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A multiscale permutation entropy based approach to select wavelet for fault diagnosis of ball bearings

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Abstract

The detection and diagnosis of bearing health status using vibration signal has been an important subject for extensive research over the past few decades. The objective of this paper is to proposed permutation entropy as a tool to select best wavelet for feature selection for the detection as well as fault classification of ball bearings. The continuous wavelet coefficients of the time domain signal are calculated at real, positive scales using various real and complex wavelets. Best wavelet and corresponding scale is selected based on minimum permutation entropy. Eleven statistical parameters were used for defect classification in outer race, inner race, ball defect and healthy bearing respectively. Proposed methodology for fault classification is compared with two artificial intelligence techniques such as artificial neural network and support vector machine. Results revealed that permutation entropy based feature extraction techniques provide higher classification accuracy even when there is a slight variation in operating condition which is useful for development of online fault diagnosis.

Keywords

Fault diagnosis, permutation entropy, wavelet selection, support vector machine, artificial neural network

1. Introduction

The condition monitoring techniques of complex machines using vibration analysis has gained considerable attention from researchers across the globe. Majority of problems in rotating machinery are caused by faulty gears, bearings etc. Fault diagnosis of rolling bearings is extremely important for production efficiency and plant safety. Tandon and Choudhury (1999) review demonstrated the effectiveness of various vibration and acoustic measurement technique for fault diagnosis of rolling element bearing. Vibration signal obtained from various rotating parts exhibits certain characteristics, that by observing time domain and frequency domain, plot presence of defect can be judged. Time domain, frequency domain, time frequency domain techniques for fault detection in mechanical systems has been investigated by many researchers (Honarvar and Martin, 1997; Engin et al., 1999; Harsha et al., 2006; Wang and Gao, 2003; Peng and Chu, 2004; Kankar et al., 2011a,b; Kankar et al., 2012). Due to continuous variation in loading conditions, friction, interaction of rotating elements machine system exhibits nonlinear behavior. A good alternative in the form of nonlinear parameter estimation techniques have been used by researchers (Pincus, 1995; Signorini et al., 2003; Li et al., 2008) to extract hidden features present in signal. Techniques such as lyapunov exponent (Ding and Li, 2007), correlation dimension (Naranjo and Otero, 2005) for fault diagnosis of rotating machine has been investigated.

Concept of entropy as a measure of disorderness and complexity has achieved significant attention.Various types of entropy such as approximate entropy (ApEn) (Yan and Gao, 2007) and multiscale entropy (MSE) (Tiwari et al., 2013) are used to analyze complexity of vibration signals. It is observed that the inception of

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fault and its growth rate can be efficiently correlated with changes in complexity values from rotating machinery. Yan et al. (2011) used permutation entropy as a new complexity measure for the health characterization of rotating machinery. The concept of permutation entropy is introduced by Bandt and Pompe (2002). For a given time series permutation pattern is defined by the ordered relations among different values.The temporal information (up and down in signal) can be easily detected by permutation entropy by counting ordinal patterns. MSE was proposed by Costa et al. (2002) and Wu et al. (2012) combines the concept of multiscale and permutation entropy for bearing fault diagnosis and classification. In this paper the continuous wavelet coefficients of the vibration signal obtained from machine are calculated at real, positive scales using various real and complex wavelets viz. symlet, coiflet, shannon and complex morlet. Permutation entropy is calculated at various scales and the scale giving least permutation entropy is selected. The wavelet giving least permutation entropy is used for statistical parameters calculation. Feature vector is formed for different fault conditions and rotating speed. This feature vector is fed as an input for fault classification using artificial neural network and support vector machine. Results revealed that the proposed feature extraction method gives improved results than the conventional feature extraction methods. Figure 1 shows the overall methodology for fault diagnosis.

2. Permutation entropy

When complexity of a given time series is measured entropy serves as a best tool and replaces classical methods such as Fourier Transform. But traditional approach in entropy calculation neglects the effect of temporal order of values in successive time series. By considering this fact time series is encoded in to sequence of symbols which reflects the rank order of successive elements in sequence of length. Costa et al. (2002) have developed MSE for the analysis of physiologic time series, in which initially sample entropy (SampEn) was calculated and based on the concept of multiscale, various entropies can be calculated. Both Multiscale permutation entropy (MPE) and Shannon entropy (SE) are measure of uncertainty/complexity of the signals. Shannon entropy is useful for estimation of complexity of time series based on single scale while MPE is useful to calculate complexity of time series after comparing neighboring values and entropy over multiple scales. By doing so, permutation entropy directly account for the temporal information contained in the time series (Massimiliano et al., 2012). Further, it has the quality of simplicity, robustness and very low computational time.

