Induction Motor Fault Diagnosis Based on Fuzzy Support Vector Machine

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Keywords: Induction motor, Fuzzy Support Vector Machine, Membership function, Wavelet analysis, Fault diagnosis.

Abstract: In order to solve the problem of correctly identifying fault classes in induction motor fault diagnosis and improve the accuracy of the classification, a novel fault diagnosis method of the classification model based on the Fuzzy Support Vector Machine (FSVM) is proposed in this paper. The fault pattern classifier was trained, which the fuzzy membership of the feature vectors is computed by a controllable factors algorithm membership function to overcome the sensitivity to noise and outliers. After the stator current was sampled, the fault feature was extracted from the sampling data through wavelet analysis and used as the input of the FSVM. A multi-class fault classifier was constructed to identify different faults, which was based on one to one strategy and mixed matrix combination. Experiment results show that the Fuzzy Support Vector Machine (FSVM) has good performance for classification over non-linear and high dimension and small sample sets. This method improves the accuracy in rotor fault diagnosis.

1 INTRODUCTION

The induction motor has been widely used in many industries, with its simple structure, low cost and durability. However, due to heavy load or frequent starting/braking, the connected region of rotor bars and end rings is prone to breakage and other failures. Therefore, early detection of the induction motor rotor fault is significant value. Since the 1990s, many scholars have applied artificial intelligence techniques into induction motor fault diagnosis and achieved remarkable results.

Papers (QIU Arui, 1999; Dong Jianyuan, 1998; Filippetti F, 2000) show us better diagnostic results in induction motor fault diagnosis technology, using Radial basis function (RBF) neural network, BP neural network and fuzzy neural network approach. Essays (Cao Zhitong, 2004; Chen Liyuan, 2006; Fang Ruiming, 2007) proposed motor fault diagnosis technology based on the support vector machine method, helping to deepen and develop research into motor fault diagnosis technology so as to achieve a better recognition effect.

Support vector machine (SVM) is a general-purpose machine learning method based on statistical learning theory, which effectively solved learning problems, such as small samples, high dimensions and nonlinearity (VAPNI V, 1995), overcoming the difficulty of determining reasonable structure and the presence of local optima in artificial neural network learning. But SVM has some limitations, such as sensitive reaction to the noise or outlier in training samples, the accuracy of classification of samples not completely belonging to one of the two categories were low. The samples collected during fault diagnosis often contain noise and outliers, these samples including "abnormal" information are often located near classification plane in the feature space, thus affecting the diagnostic results (Computer Engineering and Applications, 2009).

In this case, we adopted a fuzzy support vector machine (FSVM) fault diagnosis method based on subordinate degree function determining method of controllable factor, different samples with different weights punishment, determined the subordinate degree of training sample, eliminate the effects of noise and outliers in fault diagnosis. We input the training set into FSVM classification method, trained to get the fault diagnosis model, then input test set into the fuzzy SVM model that sufficient trained to achieve the identification of different fault types.

Li, S.
Induction Motor Fault Diagnosis Based on Fuzzy Support Vector Machine.
In *3rd International Conference on Electromechanical Control Technology and Transportation (ICECTT 2018)*, pages 588-592
ISBN: 978-989-758-312-4

2 FUZZY SUPPORT VECTOR

Taiwan scholars Chun and Shen proposed the concept of fuzzy support vector machines, fuzzy logic was introduced into the standard support vector machines, assigned each sample a subordinate degree value, adopted different penalties weighting factor for different samples. In addition to the features and generic identity of training samples, but also added the fuzzy subordinate degree, showed the degree of the sample belongs to a class, with a unique value.

Discriminant function corresponding to the optimal classification plane is:

$$f\left(x\right)=\operatorname{sgn}\left(\sum_{x_i\in SV} w_i K\left(x_i,x\right)+b\right) \qquad (1)$$

Where, $K\ (x_i, x)$ is the kernel function.

Transfer the complex inner product on high dimensional feature space, which was difficult to achieve, into a simple function calculation easily to implement on low-dimensional space.

3 FAULT DIAGNOSIS METHOD BASED FSVM

3.1 The Basic Principle of Fault Diagnosis

The basic principle of fault diagnosis and processes is shown in Figure 1. After the signal processing of collected information, computing the fuzzy subordinate degree of training sample point, obtained the trained fuzzy support vector machine network model, then applicate FSVM fuzzy classification rules in the fault diagnosis process.

