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Particle swarm optimization support vector machine-based coal and rock cutting tool load spectrum identification method

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Abstract. The goal of this research is to achieve safe and efficient excavation of coal and rock tunnels with complex geological structures, and to enhance the self-sensing ability of coal and rock cutting equipment and tools. Particle swarm optimization support vector machine is used to identify the cutting state of disc cutting tools. EDEM finite element analysis software is used to analyze cutting process characteristics of the disc cutting tool when used to cut through coal and rock with different compressive strengths. Empirical mode decomposition is used to decompose the load spectrum characteristics; for this purpose, the first-order and seventh-order intrinsic mode functions containing all the feature information of the original signal of the load spectrum are selected. The sample entropy is calculated as the feature input vector. The extracted feature vector is input into the trained support vector machine model and the particle swarm optimization support vector machine model. By extracting the sample entropy of the load spectrum of the disc cutter as the feature vector, the particle swarm optimization support vector model is used to identify the cutting state of the coal and rock. The recognition accuracy of the support vector machine model before and after the improvement is compared and analyzed. The results show that compared to the unoptimized support vector machine, the support vector machine optimized by particle swarm optimization can identify the load spectrum of the coal more quickly and accurately. The recognition accuracy is 96,82%, which verifies the effectiveness of the particle swarm optimization support vector machine model in identifying the load spectrum of the coal and rock disc cutter.

Keywords: disc cutter, coal and rock, discrete element modeling, feature vector, particle swarm optimization

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МАШИНОСТРОЕНИЕ
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Метод распознавания диапазона нагрузок дискового резака при резке угля и горной породы на основе метода опорных векторов оптимизации роя частиц

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Резюме. Цель – выявление решений, направленных на обеспечение безопасной и эффективной экскавации сложных геологических формаций угольных и каменных месторождений в туннелях, а также на повышение чувствительности оборудования и инструментов для резки угля и породы. Для идентификации состояния реза дискового инструмента был использован метод оптимизации роя частиц, поддерживающий метод опорных векторов. Программный продукт конечно-элементного анализа EDEM был использован для анализа характеристик дисковых резаков, применяемых для резания угольных пород с различными пределами прочности на сжатие. Спектральные характеристики нагрузки на резак были разложены на эмпирические моды, при этом были выбраны компоненты внутренних колебаний первого и седьмого порядка, содержащие всю характерную информацию из исходного сигнала спектра нагрузки. Вычисленная энтропия сигнала была использована в качестве входного вектора признаков. Извлеченные векторы признаков были введены в модель опорных векторов и модель оптимизации роя частиц с поддержкой метода опорных векторов. В результате проведенных исследований на основе спектра нагрузки дискового резака была испытана модель оптимизации роя частиц с поддержкой модели опорных векторов для распознавания состояния резания и сравнивалась ее точность с неоптимизированной моделью опорных векторов. Полученные результаты указывают, что по сравнению с неоптимизированной моделью метода опорных векторов модель оптимизации роя частиц с поддержкой модели опорных векторов может быстрее и точнее идентифицировать спектр нагрузки режущего диска для резания угольной породы. Точность распознавания составляет 96,82%, что подтверждает эффективность данной модели при определении спектра нагрузок режущего диска, применяемого для работы с угольными породами.

Ключевые слова: дисковая фреза, уголь и горная порода, моделирование методом дискретных элементов, вектор признаков, оптимизация роя частиц, метод опорных векторов оптимизации роя частиц

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ВВЕДЕНИЕ

Cantilever roadheader is the main equipment in coal mines, and its working environment is complicated. The load spectrum of the working mechanism of the tool cutting coal and rock, which contains rich information, and the characteristics of the load spectrum under different working conditions can help identify the cutting state of the tool, which has certain practical significance to improve the intelligent cutting of roadheader [1, 2].

The load spectrum of coal and rock cut by disc tool is nonlinear and has certain randomness, so there are some difficulties in extract its frequency features. The variational modal decomposition (VMD) needs to determine the number of modes and their boundary effects artificially in advance when extracting the sample entropy as a feature vector, which limits its application. The wavelet transform algorithm is used to extract the features of the disc tool load spectrum with partial energy signal loss and the limitation of basis function selection, which is not suitable for its decomposition [3]. For the characteristics of the research subject, the sample entropy of intrinsic mode function (IMF) component is obtained by empirical mode decomposition (EMD), and the characteristic information of the disc tool load is extracted effectively by solving the problems of preset modal number and basis function selection [4–6]. Compared to neural networks, support vector machines (SVMs) are suitable for solving high-dimensional, small-sample, nonlinear problems and can effectively classify small-sample data, but it is particularly important to select appropriate SVM parameters, otherwise they are prone to fall into local optima and poor state recognition rates [7–9].