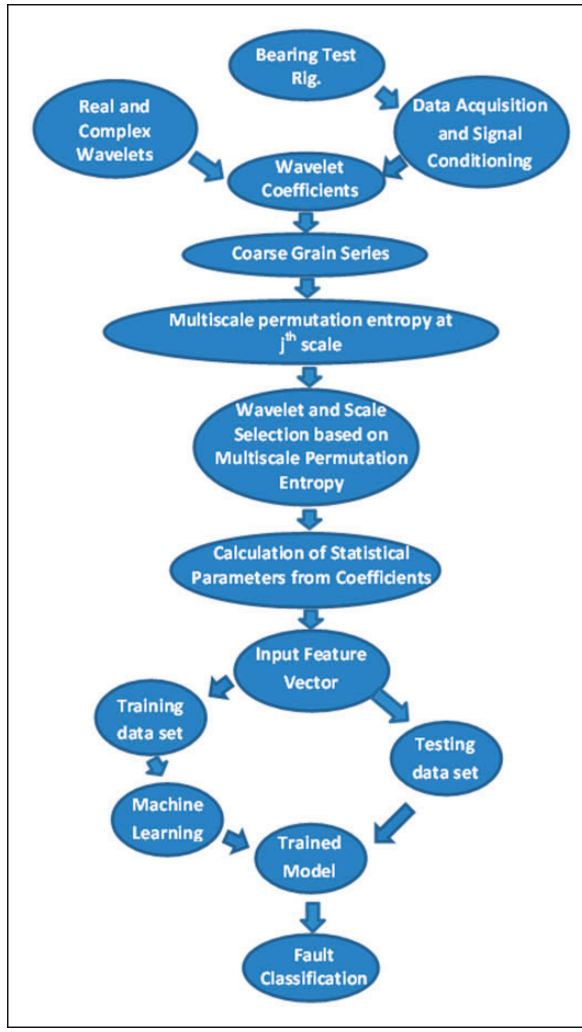

Figure 1. Multiscale permutation entropy based fault diagnosis methodology.

Therefore, features vector consisting of MPE provide better information about the physical phenomenon like occurrence of faults in the rotor bearing system. Permutation entropy was introduced as a computational efficient method for extracting the information form complex system. At each time 's' of a given a time series (Massimiliano et al., 2012)

$$X = (x_1, x_2, x_3 \dots x_n) \tag{1}$$

a vector composed of the m^{th} subsequent values is constructed

$$S \rightarrow (X_\tau, X_{\tau+1}, \dots, X_{\tau+(m-2)}, X_{\tau+(m-1)}) \tag{2}$$

where m is called embedding dimension and tells how much information is present in a vector and τ is time delay. For a given embedding dimension there will be m! possible permutation π of order m. To the vector in equation (1) an ordinal pattern is associated defined as permutation π which fulfills

$$X_{s+ro} \leq X_{s+r1} \leq \cdots \leq X_{s+rm-2} \leq X_{s+rm-1} \tag{3}$$

Thus, values are arranged in ascending orders and a permutation pattern π is constructed with offset values. By doing so it is possible to extract information about the dynamics of system considered for the study.

Permutation entropy employs the concept of shannon entropy by analyzing the relative frequency of patterns generated form time series. The permutation entropy (PE) is defined as

$$\mathrm{PE} = -\sum_{i=1}^{m} \pi_i \ln \pi_i \tag{4}$$

Permutation entropy depends mainly on selection of embedding dimension 'm' and time delay 'τ'. Bandt and Pompe (2002) suggested that value of embedding dimension 'm' should be $3 \leq m \leq 7$ and time delay $\tau = 1$.

Normalized permutation entropy is given by

$$\mathrm{NPE} = -\frac{PE}{\ln\ m!} \tag{5}$$

where ln $m!$ denotes maximum PE value.

