Research on Fault Diagnosis Method of Blast Furnace Based on Clustering Combine SVMs Dynamic Pruned Binary Tree

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Abstract—**Since fault diagnosis of blast furnace is very important in manufacturing, in this paper, a new strategy based on clustering combining SVMs pruned binary tree is proposed to solve diagnosis problem in blast furnace. According to the relations of categories in multi-class problem, it is needless to distinguish all the sorts. In order to improve classification efficiency, advantage of clustering and support vector machine is combined. According to the similarity of different samples' sorts, a binary tree is constructed rationally to accelerate fault diagnosis efficiency. The class similarity is determine according to class distance and distribution sphere in feature space, the similarity is used to determine the classification order of hierarchical multi-class classify SVMs. The training samples and corresponding SVMs sub-classifiers are selectively re-constructed to make sure bigger classification margin and good generalization ability. The results of simulation experiments show that the proposed method is faster in training and classifying, better in classification correctness and generalization.**

I. Introduction

THE industry process monitoring and fault diagnosis system is one of the most important subsystems of the process industry. With the progress of modern industries become large-scale and integrated, processes became more and more complex, the measured variables increased and the requirement to operators enhanced. Once fault occurs, it might cause large casualties and serious economic losses .At present, the applications of artificial intelligence on fault diagnosis of blast furnace are mainly based on expert system and neural networks [1]. However, the former has the difficulty of knowledge acquisition, and the latter needs a great deal of training samples and training time, which is used only on off-line diagnosis.

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In this paper, an artificial intelligent method— support vector machines (SVMs), which is based on the structural risk minimization and statistics learning theory is studied. The Support Vector Machine (SVMs), which was originally designed by Vapnik in 1995 is a learning approach for binary classification and it has been applied in many fields [2]. It could conquer dimension disaster [3], avoid over-fitting and local least point, resolve non-linear problem and has advantage on generalization. Along with high-speed development of the information science and high-fusion of different fields, SVMs has become the research hotspot in machine learning and intelligence system. It has been applied widely in pattern recognition [4], image processing [5] and text categorization [6], etc. The basis of SVMs is construct hyperplane with maximum margin separating two-class samples. It is to say that given a training set of instance-label pairs, where $x \in R^d$, $y \in \{+1,-1\}$, map the input vectors into high dimension space H through $\phi{:}R^m \rightarrow R^n$ change the problem into linear, then the hyperplane defined as $(\omega.\phi(x))+b$ could be achieved through resolve a quadratic programming problem. Last, recognize or predict samples using support vectors and decision-making function.

II. SVMs Multi-Class Classification Methods

To generalize SVMs to multi-class problems, several strategies have been proposed. At present there are two types of approaches for multi-class SVM.(1) Construct a series of two types of classifiers in some way, and make them together to achieve multi-class classification. (2)By solving a single optimization problem, to achieve multi-class classification. Although the second class method looks simple, but solving Optimization problem is more complex, and the classification accuracy is not enough precise. So the first method is more commonly used. The first methods mainly include One-against-All"(OAA)."One-against-One"(OAO).

"OAA" is the earliest approach for multi-class SVMs. It constructs K binary SVMs to classify *K*-classes. The *i*th classifier is trained while labeling all the samples in the *i*th class as positive and the rest as negative. The classification speed is fast, but its training is the most computationally expensive because each SVM is optimized on all the *N* training samples.

"OAO" use all the binary pairwise combinations of the K classes. Thus, "OAO" model consists of K(K-1)/2 binary SVMs. The overall training speed is faster than "OAA" but the number of classifiers increases greatly along with the increasing of *K*, so the decision speed is slow.

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Several works also explored the combination of binary SVMs in a hierarchical structure. The hierarchical multi-class SVMs with binary tree architecture is the most important[7],which two hierarchically divides the data set into subsets from root to the leaf until every subset consists of only one class. The construction order of binary tree has greatly influence on the classification performance. An improved hierarchical multi-class SVM with binary tree architecture is proposed based on the class similarity which is proposed according to the class distance and class distribution in the feature space to maximize the distance between two group centers and minimize the variance in each group. Such architecture assures that the separability between upper nodes is larger than the lower nodes. Only K-1 binary classifiers are constructed to make it very fast in terms of testing time comparing with other algorithms.

III. Clustering Combine Dynamic Druned Binary Tree Algorithm

In the process of blast furnace fault diagnosis, fault samples themselves have special relations each other [8]. The common character is the class' sequences presented are correlative. The transition between abnormal state and normal state or between abnormal states is usually gradual. Fig.1 shows a simple example of state transition, if fault 2 occurs, it is considered that the information of fault 1 is useless; this sort could be pruned.

