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Multi fault detection of the roller bearing using the wavelet transform and principal component analysis

Jaafar Khalaf Ali, Qusai Talib Abdulwahab, Sajjad Nayyef Abdulkareem

Mechanical Engineering Department, College of Engineering, Basrah University, Ministry of Higher Education & Scientific Research, Basrah, Iraq.

Abstract
Vibration monitoring and analysis techniques are the key features of successful predictive and proactive maintenance programs. In this work, advanced vibration analysis techniques like Wavelet transform, Principle Component Analysis (PCA) and Squared Prediction Error (SPE) have been used to detect the faults in bearing. Discrete Wavelet Transforms (DWT) decomposes signal to high and low frequencies. PCA is employed to extract important feature and reduce dimension. SPE is used to detect the bearing faults. The experimental data is collected from Spectra Quest's Machine Fault Simulator (MFS-4) apparatus. In this study, four rollers were bearing defects (ball defect, outer race defect, inner race defect and combined defect) for 1" and 3/4" bearing. From the results, the suggestion techniques can be used to detect multi-faults in the bearings. The results show that the best wavelet function is Coiflets4 in this method.

Keywords: Fault detection; PCA; Wavelet; SPE; Roller bearing.

1. Introduction
Recently a lot of uses of the rotary machine are used more than the previous. So it is necessary to have a good diagnosis system through which it can detect faults and warn the user before the defect to be at a critical stage and so it have provided money and safety. One of these techniques is the principal component analysis (PCA) based on time-domain vibration features. PCA is a multivariate statistical analysis which applies linear transformation of data and can be used to extract very important features from high dimensional data dependent on high eigenvalue and eigenvector, reduce it to a low dimensions for easier analysis. PCA allows to reconstruction the data to denoising in signal when select useful information. Depended on eigenvalue in covariance matrix[1].The first works of the multivariate dimensional reduction which is now known as PCA were explored by Pearson in 1901 and Hotelling in 1933 [2]. The application of PCA in combination with T^2-statistic and Q-statistic has been proven powerful for fault detection and diagnosis. Ahmed et al. [3] presented a method for multi stage reciprocating compressor fault diagnostics based on PCA using T^2-statistic and Q-statistic. The result showed that suggested approach succeeded in finding single and multiple faults in the reciprocating compressor. Jia et al. [4] presented an approach for roller bearing fault diagnostics based on PCA. Statistical features (mean, standard deviation, sample variance, kurtosis, skewness, etc.) were extracted from original data as input to PCA for reducing the dimension of original features. The efficiency of the approach proposed was high accurate. Mujica et al. [5] discussed and compared some vibration analysis

techniques to diagnose and classify damage in structures like score matrix of the PCA-model, T^2-statistic and Q-statistic. The study found that the score matrix can be used as a damage detection as well as T^2-statistic and Q-statistic. When one looks at previous work related to the PCA which is used for the detection of which find extracts the feature from the raw vibration signal i.e., time- and/or frequency-domain. In this paper, an application of discrete wavelet transform (DWT) as pre-processing of time-domain vibration signal by using Multi-Resolution Analysis (MRA) before feature extraction process is attempted. This method enhances the accuracy of information obtained in the extracted features since it extracts the features from the low frequency part (cA part) and high frequency part (cd) which has been found to be useful for bearings fault detection.
The main advantage of this paper is to use combinations of approaches for feature extraction using wavelet decomposition and the PCA model, which is able of detecting bearing faults in a rotary machine.

2. Theoretical analysis

2.1 Principal component analysis

Consider a $m \times n$ data matrix,X which contains vibration data from n measured variables, m experimental trials. Each row vector x_i in this matrix refers to measurements of the different variables at the same moment in time; while each column vector x_j refers to the measurement of one variable at different time. The first step in PCA algorithm is calculating covariance matrix C_X by multiplying X by its transpose [6].

$$C_x = XX^T \tag{1}$$

As the dimension of data matrix is *(n,m)*, the covariance matrix has dimension*(n,n)*. The next step is estimating the eigenvalues and eigenvectors by applying single-value decomposition on C_X matrix [6],

$$C_X = V \Lambda V^T \tag{2}$$

where Λ is a diagonal matrix, which includes the eigenvalues of C_X from top value to bottom value($\lambda 1 \geq \lambda 2 \geq \cdots \geq \lambda n \geq 0$). In V matrix each column represents eigenvector of C_X. Eigenvectors are selected corresponding to the highest eigenvalues which contain important data to form loading matrix P. The dimension of P is (n, a) where a is number of the selected eigenvectors. The aim of P is to minimize the dimensional space of the measured variables [6].

