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Research Article

Optimization and Simulation of Monitoring Technology of Blasting Rock Movement Trajectory Based on the Improved SVM Algorithm

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In most cases, the blasting object is the rock mass. Because the rock mass has the characteristics of anisotropy and inhomogeneity, there are often structural surfaces such as joints, fissures, faults, and weak interlayers, but details are basically impossible. Compared with the rock, these structural surfaces are weak parts, and the explosive energy required for breaking is smaller. It is difficult to take into account the existence of each weak side when the explosives are arranged in the blasthole. Therefore, after the explosive explodes in the rock mass, the explosive gas will first rush out from these weak parts, entraining individual fragments to form flying rocks. Aiming at the problem that it is difficult to accurately obtain the rock motion information in the blasting process of open-pit mines, this paper selects the kernel function to establish the support vector machine model and optimizes the parameters of the support vector machine model to obtain the optimal blasting rock trajectory prediction model. Under the protection of special protection devices, the information of the rock movement during the blasting process is collected at a higher frequency, and the analysis algorithm of the rock movement characteristics is researched on the basis of inertial navigation technology. The algorithm is used to analyze and output the rock movement. The curve of velocity, position, and kinetic energy provides a theoretical and technical basis for the study of rock movement law in the blasting process of open-pit mines. Through the experimental analysis, based on the cross-validation method, through the support vector machine model parameter optimization and comparison evaluation parameters, the optimal prediction model of the blasting rock trajectory is obtained as the support vector machine model based on the radial basis kernel function. The mean value of root mean square error and mean absolute error of this model are 0.102 and 0.0674, respectively, and the performance is the most robust among the three types of models.

1. Introduction

Blasting is an important means of open-pit mine production. The blasting process releases huge energy, a part of which is used to break the rock mass, and a part of it is used to throw the broken ore rock. The movement speed changes and movement trajectories of the ore rock at different positions during the blasting process are studied. The characteristics and laws can reflect various situations such as energy efficiency, ore depletion, and safety risks in blasting production and provide a scientific basis for the evaluation of blasting effects [1, 2]. Relevant scholars have done a lot of research work on the movement characteristics and laws of ore rock during the blasting process, mainly using the following methods. One is the high-speed photography method combined with the theoretical analysis method. By monitoring the blasting process and combining the blasting funnel theory, the velocity distribution of ore and rock and the proportion of explosive energy in each part of the blasting process are established, so as to provide a basis for the adjustment and optimization of blasting parameters. One is to use color marking to mark the ore and rock before blasting and pass the mark after blasting the ore to measure the movement of ore and rock and combine the empirical formula to establish a ore-rock movement model, so as to determine the amount of waste rock mixed into the ore during the blasting process. The rock movement is more convenient to measure [3]. With the development of computer technology, more and more scholars use model experiments and numerical simulations on the basis of theoretical research to study the movement characteristics and laws of blasting ore and rocks, so as to provide reference for the safety protection of flying rocks during blasting. In recent years, with the emergence of machine learning and artificial intelligence, some scholars have used different learning algorithms to learn from previous blasting data and established rock movement models based on different blasting parameters to predict the movement of blasted rock [4, 5].

However, the environment of the blasting site is very harsh. The high-speed photography method is affected by the blasting smoke at the blasting site and cannot completely monitor the movement process of the ore rock. Due to the uniqueness and complexity of rock masses at different blasting sites, the accuracy and authenticity of methods such as model experiments, numerical simulations, and machine learning based on theoretical methods are insufficient [4]. Since the inertial sensor can collect and store the corresponding motion information at a higher frequency when it moves with the object, and has a built-in independent power supply, it can work normally without relying on the outside world [6–9], so it has special protection. In the case of the device, the movement information of the ore rock can be collected during the blasting process. Therefore, this paper proposes an experimental research method based on the inertial navigation technology to study the characteristics and laws of the blasting rock movement. It is proved by field experiments that this research method has obvious advantages compared with other research methods, which can accurately obtain the real movement characteristics of ore-rock movement.

As an important technology for mining, blasting technology has an indispensable position. In the underground ore mining of mines, blasting technology is almost always used regardless of tunneling or rock-breaking mining. The rational application of blasting technology can not only improve production efficiency but also help to improve the safe production environment in the well. In view of different mine environments, selecting reasonable blasting parameters is the key to safe and efficient production, so the optimization of blasting parameters is a topic that has received much attention. There are many ways to optimize the selection of blasting parameters mainly through comparison with the mature experience of similar mines and calculation of formulas. With the rapid development of computer technology, the optimization and selection of parameters in recent years has gradually been combined with intelligent algorithms, which has also become the blasting parameter. The method of obtaining blasting parameters through the on-site blasting test is reliable, but the cost is high and the efficiency is poor. For the research of blasting parameter optimization that requires a large amount of statistical data, the on-site test is not suitable. In order to improve the optimization efficiency of blasting parameters, the research of blasting parameter optimization in this paper mainly selects the means of combining the support vector machine model with the practice.

The innovations of this paper are as follows: Since rock blasting is a complex nonlinear system affected by multiple factors, the prediction of blasting rock trajectory is a multivariable prediction problem. This paper improves on the basis of the support vector machine model and establishes the prediction model of blasting ore, and the rock trajectory is verified, and the validity of the model prediction is verified by the cross-validation method.

The paper is arranged as follows: Chapter 1 introduces the related research on rock blasting parameters by relevant scholars and makes a summary based on the above research; Chapter 2 introduces the support vector machine and improves it based on the traditional model; Chapter 3 explains the blasting experiments carried out in this study which is cross-validated based on the experimental results; and the fourth chapter is the total of the full text.

2. Related Work

The damage degree and process control of explosives to rock are mainly realized by blasting parameters. Regarding the determination of blasting parameters, many scholars at home and abroad have conducted a lot of research on it, and some scholars have tried to give clear and unified conclusions. Therefore, there is no theory and conclusion about the calculation of blasting parameters that can be adapted to all production environments [10].

