Probabilistic neural Network with statistical feature for fault diagnosis of permanent magnet motor

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Abstract

Permanent magnet motors are very important components in commercially available equipments and industrial applications due to high reliability and robust performance, and it is important to take an appropriate and effective approach to diagnose fault for them. The implementation of probabilistic neural network (PNN) with the statistical features for permanent magnet motor is developed in this paper, and the statistical features are determined according to the stator current characteristics of motor to effectively reduce dimensionality of sample space. The experimental results demonstrate that, compared with RBF network, the proposed method is more effective in identifying various types of faults.

Keywords: Permanent Magnet Motor, Probabilistic Neural Network, Statistical Feature

1 Introduction

Nowadays motors are the most extensively applied to all types of industries owing to their high reliability, simple construction and robust design [1]. Especially for permanent magnet motors, they have been used in many modern industrial fields owing to their high efficiency, low weight place and high torque [2]. But they are always exposed to a variety of complex environments and conditions which are accompanied with the natural aging process of any machine, moreover, they are very sensitive to the strict constraints because of the environment of embarked systems, thus causing the motor various failures. In this way, Fault detection of electrical machines has received extensive attentions in recent years. There are many methods to detect mechanical and electrical problems in motors, which include vibration, stator current, magnetic flux density, etc. Direct observation and measurement method is used in detecting traditional motor fault diagnosis, but it is unable to meet the requirements of modern motor manufacturers [3]; Parameter estimation method needs to establish a precise dynamic model of the motor and identify the motor electromagnetic parameters through the model, thus resulting in unclear fault characteristics [4, 5].

Recently BP neural network is developed for fault diagnosis of motors and many electric power systems [6-8]. However, BP neural network has the shortcomings of slow convergence speed and a tendency to the local optimum which have a serious impact on its generalization ability to fault diagnosis [9, 10].

PNN, as a subgroup of Radial Basis Neural Networks, is good suitable for dealing with classification problems, it is based on Parzen's method of density estimation and Bayes' decision strategy. The most important advantage of PNN is the simple structure, training manner and only one free parameter. In PNN, the smoothing factor has to be adjusted by the user and it can be adjusted at run time without the requirement of network retraining. So a significant contribution in this work is that the composition of statistical features is used to train PNN as a novel classifier for the fault diagnosis of permanent magnet motor, and to evaluate performance of the classifier the BP network is compared in term of the classification accuracy and train time.

2 Probabilistic neural network

The PNN was first proposed by Specht [11], it can be considered as a normalized radial basis function network in which there is a hidden unit centred at every training case, the probability density is the scaled sum of the kernel function for all training samples and the Gaussian function is used frequently. For PNN, his most important advantage is that it has a simple structure and only one free pamaerter named as the smoothing factor; one can adjust it without having to consider network retraining at run time. The probability density function is expressed as follows:

$$\hat{f}_j(\vec{x}) = \frac{1}{(2\pi)^{p/2}\sigma^p m_j}\sum_{i=1}^{m_j} exp\left(-\frac{(\vec{x}-\vec{x}_{ij})^T\cdot(\vec{x}-\vec{x}_{ij})}{2\sigma^2}\right), (1)$$

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where, $\hat{f}_j(\vec{x})$ is the probability of vector $\vec{x}$ occurring in set m_j, $\hat{f}_j$ is the estimated density for the *j*-th class, $\vec{x}$ is test case, $\vec{x}_{ij}$ is *i*-th training sample of the *j*-th class, *p* is dimensionality of $\vec{x}_{ij}$, σ: is the smoothing factor, m_j is number of training cases in the *j*-th class.

PNN is a four-layered feed-forward network topology that implements Bayes' decision criterion, the simple architecture is depicted in Figure 1.

