RVM - BASED ADABOOST SCHEME FOR STATOR INTERTURN FAULTS OF THE INDUCTION MOTOR

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Abstract:

This paper presents an AdaBoost method based on RVM (Relevance Vector Machine) to detect and locate an interturn short circuit fault in the stator windings of IM (Induction Machine). This method is achieved through constructing an Adaboost combined with a weak RVM multiclassifier based on a binary tree, and the fault features are extracted from the three phase shifts between the line current and the phase voltage of IM by establishing a global stator faulty model. The simulation results show that, compared with other competitors, the proposed method has a higher precision and a stronger generalization capability, and it can accurately detect and locate an interturn short circuit fault, thus demonstrating the effectiveness of the proposed method.

1 Introduction

Nowadays induction motors are widely used in many industrial processes owing to their high reliability, simple construction and robust design, but undoubtedly they are always exposed to a variety of complex environments and conditions which are accompanied with the natural aging process of any machine, thus causing various motor failures [1, 2]; as a result, their maintenance and fault detection become more and more important. Fault detection of IM has now received extensive attentions since according to some studies [3, 4, 5], in recent years, stator faults have been responsible for 37% of the IM failures [6, 7]. The most frequent IM failures are stator winding faults, resulting from the phase to phase, turn to turn, or winding to earth short circuit. For better detection of an interturn short circuit fault in the stator windings, modelling of IM with shorted turns is the first step in constructing turn fault detection systems. It follows that the simulated models of transient and steady state behavior of IM enable correct evaluation of the measured data by diagnostics techniques [8], and thus many models have been successfully used to study the transient and steady state behavior of IM with short circuited turns.

For the location and detection of an interturn short circuit fault, its essence is pattern recognition, and the different phase faults are treated as labels of a classifier. Many approaches based on pattern recognition for interturn short circuit fault such as ANN (Artificial Neural Networks) [9], SVM (Support Vector Machine) have been recently used. Given the fact that it is very hard to obtain good generalization results when the training samples are

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insufficient, and that they can be also easily trapped in a local optimum [10], the ANN approach based on the statistical characteristics of large-scale samples is used; by contrast, SVM as a machine learning method based on statistical learning theory, exhibits excellent performances in dealing with the classification questions. However, it entails some significant shortcomings, i.e., it is affected by the difficulty of appropriately selecting its parameters, so data and computation used to determine them have no result, its output is a point estimate rather than a conditional distribution, moreover, it does not allow for the free use of an arbitrary kernel function owing to the rule of Mercer's condition [11].

RVM [12] is a probabilistic sparse kernel model identical in functional form to SVM, where a Bayesian approach to learning is adopted through introducing a prior over the weights governed by a set of hyperparameters. RVM can obtain a generalization performance comparable to SVM by using dramatically fewer training samples. Furthermore, it suffers from none of the other limitations of SVM outlined above, and it is good classification ability with great sparsity/ efficiency.

AdaBoost [13, 14] is the latest data mining method for increasing the learning ability of a prediction system, and it can be used in conjunction with many other types of learning algorithms. In this way, it can not only increase the classification accuracy in any given weak classifier but also improve the generalization ability in strong classifiers.

In this paper, the AdaBoost algorithm incorporated with the RVM multiclass classifier based on a binary tree is used to detect and locate an interturn short circuit fault in the stator windings of IM. Meanwhile, the fault features are extracted from the three phase shifts between the line current and the phase voltage of the IM by establishing a global stator faulty model. The simulation results illustrate accordingly that the proposed approach is very effective.

