Prediction of dilatancy of tunnel surrounding rock in coal measure strata: A case study of Huainan mining area

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Abstract. In this study, the dilatancy of tunnel surrounding rock in coal measure strata was comprehensively investigated by means of field monitoring, theory analysis and algorithm analysis. The study reveals that dilatancy is related to many phenomena of coal mine disasters such as gas outburst, rib spalling and rock burst. Accordingly, the method of predicting these phenomena through dilatancy monitoring was proposed. Furthermore, a method based on support vector machine was proposed to predict the dilatancy of coal seams, and the dilatancy limit of coal and rock mass was defined as the criterion for judging whether a working face was to undergo dynamic disasters. A working face will undergo disasters when its dilatancy exceeds the dilatancy limit, in which case the support of working face should be strengthened. The criterion was then verified in the stope. The research results have important guiding significance for prediction and prevention of coal seam disasters.

1. Introduction
With the construction and development of basic transportation in China, more and more tunnels pass through coal measure strata and gas-bearing strata. Coal measure strata are common soft and weak surrounding rocks which have low strength, developed joints and fractures, smooth joint surfaces, poor interlayer cementation and uncontrollable stability. Moreover, affected by gas occurrence in coal measure strata, the deformation characteristics of tunnel surrounding rock become more complicated [1, 2]. Surrounding rock instability accidents caused by tunnel construction are also constantly increasing. Hence, it is urgent to find an effective method to evaluate the risk of tunnel surrounding rock instability in coal measure strata. Researches on excavation projects in gas-bearing coal seams show that the process of coal seam deformation and failure is accompanied by dilatancy phenomenon, namely, an important mechanical behavior in the process of deformation and failure of gas-bearing coal [3]. Pan et al. conducted experiments on impact coal with different properties and strengths, revealing that dilatancy occurred before the failure of coal seams with different impact tendencies [4]. The investigation on coal mine roadways which have undergone surrounding rock instability and damage shows that the process of roadway floor heave, gas outburst and other disasters are accompanied by dilatancy phenomenon, and dilatancy phenomenon can serve as precursor information of the above-mentioned disasters [5-8]. Therefore, it is of great engineering significance to predict the occurrence of gas outburst, rib spalling and rock burst in tunnel surrounding rock in coal measure strata through coal and rock mass dilatancy (CRMD).

Support vector machine (SVM) [9], which is jointly proposed by Vapnik and his collaborators, is a new universal learning method based on the theory of Vapnik Chervonenks (VC) dimension and the principle of structure risk minimization. It can solve practical problems such as nonlinearity, small
sample, high dimensionality and local minimum. SVM has become one of the new research hotspots of machine learning and has been successfully applied to pattern recognition, function approximation and time series prediction. CRMD prediction can be regarded as the approximation of a complex nonlinear relationship between dilatancy and its various influencing factors. Therefore, the study attempts to apply the SVM principle to CRMD prediction. Based on limited sample information, a SVM model was established to predict CRMD. Field experiments show that this method can achieve relatively good prediction results and is of great significance for the prediction and control of surrounding rock disasters in coal measure strata.

2. Factors affecting coal rock mass dilatancy
The analysis of factors affecting CRMD is the basis for CRMD prediction, so these factors are taken as input vectors. CRMD is affected by many factors, because coal mining is characterized by complex mining environment and different geological structures. After years of effort, scholars have constantly supplemented relevant data in previous researches on coal mining. In light of these data, this study summarized the following five main influencing factors: (1) original rock stress which refers to the stress state of rock mass before being disturbed by excavation: It has an important impact on roadway excavation and coal mining because its strength is greatly affected by the confining pressure of rock; (2) mining-induced stress concentration factor which refers to the ratio of mining-induced stress concentration around the working face to the original rock stress: It is the main factor controlling coal and rock mass failure; (3) gas pressure which refers to the pressure of free gas contained in coal seam pores, or the pressure of gas acting on pores; (4) compressive strength of gas-containing coal; (5) gas content.