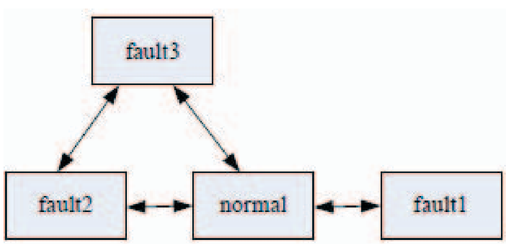

Fig.1. Transition of states

Fig.1 shows a simple example of state transition, if fault 2 occurs, it is considered that the information of fault 1 is useless; this sort could be pruned.

How to reduce identification time and keep classification precision is the key to solve the problem. Thus, a new algorithm of clustering combining SVMs pruned binary tree is proposed in this paper. It wipes off the training non-appearance samples temporarily from classification system. According to the current estimated state, prune sub-trees impossibly occurs. That is, wipe off *i* sorts with lest comparability from the n sorts. Then following the manual definition or automatic computation of similarity, reconstruct binary tree dynamically. The new binary tree reduces the amount of original classifiers to n-1-*i*. It could not only keep classification precision, but also save identification time in the condition of large scale samples.

The key to construct binary tree is defining hierarchy of sub-task properly. The performance of upper classifier has much greater influence on the generalization performance of the whole classification model. The earlier the class is classified, the bigger the classification area is. At present there are two methods to construct binary tree:

1) classifying the class which can be easier to be classified firstly to make sure that the upper SVMs classifier has much more generalization performance;

2)classifying the class which has the most extensive distribution firstly to make sure that it has the biggest classification area.

In this paper, The class similarity is proposed which consider not only the class distance but also the class distribution; the binary tree is constructed from the top to bottom, samples having bigger class similarity is clustered the same sort,thus the upperst nods of SVMs root binary tree are produceed.According to this principle,the lowwer nods are produced in order. There are some formulas involved in the paper.

the center of class *i* in the feature space is defined as:

$$m_i = \frac{1}{l_i} \sum \varnothing(x_s) \tag{1}$$

the distance between class *i* and *j* class in the feature space is:

$$D_{ij} = \|m_i - m_j\| = \sqrt{\frac{1}{l_i^2} \sum_{s=1}^{l_i} \sum_{s=1}^{l_i} K(x_s, x_s) - \frac{2}{l_i l_j} \sum_{s=1}^{l_i} \sum_{t=1}^{l_j} K(x_s, x_t) + \frac{1}{l_j^2} \sum_{t=1}^{l_j} \sum_{t=1}^{l_j} K(x_t, x_t)} \tag{2}$$

class similarity is defined as:

$$\text{similar}(i, j) = {R_i^2 + R_j^2} \Big/ {\|m_i - m_j\|^2} \tag{3}$$

where

$$\left(R_i = \max_{t=1 \ldots l_i} \|x_t - m_i\| \right)$$

The procedure of clustering combining SVMs dynamic pruned binary tree algorithm is as follows:

Step1: Computing the class similarity of samples according to the formula (3);

Step2: Selecting two classes with the biggest similarity(i, j) to train SVMs and unite the two classes as a new class; Computing the new united class center and class distance according to the formula (1) and (2), computing the similarity between the united class and the other classes according to formula (3); Repeat the process until the all samples are clustered two classes.

Step3:Construct the most upper SVMs of binary tree.

Step4:Identify the first input text sample, recording the sample status.

Step5: Reconstruct the pruned binary tree; Use residuary samples as root samples to distinguish the last predicted sample's sort; Rank the similarity from high to low and construct sub-tree one by one. Each sub-tree can be regarded as a one-against-rest SVMs classifier. If there are samples with the same similarity, choose any one as the predicted sort by random. The new SVMs binary tree' leaves on each level are depth-first ergodicity from high similarity to low.

Step6: Predict new sample. If it belongs to the last sort, keep the binary tree and go to step5;

Step7: If the sort changes, reconstruct the binary tree and go to step 4;

End.

For example,classifying five categories is shown in Fig.2.If fault 4 occurs,exclude impossible fault 1 and fault 2,use the remanent as the root node to identify the current fault 4.

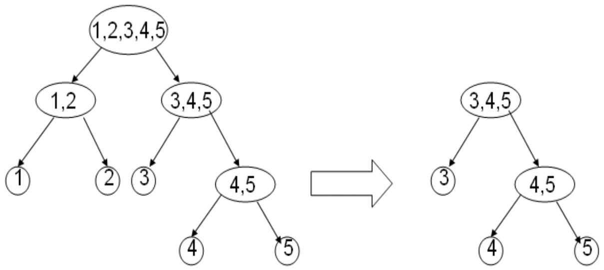

Fig.2 Clustering combining SVMs pruned binary tree

Fig. 2 shows five categories classifying process.

