Fault Diagnosis for Electrohydraulic Servo Valve Based on Support Vector Machine

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***Abstract*-Fault diagnosis for hydraulic components has features of nonlinearity and high dimensional pattern identification, so it's difficult to do it accurately with small sample using some common methods. Aimed at this problem, fault analysis for electro-hydraulic servo valve is carried on and the thought of symptom parameters reflecting the running status is illustrated.firstly. Then combining with function in the toolbox of MATLAB, the function to carry out multi-classification fault diagnosis based on Directed Acyclic Graph (DAG) Support Vector Machine (SVM) theory is built. At last, an example of fault diagnosis t is taken to test and verify the effectiveness of this method.**

Keywords-multi-classification, fault diagnosis, Support Vector Machine (SVM), Directed Acyclic Graph (DAG), electro-hydraulic servo valve

I INTRODUCTION

Electro-hydraulic servo valve is widely applied in electro-hydraulic operating system of aviation, aeronautical, military equipment and various commercial installations for its fast response speed and high control accuracy. Because of its special applications and key affect, fault diagnosis accurately to electro-hydraulic servo valve is significant especially. A simulation study to electro-hydraulic servo valve using hydraulic simulation software was studyde in reference [1]. Aimed at fault diagnosis to electro-hydraulic servo valve, a singular signal dector was researched based on wavelet analysis theory in reference [2]. In recent years, artificial neural network (ANN) begins to apply to fault diagnosis of electro-hydraulic servo valve. In reference [3]-[6], BP（Back Propagation）neural network was studied to do fault diagnosis of electro-hydraulic servo valve. ANN, as principal method for fault diagnosis, has advantages of simple structure and strong problem solving ability. But ANN has shortcomings such as local optimum, weak convergence, long training time, overfitting easily and so on, and it is unsuited to solve small sample problems. Therefore, seeking a process to solve fault diagnosis with small sample is people's aim.

A Support Vector Machines (SVM) is a new study machine growing up recent years, based on statistical learning theory and Vapnic-Chervonenkis (VC) theory. SVM minimizes the structural risk to solve small sample, nolinear and high dimensional problems and obtain good generalization ability. At the same time, SVM solves some shortcomings of ANN such as small convergence rate and falling into local minimum, so it becomes a new hot after ANN. In fault diagnosis field, fault diagnosis system for hydraulic steering engine and electrohydraulic position servo valve were designed based on Support Vector Regression (SVR) in references [8]-[10]. Fault diagnosis technique for hydraulic valve was studied based Real-valued Negative Selection (RNS) and SVM theory in reference [11]. In reference [12], single valued SVM was applied to do fault diagnosis to electro-hydraulic servo valve depending on data sample from only normal status, however, this classification machine can answer only whether it's running normally or not. Actually, the fault status of electro-hydraulic servo valve is multiple and multi-classification could be solved through combining a number of single SVM. So a fault diagnosis method to electro-hydraulic servo valve based on multi-classification SVMs will be studied in this paper.

II CLASSIFICATION PRINCIPLE OF SVM

As for a binary class classification question in two dimension space, sample points are (x_1, y_1), ……,(x_i, y_i), $x_i \in R^d$, $y_i \in \{-1,+1\}$. SVM theory is such a method to search an optimal classification line $g(x) = wx+b=0$ that the line can not only divide sample points of different class, but also maximum the distance between points of different class and the line. Set the optimal classification line is H. H_1 and H_2 are lines that thread different class points separately, have a minimum distance from H and parallel with H. The sample points on H_1 and H_2 are known as Support Vector (SV). If the same classification question occures in three dimension space, the classification line would become a plane. Spread to higher dimension, the classification is known as optimal classification hyperplane. Accordingly, w and x will become vector. The meaning of hyperplane is shown in Figure 1.