Gilbride successfully applied photography and related analysis techniques to parameter optimization research and successfully improved production efficiency and reduced production costs at the same time [11]. Taylor and Firth in order to study the influencing factors of blasting rock fragmentation applied the principal component analysis methodand also used the multivariate statistical method [12]. Yennamani used artificial neural network to study the relationship between blasting backflush and its related rock and explosive and hole network parameters. After optimization, very good results are obtained [13]. La Rosa and Thornton applied multiple flash imaging technology to the statistics of blasted ore-rock trajectory, which not only improved its measurement accuracy but also saved a lot of manpower and greatly improved the efficiency of related research [14]. Amini et al. used Kuz-Ram and Monte Carlo simulations to predict blasting parameters, and the final results were proved to be reasonable and efficient [15]. Manoj and Monjezi proposed to select seven factors such as the angle of internal friction, severity, in-situ leaching, injection strength, cohesion of the topsoil layer, and fully weathered ore layer to conduct orthogonal experiments. The experimental results were analyzed using the principle of response surface methodology, and established a model to predict the stability of the in-situ leaching slope of ionic rare Earth ore [16]. Ohadi et al. intelligently optimized the blasting parameters using the KCO model, the Bond-Ram model, the Kuz-Ram model, and the EBT model and optimized the blasting parameters [17]. Yu et al. used the empirical formula method to optimize and adjust the number of blasting holes in railway tunnels and, at the same time, used the comparative research method to optimize and adjust the hole spacing and row spacing, and the optimization effect was obtained for improvement [18]. Sastry et al. used the existing blasting design, according to their existing data, combined with new requirements and new technology, and well completed the drilling and blasting method parameter optimization research [19]. Kourepenis et al. calculated and determined the blasting parameter design scheme based on experience and actual engineering needs when the blasting design scheme was uncertain [6]. Aggarwal et al. used empirical formulas to optimize blasting parameters such as blasthole row spacing, minimum resistance line, blasthole density coefficient, and bottom distance in a mine and achieved good results [7]. Shaeffer used the empirical formula to determine the charge consumption and the number of blastholes in the optimization study of blasting parameters for ore and rock excavation [8]. Perlmutter and Breit proposed to use the limit equilibrium method and discrete element numerical simulation to analyze the stability and failure mode of the open-pit mine slope on the basis of determining the relevant parameters of the slope stability. The problem is widespread, and the situation of high, steep, and complex rock slopes in large open-pit mines is particularly prominent [9].

In summary, intelligent computing and numerical simulation technology will be more and more frequently used in blasting parameter optimization research and future development direction. The previous research results have promoted the development of rock blasting to a certain extent, but the research on the prediction model of mineral rock blasting in some literatures has a small number of data samples, and the data selection is subject to a certain degree. The sample is not generated by random sampling; in addition, most of the models in the literature are tested only once, and the chance is large, which cannot prove the universality of the model.

3. Support Vector Machine Model Introduction and Algorithm Improvement

3.1. The Basic Idea of SVM. A support vector refers to the input x for some training points in the training set. The support vector machine method is a supervised learning method; that is, the category of the training point is known, and the correspondence between the training point and the category is obtained so as to separate the training set according to the category or predict the category corresponding to the new training point. In a nutshell, the support vector machine method is a classification method that firstly transforms the input space into a high-dimensional space through the Philippine linear transformation defined by the inner product function and then finds the optimal classification surface in this space. It shows many unique advantages in nonlinear and high-dimensional pattern recognition and can be extended to other machine learning problems such as function fitting.

The idea of support vector machine is created based on the optimal classification surface on the basis of linear separability, and its principle is shown in Figure 1.

In Figure 1, the optimal classification surface is relative to the multidimensional space. In the two-dimensional space, the optimal classification surface is the optimal classification line, which can accurately separate two types of data samples under the premise of ensuring the minimum empirical risk and make it the largest interval, that is, the largest classification interval.

Suppose there are two types of linearly separable sample sets (x_i, y_i), $\quad i = 1, \ldots, n, x_i \in R^d, y_{i\in}[1, -1]$, then define $f(x) = \omega x + b$ as the form of the discriminant function. This form has parameters that need to be adjusted but must be linear. The response equation is shown as

$$\omega x + b = 0. \tag{1}$$

The first job to be done is to normalize the discriminant function to ensure that all samples under different classifications must meet the constraints. It can be deduced that all classification straight lines must be within the range represented by the following equation and make the correct classification, as

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

The distance from the sample point to the hyperplane is

$$d = \frac{wx + b}{\|w\|}. \tag{3}$$

The distance of the classification line from which the response is obtained can be expressed as $2/\|w\|$, and the largest classification distance is equivalent to the smallest value of $\|w\|^2$, that is, the optimal classification hyperplane. In the case of a given sample, the selection of SVM parameters will first affect the learning ability of its model. Some scholars pointed out that the parameter selection of support vector machine not only determines its learning performance but also the size of the parameters which has a great influence on the scale of the hypothesis space and the search method of the space. In the support vector machine, it can be seen from the above description that the accuracy of the model is a contradictory community for the parameters, and the relationship between its own complexity and the parameters is also the same. For different situations, the selection of parameters is also different, and a trade-off needs to be made. The choice of parameters determines the performance of the support vector machine model. How to use the algorithm to obtain the optimal parameter combination is a problem that the support vector machine must consider. Parameter selection is the key to the quality of the support vector machine model. Manual selection is not only time-consuming and labor-intensive but also the found parameter group may not be optimal, but parameter selection can be treated as an optimization problem. Therefore, this paper

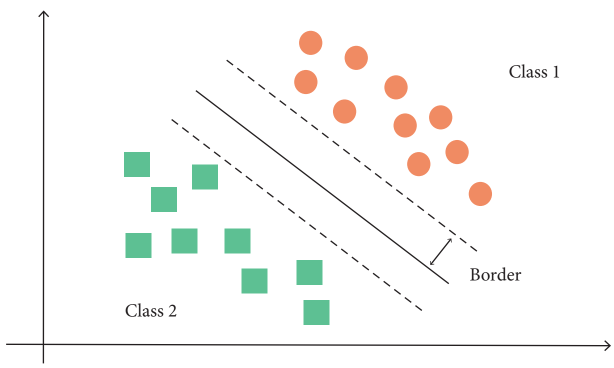

Figure 1: Basic idea of support vector machine.

considers the intelligent optimization algorithm and introduced the optimization of support vector machine parameters.

