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Target Material Identification with High Pressure Water-jet Based on Wavelet Packet Decomposition and PSO-SVM

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Keywords：high pressure water-jet, material identification, wavelet packet decomposition, support vector machine, particle swarm optimization algorithm.

ABSTRACT

In order to classify the target's material by using the reflection sound signal generated while the target was impacted by the high pressure water-jet, the reflection sound signal was pre-processed and decomposed by wavelet packet in this paper, and the optimum frequency bands of the reflection sound signal was selected through comparative experiments. The relative energy distribution of the optimally selected frequency bands sound signal was calculated as the eigenvalue for the SVM classification model. The standard particle swarm optimization algorithm (PSO) was done in this paper, and the optimized PSO was used to optimize the training parameters (penalty coefficient C and kernel function parameter σ) of the built SVM classification model. As a result, the classification accuracy of the PSO-SVM classification model can be improved, and the time of parameter optimization was reduced. The experimental results show that the classification accuracy (97.78%) was reached by using PSO-SVM classification model, and the modelling time is only 0.92sec. The overall classification accuracy of PSO-SVM classification model was apparently higher than that of BPN, PNN and SVM (K-CV, LOOCV and Grid Search) classification model.

INTRODUCTION

Sound signals, which have different characteristic value, will be produced when the targets with different materials are impacted by high pressure water-jet. Therefore Yang et al (2011) proposed that the material and geometry of special target can be detected and identified by using the reflected sound signal of high pressure water-jet and the voice recognition technology. The key technology of the target's material identifying is to research an effective sound signal processing method, which can be used to extract the characteristic value of the reflected sound signal reflecting the different materials, and to build an appropriate target material identifying model to classify the target with high accuracy. The reflected sound signal of high pressure water-jet belongs to the non-stationary sound signal. Traditional signal processing methods, such as Fourier transform etc, can not be applied to non-stationary sound signal. The wavelet analysis method developed in recent twenty years is a new time-frequency analysis method, which has characteristics of multi-resolution. The time window and frequency window of the wavelet analysis can be adjusted dynamically according to the specific shape of the signal, so Jin et al (2009) used the wavelet analysis method to process non-stationary sound signal. The wavelet packet decomposition method is a more flexible signal decomposition method, which is developed on the basis of the wavelet analysis method. Li et al (2011) realized gear fault diagnosis signal processing by using wavelet packet transform. After decomposed by the wavelet packet decomposition method, each frequency band of the reflection sound signal has part of energy of the reflection sound signal, and the relative energy distribution of these frequency bands can be used as the characteristic value to identify target material.

Xu et al (2011) mentioned that the support vector machine (SVM), which is based on statistic studying theory, employs the structural risk minimization (SRM) principle to achieve the minimization of risk. The advantage of support vector machine (SVM) is that the global optimal solution

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can be acquired even the number of samples is limited. Xu Z F et al (2011) mentioned that the faults which the neural network (NN) do have, such as slow convergence speed and easy to fall into local minimum point etc, was avoided by SVM. When SVM is used to classify the target material, two parameters (penalty coefficient C and kernel function parameter σ) of SVM classification model should be carefully selected because the classification accuracy is directly affected by the two parameters. Manoj Bhasin et al (2004) mentioned there are some existing parameter optimization methods of SVM, such as the Cross-Validation method (CV) and the Grid Search method, etc. Olivier et al (2009) proposed that the Cross-Validation method (CV) can be mainly divided into K-fold CV method (K-CV) and leave-one-out CV method (LOOCV). The K-CV method is to divide the training data into K subsets, each subset is tested as test set whereas the rest subsets are as training set. The cross validation process in K-fold CV method is repeated K times and the average recognition rate of K times cross validation is used as the optimal result. The advantage of K-CV method is that all samples are used as training set or testing set. Nevertheless, the parameter optimization time of K-CV will greatly increase when large amounts of data are given. Kai-Ying et al (2011) proposed the Leave-one-out cross validation (LOOCV) method, in which each data sample is separately treated as a test set, and the rest samples are treated as training set. Although the result of LOOCV is reliable, the calculation amount of LOOCV is much larger than other methods. LOOCV can only be used when the number of samples is small. Yan et al (2011) proposed the Grid Search method ,whose results are acquired by trying all possible parameter values with cross validation and by looking for a set of parameter values which have the highest classification accuracy. The algorithm complexity of Grid Search method is higher than advanced algorithms, and the searched result is greatly related to the search interval and search range. So Grid Search method is not suitable for rapidly optimizing parameters. The particle swarm optimization (PSO), which has been rapidly developed in recent years, is a swarm intelligence optimization algorithm. The particle swarm optimization (PSO) was used in this paper to optimize parameters (penalty coefficient C and kernel function parameter σ) of SVM model. In order to improve the PSO global optimization ability, and to avoid the problem that particles always gather at the local optimal point in the optimization process, the standard PSO algorithm was improved in this paper. As a result the activities of particles were improved in the optimization process. Currently the PSO-SVM model is mainly applied to equipment faults detection, pattern recognition and face detection etc. For example, the multi-classification of rolling bearing faults was realized by Zhiwen Liu and Hongrui Cao(2013) by building the classification model with SVM, wavelet decomposition and PSO to process the acquired vibration signal and collecting. The accurate of control chart patterns was realized by Vhid Rannaee and Ata Ebrahimzaden(2010) by building the recognition model with SVM and PSO.The PSO-SVM model was also used by Jin Wei and Zhang Jinqi(2011) to realize effective face recognition. There is no published literature indicating that PSO-SVM has been used to build target material classification model of high pressure water-jet. So The PSO-SVM classification model was built to identify target material with high pressure water-jet in this paper. And the eigenvalues of target material, which were used to identify target material, were extracted through the wavelet pocket decomposition and calculating the relative energy distribution of each frequency bands. The best extraction method of target material's eigenvalues was found through contrast test, in which signal were decomposed into different layers, and the eigenvalues were extracted with different frequency bands. Fast and accurate identification of target material of high pressure water-jet was realized when these eigenvalues were sent to PSO-SVM classification model as the input. The best classification accuracy can be reached within a short time by using PSO-SVM classification model compared with BPN, PNN and SVM (K-CV, LOOCV and Grid Search) classification model.

