Fault Detection and Diagnosis for Induction Motors Using Variance, Cross-correlation and Wavelets
웨이블렛 계수의 분산과 상관도를 이용한 유도전동기의 고장 검출 및 진단

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ABSTRACT

In this paper, we propose an approach to signal model-based fault detection and diagnosis system for induction motors. The current fault detection techniques used in the industry are limit checking techniques, which are simple but cannot predict the types of faults and the initiation of the faults. The system consists of two consecutive processes: fault detection process and fault diagnosis process. In the fault detection process, the system extracts the significant features from sound signals using combination of variance, cross-correlation and wavelet. Consequently, the pattern classification technique is applied to the fault diagnosis process to recognize the system faults based on faulty symptoms. The sounds generated from different kinds of typical motor's faults such as motor unbalance, bearing misalignment and bearing loose are examined. We propose two approaches for fault detection and diagnosis system that are wavelet-and-variance-based and wavelet-and-crosscorrelation-based approaches. The results of our experiment show more than 95 and 78 percent accuracy for fault classification, respectively.

요 약

이 논문에서는 신호 모델에 기반하여 유도전동기의 고장 검출 및 고장 진단을 위한 새로운 시스템을 제안한다. 산업현장에 적용하는 기존의 제품들은 신호가 문턱치를 넘어면 고장을 검출하는 단순한 알고리듬을 가지고 있어 고장의 유형이나 고장을 예측하는데 문제가 있다. 이 논문에서는 이러한 문제들을 해결하기 위한 시스템을 제안한다. 이 시스템은 고장 검출 과정과 고장 진단 과정으로 구성되며, 고장 검출 과정은 기계 신호음들이 웨이블렛 필터뱅크를 통과한 후 웨이블렛 계수들의 분산과 상관도를 분석하여 고장을 검출한다. 고장 진단 과정은 패턴분류기술을 적용하여 고장의 유형을 진단하게 된다. 대표적인 유도전동기 고장 유형들로서는 불평형, 미스얼라이먼트, 그리고 베어링 루스 등이 있으며, 이러한 유형들은 제안하는 시스템에서 분석되고 진단을 받게 된다. 제안하는 시스템에 적용한 결과 상관도를 이용한 방법은 78 %, 분산을 이용한 방법은 95 % 이상의 고장진단율을 보이는 우수한 결과를 나타내었다.

1. Introduction

Systems for detection and diagnosis of mal-

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functioning machines play an important role in industrial fields. This is particularly important for machines such as airplanes and ships whose failures may lead to critical situations. It is also critical in the manufacturing industry, since a bad manufacturing machine may produce many defective products dangerous to consumers. It is therefore compulsory to have an investigation for the earliest possible detection for a machine before it becomes faulty.

A fault detection and diagnosis consists of two consecutive processes[3,9] : fault detection process and fault diagnosis process as shown in Fig. 1. Generally, fault detection and diagnosis are based on measured variables by instrumental and observed variables and states by human operators. The fault detection process analyzes the measured signals such as vibration, noise, acoustic sound, pressure or bases on the analytical parameters to generate the faulty symptoms, which can be analytical symptoms or heuristic symptoms[8,10,11]. The faulty symptoms are the input of the fault diagnosis process that determines the size, type and location of the system fault[9].

An induction motor is a three phase AC motor and the most widely used machine. Its characteristic features are: simple and rugged cons-

