한국소음진동공학회 2005년도 춘계학술대회논문집, pp.945~948.

LabVIEW 기반의 PDA를 이용한 기계 진단 시스템의 개발
Development of Induction Machine Diagnosis System using LabVIEW and PDA

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Key Words: Mobile Device; Artificial Intelligence (AI); Fault Diagnosis; LabVIEW

ABSTRACT

Mobile computing devices are becoming increasingly prevalent in a huge range of physical area, offering a considerable market opportunity. The focus of this paper is on the development of a platform of fault diagnosis system integrating with personal digital assistant (PDA). An improvement of induction machine rotor fault diagnosis based on AI algorithms approach is presented. This network system consists of two parts; condition monitoring and fault diagnosis by using Artificial Intelligence algorithm. LabVIEW allows easy interaction between acquisition instrumentation and operators. Also it can easily integrate AI algorithm. This paper presents a development environment for intelligent application for PDA. The introduced configuration is a LabVIEW application in PDA module toolkit which is LabVIEW software.

1. INTRODUCTION

The induction machine is the single most common electro mechanical energy conversion device available. It is used to drive numerous important propulsion and medium transfer units. The induction machine is inherently reliable. But they do occasionally fail(1) and unplanned downtime can prove very costly. There are many ways to detect mechanical and electrical problems in induction motor. Such as the vibration analysis(2), the motor current signature analysis(3~6), electro magnetic field analysis(7), chemical analysis, temperature measurability, infrared measurement, acoustic noise analysis, and partial discharge measurement.

For each diagnosis method, engineers need basis knowledge and some experience. Unfortunately, such engineers are rare in the real world. Even if experts are available, the technical information needed by the engineers is not always to hand, or received in the first instance. With the development of artificial intelligence techniques, many intelligent systems have been employed to assist the condition monitoring task to correctly interpret the fault data, such as expert systems, artificial neural networks (ANNs), support vector machines (SVM) and fuzzy logic systems, and the results are promising(8~10).

LabVIEW allows easy interaction between acquisition instrumentation and operators. It realizes virtual instruments in form of graphical programs running on personal computers or workstations, which simplify the procedures for data acquisition and instrument control(11) Sound and Vibration toolkit in LabVIEW includes Statistical, Averaged and Zoom FFT, Harmonics, Octave, Order Tracking and Extraction. Recently, there are many remote monitoring technologies. The remote monitoring system can support single-night unmanned nighttime operations of diversified manufacturing commonly found in Japanese SME(12). In this paper we propose a fault diagnosis system which integrate artificial algorithm into LabVIEW and condition monitoring by using personal digital assistant (PDA). This remote monitoring system can support single-night unmanned nighttime operations for diversified induction machine from operator's home as the remote site.

Some researches were conducted for AI application in mobile devices (Pocket PC). But the limitation of memory and processing power made mobile devices unable to support powerful AI technology(13). So AI system is run in personal computer and then data is sent to PDA in this study.

2. MONITORING SYSTEM

2.1 Monitoring Diagram

The diagram of data flow is shown in Fig 1. The acquired signals from transducers are analog ones. Data acquisition device converts analog signal to digital. Notebook PC analyze time signal by using LabVIEW. The functions that the system provides are as follow;

- Time signal and FFT analysis
- Zoom analysis of FFT
- Orbit plot
- Waterfall analysis
- Transient signal analysis (Short FFT)

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• RMS trend monitoring based on ISO standards
• Fault diagnosis based on AI techniques with PDA
• Condition monitoring by using PDA
• Remote monitoring in the internet web site

