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Feature Selection of Acoustic Emission Signal for the Slow-speed and Heavy-load Equipment

[1]Min Li and [2]Jianhong Yang

Mechanical Engineering School

University of Science and Technology Beijing

Beijing, China

[1]limin@ustb.edu.cn,[2]yangjianhong@me.ustb.edu.cn

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Abstract—Selecting feature in slow-speed and heavy-load equipments has always been a difficult problem. A new feature selection method based on Laplacian Score is used to Acoustic Emission signal. The more capable of describing the sample clustering property, the more important the selected feature is. The method is a 'filter' and unsupervised feature selection method which is just dependent on the space distribution of the sample instead of classifier. Therefore, the method enjoys a simple algorithm and low complexity. The effectiveness of the method is verified by the AE datasets from the bearings of a blast furnace's belt conveyor.

Introduction

Slow-speed and heavy-load equipment normally runs at the speeds of 1rpm~30rpm and the fault frequency is often less than 1Hz. This leads to some restrictions on the vibration measurement due to the fact that the fault frequency is much lower than the cut-off frequency of the most vibration sensors, so it is very difficult to detect such a low frequency precisely. In addition, the defect energy at the early stage is too weak to arouse the response of the vibration sensor. Therefore, the methods based on vibration measurement is sometimes unable to effectively detect the initial stage failures of the slow-speed and heavy-load equipment[1]. Acoustic Emission (AE) is defined as transient elastic waves produced from a rapid release of strain energy caused by a deformation or damage within or on the surface of a material. The AE signal stems largely from the fault itself. Even though the defect energy is weak, it is possible to detect the 10^{-14}m vibration on the equipment surface caused by the fault with high sensitivity AE sensor. So the AE technology offers a significance advantage due to its capability of detecting and revealing initial fault signal[2-3].

An AE signal comprises about many features, such as Amplitude, RMS, Counts, etc. These features have different physical meaning and their sensitivities to a fault are also different. When a fault occurs, some of the features change dramatically, while others change mildly. Therefore, it is necessary to select the appropriate features of AE signal.

Feature selection is a process of selecting d features from a whole m features, which are able to reflect the samples clustering property. It is obvious that, as shown in Fig. 1, feature F1 can distinguish the two kinds of samples completely, but feature F2 fails. This shows that the key point of feature selection is to seek out the features which can describe the space distribution of the sample.

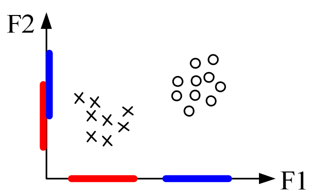

Figure 1. Schematic of feature selection

Theoretically, the optimal feature selection requires an exhaustive search of all possible feature combination, and then the feature subset with the best evaluation criterion is chosen as the result of the feature selection. However, if large numbers of features are available, this simple method becomes impractical. Suppose that an exhaustive search is applied to the m features, the search space will be $2m!$ [4]. Meanwhile, with the increasing of feature dimensions, the computational cost of the research grows exponentially. The most commonly used method for feature selection is to take the classification error rate of a classifier as the indicator to perform the advantage and disadvantage evaluation of subsets, namely the feature selection is interrelated with the classifier. This method is one of the 'wrapper' model techniques are classifier-specific and the feature subset is selected directly based on the performance of a specific classifier[5]. If a classifier is fixed, the features subsets selected normally have better classification performance. However, the method does not enjoy a good level of universality because when the classifier is changed, feature selection for it has to be undertaken. In addition, each evaluation of feature subsets involves the training and testing process. The increasing complexity of the algorithm also leads to long runtime, especially for large-scale datasets.

To minimize a classifier's influence on the feature selection, another features selection model has also been developed. It is well known as 'filter' [6]. Methods based on the filter model are classifier-independent, and only examine intrinsic properties of dataset to decide whether a feature should be maintained or removed. Data variance might be the simplest method for feature selection. The greater a feature data variance is, the more useful it will represent distribution of the dataset which the feature belongs to. Therefore, the accepted practice for m features is to use the former d greatest variances of all ones which are ranking in a descending order as the result of feature selection. However, data variance fails to reflect the clustering property of a dataset. A measurement called entropy distance was proposed for this by Dash[7]. Smaller entropy distance means better clustering of data points. Ranking the features by the measurement can remove the uncorrelated ones efficiently. In this paper, with the combination of feature variance and sample clustering property, a new feature selection based on Laplace Score[8] is used for fault diagnosis in slow-speed and heavy-load equipment. The effectiveness of the method is verified by tests on blast furnace belt bearings. And the results prove that the features selected by the method are capable of distinguishing two kinds of bearing fault conditions effectively.

