The Application of SVM in Equipment Spare Parts Multi-class Classification Problem

Zhang Jin[1], Xu Tingxue[2], Wei Yong[1], Yu Renbo[1]

(1. Graduate Students' Brigade of Naval Aeronautical and Astronautical University, Yantai, Shandong, 264000, P. R. China;

Email:zhangjin_999999@163.com

2. Weapon Science and Technology Department of NAAU, Doctor Professor, Yantai, Shandong, 264000, P. R. China)

Abstract: Aiming at the characters that the history data of equipment spare parts demand allocation is limited, the influence factors of spare parts demand allocation are numerous, and the relations between which are almost nonlinear, this paper put forward using tree multi-class classification method of SVM to realize the equipment spare parts multi-class classification, and gave an application example. The results show that the method can realize equipment spare parts multi-class classification effectively.

Key word: equipment spare parts; SVM; tree multi-class classification method

1 Introduction

Spare parts supply support is one of the ten weapon equipment integrated support factors and an important task which influences cost and efficiency in equipment supportability. Spare parts supply support also ensures equipment's fine combat readiness in peacetime, at the same time it is an important factor to retain and resume equipment's battle effectiveness in wartime[1,2]. The most of support cost of equipment is spare parts cost, so the condition of spare parts support influences weapon equipment's strategic intactness and life cycle cost directly. Spare parts support is an important content to strengthen the construction of weapon equipment, which can not be neglected.

If want to allocate equipment spare parts reasonably, we need to make sure the categories of spare parts at first. According to their different categories, adopt different allocation methods. Because there are many factors to affect spare parts' allocation, there has not been any method to ascertain the requirement of the spare parts exactly by far. Now we usually analyze history data of equipment spare parts demand allocation to carry out equipment spare parts' classification.

If we regard the influence factors, which affect spare parts demand occurrence, as independent variables to build regression model, and apply the general regression analysis method to equipment spare parts classification, the result is usually dissatisfactory. There are two main reasons. The first is that the influence factors of spare parts demand are numerous, the relations between which are almost nonlinear. But the general regression analysis method is linear model. As a result it is very hard to reflect spare parts demand's changing regulation exactly by the expression. In the end it will affect the model's prediction result. Although neural networks can be used to build the nonlinear model, it has some inherent defects, such as the over-learning problem and the local minimum problem, which will bring great inconvenience. The second is that the general regression analysis method is based on traditional statistics theory, which has superior requirement on samples content. However, the data of equipment spare parts requirement, especially new equipment spare parts' requirement, is very limited.

Support vector machine (SVM) based on statistical learning theory is a sort of new machine learning algorithm aiming at limited samples data. SVM has strict theories foundation, and they can well resolve such practical problems as nonlinearity, multi-dimension and local minima, etc. And it has attracted extensive concern in recent years. Therefore applying SVM to carry on the equipment spare parts multi-class classification have theories advantages and great practical application value.

2 Support Vector Machine（SVM）

Suppose it has known that the training set is $\{(x_1,y_1),(x_2,y_2),\cdots,(x_l,y_l)\}$, $x_i \in R^n$, $y_i \in \{1,-1\}$, $i=1,2,\cdots,l$. Choose a kernel function and an appropriate punishment function C, for transforming the nonlinear question of the input space into the linear question of the multi-dimensional feature space. Under the nonlinear condition, introduce the transform: $\varphi : R^n \to \mathrm{H}$, which can map the data from input space into a multi-dimensional Hilbert space H. According to the theory of structural risk minimization and considering the function's complicacy and fitting error, classification problem can be described as the following restricted optimization question[3]:

$$\min_{w\in H,b\in R,\varepsilon\in R^l} \quad \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{l}\varepsilon_i$$

$$s.t. \quad y_i(\omega\cdot \mathrm{x}_i + b) \geq 1-\varepsilon_i\ , i=1,\cdots,l,$$

$$C>0,\ \varepsilon_i \geq 0\ , i=1,\cdots,l$$

Where ω is the power vector, ε_i is the slack variable, b is the deviation variable.

Kernel function K should be content with $K(\mathbf{x}_i,\mathbf{x}_j)=(\boldsymbol{\varphi}(\mathbf{x}_i)\cdot\boldsymbol{\varphi}(\mathbf{x}_j))$.

Different kernel functions have different algorithms. The main kernel functions as following[4,5].