2 AdaBoost algorithm

Pattern classification is a typical application of AdaBoost algorithm. For binary classification, its main idea is that a set of weight distribution should be maintained for a set of training samples. In each iteration, the AdaBoost calls a given weak learning algorithm. The weights which correspond to the wrong samples will be increased so that weak learning is forced to be focused on the hard-to-classify samples of the training set, and the task of the weak learner is to find the right weak estimate based on weight distribution of the samples. The *k*-class classification is one of the extensions of binary classification, now AdaBoost.M1 algorithm is given to solve *k*-class problem as follows:

1. Input: a set of training samples with labels $<(x_1,y_1),\ldots,(x_N,y_N)>$, the number of cycles T.

2. Initialize: the weights of training samples: $W_i^1 = D(i) = 1/N$, for all $i=1,2,\ldots,N$.

3. Do for $t=1, 2,\ldots,T$:

(a) $P_t = \dfrac{W^t}{\sum_1^N W_i^t}$;

(b) Pass P_t on to the Component Learner, and return estimate h_t: $X \rightarrow Y$;

(c) Calculate the training error of h_t:

$$\varepsilon_t = \sum_1^N P_i^t \left[\!\left| h_t(x_i) \neq y_i \right|\!\right];$$

(d) Set $\beta_t = \varepsilon_t(1-\varepsilon_t)$;

(e) Update the weights of training samples:

$$W_i^{t+1} = W_i^t \beta_t^{1-\left[\!\left| h_t(x_i) \neq y_i \right|\!\right]};$$

4. Output:

$$h_f(x) = \arg \max_{y \in Y} \sum (\log(1/\beta_t)) \left[\!\left| h_t(x_i) \neq y_i \right|\!\right],$$

where $\left[\!\left| \circ \right|\!\right] = \begin{cases} 1, \, if \circ is\ true \\ 0, \, else \end{cases}$.

3 RVM for classification

Tipping [12] proposed RVM (Relevance Vector Machine) to recast the main ideas behind SVM in a Bayesian context. For two classes classification, given a training dataset $\{x_n, t_n\}N$ n=1, and the corresponding output is $t_n \in\{0,1\}$, the following classification model can be used to describe the mapping relation between the input pattern vector **x** and the output t:

$$t_n = y(x_n, w) + \varepsilon_n, t = y + \varepsilon \tag{1}$$

Where the errors $\varepsilon = (\varepsilon_1 \ldots \varepsilon_n)$ are modeled probabilistically as an independent zero-mean Gaussian process, with the variance σ^2, so $p(\varepsilon) = \prod_{n=1}^{N} N(\varepsilon_n \mid 0, \sigma^2)$, $w = (w_1 \ldots w_M)$ is the parameter vector and $y\ (x_n, w)$ can be expressed as a linearly weighted sum of some basis functions $\varphi\ (x)$:

$$y(x, w) = \sum_{m=1}^{M} w_m \phi_m(x) + w_0, y = \Phi w \tag{2}$$

Here $\Phi = [\varphi_1, \mathrm{L}, \varphi_M]$ is the $N \times M$ design matrix whose columns comprise the complete set of M basis vectors. Note that the form of the function (4) is equal to the form of the function for a SVM where we identify our general basis functions with the kernel as parameterized with the training vectors, $\phi_m(x) = K(x, x_m)$ and $\phi(x_n) = [1, K(x, x_n), \ldots K(x_N, x_n)]$ when $y(x|w)$ is classified, the Sigmoid function is used as:

$$p(t_i = 1 \mid w) = \sigma[y(x_i; w)] = \frac{1}{1 + e^{-y(x_i; w)}} \tag{3}$$

Then the Likelihood function is obtained as:

$$p(t \mid w) = \prod_{i=1}^{N} \sigma[y(x_i; w)]^{t_i} (1 - \sigma[y(x_i; w)])^{1-t_i} \tag{4}$$

Using the Laplace approximation, and for a fixed value of α, the mode of the posterior distribution over w is obtained by maximizing:

$$w_{MP} = \arg \max_{w} \log(p(t \mid w) p(t \mid a)) \tag{5}$$

Its Logarithmic likelihood function is:

$$\begin{gathered} \log(p(t \mid w) p(t \mid a)) = \\ \sum_{I=1}^{N} [t_i \log y_i + (1 - t_i) \log(1 - y_i)] - 0{,}5 w^T A w \end{gathered} \tag{6}$$

The mode and variance of the Laplace approximation for w are:

$$\begin{cases} w_{MP} = \sum_{MP} \Phi^T B t \\ \sum_{MP} = \left(A + \sigma^{-2} \Phi^T \Phi\right)^{-1} \end{cases} \tag{7}$$

