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Rockburst prediction and classification based on the ideal-point method of information theory

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ABSTRACT

A rockburst is a sudden dynamic process under high geostress conditions where rocks spontaneously explode. This is an important geological problem for underground construction processes. A rockburst could lead to equipment damage, casualties, and construction delays. Therefore, rockburst prediction and classification are extremely significant. A prediction and classification model is established by introducing the basic theory of the ideal-point method, considering the rockburst mechanism. Three parameters are selected as evaluation indexes, including the rock stress coefficient (σ_θ/σ_c), rock brittleness coefficient (σ_c/σ_t), and elastic energy index (W_{et}). To eliminate any correlation between the parameters, a principal component analysis based on mutual information (MIPCA) for the rockburst feature selection is used to calculate a new group of parameters. Then, using the information-entropy theory, the weight coefficients of these new evaluation indexes are confirmed. Finally, using statistics-related projects, engineering-case analyses show the feasibility and applicability of the proposed model. A computer evaluation program with a rockburst-classification interface was developed, based on the proposed model. This model and computer software can be used for other similar engineering practices in the future.

1. Introduction

A rockburst is a dynamic process in high geostress conditions, where a rapid release of energy causes rocks to spontaneously explode. This could lead to equipment damage, casualties, and construction delays (Cai, 2013; Ortlepp and Stacey, 1994). Rockbursts' complicated mechanism and numerous classification criteria make them an extremely tough problem for deep underground construction and mining engineering. Many rockburst-evaluation standards are commonly employed in current practice (as shown in Table 1). They include various factors that occur in rockbursts, and have played an important role in rockburst prediction.

Rockburst prediction is the key to preventing rockbursts (Cai, 2016). Peng et al. (2010) divided rockburst prediction into two categories: long-term and short-term. Long-term prediction's main objective is to serve as a guide for decision-making during the initial stages of a project. Short-term predictions aim to predict the time and location of a rockburst occurrence (Li et al., 2017). This research considers long-term rockburst prediction.

Many scholars have investigated rockburst predictions using data-mining methods and artificial intelligence. For instance, Wang et al. (1998) proposed a rockburst-prediction method based on fuzzy comprehensive evaluation. Some researchers (Feng et al., 1998; Li et al., 2005; Liang, 2004) have applied neural networks to rockburst predictions, and Dorigo and Blum (2005) employed an ant-colony optimization. Others have employed multidimensional extension theories (Sandru et al., 2013; Zuo and Chen, 2007) to predict rockbursts. In addition, many other mathematical methods (Li and Liu, 2015; Wang et al., 2010; Yan and Ma, 2013; Zhao, 2005) have been employed to predict rockbursts.

The above theories use different angles to forecast the rockburst, leading to certain prediction results. However, because of the complexity of the rock mass and a variety of influencing factors, it is very difficult to exactly predict the space–time distribution of a rockburst. Thus, the results of various prediction methods should be analyzed comprehensively. Moreover, each method has its own advantages and disadvantages, and understanding, predicting, and controlling rockbursts still pose a considerable challenge for underground engineering.

The rockburst mechanism is complex and includes many predictive indexes. However, most previous evaluation methods only base the

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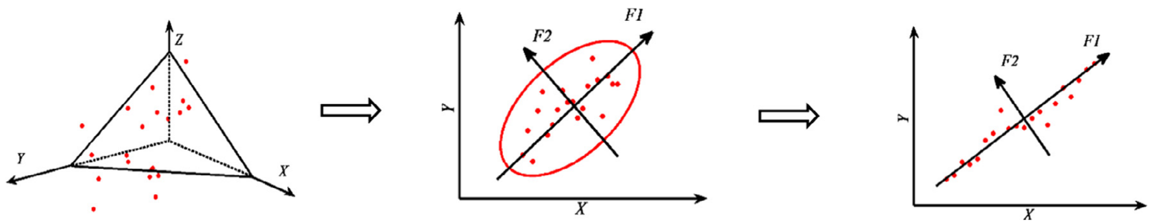
Table 1
A summary of criteria for rockburst.

Proposed by	Parameters	Classification standard			
		None (I)	Light (II)	Moderate (III)	Strong (IV)
Russenes criterion (Russebes, 1974)	σ_θ/σ_c	< 0.2	0.2–0.3	0.3–0.55	> 0.55
Hoek criterion (Hoek and Brown, 1980)	σ_θ/σ_c	0–0.34	0.34–0.42	0.42–0.56	0.56–0.70
Rock brittleness coefficient (Wang et al., 1998)	σ_c/σ_t	> 40	26.7–40	14.5–26.7	< 14.5
Depth prediction critical (Hou and Wang, 1989)	H_{cr}	Critical depth: 312.6–442.4			
Elastic energy index (Wang et al., 1998)	W_{et}	< 2	2–3.5	3.5–5	> 5

Note: σ_θ is maximum tangential stress, MPa; σ_c is uniaxial compressive strength, MPa; σ_t is uniaxial tensile strength, MPa; H_{cr} is depth, m; W_{et} is elastic energy index.



