A Combined SOM/SVM Learning Algorithm for Vibration Recognition in Nanometer Imaging Systems

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Abstract **— In order to quickly and accurately determine the causes of nanometer imaging deviation, we propose a nanometer imaging system vibration recognition model combining SOM (System Object Model) and SVM (Support Vehicle Machine). This will extract corresponding imaging deviation signal features of different vibration sources. The model first conducts an adaptive adjustment of all training samples from SOM to eliminate disturbing samples. Based on the remaining efficient samples, the SVM already built up is trained. Finally, simulation test is conducted on practical samples, and our algorithm is compared with other recognition algorithms. Results suggests that our nanometer imaging system's vibration recognition model can increase the recognition accuracy rate by more than 10%, compared with the Logistics model, the BP neural network and the SVM model. Thus it can more efficiently determine the factors influencing image deviation. Under these conditions, if nanometer imaging shows deviation, the corresponding solutions can be quickly adopted.**

Keywords - nanometer imaging; imaging deviation; signal feature; SOM and SVM diagnosis simulation

I. INTRODUCTION

Molecular imaging is a technique using the imaging probe or signals to quantitatively test internal physiological changes of biology. The technique has been successfully applied to the medical and health care field, having become an important tool of the medical imaging technical development [1-2]. Thanks to applications of the nanometer technique, the molecular imaging technique has achieved rapid development. Currently, diversified nanometer structures, such as nanoparticles, nanotubes, nanometer fluorescence, nanospheres, dendrimers and other new polymer structures, have been applied to early stage medical diagnosis and treatment [3-4].

The swift progress of the nanometer technique and the nanometer imaging technique has led to a huge improvement of the imaging methods and the molecule level to be labeled and also driven the medical molecular imaging techniques to make major breakthroughs. It can play an important role in the field of medical entity imaging. More importantly, it can test and label new-born biological cells in an extremely complex environment [5-6]. Since analysis objects of the technique have reached the molecular level, the whole imaging process suffers subtle influence of the surrounding environment. In particular, vibration of lab tables, microscopes and floors will exert a huge influence on imaging. Besides, when nanometer imaging is deviated, artificial detection cannot quickly judge causes of deviation.

Therefore, in order to seek causes of deviation of the nanometer imaging system, this paper focuses on analyzing deviation of nanometer imaging caused by different types of vibration sources. The deviation signals are used for feature extraction. Through screening and optimization of sample data, a model recognition system to recognize different vibration sources and nanometer imaging deviation is built up to quickly analyze direct causes of deviation. Based on the system, when nanometer imaging is deviated, corresponding countermeasures can be immediately adopted.

II. INTEGRATION OF THE SOM AND SVM LEARNING ALGORITHMS

A. *SOM neural network model algorithm*

The competitive-type neural network is also called the SOM neural network [7-8]. It is a kind of self-organizing competitive-type network. The network not only has the clustering ability typical to all recognition models, but also can distinguish other new sample types through the existing data sample system. The network is made up of the input layer and the output layer. The network structure is shown in Fig. 1. Assuming that the input layer has N neural cells; the competitive-type layer has M nerve cells; the network connection weight is w_{ij}, where $(i=1,2,\cdots,N;\ j=1,2,\cdots,M)$ and meets the condition of $\sum_{i=1}^{N} w_{ij} = 1$.

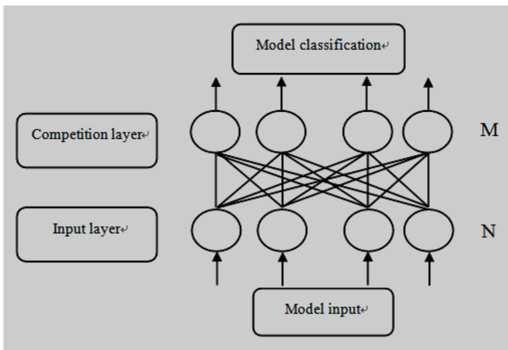


Fig. 1 SOM neural network model structure

In the competition layer, neural cells compete with each other. At last, only one or several neural cells win. In other words, the winning neural cells stand for the type model of the current input sample. The competitive neural network model algorithm flow steps are shown below:

Step 1: Choose a random value for with the section of [0 ， 1];

