진동신호를 이용한 유도전동기의 지능적 결함 진단

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Intelligent Fault Diagnosis of Induction Motors Using Vibration Signals

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Key Words : Fault diagnosis(결함 진단); Induction motor (유도전동기); Neural network(신경회로망); Genetic algorithm(유전 알고리듬);

Abstract

In this paper, an intelligent fault diagnosis system is proposed for induction motors through the combination of feature extraction, genetic algorithm (GA) and neural network (ANN) techniques. Features are extracted from motor vibration signals, while reducing data transfers and making on-line application available. GA is used to select most significant features from whole feature database and optimize the ANN structure parameter. Optimized ANN diagnoses the condition of induction motors online after trained by the selected features. The combination of advanced techniques reduces the learning time and increases the diagnosis accuracy. The efficiency of the proposed system is demonstrated through motor faults of electrical and mechanical origin on the induction motors. The results of the test indicate that the proposed system is promising for real time application.

1. Introduction

As the majority of the industry prime movers, induction motors play an important role in manufacture, transportation, etc., due to their reliability and simplicity of construction. Although induction motors are reliable, the possible of faults is unavoidable. These failures may be inherent to the machine itself or caused by operating conditions [1]. Early fault diagnosis and condition monitoring can increase machinery availability and performance, reduce consequential damage, prolong machine life, and reduce spare parts inventories and breakdown maintenance. Therefore, fault diagnosis of induction motors has received considerable attention in recent years.

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The statistical studies of EPRI and IEEE for motor faults are cited [2]. Under EPRI sponsorship on industry assessments, a study was conducted by General Electric Co. to evaluate the reliability of powerhouse motors and identify the operation characteristics. Part of this study is to specify the reason behind the motor failures. The study of IEEE-IGA was carried out on the basis of opinion as reported by the motor manufacture. The percentages of main motor faults are shown in Table 1. Through these two studies, we notice that bearings are weakest component in induction motor, then stator, rotor and others.

Table 1 Fault occurrence possibility on induction motor

	Bearing faults	Stator faults	Rotor faults	Others
IEEE	42 %	28 %	8 %	22 %
EPRI	40 %	38 %	10 %	12 %

Corresponding to the above-mentioned faults, many techniques have been proposed for motor faults detection and diagnosis. These techniques include vibration monitoring, motor current signature analysis (MCSA) [3], electromagnetic field monitoring [4], chemical analysis, temperature measurability [5], infrared measurement, acoustic noise analysis [6] and partial discharge measurement [7]. Among these methods, vibration analysis and current analysis are the most popular ones due to their easy measurability, high accuracy and reliability. In this study, the vibration signals are considered. The reliability of vibration signals are demonstrated through comparing with stator current signals.

Recently, artificial intelligence (AI) techniques, such as expert systems, artificial neural networks (ANNs), fuzzy logic systems, and genetic algorithm (GA), have been employed to assist the diagnosis and condition monitoring task to correctly interpret the fault data [8]. ANN has gained popularity over other techniques, as it is efficient in discovering similarities among large bodies of data. ANN is the functional imitation of a human brain, which simulates the human decision-making and draws conclusions even when presented with complex, noisy, irrelevant information. ANNs can represent any non-linear model without knowledge of its actual structure and can give result in a short time during the recall phase. Research of ANN has been carried out successfully for fault diagnosis, and the results are promising [9].

However, the main problems facing the use of ANN are the selection of the best inputs and how to choose the ANN parameters making the structure compact, and creating highly accurate networks. For the proposed system, the feature selection is also an important process since there are many features after feature extraction. Many input features require a significant computational effort to calculate, and maybe result in low successful rate. To make operation faster and also to increase the accuracy of the classification, a feature selection process using GA is used to isolate those features providing the most significant features for the neural network, whilst cutting down the number of features required for the network. During selection process, the network structure parameter is optimized.