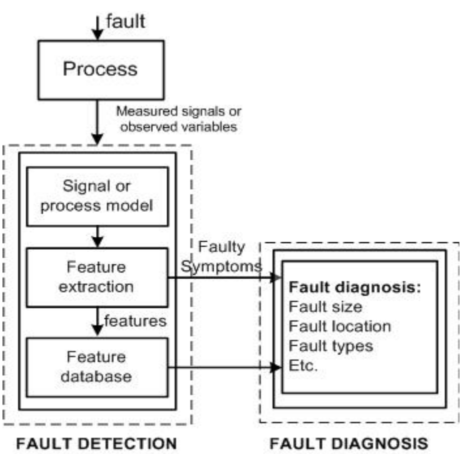

Fig. 1 General structure of model-based fault detection and diagnosis

truction, low cost and minimum maintenance, high reliability and sufficiently high efficiency, needs no extra starting motor and need not be synchronized. An induction motor has basically two parts: Stator and Rotor. The Stator is made up of a number of stampings with slots to carry three phase windings. It is wound for a definite number of poles. The windings are geometrically spaced 120 degrees apart. Two types of rotors are used in Induction motors: Squirrel-cage rotor and Wound rotor. During the operation; however, there are some kinds of faults frequently happen such as: rotor bar eccentricity and stator winding failures, misalignment, bearing faults and worn pumps.

Motor faults are typically related to core components such as stators, rotors and bearings. Surveys indicate that these components account for 88 % of motor failures[23]. There are many ways to detect the mechanical and electrical problems in induction motor[13~19], either directly or indirectly such as: vibration analysis, motor current signature analysis(MCSA), electromagnetic field monitoring, chemical analysis, noise and acoustic analysis, temperature measurability, infrared measurement and partial discharged measurement. Among these techniques, the current[7,12] and vibration analysis[22] are the most popular ones due to their easy measurability, high accuracy and reliability. Other fault detection and diagnosis techniques have been proposed for bearing faults. Bearings are important parts in induction motors since 40 percent of faults in induction motors are related to bearing faults[2,20,21].

In this paper, we proposed new approaches of fault detection and diagnosis for induction motors. We experiment with the different faults of the motor using microphones to record the sound signals produced from the motor. As vibration signal, sound signal from the motor has specific characteristics. When the condition of the motor changes the characteristics of the sound signal also varies. The motor running in the abnormal condition generates a different sound comparing with that in the normal condition. By analyzing the features of the sounds to generate the faulty symptoms in the fault detection process, we predict the motor condition in the fault diagnosis process. In this experiment, sounds from typical faults of the induction motor are collected categorized into faulty categories. Through the faulty symptoms, any sound signals generated from the motor are classified to the corresponding faulty category. Therefore, the fault recognition is made.

2. Proposed Approaches for Fault Detection and Diagnosis

2.1 Wavelet-and-variance-based Technique

In this approach, a sound signal is decomposed into smaller frequency bands using the wavelet transform, which can be referred in(1,5,6). Each of these frequency bands is applied in time-domain to calculate its variance. A collection of variance values(i.e. feature vector) from the frequency bands are considered as a faulty symptom in the fault detection process. Since a normal signal and a faulty signal are different in term of frequencies, the differences in feature vectors(variances) can be considered for differential identification of the signals. This is essential for the fault diagnosis process, which recognizes the fault based on the faulty symptoms. A variance presents the central dispersion of a sound signal data. Any two similar sound signals must have approximate variances. However, two signals, which have similar variances, are not surely guaranteed to be similar. There are also some features that have similar presentation such as mean, Kurtosis, Skewness, etc.(1,4) that we can employ such the interested features as the variance feature. Hence, in the fault detection process, the feature vector is produced and considered as the faulty symptom.

We propose a classification model for the fault diagnosis process as shown in Fig. 2.

In the *wavelet and variance* module in this model, the sound signal is decomposed into ***N*** frequency bands (one band presents a signal that contains this frequency band) using the wavelet transform. For each band, we reconstruct the signal for this band into time domain; thereafter, its variance value is calculated. Finally, a collection of variances for all frequency bands is represented by a ***N***-element feature vector for the signal(each element of the feature vector is a scalar variance value from each wavelet band). The decomposition of a sound signal using the wavelet transform is represented in Fig. 3. The sound signal is decomposed into four frequency bands (i.e. wavelet decomposition at level 2. At wavelet level ***K***, 2^K bands are produced).