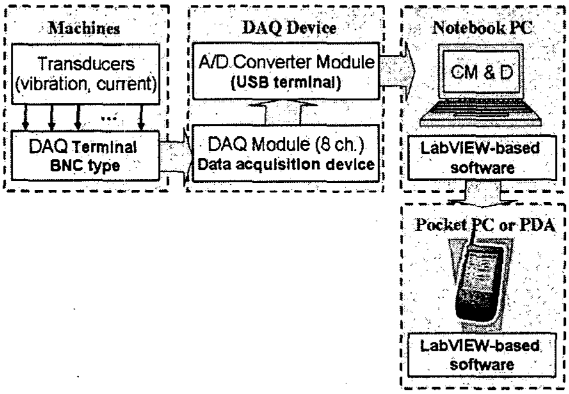


Fig. 1 The data flow diagram

Figure 2 shows the data flow chart of a notebook PC. In Fig. 2, the START contains A/D converted time signals. The Configuration sets sensitivity of the transducers, and sampling rate of the DAQ device, average and digital filtering ranges. The Display covers time and frequency domain plots, orbit, waterfall and transient signal plots. Trend Display shows the conditions of each feature after setting of trend parameters. The types of feature values include mean, skewness, kurtosis, RMS, shape factor and crest factor. Unfortunately only RMS value is specified in the ISO standard. The other features are used for artificial algorithm. The <<Data Base>> saves features. If the CMS(condition monitoring system) is No(Fault) in Fig. 2, the artificial algorithm operates and determines the faults which can be misalignment, broken rotor bar, bowed rotor, unbalance, bearing faults. At last, the notebook PC send the information which is RMS and types of faults to PDA as shown in Fig. 1.

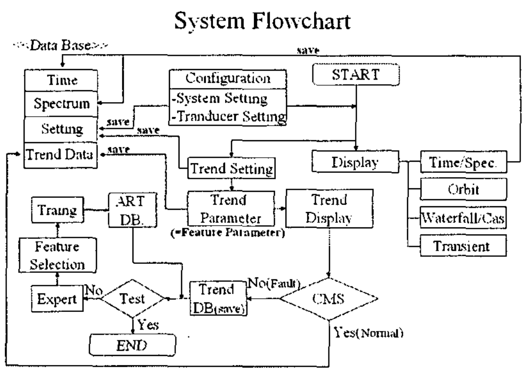


Fig. 2 The data flow chart of Notebook PC

2.2 Algorithm Flowchart

AI algorithm includes the powerful neural network. Figure 3 shows AI algorithm flowchart. After calculation of the features, PCA and ART-KNN are executed.

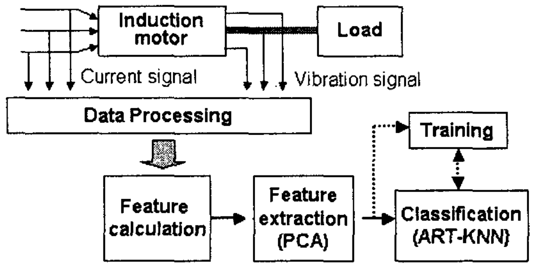


Fig. 3 Flow chart of the proposed fault diagnosis system

2.3 Features

The AI algorithm needs feature calculation. Each feature represents signal's characteristics. Table 1 shows features of vibration and current signals. Various feature parameters are calculated from time and frequency domains and regression coefficients.

Table 1 Feature parameters

Signals	Position	Feature parameters		
		Time domain	Frequency domain	Auto regression
Vibration	Vertical	• Mean • RMS	• Root mean square frequency	AR coefficients ($a_1 \sim a_8$)
	Horizontal	•Shape factor • Skewness		
	Axial	• Kurtosis • Crest factor	• Frequency Center	
Current	Phase A	• Entropy error • Entropy estimation	• Root variance frequency	
	Phase B	• Histogram lower		
	Phase C	• Histogram upper		

2.4 Feature extraction : PCA

However, too many features can cause curse of dimensionality phenomenon since irrelevant and redundant features degrade the performance of AI algorithm. PCA is a powerful method for feature extraction and dimensionality reduction. It has a wide range of different applications including cluster analysis, visualization of high-dimensionality data, regression data, compression and pattern recognition[14, 15].

2.5 Classifier : ART-KNN

ART-KNN is used as a classifier[16]. ART-KNN is a neural network which synthesizes adaptive resonance theory (ART) and the learning strategy of Kohonen neural network (KNN). It is able to carry out on-line learning without loss of previously knowledge (stable training); it can record previously trained categories adaptive to changes in the environment and is self-organizing. ART-KNN also holds these characteristics, and is more suitable than original ART for fault diagnosis of machinery.

3. EXPERIMENT AND DATA ACQUISITION

The experiments were carried out under the self-designed test rig which is mainly composed of motor, pulleys, belt, shaft and fan with changeable blade pitch

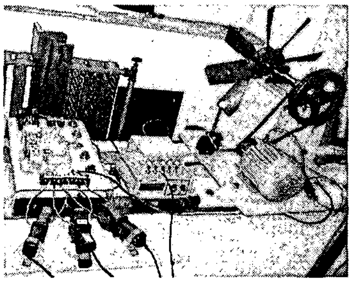


Fig. 4 Experiment apparatus

angle, as shown in Fig 4.

Six 0.5kW, 60Hz, 4-pole induction motors were used to acquire the data needed under full-load conditions. One of the motors is in normal (healthy) condition which is considered as a benchmark for comparing with faulty motors. The others are faulty motors as shown in Fig. 5. The load of the motors can be changed by adjusting the blade pitch angle or the number of the blades.

