Performance Evaluation of Multi-sensors Signals and Classifiers for Faults Diagnosis of Induction Motor

Gang Niu[a], Jong-duk Son[b], Bo-Suk Yang[c]
School of Mechanical Engineering, Pukyong National University,
San 100, Yongdang-dong, Nam-gu, Busan 608-739, South Korea
[a]niu-11@163.com, [b]skyman1231@hanmail.net, [c]bsyang@pknu.ac.kr

Abstract

Fault detection and diagnosis is the most important technology in condition-based maintenance (CBM) system that usually begins from collecting signatures of running machines using multiple sensors for subsequent accurate analysis. With the quick development in industry, there is an increasing requirement of selecting special sensors that are cheap, robust, and easy-installation. This paper experimentally investigated performances of four types of sensors used in induction motors faults diagnosis, which are vibration, current, voltage and flux. In addition, diagnostic effects of five popular classifiers also were evaluated. First, the raw signals from the four types of sensors are collected at the same time. Then the features are calculated from collected signals. Next, these features are classified through five classifiers using artificial intelligence techniques. Finally, conclusions are given based on the experiment results.

Keywords: Fault diagnosis; Induction motor; signal evaluation, classifier comparison

1. Induction

Induction motors are used in critical drivers in many industrial processes. In spite of their robustness and reliability, they do occasionally fail, and unpredicted downtime is obvious costly [1]. Therefore, the condition monitoring of machines, especially early fault diagnosis, is proved to be necessary and received wide attentions in this decade.

With industry equipments becoming more and more complex, engineers tend to utilize multi-type sensors to collect signals reflecting the running condition of diagnosed machine. By comparing the acquired signal with healthy signal (benchmarking signal), engineers can know the running condition of monitored machine. Moreover, they can identify special fault type based on their knowledge of fault signatures. However, this kind of method is hard to use even if for experts because of some practical difficulties. One reason is that the signal qualities acquired from different types of sensors are different. When facing up to many types of sensors, there is a requirement to know the performance of different types of sensors in condition monitoring and faults diagnosis. Another reason is that the collected signals in running environments are often polluted by noise which make the signal can not be accordance with the standard signature and make faults diagnosis become a hard task.

Based on this motivation, an experiment was introduced in this paper in order to investigate performances of four types of sensors that are accelerometers, current probes, voltage probes and flux used on rotating machinery. Their performances are evaluated at the level of signal, features and decisions respectively. In addition, the classification accuracies of five classifiers are also compared using the collected data. Finally, conclusions will be presented from the experiment results.

2. Experiment Process

2.1 Signal collection

In this part, a whole process of signal collection will be introduced in detail. And the collected signal from different types of sensors will be observed to evaluate the recognition performances at signal level.

2.1.1 Experiment objects

The signal collection experiment was finished at Korea Electricity Research Institute (KERI). The experiment apparatus are shown in Fig. 1. The tested equipments are thirteen 380V, 7.5 kW, 60Hz and 4-pole induction motors (A, Fig. 1). The basic specifications of them are shown in Table 1. These tested motors were set to operate at full-load conditions with one load-motor (B, Fig. 1). A coupling device (C, Fig. 1) was used to connect both shafts of tested and load motors. Among the thirteen tested motors, one is normal (healthy), which was set as a benchmark motor to be compared with the other twelve faulty motors with bowed rotor, rotor unbalance, misalignment, faulty bearing, broken rotor bar and short-turn stator winding. Each fault contains of *slight* and *severs* conditions with two motors respectively (D, Fig. 1). The faulty types of induction motors are described in Table 2.

