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IDENTIFICATION OF MECHANICAL NOISE SOURCES BASED ON SUPPORT VECTOR DATA DESCRIPTION AND SEQUENTIAL BACKWARD SELECTION

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Identification of Underwater vehicle major mechanical noise sources is a key step of the noise control in underwater vehicle. But it is usually difficult to obtain enough training samples due to complicated measure condition and the high expense of testing. So it can be regarded as a pattern recognition problem on small sample. For solving the problem, it would reduce greatly the requirement for the training samples by decreasing of selected feature dimension. But, it is difficult to obtain the fault pattern training samples in actual operation of underwater vehicle, which make the unreasonable results by the existing feature selection methods. Therefor a new feature parameter selection method, named SVDD-SBS, is put forward based on the normal training samples. At first, the unrelated features and redundancy features are eliminated by the SVDD(support vector data description) algorithm. And then, the best feature subsets are gained by SBS (sequential backward selection) method. The results of the experiment show that this feature selection method can effectively avoid the demand for the fault class training samples and obtain the best feature subsets to realize mechanical noise sources identification and classification.

Keywords: noise source identification; feature selection; support vector data description, sequential backward selection

1. Introduction

During the course of operating underwater vehicle, the status of sound stealth is dynamic. Generally believed that, the mechanical noise is the main noise source when underwater vehicle is operated at low speed [1]. Therefore, the identification and classification of the main mechanical noise is critical to control the noise of underwater vehicle and implement correctly vibration and noise reduction measures. But because the complicated internal structure and the high expense of testing in the underwater vehicle, it is usually difficult to obtain sufficient samples. So it can be regarded as a pattern recognition problem on small sample.

In the known theory [2]: for a pattern recognition problem, the number of the training samples should be 10 times bigger than the number of feature parameters if you want to obtain the better classification result. Therefore, the overfull number of the feature dimensions is an import reason to result in the small samples situation. It would greatly reduce the requirement for the training samples with the decrease of selected feature dimension. On the other hand, they are not linear relation between the number of feature numbers and the performance of the classifier [3]. The performance of the classifier possibly goes to the bad because the unrelated features and redundancy features [4]. Therefore, the feature selection method is very important [5-8]. During the identification of underwater vehicle major mechanical noise sources, the main questions of the existing feature selection methods are that it depends on the normal pattern training samples and the fault pattern training samples. But, it is difficult to obtain the fault pattern training samples in actual operation of underwater vehicle, which make the unreasonable results by the existing feature selection methods.

Therefore, a new algorithm is proposed in the paper to solve these problems, named SVDD-SBS. The results of the experiment on a cabin model show that this feature selection method can effectively avoid the demand for the fault class training samples and obtain the best feature subsets to realize mechanical noise sources identification and classification.

2. SVDD-SBS method

2.1 Support vector data description method

Support vector data description (SVDD) is a one-class classification algorithm, it was first presented by the Tax and Duin [9]. The method is inspired by the suppert vector machines by Vapnik.

Of a data set containing N data objects, $\{x_i, i=1,2,....,N\}$, a description is required. We try to find a sphere with minimum volume, containing all (or most of) the data objects. This is very sensitive to the most outlying object in the target data set. When one or a few very remote objects are in the training set, a very large sphere is obtained which will not represent the data very well. Therefore, we allow for some data points outside the sphere and introduce slack variable ξ_i. Of the sphere, described by center a and radius R, we minimize the radius

$$F(R,a,\xi_i) = R^2 + C\sum_i \xi_i \,. \tag{1}$$

Where the variable C gives the trade-off between simplicity (or volume of the sphere) and the number of errors (number of target objects rejected).

This has to be minimized under the constraints

$$(x_i - a)^T (x_i - a) \le R^2 + \xi_i \,, \forall_{i,} \xi_i \ge 0 \tag{2}$$

Incorporating these constraints in (1), we construct the Lagrangian,

$$L(R,a,\alpha_i,\xi_i) = R^2 + C\sum_i \xi_i - \sum_i \alpha_i \{R^2 + \xi_i - (x_i^2 - 2ax_i + a^2)\} - \sum_i \gamma_i \xi_i \tag{3}$$

With Lagrange multipliers $\alpha_i \ge 0$ and $\gamma_i \ge 0$. Setting the partial derivatives to 0, new constraints are obtained:

$$\sum_i \alpha_i = 1, a = \sum_i \alpha_i x_i, C - \alpha_i - \gamma_i = 0 \tag{4}$$

Since $\alpha_i \ge 0$ and $\gamma_i \ge 0$, we can remove the variables γ_i from the third equation in (4) and use the constraints $0 \le \alpha_i \le C \;\; \forall_i$.