In this work, the fault diagnosis system of induction motors is proposed by combining advanced techniques: feature extraction, GA and ART-KNN, using motor vibration signals. All the experiments were implemented on the self-designed test rig. The result shows that the proposed system is efficient and promising for real time applications.

2. Proposed fault diagnosis system

The proposed system and the overall description of the theoretical background are described. The architecture of the system is shown in Fig. 1.

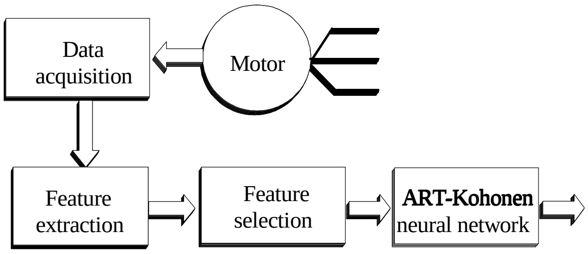

Fig. 1. Architecture of the diagnosis system.

The original vibration signals are acquired by accelerometers from test induction motors. The features of the transformed data are extracted from the database using statistical parameters, such as RMS, histogram, etc. Then GA is used as feature selector and network optimizer. The optimized neural network is able to on-line carry out without losing previous knowledge, which is suitable for and on-line condition monitoring and fault diagnosis in the real time application.

2.1. Feature extraction

Recently, on-line diagnosis systems are popular because they can detect the faults at the first time. However, the direct measured signals are not suitable for on-line use since short sampling number is deficient for diagnosis, and enough sampling number is a burden for transferring and calculation. So feature extraction of the signal is a critical initial step in any monitoring and fault diagnosis system. Its accuracy directly affects the final monitoring results. Thus, the feature extraction should preserve the critical information for decision-making. In this paper, the features of the signals are extracted from the time domain and frequency domain [10].

2.2. Feature selection using genetic algorithm

In practical application, the feature selection problem has become a quite hot topic in many fields, such as classification, data mining, image processing, and conceptual learning etc. In this study, GA is used to pick up these features, which can provide the most important information for the neural network.

There is some justification for using GA based feature selection over some other methods available, such as principal component analysis (PCA), which can be much less computationally intensive than a GA based approach. The downside to PCA is that all the available features are required for the transformation matrix to create the rotated feature space. However, it must be remembered that the drive behind the feature selection process is create a small system that requires as little processing as possible, whilst maintaining a high level of accuracy. Using PCA will still require the calculation of all the available features before the transformation matrix can be applied, and hence it requires a larger computing power on-board the hypothetical smart sensor than would be needed by using a GA that selects only the best features. The computational cost of the GA will be much higher than using a system like PCA during training and feature selection; however, this will be offset by the lower computation power required on a sensor, and hence the lower cost in manufacture. Another alternative for feature selection would be to use forward selection. One problem of forward selection is in the case where two features acting individually are relatively poor, but when used together give a much better result than two best features achieved through forward selection. The use of a GA has no such problem, as the features are selected as a unit, and the interaction between the different features as a group is tested, rather than as individual features. According to above statement, the GA is allowed to select subsets of various sizes to determine the optimum combination and number of inputs to the network.

While any successful application of GAs to a problem is greatly dependent on finding a suitable method for encoding, the creation of a fitness function to rank the performance of a particular genome is important for the success of the training process. The GA will rate its own performance around that of the fitness function. Consequently, if the fitness function does not adequately take account of the desired performance features, the GA will be unable to meet the requirements of the user.

A simple GA, which is proposed by Goldberg , is used as feature selector in this paper. A simple binary-based genome string is implemented. The genome is composed of two parts: one part determines which features are selected as an input subset from the whole database (“0” represents feature absence, “1” means feature presence), another part is used to choice the network structure parameter.