(1) the polynomial kernel function:

$$K(x_i,x_j)=[(x_i\cdot x_j)+1]^q$$

(2) the radial basis kernel function:

$$K(x_i,x_j)=\exp\left(-\frac{\|x_i-x_j\|^2}{\sigma^2}\right)$$

(3) the S kernel function:

$$K(x_i,x_j)=\tanh(v(x_i\cdot x_j)+c)$$

(4) the Fourier kernel function:

$$K(x_i,x_j)=\sum_{k=1}^{n}\frac{1-q^2}{2(1-2q\cos(x_{ik}-x_{jk})+q^2)}$$

In order to resolve the above question, introduce the Lagrange function:

$$L(\boldsymbol{\omega},b,\boldsymbol{\alpha})=\frac{1}{2}\|\boldsymbol{\omega}\|^2+\frac{1}{2}C\sum_{i=1}^{l}\varepsilon_i$$
$$-\sum_{i=1}^{l}\alpha_i(y_i((\omega\cdot \mathrm{x}_i)+b)-1+\varepsilon_i)$$

Where $\alpha=(\alpha_1,\alpha_2,\cdots,\alpha_l)^T\in R_+^l$. According to Wolfe dual definition, calculate the minimum of L concerning $\omega,b,\varepsilon,\alpha$, that is to say, make $\frac{\partial L}{\partial\boldsymbol{\omega}}=0$, $\frac{\partial L}{\partial b}=0$, $\frac{\partial L}{\partial\varepsilon}=0$ and $\frac{\partial L}{\partial\alpha}=0$,get the result:

$$\omega=\sum_{i=1}^{l}\alpha_i y_i \mathbf{x}_i$$

$$\sum_{i=1}^{l}\alpha_i y_i=0$$

$$\alpha_i=C\varepsilon_i$$

Take the result into the Lagrange function, get the dual problem of the original problem:

$$\max_{\boldsymbol{\alpha}} \quad -\frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}y_i y_j\alpha_i\alpha_j \mathrm{K}(\mathbf{x}_i\cdot\mathbf{x}_j)-\sum_{i=1}^{l}\alpha_i,$$

$$\text{s.t.} \quad \sum_{i=1}^{l}y_i\alpha_i=0,$$

$$0\leq\alpha_i\leq C, i=1,\cdots,l.$$

Solve the above optimization problem, get the optimal solution $\boldsymbol{\alpha}^*=(\alpha_1^*,\cdots\alpha_l^*)^{\mathrm{T}}$, then get

$$\boldsymbol{\omega}^*=\sum_{i=1}^{l}\alpha_i^* y_i\mathbf{x}_i\ .$$

Consequently, construct the classification hyperplane $(\boldsymbol{\omega}^*\cdot\boldsymbol{x})+b^*=0$, and get the decision function $f(x)=\mathrm{sgn}\left(\sum_{i=1}^{l}y_i\alpha_i^*K(x,x_i)+b^*\right)$. So realize the unknown samples classification.

3 Tree Multi-class Classification Method

Multi-class classification learning is an important problem with in machine learning domain, and it is applied to realistic life widely. Next, give the description of multi-class classification problem firstly[6].

According to the given training set $\{(x_1,y_1),(x_2,y_2),\cdots,(x_l,y_l)\}\in(x\times y)^l$, where $x_i\in R^n$, $y_i\in y=\{1,2,\cdots,M\}$, $i=1,2,\cdots,l$, look for a decision function $f(x): x=R^n\to y$.

Thus solving multi-class classification problem is equal to finding a rule to divide the dots of R^n into M parts. Multi-class classification problem is a extension on two-class classification problem[7].

Currently, SVM multi-class classification methods mainly include two kinds[8,9]. One is to incorporate the problem of multi-class parameters into an optimization problem. By solving the optimization problem, we can realize multi-class classification, for example the direct constructing multi-class classification machine method of SVM which Mr. Weston and others advanced; The other is to disintegrate the problem of multi-class parameters into two-class classification problems, then adopt a certain method to realize multi-class classification by combining the outputs of two-class classification machines, which is called the method of indirect constructing multi-class classification machine.

The thinking of the method of indirectly constructing multi-class classification machine roots in the traditional pattern identification method. According to the different training samples' constitute, it can be divided into the method of one type vs. the rest types, the geminating classification method, the tree multi-class classification method, etc.

The basic thought of tree SVM is from the root node adopting some method to divide the root node's categories into two child categories, and then further dividing the two child categories, thus repeating until the child category only include one sort, therefore getting a headstand bintree[10]. Finally, train the support vector classification machine on every decision nodes of the bintree, then carry out the classification of the unknown samples.

