Intelligent Fault Detection of Ball-bearings Using Artificial neural networks and Support-Vector Machine

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Abstract: Due to the importance of rolling bearings as one of the most commonly used industrial machinery elements, it is necessary to develop proper monitoring and fault diagnosis procedure to suppress malfunctioning and failure of these elements during operation. For rolling bearing fault detection, it is expected that a desired time domain analysis method has good computational efficiency. The interesting point of this investigation is the introduction of an in such systems through extracting features in time effective method for fault detection and diagnosis in such systems through extracting features in time domain from vibration signals , artificial neural networks (ANNs) and support vector machines (SMVs) that used for classification of rolling-element bearing faults. The extracted features from original and preprocessed signals are used as inputs to the classifiers for two-class (normal or fault) recognition. The classifier parameters This features are classified successfully using SVM and ANN classifier, The classifiers are trained with a subset of the experimental data for known machine conditions and are tested using the remaining set of data. The procedure is illustrated using the experimental vibration data of a rotating machine. The roles of different vibration signals and signal preprocessing techniques are investigated The performance of SVM have been found to be substantially better than ANN with the entire feature set.
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1. Introduction

Roller bearings are the important and frequently encountered components in the rotating machines that find widespread industrial applications. Therefore, fault diagnosis of the roller bearings has been the subject of extensive research. Rolling bearing faults can have many reasons, e.g. wrong design, improper mounting, acid corrosion, bad lubrication and plastic deformation [1, 2]. The process of roller bearing fault diagnosis includes the acquisition of information, extraction of features and recognition of conditions. The latter two have priority to the first one. Different methods are used for the acquisition of information; they may be broadly, classified as vibration and acoustic measurements, temperature measurements and wear debris analysis. Among these, vibration measurements are commonly used in the condition monitoring and diagnostics of the rotating machinery [3]. The vibration measurement of the roller bearing can be made using some accelerating sensors that are placed on the bearing house. When faults occur in the roller bearing, the vibration signal of the roller bearing would be different from the signal under the normal condition [4, 5, 6]. So far, many conventional vibration-signal-analysis-based methods have been applied to rotating machine fault diagnosis. Quite a few works have been done in this field, e.g. by Wang and McFadden [7], Shiroishi et al. [8], Scholkopf [9], Dellomo [10], Li et al. [11], Jack and Nandi [12], Nikolaou and Antoniadis [13], Samanta et al. [14], Al-Ghamd and Mba [15], and Purushotham et al. [16]. The possibilities of using support vector machines (SVMs) in machine condition monitoring applications are being considered only in recent years. For example, Nandi [17], and then, Jack and Nandi [18] have provided a procedure for condition monitoring of rolling element bearing. Then they improved their work by using GAs for automatic feature selection in machine condition monitoring [12, 19-20]. Samanta et al. developed a procedure similar to that of Jack and Nandi but different in processing time-domain signal [14], where only two cases were studied which are false and normal conditions. Finally, Rojas and Nandi [20] have worked on the training of SVMs by using the sequential minimal optimization (SMO) algorithm. But, multi-class Support vector machines (MSVMs), based on statistical learning theory that are of specialties for a smaller sample number have better generalization than ANNs and guarantee the local and global optimal solution are exactly the same [21]. Meantime, the learning problem of a smaller number of samples can be solved by SVM. Recently, it has been found that SVMs can be effectively applied to many applications [22-25]. Due to the fact that it is practically difficult to obtain sufficient fault samples, SVMs are introduced into rotating machinery fault diagnosis due to their high accuracy and good generalization for a smaller sample number.

In this paper, The interesting point of this investigation is the introduction of an effective method for fault detection and diagnosis in such systems through features in optioned from vibration signals , artificial neural networks (ANNs) and support vector machines (SMVs) that used for classification of rolling-element bearing faults. The extracted features from original and preprocessed signals are used as inputs to the classifiers for two-class (normal or fault) recognition. The classifier parameters This features are classified successfully using SVM and ANN classifier, The classifiers are trained with a subset of the experimental data for known machine conditions and are tested using the remaining set of data. The procedure is illustrated using the experimental vibration data of a rotating machine. The roles of different vibration signals and signal preprocessing techniques are investigated The performance of SVM have been found to be substantially better than ANN with the entire feature set.

2. Artificial neural network

The feed forward neural network, used in this work, consists of input layer, hidden layer and output layer. The input layer has nodes representing the normalized features extracted from the measured vibration signals.