2.1. Multiscale permutation entropy

Multiscale entropy proposed by Costa et al. (2002) has been used as an effective method for determining complex signal behaviors over multiple time scales. Multiscale entropy analysis can be combined with previously introduced permutation entropy by using coarse grain procedure. Successive coarse grained series can be formed from original time series after averaging the data points by selecting non-overlapping windows of increasing length β as shown in Figure 2 also known as scale factor. Thus elements of coarsed grain time series is evaluated by

$$Y_j^{(\beta)} = \frac{1}{\beta} \sum_{i=(j-1)\beta+1}^{j\beta} x_i, \quad 1 \leq j \leq \frac{\mathrm{N}}{\mathrm{S}} \tag{6}$$

where N is length of data. For each scaled series permutation entropy is calculated. For $\beta = 1$, the coarse-grained time series is simply the original time series.

Vibration signals are divided in 128 scales and continuous wavelet coefficients are calculate for each wavelet. Equations (4), (5) and (6) are used to calculate permutation entropy of each of 128 scales using number of continuous wavelet coefficients.

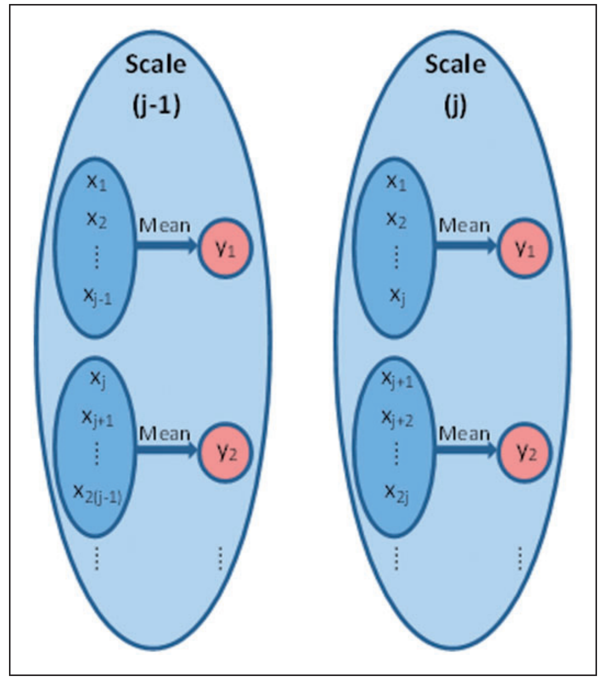

Figure 2. Coarse grain procedure.

3. Fault classification techniques

3.1. Artificial neural network (ANN)

Artificial intelligence techniques such as fuzzy logic, artificial neural network (ANN) (Hassoun, 1995) have been continuously and successfully applied for bearing fault detection and diagnosis. ANNs are made up of interconnected processing units known as neurons and it is adaptively changes its structure during learning phase. ANN is a type of supervised learning methods which can be trained by supplying data. Back propagation algorithm is used for training purpose during which weights are adjusted for error minimization between ANN predictions and outputs.

3.2. Support vector machine (SVM)

Support vector machine is a statistical learning method based on the principle of structural risk minimization and was introduced by Vapnik (1998). SVM is a supervised learning algorithm in which learning machine has allotted some set of features with class labels. In SVM, the optimal hyperplane separating the data can be obtained as a solution to the following optimization problem

$$\text{Minimize } \frac{1}{2}\|\mathrm{w}\|^2 + \mathrm{C}\sum_{i=1}^{M} \xi_i \tag{7}$$

subject to

$$y_i(w'x_i + b) \geq 1 - \xi_i \tag{8}$$

where $\xi_i \geq 0$ and $i = 1, 2, \ldots M$

4. Experimental setup

Vibration data of bearing analyzed in this paper belongs to Case Western Reserve University (CWRU) bearing data center (Loparo, 2013). Table 1 shows the dimensions of ball bearing used for study. Experimental set up is shown in Figure 3 (Loparo, 2013). The test rig consists of 2 HP induction motor, a torque transducer and a dynamometer connected by a self-aligning coupling. Signal from accelerometer is collected form drive end and fan end of motor. Drive end accelerometer signal were selected due to broader set of configurations compared to the fan end accelerometer data. Healthy bearing data is considered as base line data. Single point faults of diameters 0.1778 mm, 0.3556 mm and 0.5334 mm were inserted in inner race, outer race fault at 6 o'clock position, rolling element, and ball using electric discharge machining. Data are acquired at rotating speeds of motor as 1730, 1750, 1772 and 1797 rpm with sampling frequency 48 KHz.

