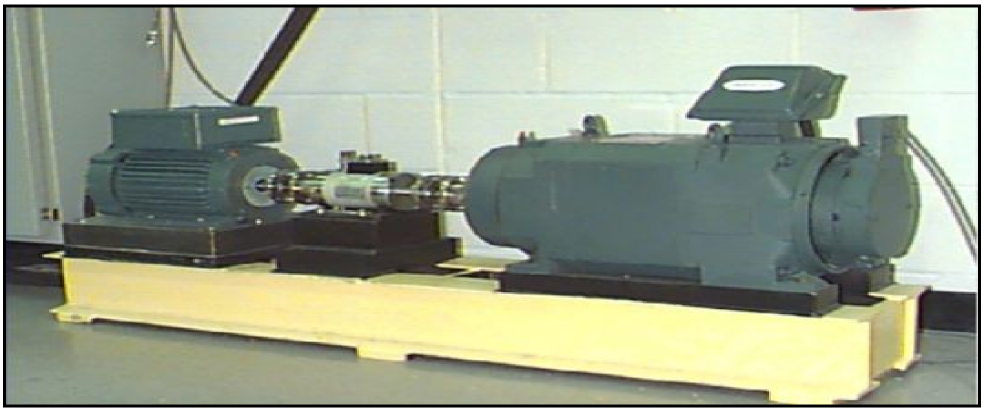


**Figure 1. The test bearings support the motor shaft [14].**

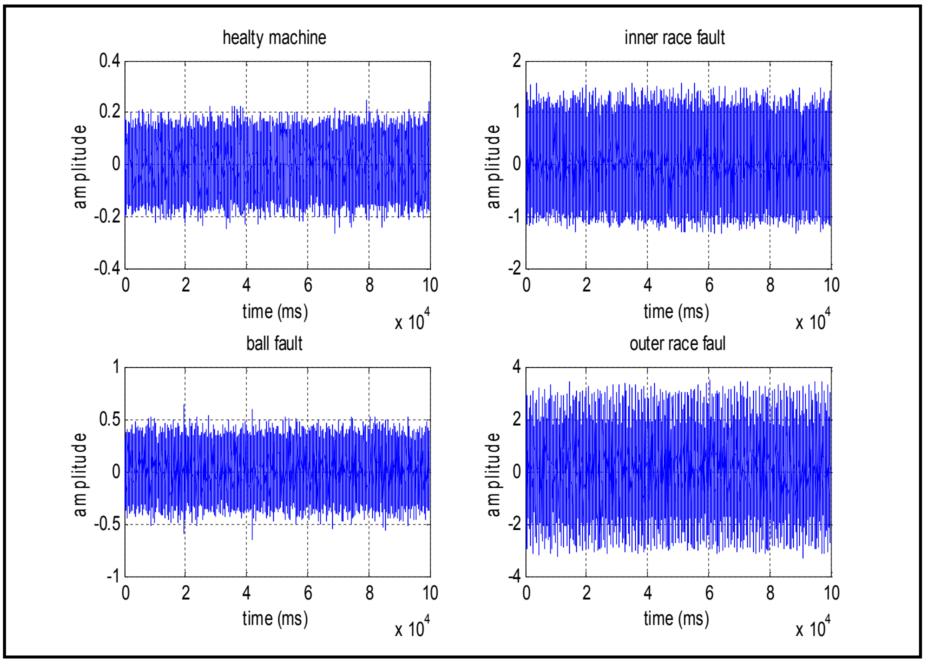



**Figure 2. Bearing vibration data**