There are various methods, both heuristic and systematic, to select the neural network structure and activation functions [26]. The number of input nodes was varied from 1 to 30 and that of the output nodes was 2. The target values of two output nodes can have only binary levels representing 'normal' (N) and 'failed' (F) bearings. The inputs were normalized in the range of 0-1. In the ANN, the activation functions of sigmoid were used in the hidden layers and in the output layer, respectively. The ANN was created, trained and implemented using Matlab neural network toolbox with Backpropagation (BPN) and the training algorithm of Levenberg-Marquardt. The ANN was trained iteratively to minimize the performance function of mean square error (MSE) between the network outputs and the corresponding target values. At each iteration, the gradient of the performance function (MSE) was used to adjust the network weights and biases. In this work, a mean square error of 10^{-5}, a minimum gradient of 10^{-10} and maximum iteration number (epoch) of 1000 were used. The training process would stop if any of these conditions were met. The initial weights and biases of the network were generated automatically by the program.

3. SVM

In order to calculate decision surfaces directly instead of modeling a probability distribution across training data, SVM makes use of a hypothetic space of linear functions in a high dimensional feature space. A support vector (SV) kernel is utilized for mapping the data from input space to a high-dimensional feature space; this makes easy the process of the problem in linear form. SVs are samples that have [28]. SVM always finds a global minimum because it usually tries to minimize a bound on the structural risk, rather than the empirical risk. Empirical risk is defined as the measured mean error rate on the training set as below:

$$R_{emp}(\alpha) = \frac{1}{2l}\sum_{i=1}^{l} | y_i - f(x_i, \alpha) | \qquad (1)$$

where l is the number of observations, y_i is the class label and x_i is the sample vector. The structural risks, defined as a structure derived from the inner class of the function in the nested subset, find the subset of the function that minimizes the bound on the actual risk. SVM achieves this goal by minimizing the following Lagrangian formulation:

$$L_p = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{l} \alpha_i y_i (x_i . w + b) + \sum_{i=1}^{l} \alpha_i \qquad (2)$$

Where α_i is positive Lagrange multiplier [27, 28]. SVM uses some kernels to map the data from the input space to a high-dimensional feature space which facilitates the problem to be processed in linear form. In this paper, linear and radial basis function (RBF), quadratic and polynomial kernels have been used.

4. Feature extraction

Statistical analysis of vibration signals yields different primary and secondary parameters. Research works have been reported (McFadden & Smith, 1984) on using these parameters in combinations to elicit information regarding bearing faults. Such procedures use allied logic often based on physical considerations. We selected eleven parameters as a basis for our study. They are mean, median, standard deviation, variance, kurtosis, skewness, , minimum, Zero Crossing Rate, Peak Rate and maximum. These features were extracted from vibration signals. The statistical features are explained below (where 'N' is the number of sample points.) Some features are explained as follows.

(a) Mean:

$$m_1 = \frac{1}{N}\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^n \qquad (3)$$

(b) Standard deviation: this parameter is a signature of the effective energy or power content of the vibration signal, and represents deterioration in bearing condition. The following formula has been used for computation of the standard deviation:

$$\sigma = \left(\frac{1}{N-1} \sum_{i=1}^{N} \left(x_i - \bar{x} \right)^2 \right)^{\frac{1}{2}} \tag{4}$$

(c) Sample variance: it is variance of the signal points which can be calculated using the following formula:

$$\sigma^2 = V = \left(\frac{1}{N-1} \sum_{i=1}^{N} \left(x_i - \bar{x} \right)^2 \right) \tag{5}$$

(d) Kurtosis: the value of this feature, which is a representative of the flatness or the spikiness of the signal, is very low for good bearings and high for faulty bearings due to the spiky nature of the signal.

$$Ku = \frac{m_4}{m_2^2} \quad , \quad (m_n = \frac{1}{N} \sum_{i=1}^{N} \left(x_i - \bar{x} \right)^n) \quad 6)$$

(e) Skewness: this feature, representing the asymmetry of a distribution around its mean, can be obtained from the formula:

$$skewenss = \frac{m_3}{m_2^2} \quad , \quad (m_n = \frac{1}{N} \sum_{i=1}^{N} \left(x_i - \bar{x} \right)^n) \ , (7)$$

(f) Minimum value: it refers to the minimum signal point value in a given signal. As the bearing parts (inner race, outer race and roller) get degraded, the vibration levels seem to go up. Hence, it can be utilized for fault detection.