3.2. Improvement of the Support Vector Machine Algorithm Based on the Kernel Function. In order to make the support vector machine model have the best generalization ability, it is mainly necessary to do two things: the first thing is to choose a kernel function; the second thing is to choose an intelligent optimization algorithm to let the model obtain a set of optimal parameter combination. At present, the selection of the kernel function is generally a single kernel function. Based on the summary of the advantages and disadvantages of the polynomial kernel function and the Gaussian radial basis function, this paper forms a mixed kernel function of the polynomial kernel function and the Gaussian radial basis function. At the same time, the intelligent optimization algorithm used in this paper is an improved differential evolution algorithm. Finally, an improved support vector machine model is established.

In the support vector machine, to select the kernel function to map the nonlinear input to the high-dimensional feature space, this paper defines the characteristics of the kernel function based on the calculation requirements of the blasting rock trajectory as

$$K(u,v)=\sum_{k=1}^{\infty}\alpha_k\phi(u)\phi(v). \tag{4}$$

It is guaranteed that the symmetric function $K(u,v)$ under L_2 is expanded with a positive coefficient $\alpha_k>0$ as

$$\int g^2(u)\mathrm{d}x<\infty. \tag{5}$$

Due to the complex factors affecting the blasting rock trajectory in the mining area, a single kernel function is often unable to achieve satisfactory prediction results. However, there are many types of kernel functions, and there is no good experience on how to choose the kernel function well. But if the kernel function is classified, it can be roughly divided into two types: the first type is the global kernel function, and the second type is the local kernel function. The polynomial kernel function is an excellent representative of the first type of global kernel function. Its advantages are that it has a strong generalization ability and a good globality in extracting data. Among them, the excellent representative of the second largest type of local kernel function is the Gaussian kernel function, which has the advantage of good learning effect, and the disadvantage is its poor generalization ability.

The first type of global kernel function and the second type of local kernel function have different performances; therefore, in terms of their performance, the first type of global kernel function and the second type of local kernel function should be considered. These two kernel functions construct a new type of kernel function according to a certain proportional relationship, as shown in Figure 2.

Although support vector machines and neural networks are both nonlinear classification models, support vector machines consist of single hidden layer, which mainly realize nonlinear classification through the trick of kernel function. The direction of the line of least resistance is the direction with the least rock resistance, and it is also the direction which is most likely to generate flying rocks. When the minimum resistance line is too small, after the explosive explodes, only a part of the energy is enough to break the rock in the direction of the resistance line, and the excess energy throws the broken rock forward, producing more and farther flying stones. When the minimum resistance line is selected is too large, the energy generated by the explosive is not enough to overcome the resistance of the rock in the direction of the resistance line, but the energy of the explosive needs to be released, so it is easy to produce rush guns at this time, which is followed by flying stones. Since the foundation of SVM is statistical theory, it has rigorous theoretical and mathematical ideas, which can overcome the unavoidable problems of neural network. At the same time, the SVM also has relatively strong approximation ability and generalization ability.

4. Experimental Design and Analysis

4.1. Experimental Site. In order to analyze the movement law of ore rock in the process of slag blasting in the open pit and the influence of the residual blasting pile on the movement of nearby ore rock, this paper selects the 31st bench blasting in the south mining area of Qidashan open pit as the experimental site, and the bench elevation is −120 m–105 m, section height is 15 m, blasting step length is 132 m, step width is 20 m–28 m, slope angle is 65°, step area is 3168 m^2, total volume is 47520 m3, and step rock volume is 104664 tons. The steps mainly include migmatites such as gray-white or flesh-red gneiss-like structure, anisotropic full-crystalline structure, and massive structure. The blasting type of the experimental blasting area is slag blasting, with a total of 62 blastholes. The rectangular hole arrangement is adopted, the hole spacing is 7.5 m, the row spacing is 6 m, and the blasting is carried out hole by hole. The stage height is 15 m, the explosive types are emulsion explosives and ammonium explosives, the maximum charge per hole is 650 kg, and the total designed charge is 37000 kg. The filling height is 8.5 meters, and the blasthole is filled with gravel. The length of the bus used for detonation is 600 m, and the

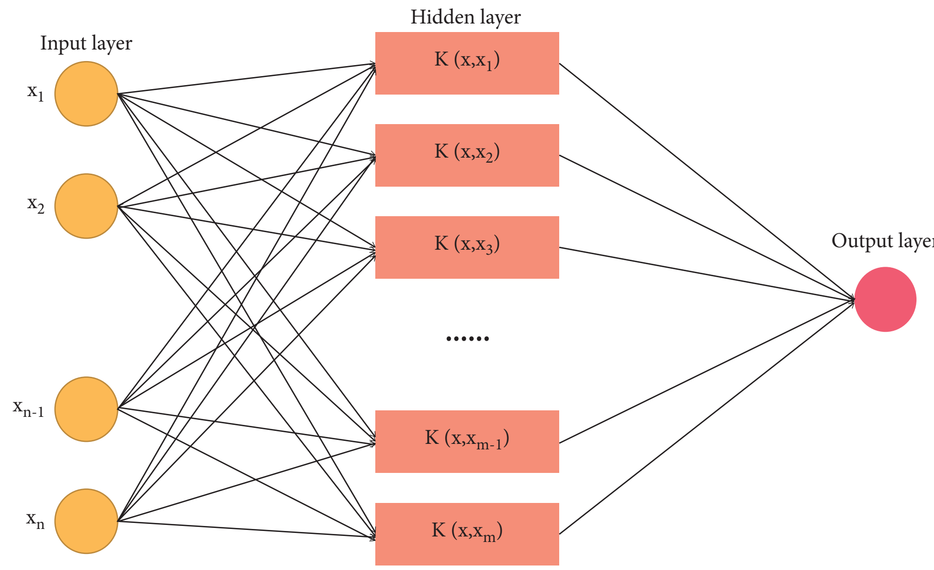

Figure 2: Structure diagram of the improved support machine.

combination of series and parallel connection is adopted. There are 130 detonating bombs, and 210 400 ms detonators are used in the hole, and 4 detonators of 25 ms, 20 detonators of 42 ms, and 41 detonators of 65 ms are used on the ground to detonate the entire blasting area for connecting.