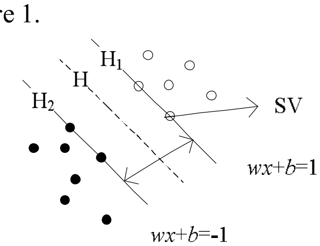

Figure 1. Optimal classification hyperplane

The distance between sample points of a class and the optimal classification hyperplane is

$$\delta = \frac{1}{\|w\|}|g(x)|$$

After defining $|g(x)|=1$, maximize δ is equal to minimize $\|w\|$ or $\|w\|^2$. Add the constraint condition that $y_i=1$ $wx_i+b\geq 1$, $y_i=-1$ $wx_i+b\leq -1$. In order to maximize the margin of classification plane and minimize the number of sample points classified incorrectly, add a relax item $\xi_i \geq 0$. So the question to search an optimal hyperplane becomes a question to solve such a quadratic programming as follows.

$$\min \Phi(w,\xi) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}\xi_i$$

$$y_i(w \cdot x_i + b) - 1 + \xi_i \geq 0, i = 1, 2, \cdots, l$$

In the formula, C>0 is constant which checks the punish level to sample points classified incorrectly, known as penalty factor. When the sum of the relax item of all outliers is constant, the bigger C is, the lose to object function is more and it's mean not wishing to give up these outliers at this time. As for some nolinear cases, SVM theory mappes input space through kernel function $K(x_i,\ x)$ to a higher dimension space in which there are some linear rules to creat linear optimal classification hyperplane.

SVM is a typical two-valued classifiter, but there is always multi-classification problem in actual fault diagnosis. At present, multi-class classifiter could be created through combining a number of single SVM. The methods of combining SVMs include 'one to one', 'one to else', Directed Aeyclic Graph SVMs (DAG SVMs) etc. The method of DAG has advantages of fast training, no classification overlap and no impartibility, so it's applied in more and more fields. The principle of DAG method is that: as for K classes, creat $K(K\text{-}1)/2$ two-valued classification SVMs and train each SVM using a couple of samples. That is to say, a classification SVM only answer that a fault belongs to the ith class or the jth class. In the diagnosis phase, form all two-valued classification SVMs to a directed aeyclic graph with a node in the top layer known as root node. In sequence, the ith layer has i nodes. Among all the nodes, the ith node in the jth layer point to the ith and the i+1 nodes in the j+1 layer. The Kth layer has K leaf nodes which mappes to K classes. The testing sample was imported through root node and according to the export of the node is -1 or 1 to decide the next node. In sequence, after K-1 discrimination the last layer will export the class of the import sample.The principle of DAG SVM for four classes can be seen in Figure 2.

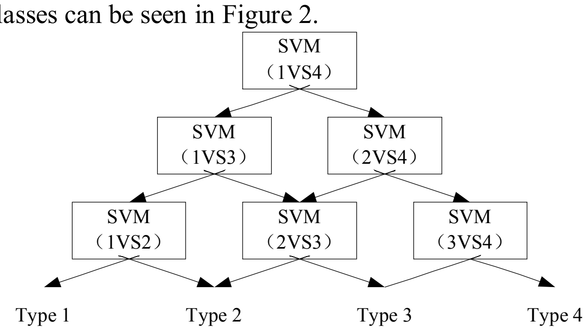

Figure 2. The principle of DAG SVM for four classes

III DESIGN OF FAULT DIAGNOSIS PROCESS BASED ON SVM

Nozzle flapper valve, as well as jet-pipe valve, is a typical class of electro-hydraulic servo valve and it is made and used widely at home. The common faults of electro-hydraulic servo valve are divided into electrical faults and machinery hydraulic faults [1]. Electrical faults include servo amplifier fault, valve coil fault, sensor fault, electric contact unsolder and so on. Machinery hydraulic faults include bobble wear, magnet demagnetization, valve pocket seal breakage, main valve core wear and so on.

The running status of valve is reflected by a series of parameters such as input current, load current, load press, inner leakage, flow gain, press gain, bandwidth and so on. When a valve is running normally, these parameters are varying in proper ranges. If there was a fault occurred, one or more parameters would exceed its normal range before eventual retirement of the valve.