$$T = XP \tag{3}$$

The T matrix is called scores matrix, and these are representing the new reduced space of the original data. It is possible to reconstruct the original data free from noisy $(\hat{X})$ as the follows [6]:

$$\hat{X} = TP^T \tag{4}$$

where E is the residual matrix, is defined as:

$$E = X - \hat{X} \tag{5}$$

Fault diagnosis by using PCA is depending on Squared Prediction Error (SPE). This is defined as [6]:

$$SPE = \hat{X}(I - PP^T)\hat{X}^T \tag{6}$$

At beginning the confidence level ($SPE_{\dot{\alpha}}$) must be found which is SPE-statistic in normal state. Thus, fault can be detected when the SPE-statistic exceed confidence level.

2.2 Discrete wavelet transform (DWT)

The DWT is discrete form of continuous wavelet transform by discretizing the mother wavelet $\psi_{s,\tau}(t)$. One of the most popular methods for discretization of the wavelet is dyadic discretization [7], given by:

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{2^j}}\psi\left(\frac{t-2^j k}{2^j}\right) \quad (7)$$

where s is replaced by 2^j and τ by $2^j k$. DWT have very important properties which it can decompose a signal into a low frequency and a high frequency part using Multi-Resolution Analysis (MRA).In which the Low frequency part called Approximated (cA) and high frequency part Detailed (cD). The DWT is a hierarchical process; hence it can be applied on several levels. In this paper, several mother wavelets are used and applied to the raw vibration signal up to 3 levels. Then, it used cA and cD from multi-sensor to build PCA input.

2.3 Algorithm of Fault Diagnosis

In this algorithm, fault detection is based on the PCA. The flowchart of this method is shown in Figure 1.