Table 1. Parameters of bearing 6205 (SKF) (drive end).

Parameter	Value
Outer race diameter	52 mm
Inner race diameter	25 mm
Ball diameter	7.94 mm
Pitch diameter	39 mm

5. Wavelet selection and features extraction

Measured vibration signal has been preprocessed through continuous wavelet transform and permutation entropy. In the present study four wavelets viz symlet, coiflet, complex morlet and complex shannon are compared and the wavelet giving least permutation entropy is selected. The continuous wavelet coefficients (CWC) of all signals are calculated at seventh level of decomposition (2^7 scales). The scale which has the least permutation entropy is selected and the statistical features of CWC corresponding to that scale is calculated. Based on wavelet selection criterion, out of these four wavelets symlet wavelet are selected as a wavelet which is giving least permutation entropy.

The following features are considered for fault diagnoses which are explained below:

a. Skewness: skewness is a measure of symmetry. A distribution or data set is symmetric if it looks the same to the left and right of the center point.

$$\text{skewness} = \frac{\sum_{i=1}^{n} (x_i - \bar{x})^3}{(n-1)s^3} \tag{9}$$

b. Kurtosis: kurtosis is a measure of whether the data are peaked or flat relative to a normal distribution.

$$\text{Kurtosis} = \frac{\sum_{i=1}^{n} (x_i - \bar{x})^4}{(n-1)s^4} \tag{10}$$

where s represents standard deviation.

c. Mean: mean value of signal generally obtained by adding all values of signal and then divided by total values.

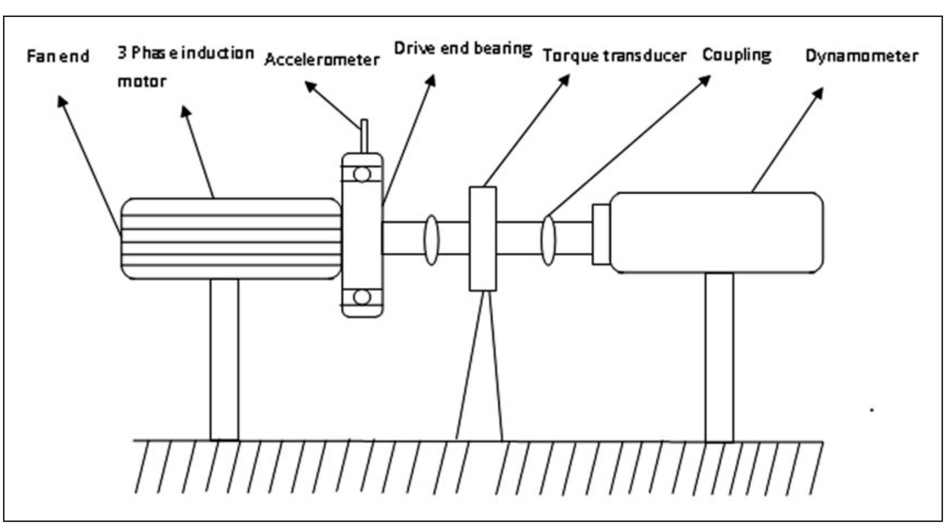

Figure 3. Schematic diagram of experimental set up.