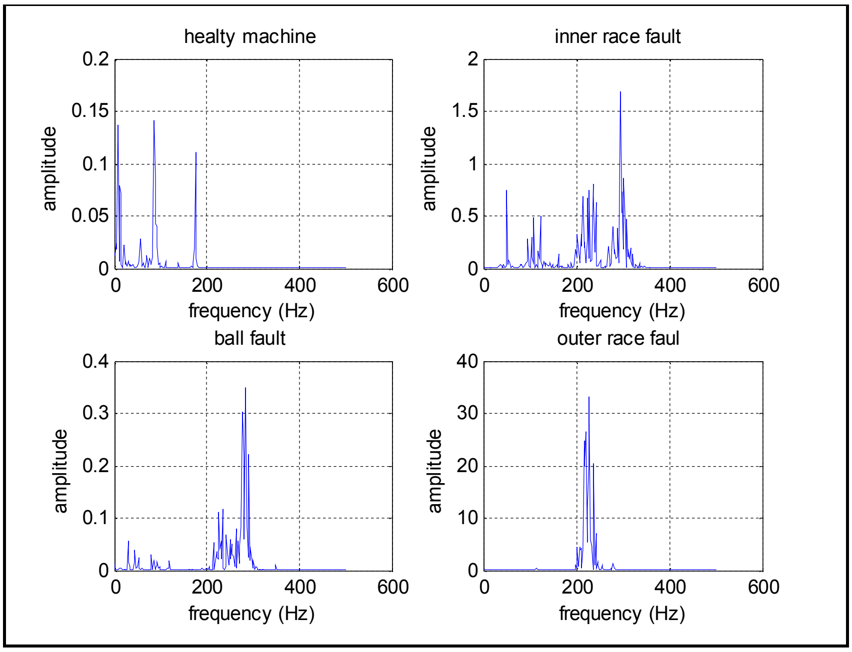



**Figure 3. Bearing vibration data spectrums**

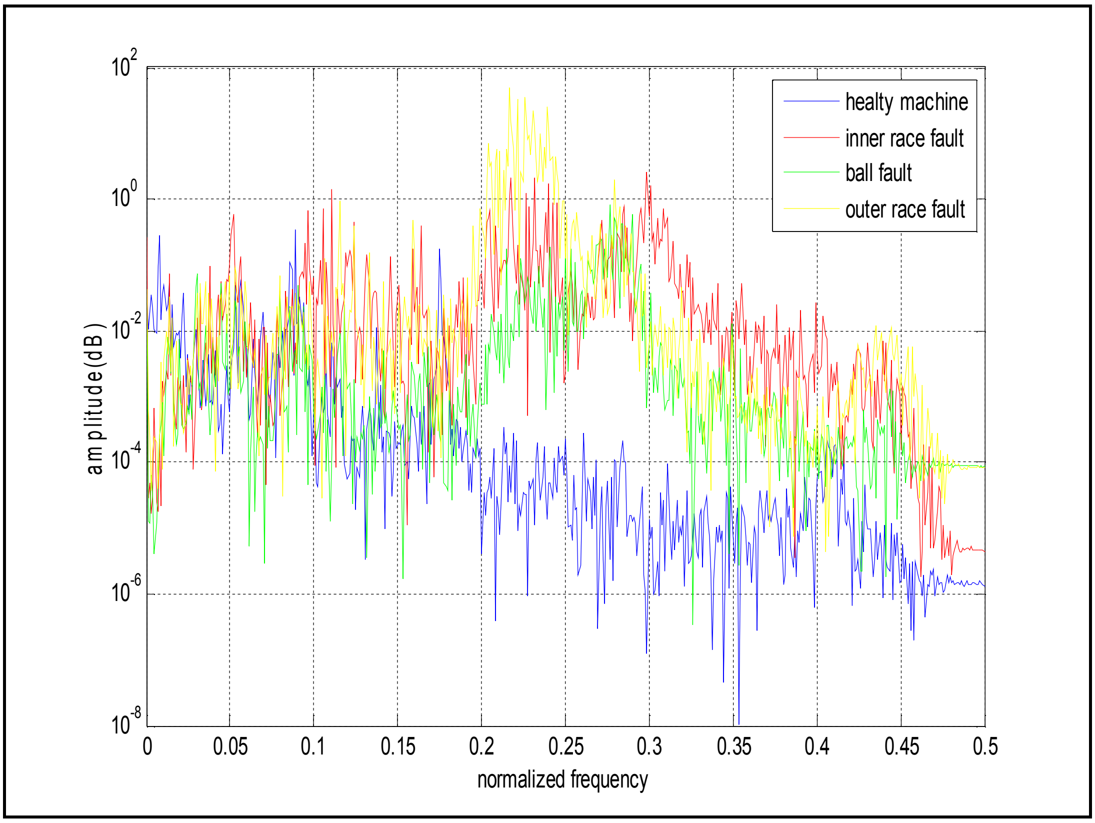



**Figure4. Bearing vibration data periodograms Classification