The rest of this paper is organized as follows. In Section 2, we briefly describe the basic principles of feature ranking, i.e., analysis the importance of the AE features based on Laplacian Score. In Section 3, an experiment on the fault diagnosis for rolling bearings in the belt conveyor is discussed. Finally, the conclusions are drawn in Section 4.

Basic principles of feature ranking

Laplacian Score is a novel feature ranking algorithm. The method is based on the observation that, in many real world classification problems, data from the same class are often close to each other. The importance of a feature is evaluated by its power of locality preserving. The key point of the method is to calculate the score of each feature, and then select the leading features based on the rank of these feature-level scores. The algorithm can be stated as follows:

Constructing the adjacency graph. As a property of feature selection, we assume that dataset consist of m data points with n dimensions or features. We shall denote $\boldsymbol{X}_i$ as i-th point of dataset $\boldsymbol{X}$, f_{ri} denote r-th feature value of the i-th point, $i = 1,2,\cdots,m$; $r = 1,2,\cdots,n$.

K-means clustering method is used to calculate the distance between the m data points. We put an edge between points i and j if $\boldsymbol{X}_i$ and $\boldsymbol{X}_j$ are 'close', i.e. $\boldsymbol{X}_i$ is among k nearest neighbors of $\boldsymbol{X}_j$ or $\boldsymbol{X}_j$ is among k nearest neighbors of $\boldsymbol{X}_i$. By constructing adjacency graph, we can confirm the adjacency relationship between the m data points.

Modeling the local geometric structure. Suppose that the points i and j are connected, the weight W_{ij} is given by

$$W_{ij} = e^{-\frac{\|x_i - x_j\|^2}{t}} \tag{1}$$

Otherwise, put $W_{ij}=0$. In the Eq.(1), t is a suitable constant. W_{ij} evaluates the similarity between the $\boldsymbol{X}_i$ and $\boldsymbol{X}_j$ if and only if the two points have an edge in k-neighborhood points. From the Eq.(1), we can see that the W_{ij} is an exponential decay function, the closer two points are, the bigger their weight are. So the W_{ij} is taken as a penalty factor, which enables the points close to each other more closer, and keep the points away from one another more farther.

Calculating the Laplacian Score. Let $\boldsymbol{f}_r=[f_{r1},f_{r2},\cdots,f_{rm}]^{\mathrm{T}}$ denotes the r-th feature, f_{ri} is the r-th feature value of $\boldsymbol{X}_i$. The Laplacian Score of $\boldsymbol{f}_r$ is calculated as below.

$$L_{\mathrm{r}}=\frac{\sum_{ij}(f_{ri}-f_{rj})^2W_{ij}}{Var(\boldsymbol{f}_r)} \tag{2}$$

Where $Var(\boldsymbol{f}_r)$, the estimated variance of the r-th feature, is often used to evaluate weather the feature $\boldsymbol{f}_r$ can reveal the information of each class or not. The $Var(\boldsymbol{f}_r)$ reflects the gloabal sturcure of the data points. In orther words, The bigger the $Var(\boldsymbol{f}_r)$ is, the better the each class can be distinguished effectively. While the $\sum_{ij}(f_{ri}-f_{rj})^2W_{ij}$ describes the local strucure. If the value of the $\sum_{ij}(f_{ri}-f_{rj})^2W_{ij}$ is small, the distance of data points is close. In this case, the data points belong to the same class. In summary, the L_{r} tends to be small and the ascending order of L_{r} for all the features indicates the importance of features. In a word, the smaller L_{r} is, the more importance of the features is.

Experiment for validation

The belt conveyor (normally runs at a speed of 2rpm) of blast furnace plays an important role in metallurgical production for the supply of raw materials like ore and coke. The supporting bearings the both sides of each tension roller always run at the speed of 60rpm with heavy loads. Due to long-term operation, the bearings frequently suffer from severe fault such as pitting, flaking and scuffing. So the healthy condition of the bearings has a great impact on the running of the belt conveyor. Therefore, it is highly necessary to monitor the bearings conditions precisely at regular intervals. AE technology was employed in this case. The equipment structure and the AE sensors location are shown as Fig. 2.

