IOP Conf. Series: Materials Science and Engineering **382** (2018) 032047 doi:10.1088/1757-899X/382/3/032047

Motor's Early Fault Diagnosis Based on Support Vector Machine

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Abstract: An induction motors early fault diagnosis method was presented in this paper, based on Motor Current Spectrum Analysis (MCSA) and Support Vector Machine (SVM). After the stator current was sampled and transferred in FFT, the fault feature was extracted as the input of the SVM. The multi-fault SVM classifier was constructed based one-against-one strategy and mixed matrix combination, to perform the fault diagnosis and classification of different types of faults. Experiment results show that the method in this essay achieved good performance of classification under nonlinear, high dimension and small sample sets, which improved the accuracy in motor fault diagnosis.

1. Introduction

In order to ensure the safety and efficiency of manufacturing, scholars in domestic and foreign nations did a lot of research on induction motor fault diagnosis. Through condition monitoring and fault diagnosis of the motor, we can achieve early fault detection and quantitative diagnosis in order to prevent the occurrence of destructive and catastrophic accidents.

Broken rotor bars and an air gap eccentricity is the common early induction motor fault. When broken rotor bars or end rings cracking, the edge frequency characteristic as:

$$f = (1 \pm 2ks) f_1, k = 1, 2, 3\cdots$$

Where, f_1, supply frequency. s ,slip.

When Static or dynamic eccentricity happens to the rotor, the gap permeance unevenness occurs in the circumferential direction, the induction harmonic component will emerge in the stator current, the frequency characteristic as:

$$f_{ecc} = f_1 \left[(R \pm n_d)(1-s)/p \pm n_w \right]$$

Where, R , the number of rotor bars. p , the poles of the motor.

Motor Current Spectrum Analysis (MCSA) is widely applied in induction motor rotor fault diagnosis research.

Single line current signal is sampled, then we can judge whether there was exist rotor fault according to the existence of characteristic frequency relevant to the fault in spectrum. This method is simple and effective, while the hardware and software fee is pretty low [1]. When the motor is running under steady-state, the slip is small, fault component and power frequency component were very close, at the same time the amplitude of the fault component is very small and changed with the fluctuation of slip, easily drowned by the power frequency leak component and ambient noise. The accuracy of fault diagnosis will be reduced due to the load type and its fluctuations [3].

On the basis of the stator current spectrum analysis, a lot of artificial intelligence methods [4] are used for feature extraction and recognition, such as neural network, which requires a lot of precise training set. Support vector machine achieved minimal actual risk based on the structure risk minimization, its topology is determined by the support vector, with a better solution to the practical problems of small samples, nonlinearity, high dimension and local minima [5].

In this paper, the motor stator current is used as the parameters of fault detection, support vector machine is used to achieve early fault diagnosis of the rotor multiple-fault.

2. Support Vector Machine and multiple-fault diagnosis

Support vector machine is a machine learning algorithm raised by Vapnik in the mid-1990s. Ultimately we achieved the purpose of learning by minimizing the learning experience risk, according to the small sample process.

Support vector machine is essentially a two-class classifier, achieved the construction of multi-class classifier by combining a plurality of two-class sub-classifiers.

For K-class classification, all possible types of two-class classifier was constructed by adopting one against one algorithm in K class training samples, we needed $\frac{1}{2}K(K-1)$ sub-classifiers to be constructed in training samples on the second-class in K-class. Then, the sub-classification results are fused in order to get the final classification result [6].

Common induction motor rotor faults include: normal running, broken rotor bars (including end ring fracture), the rotor (static or dynamic) eccentric, broken rotor bars and eccentricity occurs simultaneously. Therefore, the four states mentioned above are needed to be classified by SVM in the rotor fault diagnosis.

3. Constitute of the system

The system includes the module of current detector, signal processing and the SVM diagnostic. The hardware structure of the diagnostic system shows in Figure1.

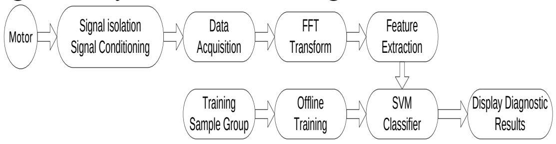

Figure 1. The hardware structure of the system

After the stator current being collected by the Hall current sensors, it was converted into an -3V--+3V AC voltage signal through the signal converter. Then convert the analog signal into digital signal through the A / D converter .The data was sent to computer through the parallel communication port.

The stator current spectrum was analyzed using the fast Fourier transform (FFT), we extracted the fault feature as the input value of the SVM system .The motor fault determination and classification was achieved using SVM system, and the diagnostic results were displayed via the Human Machine Interface.

4. Induction motor rotor fault diagnosis system based on SVM

There are four types of training data in induction motor rotor fault diagnosis, respectively corresponding to motor's four states. Based on one-against-one strategy, $n = 1/2 \times 4 \times (4-1) = 6$ SVM binary value classifiers were established and the results of sub-classifiers were fused to get the final diagnosis results. Shown in Figure 2.