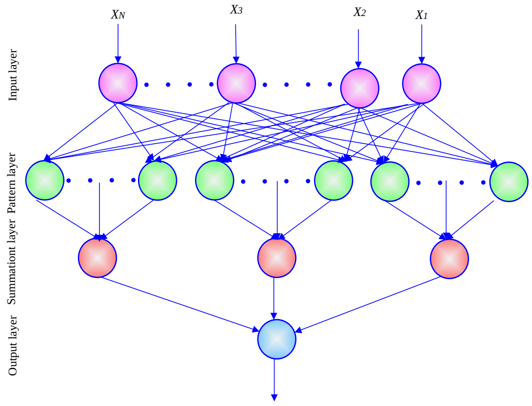

FIGURE 1 Architecture of the PNN

The PNN consists of input layer, pattern layer, summation layer and output layer [12]. The input layer simply distributes the input to the neurons in the pattern layer and does not perform any computation. For the pattern layer, it contains one pattern neuron for each training case, with an exponential activation function, a pattern neuron computes the squared Euclidean distance between a new input vector and the i^{th} training vector of the j^{th} class, the output of the neuron is calculated by the following multiscalar Gaussian function:

$$\hat{f}_j(\vec{x}) = \frac{1}{(2\pi)^{p/2}\sigma^p}\sum_{i=1}^{m_j} exp\left(-\frac{(\vec{x}-\vec{x}_{ij})^T\cdot(\vec{x}-\vec{x}_{ij})}{2\sigma^2}\right). \quad (2)$$

For each class, the summation layer contains a summation neuron, the summation neuron for the first sums the output of the pattern neurons that contain the training cases of the first class, the number of the neurons of the pattern layer is identical to the number of the training samples. The summation neuron for the second class sums the output of the pattern neurons that contain the training cases of the second class, and so on, the activation for each class in the summation neuron is identical to the estimated density function value of this class, the summation layer neurons calculate the maximum likelihood of the pattern vector by using equation (1). Finally, the output neurons of the output layer can obtain the result of the summation neurons. The neurons of the output layers are threshold discriminators that implement Bayes' decision criterion and the output neuron can generate the respective estimated probabilities for the test case, the neuron in the decision layer determines the class belongingness by:

$$l = \arg\min_{1\le k\le c}\{\rho_k\}, \quad (3)$$

where *c* is the number of classes of the training set and *l* is the estimated class.

3 Experimental results

For the permanent magnet motor, the current frequency is very high and the amplitude varies considerably with frequency, and the obtained sample is high-dimensional, it makes many classifiers become very complex and time-consuming in training process. To overcome the above difficulties, one must guarantee that a classifier should have a better classification accuracy with fewer feature dimensionalities.

TABLE 1 Statistical features definition

Feature number	Statistical features	Formula or description
Feature 1	Maximum value	Maximum amplitude value in a given current signal
Feature 2	Minimum value	Minimum amplitude value in a given current signal
Feature 3	Absolute mean value	$\sum_{i=1}^{N}\lvert x_i\rvert / N$
Feature 4	Standard deviation	$\sqrt{\sum_{i=1}^{N}(x_i-\bar{x})^2/(N-1)}$
Feature 5	Median value	Middle amplitude value separating the greater and lesser halves in a given current signal
Feature 6	Range	Difference in maximum and minimum amplitude values in a given current signal

So in order to reduce the dimensionality of the extracted samples and obtain a low-dimensional feature vectors, we need to select an appropriate sample space and implement feature extraction. Feature extraction is regarded as a process of computation of some measures for the signal, a sample set of statistical features namely Maximum, Minimum, Absolute mean value, Standard deviation, Median value and Range, are selected for the study in Table 1. These statistical features are extracted from the current signals correspondding to various faults; Table 2 describes 6 kinds of faults; Figure 2 shows 6 kinds of different current fault signals, and Table 3 shows the statistical features correspondding to Figure 2; Figure 3 shows the scatter diagrams between any two features, it is clear that the relationship characteristics between any faults are expressed, and there not exist any two features which can distinguish all the faults. A total of 240 data sets are used in the training, each of fault consists of 40 training samples, and the trained network is tested with data sets consisting of 40 test samples, in which each of fault contain 10 test samples.