3. Principle of SVM
SVM is a general machine learning method primarily invented by Vappnik on the basis of statistical theory. With a strict theoretical basis, the method can solve problems such as small samples, fractional linearity and high dimensionality and boasts excellent generalization performance for cases of small samples. The basic idea of SVM is to map input vectors to a high-dimensional feature space by choosing a nonlinear mapping beforehand and then construct the optimal separating hyperplane in this space. The basic idea is shown in Fig. 1.

![Figure 1. Model of SVM.](image)

The training sample is assumed to be

\[(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n) \in X \times Y \]

where \(X\) is the input space vector; \(n\) is the number of training samples; and \(Y\) is the mode space, and \(Y=\{+1, -1\}\).

The separating hyperplane is assumed to be

\[y = \text{sign} \left[ (w \cdot x) + b \right] \]

where \(w\) is the weight vector; \(x\) is the input vector; and \(b\) is the threshold value.
For separable hyperplane classifiers, the classification condition without any training error is
\[ y_i \left[ (w \cdot x_i) + b \right] \geq 1 \quad (i = 1, 2, \ldots, n) \tag{3} \]

In practice, input variables are usually transformed nonlinearly first. The nonlinear transformation maps data in the input space \( R^n \) to a feature space \( G \). For example,
\[ \Phi : R^n \rightarrow G \quad x \rightarrow \Phi (x) \tag{4} \]

Thus, the separating hyperplane is transformed to
\[ y = \text{sign} \left[ w \cdot \Phi (x) + b \right] \]

The constraint for error-free classification in the feature space is
\[ y_i \left[ w \cdot \Phi (x_i) + b \right] \geq 1 \quad (i = 1, 2, \ldots, n) \tag{5} \]

The goal of learning is to find \( w \in G \) and scalar \( b \) to minimize the expected risk. According to the theory of VC dimension, an upper bound of minimizing empirical risk and model complexity can be expressed as the following quadratic programming problem:
\[ \min_{w, b} \frac{1}{2} \left\| w \right\|^2 \tag{6} \]

For the quadratic programming problem, the Lagrange multiplier \( \alpha_i \geq 0, i = 1, 2, \ldots, n \) is introduced for each constraint of Eq. (3). The following Lagrangian function is obtained:
\[ L (w, b, \alpha) = \frac{1}{2} \left\| w \right\|^2 - \sum_{i=1}^{n} \alpha_i \left[ y_i \left[ w \cdot \Phi (x_i) + b \right] - 1 \right] \tag{7} \]

The task then becomes the minimization of \( w \) and \( b \) and the maximization of \( \alpha_i \). In the optimal case, \( \frac{\partial L}{\partial b} = 0 \) and \( \frac{\partial L}{\partial w} = 0 \) exist according to the K-T condition. Eq. (8) can be acquired by calculation:
\[ \begin{aligned}
\sum_{i=1}^{n} \alpha_i y_i &= 0 \\
\alpha_i &\geq 0, i = 1, 2, \ldots, n \\
\sum_{i=1}^{n} \alpha_i &= 0 
\end{aligned} \tag{8} \]

By substituting Eq. (6) into Eq. (4), the following dual quadratic programming problem can be obtained:
\[ \begin{align*}
\max \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j [\Phi (x_i) \cdot \Phi (x_j)] \\
s.t. \quad \alpha_i &\geq 0, i = 1, 2, \ldots, n \\
\sum_{i=1}^{n} \alpha_i y_i &= 0
\end{align*} \tag{9} \]