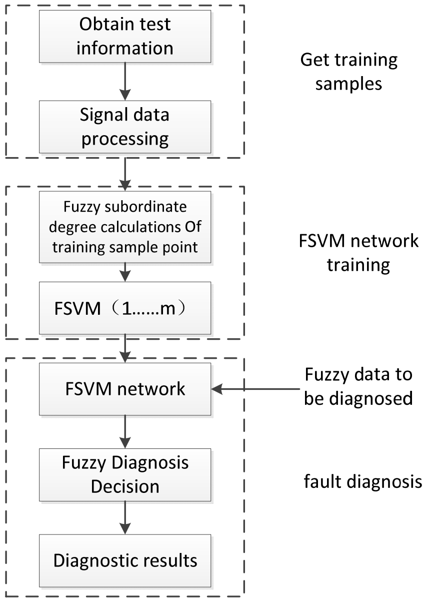

Figure 1 Fault diagnosis procedures based on FSVM

3.2 Determine the Subordinate Degree Function

The basic idea of Fuzzy Support Vector Machine is to endow subordinate degree belongs to a certain class to different sample, subordinate degree reflects the importance of sample to its training, select the appropriate subordinate degree function in a given problem directly affects the classification results. Under normal circumstances, the principle of determine the subordinate degree is the relative importance of the sample in the class, according to the actual problem, or need, select the appropriate fuzzy subordinate degree function to calculate the subordinate degree of each sample point.

Given sample set S, assumed positive class contains p samples $\left\{x_i \middle| i=1,2,\cdots p\right\}$, The average x_+ for its category as the central positive class, negative class contains q samples $\left\{x_j \middle| j=1,2,\cdots q\right\}$, The average x_- for its category as the central negative class, $p + q = l$.

$$x_+ = \frac{1}{p}\sum_{i=1}^{p} x_i \quad x_- = \frac{1}{q}\sum_{j=1}^{q} x_j .$$

Thus the center distance between two types, $T=\left\|x_+ - x_-\right\|$, the distance of each positive sample from the positive class center, $r_i^+ = \left\|x_+ - x_i\right\|$, the distance of each negative sample from the negative class center, $r_i^- = \left\| x_- - x_i \right\|$.

Assuming the sample point of the positive class and the negative class can be included in a hypersphere, respectively, the radius of hypersphere where include the positive and negative class can be calculated as follows:

$$r_+ = \max_{\{x_i : y_i = +1\}} \left\{ r_i^+ \right\}, \quad r_- = \max_{\{x_i : y_i = -1\}} \left\{ r_i^- \right\} \qquad (2)$$

Radius control factor ε, where $\varepsilon > 0$, given a small positive number σ previously, as the noise and isolated points of subordinate degree, and its function can be obtained as follows:

$$s_i = \begin{cases} \begin{cases} \dfrac{\delta + r_i^+}{r_+ + \delta} & r_i^+ \le T \cdot \varepsilon \\ \sigma & r_i^+ > T \cdot \varepsilon \end{cases} & if \quad y_i = 1 \\ \begin{cases} \dfrac{\delta + r_i^-}{r_- + \delta} & r_i^- \le T \cdot \varepsilon \\ \sigma & r_i^- > T \cdot \varepsilon \end{cases} & if \quad y_i = -1 \end{cases} \qquad (3)$$

Where: δ is a small positive number, in order to ensure $s_i > 0$ .The subordinate degree values of support vector improved in this way, meanwhile, also reduces the value of subordinate degree values of noise points.

According to experience of numerical experiment.

$$\varepsilon = (0.2 \sim 0.4)\frac{r_+ + r_-}{T}$$

4 INDUCTION MOTOR FAULT DIAGNOSIS SYSTEM BASED ON FSVM

4.1 System Configuration

In this paper, several typical rotor failure experiments are simulated using a rotor test rig. Stator current data was collected for each failure mode is used as fault samples at the rated speed. The hardware of the diagnostic system structure is shown in Figure 2, including current signal detection, signal processing and FSVM diagnostic.

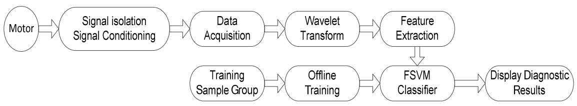

Figure 2 Configuration of fault diagnosis

1) Fault signal detection:

After stator current is collected by the Hall current sensors, it is Converted into an AC voltage signal between -3 ~ + 3V through Signal Conditioners. Subsequently, it is converted to a digital signal by the A / D conversion. The data is transferred to the computer through the parallel port communications.

