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Bayes discriminant analysis method to identify risky of complicated goaf in mines and its application

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Abstract: A Bayes discriminant analysis method to identify the risky of complicated goaf in mines was presented. Nine factors influencing the stability of goaf risky, including uniaxial compressive strength of rock, elastic modulus of rock, rock quality designation (RQD), area ratio of pillar, ratio of width to height of pillar, depth of ore body, volume of goaf, dip of ore body and area of goaf, were selected as discriminant indexes in the stability analysis of goaf. The actual data of 40 goafs were used as training samples to establish a discriminant analysis model to identify the stability of goaf. The results show that this discriminant analysis model has high precision and misdiscriminant ratio is 0.025 in re-substitution process. The instability identification of a metal mine was distinguished by using this model and the identification result is identical with that of practical situation.
Key words: goaf; risky identification; Bayes discriminant analysis; metal mines

1 Introduction

In mining process of metal mines, a large number of underground goafs were brought about by using room and pillar method, a comprehensive law method and shrinkage method [1,2]. On the other hand, for most metal mines, such as Dachang mining, Luanchuan molybdenum, Changba zinc, Qinling gold and Kaiyang phosphate rock, there are also some underground goafs because of more than ten years non-governmental predatory exploitation. Statistics show that, in most mine accidents, goaf collapse is a very common incentive. And goaf has become one of main sources of harm, and is also risky in production [3,4]. Therefore, the risky identification of goaf is very important to ensure safety production of open and underground mining operations and to avoid the occurrence of major accidents in mines [5].

Many scholars have done a lot of work about risky identification. CHEN [6] has presented a monograph on the hazard identification, control and evaluation of the system discussed. And fuzzy comprehensive evaluation method (FCEM) [7], grey clustering analysis method (GCAM) [8,9] and artificial neural network (ANN) [10,11] theory have been used and got good effectiveness. Distance discriminant analysis method is a statistical analysis method based on observed characteristics (discriminant factor) of a certain number of samples and discriminant criterion, which had been used in mining and safety engineering recently [12−14]. However, for distance discriminant analysis method, the prior probability of each collectivity (Classification grade) is not taken into account and the difference of loss produced by mistake-discrimination is also neglected [11]. To solve the faults of distance discriminant analysis method, a Bayes discriminant analysis (BDA) model was presented to predict the stability of open pit slope in metal mines.

In the present work, in combination of the Bayes discriminant analysis theory and actual situation and stability factors of goaf, a Bayes discriminant analysis model is built and used in a practical engineering.

2 Bayes discriminant analysis method

2.1 Basic ideology of Bayes discriminant

Bayes discriminant is a probability discriminant

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analysis and various types of distribution density functions should be obtained before proceeding. The priori distribution was used to descript the level of awareness of the study collectivity before extracting samples, and then the posterior distribution was obtained by modifying the priori distribution based on extracted samples, followed by a variety of statistical inference. Following is a brief introduction and a variety of types of general overall Bayes discriminant [15].

2.2 Bayes discriminant of two normal collectivities

Suppose $\boldsymbol{G}=(\boldsymbol{X}_1,\boldsymbol{X}_2,\cdots,\boldsymbol{X}_P)^{\mathrm{T}}$ is a collectivity with p member indexes(Considering p indexes), and there are two collectivities, $\boldsymbol{G}_1$, $\boldsymbol{G}_2$, with distribution density functions, $\boldsymbol{f}_1(\boldsymbol{X}), \boldsymbol{f}_2(\boldsymbol{X})$. Suppose the priori distributions of $\boldsymbol{G}_1$ and $\boldsymbol{G}_2$ are

$$p_1=P(\boldsymbol{G}_1),\quad p_2=P(\boldsymbol{G}_2) \tag{1}$$

with $p_1+p_2=1$. $c(2|1)$ is the loss caused by misjudging $\boldsymbol{G}_1$ to $\boldsymbol{G}_2$, and $c(2|1)$ is the loss caused by misjudging $\boldsymbol{G}_2$ to $\boldsymbol{G}_1$.