CLASSIFICATION PRINCIPLE OF SVM

The basic classification idea by using support vector machines (SVM) is to construct a hyper-plane as classification plane which makes the margin between two kinds of data sample reaches maximum .

Given a linear separable sample set (x_i , y_i), i =1,…,n, $x_i \in R^d$, $y_i \in \{-1,+1\}$, the classification plane equation of the two sample set can be expressed as follows:

$$\boldsymbol{\omega} \cdot \boldsymbol{x} + \boldsymbol{b} = 0 \quad , \tag{1}$$

where $\boldsymbol{\omega}$ denotes a coefficient vector, and $\boldsymbol{b}$ denotes threshold value or offset.

If a condition is met by the classification surface to all the samples, the classification margin is equal to $2/\|\boldsymbol{\omega}\|$, and the maximum margin is equivalent to the minimum $\|\boldsymbol{\omega}\|^2$. The condition is expressed as follows:

$$y_i[(\boldsymbol{\omega} \cdot x_i) + \boldsymbol{b}] - 1 \geq 0,\ i = 1,...,n\ . \tag{2}$$

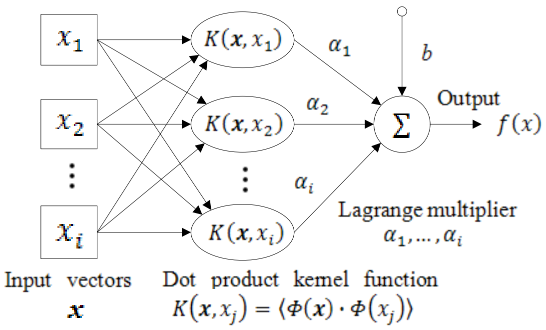
The classification surface, which meets equation (2) and makes $\|\boldsymbol{\omega}\|^2/2$ be the minimum value, is the optimal classification surface H. When the minimum value of the function $\phi(\omega)=\|\boldsymbol{\omega}\|^2/2$ is obtained under the constraint of equation (2), the optimal classification surface function can be acquired and is expressed as follows:

$$f(x)=\operatorname{sgn}\{(\boldsymbol{\omega}\cdot\boldsymbol{x})+\boldsymbol{b}\}. \tag{3}$$

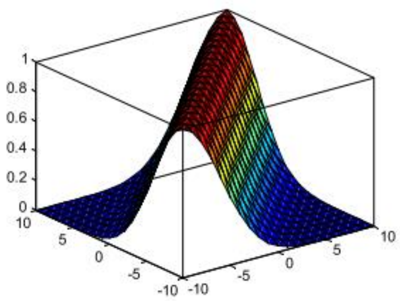
For non-linear classification question, the satisfied classification effect often cannot be acquired from the optimal classification surface in the original space. The optimal classification surface having satisfied classification effect can be acquired by complicated non-linear transformation. To realize the complicated non-linear transformation, the dot product kernel function $K(x_i,y_j)=\langle\phi(x_i)\cdot\phi(x_j)\rangle$ is employed, which makes the non-linear classification problem in original space be transformed to linear classification problem in high dimension space. The classification function then is changed as follows:

$$f(x)=\operatorname{sgn}(\sum_{i=0}^{n}\alpha_i y_i K(x_i,\boldsymbol{x})+\boldsymbol{b}), \tag{4}$$

where α_i denotes the corresponding Lagrange multiplier.