2) Feature extraction (signal processing):

To analysis stator current spectrum using wavelet transform, and then to extract the fault feature, which is used as the input of the FSVM system.

3) Fault identification (learning phase):

To study the sample, and achieving the fault category learning, recognition.

4) Fault diagnosis (testing phase):

To complete the motor fault determination and classification using FSVM system, diagnostic results are displayed through man-machine interface.

4.2 Experiment and Analysis of the System

4.2.1 Acquisition of the Data Sample

Two poles motor is used as a test prototype, 1. 5 kW, 50 Hz, 220 V. Eddy current dynamometer is used as the motor load. Under the load stability conditions (s = 0.06), the stator current signal are taken respectively measured when the following states:

① no fault ② squirrel-cage rotor continuous two broken bars ③a fracture of the rotor end ring ④ rotor static eccentricity⑤ rotor dynamic eccentricity ⑥ broken rotor bar and eccentricity faults occur simultaneously.

The sampling frequency is 4096Hz and each data length of the sample is 512 points. Each failure mode selected 40 sets of data samples, a total of 240 sets of data, consisting of six training sample set.

4.2.2 Experiment and Analysis

(1) Feature extraction

After getting the training data, analysis the current signal by wavelet transform. Wavelet energy eigenvalues are extracted and the corresponding samples was constructed.

(2) Select the penalty factor C and kernel function

Penalty factor C is used to describe the balance between the largest classification border and the classification error during the process of training. When the greater the C is, the correct the classification results of training samples is. But at the same time the generalization ability decreased. In the fuzzy support vector machine, the penalty factor is fuzzy. The different penalty factor is chose according to the different samples, indicating the importance of the samples during training SVM. The grid search and the cross-validation method was used to get the penalty factor C = 78.

The selection of the kernel function has not yet formed a unified, effective rules, the most commonly used kernel functions include linear, polynomial, Gaussian and sigmoid kernel function. In this paper, the Gaussian radial basis function is used the kernel function.

$K(x_i, x_j) = \exp\left[-\frac{\|x_i - x_j\|^2}{2\delta}\right]$,Parameters δ =4。

(3)The fusion strategy of the sub-classifier output

Induction motor rotor fault diagnosis is a multi-class classification. After the various sub-classifier training is completed, the proper integration of the various sub-categories is needed in order to obtain the result of classification.

The voting decisions, binary tree, neural network method and mixed matrix method is commonly used the Fusion algorithm. The different fusion strategy has the greater impact on the classification results. In this paper, mixed matrix method can achieve more satisfactory accuracy, consuming far less than the neural network method.

(4) Diagnostic Analysis

For each failure mode, 10 samples were taken as the training samples in order to establish the diagnosis FSVM model.

The training sample is input the model, and the correct diagnosis ratio was 100%.The classification can be completely correct. Secondly, the test samples (30 samples for each fault) are inputted FSVM network in order to training model, At last , the mixing matrix method is used to judge the output of the model, determining the sample belong to what type.

Table 1: Fault diagnosis result

Failure mode	Diagnostic results	
	SVM	FSVM
Normal	28	28
Broken bars(or end ring fracture)	55	58
Eccentric(static or dynamic)	50	54
Broken bars and Eccentric	24	26
Accuracy (%)	87.2	92.5

The results can be inferred from the calculation: the correct diagnosis ratio of the standard SVM was only 87.2%.This shows the effect of a simple diagnostic based on the SVM method is not ideal. The fault diagnosis accuracy rate (92.5%) based on the FSVM significantly improved. This verifies the effectiveness and feasibility of the fault diagnosis method based on FSVM.

5 CONCLUSIONS

This paper presents a new method, which fuzzy support vector machine applied to the induction motor fault diagnosis. The fuzzy support vector machine classifier as a failure mode, using class mean distance to determine the fuzzy membership functions, therefore, it can distinguish between different fault samples, effectively eliminate the effects of isolated points and wild ideas on the diagnostic results. Under the small sample circumstances, the different failure of classification can be achieved.

Induction motor rotor fault, throughout the wavelet transform each band energy of the frequency component of the stator current is normalized, used as the fault feature vectors, input the support vector machines for training. This weakens the impact of load changes and noise on diagnostic accuracy. Test results show that: fault diagnosis model based on fuzzy support vector function can correctly diagnosed induction motor rotor fault, thanks to structural risk minimization principle, taking into account the training error and generalization ability, with the ability of good classification.

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