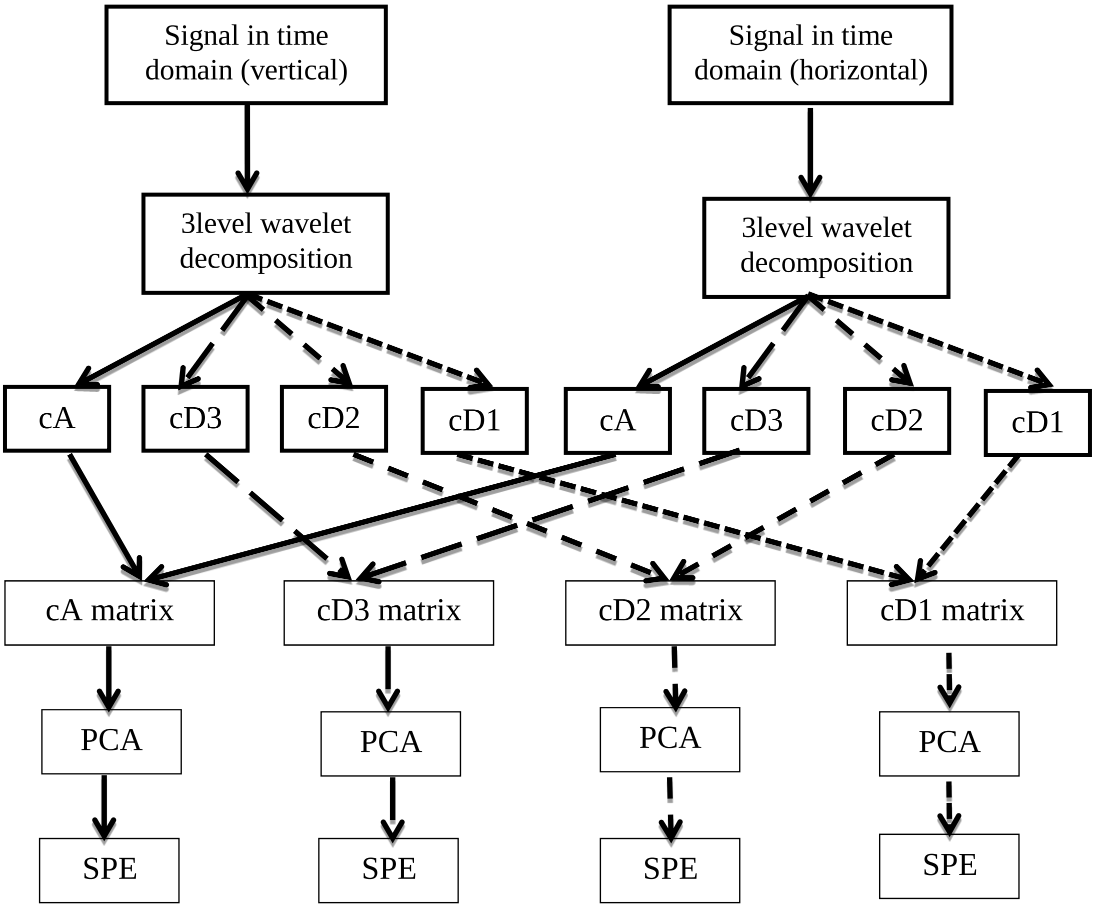

Figure 1. Flow chart of MSPCA_SPE method [8].

- Stage 1, training data.

1. Obtain vibration signal in time domain from normal bearing.
2. Employ DWT up to 3 levels.
3. Select the approximate (cA) from each sensor and set in matrix and also select the Detail (cD) from each sensor.
4. Estimate the loading matrix P and Λ of cA matrix, cD1 matrix, cD2 matrix and cD3 matrix.
5. Estimate confidence level SPE_{α} for cA matrix, cD1 matrix, cD2 matrix and cD3 matrix.

- Stage 2, testing data.

1. Obtain vibration signal in time domain from normal bearing.
2. Employ DWT up to 3 levels.
3. Select the approximate (cA) from each sensor and set in matrix and also select the Detail (cD) from each sensor.
4. Estimate the loading matrix P and Λ of cA matrix, cD1 matrix, cD2 matrix and cD3 matrix.

5. Estimate SPE for cA matrix, cD1 matrix, cD2 matrix and cD3 matrix.
6. If SPE exceed confidence level, a fault has been detected.

3. Experimental work

The suggested technique in this paper was verified using the Spectra Quest's MFS which is an innovative tool for studying signatures of common machinery faults without compromising factory production or profits. The system, which is fits on a desktop and weighs about 150 pounds, reflects a modular design that provides versatility, operational simplicity and robustness. Each component of the simulator is machined to high tolerances so it can be operated without any significant conflicting vibration. Then, depending on the situation that want to be analyzed, can introduce various faults either individually or jointly in totally controlled environments as shows in Figure 2.

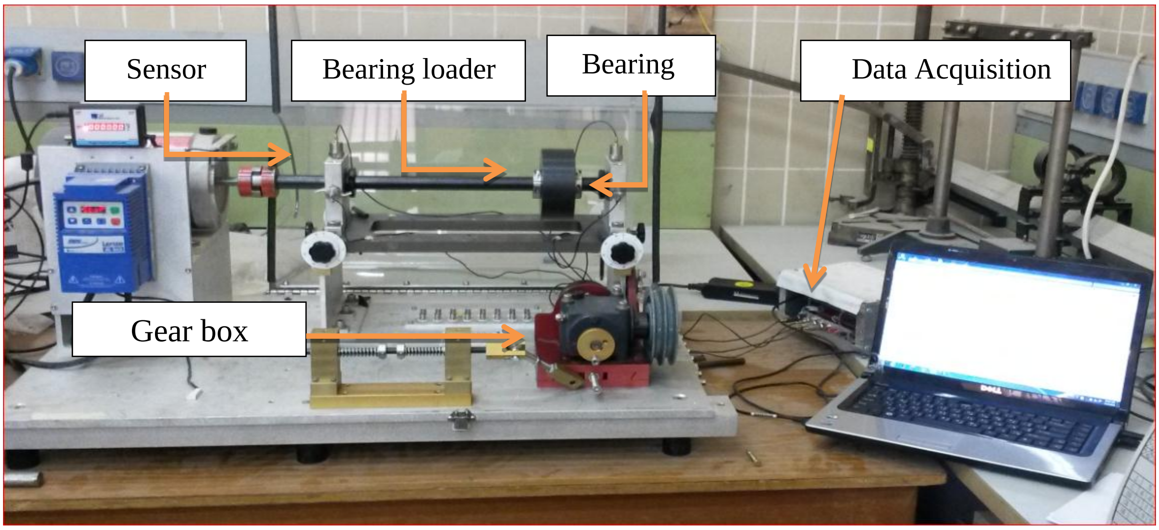

Figure 2. Spectra Quest's MFS [9].