(a) Structure of SVM



(b) RBF kernel function

Fig.1.Structure of SVM and RBF kernel function

The common kernel functions include the polynomial kernel function, the radial basis kernel function and S shape function. The radial basis kernel function was selected as kernel function of target's material classification model due to the results of optimization experiments. Structures of SVM and the RBF kernel function are shown in Figure 1.

TARGET MATERIAL CLASSIFICATION MODELING PRINCIPLE BASE ON POS-SVM

Eigenvalue extraction principle based on wavelet packet decomposition

The reflected sound signal which was acquired when high pressure water-jet impacted target can be decomposed to many signal components of different frequency bands by wavelet packet decomposition. Each frequency band signal component contains part of energy of the original reflected sound signal, which can be expressed as follows:

$$E_k=\int_{-\infty}^{+\infty} f_k(t)^2\,dt\,, \tag{5}$$

where $f_k(t)$ is a frequency layer, k is the serial number of frequency layer.

The energy relationship among each decomposed frequency layer and the reflected sound signal is expressed as follows:

$$E_f=\sum_{k=1}^{n}E_k,\quad k=1,\ldots,n\ , \tag{6}$$

where n is the number of decomposed frequency layer.1

Because the relative energy distributions of signal components reflecting different target materials are different, the relative energy distribution can be used as the eigenvalue to identify target's material.

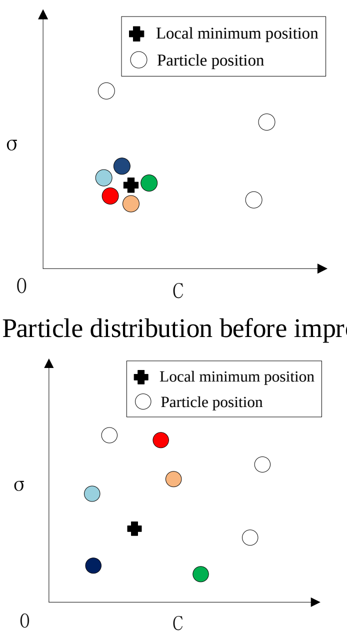
Basic Algorithm for SVM Classification Model Parameter Optimization Based on Improved PSO

The particle swarm optimization (PSO) is a swarm intelligence optimization algorithm. When the particle swarm optimization (PSO) algorithm is used to optimize the parameters of target's material classification model, the optimal parameters can be acquired through random initialization of parameters and iterative search. The standard particle swarm optimization (PSO) algorithm can be expressed as follows:

$$\begin{aligned}v_{ij}(t+1)=wv_{ij}(t)+c_1r_{1j}(t)[p_{ij}(t)-x_{ij}(t)]\\+c_2r_{2j}(t)[p_{gj}(t)-x_{ij}(t)]\end{aligned}\ ,(7)$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \quad , \qquad (8)$$

where w is the inertia weight, c_1, c_2 are accelerating factors, r_{1j}, r_{2j} are random numbers in the range of [0,1], $x_{jj}(t)$ is the current position of individual i in the j dimension space, $v_{ij}(t)$ is the current velocity of individual i in the j dimension space, $p_{ij}(t)$ is the individual's i best position found so far, $p_{gj}(t)$ is the global best position found so far.



（a）Particle distribution before improved

（b）Particle distribution after improved

Fig.2 the PSO particle distribution

When the standard PSO algorithm was used to optimize parameters, it cannot ensure that the resulting parameters are global optimal solution [11]. So the standard PSO algorithm was improved by increasing the activity of particles to ensure that the obtained parameters after PSO optimal processing were global optimal solutions. When particles gathered around the local minimum point in the process of iteration, the velocity of these particles will be very small and the activities of these particles also are lower than other particles. While the velocity of a particle is less than a certain small value in the process of iteration, the particle's position (value of model parameters) will be randomly re-set to the improve activity of particles. So the PSO ability of obtaining the global optimal solution is also improved. The schematic diagram of the PSO particle distribution before improved and after improved is shown in Figure 2.