Table 1 Basic specification of the motor tested

Model number	HL133SR202E2	Rotating speed	1760 rpm
Frame	132M	Number of pole	4
Type	HL-SD	Weight	686 N
Bearing (DE)	6208zzc3	Voltage	380 V
Bearing (NDE)	6208zzc3	Power	7.5 kW
Current	28.2/16.3 A	Number of rotor bar	28
Line frequency	60 Hz	Number of stator slot	46

Table 2 Description of faulty types of the motor tested

Faults types	Fault details	
	Slight condition	Severs condition
Bowed rotor	0.2 mm	0.3 mm
Rotor unbalance	1 phase, 20 g	1, 3 phase; 20 g
Misalignment	0.2 mm	0.3 mm
Faulty bearing	Flaking	False brinelling
Broken rotor bar	1	2
Short-turn stator winding	5 turns	10 turns

2.1.2 Experiment apparatus

In order to evaluate the performances of different types of sensors, 21 sensors containing 5 types of signals were used. Among them, three accelerometers were adhered onto horizontal, vertical, axial directions at driver end of tested motor; three AC current probes were circled around three phases of electrical wire; at the same, three AC voltage probes were connected to the jointers of three phases of electrical wire, the left were twelve flux sensors installed onto the winding in tested motor with two types: fulx1 and fulx2. In addition, a connected-ground cable was utilized to decrease the influence of electromagnetism-noise to collected signal. The used sensors are shown in Fig 2.

The collected signal was enlarged firstly through an amplifier and then was sent into a signal analyzer for A/D transform and filtering. At last, the treated signal was recoded into a laptop for future analysis. The maximum frequency of sampling signals was 2 kHz and the number of sampled data was 8192. For each condition, 20 samples were measured, 10 of them were used for training parameter of the classifiers and the other 10 for the test.