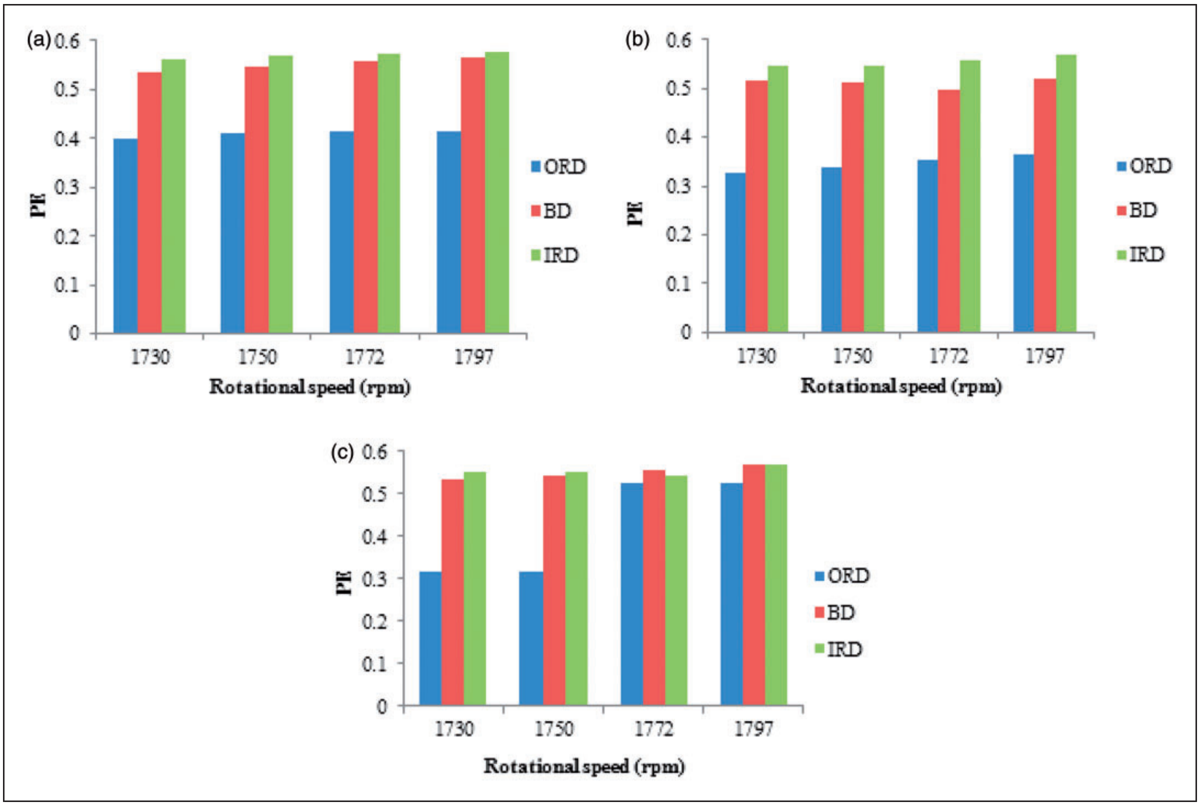

Figure 4. Effect of rotational speed on permutation entropy (a) 0.1778 mm hole, (b) 0.3556 mm hole and (c) 0.5334 mm hole.

d. Peak value: the peak value of the signal is the highest value the signal reaches above a reference value. The reference value normally used is zero.
e. Minimum value: represents minimum value in a particular data set of signal.
f. Standard deviation: standard deviation is a measure of energy content in the vibration signal.

$$\text{Standard deviation} = \sqrt{\frac{n\sum \chi^2 - (x)^2}{n(n-1)}} \tag{11}$$

g. Variance: variance is a measure of how far a set of numbers is spread out from mean value. It is calculated as

$$\text{Variance } (\text{s}^2) = \frac{(x_i - \bar{x})^2}{\text{n} - 1} \tag{12}$$

here x_{i} represents data element, $\bar{x}$ represents mean value and n represents total number of observations.
h. RMS value: the RMS value of a set of values is the square root of the arithmetic mean (average) of the squares of the original values.
i. Crest factor: it is the ratio of peak value of signal to its RMS value

$$\text{Crest factor} = \text{peak value/rms value}$$

j. Form factor: it is the ratio of RMS value to average value of signal.

$$\text{Form factor} = \text{RMS value/mean value}$$

These statistical features along with rotor speed are used initially to form feature vector and are fed as an input to machine learning techniques such as ANN, SVM for classification of faults.

6. Results and discussion

The difference between various fault conditions is not easily distinguished by time domain and frequency domain signals. An attempt has been made in the present study to analyze the effect of permutation entropy on different fault conditions such as outer race defect, ball defect and inner race defect with shaft rotation 1730, 1750, 1772, 1797 rpm and with different defect conditions as 0.1778 mm, 0.3556 mm and 0.5334 mm holes. Plot between permutation entropy and rotational speed is shown in Figure 4.