Assuming that we have **P** faulty categories, to classify one signal into one of the **P** faulty categories, it is necessary to define a set of features that contains majority important feature of that category (i.e. the reference feature vector); therefore, the trained signal should be compared

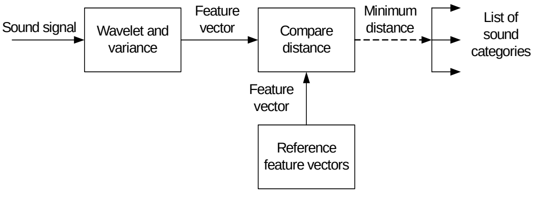

Fig. 2 Proposed classification model using wavelet and variance based technique

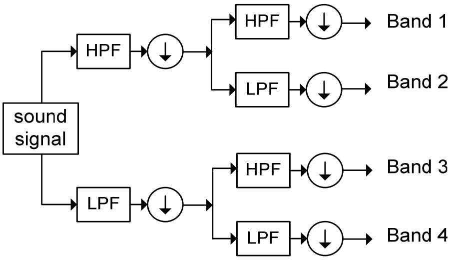

Fig. 3 Sound signal decomposition using wavelet at level 2

with the reference feature vector. The methods for selecting the reference feature vector are various such as the vector that has the minimum Euclidean distance with other feature vectors in the category. In this paper, we determine the reference feature vector that contains collection of variance values of entire wavelet bands with each variance value of the reference feature vector is the mean of all variance values from sample signals in that category.

In the *classifier* module, the Euclidean distances between the feature vectors extracted from trained signals and each reference feature vector from **P** categories are made. Normally, two signals are similar if their Euclidean distance gets a minimum; hence, the minimum distance provides the information of the category that the trained signal should be classified to. Suppose that X is the feature vector from the trained signal and Y is the feature vector from the reference signal. Each vector has $\boldsymbol{N}$ elements with the coordinates $\{X_1,X_2,...,X_N\}$ and $\{Y_1,Y_2,...,Y_N\}$ respectively. The Euclidean distance can be calculated as follows:

$$D_{XY}=\sqrt{\sum_{i=1}^{N}(X_i-Y_i)^2} \tag{1}$$

The final decision for classification is that an arbitrary trained signal is referred to the equivalent signal category if it is the most similar to the reference feature vector of this category as well as the Euclidean distance must be smaller than an assigned threshold. The threshold may be allocated to a scalar value depending on faulty conditions(normally, assigned by the expert's experience). The threshold assures that the trained signal is classified to the correct faulty category. Sometimes, the trained signal is the most similar to a specific faulty category through the minimum Euclidean distance comparing with the other category; however, this trained signal and the other signals in the faulty category are fairly distinctive. In this case, this trained signal may belong to another faulty category or this signal gets a big disturbance from the outside environment.

2.2 Wavelet-and-crosscorrelation-based Technique

In this proposed approach, the cross-correlation function is utilized to examine the similarity between two signals. Cross correlation is a standard method of estimating the degree to which two series are correlated. Consider two series $x(n)$ and $y(n)$, where $n=1,2,3,...,N$. The cross correlation R_{xy} at delay k is defined as :

$$R_{xy}(k)=\frac{\sum_{n=1}^{N}(x(n)-\mu_x)*(y(n-k)-\mu_y)}{\sqrt{\sum_{n=1}^{N}(x(n)-\mu_x)^2}\sqrt{\sum_{n=1}^{N}(y(n)-\mu_y)^2}} \tag{2}$$

where μ_x and μ_y are the mean of $x(n)$ and $y(n)$, respectively. If two signals are similar, the strong correlation should be at the delay of the middle point and its value should be nearly 1. Figure 4 shows the cross-correlation between two similar signals with the maximum value of correlation of approximate 0.8 at the middle point. Two signals in a same faulty category should have similar spectrum in some important frequency bands; however, they also may have some different spectrum in some less important bands. Therefore, two signals classified into the same category must be similar in some frequency bands wherein high energies exist. In this approach, we proposed an approach to use the wavelet and cross-correlation techniques for fault detection and fault diagnosis processes. The basic idea of this approach is to find the most important frequency bands for each reference signal in each faulty category. Then, the comparison between the trained signal and the reference signal is checked just in the most important frequency band.