Target Material Classification Model Based on PSO-SVM

If the SVM method and the acquired relative energy distributions of signal components with different frequency range are used to classify the target's material, the penalty coefficient C and kernel function parameter σ, which are the important parameters of SVM classification model, need to be optimized to reach the optimal classification effect.When the improved PSO algorithm was used to optimize parameters of SVM classification model, each particle's velocity and position need to be adjusted by using equation (7), (8) and the current best position $p_{ij}(t)$, the best position of the swarm $p_{gj}(t)$. The best position of individuals and the swarm ($p_{ij}(t)$ and $p_{gj}(t)$) are determined by the fitness of the objective function, and the classification accuracy of SVM target material classification model is used as fitness in this paper. The iterative process of the improved PSO algorithm is ended when the preset iteration number is reached or the preset minimum end condition is met, and then the optimal parameters (C and σ)are acquired. The optimized parameters then are used to build PSO-SVM target material classification model, and the corresponding mathematical description is as follows.

From equation (2), a Lagrange function can be defined as follows:

$$L(\omega,b,\alpha) = \frac{1}{2}\|\omega\|^2 - \sum_{i=1}^{n}\alpha_i[y_i(\omega\cdot x_i+b)-1] \quad ,(9)$$

where $\alpha_i \geq 0$ denotes Lagrange multiplier.

To get the minimal value of equation (9), the partial differential equations for ω, b, α_i were done and the partial results are set equal to zero respectively, which can be expressed as follows:

$$\begin{cases} \frac{\partial L}{\partial \omega} = 0 \Rightarrow \omega = \sum_{i=1}^{n}\alpha_i y_i x_i \\ \frac{\partial L}{\partial b} = 0 \Rightarrow \sum_{i=1}^{n}\alpha_i y_i = 0 \\ \frac{\partial L}{\partial \alpha_i} = 0 \Rightarrow y_i(\omega\cdot x_i+b)-1=0 \end{cases} . \qquad (10)$$

According to the constraint conditions of equation (2) and (10), and when the RBF function was selected, the objective function of SVM was changed as follows:

$$\begin{cases} \min \dfrac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} y_i y_j \alpha_i \alpha_j \exp\left(-\dfrac{|x-x_i|^2}{\sigma(t)^2}\right) \\ -\sum_{j=1}^{l}\alpha_j \\ s.t. \sum_{i=1}^{l} y_i \alpha_i = 0 \\ 0 \le \alpha_i \le C(t) i = 1,\dots,l \end{cases} \quad .(11)$$

A set of Lagrange multiplier factor solution $\boldsymbol{\alpha}^* = (\alpha_1^*, \dots \alpha_l^*)^T$ is obtained from solving the equation (11). A positive component $0 \le \alpha_j^* \le C$ is selected from $\boldsymbol{\alpha}^*$, and the threshold value b^* is calculated as follows:

$$b^* = y_i - \sum_{i=1}^{l} y_i \alpha_i^* \exp\left\{-\frac{|x-x_i|^2}{\sigma(t)^2}\right\}. \quad (12)$$

So the classification function (4)can be changed as follows:

$$b^* = y_i - \sum_{i=1}^{l} y_i \alpha_i^* \exp\left\{-\frac{|x-x_i|^2}{\sigma(t)^2}\right\} . \quad (13)$$

In the PSO algorithm, the fitness values need to be calculated as the movement basis of particles. When the results of equation (13) are calculated, the classification accuracy of SVM model is also calculated as fitness for PSO. The calculation formula is shown as follows:

$$g[\gamma(t)] = \left(\frac{M_{error}}{M_{total}}\right) \times 100 \quad , \quad (14)$$

where $\gamma(t) = \{\sigma(t), C(t)\}$ denotes the particle's position, and also the parameter value of SVM classification model, M_{error} denotes classification error number, M_{total} denotes total number of test set.

The best position of particles is determined by equation as follows:

$$p_{gj}(t+1) \begin{cases} p_{gj}(t) & g[\gamma(t+1)] \ge g[p_{gj}(t)] \\ \gamma(t+1) & g[\gamma(t+1)] < g[p_{gj}(t)] \end{cases}, \quad (15)$$

where $p_{gj}(t+1)$ is used in equation (7), (8) to influence the movement of particles.

When the parameters of SVM classification model, such as C and σ, are optimized by using the improved PSO, PSO-SVM target material classification model is built by using these optimized parameters.The basic steps of building PSO-SVM target material classification model are described as follows:

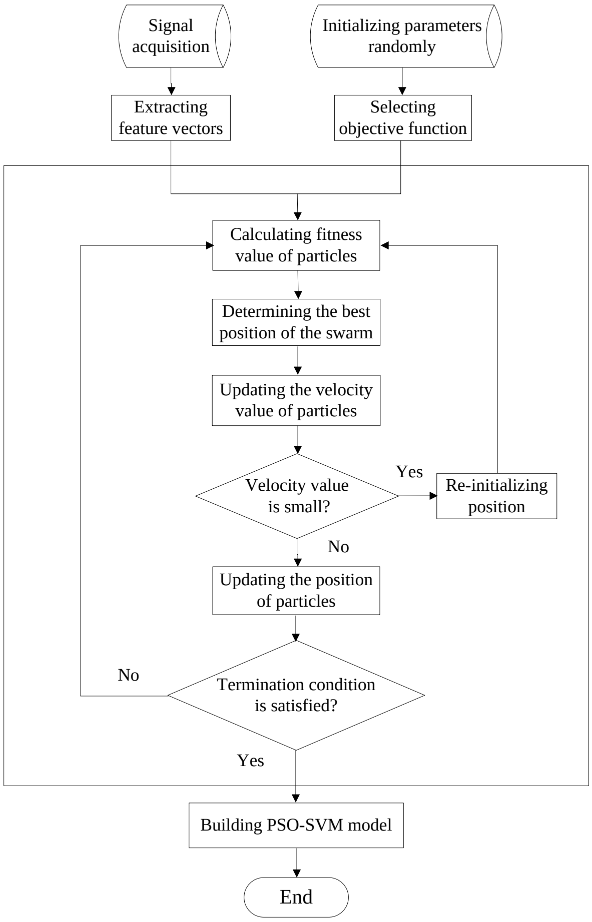


Fig.3 Flow chart of PSO-SVM classification model

Step 1: Collecting the target reflection sound signal of high pressure water-jet, decomposing these sound signals with wavelet pocket decomposition and extracting the eigenvalues of target material.

Step 2: Selecting the objective function, initializing the position, velocity and other parameters of particles and calculating the fitness value of particles.

Step 3: Determining the optimal position of individual particles p_{ij} by calculating and comparing the fitness value of particles according to equation (14), (15).

Step 4: Calculating the fitness value of the best position of individuals p_{ij} and the swarm p_{gj} according to equation (12), and updating the best position of the swarm p_{gj} according to equation (15).

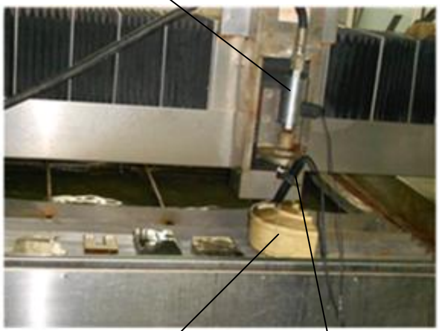
Step 5: Updating the velocity value of particles according to equation (7). If the absolute value of a particle's velocity is less than a small value, the particle's position will be reset randomly.

Step 6: Updating the position value of particles according to equation (8).

Step 7: Checking whether the termination conditions are reached. If one of termination conditions is met, the iteration cycle of PSO will be ended. Otherwise, return to step 2.

Table 1 The value of experimental settings

Jet nozzle diameter	0.8mm
Jet nozzle type	Long cylindrical nozzle
Water pressure	10Mpa
Impacting distance	100mm
Spray angle	90°
Data sampling rate	20KHz
Moving speed	120mm/minute



(a)

(b)

Fig.4 Experimental device and targets

Step 8: Building PSO-SVM target material classification model by using optimized parameters (penalty coefficient C and kernel function parameter σ). The flow chart of building the PSO-SVM classification model is shown as Figure 3.

Design of experimental device and experimental scheme

The former mixed abrasive jet equipment was used as detection equipment, and the experimental settings were selected according to the former optimal experiment results, the value of these selected experimental settings are shown in Table 1.

The ZL-301 high precision sound micro phone and the matching signal conditioning box were used to build the acquisition unit of reflected sound. The reflected sound signal data were sent to computer by using NI USB-6229 data acquisition device, and were analyzed and processed through MATLAB software. The plastic mine, stone and brick were selected as the detected target. The experimental device and targets are shown in Figure 4.

The basic experimental procedure is described as follows:

Step 1: Three targets that with different materials (plastic mine, stone and brick) were laid in order on the high pressure water-jet experimental bench.

Step 2: Turning on the water-jet device, setting experimental settings and impacting targets with high pressure water-jet in turn.

Step 3: Acquiring target's reflection sound signal by using data acquisition device, and the acquired reflection sound signal is shown in Figure 5.