Suppose the given training set has M kinds of data, construct a series of two-class questions appropriately. It can found a decision function for each two-class question and then get M-1 decision functions $\{f^1,\cdots,f^{M-1}\}$ in all. If the decision functions are completely correct, each of M-class classification has its corresponding sequence whose length is M-1 and elements are -1 or 1. Arrange these sequences in the order as first class, second class, and we can get a coding matrix Q with m rows and m-1 columns. To judge the adscription of a testing input x ,firstly, according to the M-1 decision functions which have been already got, get the sequence whose length is M-1, and elements are 1 or -1, and then compare the sequence with the coding matrix Q. If the choice of the two-class problems is reasonable, and the decision functions are accurate, correspondingly the coding matrix should have and only have one row equal to the sequence. The code of the row is the classification of the input x.

The main advantages of the tree multi-class classification method are the less number of the SVM needing training and their training samples. And there is no need to spread all support vector classification machines, which have faster training and classification speed. Its advantages are more obvious for multi-classification problems. The emphasis and difficulty of the method are how to define the subtasks or the design of the tree structure, and how to overcome the error accumulation of the tree structure.

4 An Application Example

There are many factors affecting equipment spare parts demands. The most important one is the reliability level of working parts. If the reliability level of working parts is low, failures easily occur to the working parts. At this time some spare parts are needed to support the equipment. So the reliability level of working parts is one of the important factors which influence spare parts allocation. The secondary one is the maintainability level of failure parts. If the maintainability level of failure parts is high, the failure parts can be repaired rapidly and continue to work or launch into working again as the following spare parts. In this situation there is no need to store a great number of spare parts. On the contrary, if the maintainability level of failure parts is very low, it is necessary to store proper number of spare parts in order not to influence the normally working of the equipment. In addition, the cost factor of purchasing spare parts also needs to be considered. According to the statistic, expensive spare parts are mostly key parts, whose quantity are little, but cost for purchasing them accounts for a great part of the spare parts' total cost. Furthermore, there are other factors, such as key level, etc.

In order to realize the following spare parts' reasonable allocation, it is necessary to adopt different allocation methods according to different categories of spare parts. The paper adopts support vector classification

Table 1 Eigenvalue and Categories of Spare Parts Samples

Character Order	MTBF/10^3h	MTTR/h	Price/Yuan	Category
1	0.04	8.22	16	1
2	O	6.84	8	1
3	0.2	7.63	15	1
4	0.07	6.36	20	1
5	0.3	8.21	50	1
6	0.05	9.3	60	1
7	0.6	12	30	1
8	0.02	8.5	40	1
9	10	2.74	160	2
10	8	1.27	40	2
11	12	3.65	120	2
12	9	2.36	80	2
13	7.6	1.56	60	2
14	11	4.15	100	2
15	7	1.58	30	2
16	11	2.15	90	2
17	0.333	1.37	800	3
18	0.125	1.25	700	3
19	0.28	2.13	500	3
20	1	0.82	400	3
21	0.54	8.5	500	3
22	0.25	3.6	450	3
23	0.63	2.36	600	3
24	0.85	1.54	300	3
25	2	1.37	80	4
26	1.6	2.74	40	4
27	1.2	1.54	30	4
28	1.1	2.71	50	4
29	0.3	3.69	50	4
30	0.4	2.15	20	4
31	0.6	1.54	60	4
32	0.8	3.15	30	4

Example 1: Aiming at the attributes of a new machine to build the spare parts multi-class classification model, and tests the model by an example.equipment's spare parts, mainly consider three influence factors: reliability, maintainability and cost, select Mean Time Between Failures (MTBF), Mean Time to Repair (MTTR) and the price of spare parts as their three characters. 32 kinds of characteristic values and categories of the equipment's spare parts samples can be seen in Table 1.

Through each sample's eigenvalue in the table, we can know that category 1 shows low reliability, time-consuming maintenance, and low price of the spare parts, it is necessary to allocate a great number of the following spare parts; category 2 shows high reliability and infrequent failure of the spare parts, so it is not necessary to allocate following spare parts basically; category 3 shows low reliability of the spare parts and it is necessary to allocate the following spare parts, but because the spare parts are expensive, considering cost problem, on the precondition of guaranteeing the equipment's normal work the following spare parts should be allocated as small as possible; the spare parts of category 4 have no obvious characters, and belong to general spare parts, whose number depends on the actual need circumstance.

The tree structure of the spare parts classification can be seen in Fig. 1. Realize the tree multi-class classification method of SVM by MATLAB. Select radial basis kernel function and define the value of parameter C by the mesh search method, construct the decision function $\{f^1, f^2, f^3\}$ and the coding matrix Q, consequently realize the classification of the spare parts which categories are unknown. Its flow can be seen in Figure. 2.