2.2.1. GA operators

There are three fundamental operators of GA: selection, crossover and mutation. The aim of the selection procedure is to reproduce more copies of individuals whose fitness values are higher than others. This procedure has a significant influence on driving the search towards a promising area and finding food solutions in a short time. The roulette wheel selection is used for individual selection. The selection probability $P_s(s_i)$ of the ith individual is expressed as following equation:

$$P_s(s_i) = \frac{f(s_i)}{\sum_{j=1}^{N} f(s_j)}, \quad (i = 1 \sim N) \tag{2}$$

where s is a individual, f(si) is the fitness value of the ith individual and N is the number of individual. According to the values of Ps(s), each individual is defined for the widths of slots on the wheel.

The crossover operator is used to create two new individuals (children or offspring) from two existing individuals (parents) picked from the current population by the selection operation. There are also several ways of doing this. One point simple crossover is used for this process. After that, all individuals in the population are checked bit by bit and the bit values are randomly reversed according to a specified rate.

The mutation operator helps the GA avoid premature convergence and find the global optimal solution. In the binary coding, this simply means changing 1 to 0 and vice versa. In the standard GA, the probability of mutation is set equal to a constant. However, it is clear in examining the convergence characteristics of GAs that what is actually desired is a probability of mutation which varies during generational processing. In early generations, the population is diverse and mutation may actually destroy some of the benefits gained by crossover. Thus, in early generations it would be desired to have a low probability of mutation. In later generations, the population is losing diversity as all members move ‘close’ to the optimal solution, and thus a higher probability of mutation is needed to maintain the search over the entire design space. Thus, the selection of the probability of mutation must carefully balance these two conflicting requirements. The mutation probability $P_m(s_i)$ is then tied to the diversity measure through an exponential function:

$$P_m(s_i) = 1 - 0.99 \exp(-4 \times N_i / N_t) \tag{3}$$

where N_i and N_t are the number of current generation and total generation, respectively.

2.2.2. Formulation of optimization

Since GA is used for feature selection and neural network optimization according to selected features, the objective function should relate with features and network structure parameter. In the real application, the number of features and neurons and the value of network parameter are the smaller the better. The reason is the small features and neurons can reduce the calculation time and make network structure compact. Thus the objective function is as following:

$$f(s) = \frac{F_n}{F_T} \times \frac{N_n}{N_{\max}} \times \rho \qquad (4)$$

where selected features F_n and network similarity ρ are variable, their ranges are 0-63 and 0-1 respectively. The number of neurons N_n is determined by F_n and ρ. The minimum function value $f(s)$ is searched by GA under 100% classification.

2.3. ART-Kohonen neural network (ART-KNN)

The architecture of ART-KNN is shown in Fig. 2. It is similar to ART1's, excluding the adaptive filter. ART-KNN is also formed by two major subsystems: the attentional subsystem and the orienting subsystem. Two interconnected layers, discernment layer and comparison layer, which are fully connected both bottom-up and top-down, comprise the attentional subsystem. The application of a single input vector leads to patterns of neural activity in both layers. The activity in discernment nodes reinforces the activity in comparison nodes due to top-down connections. The interchange of bottom-up and top-down information leads to a resonance in neural activity. As a result, critical features in comparison are reinforced, and have the greatest activity. The orienting subsystem is responsible for generating a reset signal to discernment when the bottom-up input pattern and top-down template pattern mismatch at comparison, according to a similarity. In others words, once it has detected that the input pattern is novel, the orienting subsystem mush prevent the previously organized category neurons in discernment from learning this pattern (visa a reset signal). Otherwise, the category will become increasingly non-specific. When a mismatch is detected, the network adapts its structure by immediately storing the novelty in additional weights. The similarity criterion is set by the value of the similarity parameter. A high value of the similarity parameter means than only a slight mismatch will be tolerated before a reset signal is emitted. On the other hand, a small value means that large mismatches will be tolerated. After the resonance check, if a pattern match is detected according to the similarity parameter, the network changes the weights of the winning node.