of Analytical Vibratory Signal Bearing The Optimization**

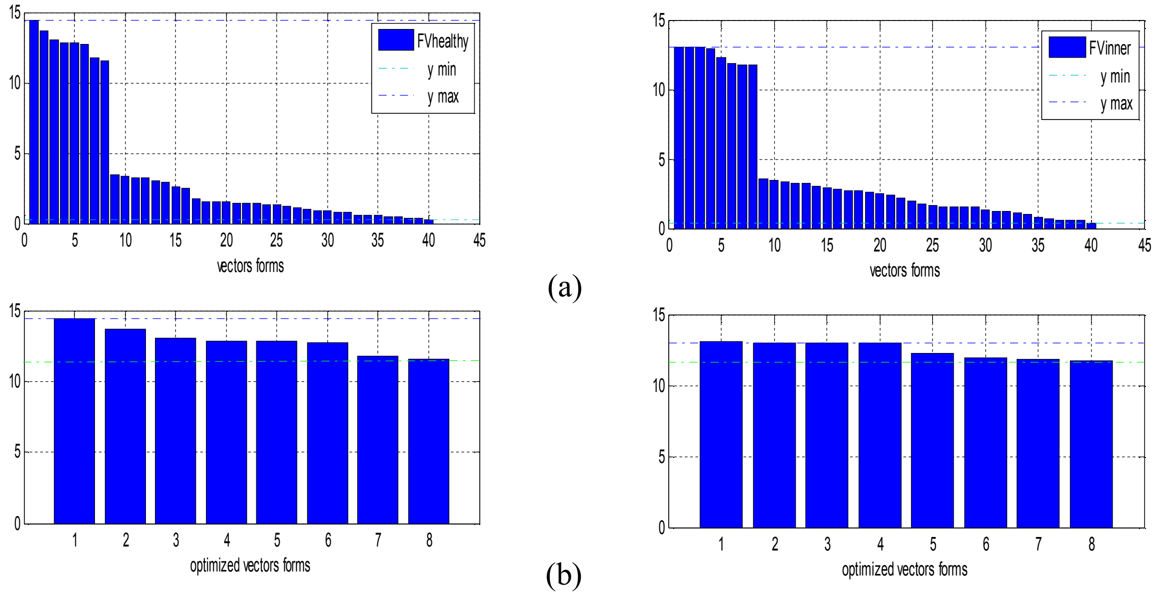
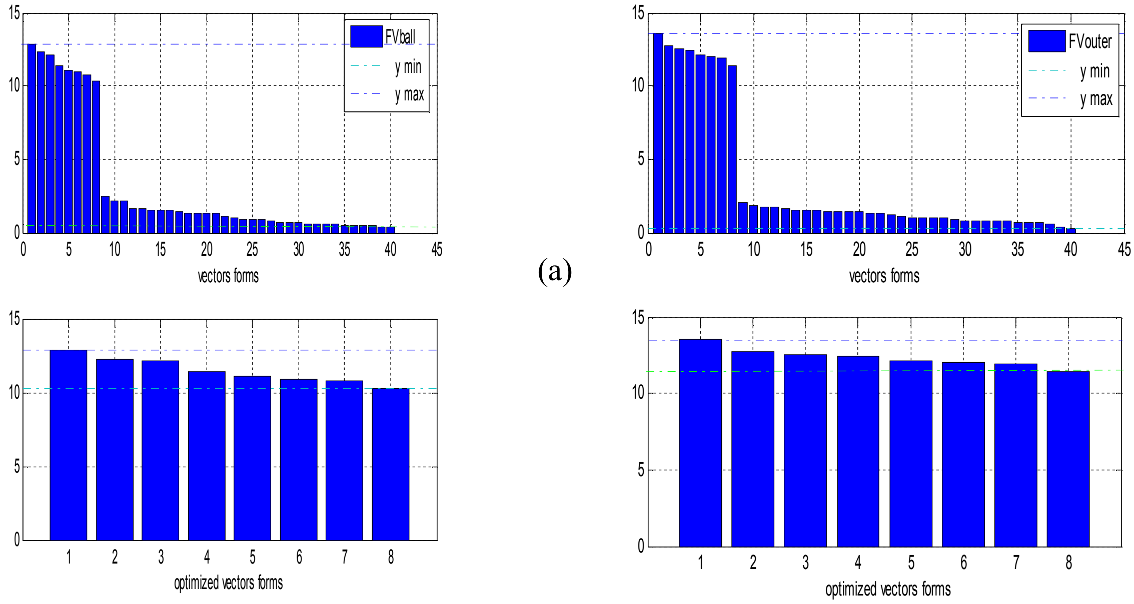
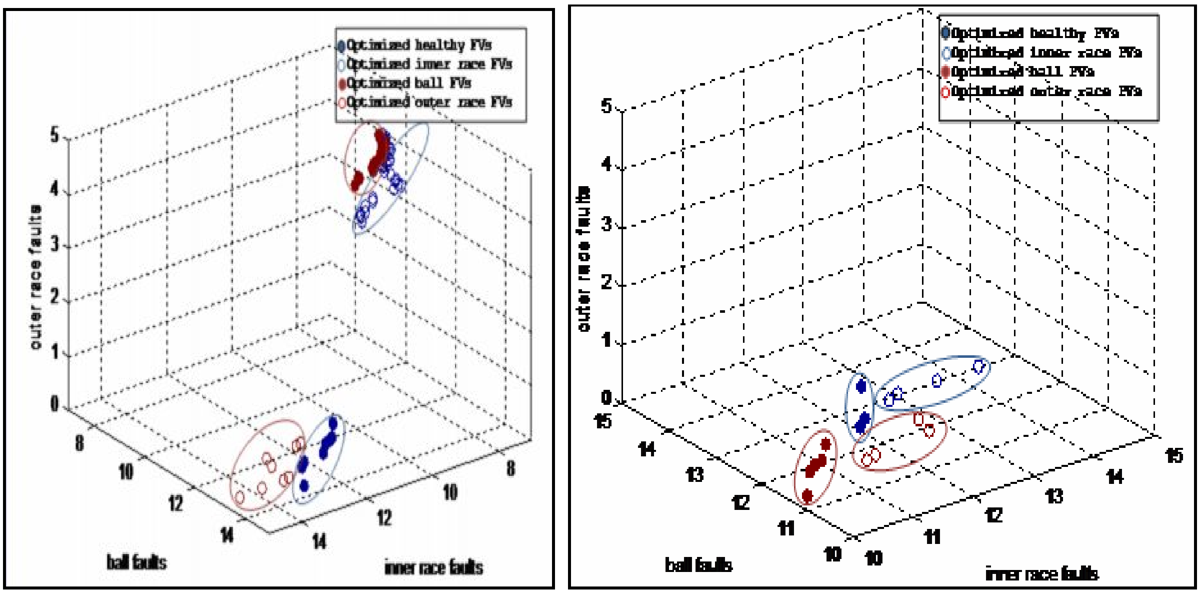