Four common faults were considered: a ball fault (fault1), inner race fault (fault2), outer race fault (fault3), and combination of a ball, inner race and outer race fault (fault4). Two accelerometers were mounted on the bearing house respectively on the vertical direction (channel 1), and on the horizontal direction (channel 2). The internal diameter bearing is 1" and 3/4. The speed is 45 Hz (2700 RPM). The number of samples is 4096 and sampling rate is 2048 sample/sec. Bearing defects are typically classified as to the location with the bearing assembly:

- Inner race fault (alias ball pass frequency or BPFI),
- Outer race fault (alias ball pass frequency outer or BPFO),
- Rolling element fault (alias ball spin frequency or BSF),

The fault bearings are supplied by the manufacture of MFS as shown in Figure 3. These bearings have been used in experiments for the purpose of obtaining the necessary data to identify these faults.
The fundamental fault frequencies BPFI, BPFO and FTF are calculated by the following formulas:

$$BPFI = \frac{N_b}{2} S\left(1 + \frac{B_d}{P_d} cos\theta\right) \tag{8}$$

$$BPFO = \frac{N_b}{2} S\left(1 - \frac{B_d}{P_d} cos\theta\right) \tag{9}$$

$$FTF = \frac{S}{2}\left(1 - \frac{B_d}{P_d} cos\theta\right) \tag{10}$$

$$BSF = \frac{P_d}{2B_d} S\left[1 - (\frac{B_d}{P_d} cos\theta)^2\right] \tag{11}$$

where: N_b: The number of ball, B_d: Ball diameter, P_d: pitch diameter, S: rotational Speed and θ: Contact angle. And, the rotor bearing specification are shown in Table 1.

Figure 3. Faulted bearings.

Table 1. Rotor bearing specification.

Component	FTF	BSF	BPFI	BPFO
1/2" RB	0.378	1.992	4.95	3.048
5/8" RB	0.378	1.992	4.95	3.048
3/4" RB	0.378	1.992	4.95	3.048
1" RB	0.402	2.322	5.43	3.572

where RB denotes the roller bearing.

3.1 Method of bearing test

The MFS will be configured to eliminate all defects with the exception of one defective rolling element bearing. Specifically, the machine will be placed in excellent alignment with good bearings. A bearing loader will be installed center board bearing. Baseline data will be collected at several speeds. A defective bearing will then be installed in the outboard position. Data will be collected at identical speeds. Baseline measurements will be compared with the vibration signatures of the defective bearings.

3.2 Overall procedure

The MFS will be configured to collect data first on good quality inboard and outboard rotor bearings. It is essential that the machine be properly aligned. Defective bearings will be introduced one at a time and data collected.

1. Installed good bearings in both inboard and outboard positions.
2. Collected data with 10 KHz frequency range.
3. Removed the outboard bearing and replaced it with a BSF defected bearing.
4. Collected data 10 KHz frequency range.
5. Removed the outboard bearing and replaced with a BPFI defected bearing.
6. Collected data 10 KHz frequency range.

7. Removed the outboard bearing and replaced with a BPFO defected bearing.
8. Collected data 10 KHz frequency range.
9. Removed the outboard bearing and replaced with a combination defected bearing.
10. Collected data 10 KHz frequency range.

4. Results and discussions

Since the objective of this work is to illustrate the application of the DWT, PCA and SPE techniques in faults detection in roller bearing. Multi faults in roller bearing are discussed with deferent discrete wavelet function and discrete wavelet coefficients. Fault diagnosis process in this method depends largely on confidence limit SPEά (maximum value for SPE in normal case which is symbolized by the red line in SPE plot). Grounded on that, it can observe the fault when the SPE values exceed the confidence limit SPEά. However, the bearing is normal when the SPE values are less than the confidence limit.

Figure 4 shows bearing vibration analysis by using MSPCA_SPE based on approximate coefficient for 1" bearing size. The used wavelet function is discrete Daubechies1, and the level of discrete wavelet decomposition is three. One of the principal components (PCs) has been picked.

Fault detection based on SPE is shown in Figure 3. Upper plots represent SPE for different cases. The first plot (a) signifies normal bearing, and the second (b) indicates faulty bearing with outer race fault, while the third plot (c) denotes faulty bearing at inner race. Bearing with ball fault is indicated in the fourth plot (d), and the fifth (e) represents faulty bearing with combined defect. However, the last one in the upper plots (f) represents test bearing. Lower plots represent eigenvalue for different cases.