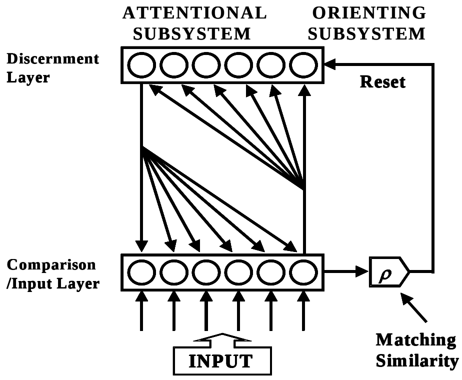

Fig. 3. Architecture of the ART-KNN network.

The learning strategy is introduced by the Kohonen neural network. The Euclidean distances of all weights between input vector X and each neuron of the discernment layer are evaluated as the similarity given by Eq. (15), the smallest one becomes the winning neuron.

$$\|B_J - X\| < \|B_j - X\|, \quad j, J = 1, 2, \ldots, n; j \neq J \qquad (5)$$

where B_j is the weight of jth neuron in the discernment layer, B_J is the weight of the winning neuron. After producing the winning neuron, input vector X returns to the comparison layer. The absolute similarity S is calculated by

$$S = \frac{\| B_J \| - \| B_J - X \|}{\| B_J \|} \qquad (6)$$

If B_J and X in Eq. (6) are same, $\| B_J - X \|$ is equal to 0, and S is 1. The larger the Euclidean distance between B_J and X is, the smaller S is. A parameter ρ is introduced as the evaluation criterion of similarity. If $S > \rho$, it indicates that the Jth cluster is sufficiently similar to X. So X belongs to the Jth cluster. In order to make the weight more accurate to represent the corresponding cluster, the weight of Jth cluster is improved by the following equation:

$$B_J = (\mathrm{n\ BJ\ 0} + \mathrm{X})/(\mathrm{n} + 1) \qquad (7)$$

where BJ is the enhanced weight, $B_{J\,0}$ is the origin weight, and n is changed time.

On the contrary, as $S < \rho$, it means that X is much different with the Jth cluster. Thus there is no cluster that matches X in the original network. The network needs one more neuron to remember this new case by resetting in the discernment layer. The weight of new neuron is given by

$$B_{n+1} = X \tag{8}$$

3. Experiment process and results

The experiment was carried out under the self-designed test rig, which is mainly composed of motor, pulleys, belt, shaft and fan with changeable pitch blades, shown in the Fig. 3.

Fig. 3. Experiment apparatus.

Six 0.5kW, 60Hz, 4-pole induction motors are used to make the data needed under full-load conditions. One of the motors is normal (healthy), which is considered as benchmark for comparing with faulty ones. Others are faulty: broken rotor bar, bowed rotor, bearing outer race fault, rotor unbalance and adjustable eccentricity motor (misalignment), shown in Fig. 4. The conditions of faulty induction motors are described in Table 2. The load of the motors is simulated with an eight-blade fan, which can be changed by adjusting the blade angle or the number of the blades.

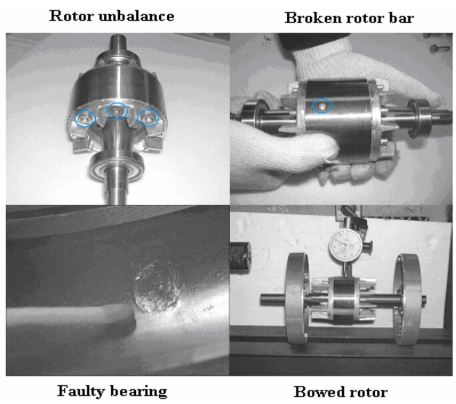

Fig. 4. Faults on the induction motors.