(a) Data representation (b) Dimension reduction (c) Second dimension reduction

Fig. 1. Principal components determination.

model on its construction-project background, so they cannot serve a wide range of applications (Coli et al., 2010; Feit et al., 2002; Lv et al., 2005; Zhang and Fu, 2008; Zhang et al., 2004). On the other hand, almost all projects include the rock stress coefficient, rock brittleness coefficient, and elastic energy index; therefore, we selected these three common rockburst parameters as evaluation indexes for a wide range of applications. A model for predicting and classifying rockbursts is proposed, based on the ideal-point method of information theory. Compared with other prediction methods, we show the feasibility and applicability of our proposed method based on statistics-related projects.

2. Methodology using the ideal-point method of information theory

2.1. Principal component analysis based on mutual information (MIPCA)

To establish the predictive models and avoid the duplication of information among the selected parameters in this research, principal component analysis (PCA) was employed in the initial analysis stage. PCA is a statistical analysis method based on the K-L transformation (Jorgensen, 2007). Its basic idea is to reduce the dimensions, while ensuring that the reduced-dimension data sets keep as much of the original information as possible.

Using a linear conversion, the original space is converted to a low-dimensional principal component space, and the new features after the conversion are the main component. Fig. 1(a) shows a three-variable data set, which is measured in the X-Y-Z coordinate system. For a given data set, PCA reduces the dimension, as shown in Fig. 1(b). F1 is the principal direction and F2 is the second important direction in Fig. 1(b) and (c). Then, PCA finds the axis system (i.e., the F1-F2 system in Fig. 1(c)).

In previous research, PCA has usually computed new variables, based on linear combinations of the original variables (Salimi et al., 2016). These variables are selected by calculating the covariance matrix (Engelbrecht, 2007; Jolliffe, 1986). However, the covariance matrix can only reflect a linear correlation between two variables; it cannot determine nonlinear relationships. Mutual information (Shannon and Weaver, 1963) can determine the total amount of information between two variables, based on information theory (Fan et al., 2013). The best advantage of the mutual information method is that it is not limited to linear relationships. Therefore, MIPCA's applicability is wider than PCA, and MIPCA has attracted wide attention in the feature-selection field (Battiti, 1994; Kwak and Choi, 2002; Yang and Moody, 1970). In this paper, we use MIPCA to determine the weight coefficients of the evaluation indexes.

Mutual information can define the interdependence strength between variables that are not limited to a linear correlation, and it represents the amount of information that is common to both variables. For two given random variables X and Y, if $p(x)$ represents the X marginal distribution, then $p(y)$ represents the Y marginal distribution and $p(x, y)$ represents the joint probability distribution of X and Y. Then, the mutual information $I(X; Y)$ of X and Y is defined as follows:

$$I(X;Y) = \sum_x \sum_y p(x,y) \log \frac{p(x,y)}{p(x)p(y)} \tag{1}$$

When variables X and Y are completely independent, the mutual information has a value of 0, which means there is no overlapping information between the two variables. In contrast, the higher the degree of interdependence, the larger the amount of mutual information; thus, the two variables have more information in common. The MIPCA calculation process is as follows:

Step 1: Calculate the mutual information matrix:

$$\sum I_{XY} = \begin{bmatrix} I(1,1) & I(1,2) & \cdots & I(1,P) \\ I(2,1) & I(2,2) & \cdots & I(2,P) \\ \vdots & \vdots & \vdots & \vdots \\ I(P,1) & I(P,2) & \cdots & I(P,P) \end{bmatrix}, \tag{2}$$

where ΣI_{XY} serves as the value of the mutual information, and the mutual information matrix is a real symmetric matrix (which means $I(i, j) = I(j, i)$). The diagonal elements of the matrix represent the variable's self-information and information entropy, and the non-diagonal elements represent the mutual information between two variables.

Step 2: Calculate the eigenvalues and eigenvectors of the mutual information matrix, according to Eqs. (3) and (4). Then, sort the eigenvalues in descending order and find the corresponding eigenvectors.

$$|\lambda E - \sum I_{XY}| = 0 \tag{3}$$

$$B' \sum I_{XY} B = \Lambda, \tag{4}$$

where λ denotes the eigenvalue and E is a unit matrix. $B(\beta_1, \beta_2, \ldots, \beta_p)$ is a matrix of feature vectors, B' is the matrix transposition of B, and $\Lambda(\mu_1, \mu_2, \ldots, \mu_p)$ represents a diagonal matrix consisting of eigenvalues.