Step 2: Choose a random model, X, from T learning models, for the network's output layer, and work out the input value, , of various neural cells in the competition layer according to Eq.1 below:

$$S_j = \sum_{i=1}^{N} w_{ij} X_i \qquad (1)$$

Where, $i = 1, 2, \cdots, N$; Xi stands for the i element among the sample vectors;

Step 3: Adopt the corresponding neural cell of the maximum value among S_j ($j = 1, 2, \cdots, M$), and set the output status to be "1" and the output status of all the other neural cells to be "0;" (In other words, according to the competition mechanism, the neural network, k, with the maximum weighting value in the competition layer wins. The output ak is shown in Eq. 2:

$$a_k = \begin{cases} 1, & s_k > s_j, \forall j, k \neq j \\ 0, & \text{Other} \end{cases} \qquad (2)$$

Step 4: Modify the connection value connected with the winning neural cell according to the following equation, and remain the weight value connected with the other neural cells the same. The weight value is shown in Eq. 3:

$$w_{ij} = w_{ij} + a\left(\frac{X_i}{m} - w_{ij}\right) \qquad (3)$$

Where, $i = 1, 2, \cdots, N$; a is the learning parameter (0<a<1), which is mainly within the range of 0.01~0.03; m stands for the number of neural cells with the output value of "1" in the output layer.

Step 5: Choose another learning model, return to the third step until there are T learning models provided for the network, and return to the second step until the adjustment amount of the connecting weight is extremely small.

B. SVM model algorithm

The Support Vector Machine (SVM) model [9-10] is built on the Vapnik-Chervonenkis (VC) Dimension Theory and the Structure Risk Minimization (SRM) principle. According to the limited sample information, the optimal compromise is seeking between the learning capacity and the model complexity so as to achieve the optimal generalization ability. The basic idea is explained through the optimal classification plane shown in Fig. 2. In Fig. 2, the solid and empty points stand for different data samples, respectively; H stands for the optimal classification hyper-plane, $\omega^T x + b = 0$; H1 and H2 stands for data sample lines parallel to classification lines and closest to classification lines; the distance between H1 and H2 is called the classification interval.

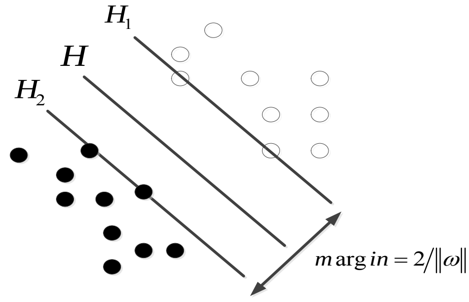


Fig. 2 Optimal classification plane schematic diagram

The above optimal classification hyperplane, H, can maximize the classification interval under the condition that two types of data samples are correctly divided. Therefore, Eq. 4 shown below can be obtained:

$$\begin{cases} \omega^T x_i + b \geq 1, & y_i = +1 \\ \omega^T x_i + b \leq -1, & y_i = -1 \end{cases} \qquad (4)$$

Namely:

$$y_i(\omega^T x_i + b) \geq 1, i = 1, 2, ..., N \qquad (5)$$

The corresponding classification decision-making function is shown in Fig. 6 below:

$$f(x) = sign[\omega^T x + b] \qquad (6)$$

It can be easily proved that the optimal classification plane is actually the minimized hyper-plane meeting the conditions of Eq. 7 below:

$$\Phi(\omega) = \|\omega\|^2 \qquad (7)$$

When data are linearly inseparable, the least wrongly classified samples and the maximum classification interval can be compromised. Therefore, ξ is introduced. The model is converted into a quadratic programming problem with constraint conditions. (See Eq. 8 below)

$$\min \Phi(\omega, \xi) = \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{N} \xi_i$$
$$st. \begin{cases} y_i(\omega^T x_i + b) \geq 1 - \xi_i \\ \xi_i \geq 0, i = 1, 2..., N \end{cases} \qquad (8)$$

Where, ξ_i stands for the slack variable which can, to some extent, control the wrong classification rate; C is the model's punitive factor, which can control the punishment degree of the wrongly classified samples.