In the upper plots, the numbers of points are equal to the number of cA points of cA. Success of this method has been verified practically through analysis the signal from faulty bearing. The SPE has been determined and compared with the confidence limit $SPE_{\acute{\alpha}}$ as shown in the upper half of Figure 4.

It is important to point out that this technique succeeds in fault detection for bearing size 1" and 3/4" for all coefficient Approximate (cA) and Detail (cD1, cD2, cD3) as shown in Figures 5 and 6.

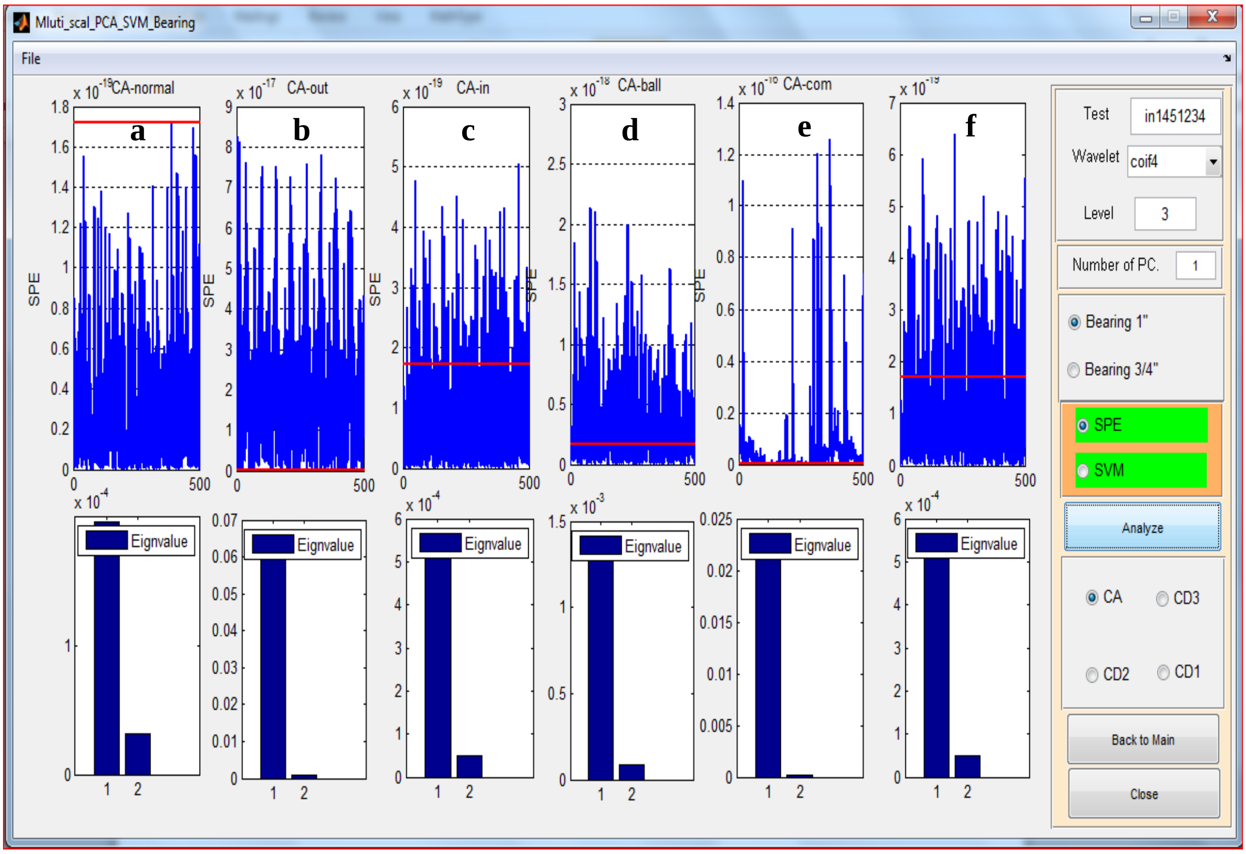

Figure 4. MSPCA_SPE for bearing 1"using discrete Coiflets 4 wavelet function based on approximate coefficient (cA).