Based on preceding fault analysis, regard every fault status and a normal status of a valve as a class separately, then a fault diagnosis problem will become a classification problem and the classification foundation will be the parameters which reflect the running status of a valve. These parameters could be obtained by direct measurement or indirect calculation, but one of which to be selected would be determined through the application scope of the valve, the difficulty level of signal acquisition and proper fund at last. Generally, select as much as possible parameters in order to take in more information of the running status to do fault diagnosis accurately. After that, regard each fault status as a type and the normal status a type. Then a fault diagnosis problem will become a classification problem based on parameters reflecting the running status. The parameters could be obtained by direct measurement or indirect calculation. Generally, select as much as possible parameters in order to take in more information of the running status to do fault diagnosis accurately. Then fault diagnosis becomes a process to solve a nonlinear mapping from symptom parameter assemble to fault assemble (containing a normal status). There are two phases, training and diagnosis, in this process shown in Figure 4.

Set the number of types in fault assemble is K, the number of parameters in symptom parameter assemble is m. Eparately collect N groups symptom parameter from each fault status as training samples. Set the training sample from the Type i (i=1, 2, …, K) is $\boldsymbol{x}_i$ and its target output is $\boldsymbol{y}_i$. $\boldsymbol{x}_i$ is an $m\times N$ matrix, $\boldsymbol{y}_i$ is an N dimension vector and every element of it is 1.

Sign the SVM that divides Type i and Type j as S_{ij} and its input and target output are

$\boldsymbol{X}\{i, j\} = [\boldsymbol{x}_i, \boldsymbol{x}_j]$

$\boldsymbol{Y}\{i, j\} = [\boldsymbol{y}_i, -\boldsymbol{y}_j]$

Train S_{ij} importing $\boldsymbol{X}\{i, j\}$ and $\boldsymbol{Y}\{i, j\}$ into classification function

[*nsv* ***alph****a* *bias*] = svc($\boldsymbol{X}\{i, j\}$, $\boldsymbol{Y}\{i, j\}$, *ker*, *C*)

In the function, *ker* is a type of kernel function and taken 'rbf' as usually. *C* is a penalty factor and taken an infinite value as usually. ***Alpha*** is a vector of Lagrange operator. *nsv* is the number of support vectors.

In order to train each SVM at a time, build a function as follow:

[***X***, ***Y***, ***al***, ***bi***, *alltime*, *maxtime*]=dag_train (*K*, *m*, *N*, *ker*, *C*)

In the function, ***al*** is a three dimensional matrix and ***al***(:, *i*, *j*) is equal to ***alpha*** from S_{ij}. ***bi*** is a matrix of *bias* and ***bi***(*i*,*j*) is equal to *bias* from S_{ij}. *alltime* is the total time to train all SVMs. *maxtime* is the longest time to train some single SVM.

Once there is a fault occurred, collect the parameters in current status to get a check waiting sample $\boldsymbol{x}_0$. Import $\boldsymbol{x}_0$ into the check function of S_{ij}

predictedY = svcoutput($\boldsymbol{X}\{i, j\}$,$\boldsymbol{Y}\{i, j\}$, $\boldsymbol{x}_0$, *ker*, **alpha**, *bias*, *actfunc*)

In the function, *predictedY* is the expected check result from S_{ij}. When *predictedY* is 1, $\boldsymbol{x}_0$ belongs to Type i. When *predictedY* is -1, $\boldsymbol{x}_0$ belongs to Type j. *actfunc* is activation function with 0 to sign hard classification and 1 soft classification.

Collected q groups of parameters in current status, the check waiting samples will be an $m\times q$ matrix. If collect q groups of parameters in every status in fault assemble, the check waiting samples will be an $m\times q\times K$ matrix. Set the check waiting samples as $\boldsymbol{X}_0$, build a function as follows:

$\boldsymbol{pY}$ = dag_diagnose($\boldsymbol{X}$, $\boldsymbol{Y}$, $\boldsymbol{X}_0$, *ker*, ***al***, ***bi***, *actfunc*, K, q)

In the function, $\boldsymbol{pY}$ is the expected result matrix and $\boldsymbol{pY}(i, j)$ is the diagnosis result of the ith sample from Type j. The process of importing a two- dimension X_0 into SVMs to do fault diagnosis following DAG is shown in Figure 3.