TABLE 2 Fault definition

Fault numbers	Fault description
Fault 1	The rusty spot in the bearing inner and outer rings and ball
Fault 2	Something wrong with the bearing retainer
Fault 3	A greater pitting in the bearing inner ring
Fault 4	Something wrong with the two bearing concentricity
Fault 5	A phase winding short circuit
Fault 6	No fault

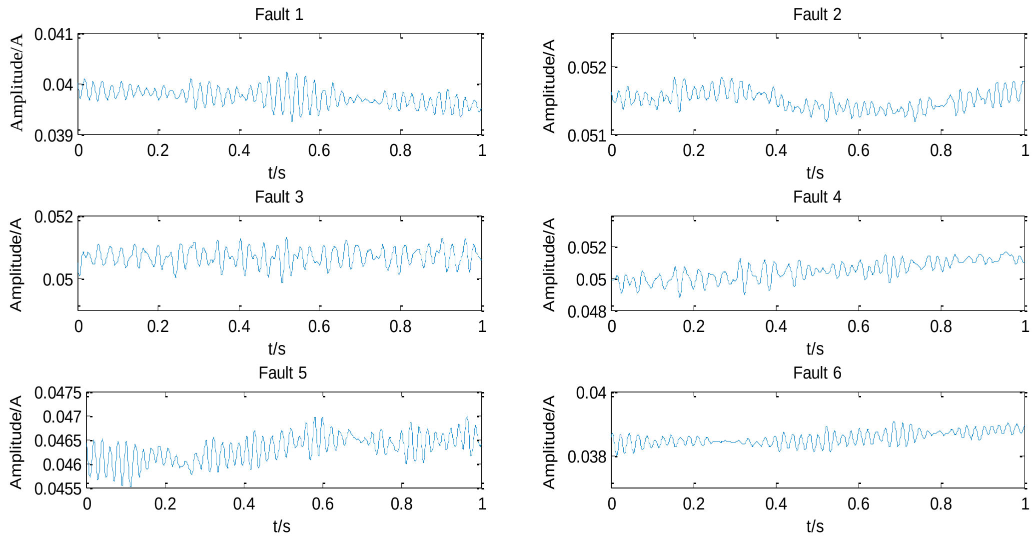

FIGURE 2 6 kinds of different current fault signals

TABLE 3 Statistical features corresponding to Figure 2

Fault number	Statistical features						Output					
	Feature 1	*Feature 2*	*Feature 3*	*Feature 4*	*Feature 5*	*Feature 6*						
1	0.03968	0.03923	0.03948	0.00010	0.00045	0.03948	1	0	0	0	0	0
2	0.05153	0.05096	0.05117	0.00012	0.00057	0.05117	0	1	0	0	0	0
3	0.05111	0.05013	0.05065	0.00024	0.00099	0.05065	0	0	1	0	0	0
4	0.05341	0.05115	0.05232	0.00049	0.00227	0.05232	0	0	0	1	0	0
5	0.04694	0.04574	0.04633	0.00026	0.00120	0.04633	0	0	0	0	1	0
6	0.03871	0.03825	0.03846	0.00011	0.00046	0.03845	0	0	0	0	0	1

The PNN and statistical features are used in fault classification of the permanent magnet motor, the network architecture and the training process are also taken into account, in addition, the performance of network generally depends on the sizes of the training set and test sets. In the developed classifiers for classification, the smoothing factor plays a viral role in the PNN, and an appropriate smoothing factor is often data dependent, meanwhile, the proper choice for the smoothing factor also improves the accuracy of the PNN. If the smoothing factor is too small, individual training patterns will be regarded only in isolation, and we only can obtain a nearest neighbor classifier, but if the smoothing factor is too high, details of the density can be blent together [13]. In general, there is no uniform approach for solving determine the smoothing factor, but we can determine it by minimizing the error, we use different smoothing factors to evaluate the performance of the PNN.

20 different values that range from 0.1 to 2 are adopted in order to better evaluate the performance to train a more accurate model. The estimation results of the PNN for the training samples using the above given values are depicted in Figure 4. It can be seen that the smoothing factor largely has effects on the training accuracy for PNN, and that the value σ = 0.9 generates the smallest training error.