4.2. Experimental Equipment. In this study, a high-precision MEMS inertial navigation sensor with automatic storage function is selected. The sensor size is 51.3 mm ∗ 36 mm ∗ 15 m and has an SD card slot. When the SD card is inserted, it will automatically turn on and work. There is an independent power supply inside, which can continuously, completely, and independently work for up to 5 hours, and the sensor records the acceleration and angular velocity of the three axial directions, respectively, at a frequency of 200 Hz. Among them, the acceleration accuracy is 0.01 g, and the angular velocity accuracy is 0.05°/s. The details of the sensor are shown in Figure 3.

According to the actual size of the sensor and the hole diameter of the blasthole, the design scheme of the special protection device for the sensor is determined. According to the design, the protection device is divided into two layers: inner and outer layers. The inner layer is a cuboid structure, which chooses PE pearl cotton material for production and uses soilworks software to carry out mechanical numerical simulation of the design protection device before production to determine its protection effect on the sensor, and the design diagram of the protection device is shown in Figure 4.

The protection device is made according to the design plan. In order to facilitate recycling and weighting, a color protection bag with better quality is equipped on the outside of the protection device, and the weight is placed in the protection bag to make its weight similar to the weight of the rock. The physical protection device is shown in Figure 5.

Figure 3: Inertial sensor for the experiment.

4.3. Experimental Process Design. In this paper, the support vector machine is used to predict the blasting rock trajectory. First, the rock pressure monitoring data sequence is normalized, then the embedded parameters of the phase space are determined, and then the phase space of the rock pressure monitoring data sequence is reconstructed. Then, the training sample set is established, then the test sample is set, and the prediction model is trained with the training sample set, and finally, the validity of the trained prediction model is verified with the test sample set. In order to avoid the too different magnitudes of each variable in the input variables affecting the training effect, the training data samples of the support vector machine should be normalized. When using the support vector machine to predict the mine pressure monitoring data, the radial basis function is used with the kernel function, and the cross-validation

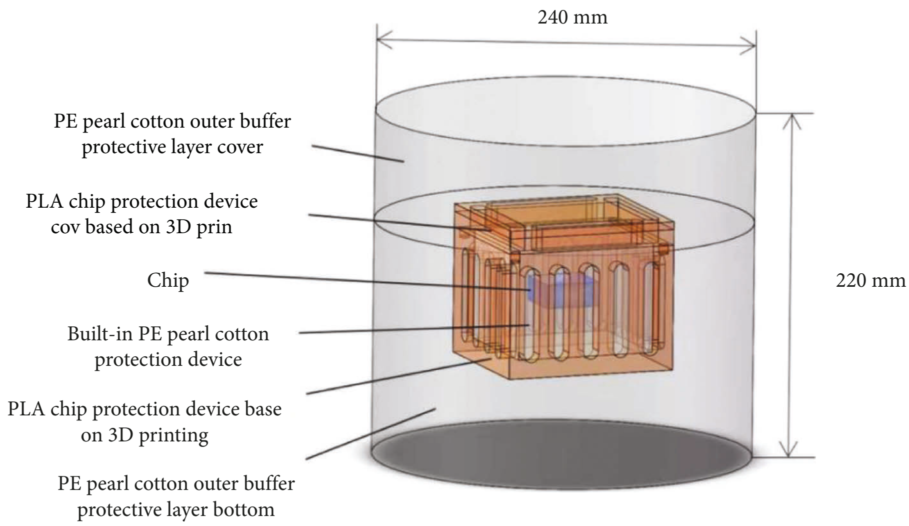

Figure 4: Design of the protection device.

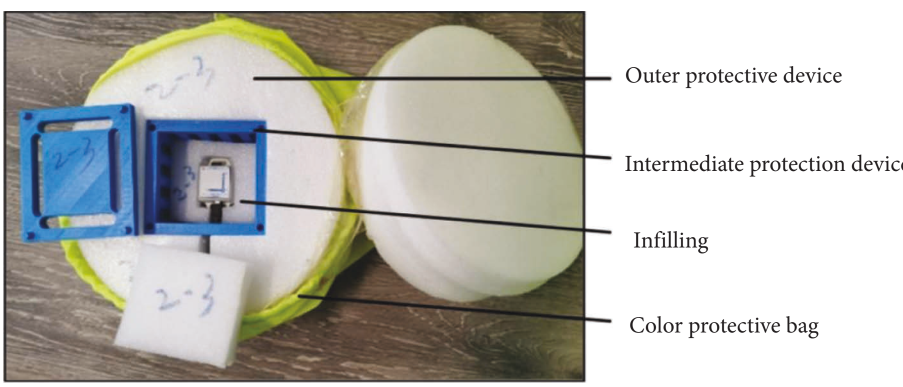

Figure 5: Entity diagram of the protection device.

method is used to optimize the parameters of the penalty parameter X_i and the kernel function y_i as

$$X_i = \overline{x}_i + \int X^2(x)\mathrm{d}x, \tag{6}$$

$$\begin{aligned} y_i &= f(X_i) \\ &= x_{i+1+(m-1)\tau}. \end{aligned} \tag{7}$$

The data collected on-site are analyzed and divided into training set and test set. The training set that needs to be trained is input into the neural network prediction model, the network is trained, and then the test set is input into the neural network prediction model. The effects are compared, and a more appropriate method is selected to predict the blasting effect. In the mining area, six blastholes were selected as experimental blastholes, and inertial sensors were embedded near the surface of each blasthole (not embedded in the blasthole packing). The sensors were placed horizontally, and the positive direction of the X axis was in the vertical slope in outward direction, and the sensor numbers are 1-1, 1-2, 2-1, 2-2, 3-1, and 3-2. According to the blasting design, the blasting sequence of the blastholes where each sensor is located is from morning to night: 2-2 (149 ms), 3–2 (157 ms), 3–1 (237 ms), 2–1 (298 ms), 1–2 (42 ms), and 1–1 (592 ms). The layout of the sensor is shown in Figure 6.