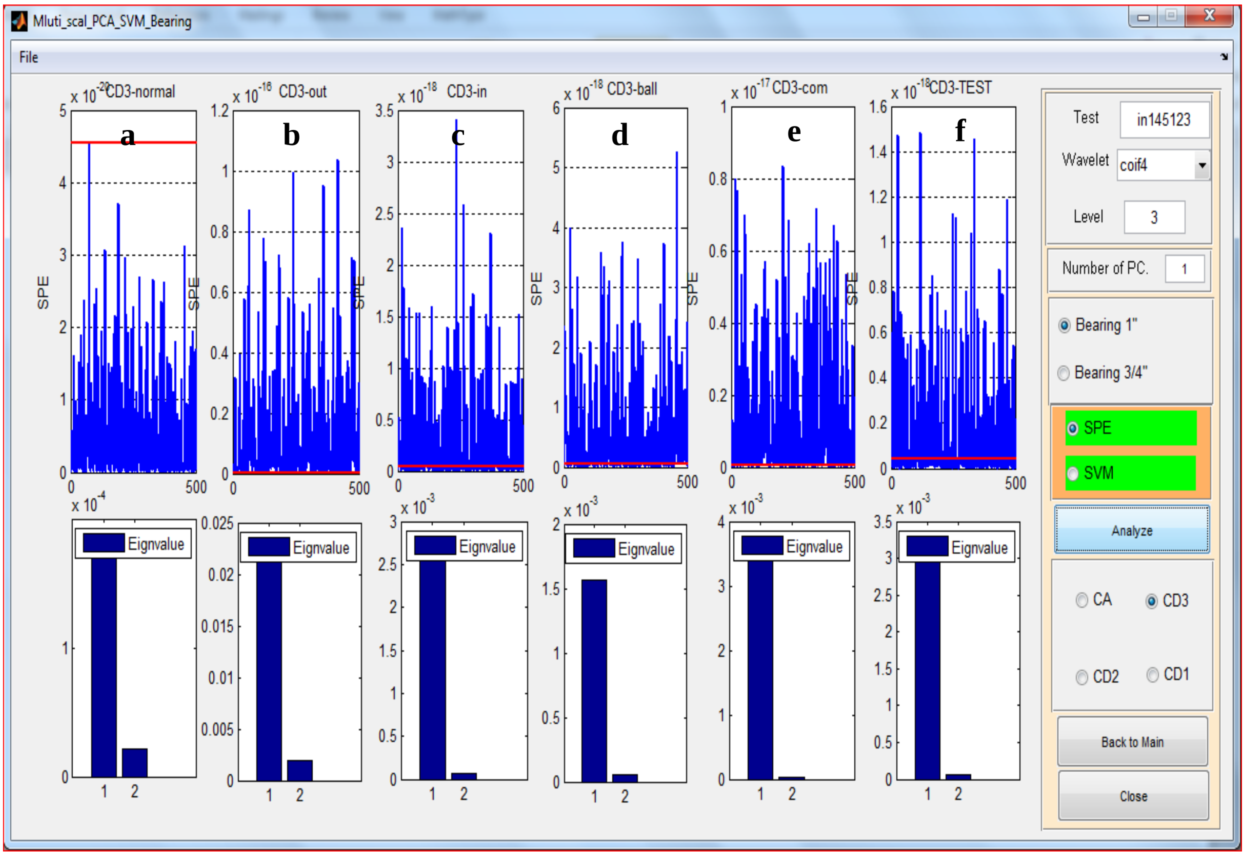

Figure 5. MSPCA_SPE for bearing 1"using discrete Coiflets4 wavelet function based on detail coefficient3 (cD3).