The proposed faulty classification model for fault diagnosis process is described in Fig. 5 with the details described as follows:

Feature extraction : As previously mentioned, a signal is decomposed into a number of frequency bands using the wavelet transform. The frequencies in the FFT(fast time Fourier transform[1]) domain of each band are practiced as features.

Dictionary : For each category, a standard signal is selected as a reference signal that is closest to the other sample signals in the same category. After using the wavelet transform to decompose the reference signals from all categories into frequency bands(suppose ***N*** bands created), each frequency band are saved to the dictionary as the frequency feature vectors, which are used to make cross-correlations with trained signals. Therefore, in a dictionary for a faulty category, there are ***N*** frequency feature vectors existing.

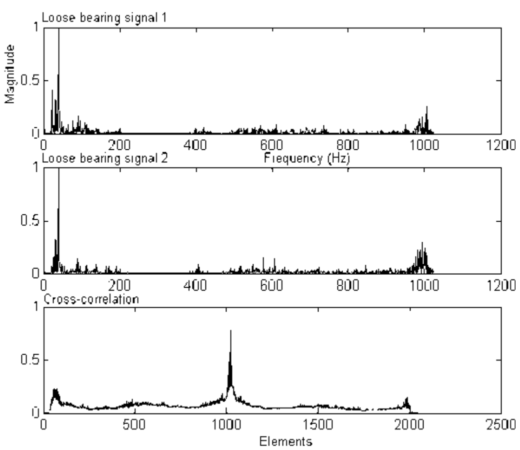

Fig. 4 Cross-correlation of two signals in the same loose bearing category

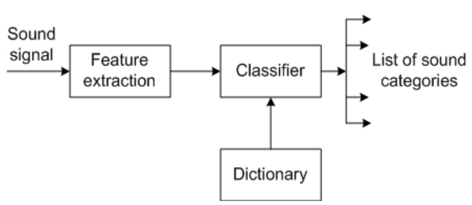

Fig. 5 Proposed classification model using wavelet and cross-correlation based approach

Classifier : The classifier module assorts any trained signal into one of the faulty signal categories by authenticating the affinity between the signal and each category reference signal. The trained signal is classified to a faulty category if it is close to the reference signal of this faulty category. As we mentioned above, in order to compare a trained signal with each category reference signal(saved as frequency feature vectors in the dictionary), each corresponding band from two signals are compared by checking their cross-correlation. Only the important frequency bands are considered. The cross-correlations at the strongest correlation points of the important frequency bands are used and assigned the equivalent thresholds depending on the expert's experience.

3. Results and Discussions

3.1 Database

Due to the circumscription of experiment, there are restricted databases generated including four cases of the motor's faults and one normal case, they are: BF(fault bearing), LO(loose bearing), UN(unbalance bearing), and MIS(misalignment bearing) and NOR(normal bearing) sound signals. For each case, a one-second duration segment of a sound signal is stored as a separate signal. In this experiment, there are 42 sound signals used for training with nine signals for BF, nine for NOR, eight for LO, seven for UN and nine for MIS. This set of sound signal is referred to the testing database. To select the reference sound signal for each category, a database of 25 sound signals are used with five signals for each category. For each category, a reference sound signal is assigned as one in the five signals that is the most similar to the other signals. Once the reference sound signal has been chosen for each category, the reference feature vector is easily produced using the previously mentioned approach.

The characteristics of reference signals of five categories in time domain and frequency domain are represented in Fig. 6 and Fig. 7, respectively. In time domain, reference signals are different from each other; therefore, the features calculated in time domain such as mean, variance, and Kurtosis are also different. In frequency domain, low frequency components of five signals exist stronger than the other components. The low frequency components from MIS category reference signal are stronger than that from the other categories. The frequency characteristics of reference signals lead us to consider the best frequency components for fault recognition. In this case, the low frequency components are strongly significant to consider than the other components.