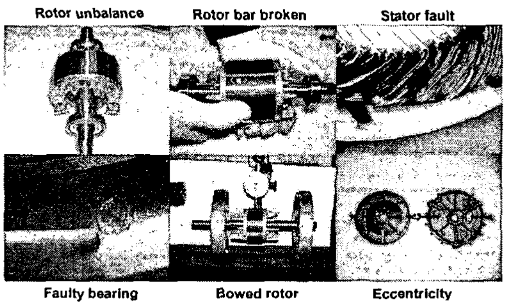


Fig. 5 Faults on the induction motors

4. SYSTEM PROGRAM AND DISCUSSION

4.1 Condition monitoring (RMS) based on LabVIEW

This program depends on ISO10816/3. The AI Result displays the diagnosis result, in the form of number among the 9 possible faults; 1. Angular Misalignment, 2. Bowed Rotor, 3. Broken Rotor Bar, and so on. Table 2 shows vibration standard of industrial machine, where B/C and C/D mean alarm and trip levels respectively. Each value should multiply constant 1.25. If the signal is over the standard level specified in Table 2, the program rings alarm or trip. At the same time, it automatically operates the AI algorithm.

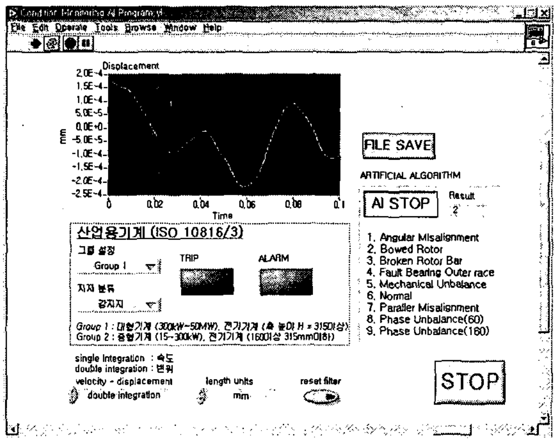


Fig. 6 Condition Monitoring Window

Table 2 Vibration standard of industrial machine (ISO 10816/3)

Support	Level	Vibration Displacement (μm, rms)		Vibration Velocity (mm/s, rms)	
		Group 1	Group 2	Group 1	Group 2
Rigid foundation	A/B	29	22	2.3	1.4
	B/C	57	45	4.5	2.8
	C/D	90	71	7.1	4.5
Flexible foundation	A/B	45	37	3.5	2.3
	B/C	90	71	7.1	4.5
	C/D	140	113	11.0	7.1

Notice: Group 1: Large scale machinery (300kW~50MW), electric machinery (Axial Height $H \geq 315mm$)

Group 2: Middle scale machinery ($15 \sim 300kW$), electric machinery ($160 \leq H \leq 315mm$)

4.2 Data Base for AI algorithm

AI algorithm needs features. Each feature is saved in the DB and is used in the AI algorithm. In Fig. 7, each window shows one of the features mentioned above. Channel, sensor sensitivity, sampling rate, ranges of filtering are set at panels at the bottom of the main window. Simultaneously features are saved in the database (DB).

This program made by PDA module toolkit which is a LabVIEW software. Figure 8 shows PDA emulator. Figure 8(a) indicates normal condition according to the ISO 10816/3 standard level. PDA can show RMS value and types of faults. Figure 8(b) indicates that the motor fault is bowed rotor. The PDA can also indicate alarm and trip by color difference according to the acquired signal level.

When the condition of the monitored induction motor is in normal condition, the color of the indicator is green.

But if the signal is over the ISO standard level, the color changes to red. Displays in Fig. 6 and Fig. 7 can be seen in the internet web site.