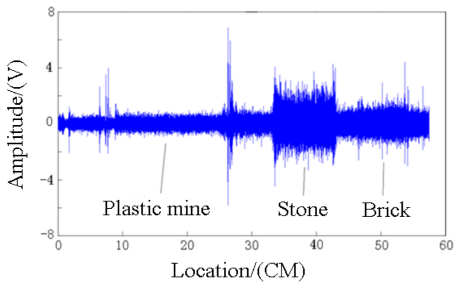


Fig.5 Signal waveform of target's reflection sound

RESULT ANALYSIS OF TAGET MATERIAL RECOGNITION

Eigenvalues extraction

The boundary positions of targets were found in the acquired reflection sound signal by using the modules maxima algorithm. 150 signal samples, which are corresponding to three target materials, were cut out from the acquired reflection sound signal according to the target boundary positions. Each signal sample has 4096 signal points, and 60 samples were used as training samples and 90 samples as test samples.

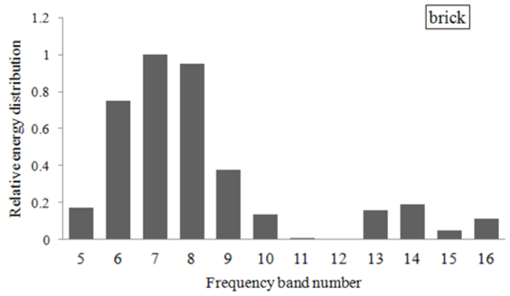
Table 2. Classification accuracy of different eigenvalues

Decomposing layers	Used frequency bands	Classification accuracy(%)
3	4	89
	6	91.67
	8	40.3
4	10	94.33
	12	97.78
	14	95.33
	16	35.67
5	18	97.33
	20	96
	22	65
	24	71

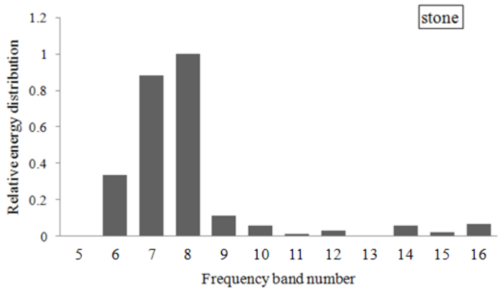
Table 3. Feature vectors of 90 test samples

NO.	1	2	3	4	5	6
1	0.11	0.39	1	0.57	0.18	0.11
2	0.06	0.20	1	0.49	0.22	0.11
3	0.08	0.30	1	0.49	0.18	0.11
:	:	:	:	:	:	:
:	:	:	:	:	:	:
31	0.01	0.176	1	0.47	0.16	0.09
32	0.02	0.220	1	0.52	0.205	0.10
33	0.01	0.337	1	0.79	0.270	0.14
:	:	:	:	:	:	:
:	:	:	:	:	:	:
88	0.19	0.628	1	0.86	0.229	0.12
89	0.25	0.869	0.97	1	0.267	0.05
90	0.16	0.805	1	0.93	0.400	0.16
NO.	**7**	**8**	**9**	**10**	**11**	**12**
1	0	0.02	0.05	0.04	0.01	0.03
2	0	0.01	0.06	0.02	0.005	0.025
3	0	0.015	0.058	0.036	0.02	0.038
:	:	:	:	:	:	:
:	:	:	:	:	:	:
31	0.02	0.021	0	0.008	0.030	0.048
32	0.01	0.025	0	0.005	0.033	0.067
33	0.01	0.018	0	0.016	0.023	0.074
:	:	:	:	:	:	:
:	:	:	:	:	:	:
88	0.01	0	0.119	0.137	0.030	0.093
89	0.02	0	0.148	0.161	0.013	0.108
90	0.02	0	0.206	0.246	0.055	0.146

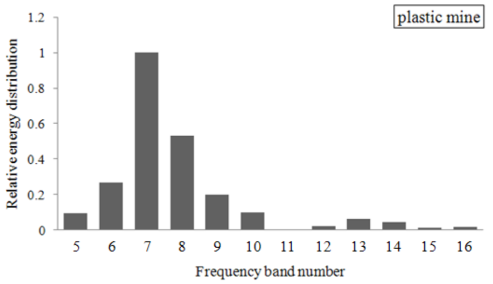
In order to find the satisfied eigenvalues extraction method, which can reach the highest classification accuracy, the signal samples were decomposed into 3, 4 and 5 layers by using wavelet packet decomposition. So the original reflected sound signal was divided into 8, 16, 32 signal components from low frequency to high frequency. And different eigenvalues constructed with different frequency bands of signal samples, which was selected from high frequency band to low frequency band, were acquired. The classification accuracy of each eigenvalue was calculated by using PSO-SVM classification model. The classification accuracies of different eigenvalues are shown in Table 2.