As shown in Figure 4 effect of bearing rotational speed on PE value is investigated for each fault class and various defect conditions. When speed increases PE value also increases for outer race defect, inner race

Table 2. Sample input vector for ANN/SVM.

SKEW	KURT	MEAN	PEAK	MIN	STD	VAR	RMS	CREST	FORM	SPEED	CLASS
−2.5029	8.173	−0.3317	0.1189	−2.5954	−2.5954	0.3979	0.7105	0.1674	−2.1418	7_1730	IRD
1.0995	3.7447	−0.2443	0.0326	−0.3973	0.1016	0.0103	0.2644	0.1234	−1.0824	7_1750	IRD
0.3674	1.7187	−0.0381	0.177	−0.1793	0.1121	0.0126	0.118	1.5003	−3.0949	14_1772	ORD
0.7579	2.173	−0.7768	0.4525	−1.3912	0.5946	0.3535	0.9768	0.4632	−1.2575	14_1797	ORD
1.7013	6.4123	0.0201	0.2474	−0.0729	0.0598	0.0036	0.0629	3.9332	3.1268	14_1797	BD
−0.7901	3.1392	−0.0666	0.0894	−0.3061	0.0912	0.0083	0.1127	0.7935	−1.6911	21_1730	BD
0.0413	1.8833	−0.0141	0.1369	−0.1583	0.0889	0.0079	0.0896	1.5271	−6.3762	1772	HB
0.5165	3.2126	−0.034	0.1034	−0.1163	0.0445	0.002	0.0559	1.8505	−1.6407	1797	HB

SKEW: Skewness, KURT: Kurtosis, MEAN: Mean value, PEAK: Peak value, MIN: Minimum value, STD: Standard deviation, VAR: Variance, RMS: Root mean square value, CREST: Crest factor, FORM: Form factor, SPEED: Rotational speed, CLASS: Classes considered for study: Inner race defect (IRD), Outer race defect (ORD), Ball Defect (BD), Healthy bearing (HB).

Table 3. Confusion matrix for artificial neural network (ANN) using symlet wavelet (minimum permutation entropy).

Training set					Testing set				
IRD	ORD	BD	HB	Classified as	IRD	ORD	BD	HB	Classified as
12	0	0	0	IRD	12	0	0	0	IRD
1	11	0	0	ORD	1	11	0	0	ORD
0	0	12	0	BD	0	0	12	0	BD
0	0	0	4	HB	0	0	0	4	HB

IRD: Inner race defect, ORD: Outer race defect, BD: Ball defect, HB: Healthy bearing.

Table 4. Confusion matrix for support vector machine (SVM) using symlet wavelet (minimum permutation entropy).

Training set					Testing set				
IRD	ORD	BD	HB	Classified as	IRD	ORD	BD	HB	Classified as
11	1	0	0	IRD	11	1	0	0	IRD
0	12	0	0	ORD	0	12	0	0	ORD
0	0	12	0	BD	0	0	12	0	BD
0	0	0	4	HB	0	0	0	4	HB

Table 5. Numeric prediction success of symlet (minimum permutation entropy).

	ANN		SVM	
Parameters	Training set	Test set	Training set	Test set
Correctly classified Instances	39 (97.5%)	39 (97.5%)	39 (97.5%)	39 (97.5%)
Incorrectly Classified instances	1 (2.5%)	1 (2.5%)	1 (2.5%)	1 (2.5%)
Kappa statistic	0.9653	0.9653	0.9653	0.9653
Total number of instances	40	40	40	40

ANN: artificial neural network, SVM: support vector machine.

Table 6. A comparative study between current work and previous work published in literature.