Where B is $N \times N$ diagonal matrix with $b_{nn}=f(x_n;w)(1-f(x_n;w))$, the marginal likelihood is:

$$\begin{gathered} p(t \mid x, a) = \int p(t \mid x, w) p(w \mid a) dw = \\ p(t \mid x, w_{MP}) p(w_{MP} \mid a) (2\pi)^{M/2} \left|\sum_{MP}\right|^{1/2} \end{gathered} \tag{8}$$

When maximizing the above equation with respect to each α_i, one eventually obtains:

$$\begin{cases} \alpha_i^{new} = \dfrac{\gamma^i}{\mu_i^2} \sum_{MP} \Phi^T B t \\ \left(\sigma^2\right)^{new} = \dfrac{\|t - \Phi\mu\|^2}{N = \sum_{i=0}^{N} \alpha_i \Sigma_{i,i}} \end{cases} \tag{9}$$

One gives first guess value of a, then renews unceasingly through the above step to approach w_{MP}; once the iteration procedure has converged to the most probable values, the majority of a_i will be 0, other a_i are close to infinity and their corresponding x_i are relevant vectors.

4 The stator faulty model and the faulty features

4.1 Global stator faulty model

To obtain the healthy and faults of a three phase induction motor, we use the global stator faulty model proposed in [15, 16], which is described in Fig. 1. It can be seen that the model includes the common and differential parts, the first one corresponds to the dynamic model in healthy operation, and the second one corresponds to the dynamic model in faulty operations.

Fig. 2 shows a three phase two-pole induction motor with a short-circuit winding at phase B, this fault induces in the stator new windings B_{cc} short circuit and is localized according to first phase by the angle $\theta_{cc}=2\pi/3$.

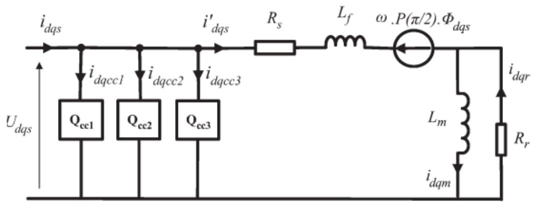

Figure 1. Global stator faulty model.

Two parameters are introduced in the differential part through defining the faults in the stator as follows [16]:

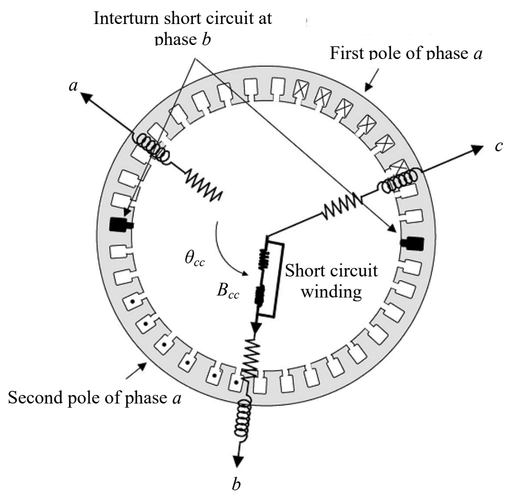

Figure 2. Short circuit winding representation.

The location parameter, θ_{cc}, is the angle between the inter turn short circuit stator winding and the first stator phase axis, which can take only one of three values 0，$2\pi/3$ and $4\pi/3$ and which corresponds to the short circuit on the phases A, B and C, respectively. The detection parameter, μ_{cc} is the ratio between the number of interturn short-circuit windings and the total number of turns in the healthy phase used to quantify the unbalance:

$$\mu_{cc_k}=\frac{n_{cc_k}}{n_s} \tag{10}$$

Here n_{cck} is the number of shorted turns and n_s is the number of turns at each phase. The short-circuit currents in the differential part can be described below:

$$i_{cc_k}=\frac{2\eta_{cc_k}}{3R_s}P(-\theta)Q(\theta_{cc_k})P(\theta)U_{dq} \tag{11}$$