It can be known from the dual quadratic programming problem that \( \Phi (x_i) \) only interacts through the inner product. According to the Mercer’s theorem, the function \( k(u, v) \) that satisfies Mercer’s condition becomes Mercer’s kernel function. Then, there exists a space \( H \) and a mapping \( \Phi: R^n \rightarrow G \) which leads to \( k(u, v) = \Phi (u) \cdot \Phi (v) \). Therefore, the technique can be adopted to directly calculate the inner product of image in the feature space with the aid of data in the input space. The coefficient \( \alpha_i \), where \( i = 1, 2, \ldots, n \) can be acquired by solving the dual problem. The vector \( x_i \) corresponding to \( \alpha_i \neq 0 \) is called a support vector, and a nonlinear decision function is obtained:
\[ f (x) = \text{sign} \left[ \sum_{i=1}^{n} y_i \alpha_i [\Phi (x) \cdot \Phi (x_i) + b] \right] = \text{sign} \left[ \sum_{i=1}^{n} y_i \alpha_i k (x, x_i) \right] \tag{10} \]
There are certain distances between both types of sample and the decision surface, and any separating hyperplane may be separated wrongly when the training set is linearly inseparable. Considering the two facts, the relaxation variable $\xi_i \geq 0$ is introduced. The constraint is

$$y_i [\langle w \cdot x_i \rangle + b] + \xi_i \geq 1, \quad (i = 1, 2, \ldots, n)$$

A penalty parameter $C$ that determines a trade-off between the empirical error and model complexity is introduced. In this case, the problem of optimal separating surface is

$$\min = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{n} \xi_i$$

s.t. $y_i [\langle w \cdot x_i \rangle + b] \geq 1 - \xi_i, \quad (i = 1, 2, \ldots, n)$

At present, the most commonly used kernel functions are polynomial kernel functions, Gaussian radial basis kernel functions and Sigmoid kernel functions. The selection of an appropriate kernel function is the key to nonlinear regression and plays an important role in model building. The currently commonly used solutions for the quadratic optimization problem in Eq. (10) include the SMO method, the decomposition method, etc. Among them, the decomposition method is able to quickly get the optimal result in the process of sample learning.

4. Analysis of on-site monitoring and prediction results

The prediction of CRMD based on SVM is actually the establishment of a relationship between the factors affecting CRMD and the occurrence of dilatancy. The kernel function adopted in this study is a radial basis function (RBF):

$$K(x, x_i) = \exp\left(-\gamma \|x - x_i\|^2\right)$$

SVM mainly contains two parameters, namely the kernel function parameter and the penalty parameter $C$. The difference in parameters directly influences the learning efficiency and generalization performance of SVM. In this study, the trial algorithm was employed to learn whether CRMD would occur according to the selected samples, and the appropriate parameters were obtained by testing. According to the above description, 5 main factors affecting CRMD were selected, and 18 actual monitoring sample data were chosen as training samples. The training results are listed in Table 1.

In Table 1, the case in which rock dilatancy exceeds the dilatancy limit is defined as “1”, while the case in which rock dilatancy does not exceed the dilatancy limit is defined as “0”. For the actual monitoring samples No. 3, 5, 6, 8, 9, 11, 12, 15 and 18, their dilatancy amounts all exceed the dilatancy limit, indicating the occurrence of disasters. For the rest of monitoring samples, their dilatancy amounts do not exceed the dilatancy limit, indicating no occurrence of disasters. It can be seen that the final training results obtained by the trial algorithm are 100% coincident with the actual monitoring results.