Rewriting Eq. (3) and resubstituting Eqs. (4) give to maximize with respect to α_i

$$L = \sum_i \alpha_i (x_i \cdot x_j) - \sum_{i,j} \alpha_i \alpha_j (x_i \cdot x_j) \tag{5}$$

With constraints $0 \le \alpha_i \le C, \sum_i \alpha_i = 1$.

The second equation in (4) states that the center of the sphere is a linear combination of data objects, with weight factors α_i which are obtained by optimizing Eq. (5). Only for a small set of objects the equality in Eq. (2) is satisfied: these are the objects which are on the boundary of the sphere itself. For those objects the coefficients α_i will be non-zero and are called the support objects.

2.2 Sequential backward selection method

The sequential backward selection method (SBS) is a selective sequence from corpora to subset. Firstly, all feature parameters are optional. Then, a feature parameter, which the least contribution to the rule function, is found and deleted from the feature parameters corpora. At last, it repeats the second step and stop until the residual the numble of the feature parameters meet the requirement.

The superiority of this method is pay close attention to the statistics correlation character of the feature parameters, so under the condition of using the same rule function, its calculate performance and robustness precede the sequential forward selection method. Furthermore, the method can continuously keep watch on the loss of the information content.

2.3 SVDD-SBS method

In case of only normal pattern training samples, the number of the feature parameters is d. The feature parameters set is $Q=[x_1, x_2, \cdots, x_d]$. We hope select the optimal m feature parameters from the d feature parameters($m<d$). The detailed steps of SVDD-SBS algorithm are as follows.

Step 1, training the classifier of each feature parameter based on the SVDD algorithm;

Step 2, the other normal samples constitute the testing samples set. Using the testing samples set, the correct recognition rate P_i of each feature parameter SVDD classifier is obtained. If $P_i=0$, the feature parameter is useless feature, and delete it from the feature parameter set Q;

Step 3, the residual feature parameters comprised a new training sample $Q_1=[\chi_1, \chi_2, \cdots, \chi_{n1}]$. Base on the SVDD algorithm, the Lagrange multiplier α_i of each feature parameter is calculated, obtained the sequence $\alpha_i\ (i=1,\cdots,n)$. If $\alpha_i=0$, the feature parameter is redundant feature, and delete it from the feature parameter set Q_1;

Step 4, the residual feature parameters comprised a new training sample $Q_2=[\chi_1, \chi_2, \cdots, \chi_{n2}]$. Based on the SBS algorithm, it calculate the radius R_i and correct recognition rate P_i using the SVDD algorithm in turn. Constituting evaluation rule function:

$$J_i=\frac{1}{P_i \times \frac{1}{R_i}} \tag{6}$$

If the J_i is least, the feature parameter χ_i is deleted from the feature parameter set Q_2.

Step 5, it repeats the step 4, and stop until the residual the numble of the feature parameters meet the requirement or the performance of the residual feature parameters classifier is exceed the threshold. The residual feature parameters compose the optimal feature subset.

3. Experiment and results

For demonstrating the effectiveness of the proposed SVDD-SBS model, an experiment was carried out in the 1:1 cabin model of underwater vehicle. We disposed one exciter and one rotor vibration test-bed in the cabin, as is shown in Fig. 1 and Fig. 2.