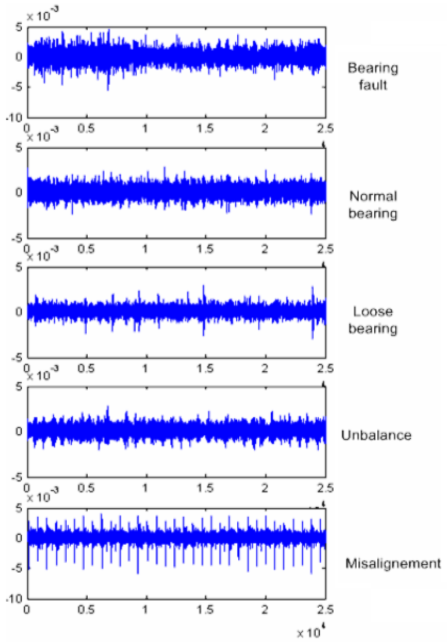

Fig. 6 The waveform of Five reference signals from BF, NOR, LO, UN and MIS categories in time domain

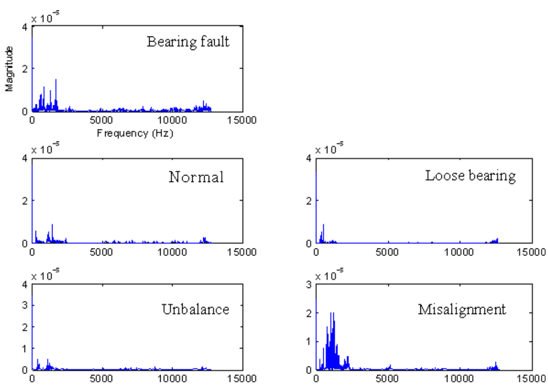

Fig. 7 FFT five reference signals from BF, NOR, LO, UN and MIS categories

3.2 Results and Discussions

(1) Results of Wavelet-and-variance-based Approach

The threshold is assigned to 10^{-7}. Only the trained sound signal with minimum Euclidean distance with other category's reference feature vectors less than the threshold is considered, or otherwise neglected. The testing database are trained on this approach, consequently we can conclude the results in Table 1, 2 and 3.

Table 1 shows the Euclidean distance between the sound signals in the loose bearing fault category and the reference feature vectors of faulty categories. The bold numbers represent the minimum distance. Associating with the threshold value, it is obviously said that all of eight signals trained are classified to the LO(loose bearing) category. The difference between the bold numbers and the others also provides the significant information that those signals and other categories are strongly distinctive.

Besides, Table 2 illustrates an example of a training process where one arbitrary signal from each category is trained. The first signal supposed to be classified to the BF category is; however, not classified to any category. It is because the minimum Euclidean distance obtained is greater than the threshold. Even this signal is the most similar to the reference signal of the BF category, the big distance does not ensure for a correct classification. The other signals are classified to the exactly corresponding categories. Finally, the total classification results are presented in Table 3. Among nine signals in the BF category, two signals are not correctly classified since their corresponding Euclidean distances are not less than the assigned threshold; however, the other signals are classified properly to the corresponding categories. The overall classification accuracy reaches more than 95 percent.