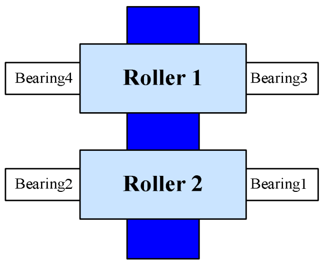

Figure 2. Layout of equipment structure and AE sensors location

The AE sensors were fixed in the vertical direction of the bearings. The PAC-Ⅱinstrument was used for data acquisition. Two kinds of samples were obtained, namely early faults and terminal ones. Each kind contains 40 data points. Let us take the Bearing3 to describe the process of feature selection. Firstly time domain features of AE were computed as shown in Fig. 3.

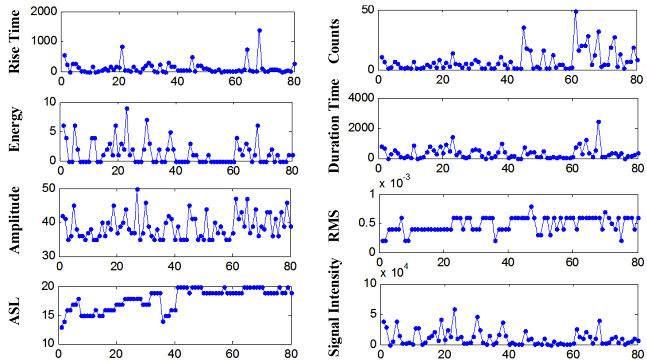

Figure 3. Time domain features of AE

The feature ranking of eight AE features were calculated by Laplacian Score and the results was ranked by the importance degree as listed in Tab. 1. As can be seen, the score of RMS is smallest one indicating the feature RMS ranks the first by its importance. The score of Ring Time is the greatest but the feature is the least important. In Fig. 4 and Fig. 5, data distributions are represented by different features.

TABLE I. RESULT OF FEATURE RANKING

Feature	Rise Time	Counts	Energy	Duration Time
L_r	1.6595	1.0983	0.6472	1.3791
Feature Ranking	8	6	3	7
Feature	Amplitude	RMS	ASL	Signal Intensity
L_r	1.0874	0.0200	0.0212	0.6478
Feature Ranking	5	1	2	4

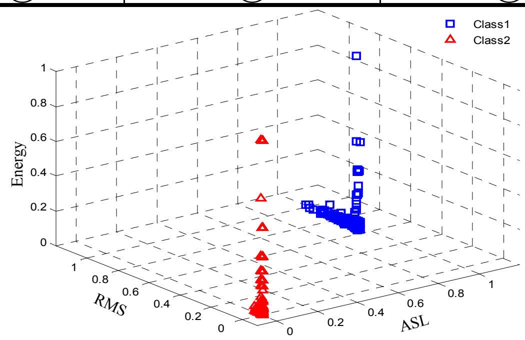

Figure 4. Data distribution represented by the first three important features

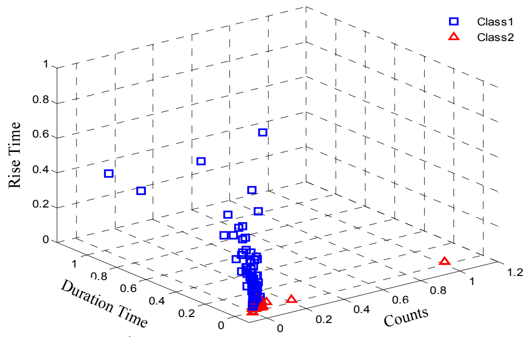

Figure 5. Data distribution represented by the last three features

Different AE features are sensitive to fault in varying degrees when they are employed in the fault diagnosis. As is shown in Fig. 4, the appropriate feature combinations (RMS, ASL and Energy) will distinguish the two kinds of fault directly. This result has shown very effective in removing irrelevant and redundant features, increasing learning accuracy, and enhancing learning comprehensibility.

Otherwise, in Fig. 5, great difficulty will be caused for the last three features. In this case, taking Duration Time, Count and Rise Time as the main feature parameters make the fault classification for equipment more inaccurate and ineffective.

Conclusions

(1) A feature selection method based on Laplacian Score, with the combination of feature variance and sample clustering property, is used for AE signal. A new feature score is introduced. The smaller score value means the feature enjoys a higher importance degree and stronger ability for reflecting a sample clustering property.

(2) The application of AE measurement for condition monitoring of the slow-speed and heavy-load equipment is gaining ground. It is proved that three key features of AE signal, RMS, ASL and Energy, will obviously facilitate the feature selection for slow-speed and heavy-load equipment. This provides a favorable reference for the application of AE detecting technology in other similar equipments.

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