The state space representation of the stator faulty model is given by:

$$\begin{cases} X(t)=A(\omega)X(t)+BU(t) \\ Y(t)=Cx(t)+D(\theta_{cc_k},\mu_{cc_k})U(t) \end{cases} \tag{12}$$

$$X=[i_d,i_q,\phi_d,\phi_q]^T \tag{13}$$

$$U=[U_d,U_q]^T \tag{14}$$

$$Y=[i_d,i_q]^T \tag{15}$$

$$A=\begin{bmatrix} A_{11} & A_{21} \\ A_{12} & A_{22} \end{bmatrix} \tag{16}$$

$$A_{11}=\begin{bmatrix} -\frac{R_s+R_r}{L_f} & \omega \\ -\omega & -\frac{R_s+R_r}{L_f} \end{bmatrix} \tag{17}$$

$$A_{12}=\begin{bmatrix} \frac{R_r}{L_f L_m} & \frac{\omega}{L_f} \\ -\frac{\omega}{L_f} & \frac{R_r}{L_f L_m} \end{bmatrix} \tag{18}$$

$$A_{21}=\begin{bmatrix} R_r & 0 \\ 0 & R_r \end{bmatrix} \tag{19}$$

$$A_{22}=\begin{bmatrix} -\frac{R_r}{L_m} & 0 \\ 0 & \frac{R_r}{L_m} \end{bmatrix} \tag{20}$$

$$B=\begin{bmatrix} 1/L_f & 0 & 0 & 0 \\ 1/L_f & 0 & 0 & 0 \end{bmatrix}^T \tag{21}$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix} \quad (22)$$

$$\omega = \frac{T_e - T_l}{\tau_m} \quad (23)$$

$$D\left(\theta_{cc_k}, \mu_{cc_k}\right) = \left[\sum_{k=1}^{3} \frac{2\eta_{cc_k}}{3R_s} P(-\theta) Q\left(\theta_{cc_k}\right) P(\theta)\right] (24)$$

$$Q\left(\theta_{cc_k}\right) = \begin{bmatrix} \cos\left(\theta_{cc_k}\right)^2 & \sin\left(\theta_{cc_k}\right)\cos\left(\theta_{cc_k}\right) \\ \sin\left(\theta_{cc_k}\right)\cos\left(\theta_{cc_k}\right) & \sin\left(\theta_{cc_k}\right)^2 \end{bmatrix} \quad (25)$$

$$P(\theta) = \begin{bmatrix} \cos(\theta) & \cos(\theta + 2\pi/3) \\ \sin(\theta) & \sin(\theta + 2\pi/3) \end{bmatrix} \quad (26)$$

Where T_e and T_i are the electromagnetic and the load torques respectively, τ_m is the mechanical time constant, i_d and i_q are the dq stator current components respectively, φ_d and φ_q are dq rotor flux linkage components, U_d and U_q are the dq stator voltage components, θ is the electrical angle, and $\omega = d\theta / dt$ is the electrical angular velocity, R_s and R_r are the stator and the rotor resistances, L_f and L_m are the leakage inductances referring to the stator and the magnetizing inductance, respectively.

4.2 Determination of faulty features

The determination of faulty features is a key step in any monitoring and fault diagnosis systems which directly affect the diagnosis accuracy of the systems. For the induction motor with stator interturn faults under normal operation and unbalanced conditions, phase voltages and line currents are the same in magnitude but shifted by $2\pi/3$ electric angle. However, under faulty operation, not only the phase currents are unequal but also the phase shifts.

When the number of short circuit interturn and the load torque changes the induction motor parameters such as the global leakage inductance L_f, the stator resistance R_s and the magnetizing inductance L_m change, respectively, thus each phase shift can be expressed by the following equation[17]:

$$\theta = \arctan \frac{R_s}{X_s} \quad (27)$$

Here, R_s and X_s are the stator resistance and the stator reactance, respectively. Fig. 3-5 show the three phase shifts under different shorted turns and under a load torque of 3Nm for fault on phase A, B and C, respectively. Consequently, it can be seen that, for fault on phase A, B and C, each phase shift is also different, moreover, with an increase in shorted turns, this difference becomes obvious, thus performing the sensitivity of the phase shifts for the interturn shorted circuit fault. The phase shift is therefore an idea feature, i.e., an indictor of the location for stator shorted circuit fault.