**Figure.5 Vectors forms of healthy bearing and Vectors forms of inner race faults (a) befor optimization (b)after optimization**




(b)

**Figure.6. Vectors forms of ball faults and Vectors forms of outer faults (a) before optim ization (b)after optimization**




(a) (b)

**Figure 7.k means clustering for vector forms ofhealthy bearing, inner race, ball and outer faults bearing: (a) before optimization (b) after optimization**

## Discussion

Since, we cannot use the Analytics vibration signals (AVS) directly due to their very low values. We have proposed pretreatment methods before TFR. We have proposed a method for calculating a parameter very interesting to know the parameter $\xi$ of the cloud dispersion of points. This parameter is used to calculate the TFR and extraction vectors forms.

The Optimization of vectors forms for four class's healthy bearing, inner race, ball and outer faults bearing will be due by Particle Swarm optimization algorithm. With the optimization criterion, the optimization of vectors forms will be fitting and executing to extract pertinent points.

Figures 6,7,8 and 9 have a representation of vectors forms for four classes healthy bearing, inner race, ball and outer faults bearing before and after optimization by Particle Swarm optimization algorithm. We were able to reduce the size of point in the vectors forms in classes. before optimization, each classes is characterized by four vectors forms and each vectors forms comported ten points (element) relevant called scores or high contrast in the sense of Fisher. after optimization, each classes is characterized by four vectors forms and each vectors forms comported only two points (element) relevant also called scores or high contrast in the sense of Fisher.These optimized vectors forms can be easily used by beings classification techniques or artificial intelligence. the figures 10 and 11 Shawn clearly a classes position for a vector forms of analytical vibration signals clustering by k means algorithm. This figure gives us a separation between four class's healthy bearing, inner race, ball and outer faults bearing before and after optimization by Particle Swarm optimization algorithm.

## Conclusion

In this paper, we have used time-frequency representation dependent class signal (RTFDCS) and particle swarm optimization for Classification Vibration Data of healthy bearing, inner race, ball and outer faults bearing. in the first part, we are used our vibration signal of four classes healthy bearing, inner race, ball and outer faults bearing for the diagnosis, and because of their vibration signals have low values applies the Hilbert transform methods for pretreatment of these vibratory signals before the RTFDCS, that allow the calculus the cloud points dispersion parameter, this parameter shown clearly the points are very separated for healthy bearing, inner race, ball and outer faults bearing. the following ,the optimization processing, illustrate that each classes is characterized by four vectors forms and each vectors forms comported only two points (element) relevant also called scores or high contrast in the sense of Fisher. These processing results give us a separation between the classes that's valid by k means algorithm clustering.

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