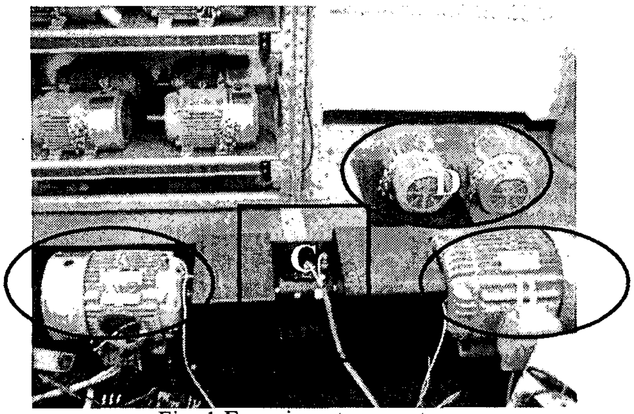


Fig. 1 Experiment apparatus

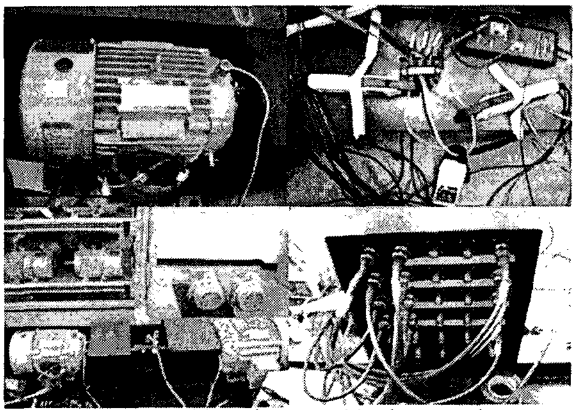


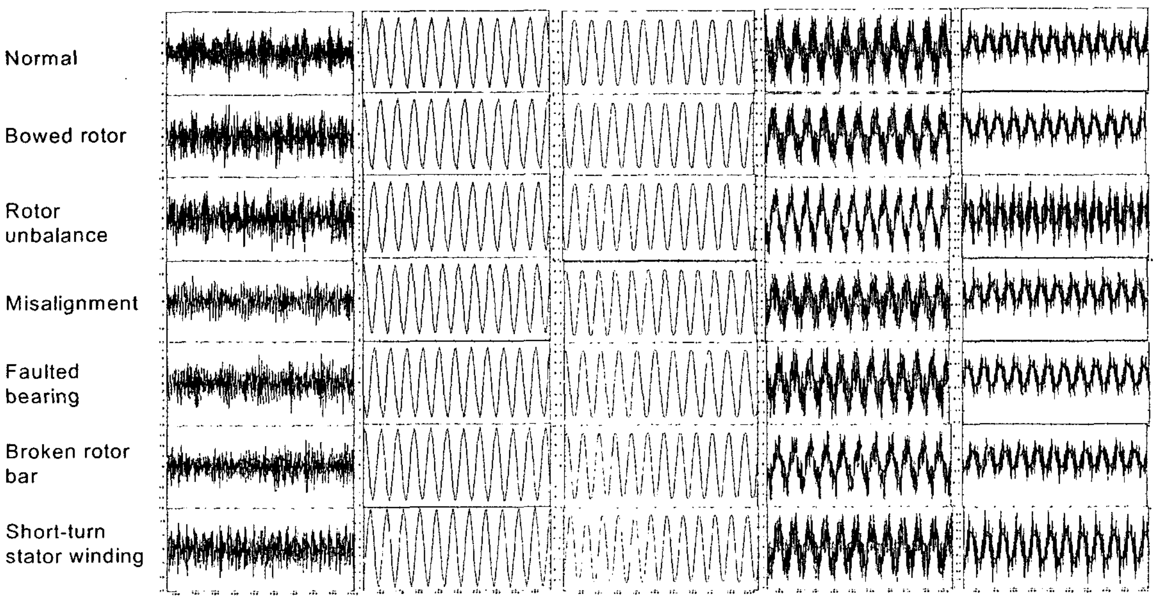
Fig. 2 Sensors and locations used in the experiment

2.1.3 Description of signal collected

The waveforms of collected time-domain signal from acceleration, current, voltage, flux1 and fulx2 are shown in Fig. 3. It can be seen that, there are some differences in waveform of each condition if one observe acceleration, flux1 and flux2 signal. However, there is no obvious difference in the waveforms of current and voltage signal.

2.2 Feature calculation

After the five types of signals were collected from the 13 tested motors, a process of features calculation was exerted. Although the time series data contain abundant feature information, the important part cannot show intuitively and much unnecessary information also is contained. Therefore, the feature extraction is essential for effectual estimation of conditions of machine. Statistical parameters, calculated in the time domain, frequency domain and auto-regression, are generally used to define average properties of acquired data [2]. 21 values of features are acquired from each sensor consisting of the time domain (10 features), frequency domain (3 features) and regression estimation (8 features) shown in Table 3.