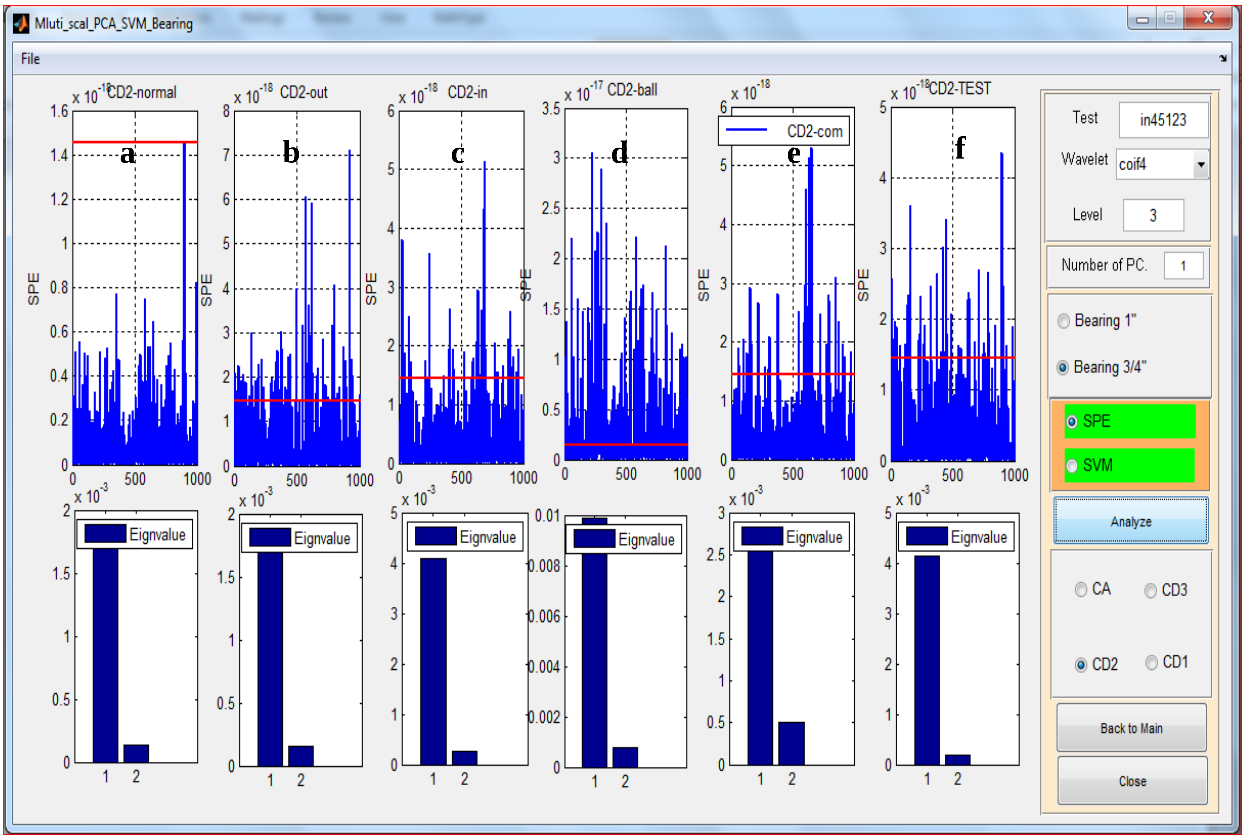

Figure 6. MSPCA_SPE for bearing 3/4"using discrete Coiflets4 wavelet function based on approximate coefficient (cA).

In addition, the best discrete wavelet function for this method is Coiflets4. The preferable coefficient that used for detection is Approximate because the fault frequencies (2x-5.5x) is located in cA rang frequencies.
When compare the previous results that have been used Coiflets4 function in vibration analysis with the results used another function like Symlets4 function as shown in Figure 7. It is noted that the use of Coiflets4 much better from use Symlets4 because it has succeeded in diagnosis all faults , while Symlets4 failed to diagnose some defect in roller bearing (Figures 4 and 7).