(a) brick



(b) stone



(c) plastic mine

Fig.6 Cylindrical distribution diagram of three target materials' eigenvalues

Since the used frequency bands (26-32) of 5 decomposing layers correspond to the low classification accuracy (less than 50%), it is not summarized in Table 2 for simplicity. It can be seen from Table 2 that the highest classification accuracy was acquired by the eigenvalue constructed with 12 high frequency bands (from 5^{th} to 16^{th}frequency bands) of signal samples which was decomposed into 4 layers. By the comparison result, the method that decomposing sound signal into 4 layers and constructing with 12 high frequency bands of sound signal components was selected as construction method of target material's eigenvalues. The 1^{st} frequency band of signal samples is 0~625Hz and the 16^{th} frequency band of signal sample is 9375~10000Hz.Eigenvalues of 90 test samples, which was constructed with 4 layers wavelet pocket decomposition and high 12 frequency bands, are shown in Table 3.

Cylindrical distribution figures of three target materials' eigenvalues were also built to show the difference of eigenvalues of three target materials, which are shown in Figure 6. It can be seen from Fig.6 that the difference among three target materials' eigenvalues is obvious. So the eigenvalues constructed by the method mentioned above can be used as the basis of target material recognition of high pressure water jet.

Target material classification and comparative experiments results analysis

By using the improved PSO algorithm, the optimal value of model parameters (C=9917.5 and σ=3.27) of PSO-SVM target material classification were acquired. In the improved PSO algorithm the particle number *n* was set to 20, and the inertia weight factor w was linearly reduced from 0.9 to 0.4. In order to compare the actual classification effect, BPN, PNN, SVM (K-CV, LOOCV and Grid Search) classification models were also built, the value of these classification models' parameters are shown in Table 4.

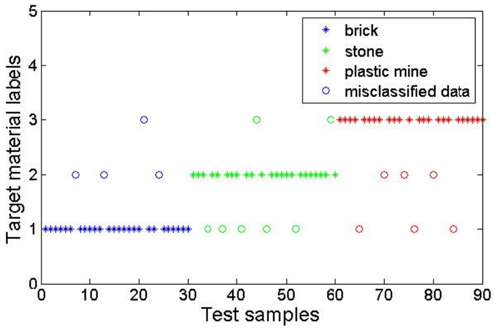
Three layers network structure was adopted by BPN classification model. Tansig and logsig were selected as transfer function of hidden layer and output layer and parameter, trainlm was selected as training function. The training step was set to 1000 steps.

Table 4parameter values of different target material classification model

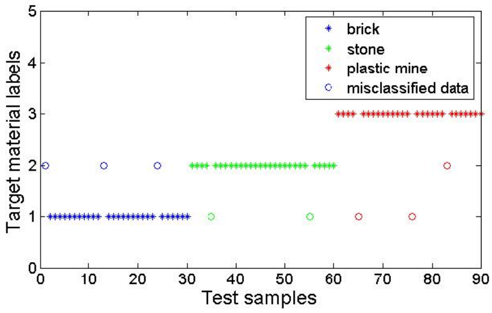
models	Para.1	Para.2	Para.3	Para.4	**Para.5**
BPN	Step=1000	Layer=3	-	-	-
PNN	-	-	-	-	-
Grid Search	-	C_{min}=1	C_{max}=16384	σ_{min}=0.0625	σ_{max}=64
K-CV	K=3	C_{min}=1	C_{max}=16384	σ_{min}=0.0625	σ_{max}=64
LOOCV	N=90	C_{min}=1	C_{max}=16384	σ_{min}=0.0625	σ_{max}=64
PSO-SVM	*n*=20	C_{min}=0	C_{max}=20000	σ_{min}=0	σ_{max}=20

Probabilistic neural network (PNN) is a kind of network structure classifier which based on Bayesian optimization rules, and belongs to a kind of self-organization neural network. When the PNN was used to build classification model, the value of training parameters weren't needed to set. The classification model could be built automatically according to the characteristics of the data itself by PNN.

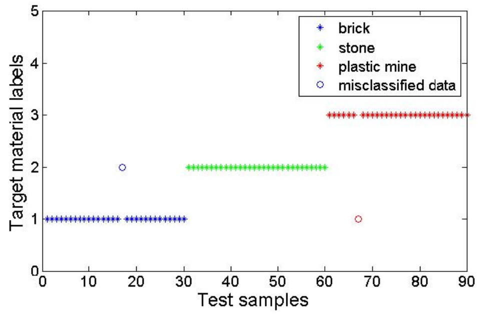
When the method of Grid Search was used to optimize parameters of SVM classification model, the parameter optimization range were set as follows: penalty coefficient C (1-16384) and kernel function parameter σ (0.0625-64).The 3 fold cross validation was adopted when the SVM (K-CV) target material