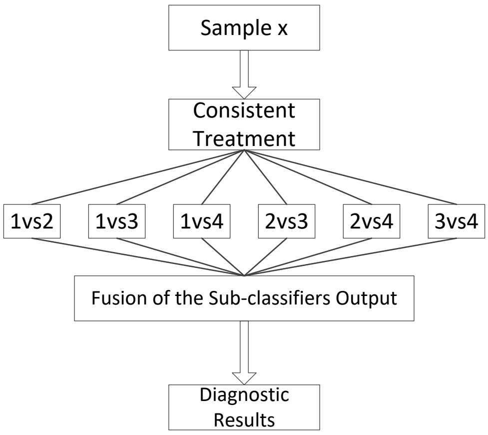

Figure 2. The results of sub-classifiers

4.1. Acquisition of the sample data

Select a bipolar motor as a test prototype, under the condition of 1.5kW, 50Hz, 220V, while eddy current dynamometer is motor load.

Under the steady load condition(s=0.06), the stator current was measured under below conditions respectively: 1.no fault; ② two consecutive broken rotor bars ③ one rotor end ring fracture; ④ rotor static eccentricity; ⑤ rotor dynamic eccentricity; (6) broken rotor bars and eccentric failures simultaneously.

The sampling frequency is 1KHz and the sampling length is 10s.The test was repeated 20 times under above state. Select ten experimental data of above test as the study samples, other ten as the test samples, therefore we had 60 study samples and 60 test samples in all.

4.2. Features Extraction

After obtaining the training data, the current signal was analyzed via the FFT to obtain frequency spectrum. The average of spectral values under the normal motor's state was used as reference value and the measurement-to-reference ratio was used as the final input.

4.3. Experiment and Analysis

(1) he selection of the penalty factor C and kernel function

The penalty factor C describes the balance between the maximum classification boundary and the classification error in the training process. The greater of the C value, the more accurate of the classification results of training samples, while the generalization ability decreased.

When Gaussian Radial Basis Function (RBF) was adopted as the kernel function, the number of support vectors were increased relatively, and the classification accuracy was improved. This proofed RBF kernel function can provide a lot of flexibility in nonlinear mapping of the input data, which is suitable for complex, nonlinear, non-separation classification. The coefficient σ can control the kernel width of RBF [6].

Table 1. Fault type

Fault type	study samples	test samples
no fault	5	15
broken bars	15	5
end ring fracture	10	10
static eccentricity	5	5
dynamic eccentricity	10	10
Broken bars and eccentricity	15	15

(2) Fusion strategy of the sub-classifiers output

The induction motor rotor's fault diagnosis is a multiclass classification problem. It's needed to fuse the six subcategory properly after completed the training of the six sub-classification, to get the final classification result. The common fusion algorithm includes the voting decisions, the binary tree, neural network and mixed matrix. The different fusion strategy had great effect on the classification results.

Table 2. Training and test results

Classifier	number of support vector	Training Accuracy %	Test Accuracy %
1vs2	51	100	100
1vs3	25	100	100
1vs4	79	97	96
2vs3	34	96	98
2vs4	65	95	94
3vs4	34	94	94

In this paper the mixed matrix method was adopted, consuming far less time than neural network method, which achieved more satisfactory accuracy.

Table 3. Correct classification rate based on mixed matrix method

Fault type	Correct classification rate (%)
no fault	100
broken bars	100
end ring fracture	97.8
static eccentricity	94.1
dynamic eccentricity	94.7
Average value	97.32

(3) Analysis of fault diagnosis result

Table 4. Fault diagnosis

Actual state	Diagnostic results			
	Normal	Broken bars	Eccentric	Broken Bars
Normal	15	0	0	0
Broken bars	0	13	0	2
Eccentric	0	0	14	1
Broken bars and Eccentric	0	1	1	12

The conclusion can be inferred from Table 5 that 55 samples can be correctly diagnosed in 60 test samples and the correct accuracy was 91.7%, which can meet the needs of actual projects.

The further analysis on the system showed that it was able to identify the state of the motor accurately, while the fault symptoms of broken rotor bars and an air gap eccentricity were intertwined, which belongs to the progressive fault The 3 misclassified samples were occur from the misjudgment of the fault state between broken rotor bars and air gap eccentricity.

5. Conclusions

In this paper, the induction motor rotor fault is converted to pattern classification. The appropriate support vector machine is constructed in order to complete the fault diagnosis and classification. The motor stator current was sampled, then we obtained the stator current spectrum by FFT transform. Using the normalized spectrum signal as the input parameter, the multi-fault SVM classifiers were constructed using one against one algorithm and the mixing matrix combination strategy, then performed the diagnosis and classification to the different types of fault.

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The experimental results show that this method can achieve the fault classification of the motor fault diagnosis effectively, while small sample set, nonlinear and high dimensionality, which brought about the satisfactory results.

Currently, the method has been applied to induction motor fault detection and diagnosis of a mine ventilation system, it works well in industrial production, and has some promotional value.

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