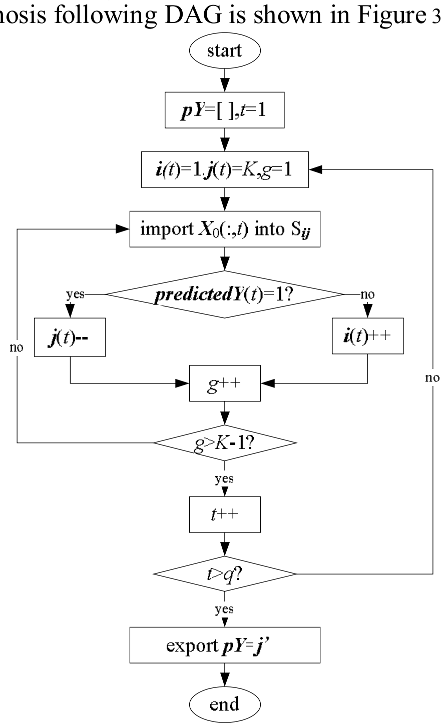

Figure 3 The process of diagnosis

After finished the program of training and diagnosis in MATLAB, some testing have be done using emulation data in order to discuss the influence to diagnosis result from parameter K, N and m. Testing results are shown in

.

It can be seen from Table I that the training time was influenced by K, N and m. As the else parameters are constant, the bigger N or m is, the longer the time to train a SVM is. K determines the number of SVMs, so the bigger it is, the longer the time to train all SVMs is. At the same time, the accuracy of diagnosis result has some connection with K, N and m. As the else parameters are constant, the bigger K is, the lower the accuracy is. The bigger N or m is, the higher the accuracy is.

IV EXAMPLE OF FAULT DIAGNOSIS

Take a two-stage moving-coil electro-hydraulic servo valve whose model is FF106A-234 as an object. Take four significant fault status and a normal status of this valve to form fault assemble $\boldsymbol{T}$: T_1-normal status, T_2- one end of valve core position-limit, T_3-one end of fixed orifice blockage, T_4- zero position of servo valve misalignment, T_5- valve core wear. Take three parameters which reflect running status to form symptom parameter assemble $\boldsymbol{P}$: P_1(mA)- input current, P_2(MPa)- pressure difference at oil-in, P_3(MPa)- pressure difference at oil-return port.When the system pressure is 3MPa, collect 16 groups of parameter datas which come reference [6] from each status in $\boldsymbol{T}$ as P_1 changes from -10 to +10. The data from reference [6] is shown in Table II.

Take 14 groups of data as training samples and the other two groups as testing samples. Do fault diagnosis using the aforesaid method. The time to train all 10 SVMs is 0.8s and the testing result is

$$\boldsymbol{pY}=\begin{pmatrix} 2 & 2 & 3 & 4 & 5 \\ 1 & 2 & 3 & 4 & 5 \end{pmatrix}$$

The testing result indicates that 9 out of 10 testing samples are classified accurately. However, choose different groups of data as training samples and testing samples separately, the testing result will be different even to appear great error at sometimes. Adjusting some parameters properly is help to reduce the error, for example, increase the training number N or symptom parameter number m. In a word, the method of fault diagnosis for electro-hydraulic servo valve based on SVMs is fast and accurate. Compared with thousands of trainings using BP neural network in reference [6], this method is simple and easy to do, so it needs developed and improved necessarily.

V SUMMARIES

Based on minimizing the structural risk theory, SVM which gives consideration to empirical risk and generalization ability has an unique advantage to do fault diagnosis with small sample. Aimed at fault diagnosis of electro-hydraulic servo valve, this paper has done below work based on multi-classification SVMs theory.

(1) Combining some references, through extracting symptom parameter assemble and fault assemble, fault analysis for electro-hydraulic servo valve is done and the thought of fault diagnosis through solving the nonlinear mapping from symptom parameter assemble to fault assemble is illustrated.

(2) The method of fault diagnosis for electro-hydraulic servo valve based on DAG SVMs is studied. The principle of the method is illustrated and the program in MATLAB is realized. At last, an example is

done to indicate the effectiveness of this method in limited training samples.

At present, more researchers are seeking ways to combine SVM theory with expert system, fuzzy logic and ANN to form some synthesized methods. Therefore, fault diagnosis based on SVM will be used more maturely and widely.