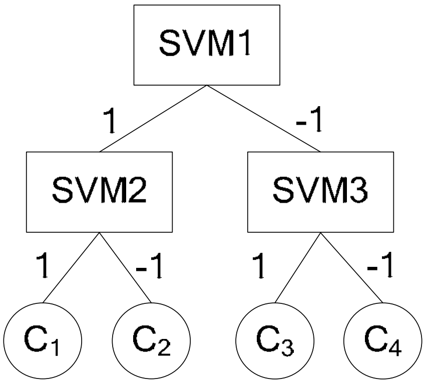

Figure. 1 the tree multi-class classification method

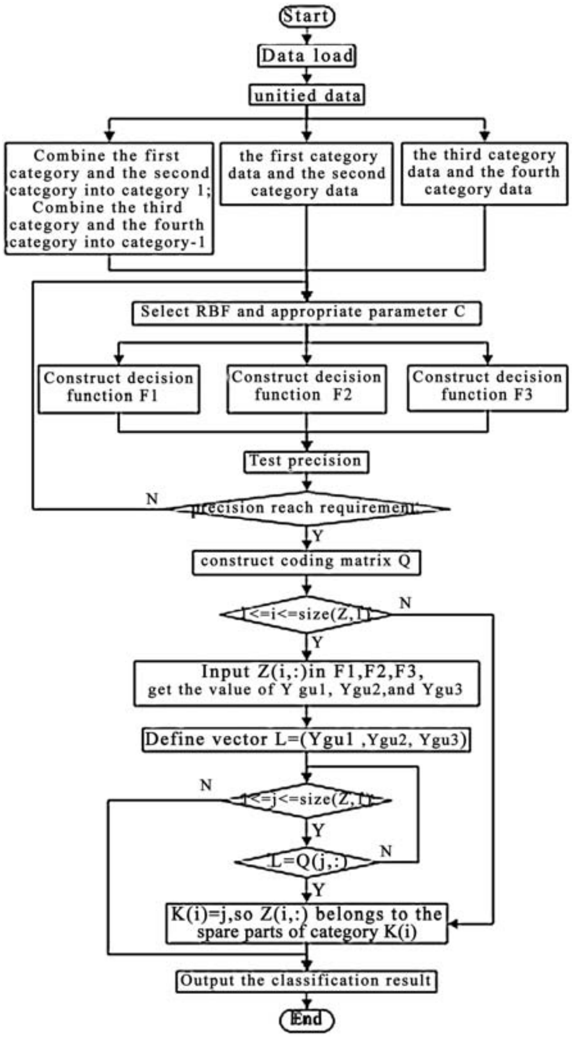

Figure 2 spare parts multi-class classification flow

Run the MATLAB program and construct the coding matrix Q on the precondition of making sure the decision function meets the precision demand.

$$Q = \begin{array}{c} \\ \\ \\ \\ \end{array}\begin{array}{cccc} f^1 & f^2 & f^3 & \\ \left[\begin{array}{c}1\\1\\-1\\-1\end{array}\right. & \begin{array}{c}1\\-1\\-1\\-1\end{array} & \left.\begin{array}{c}-1\\-1\\1\\-1\end{array}\right] & \begin{array}{c}C_1\\C_2\\C_3\\C_4\end{array}\end{array}$$

By calculating, the classification results of the following six kinds of testing spare parts samples can be seen in Table 2.

Table 2 Classification results

Character Order	MTBF/10^3h	MTTR/h	Price/Yuan	Classification result
1	0.02	10.3	70	1
2	13	4.65	150	2
3	0.74	9.5	650	3
4	0.5	3.69	45	4
5	0.18	3.11	60	4

The classification results of the program are consistent with the practical classification results, which shows that SVM has some advantage in dealing with limited samples data, at the same time proves the tree multi-class classification method of SVM can realize equipment spare parts multi-class classification effectively, which has great practical application value.

5 Conclusion

SVM has strict theories foundation, and they can well resolve such practical problems as nonlinearity, multi-dimension and local minima, etc. Aiming at the characters that the history data of equipment spare parts demand allocation is limited, the influence factors of spare parts demand allocation are numerous, and the relations between which are almost nonlinear, this paper put forward using tree multi-class classification method of SVM to realize the learning of equipment spare parts limited samples data, and gave an application example. The results show that the method can solve the problem of equipment spare parts multi-class classification effectively, which has some practical application value.

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