Table 1 Euclidean distance between the feature vector of each signal in Loose bearing fault category and other category's reference feature vectors (multiply by 10^{-5})

Loose bearing signal	Category				
	BF	NOR	LO	UN	MIS
1	0.3958	0.0357	**0.0003**	0.0155	0.2101
2	0.3900	0.0347	**0.0001**	0.0145	0.2066
3	0.3805	0.0322	**0.0003**	0.0130	0.2012
4	0.3927	0.0343	**0.0002**	0.0145	0.2081
5	0.3961	0.0346	**0.0001**	0.0146	0.2092
6	0.3891	0.0335	**0.0002**	0.0139	0.2034
7	0.3782	0.0304	**0.0002**	0.0121	0.1971
8	0.3900	0.0347	**0.0001**	0.0145	0.2066

Table 2 Euclidean distance between a feature vector of an arbitrary signal in each category and other category's reference feature vectors (multiply by 10^{-5})

Signal (belonging category)	Category				
	BF	NOR	LO	UN	MIS
1 (BF)	**0.0056**	0.2170	0.3819	0.2692	0.0890
2 (NOR)	0.2168	**0.0007**	0.0347	0.0053	0.0975
3(LO)	0.3961	0.0346	**0.0001**	0.0146	0.2092
4(UN)	0.2693	0.0049	0.0146	**0.0004**	0.1288
5(MIS)	0.0723	0.0996	0.2067	0.1383	**0.0009**

Table 3 Classification results. Ca : classification accuracy

Categories (# of signals)	Category					
	BF	NOR	LO	UN	MIS	CA%
BF (9)	7	0	0	0	0	77.8
NOR (9)	0	9	0	0	0	100
LO (8)	0	0	8	0	0	100
UN (7)	0	0	0	7	0	100
MIS (9)	1	0	0	0	9	100
Overall						95.6

In Fig. 6, the reference signals from LO, UN and MIS categories are distinctive from the others; hence, the equivalent variance values are also different from the others. However, the waveforms of reference signals from BF and NOR category are quite similar. That may explain why two signals from BF category are not classified correctly. However, with more than 95 % of classification accuracy, this is very promising approach.

(2) Results of Using Wavelet-and-crosscorrelation-based Approach

In this approach, thresholds are also needed to estimate the similarity between two signals. Depending on the characteristic of the category, a threshold for each wavelet band may be different. For instance, the thresholds for the most significant bands are commonly higher than that of the less important bands.

Each signal in the testing database is trained by this approach. To classify a signal into a specific category, we need to examine the similarity between this trained signal and the reference signals as well as consider the similarity in the most important frequency band. Each wavelet band from the trained signal is cross-correlated to equivalent wavelet band from reference signals. This band is assigned to the specific category if their cross-correlation value gets maximum and higher than the others. Like previous approach, we also use the same approach for selecting the reference signal in the 25 sound signals database and we also use the testing database for training.

We demonstrate the results of experiment through Table 4. As previously mentioned, it is meaningful to estimate which frequency bands of a signal are the most important. For example, in Figure 8 representing the spectrum of a LO signal, the most important frequency bands are 1, 2, 5 and 8. Therefore, to distinguish the LO signal from other category signals, the wavelet bands 1, 2, 5 and 8 are more significant to examine. Table 4 presents the maximum cross-correlation value of the eight wavelet bands from an arbitrary LO signal and corresponding wavelet bands of reference signals. The bold numbers present the maximum value in a row. In the two first, fifth and eighth frequency bands, the maximum values belong to the LO category; however, in the other bands the maximum values belong to other categories. As previously mentioned, for the LO signal, first, second, fifth and eighth bands are the most significant bands; hence, this signal is clearly classified to the LO category.

The thresholds for each the wavelet bands are assigned as shown in Table 5. We just consider the important bands and neglect the other bands since only the important bands provide the essential information for identifying the faults. The thresholds are dependent on the engineering expert's experience. In this experiment we set the thresholds using our feel on the sound and vision on frequency spectrum. Finally, the total classification results are presented in Table 6. Among nine signals in the BF category, five signals are not correctly classified that is a big trouble in this approach. The overall classification accuracy reaches more than 78 percent.