The main idea of the experimental method design is to embed the high-precision inertial sensor in the open stope according to the blasting site layout plan under the condition of special protection devices. In the end, recover the sensor and extract the sensor data, and then finally study the relevant data analysis to analyze the movement data of the ore rock during the blasting process so as to obtain the movement speed, kinetic energy, and trajectory of the ore rock, and study the movement law of the ore rock and technical process as shown in Figure 7.

The specific process of the experiment is as follows: (1) Insert the SD card into the inertial navigation sensor (automatically turn on after insertion); (2) place the sensor horizontally in the protection device according to the calibration direction of the protection device; (3) use the computer to communicate with the inertial navigation device through the data cable connecting the sensors, and then calibrate and adjust the sensor parameters; (4) embed the

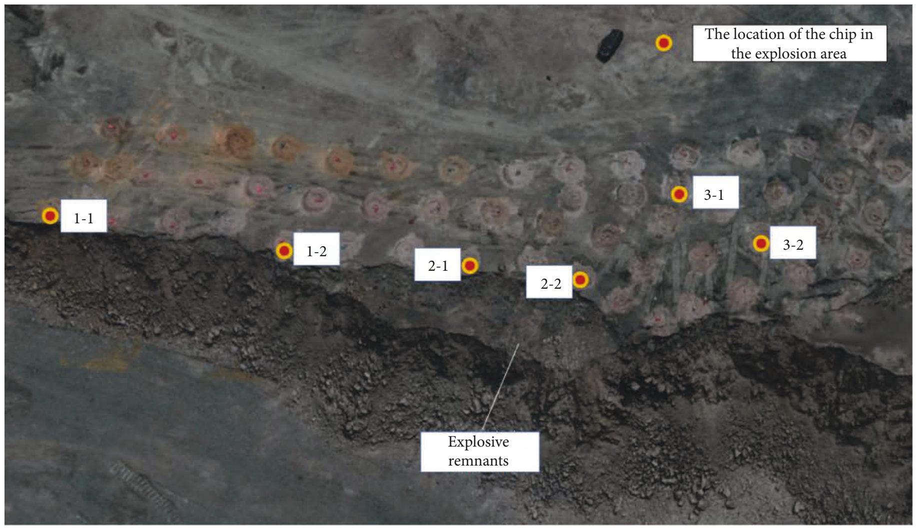

FIGURE 6: Sensor arrangement scheme.

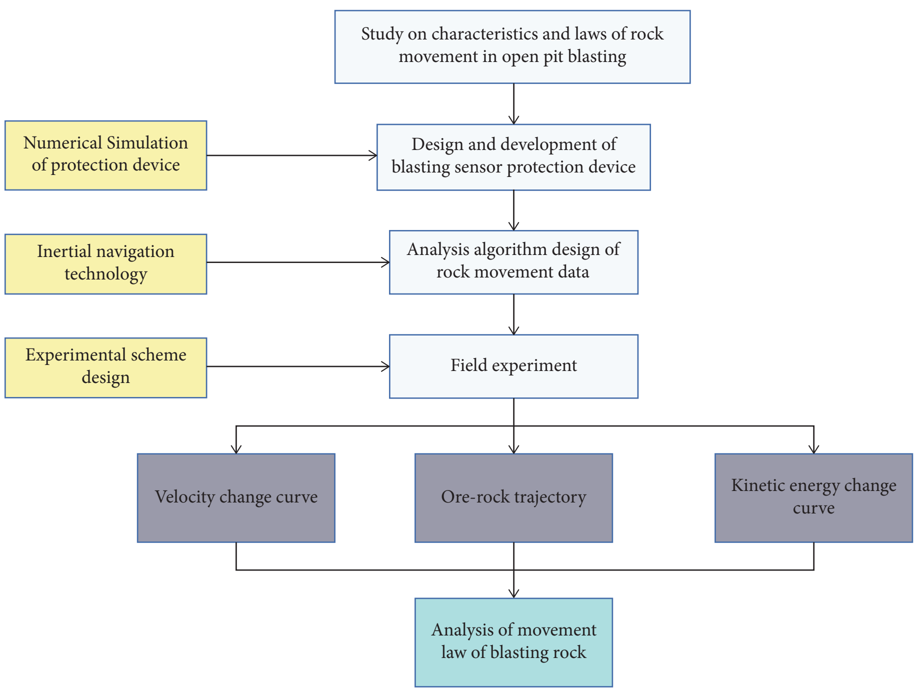

FIGURE 7: Experimental technical process.

protection devices in the blasting site according to the design plan; and (5) after the blasting, recover the inertial navigation sensor, take out the SD card, and extract the data.

During the blasting process of the mine, there are many factors that affect the blasting effect. All the known influencing elements are screened through the support vector machine algorithm, and the important influencing parameters are obtained as the input parameters of the support vector machine model. Support the use of the feature attributes in the support vector machine algorithm model to filter the main influencing factors, randomly give each feature a random weight, and select a certain number of features each time, with the previous intersection for training and learning, after continuous cycles, finally. The degree of influence of the remaining factor features on the classification task can be determined.