C. The principle of the model combining the SOM and SVM models

Based on the structure of the above SOM network and its model algorithm principle, it can be seen that the model can conduct self-adaptive classification and adjustment of input data. In other words, according to specific analysis requirements, disturbing data remaining in data samples can be eliminated, while valid data in samples can remain. In this way, data validity can be enhanced. Without disturbing data, the SVM model can obtain the locally optimal solution during the training process. Below are steps to build the nanometer imaging system's vibration recognition model based on the SOM and SVM models:

Step 1: Extract corresponding imaging displacement deviation data under different vibration sources;

Step 2: Extract features of signal data collected to obtain the imaging displacement deviation feature value of all data samples;

Step 3: Put all samples extracted from Step 2 as the input information of the SOM network. According to the practical number of recognition types, the corresponding judgment types are set so as to eliminate the disturbing data from the training samples and obtain optimal samples.

Step 4: Adopt optimal samples obtained through Step 3 as training samples of the SOM network, based on which a complete nanometer imaging system's vibration recognition model is built.

III. NANOMETER IMAGING SYSTEM'S VIBRATION RECOGNITION BASED ON THE SOM AND SVM MODELS

A. Feature extraction of nanometer imaging system's vibration signals

During the operation process of the nanometer imaging system, vibration will result in certain deviation of imaging. Different types of vibration sources have different influence. The displacement deviation data corresponding to different types of vibration disturbance can be collected. Through feature extraction, signal feature vectors of different vibration types can be finally obtained. At last, they are adopted as input information of the recognition system. This paper summarizes three vibration types, including the lab table vibration, the microscope vibration and the ground vibration. The wavelet feature entropy extraction algorithm is employed to conduct feature extraction of their displacement dviation vibration signals. Below are specific steps:

Step 1: Conduct standardization of the displacement deviation vibration signals and control their signal value within [0, 1];

Step 2: Adopt the wavelet threshold function shown in Eq. 9 to filter standardized signals obtained in Step 1, and preserve feature information of various details.

$$\hat{x} = T(x,t) = \begin{cases} \operatorname{sgn}(x)\cdot\dfrac{tmp1+|tmp1|}{2} & |x| \ge t \\ \operatorname{sgn}(x)\cdot\dfrac{(t-at)(tmp+|tmp|)}{2(t-t_0)} & |x|<t\ \&\ |x|>t_0 \end{cases} \tag{9}$$

Where, $tmp = |x| - t_0$ and $tmp1 = |x| - at$, where a is the control coefficient and $0 < a < 1$.

Step 3: Use the wavelet, 'wname', to conduct N-layer wavelet packet decomposition of signals obtained through Step 2 to obtain the detail coefficient of various layers. The coefficient of various layers undergoes reconstruction. During the reconstruction process, the coefficient of the i node in the m layer is adopted to extract its reconstruction signal, S_{mi}. The energy, $E_{mi} = \sum_{i=1}^{k} |S_{mi}|^2$, of the reconstruction feature signal, S_{mi}, can be worked out. Besides, the energy information obtained by various nodes is normalized and the feature value vector of vibration signals can be obtained. The energy information normalization is based on Eq. 10 below:

$$\vec{E} = \frac{E_{mi}}{\sqrt{\sum_{i=1}^{k} E_{mi}}} \tag{10}$$

Where, k stands for the number of nodes decomposed by the m layer wavelet packet decomposition; E_{mi} stands for the energy of the i node of the m layer; $\vec{E}$ stands for the feature value vector of vibration signals;

According to the above feature extraction steps, the imaging displacement deviation information caused by the lab table vibration is adopted as a case for feature extraction analysis. The displacement deviation signals caused by the vibration source are shown in Fig. 3 below:

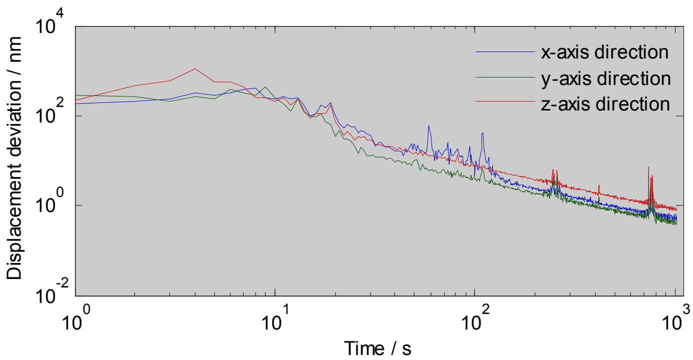


Fig. 3 Imaging displacement deviation value caused by the lab table vibration

The actual displacement is deviation in three directions. It is necessary to conduct feature extraction of each, respectively. Through standardization of deviation data in various directions, feature extraction is conducted. Here, the "db5" wavelet function is adopted for denoising. The number of decomposition layers is "3." The control coefficient, a, of the wavelet threshold function is set to be "0.2." With the entropy as the standard, vibration signals after denoising obtained above also undergo the three-layer wavelet packet decomposition based on the "db5" wavelet function. Then, the coefficient of various nodes in the third layer is reconstructed. The reconstructed signal, S_{mi}, of various node coefficients is shown in Fig. 4 below:

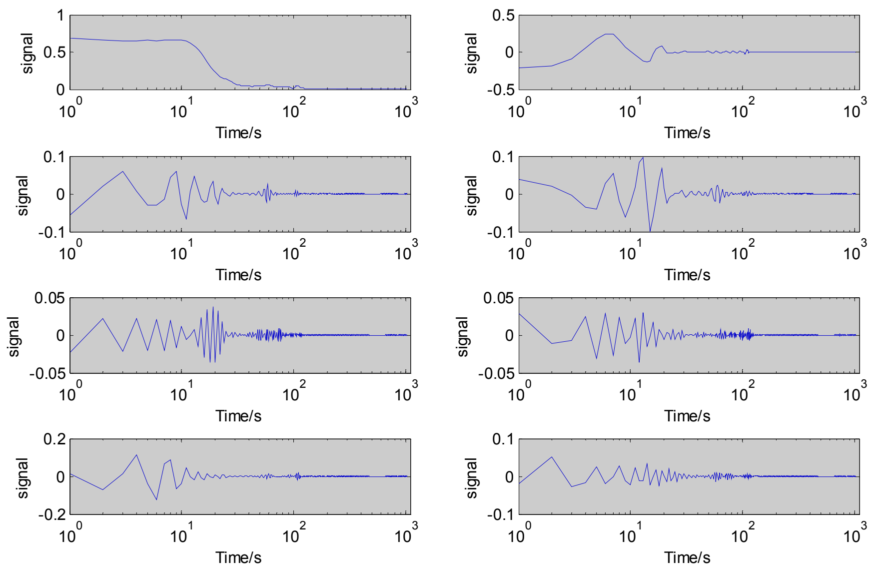


Fig. 4 Feature reconstruction signal value of various nodes (x-coordinate direction)

The total energy, E_{mi}, of the reconstructed feature signals of various nodes is worked out and undergoes normalization. The final signal feature vectors obtained are shown in Eq. 11 below:

$\vec{E}_x$ = [0.9987,0.0497,0.0041,0.0081,0.0021,0.0014,0.0086,0.0018] （11）

Similarly, the feature extraction in the y-coordinated direction and the z-coordinate direction is conducted according to the above steps. The signal feature vectors thus obtained are shown in Eq. 12 and Eq. 13 below:

$\vec{E}_y$ = [0.9995,0.0239,0.0076,0.0131,0.0103,0.0031,0.0130,0.0021] （12）

$\vec{E}_z$ = [0.9930,0.0657,0.0041,0.0927,0.0114,0.0280,0.0092,0.0046] （13）

Work out the average value of the displacement deviation feature vectors obtained in various directions. The final feature vector of the lab table vibration source is: $\vec{E}$ =[0.9971,0.0464,0.0053,0.0380,0.0079,0.0108,0.0103,0.0028].

Conduct feature extraction of vibration source signals of other types. 50 samples of each vibration source type are analyzed. There are 20 test samples. In total, there are 150 training samples and 60 test samples. Table 1 below lists the signal feature vectors of some different vibration sources.

TABLE 1. SIGNAL FEATURE VECTORS OF DIFFERENT VIBRATION SOURCES

Vibration source	Feature vector	Type coding
Lab table	[0.9971,0.0464,0.0053,0.0380,0.0079,0.0108,0.0103,0.0028]	[1,0,0]
Lab table	[0.9975,0.0468,0.0130,0.0428,0.0124,0.0113,0.0178,0.0081]	[1,0,0]
Lab table	[0.9973,0.0504,0.0139,0.0404,0.0128,0.0121,0.0168,0.0044]	[1,0,0]
Microscope	[0.9992,0.0507,0.0059,0.0430,0.0096,0.0164,0.0162,0.0093]	[0,1,0]
Microscope	[0.9996,0.0506,0.0083,0.0377,0.0093,0.0111,0.0111,0.0042]	[0,1,0]
Microscope	[0.9998,0.0459,0.0133,0.0464,0.0118,0.0147,0.0126,0.0108]	[0,1,0]
Ground	[0.9968,0.0499,0.0053,0.0466,0.0070,0.0176,0.0174,0.0105]	[0,0,1]
Ground	[0.9969,0.0494,0.0069,0.0450,0.0112,0.0189,0.0111,0.0045]	[0,0,1]
Ground	[0.9961,0.0454,0.0043,0.0370,0.0069,0.0098,0.0093,0.0018]	[0,0,1]