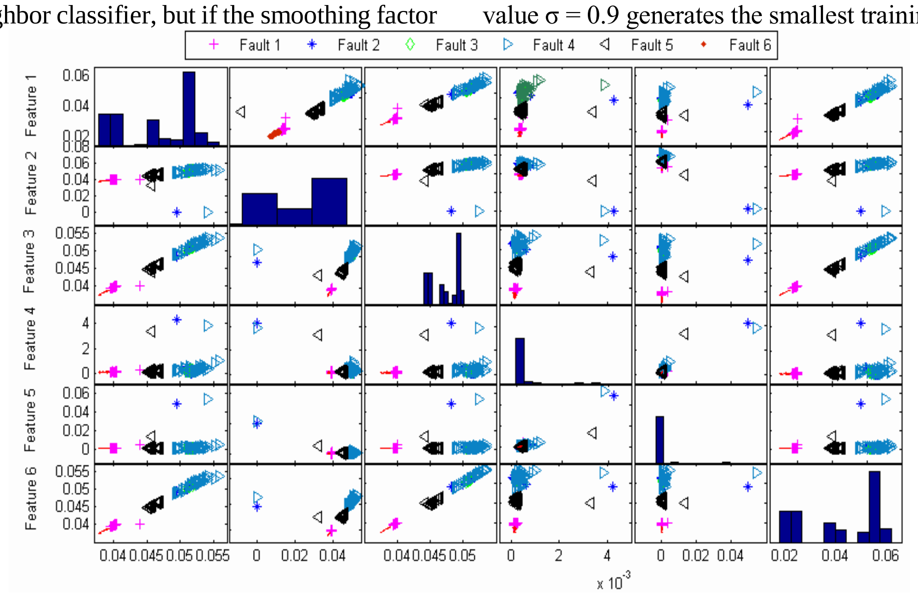

FIGURE 3 Scatter diagram between any two features

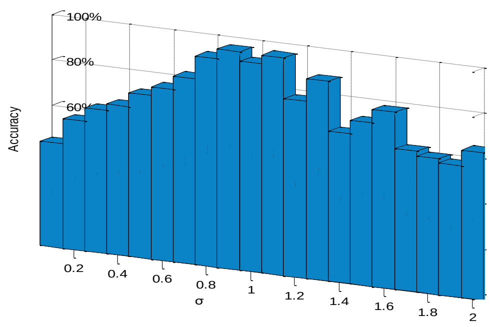

FIGURE 4 Effects of smoothing factor on training error

To compare the performance of the proposed method, the authors also processes RBF neural network for the experiment. The RBF network has three layers, including an input layer, a hidden layer with a nonlinear RBF function for activation and a output layer, the input of the network linearly combines radial basis function with some neuron parameters. For the experiment, the neuron number of the input layer of the RBF network is 6, the neuron number of the hidden layer is self-determining by autonomously increasing other neuron into it, the neuron number of the output layer of the RBF network is 6, and its training parameters are set as follows: the target error is set as 0.001 and the epoch is set as 800, the training process of RBF network is depicted in Figure 5. Then the two trained classifiers are used in testing using 60 testing samples, the comparison results of the between the two classifiers are shown in Table 4, it can be seen that from Table 4, compared with RBF network, the PNN classifier is more timesaving in training and has a higher test accuracy, thus manifesting more robustness, when the representative training samples is enough, a Bayesian optimal classifier must be obtained.

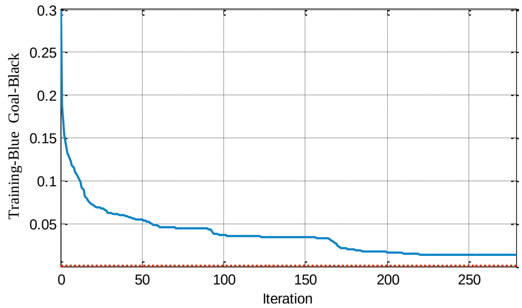

FIGURE 5 Training process of RBF

TABLE 4 Comparison between BP neural network and DDAG-SVM

Method	Training accuracy	Testing accuracy	Training time
PNN	97.62%	95.62%	0.60s
RBF	96.46%	92.08%	17.82s

4 Conclusion

In this study, PNN is used as a robust classifier for diagnosing various faults using the statistical features extracted from the stator current signals of the permanent magnet motor, the extracted statistical features effectively reduce dimensionality of sample space, the comparative experiment shows its the superiority of the performance, and the proposed method in the present work gives a possible application to the monitoring system in industry, which can largely reduce the accidents and ensure the safety of human life.

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