For this research, the disc tool load spectrum is taken as the research subject to address the above problems, EMD decomposition is used to extract the sample entropy as the feature vector, particle swarm optimization (PSO) algorithm is used to adaptively select the parameters of the support vector machine, algorithm validation is performed on the disc tool cut coal and rock load spectrum dataset that is classified and identified by support vector machine (SVM) and PSO-SVM. Its accuracy on the load spectrum recognition is explored, and the application of PSO-SVM model for coal and rock-cutting disc tool recognition based on the load spectrum is realized.

FEATURE EXTRACTION OF DISC TOOL LOAD SPECTRUM

Simulation analysis of coal and rock cut by disc tool using discrete element modeling software EDEM was conducted with the following parameters: the density of coal and rock is 1280, 2460, and 2630 kg/m^3; Poisson's ratio of coal and rock is 0,28, 0,24, 0,23, and 0,31; elastic modulus of coal and rock is 2010, 3260, and 12100 MPa; normal contact stiffness of coal and rock is $1{,}108\times10^8$, $9{,}744\times10^8$, and $7{,}472\times10^7$ N/m^3; and tangential contact stiffness of coal and rock is $8{,}514\times10^7$, $1{,}068\times10^9$, and $8{,}545\times10^8$ N/m^3; the density of disc tool is 17850 kg/m^3; Poisson's ratio of disc tool is 0,31. According to the discrete element method theory, the coal and rock is regarded as composed of discrete particles [10, 11]. In the discrete element software EDEM, the coal and rock particle model is established as a spherical particle with a diameter of 4 mm and a contact radius of 4.6 mm. The wedge angle of the disc tool is 55°, and the simulation model of the disc tool cutting coal and rock is shown in Fig. 1.

The stress cloud of the disc tool is shown in Fig. 2 for the situation when the simulated disc tool is used to cut the broken coal and rock. The derived load data can be obtained under three cutting states, and the data is then input into Matlab to obtain the corresponding load spectrum.

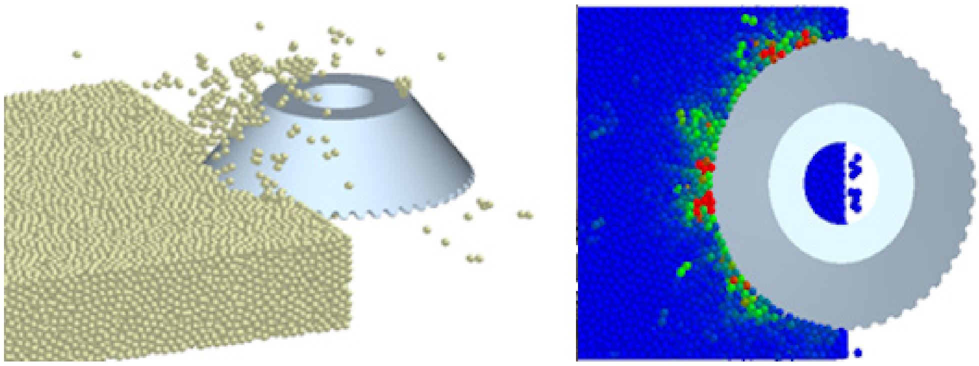


Fig. 1. Discrete element modeling of disc cutting tools for crushing coal and rock
Рис. 1. Конечно-элементное моделирование дисковых резцов для дробления угля и горной породы методом дискретных элементов

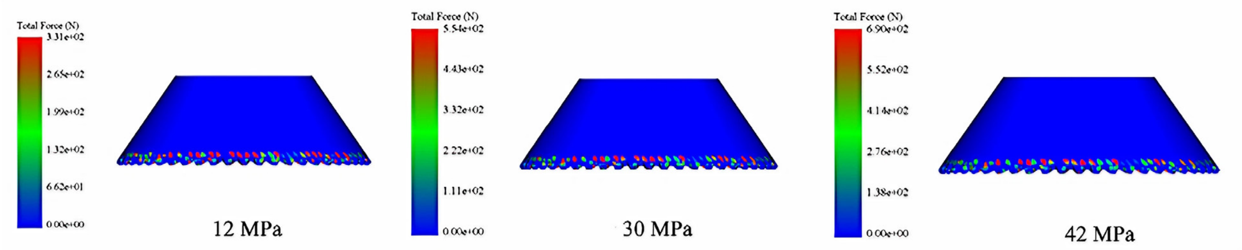


Fig. 2. Simulation stress cloud map of disc cutting tools
Рис. 2. Карта облака напряжений при моделировании дисковых резаков