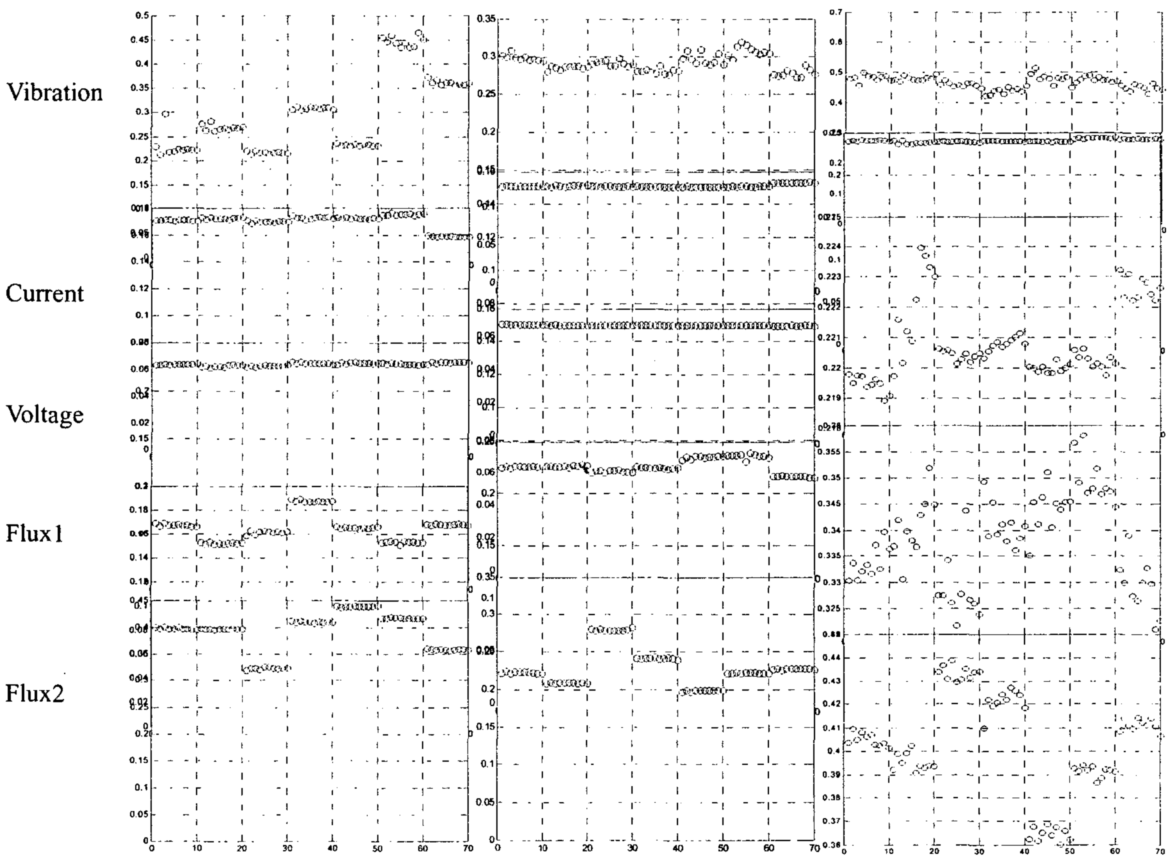


(a) Vibration (b) Current (c) Voltage (d) Flux1 (e) Flux2

Fig. 3 Time signal waveform of each condition for different sensors

Table 3 Description of values of features of signals

Signals	Position	Values of features of signals		
		Time domain	Frequency domain	Auto regression
Vibration	▪ Vertical ▪ Horizontal ▪ Axial	• Mean • RMS • Shape factor • Skewness • Kurtosis • Crest factor • Entropy error • Entropy estimation • Histogram lower • Histogram upper	• Root mean square frequency • Frequency center • Root variance frequency	• AR coefficients ($a_1 \sim a_8$)
Current Voltage Flux1 Flux2	▪ Phase A			



(a) RMS (b) Kurtosis (c) Crest factor

Fig. 4 Features map of five types of signal

Among the calculated features, three of them are chosen randomly and mapped in Fig. 4. It can be seen that on the whole, flux 2 is the best, which can generate easy-discriminated features distribution. By comparison, vibration and flux1 are a little worse, while current and voltage are the worst. The results are consistent with the observed time-domain waveforms above.

2.3 Features classification

Based on the calculated features, more accurate evaluation was considered for the four types of sensors: Acceleration, current, voltage, flux in order to find the appropriate ones for the task of fault diagnosis. The features of only one channel of each sensor type were used. The performance of classification was evaluated using five classifiers (SVM, LDA, k-NN, RFA, ART-KNN) respectively.

• *Support Vector Machine (SVM):* SVM [3] is based on the statistical learning theory. This technique can lead to good recognition rate with a few training samples. Kernel function is an important parameter which contains linear, polynomial, Gaussian RBF and sigmoid.

• *Linear discriminant analysis (LDA):* LDA [4] is popular for features drop-dimension and also can be used for classification. It projects features from parametric space onto feature space through a linear transformation matrix. This classifier can be efficiently computed in the linear case even with large data sets.