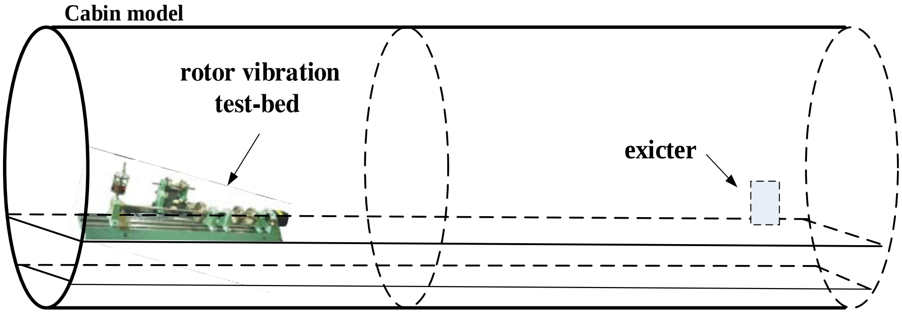

Figure 1: Sketch map of the experiment

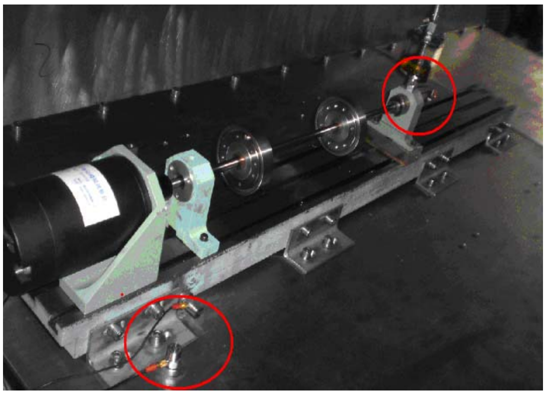

Figure **2**: The location of accelerometer on the rotor test-bed

In this experiment, we designed four kinds different work conditions. The first work condition simulated the normal condition and the other work conditions simulated fault patterns, which are illustrated in table 1.

Table 1: Work conditions of experiment

Work condition serial number	Exciter	rotor vibration test-bed	
		Work pattern	remark
1	open	normal	——
2	open	friction	Install the friction screw
3	open	imbalance	Install balance screw on the four different positions
4	open	Friction+ imbalance	Install the friction screw and four balance screws

The system sampling frequency is 4096Hz. Each group of data sampling time is 100 seconds. We select each signal consecutive 4096 sampling points from each signal as a sample data. Each group of signals take 100 samples.

Choosing ten feature parameters composed the selected feature parameter corpora that include peak value、square root of amplitude、root-mean-square value、standard deviation、mean value、kurtosis factor、skewness factor、waveform factor、impulse factor and margin factor. For convenient expression, T1~T10 are used to substitute the ten feature parameters. Using the SVDD-SBS method, the result of the feature parameter selection listed in the table 2.

Table 2: Results of feature parameter selection

Step / feature	1	2	3	4	5	6
T1	0.9	0.11	0.31	0.56	1.04	----
T2	0.52	0.11	0.31	1.13	1.10	1.04
T3	0.92	0	----	----	----	----
T4	0.58	0	----	----	----	----
T5	0.54	0	----	----	----	----
T6	0	----	----	----	----	----
T7	0	----	----	----	----	----
T8	0.96	0.16	0.28	----	----	----
T9	1	0.16	0.34	0.52	----	----
T10	1	0.16	0.36	0.58	1.13	1.1
The serial number of the delete feature	T6、T7	T3、T4、T5	T8	T9	T1	T2

For verify the performance of the SVDD-SBS, it compared with the feature parameter selection methods based on multiclass samples. By comparising these methods based on multiclass samples, the method based on distance rule function [10] is selected.

Table 3: Order of feature selection

Method / Feature order	method based on distance rule function			SVDD-SBS
	normal sample VS friction sample	normal sample VS imbalance sample	normal sample VS Fric-tion+imbalance sample	normal sample
1	T8	T8	T8	T10
2	T2	T2	T2	T2
3	T5	T10	T4	T1
4	T4	T3	T5	T9
5	T1	T4	T1	T8
6	T10	T5	T10	T5
7	T3	T1	T3	T4
8	T6	T6	T6	T3
9	T7	T9	T9	T6
10	T9	T7	T7	T7

From the table 3, we can see that the order result of feature selection method based on distance rule function is different for three fault patterns. It shows that they are correlated between the method and fault pattern for the method based on multiclass samples.

The samples of work condition 1 and work condition 4 are selected for farther analysis. The 50 samples of each work condition are selected as training set, other samples compose the testing set. Becase the LDC (Linear Discriminant Classifier) [11] has no use for setting parameters, the classifier is selected. According as the feature order of the fourth column in the table 3, the feature parameters are used step by step. The identification right rate of the classifier is obtained to the feature selection method based on multiclass samples. Then, according as the feature order of the fifth column in the table 3, the calculation is repeated. The identification right rate is obtained to the SVDD-SBS feature selection method. The calculation result for two methods are showed in the Fig. 3.