In EDEM, 30 samples were collected for each class of states, and divided into training and test sets with a ratio of 7:3. The disc tool starts to enter at the coordinate zero point, and more than 1500 valid data samples are collected for each state, and the three truncated coal and rock state load spectra are shown in Fig. 3.

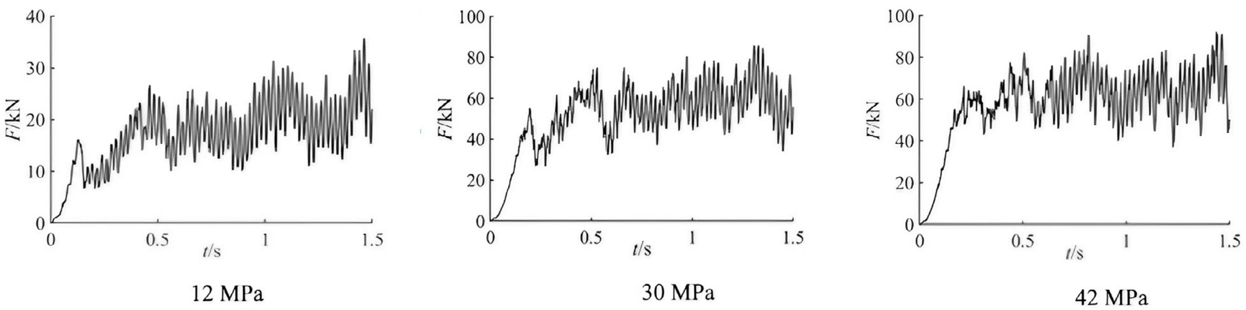


Fig. 3. Three load state curves
Рис. 3. Три кривые нагрузки различных состояний

PSO-SVM STATE IDENTIFICATION MODEL, SUPPORT VECTOR MACHINE PRINCIPLE

Support vector machine (SVM) has improved the generalization ability in finding the process that minimizes the overall structured risk, so that good regression ability can still be maintained in small samples of the truncated load spectrum. The disc tool truncated coal and rock load spectrum has nonlinearity, and there exist sample sets (x_1, y_1), (x_2, y_2), ---, (x_n, y_n), --- , $x_n \in R_i$, $y_n \in R$, (n = 1, 2, ---, i), and the basic idea is to use the nonlinear mapping $\varphi(x)$ to map into the high-dimensional space and perform linear regression to obtain the function as follows:

$$f(x) = \omega\phi(x) + b\,, \tag{1}$$

where ω is the regression function weight vector; b is the bias with non-unique dimension.

After removing the idiosyncratic points in the nonlinear case, the remaining part is linearly inseparable, implying that this point is less than 1. The relaxation variable ζ_i is introduced to construct the optimal hyperplane with the constraint:

$$\omega\phi(x)+b \geq 1-\xi_i \tag{2}$$

The optimization function is expressed as follows:

$$\min_{\omega,b,\xi}\frac{1}{2}\|\omega\|^2+C\sum_{i=1}^{N}\xi_i, \tag{3}$$

where C is a constant that constrains the degree of penalty:

$$\text{s.t } y_i(\omega\phi(x)+b) \geq 1-\xi_i, i=1,2,\cdots, N \tag{4}$$

$$\xi_i \geq 0, \quad i=1,2,\cdots N.$$

Using Lagrange multipliers, the Lagrange function is established, while the kernel function k(x_i, x_j) is introduced, and the SVM regression function expression is obtained as:

$$f(x)=\sum_{i=1}^{N}(a_i-a_i^*)K(x_i,x_j)+b, \tag{5}$$

where a_i, a_i^* is Lagrange multipliers, $a_i \geq 0$, $a_i^* \geq 0$, $a_i \times a_i^* = 0$.