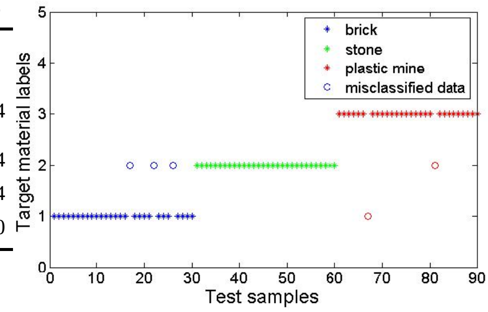
(a) BP



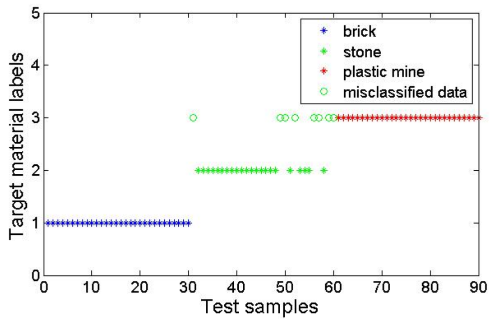
(b)PNN



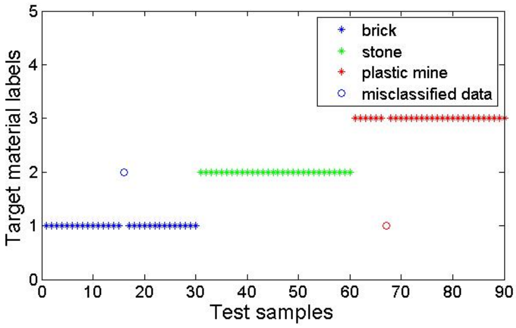
(c) Grid Search



(d)K-fold CV



(e)LOOCV



（f）PSO-SVM

Fig.7 Classification results of classification models (test samples)

Table 5Classification accuracy and modelling time of classification models

models	C	σ	Classification accuracy/%	Modelling time/sec
BPN	-	-	81.1	2.54
PNN	-	-	91.11	0.45
SVM(Grid)	32	2	97.78	3.5
SVM(K-CV)	512	1	93.33	0.74
SVM(LOOCV)	16	4	91.11	5.3
PSO-SVM	9917.5	3.27	97.78	0.92

classification model was built, and the optimization range was equal to the Grid Search method. The optimization range of LOOCV optimization method was also equal to the Grid Search method.

The eigenvalues constructed from training samples were used as the input of PSO-SVM target material classification model and other classification models built above to train the models. These models' classification results of test samples are shown in Figure 7. It can be seen from Fig.7 that the highest classification accuracy (97.78%) was acquired when PSO-SVM and SVM (Grid Search) classification model were used to classify target materials.

CONCLUSIONS

a. The construction method of target materials' eigenvalues, which was based on wavelet packet decomposition, was proposed in this paper. And the optimal frequency bands of the reflection sound signal, which used to construct eigenvalues, were found through multiple sets of decomposition experiments.

b. In order to improve the classification accuracy of target material, the standard PSO algorithm was improved through increasing the activity of particles. By combining the improved PSO with SVM classification model, the ability of obtaining the global optimal parameter values and the classification accuracy of PSO-SVM target material classification model were also improved.

c. Three kind of target materials (brick, stone and plastic mine) and BPN, PNN, SVM(K-CV, LOOCV and Grid Search) classification model were used in the experiments to comparing the classification accuracy of PSO-SVM classification model. It was shown from the experimental results that the highest classification accuracy is reached by using PSO-SVM classification model to classify the three target materials within a short time, and the model can be effectively used to identify the target materials with high pressure water-jet.

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基於小波包分解和 PSO-SVM 的高壓水射流靶物材質識別

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摘 要

為了利用高壓水射流衝擊反射聲信號進行靶物材質識別，本文對採集的反射聲信號進行預處理和小波包分解，提取各頻率段的相對能量分佈作為特徵向量值輸入支援向量機（SVM）分類模型。為了提高模型識別準確率和減少參數優化時間，本文利用改進的粒子群優化演算法(PSO)來優化 SVM 分類模型的訓練參數 C 和σ。詳細介紹了 PSO-SVM 和短時能量法基本原理和演算法，設計了相關試驗裝置。選擇塑膠地雷、石塊、磚塊作為試驗物件進行試驗，利用上述方法對試驗結果進行處理和驗證。試驗結果證明，以小波包分解後的高 12 層信號能量分佈作為特徵值能夠得到較好的靶物材質識別效果。應用 PSO-SVM 靶物分類模型識別靶物材質，正確率可以達到 97.78%，而且演算法執行時間僅為 0.92 sec，總體識別效果明顯高於 BPN、PNN、SVM(K-CV,LOOCV and grid search) 分類效果，完全可以用於高壓水射流靶物材質識別。