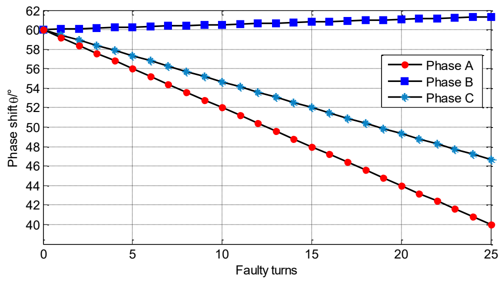

Figure 3. Each phase shift for fault on phase A.

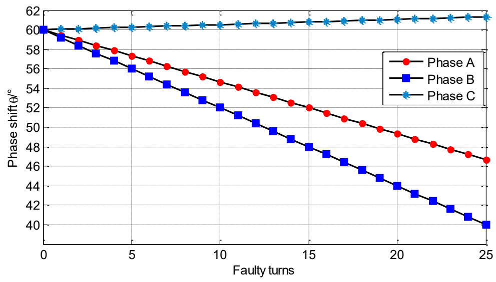

Figure 4. Each phase shift for fault on phase B.

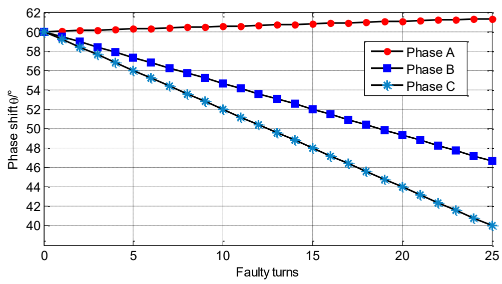

Figure 5. Each phase shift for fault on phase C.

For RVM, the choice of kernel is important to its performance when there is no prior knowledge in the learning process and when the Gaussian kernel function outperforms the other. The Gaussian kernel function is given as:

$$K(x,y)=\exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right) \quad (28)$$

Here σ is a width factor which shapes the width of the Gaussian kernel function, the performance of RVM classifier depends mainly on the selection of σ.

As there are four different conditions including one normal and three faulty ones for the stator, this binary classifier needs to be popularized into a multiclass classifier. The method based on binary tree is used for dividing all conditions into two subclasses, then further ones into two secondary subclasses. Being processed as such until all the nodes contain single conditions, the nodes are the leaves of a decision tree. So by this method, the multiclass classification problem is decomposed into multiple binary classification problems corresponding to k-1 RVM classifiers; Fig. 6 illustrates the weak RVM multiclass classifier based on binary tree.

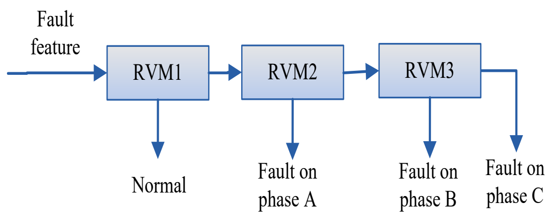

Figure 6. Weak RVM multiclass classifier based on binary tree.

In this work, the RVM multiclass classifier based on binary tree is used as a classifier of Adaboost, and its kernel parameter σ is set to be relatively large and same/equal in the three weak classifiers. The adequate decreasing step length σ_{step} is set to be the kernel parameter σ of each RVM classifier and the same σ can be used many times for each iteration of each classifier as long as the classification error of the multiclass classifier is less than 0.5. These weight training samples are adjusted according to the classification error until the kernel parameter σ of each binary classifier achieves the threshold σ_{min} or until the training error is satisfied.

The process of AdaBoost-RVM multiclassifier is described as follows:

1. Input: a set of training samples with labels $<(x_1,y_1),\ldots,(x_N,y_N)>$, the number of cycles T.

2. Initialize: the weights of training samples: $W_i^1 = D(i) = 1/N$, for all i=1,2,…,N. The minimum of σ is σ_{ini}, the step size of σ is σ_{step}, the threshold is σ_{min}.