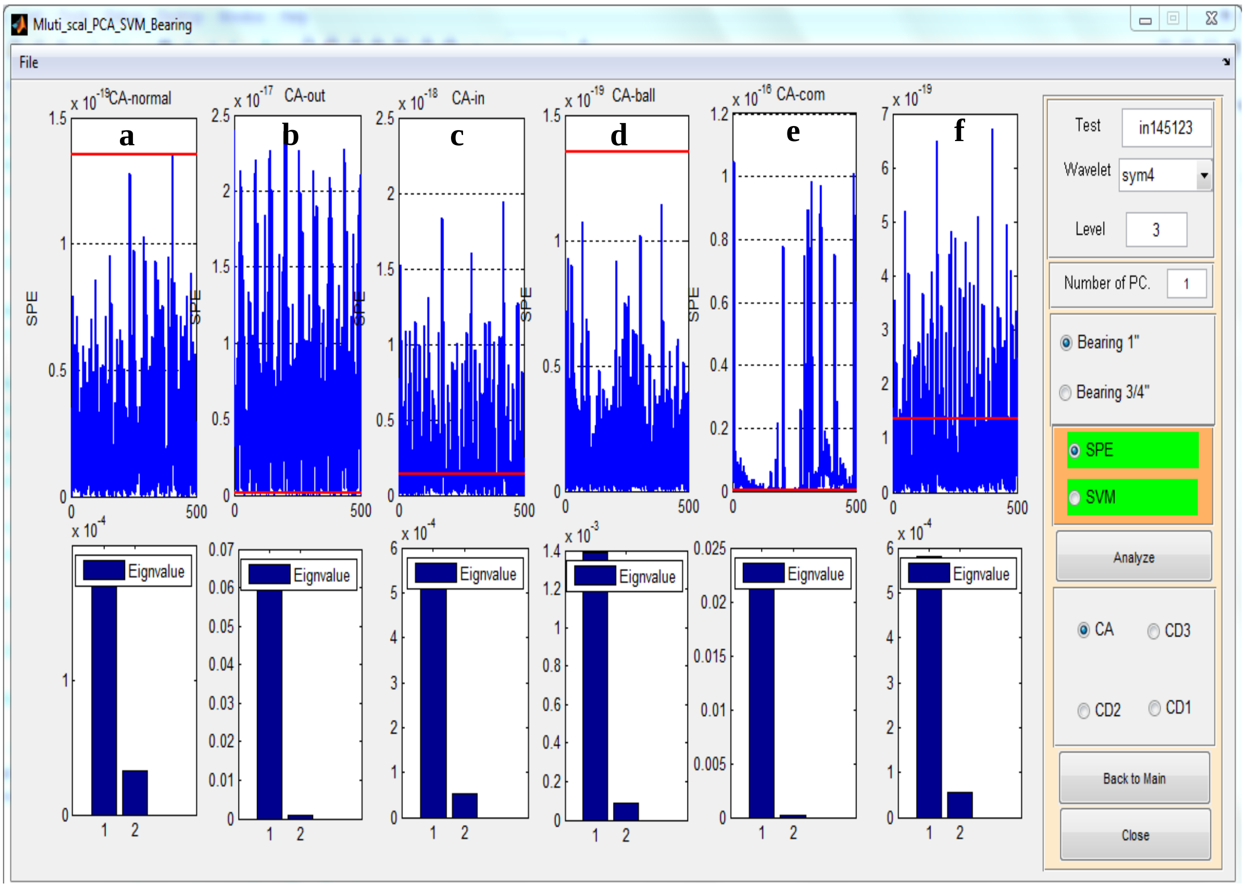

Figure 7. MSPCA_SPE for bearing 1"using discrete Symlets4 wavelet function based on approximate coefficient (cA).

5. Conclusion

This paper proposed the new combined techniques using the DWT and PCA method to detect faults in a bearing. . DWT used to decomposes signal to high and low frequencies. PCA is employed to extract important feature and reduce dimension. SPE is applied to detect the bearing faults. From the result
1- This connection between these methods has high performance to detect different faults in bearing.
2- In this connection, the best DWT is Coiflets4.
3- The best coefficient to detect bearing faults is approximate coefficient (cA).

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Jaafar Khalaf Ali, Ph.D. in Mechanical Engineering, College of Engineering, Basrah University, Iraq. Specialization: Applied mechanics, Graduation Date: 2012. M.Sc. In Mechanical Engineering, College of Engineering/University of Basrah/Iraq. Specialization: Applied mechanics, Graduation Date: 1998. B.Sc. In Mechanical Engineering/ College of Engineering/University of Basrah, Iraq. Specialization: General Mechanics, Graduation Date: 1996.
E-mail address: jaafarkhalaf@gmail.com

Qusai Talib Abdul Wahab, Ph.D. in Mechanical Engineering, College of Engineering, Basrah University, Iraq. Specialization: Applied mechanics, Graduation Date: 2005. M.Sc. In Mechanical Engineering, College of Engineering/University of Basrah/Iraq. Specialization: Applied mechanics, Graduation Date: 2000. B.Sc. In Mechanical Engineering/ College of Engineering/University of Basrah, Iraq. Specialization: General Mechanics, Graduation Date: 1994.
E-mail address: qusai.talib@gmail.com

Sajjad Nayyef Abdulkareem, Researcher in Applied Engineering, Department of Mechanical Engineering, Basrah University, Iraq. B.Sc. In Mechanical Engineering, College of Engineering, University of Basrah, Iraq. Specialization: General Mechanics, Graduation Date: 2013.
E-mail address: sajjad4iq@yahoo.com