B. Elimination of disturbing training samples based on the SOM

Since there are valid disturbing samples among collected samples, object types analyzed by the model can be divided into three types. Therefore, all feature vectors extracted are adopted as the input information of the SOM. Among them, the number of judgment types of the SOM network is 3, and parameters to build the network are shown in Table 2 below:

TABLE 2. PARAMETERS TO BUILD THE SOM NEURAL NETWORK

Parameters	Set value	Parameters	Set value
Layout function	Hextop	Learning rate during the adjustment period	0.15
Distance function	Linkdist	Adjacent distance during the adjustment period	10-5
Learning rate of the ranking period	0.25	Network iterations	100
Stepsize of the ranking period	220	Network training function	Trainru

When the SOM network iteration comes to an end, the corresponding category serial number of various samples obtained are shown in Fig. 5 below:

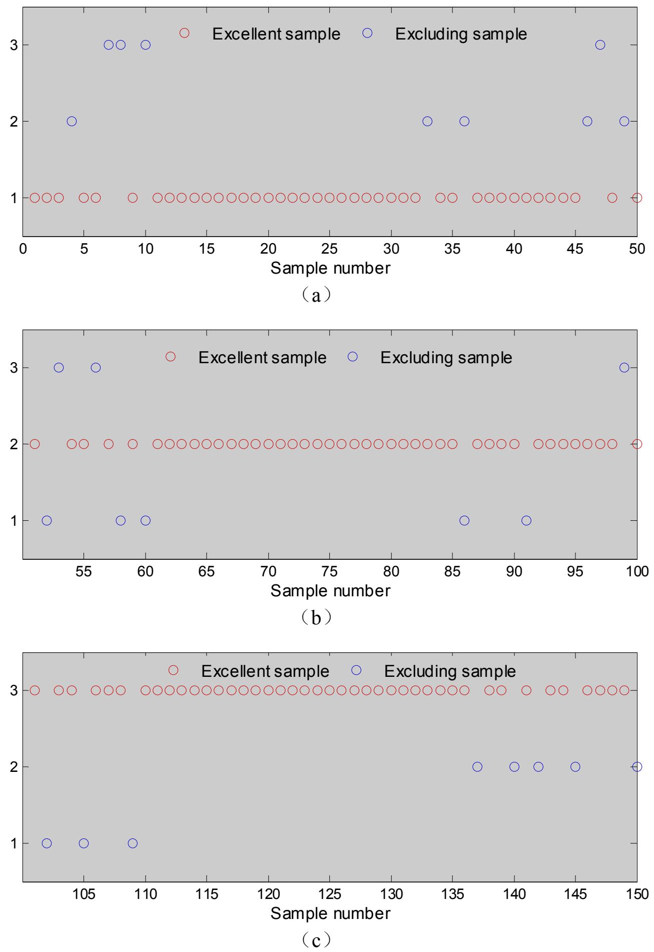


Fig. 5 Elimination of disturbing samples from samples of different vibration sources (Fig. a stands for the lab table; Fig. b stands for the microscope; Fig. c stands for the ground)

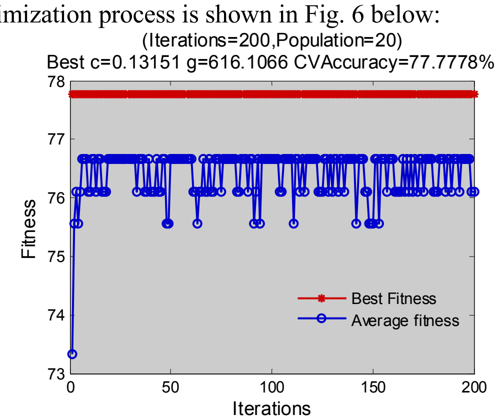
Based on the above iteration results of the SOM network, the data sample results of the lab table vibration and the self-adaptive adjustment of tree types of vibration source data, it can be seen that the major serial number of the lab table vibration samples is “1;” the major serial number of the microscopic vibration samples is “2;” the major serial number of ground vibration samples is “3.” Meanwhile, based on Fig. a above, it can be seen that the serial number of nine samples among the vibration samples is labeled as vibration sources of other types. Therefore, samples of the part are defined as disturbing samples, which should be eliminated. Similarly, there are eight samples in microscopic vibration and ground vibration which are labeled as vibration sources of other types. Thus, 25 samples in total are eliminated. In other words, through sample screening, there are 125 valid samples.