The artificially selected parameters of the kernel function g, and the constant C, which constrains the degree of penalty, have poor generalization ability. Thus, it is necessary to optimize the penalty coefficient C in the SVM model and the parameters of the selected kernel function when using SVM for load spectrum classification, and to optimize the hyperparameters of the SVM using the PSO algorithm to improve the accuracy of the SVM in recognizing the load spectrum.

PSO ALGORITHM

PSO is initialized as a population of random particles (random solutions), and the optimal solution is found by iteration. In each iteration [12–14], the particle updates itself by tracking two "extremes" (*pbest*, *gbest*). *pbest* and *gbest* are the individual and population optimums, respectively, and after finding these two optimums, the particle updates its velocity and position as:

$$v_i = wv_i + c_1r_1(pbest_i - x_i) + c_2r_2(gbest - x_i)$$
$$x_i = x_i + v_i, \tag{6}$$

where i = 1, 2, …, N; N is the total number of particles in this cluster; v_i is this cluster; v_i is the velocity of the particles; r_1 and r_2 are random number between 0 and 1; x_i is the current position of the particle; c_1 and c_2 are the learning factors (usually $c_1 = c_2 = 2$); w is the inertia factor; and the two listed equations are the standard forms of PSO.

The larger the value of the inertia factor, the stronger the global search ability and the weaker the local search ability; the smaller the value, the weaker the global search ability and the stronger the local search ability. In order to get a better inertia factor, a linear decreasing weight (LDW) strategy is used, as shown in the following equation, which will become smaller and smaller as the number of iterations increases:

$$w' = (w_i - w_e)(G_k - g)/G_K + W_e, \tag{7}$$

where w_i is the initial inertia factor, w_e is the inertia factor at the maximum number of iterations, G_K is the number of iterations, g is the global optimum.

For different search problems, the global and local search capabilities can be adjusted so that the PSO algorithm can optimize the parameters of the SVM.

IMPROVED PSO-SVM ALGORITHM

In this paper, the particle swarm algorithm is used to optimize the SVM by determining the number of populations and the maximum number of iterations [15–17], and adjusting its speed and position according to the current individual extremum it finds and the current global optimal solution shared by the whole particle swarm [18–20]. The principle of the disc tool cutting state recognition model of the roadheader mentioned in the paper is to perform EMD decomposition on the collected disc tool load spectra, extract the sample entropy of each IMF component as a feature vector, divide it into training set and test set, input to the state recognition model of particle swarm algorithm optimized SVM, and obtain the recognition results.

IDENTIFICATION OF TRUNCATED STATE LOAD SPECTRUM, EMD DECOMPOSITION

The EMD decomposition is calculated as follows.

According to the signal x(t), the local maxima and local minima are connected by three spline curves, so that the whole signal sequence is between the upper and lower envelopes, Find the mean value of the two m_1(t), to obtain h_1(t) as follows:

$$x(t) - m_1(t) = h_1(t). \quad (8)$$

If $h_1(t)$ does not satisfy the precondition, consider $h_1(t)$ as a new signal sequence and apply the previous equation to find one that satisfies the condition, denoted as $c_1(t)$. $c_1(t)$ represents the EMD decomposition of the obtained signal sequence.

Separate the signal sequences and obtain a new signal sequence as follows:

$$r_1(t) = x_1(t) - c_1(t). \quad (9)$$

Consider $r_1(t)$ as a new signal sequence $x(t)$, process it according to step 1 and step 2, and record the remaining signal sequence as i, where i is taken as 1, 2, … m and repeat equation in step 1 m times, and stop when the termination condition is satisfied, resulting in the following:

$$\begin{cases} r_1(t) - c_2(t) = r_2(t) \\ r_2(t) - c_3(t) = r_3(t) \\ \vdots \\ r_{m-1}(t) - c_m(t) = r_m(t) \end{cases}. \quad (10)$$

The signal sequence is decomposed from equations from steps 1 and 2 as follows:

$$s(t) = \sum_{i==11}^{m} c_i(t) + r_m(t), \quad (11)$$

where $r_m(t)$ is the residual term.

To ensure that the IMF component is meaningful, the standard deviation is used to determine when the «sieving» is over.

$$Z = \sum_{t=0}^{T} \frac{|h_{i-1}(t) - h_i(t)|^2}{h^2_{i-1}(t)}, \quad (12)$$

where T is the total time of the discrete signal sequence.

To ensure the stability and linearity of the IMF component and to ensure that the eigenmodal function has the corresponding physical significance, Z is taken as 0,2.