Fault condition	Fault description	Others
Broken rotor bar	Number of broken bar: 12	Total number of 34 bars
Bowed rotor	Shaft deflection: 0.075 mm	Air-gap: 0.25 mm
Faulty bearing	A spalling on outer race damage	#6203
Rotor unbalance	Unbalance mass on the rotor: 8.4g	
Eccentricity	Parallel and angular misalignments	Adjusting the bearing pedestal

Table 2 The description of faulty induction motors

The vibration signals obtained from three directions are calculated by the 21 statistical parameters to extract the features, such as mean, RMS, skewness, kurtosis, shape factor, crest factor, frequency center, entropy estimation and histogram, etc.

One problem appears after the feature extraction. There are too many input features (3×21 = 63) that would require a significant computational effort to calculate, and maybe result in low the accuracy of the monitoring and fault diagnosis. Thus GA for feature selection is used in this paper to isolate those features providing the most significant information for the neural network, whilst cutting down the number of inputs required for the network. The parameters of GA settings are listed in Table 3.

Parameter	Setting
Population No.	200
Genome No.	63
Selection type	Roulette wheel
Crossover	Simple one point crossover
Mutation	$P_m(s_i) = 1 - 0.99 \exp(-4 \times N_i / N_t)$
Maximum generation	20

Table 3 Binary genetic algorithm parameters setting for feature selection

The final selection results by GA are shown in Table. 4 and Fig. 5. The input features are selected, and the network parameter is optimized corresponding to the selected features.

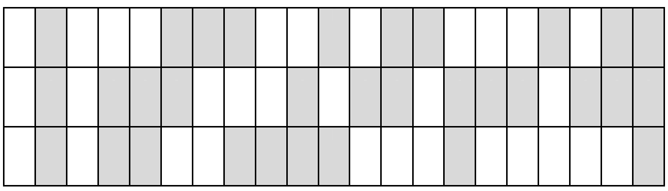

Table 4 Feature selection based on GA

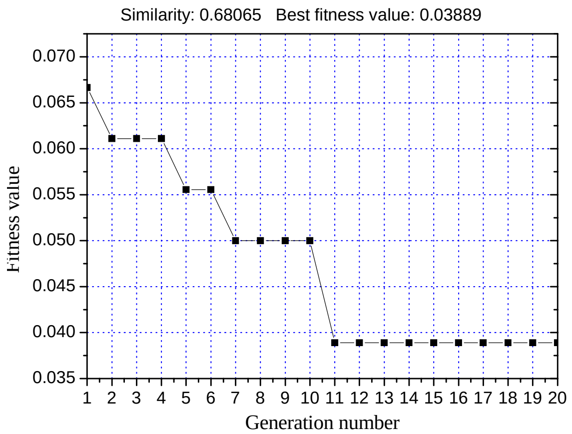

Fig. 5. Convergence curves of GA under full-load conditions

In Table 4, row represents accelerometer signal, column is feature, and darkness block means selected features. Total 32 features are selected from original feature data based (63 features), which reduces the calculation time and increases the diagnosis accuracy. Based on the structure optimized by GA, the classification ration can reach 100%, and just seven neurons are used. Simpler network structure and fewer features make the proposed system more reliability, and suitable for real-world on-line condition monitoring and fault diagnosis.

4. Summary and conclusions

In this paper, a fault diagnosis system for induction motors was proposed. The proposed system uses feature extraction techniques to extract the features from motor vibration signals. Then the input features selected by the genetic algorithm enter the input vectors of the ART-KNN. Since the network can be carried out on-line, the system can learn and classify at the same time. The proposed system was tested by signal obtained from six induction motors under full-load conditions. One is normal motor, others are subject to the faults: broken rotor bar, fault bearing (outer race), unbalance rotor, bowed rotor, misalignment. The test results are very satisfied. It is promising for the real time application. The results of this study allow us to offer the following conclusions:

- Vibration signals can carry out condition monitoring and fault diagnosis for induction motor.
- Genetic algorithm is suitable for feature selection and can optimize the network simultaneously.
- The proposed system has high effectiveness, and the success rate can reach above 100% for the tested faults.

Acknowledgments

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