C. Analysis of nanometer imaging system's vibration recognition

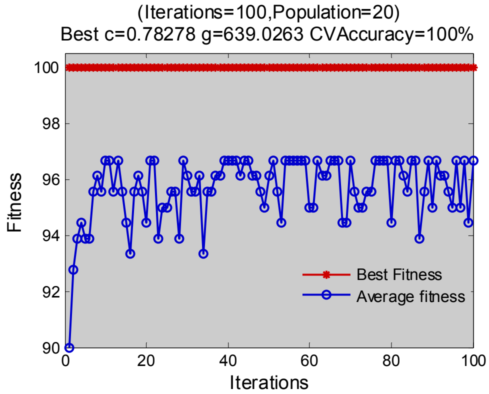
Adopt the feature vectors of 150 training samples collected in total as the input information of the SVM model. The SVM parameter results obtained through the genetic algorithm optimization are shown in Table 3 below. The model's optimization process is shown in Fig. 6 below:

TABLE 3. OPTIMIZATION RESULTS OF THE SVM PARAMETERS

Parameters	SVM	SOM+SVM
c	0.13151	0.78278
g	616.1066	639.0263
Accuracy	77.7778%	100%



(a)



(b)

Fig. 6 Iteration chart of the SVM parameter optimization based on the genetic algorithm (Fig. a directly uses SVM results; Fig. b stands for combined results of "SOM+SVM")

From the above simulation results, it can be seen that, if the feature value obtained is directly extracted as the input information of the SVM model, the model might be unable to achieve the optimal value at the end of training due to existence of too many invalid disturbing samples. After SOM screening of samples' feature data, since various types of samples are all in their optimal value, the SVM model can achieve optimal value during the training process. Meanwhile, the parametric value obtained by the SVM model shows that the core recognition parameters, c and g, of SVM and "SOM+SVM" are inconsistent, suggesting differences of recognition accuracy rate of the two.

In order to mor directly reflec the validity of the "SOM+SVM" model in this paper, the recognition accuracy results of samples based on the Logistic model, the BP network model, the SVM model and the "SOM+SVM" model are also provided (See Fig. 4 below):

TABLE 4. COMPARISON OF THE RECOGNITION ACCURACY RATE BASED ON DIFFERENT MODELS

Model algorithm	Number of training samples	Number of test samples	Number of correctly recognized test samples	Recognition accuracy rate (%)
Logistic model	150	60	38	63.33%
BP model	150	60	37	61.67%
SVM model	150	60	46	76.67%
"SOM+SVM" model	125	60	55	91.67%

Based on comparison results of various models shown in Fig. 4, it can be seen that the number of training models should be increased without limits. When there are huge disturbing samples in the model, the well-trained model will show poor recognition accuracy. The above test results show that the recognition model algorithm combining the SOM and SVM model is more accurate than the other model algorithms. Besides, the former can more efficiently recognize the actual vibration signal type which the displacement deviation is corresponding to during the nanometer imaging process.

IV. CONCLUSIONS

This paper first analyzes development and applications of the nanometer imaging technique, and points out factors disturbing the nanometer imaging process. At last, in order to quickly analyze disturbing factors of the nanometer imaging system, this paper puts forward a nanometer imaging system's vibration recognition model combining the SOM (System Object Model) and the SVM (Support Vehicle Machine) model by extracting corresponding imaging deviation signal features of different vibration sources. The model first conducts the adaptive adjustment of all training samples based on the SOM network to eliminate disturbing samples. Based on the remaining efficient samples, the SVM already built up is trained. At last, simulation test is conducted of practical samples, and the algorithm put forward in this paper is compared with other recognition algorithms. Results suggests that the nanometer imaging system's vibration recognition model put forward in this paper can eliminate disturbing data in training samples, so its recognition accuracy rate is much higher than that of the Logistics model, the BP neural network and the SVM model.

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