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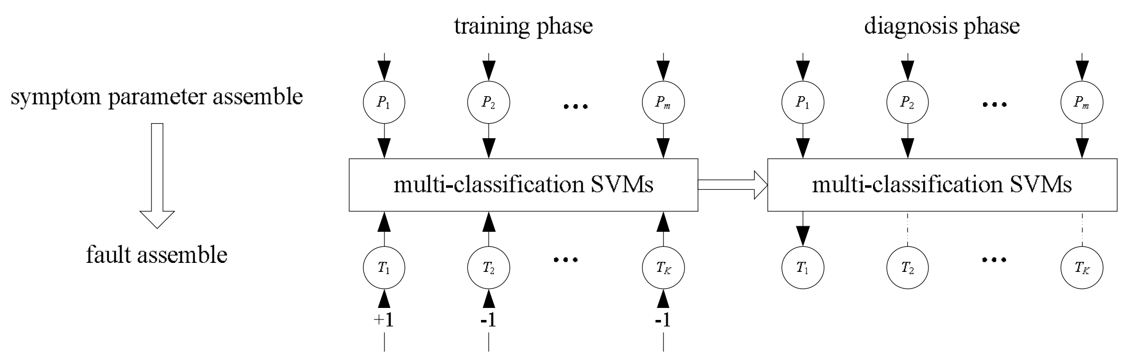

Figure 4. The principle of fault diagnosis based on SVMs

TABLE I. TESTING RESULTS OF FAULT DIAGNOSIS

	K	*N*	*m*	*p*	SVMs	*alltime*(s)	*maxtime*(s)	accuracy
1	5	5	5	5	10	0.11	0.03	76%
2	5	10	5	5	10	0.20	0.05	88%
3	5	20	5	5	10	0.50	0.06	96%
4	5	10	10	5	10	0.27	0.05	100%
5	5	10	20	5	10	0.33	0.06	100%
6	20	10	5	5	190	10.8	0.08	87%

TABLE II. THE DATA OF ELECTRO-HYDRAULIC SERVO VALVE

T	T_1~T_5	T_1		T_2		T_3		T_4		T_5	
P	P_1	P_2	P_3	P_2	P_3	P_2	P_3	P_2	P_3	P_2	P_3
1	10	1	1	1	1	1	1	1	1	1	1
2	8.67	0.95	0.95	0.98	0.97	0.98	0.99	0.99	0.99	0.92	0.96
3	7.33	0.96	0.97	0.97	0.98	0.98	1.0	0.98	0.99	0.91	0.97
4	6.0	0.96	0.97	0.96	0.99	0.99	0.97	0.98	1.0	0.91	0.97
5	4.56	0.95	0.96	0.98	0.99	0.97	1.0	0.91	0.97	0.89	0.94
6	3.22	0.90	0.97	0.94	0.98	0.98	0.97	0.67	0.85	0.86	0.97
7	1.89	0.94	0.93	0.85	0.94	0.95	0.97	-0.53	0.09	-0.12	0.89
8	0.556	0.33	0.73	0.34	0.71	0.96	0.97	-0.73	-0.59	-0.35	0.57
9	-0.556	-0.54	-0.28	0.13	0.44	0.97	0.98	-0.83	-0.63	-0.68	0.17
10	-1.89	-0.93	-0.81	0.17	0.26	0.97	0.96	-0.78	-0.74	-0.85	-0.81
11	-3.22	-1.0	-0.96	0.16	0.18	0.97	0.99	-0.80	-0.76	-0.96	-0.94
12	-4.56	-0.99	-0.98	0.14	0.18	0.97	0.97	-0.77	-0.76	-0.95	-0.95
13	-6.0	-0.98	-1.0	0.14	0.16	0.99	0.99	-0.77	-0.76	-0.96	-0.98
14	-7.33	-0.98	-0.99	0.15	0.16	0.97	0.97	-0.77	-0.77	-0.98	-0.95
15	-8.67	-0.98	-0.98	0.15	0.16	0.97	0.97	-0.78	-0.77	-0.96	-1.0
16	-10	-0.99	-0.99	0.15	0.15	0.96	0.96	-0.78	-0.78	-0.94	-0.98