| Sample No. | Original rock stress /MPa | Mining-induced stress concentration factor /K | Gas pressure /MPa | Compressive strength /MPa | Gas content /m³/t | Actual dilatancy situation | Remark | Training result |
|------------|--------------------------|---------------------------------------------|------------------|--------------------------|------------------|--------------------------|--------|----------------|
| 1          | 9.9                      | 1.6                                         | 0.1              | 32                       | 8.11             | 0                        | 714 airway of Qinan Coal Mine | 0      |
| 2          | 9.9                      | 1.8                                         | 0.3              | 32                       | 8.11             | 0                        | Upper side of 714 machine roadway of Qinan Coal Mine | 0      |
| 3          | 9.9                      | 2.6                                         | 0.45             | 32                       | 8.11             | 1                        | 714 machine roadway of Qinan Coal Mine | 1      |
| 4          | 8.8                      | 0.9                                         | 0.1              | 14                       | 4.5              | 0                        | 724 airway of Qinan Coal Mine | 0      |
5  8.8  1.5  0.38  14  4.5  1  Upper side of 724 machine roadway of Qinan Coal Mine 1
6  8.8  1.8  0.45  14  4.5  1  Lower side of 724 machine roadway of Qinan Coal Mine 1
7  11  1.1  0.2  17  9  0  17218 airway of Zhangji Coal Mine 0
8  11  1.5  0.3  17  9  1  Upper side of 17218 machine roadway of Zhangji Coal Mine 1
9  11  1.5  0.37  17  9  1  Lower side of 17218 machine roadway of Zhangji Coal Mine 1
10 11  1  0.1  19  9  0  11121 airway of Zhangji Coal Mine 0
11 11  1.55  0.15  19  9  1  Upper side of 11121 machine roadway of Zhangji Coal Mine 1
12 11  1.7  0.2  19  9  1  Lower side of 11121 machine roadway of Zhangji Coal Mine 1
13 12  0.8  0.3  24  4.7  0  12418 airway of Xieqiao Coal Mine 0
14 12  1.25  0.5  24  4.7  0  Upper side of 12418 machine roadway of Xieqiao Coal Mine 0
15 12  1.7  0.7  24  4.7  1  Lower side of 12418 machine roadway of Xieqiao Coal Mine 1
16 12  0.85  0.2  19  4.7  0  12313 airway of Xieqiao Coal Mine 0
17 12  1  0.4  19  4.7  0  Upper side of 12313 machine roadway of Xieqiao Coal Mine 0
18 12  1.33  0.65  19  4.7  1  Lower side of 12313 machine roadway of Xieqiao Coal Mine 1

Table 2. Classification results based on the SVM model of CRMD.

| Sample No. | Original rock stress /MPa | Mining-induced stress concentration factor /K | Gas pressure /MPa | Compressive strength /MPa | Gas content /(m³/t) | Actual dilatancy situation | Remark | Prediction result |
|------------|---------------------------|---------------------------------------------|-------------------|--------------------------|-------------------|--------------------------|--------|------------------|
| 19         | 12.8                      | 1.9                                         | 0.74              | 17                       | 6                 | 1                        | Upper side of 62110 machine roadway of Xinzhuangzi Coal Mine | 1      |
| 20         | 10.78                     | 1.34                                        | 0.33              | 21.8                     | 6.67              | 0                        | Upper side of 54108 machine roadway of Xinzhuangzi Coal Mine | 0      |
After the training of 18 samples, dilatancy in sample No. 19 (upper side of 62110 machine roadway of Xinzhuangzi Coal Mine) and No. 20 sample (upper side of 54108 machine roadway of Xinzhuangzi Coal Mine) was predicted. The prediction results are given in Table 2. The dilatancy amount of sample No. 19 exceeds the dilatancy limit, suggesting that it will undergo disasters; the dilatancy amount of sample No. 20 does not exceed the dilatancy limit, suggesting that it will not undergo disasters. Later practice proves that the actual situation is consistent with the predicted results.

5. Conclusion
(1) The dilatancy phenomenon is the precursor information of surrounding rock instability disasters in coal-bearing tunnels, such as gas outburst, rib spalling, rock burst and floor heave. CRMD prediction helps to predict and prevent the above surrounding rock instability disasters.

(2) Based on the SVM method, a prediction model of CRMD was constructed. In this model, the main affecting factors include original rock stress, gas pressure, compressive strength of coal and rock mass, mining stress and gas content. A new method of prediction of surrounding rock dilatancy of coal-bearing tunnel was put forward.

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