4.4. Prediction Based on the Improved Support Vector Machine Model. The reasons that affect the blasting rock trajectory mainly include four categories: one is blasting parameters, the second is explosive blasting parameters, the third is rock mass structure characteristics, and the fourth is physical and mechanical properties of intact rock and discontinuity. Among them, the blasting parameters include diameter of blasthole, blasthole depth, blasthole spacing, charge length, blasthole angle, blasthole filling length, minimum resistance line, and step height. The above indicators are all controllable, while blasthole diameter is the most important indicator of the above parameters. Explosion parameters of explosives include type of explosive, density of explosives, power, and intensity. The physical and mechanical properties of intact rock and discontinuity include rock mass density, dynamic compressive strength, dynamic tensile strength, shear strength, dynamic elastic modulus, hardness, and mineral composition. The influence of the above factors on the distribution characteristics of the blasting rock trajectory is nonlinear, and it is difficult to obtain a universal empirical formula that includes all parameters. For the establishment of the ore rock trajectory prediction model for ore blasting, on the basis of fully considering the above four types of influencing factors, seven important indicators are selected, which are the ratio of blasthole spacing to resistance line, the ratio of step height to resistance line, the resistance line to shot, the ratio of hole diameter, the ratio of blasthole filling length to resistance line, the unit consumption of explosive, and in-situ block size and elastic modulus.

The data collected at the mine blasting site is analyzed and divided into training set and test set. The training set that needs to be trained is input into the neural network prediction model, the network is trained, and then the test set is input into the neural network prediction model. Then it is compared with the actual effect, and a more appropriate method is chosen to predict the blasting effect. The effective blasting data are obtained by selecting 10 groups of ore rocks, as shown in Table 1. Among them, 0 means that the blasting effect is good, 1 means that the blasting effect is good, and 2 means that the blasting effect is average.

Table 1: Sample data sheet.

Minimum blasting resistance line/m	Unit explosive consumption/ (kg/m^3)	Blasting funnel angle/(°)	Working face width/ m	Real effect
3.927	1.256	125.37	32.5	0
3.476	0.894	140.24	34.6	0
4.569	0.884	135.36	29.5	1
4.326	1.324	134.63	30.6	0
3.326	1.136	142.58	33.5	0
2.969	0.836	125.51	33.3	2
2.453	0.967	123.36	38.5	0
3.656	1.013	133.85	36.6	0
3.337	0.804	137.93	29.9	1
2.969	0.934	129.81	30.9	0

When evaluating the blasting rock trajectory prediction model, two indicators, root mean square error (RMSE) and mean absolute error (MAE), are selected. Among them, RMSE is used to measure the deviation between the observed value of the model and the true value. The MAE can better reflect the actual situation of the predicted value error. Generally speaking, the smaller the value of the two, the more robust the model, and the better the performance. The calculation formulas of the two evaluation indicators are (9)

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} \left(x_i - \widehat{x}_i\right)^2}{n}}, \tag{8}$$

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} \left|x_i - \widehat{x}_i\right|}{n}. \tag{9}$$

4.5. Analysis of Experimental Results. Put the data in the inertial sensor SD card on the computer, read the data through the sensor host computer and save it in txt text format, then convert the txt format data into Excel format and then perform data interception, and remove a large amount of useless data recorded before and after blasting and keep blasting. Useful motion data during the period contains the data content which includes the acceleration of the three axes (ax, ay, az), the angular velocity of the three axes (ωx, ωy, ωz), and the inertial navigation trajectory solution written in MATLAB software. The algorithm program performs data calculation, and the motion trajectory of each sensor is shown in Figures 8, 9, 10, 11, 12, and 13.

Since the experimental stope is blasting with loose slag, sensors 1-1 and 1-2 are located near the outermost row of blastholes, that is, near the slope, and there is no blasting pile left from the previous blasting outside the slope, which is a normal slope; sensor 2-1 and 2-2 are located near the side slope but compared with the first group, and there are explosive piles left from the previous blasting outside the slope; sensors 3-2 and 3-2 are located near the middle blasthole of the stope, and the slope is far away.

Figure 14 and 15 show the distribution diagrams of the root mean square error and the mean absolute error generated by different kernel functions in the prediction process through multiple experiments.

It can be seen from Figures 14 and 15 that the radial basis kernel function is the kernel function with the highest recognition rate and the best performance, and the mean value of the root mean square error and the mean absolute error of the blasting rock trajectory prediction model is the lowest, which are 0.102 and 0.0674, respectively. The evaluation indexes of linear kernel function and radial basis kernel function are relatively similar. In the fifth experiment, the performance of the linear kernel function is slightly higher than that of the radial basis kernel function, but the other nine experiments have proved the superiority of the radial basis kernel function. This shows that the optimal model is determined by only one random experiment, and the random error is large, and it is more scientific and reasonable to use the mean value of the evaluation parameters as the criterion for the optimal model through multiple random experiments.

The motion trajectory of each sensor as a whole shows that it is thrown up and then dropped. During this period, there is a certain horizontal displacement. The direction and size of the horizontal displacement of each sensor are different. The direction of the horizontal displacement shows a certain randomness, and the horizontal displacement is the largest. The sensor 1-2 is about 11.5 m, the direction is along

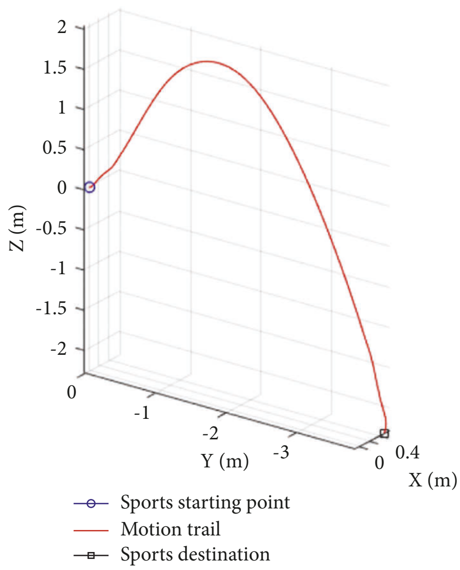

Figure 8: Movement track of sensor 1-1.