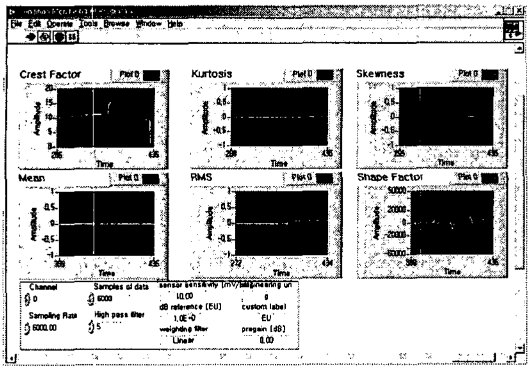
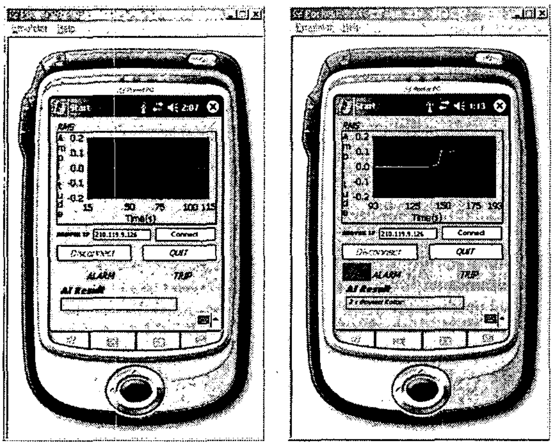


Fig. 7 Configure features

4.3 PDA display



(a) Normal condition (b) Alarm condition

Fig. 8 PDA condition monitoring

The motor is in alarm or trip level, the indicator changes to red color. Figure 8(b) displays alarm condition. At this stage notebook PC automatically operates AI Algorithm. Simultaneously we can see the AI result in PDA.

5. CONCLUSION

Conditions and restrictions for the application of the PDA for induction motor fault detection at various fault conditions have been discussed. LabVIEW based measurement enables monitoring of induction motor conditions in real time. When the measured signal is higher than the ISO standard, AI algorithm operates automatically to diagnose the types of induction motor faults. The results can be displayed in PDA screen some distance away from the measurement point. This application allows a fast failure state estimation including the representation of the most significant state variables.

Reference

(1) B.S. Yang, S.K. Jeong, Y.M. Oh, Andy Tan, "Case-based reasoning system with Petri nets for induction motor fault diagnosis," Expert Systems with Applications 27(2) (2004) 301-311.

(2) W.R Finley, M.M. Hodowanec, W.G. Holter, "An analytical approach to solving motor vibration problems," IEEE Trans. on Industry Applications 36(5) (2000) 1467-1480.

(3) W.T. Thomson, M. Fenger, "Current signature analysis to detect induction motor faults," IEEE Trans. on Industry Applications 7 (2001) 26-34.

(4) W.T. Thomson, D. Rankin, D.G. Dorrell, "On-line current monitoring to diagnose airgap eccentricity in large three-phase induction motors- Industrial case histories," Verify The Predictions 14 (4) (1999) 1372-1378.

(5) S. Williamson, K. Mirzoian, "Analysis of cage induction motors with stator winding faults," IEEE Trans. on Power Apparatus and Systems Pas-104 (1985) 1838-1842.

(6) R.R. Schoen, T.G. Habetler, F. Kamran, "Motor bearing damage detection using stator current monitoring," IEEE Trans. on Industry Applications 31 (6) (1995) 1274-1279.

(7) F. Thollon, A. Jammal, G. Grellet, "Asynchronous motor cage fault detection through electromagnetic torque measurement," European Trans. Electrical Power 3 (1993) 375-378.

(8) B. Samanta and K.R. Al-Balushi, "Artificial neural network based fault diagnostics of rolling element bearings using time-domain features," Mechanical System and Signal Processing 17 (2) (2003) 317-328.

(9) M. Ge, R. Du, G. Zhang and Y. Xu, "Fault diagnosis using support vector machine with an application in sheet metal stamping operations," Mechanical System and Signal Processing 12 (1) (2004) 143-159.

(10) C.T. Kowalski, T. Orlowska-Kowalska, "Neural network application for induction motor faults diagosis," Mathematics and Computers in Simulation 63 (3-5) (2003) 435-448.

(11) ABView User manual, National Instruments, Austin(TX), USA, 1992

(12) Wan-Young Chung, Sung-Ju Oh, "Remote monitoring system with wireless sensors module for room environment", Sensors and Actuators B xxx(2005) xxx-xxx.

(13) Lynne Hall,Adrian Gordon, Lynne Newall, Russell James "A development environment for intelligent applications on mobile devices" Expert Systems with Applications 27(2004) 481-492

(14)X. Wang, K.K. Paliwal, "Feature extraction and dimensionality reduction algorithms and their applications in vowel recognition," Patter Recognition 36 (2003) 2429-2439.

(15) K.I. Diamantaras, S.Y. Kung, "Principal Component Neural Networks," Theory and Applications, New York, John Wiley & Sons, (1996).

(16) B.S. Yang, T. Han, J.L. An, "ART-Kohonen neural network for fault diagnosis of rotating machinery," Mechanical System and Signal Processing 18 (3) (2004) 645-657