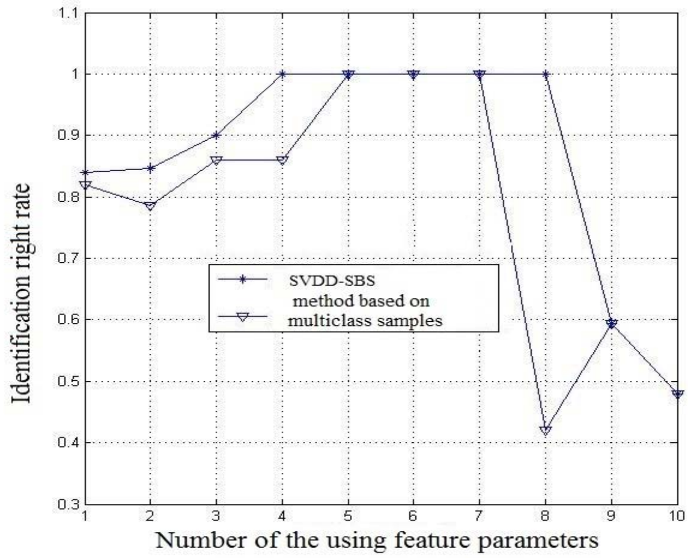

Figure 3**:** Comparison of identification right rate

From the Fig. 3, we can see that:

(1) The SVDD-SBS method avoid the demand for the fault class training samples, and its identification right rate clearly excelled the method based on multiclass samples.

(2) Because the SVDD-SBS method attention to the statistics correlation character of the different feature parameters, the identification right rate rises steadily along with the using more feature parameters. For the feature selection method based on multiclass samples, the identification right rate decrease when the second feature parameter was joined the feature set.

(3) The useless feature, which such as the features T6 and T7, resulted in a considerable reduction of identification right rate. The SVDD-SBS method delete useless feature in the first place. It availably decreased the influence to identification right rate.

(4) Because the SVDD-SBS method delete redundant feature in the first place, the identification right rate attained optimum when using three feature parameters. For the feature selection method based on multiclass samples, the identification right rate attained optimum when using four feature parameters.

4. Conclusion

A new feature parameter selection method, named SVDD-SBS, is put forward based on the normal training samples. At first, the unrelated features and redundancy features are eliminated by the support vector data description algorithm. And then, the best feature subsets are gained by sequential backward selection method. The results of the experiment show that this feature selection method can effectively avoid the demand for the fault class training samples and obtain the best feature subsets to realize mechanical noise sources identification and classification.

REFERENCES

1 Wu Guoqing. Ship radiated-noise recognition(Ⅰ) the overall framework, analysis and extraction of line-spectrum[J]. Journal of Acoustics, 1998, 23(5): 394-400.

2 Jain A K，Chandrasekaran B．Handbook of statistics [M]．North-Holland Publishing Company，1982:835-855．

3 Edward R.Dougherty ,Seungchan Kim,Yidong Chen. Coefficient of determination in nonlinear signal processing[J]. signal processing 80(2000), 2219-2235.

4 Yao Xu, Wang Xiao-dan, Zhang Yu-xi, Quan Wen．Summary of feature selection algorithms[J]．Control and Decision，2012，27(2)：161-166．

5 Dash M，Liu H．Consistency based search in feature selection[J]．Artificial Intelligence，2003，151：155-176．

6 Jain A K，Duin R P W，Mao J．Statistical pattern recognition: A review[J]．IEEE Transactions on Pattern Analysis and Machine Intelligence，2000，22(1)：4-37．

7 Guyon I，Elisseeff A．An introduction to variable and feature selection[J]．Journal of machine learing research，2003，3：1157-1182．

8 Reinhold H，Luciana V D．Feature selection for ERS-1/2 InSAR Classification: High Dimensionality Case[J]．Proc of Int'l Geoscience and Remote Sensing Symp Proceedings，1998，1605-1607．

9 D.M.J. Tax, R.P.W. Duin, Support Vector Domain Description, Pattern Recognition Letters, 1999,20(11-13):1191-1199.

10 Xiao Jian-hua．Intelligent Pattern Identification Method[M]．South China University of Technology Press，2005：1-3．

11 Friedman J H．Regularized Discriminant Analysis [J]. Journal of the American Statistical Association，1989，84(405)：165-175．