3. Do for t=1, 2,…,T:

(a) $P_t = \dfrac{W^t}{\sum_1^N W_i^t}$;

(b) Train RVM multiclass classifier h_t and pass P_t on to it, then return estimate: h_t: $X \rightarrow Y$;

(c) Calculate the training error of h_t:

$$\varepsilon_t = \sum_1^N P_i^t \left[\left| h_t(x_i) \neq y_i \right|\right];$$

(d) If $\varepsilon_t > 0{,}5$ and $\max(\sigma_{RVM1}, \sigma_{RVM2}, \sigma_{RVM3}) \geq \sigma_{\min}$, then
$\max(\sigma_{RVM1}, \sigma_{RVM2}, \sigma_{RVM3}) = \max(\sigma_{RVM1}, \sigma_{RVM2}, \sigma_{RVM3}) - \sigma_{step}$
and return to (b), or continue

(e) Set $\beta_t = \varepsilon_t(1-\varepsilon_t)$;

(f) Update the weights of training samples:

$$W_i^{t+1} = W_i^t \beta_t^{1-\left[\left|h_t(x_i)\neq y_i\right|\right]};$$

4. Output:

$$h_f(x) = \arg \max_{y \in Y} \sum (\log(1/\beta_t)) \left[\left| h_t(x_i) \neq y_i \right|\right],$$

where $\left[\left|\circ\right|\right] = \begin{cases} 1, \ if \circ is\ true \\ 0, \ else \end{cases}$.

5 Simulation results and analysis

To evaluate the proposed method of the location of stator interturn faults in IM in this paper, the simulation data are required. For this purpose, a range sample sets are acquired through the global stator faulty model, which contains different conditions under different shorted turn faults. All samples are under three different load conditions, and each load condition contains the normal faults and faults ranging from 1 to 15 shorted turns, thus a total of 138(3+15×3×3) samples constitute a sample set. In this way, 2/3 of them present the training samples, the rest are used as test samples to test the performance of the method of faults location. Fig. 7 shows the acquired samples set, the parameters of AdaBoost-RVM are set as follows: σ_{ini}=3, σ_{min}=0.1 and T=100.

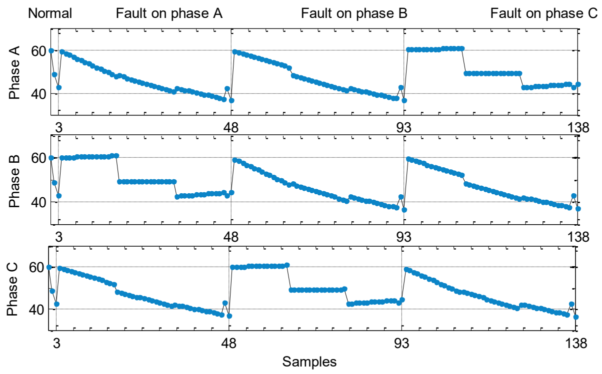

Figure 7. Samples set.

In order to observe the influence of the step length σ_{step} on the AdaBoost-RVM, σ_{step} is taken as 0.1, 0.2 and 0.3 to training. Fig. 8 illustrates the influence of different σ_{step} on AdaBoost-RVM. It can be found that the change of σ_{step} is less sensitive to the final result. With an increase of the iterative times, the number of the combined RVM multiclass classifier is also increased. At the early period of the iteration, the decrease of σ does not much contribute to the training accuracy, while with an increase in iteration, the accuracy begins to rise rapidly until the σ of three binary RVM classifiers has been reduced to a certain degree. From the convergence speed, the multiclass RVM classifier with the value σ_{step}=0.1 is the fastest, but, although the convergence processes of model training are different, the final training accuracy is stable.

For comparison, BP (Back Propagation) neural network algorithm, AdaBoost-BP algorithm [18] and RVM algorithm are also used to this data set. Fig. 9 shows the comparison curves of training processes of the four methods, though the four methods all can achieve a very low error in the given iterations, their convergence speeds are different.