IV. SIMULATION EXPERIMENTS

In order to compare the proposed algorithm's capability with other algorithms, fault diagnosis simulation experiments of blast furnace are done with actual production data of a large-scale steel enterprise, in this paper, consider five key fault diagnosis of blast furnace such as pipe fracture, cooler, warmer , hanging and slip.

SVMs OAA algorithm， SVMs OAO algorithm and clustering combine SVMs dynamic pruned binary tree algorithm are compared to show which is the best for fault diagnosis of blast furnace, four kernel function constructed multiclassifier are used ,that are

Polynomial kernel function:

$$K(\mathbf{x},\mathbf{x}_i)=\left[(\mathbf{x}\bullet\mathbf{x}_i)+r\right]^d \quad r=2,d=2 \tag{4}$$

Radial basis function:

$$K(\mathbf{x},\mathbf{x}_i)=\exp(-\gamma|\mathbf{x}-\mathbf{x}_i|^2) \quad r=2 \tag{5}$$

Sigmoid kernel function:

$$K(\mathbf{x},\mathbf{x}_i)=\tanh\left(\gamma(\mathbf{x}\bullet\mathbf{x}_i)+c\right) \quad r=2,c=2 \tag{6}$$

Linear kernel function:

$$K(\mathbf{x},\mathbf{x}_i)=\mathbf{x}\bullet\mathbf{x}_i \tag{7}$$

The results of simulation are shown from Table Ⅰ to Table Ⅲ correspondingly . TABLE Ⅰ is the experiment results of SVMs OAA algorithm, TABLE Ⅱ is the experiment results of SVMs OAO algorithm, TABLE III is the experiment results of SVMs dynamic pruned binary tree,C is penalty parameter.

TABLE Ⅰ
SVMs OAA ALGORITHM EXPERIMENTS RESULTS

Multi-classification Algorithm (OAA)		Testing samples	Accuracy	Testing time(s)
Kernel Function C=10	linear	500	0.8038	0.72
	rbf	500	0.9456	0.92
	polynomial	500	0.8014	2.57
	sigmoid	500	0.3570	2.49

TABLE Ⅱ
SVMs OAO ALGORITHM EXPERIMENTS RESULTS

Multi-classification Algorithm (OAO)		Testing samples	Accuracy	Testing time(s)
Kernel Function C=10	linear	500	0.9456	0.93
	rbf	500	0.9480	0.37
	polynomial	500	0.9480	0.20
	sigmoid	500	0.8960	0.07

TABLE Ⅲ
CLUSTERING COMBINE DYNAMIC PRUNED BINARY TREE ALGORITHM EXPERIMENTS RESULTS

Multi-classification Algorithm (Clustering combine SVMs dynamic pruned binary tree)		Testing samples	Accuracy	Testing time(s)
Kernel Function C=10	linear	500	0.9385	1.51
	rbf	500	0.9637	0.93
	polynomial	500	0.9385	1.54
	sigmoid	500	0.3593	0.06

It is concluded that clustering combine SVMs dynamic pruned binary tree algorithm with radial basis function kernel function does better than "OAA"and "OAO" algothrim with the four kinds of kernel functions; the clustering combine SVMs dynamic pruned binary tree with radial basis function kernel function not only reduces more testing time but aslo has the highst diagnose accuracy. Though SVMs OAO algorithm with rbf kernel function and polynomial kernel function even has shorter testing time,as data increases, error rate become increasingly evident.

Table Ⅳ shows the diagnose results of five blast furnace faults using the clustering combine SVMs dynamic pruned binary tree algorithm, choosing radial basis function as kernel function . The five blast furnace faults are pipe fracture , cooler, warmer , hanging and slip. It is shown that five blast furnace faults could be identified efficiently and quickly and the error rate is not more than 0.4%, hence,clustering combine SVMs dynamic pruned binary tree algotrithm is feasible to blast furnace diagnosis.

TABLE. Ⅳ
CLASSIFICATION Result

Fault status	Training samples	Testing samples	Accuracy (%)
pipe fracture	100	100	96.25
cooler	100	100	95.43
warmer	100	100	94.38
hanging	100	100	95.46
slip	100	100	96.74

Ⅴ. CONCLUSION

The number of training samples decrease from upper level to lower level for clustering combine SVMs dynamic pruned binary tree algorithm, the number of SVMs classifier are also reduced, so the training speed is faster;the testing speed is improved; the classification order is determined according to the classes similarity. Comparing with "OAO","OAA", The simulated experiment results show that the proposed clustering combine SVMs dynamic pruned binary tree algorithm has faster speed, better classification accuracy and generalization performance.

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