• *k nearest neighbors (k-NN):* k-NN [5] is an easy and effective classifier. The aim is to find the nearest neighbors of an unidentified test pattern within a hyper-sphere of pre-defined radius in order to determine its true class. It can detect a single or multiple number of nearest neighbors.

• *Random forests algorithm* (RFA) [6, 7]: is a classifier consisting of a collection of tree-structured classifiers $\{h(x, \Theta_k), k = 1, 2, \ldots\}$ where the Θ_k are independent identically distributed random vectors and each tree casts a unit vote for the most popular class at input x.

• *Adaptive resonance theory-Kohonen neural network* (ART-KNN) [8]: ART-KNN is a neural network that synthesizes the theory of ART and the learning strategy of the Kohonen neural network (KNN).

The parameters setup of each classifier is shown in Table 4 and classification accuracy of train and test set is shown in Table 5.

Table 4 Parameters of individual classifier

Classifier	Parameters values
SVM	Linear kernel function, Euclidean distance type, one against all model
k-NN	$k = 3$
RFA	No. of variables randomly sample = 10, No. of trees = 1000, seeds = 123
ART-KNN	Distance-based optimization, initial similarity = 0.6, iterative step = 0.004, iterative No. = 20

Table 5 Diagnosis accuracy of train and test set

Signal type		Accuracy rate of each classifier				
		SVM	LDA	k-NN	RFA	ART-KNN
Acceleration	Training	1	0.9923	0.9846	1	0.9615
	Test	1	0.9923	0.9846	1	0.9462
Current	Training	1	0.9385	0.9462	1	0.9923
	Test	0.9308	0.7769	0.8769	0.9385	0.5385
Voltage	Training	1	1	1	1	0.9923
	Test	0.9846	0.9846	0.9462	1	0.9154
Flux1	Training	1	0.9846	0.9923	1	0.9923
	Test	0.9769	0.9231	0.9385	1	0.9538
Flux2	Training	1	1	1	1	0.9923
	Test	1	1	1	1	0.9692

3. Results and Discussion

This paper experimentally investigated performances of four types of sensors used in induction motors faults diagnosis, which are vibration, current, voltage and flux. According to the final experiment results shown in Fig. 5, some conclusions can be summarized. To compare sensors performance, the signal of flux2 and acceleration can give excellent effect. The next are voltage and flux1, while current signal is the worst. To compare the performance of classifiers, the orders from good to bad are RFA, SVM, k-NN, LDA and ART-KNN. When the signal is hard to distinguish (such as current signal), the performance of classification becomes quite different.

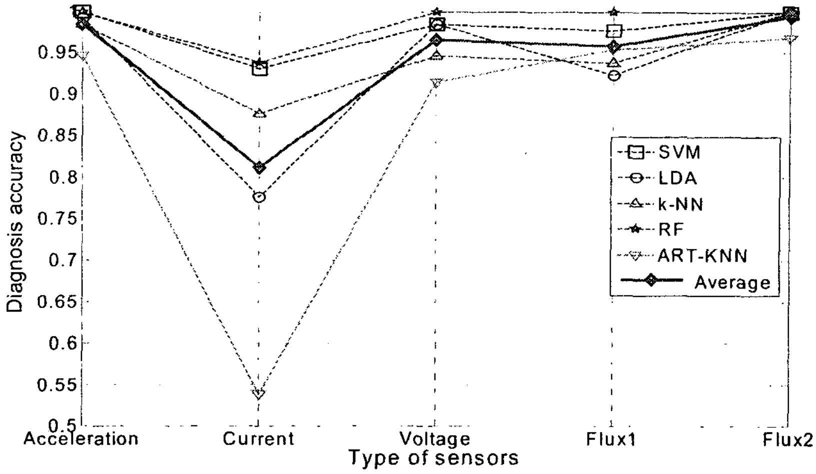


Fig. 5 Comparison of diagnosis performance for test set

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