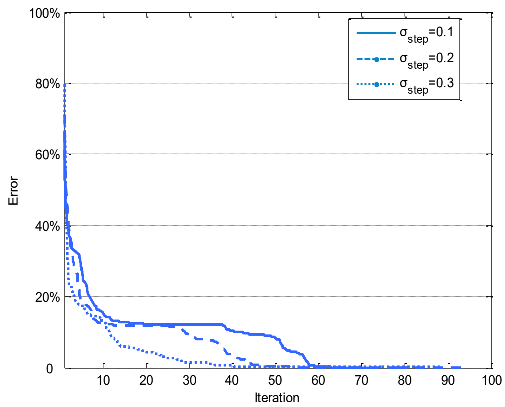

Figure 8. Influence of σ_{step} on Adaboost-RVM.

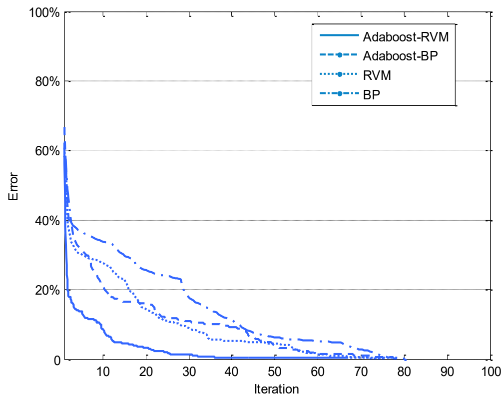

Figure 9. The comparison curves of training processes of four methods.

It can be clear that the accuracy of AdaBoost-RVM algorithm is better than that of the other three. Since the cross-validation time of the kernel function parameter is relatively longer, the convergence speed of the RVM is slower, and the performance of the BP is similar to that of RVM. It is worth noting that the Adaboost-BP has a lower convergence speed, because that BP, as a multiclass classifier, trains its thresholds and weighs by the initial random values in each iteration, thus causing a waste of time. The training and test performances of the four algorithms are shown in Table 1 where it can be seen that the BP classifier and the RVM classifier have a similar performance, the AdaBoost-BP comes second, and the AdaBoost-RVM is the best.

For the AdaBoost-RVM, three RVM kernel function parameters σ in weak classifier alternately diminish so that the precision gained each time is appropriate. It makes distribution weight not too great for some hard-to-classify samples, thus effectively controlling samples frequency obtained by re-sampling and avoiding weight expansion problem [19]. After 100 iterations, the obtained repeated sampling frequency is shown in Figure 10 from which it can be seen that the repeated rate of some samples selected, named key learning samples, is higher than the repeated rate of other samples named rich information samples. The case in which some samples have too high frequencies does not appear due to the appropriate control of the weight value.

Table 1. The performance of four methods

Algorithm	Training accuracy (Error number)	Training time	Test accuracy (Error number)
AdaBoost-RVM	100% (0)	27.8s	97.63% (1)
AdaBoost-BP	100% (0)	36.5s	95.65% (2)
RVM	98.91% (1)	21.7s	91.30% (4)
BP	98.91% (1)	29.2s	93.48% (3)

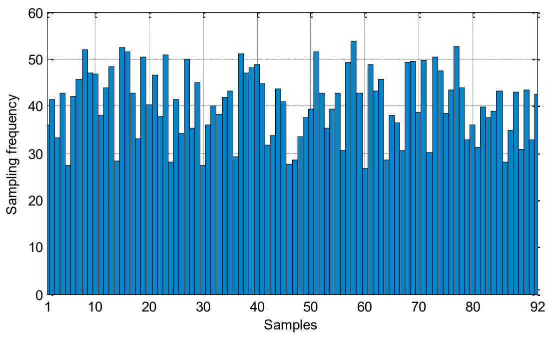

Figure 10. The frequency distribution of training samples.

6 Conclusions

An effective method for detecting and locating an interturn short circuit on the stator windings of IM is proposed. This diagnosis method establishes the AdaBoost algorithm combined with weak RVM multiclassifier based on a binary tree, and the three phase shifts between the line current and the phase voltage of IM are hence used as fault features. The modeling idea of this method is clear and easy to operate. The simulation results demonstrate that the proposed method has higher diagnosis accuracy and a better generalization capability than its counterparts.