SAMPLE ENTROPY

The sample entropy (SE) is a measure of the complexity of the time series and is calculated as follows.

1.For the time series $\{x(i) = x(1), x(2), \cdots, x(N)\}$, the reconstructed time series is obtained as follows:

$$\{x(i)\} = \{x(i), x(i+1), \cdots, x(i+m-1)\} \frac{n!}{r!(n-r)!}, \quad (13)$$

where m is the embedding dimension and N represents the time duration.

2. Calculate the distance in the new time series with the formula

$$d_{ij} = d[x(i), x(j)] = \max[|x(i+k), x(j+k)|], \quad (14)$$

where d_{ij} is the one with the largest difference of the corresponding element.

3. Calculate the amount of distance d_{ij} less than the similarity tolerance r to obtain $B_i^m(r)$, which is given by the following formula:

$$B_i^m(r) = \frac{d_{ij} < r}{N - m}, i \in [1, N - m] \quad (15)$$

4. Find the mean of $B_i^m(r)$ using the formula:

$$B^m(r) = \frac{1}{N - m + 1} \sum_{i=1}^{N-m+1} B_i^m(r). \quad (16)$$

5. For the $m+1$-dimension, repeat steps 1 to 5 to obtain $B^{m+1}(r)$.

The SE definition formula for the original sequence is expressed as follows:

$$SampEn(m,r) = \lim_{N \to \infty}[-\ln \frac{B^{m+1}(r)}{B^m(r)}]. \quad (17)$$

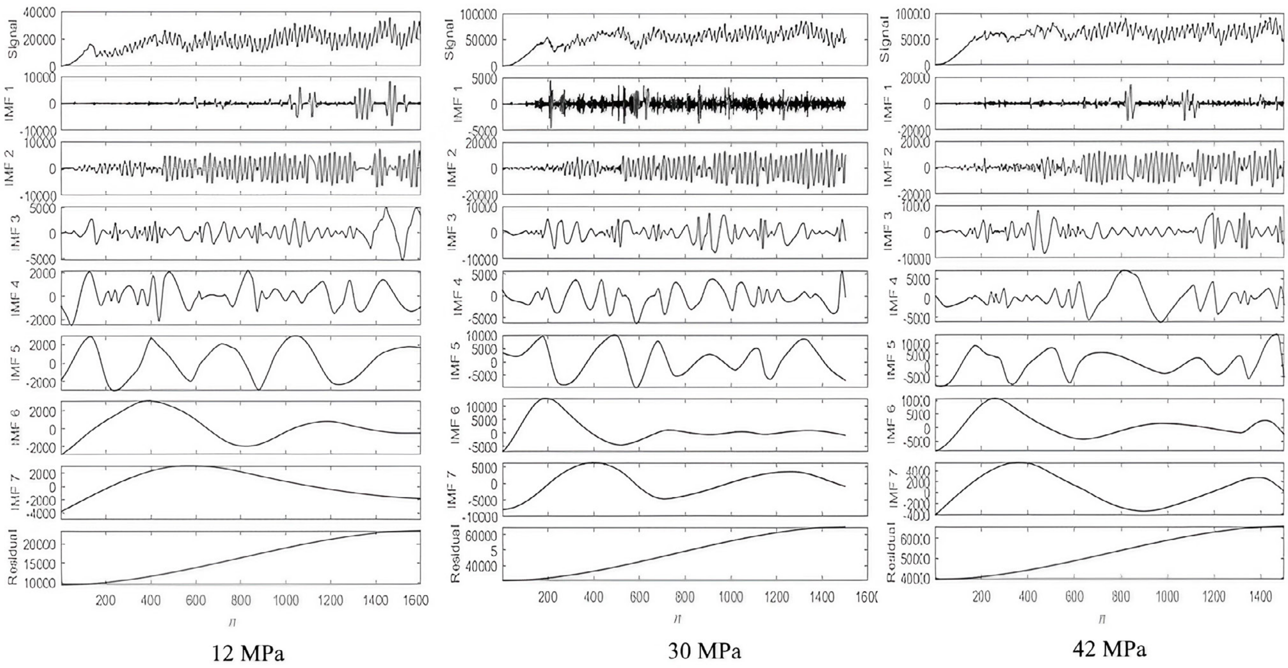
When it is a finite number, its formula is expressed as follows:

$$SampEn(m,r,N) = \ln B^m(r) - B^{m+1}(r). \quad (18)$$

FEATURE EXTRACTION AND RESULT ANALYSIS

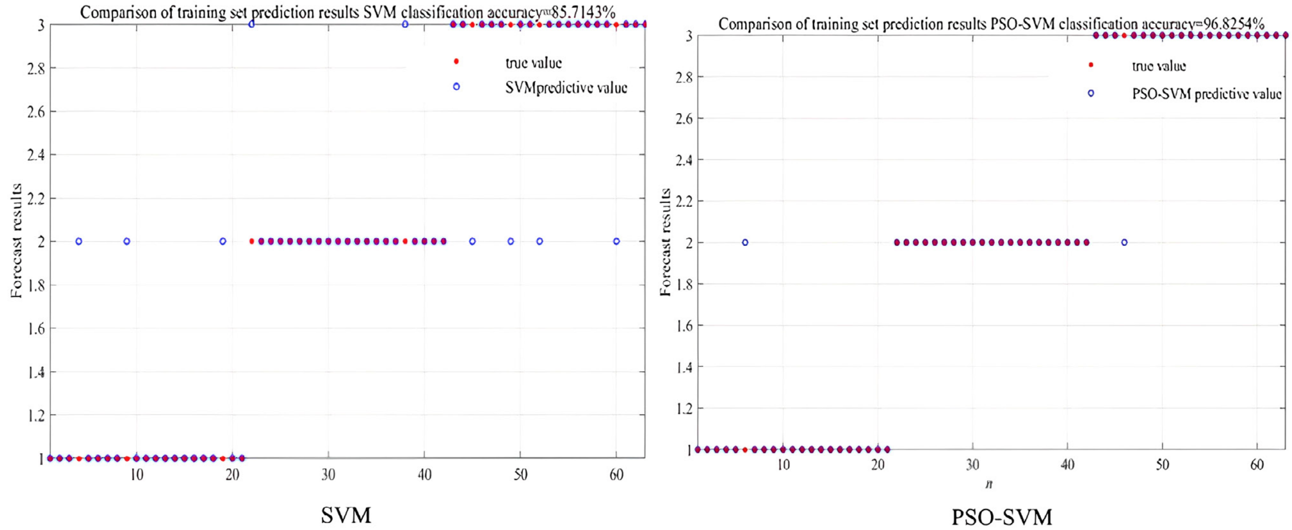
The results of using the EMD algorithm to adaptively decompose the load spectrum are shown in Fig. 4.

Because of the different number of IMF components obtained from EMD decomposition of different types of load spectra, in order to maintain the same length of feature vectors in different states and include all information of the original load spectrum, the first 7 IMF components are selected to represent the original load spectrum. The extracted sample entropy values are calculated. 21 sets of data from each cutting state load spectrum were selected as the training set, and the remaining 9 sets of data as the test set. To verify the advantages of the PSO-SVM model proposed in the article, it was compared with the unoptimized SVM model with an initial population of 1000 and a maximum number of iterations of 300. The experimental results are



a **b** **c**

Fig. 4. EMD decomposition of different cutting load spectra (a, b, c)
Рис. 4. Эмпирическая модальная декомпозиция различных спектров нагрузки при резке (a, b, c)



a **b**

Fig. 5. SVM and PSO-SVM recognition results (a, b)
Рис. 5. Результаты распознавания метода опорных векторов и модели оптимизации роя частиц с поддержкой метода опорных векторов (a, b)

shown in Fig. 5.

The classification accuracy of SVM is 85,71%, and the recognition accuracy of PSO-SVM is 96,82%. Compared with unoptimized, particle swarm optimization algorithm has shorter optimization time and higher optimization accuracy.

CONCLUSION

The recognition algorithm of disc cutting tool load spectrum based on PSO-SVM utilizes PSO adaptive optimization of SVM parameters. The disc cutting tool cutting coal and rock load spectrum is selected as the test set, and the accuracy of support vector machine model recognition before and after improvement is compared and analyzed. The results show that by extracting the sample entropy of the cutting state load spectrum of the disc cutter as the feature vector and using the PSO-SVM model to identify the cutting state of coal and rock, the time and accuracy of the tool cutting are better than those of the unoptimized SVM, with less time consumption and a recognition accuracy of 96,82%. Based on the PSO-SVM model, an analysis was conducted on the dataset of coal and rock load spectra for disc cutting tools, verifying the effectiveness of the PSO-SVM model in identifying coal and rock load spectra for disc cutting tools.

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