References	Machine learning method used	Mechanical component	Faults considered	Efficiency of classification (%)	Techniques used for vibration analysis	Remarks
Prabhakar et al. (2002)	NA	Rolling element bearings	One scratch mark each on inner race (on the track) and outer race (on the track), two scratch marks on outer race (180° apart on the track), one scratch mark on each of inner race and outer race (on the track).	NA	Daubechies 4	Wavelet not compared
Abbasion et al. (2007)	SVM	Rolling element bearings	Bearing looseness, defects in rolling elements and bearing raceways.	100 by SVM (testing)	Meyer wavelet	Wavelet denoising
Qiao et al. (2007)	SVM	Rolling element bearings	Fault at ball, inner race, outer race and normal bearing.	100,62.50 (training and testing)	Improved wavelet packet transform	Time series data used
Tyagi (2008)	ANN,SVM	Rolling element bearings	Fault at ball, inner race, outer race and normal bearing.	96 and 97 by ANN and SVM (testing)	Discrete wavelet transform	Time series data used
Al-Raheem et al. (2010)	ANN	Rolling element bearings	Fault at ball, inner race, outer race and normal bearing.	100,97.5,72.1 (training)	Laplace wavelet analysis	Time series data used
Yaqub et al. (2012)	KNN	Rolling element bearings	Inner race, outer race, ball.	91.23 by KNN (training and testing)	Stationery wavelet transform, Db5	Time series data used
Wu et al. (2012)	SVM	Rolling element bearings	Fault at ball, inner race, outer race and normal bearing.	97–100 by SVM (training and testing)	NA	Time series data used
Sun et al. (2012)	Envelope spectrum correlation	Rolling element bearings	Fault at ball, inner race, outer race.	95 (testing)	Discrete wavelet transform	Time series data used
Yaqub et al. (2013)	NA	Rolling element bearings	Inner race, outer race, ball.	NA	NA	Multiple point defect model
Present work	ANN, SVM	Rolling element bearings	Inner race, outer race, ball fault and healthy bearing.	97.5,97.5 by ANN and SVM (both for training and testing) respectively	Symlet2, coiflet2, complex morlet, complex shannon	Wavelets are compared

defect, and ball defect respectively as shown in Figure 4. It is clear that with identical fault condition, PE is minimum for outer race defect and maximum for inner race defect. This elucidate that defect in inner race is more severe as compared to ball defect and outer race defect for all shaft rotation considered in this study. It can be explained by the fact that vibration signals from inner race defect exhibits higher irregularity, giving higher PE value. Moreover for identical speed and various fault conditions vibration from inner race defect contains more frequency components due to interaction between rolling element and defect which also results in a higher PE value. As rotational speed increases PE value also increases. Minimum PE value is obtained at 1730 rpm for outer race defect and maximum PE value is obtained at 1797 rpm for inner race defect and is shown in Figure 4. From Figure 4 it can be seen that permutation entropy is able to distinguish clearly between fault classes at various fault conditions even when there is a slight variation in rotational speed.

Training and testing of data sets has been carried out using WEKA software (Hall et al., 2009) with ANN and SVM as classifiers. A sample input vector is shown in Table 2. Total 40 instances and 11 features are used for the study. The embedded dimension m and the time delay τ of MPE selected was 3 and 1 respectively. For symlet wavelet, training and testing accuracy using machine learning techniques i.e. ANN, SVM are shown in Table 3 and 4.

For training and testing set ANN correctly predicted Inner race defect (IRD), Ball defect (BD) and Healthy bearing (HB), while 1 out of 12 predicted incorrectly for outer race defect (ORD) case. Similarly for training and testing set SVM correctly predicted ORD, BD, HB while incorrectly predicted 1 out of 12 for IRD case. Correctly classified test instances for ANN and SVM are 97.5% and 97.5% respectively and for testing classification accuracies for ANN and SVM are 97.5% and 97.5% respectively as shown in Table 5. It is clear from the above results that classification accuracy of ANN and SVM is the same for both training and testing. Both SVM and ANN come under supervised learning methods and are efficient in classifying data. A comparative study between the present work and published literature is shown in Table 6.

7. Conclusions

Feature extraction and fault classification using time-frequency domain techniques such as wavelet is considered best in recently reported literature. For any classification problem it is important to select the most appropriate mother wavelet. In the present study, permutation entropy based wavelet selection criterion has been used for selecting wavelet and corresponding features are extracted from wavelet coefficients. Symlet wavelet is selected based on the permutation entropy criterion. In total 11 features have been considered. Classification results of ANN and SVM are compared and results show that both ANN and SVM give identical classification results. From the above mentioned results it can be concluded that proposed methodology based on permutation entropy along with machine learning techniques shows potential application for development of real time fault diagnosis system.

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