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References

[1] Karami, F., Poshtan, J., Poshtan, M.: *Detection of broken rotor bars in induction motors using nonlinear Kalman filters*, ISA Transactions, 49 (2010), 189-195.

[2] Siddique, A., Yadava, G. S., Singh, B.: *A review of stator fault monitoring techniques of induction motors*, IEEE Transactions on Energy Conversion, 20 (2005), 106-114.

[3] Cusido, J., Romeral, L., Ortega, J. A.: *Fault detection in induction machines using* J.A. *power spectral density in wavelet decomposition*, IEEE Transactions on Industrial Electronics, 55 (2008), 633-643.

[4] Kowalski, C.T., Orlowska-Kowalska, T.: *Application of Neural Networks for the Induction Motor Faults Detection, Mathematics and Computers in Simulation,* 63 (2003), 435-448.

[5] Bacha, K., Salem Ben, S., Chaari, A.: *An improved combination of Hilbert and Park transforms for fault detection and identification in three-phase induction motors*, International Journal of Electrical Power & Energy Systems, 43 (2012), 1006-1016.

[6] Filippetti, F.: *State of art of model diagnostic procedures for induction machines inter-turns short circuits*, Proc. IEEE SDEMPED, Gijon, Spain, Sep. 1999, 19–31.

[7] Siddique, A., Yadava, G.S.: *A review of stator fault monitoring techniques of induction motors*, IEEE Transactions on Energy Conversion, 20 (2005) 106-114.

[8] Arkana, M., Kostic-Perovic, D., Unsworth, P. J.: *Modelling and simulation of induction motors with inter-turn faults for diagnostics*, Electric Power Systems Research, 75 (2005), 57–66.

[9] Mirceska, A., Kulakov, A., Stoleski, S.: *The Role of Artificial Neural Networks in Detection of Pulmonary Functional Abnormalities*, Engineering Review, 29 (2009), 1-11.

[10] Kim, K.J., Han, I.: *Genetic algorithms approach to feature discretization in artificial neural networks for the prediction of stock price index*. Expert Systems with Application, 19 (2008), 125–132.

[11] Hernández, N., Talavera, I., Biscay, R. J., Ferreira, M. M. C., Porro Muñoz, D.: *Relevance vector machines for multivariate calibration purposes*, Chemometrics, 22 (2008), 386-694.

[12] Tipping, M. E.: *The relevance vector machine*, Advances in Information Processing System, 2 (2000), 652-658.

[13] Schapire, R. E., Singer, Y., Bartlett, P., Lee W.: *Boosting the margin: a new explanation for the effectiveness of voting methods*, The Annals of Statistics, 26 (1998), 1651–1686.

[14] Dietterich, T.G.: *An experimental comparison of three methods for constructing ensembles of decision trees: bagging, boosting, and randomization*, *Machine Learning,* 40 (2000), 139-157.

[15] Bouzid, M., Champenois, G., Bellaaj, N. M., Signac, L., Jelassi, K.: *An Effective Neural Approach for the Automatic Location of Stator Interturn Faults in Induction Motor*, IEEE Transactions on Industrial Electronics, 55 (2008), 4277-4289.

[16] Bachir, S. S., Tnani, J. C., Trigeassou, G.: *Champenois Diagnosis by parameter estimation of stator and rotor faults occurring in induction machines, Industrial Electronics*, IEEE Transactions on Industrial Electronics, 53 (2006), 963 – 973.

[17] Dash R.N., Subudhi B., Das S.: *A comparison between MLP NN and RBF NN techniques for the detection of stator inter-turn fault of an induction motor*, International Conference on Industrial Electronics, Control and Robotics, Rourkela, India, 2010, 251-256.

[18] Li X., Wang L., Eric S.: *AdaBoost with SVM-based component classifiers,* Engineering Applications of Artificial Intelligence, 21 (2008), 785-795.

[19] Ratsch, G., Onoda, T., Muller, K. R.: *Soft Margins for Adaboost*, Machine Learning, 42 (2001), 287-290.