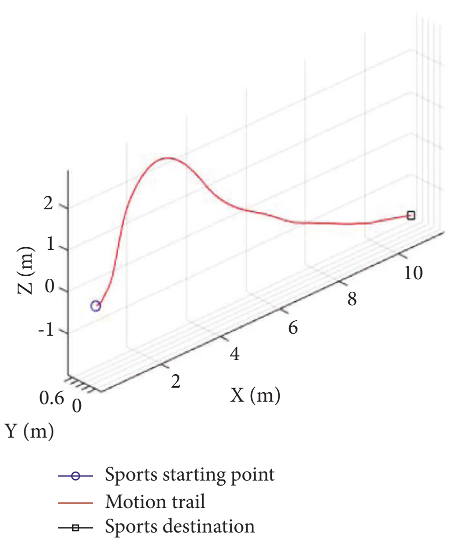

Figure 9: Movement track of sensor 1-2.

the positive direction of the X-axis, the horizontal displacement of other sensors is about 3 m, and the direction is random, indicating that when the X-axis; in the vertical direction, the largest upward displacement is sensor 3-1, which is about 5.3 m, and the smallest upward displacement is sensor 1-1, which is about 2 m; the largest downward displacement is sensor 2-2, which is about 4.8 m, and the smallest downward displacement is sensor 2-1, which is about 0.2 m. By comparing the three-dimensional models before and after the stope blasting, the placement of all sensors conforms to the actual situation on-site.

By analyzing the direction and size of the horizontal displacement of the sensor, it is shown that the movement direction of the sensor near the slope position is mainly along the direction perpendicular to the nearest free surface, and the smaller the distance from the free surface, the greater

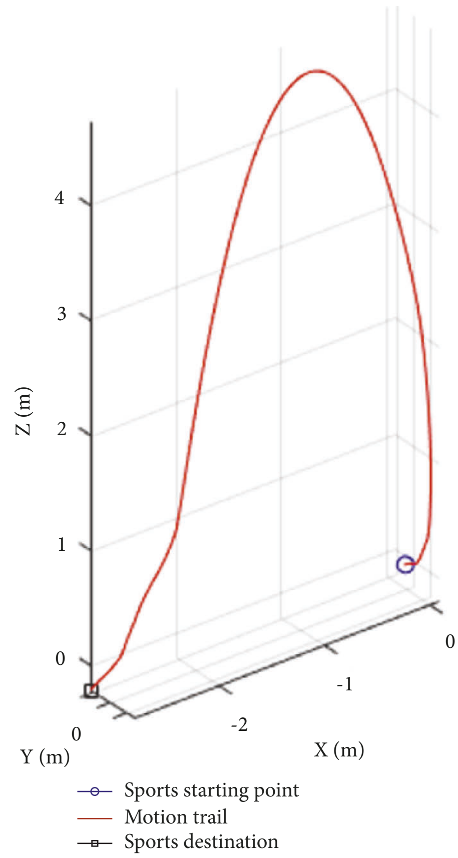

Figure 10: Movement track of sensor 2-1.

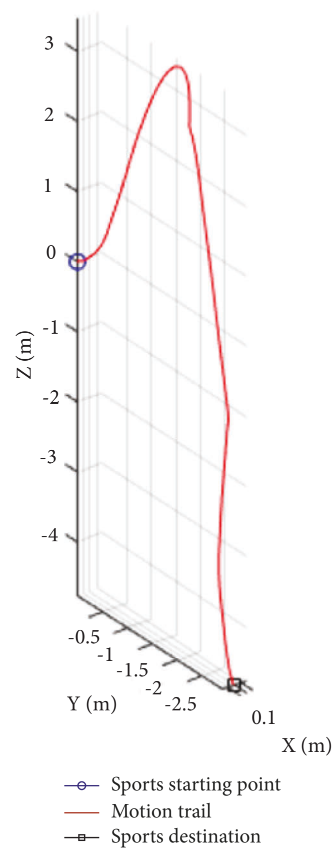

Figure 11: Movement track of sensor 2-2.

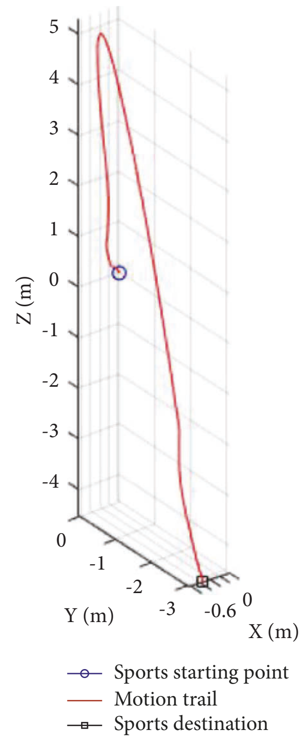

FIGURE 12: Sensor 3-1 motion track diagram.

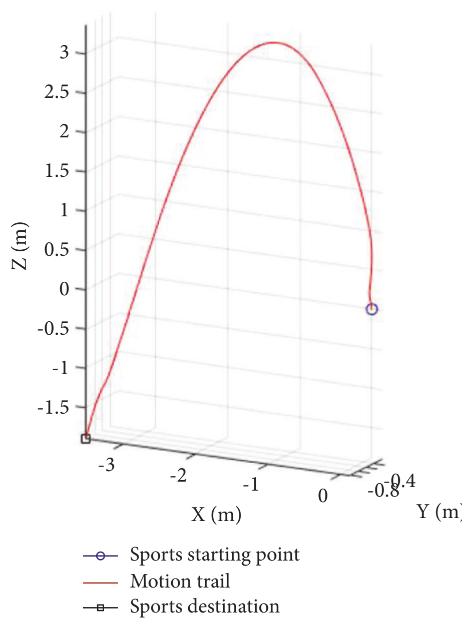

FIGURE 13: Movement track of sensor 3-2.

the horizontal displacement of the sensor. Among them, when the sensor is located at the edge and corner of the stope, such as sensor 1-1, its movement direction will be affected by the nearby blastholes and shifted to the direction without blastholes; for sensors 2-1 and 2-2, the free surface with the shortest distance will be changed by the influence of the residual explosion, and the movement direction will show randomness. By analyzing the uplift height of the sensor, it is found that the uplift height of the sensor at the slope position is lower than that of the sensor in the middle of the stope and the uplift height of the sensor near the slope, where there is an external explosion that is greater than that