(g) Maximum value: it refers to the maximum signal point value in a given signal.

5. Experimental Procedure

Two data sets, each containing twenty data files, were collected from Two bearings which are the same but with different faults. The first data file was collected from each test bearing when the loading was zero, and the bearing was Running at the highest speed (3000 rpm). The load was then increased step by step, the speed was kept at 3000rpm, and four other data files were collected. The load was then brought back to zero, and speed was decreased by 500 rpm; then, the next five data files were collected under five different loads similar to the first five data files. This procedure was continued until all twenty five sets of data were collected. The sampling frequency was chosen as 41.67 kHz; this sampling frequency along with the data record size of 4098 guarantees that the sampling procedure covers at least 1.6 revolutions of shaft at the lowest speed.

The diagram block of detection of the type of faults in bearings has been illustrated in Table (1).

6. TEST BEARINGS

An impact impulse is generated every time a ball hits a defect in the raceway or every time a defect in a ball hits the raceway. Each of such impulses excites a short transient vibration in the bearings at its natural frequencies. Each time this defect is rolled over, an impact is produced whose energy depends on the severity of the defect. Many failure modes of a rolling element bearing produce such a discontinuity in the path of the rolling elements. Moreover the majority of rolling element bearing failure cases begin with a defect on one of the raceways. In this research, defects on inner raceway (IRD) and normal Bearing (GBR) are used.

7. Conclusion

Due to the importance of rolling bearings as one of the most populous used industrial machinery elements, development of proper monitoring and fault diagnosis procedure to suppression malfunctioning and failure of these elements during operation is necessary. For rolling bearing fault detection, it is expected that a desired time domain analysis method has good computational efficiency. A procedure is presented for diagnosis of bearing condition using two classifiers, namely, ANNs and SVMs with feature selection from time-domain vibration signals. The roles of different vibration signals and signal preprocessing techniques have been investigated. The performance of SVM have been found to be substantially better than ANN with the entire feature set.

8. Figures and Tables

8.1. Figures

In this section, the diagram block of detection of the type of faults(Fig.1), the original acceleration vibration signal for two types of faults at 3000rpm speed and 500N load have been shown (Fig.2).

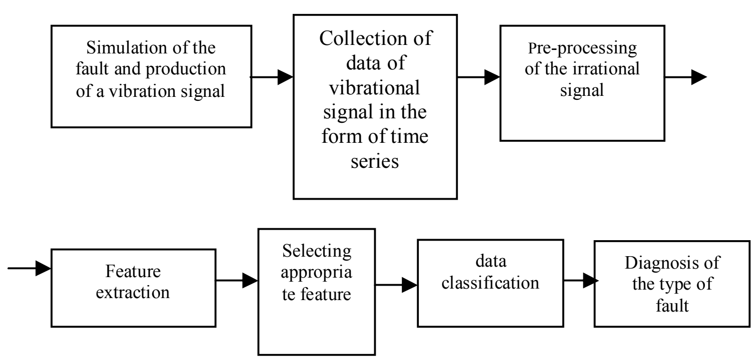
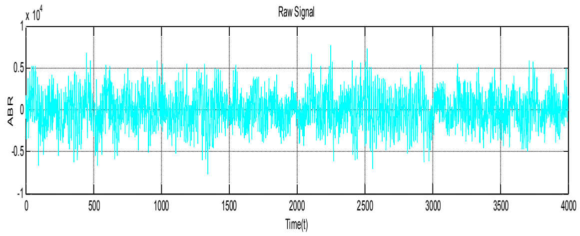


Fig. 1: the diagram block of detection of the type of faults.

(a)



(b)

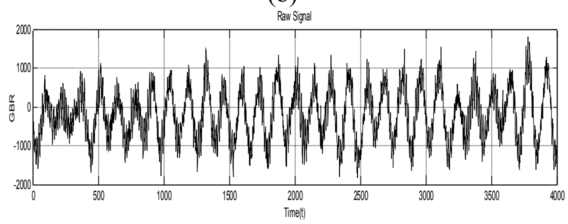


Fig.2: Original acceleration vibration of the signal for two different faults, (a): Inner race way fault, (b) Good bearing

8.2. Table

In this section, the roller bearing fault diagnosis for two type faults at 3000rpm speed and 1000N load have been shown in Table 1.

TABLE 1: Performance comparison of classifiers with different number of features

Number of features	Test success (%)	
	SVM	PNN
4	68	58
7	85	79
11	94	89

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