In this approach using wavelet technique and

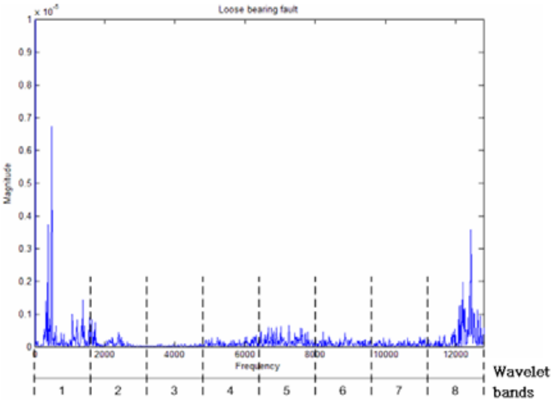

Fig. 8 FFT of a loose bearing fault signal

differences of frequency components to recognize the normal signal and faulty signal. However, in the BF category itself, the distribution of frequency

Table 4 Maximum cross-correlation value of 8 wavelet bands from an arbitrary LO trained signal and corresponding wavelet bands of reference signals of the entire categories

Wavelet bands	Category				
	BF	NOR	LO	UN	MIS
1	0.8794	0.9779	**0.9973**	0.9871	0.7756
2	0.4242	0.4562	**0.6042**	0.4228	0.3307
3	0.4423	0.5173	0.4303	**0.5269**	0.3953
4	0.4850	**0.5078**	0.4927	0.4934	0.4422
5	0.5482	0.5762	**0.7062**	0.5373	0.6388
6	0.5518	**0.5548**	0.5372	0.5329	0.4913
7	0.5102	0.5451	**0.5805**	0.5546	0.5096
8	0.5126	0.5469	0.5324	**0.5604**	0.5344

Table 5 Assigned thresholds for each frequency bands for each category. If a band is not important to consider then in the table, it is marked as 'x'

Wavelet bands	Category				
	BF	NOR	LO	UN	MIS
1	**0.7**	**0.98**	**0.99**	**0.99**	**0.95**
2	**0.6**	**0.55**	**0.6**	**0.55**	**0.75**
3	x	x	x	x	x
4	**0.55**	x	x	x	0.6
5	**0.55**	x	x	x	x
6	x	x	x	x	x
7	x	**0.55**	x	x	x
8	x	x	x	x	x

Table 6 Classification results. Ca : classification accuracy

Categories (# of signals)	Category					
	BF	NOR	LO	UN	MIS	CA%
BF (9)	4	0	0	0	0	44.4
NOR (9)	0	7	0	0	0	77.8
LO (8)	0	0	8	0	0	100
UN (7)	0	0	0	5	0	71.4
MIS (9)	0	0	0	0	9	100
Overall						78.7

components in signals are not completely resemble. In some frequency bands, signals from different categories have similar presentation of frequency components. That is why the results of classification for BF category are not satisfied. Improving the approach to solve this problem is our future work. Even not good results for some category, this is a very promising approach. Considering the frequency components in the most frequency bands is the best way to find the faults since the frequency components are related to physical phenomena.

4. Conclusions

By investigating the characteristics of faults normally happened in operating induction motors, we implemented an experiment on an induction motor. From the experiment, a set of sound signals from different faults of the induction motor is generated. We also proposed two approaches to deal with how to recognize the motor's faults through the sound signal that the motor generates. We exploited the combination between the variance and the cross-correlation with the wavelet to extract the significant features of sound signals, which is known as the faults symptoms for the fault detection process. The results of the fault diagnosis process via the classification accuracy shows the potential of the approach using these extracted features. Moreover, the various results from each approach may offer valuable information for different kinds of applications in fault detection and diagnosis. The previous techniques such as limit checking and process model-based have their own disadvantages. The limit checking technique is simple, easy to implement and suitable for a small systems; however, it has a limit information of fault and faults are unpredictable. The rarely used technique and process model-based describe details of the faults; however, it is very complex, difficult to deploy and not suitable for a small systems such as induction motors. Our approaches to fault detection and diagnosis are easy to implement, believable and suitable for induction motors. The short-coming of this work is the limit of faulty categories. We deal with some typical faults of motors; however, many faults may happen in an operating motor that need to be considered.

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