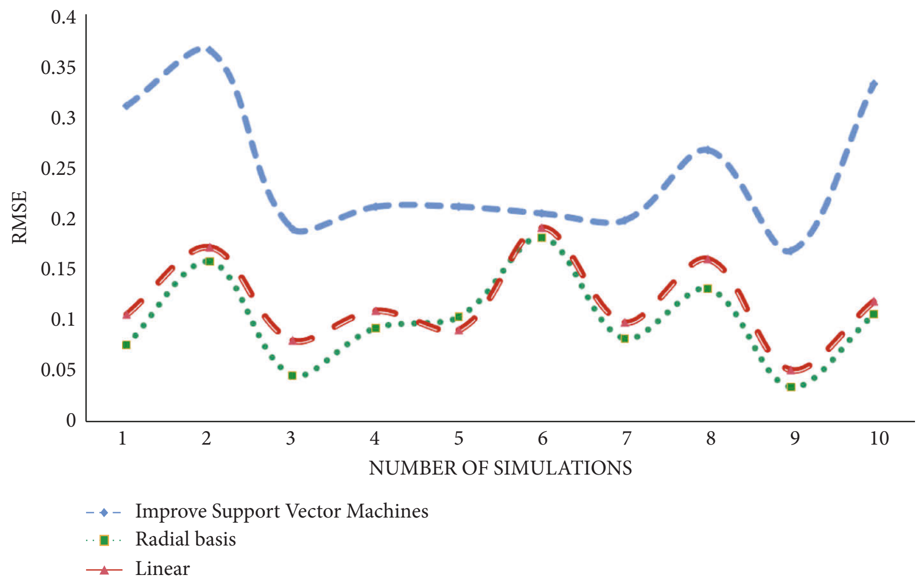

Figure 14: Root mean square error distribution of different kernel functions.

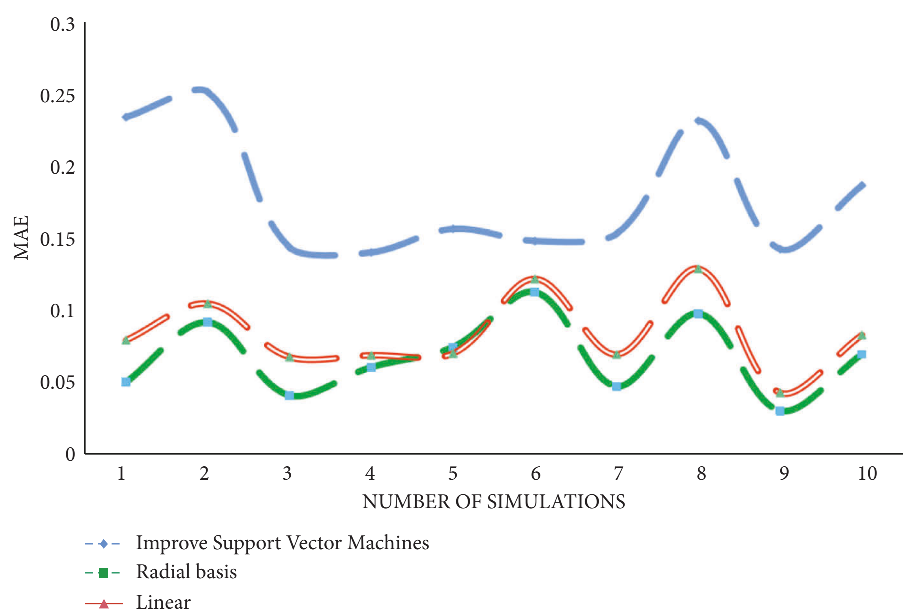

Figure 15: Distribution of the mean absolute error of different kernel functions.

of the sensor without the external explosion, indicating that the farther the blasting hole is from the free surface during the blasting process, the higher the energy acting on the vertical direction.

5. Conclusions

The main conclusions are as follows:

(i) This paper innovatively proposes a research method that uses high-precision MEMS inertial navigation sensors to monitor the movement characteristics of ore and rocks during stope blasting. The results obtained through field experiments show that this method can record more realistically and accurately. The movement state and characteristics of ore rock during blasting.

(ii) The change process of the movement speed of ore rock is divided into five stages, and each stage has a different shape; many collisions will occur during the initial acceleration process, and few collisions occur in other stages.

(iii) The movement trajectory of the ore rock shows that it is thrown up and then dropped; accompanied by a certain horizontal displacement during the period, the ore rock at the slope position generally moves in the direction of the vertical nearest free surface, and the movement direction of the ore rock in the middle of the stope has a certain movement direction and randomness.

(iv) During the blasting process, the energy generated by the explosive mainly acts on the vertical direction, and the farther the blasthole is from the free surface position, the more energy acts on the vertical direction. The action efficiency of blasting energy is higher than that of the slope, and the action efficiency of blasting energy is higher than that of the ordinary slope.

(v) Under the full consideration of various influencing factors of ore rock blasting trajectory, the ratio of blasthole spacing to resistance line, the ratio of step height to resistance line, the ratio of resistance line to blasthole diameter, and the length of blasthole filling and resistance are selected. The ratio of the line, the unit consumption of explosives, the size of the in-situ block, and the elastic modulus, and a total of seven types of important indicators carry out research on the prediction model of the ore-rock trajectory for ore-rock blasting.Based on the cross-validation method, through the support vector machine model parameter optimization and comparative evaluation parameters, the optimal prediction model of the blasting ore and rock trajectory is obtained as the support vector machine model based on the radial basis kernel function. The mean value of root mean square error and mean absolute error of this model are 0.102 and 0.0674, respectively, and the performance is the most robust among the three types of models.

The field experiment results show that according to the characteristics of inertial sensors that can work completely independently, it is feasible to use high-precision inertial sensors to monitor the movement characteristics of ore and rock during stope blasting and the state and characteristics of rock movement during blasting. However, since the inertial sensor needs to use the median method to integrate the data once or twice with respect to time in the solution process, there is a certain error in this method, and the error will gradually accumulate with the increase of time. Therefore, in the future, in the process of research, the calculation method of the inertial sensor should be further optimized so as to make the obtained experimental data more real and reliable [20].

Data Availability

All data, models, and code generated or used during the study are included in the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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