When $\boldsymbol{\Sigma}_1=\boldsymbol{\Sigma}_2=\boldsymbol{\Sigma}$ for two normal collectivities, $\boldsymbol{G}_1$, $\boldsymbol{G}_2$, with $c(2|1)=c(1|2)$, Bayes discriminant function can be expressed as:

$$W_j(\boldsymbol{X})=(\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu}_j)^{\mathrm{T}}-0.5\boldsymbol{\mu}_j{}^{\mathrm{T}}\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu}_j+\ln p_j,\ j=1,\ 2 \tag{2}$$

Then, generalized squared distance function can be obtained as follows:

$$d_j^2(\boldsymbol{X})=(\boldsymbol{X}-\boldsymbol{\mu}_j)^{\mathrm{T}}\boldsymbol{\Sigma}^{-1}(\boldsymbol{X}-\boldsymbol{\mu}_j)-2\ln p_j \tag{3}$$

with $\boldsymbol{\mu}_1$ and $\boldsymbol{\mu}_2$ as mean vectors of $\boldsymbol{G}_1$, $\boldsymbol{G}_2$. And then posteriori probability function can be obtained:

$$P(\boldsymbol{G}_j\mid\boldsymbol{X})=\frac{p_jf_j(\boldsymbol{X})}{p_1f_1(\boldsymbol{X})+p_2f_2(\boldsymbol{X})} \tag{4}$$

Because $p_jf_j(\boldsymbol{X})\propto\exp[-0.5d_j^2(\boldsymbol{X})]$, then

$$P(\boldsymbol{G}_j\mid\boldsymbol{X})=\frac{\exp[-0.5d_j^2(\boldsymbol{X})]}{\exp[-0.5d_1^2(\boldsymbol{X})]+\exp[-0.5d_2^2(\boldsymbol{X})]} \tag{5}$$

Normally, $\boldsymbol{\mu}_1$, $\boldsymbol{\mu}_2$ and $\boldsymbol{\Sigma}$ are unknown and their estimation values $\hat{\boldsymbol{\mu}}_1$, $\hat{\boldsymbol{\mu}}_2$ and $\hat{\boldsymbol{\Sigma}}$ can be obtained from training samples, then

$$\hat{d}_j^2(\boldsymbol{X})=(\boldsymbol{X}-\hat{\boldsymbol{\mu}}_j)^{\mathrm{T}}\hat{\boldsymbol{\Sigma}}^{-1}(\boldsymbol{X}-\hat{\boldsymbol{\mu}}_j)-2\ln p_j \tag{6}$$

The estimation of posteriori probability function is

$$\hat{P}(\boldsymbol{G}_j\mid\boldsymbol{X})=\frac{\exp[-0.5\hat{d}_j^2(\boldsymbol{X})]}{\exp[-0.5\hat{d}_1^2(\boldsymbol{X})]+\exp[-0.5\hat{d}_2^2(\boldsymbol{X})]} \tag{7}$$

Bayes discriminant criterion can be expressed as:

$$\begin{cases}\boldsymbol{X}\in\boldsymbol{G}_1,\text{when }\hat{P}(\boldsymbol{G}_1\mid\boldsymbol{X})\geq\hat{P}(\boldsymbol{G}_2\mid\boldsymbol{X})\\ \boldsymbol{X}\in\boldsymbol{G}_2,\text{when }\hat{P}(\boldsymbol{G}_1\mid\boldsymbol{X})<\hat{P}(\boldsymbol{G}_2\mid\boldsymbol{X})\end{cases} \tag{8}$$

2.3 Bayes discriminant of multi-normal collectivities

Suppose $\boldsymbol{G}_j\sim N_p(\boldsymbol{\mu}_j,\boldsymbol{\Sigma}), j=1,2,\ldots,k$ (k>2), and $c(j\mid i)=\begin{cases}1, & j\neq i\\ 0, & j=i\end{cases}$. Bayes discriminant function is expressed as Function (2).

Generalized squared distance function can be obtained as follows:

$$d_j^2(\boldsymbol{X})=(\boldsymbol{X}-\boldsymbol{\mu}_j)^{\mathrm{T}}\boldsymbol{\Sigma}^{-1}(\boldsymbol{X}-\boldsymbol{\mu}_j)-2\ln p_j \tag{9}$$

Posteriori probability function is

$$P(\boldsymbol{G}_j\mid\boldsymbol{X})=\frac{\exp[-0.5d_j^2(\boldsymbol{X})]}{\sum_{i=1}^{k}\exp[-0.5d_i^2(\boldsymbol{X})]} \tag{10}$$

Then optimal division can be obtained as:

$$\begin{aligned}\boldsymbol{X}\in\boldsymbol{G}_j:&\{W_j(\boldsymbol{X})=\max_{1\leq i\leq k}W_i(\boldsymbol{X})\}\\ &=\{P(\boldsymbol{G}_j\mid\boldsymbol{X})=\max_{1\leq i\leq k}P(\boldsymbol{G}_i\mid\boldsymbol{X})\}\end{aligned} \tag{11}$$

$\boldsymbol{\mu}_1$, $\boldsymbol{\mu}_2$, $\cdots$, $\boldsymbol{\mu}_k$ and $\boldsymbol{\Sigma}$ can be replaced with the expected values, $\hat{\boldsymbol{\mu}}_1$, $\hat{\boldsymbol{\mu}}_2$, $\cdots$, $\hat{\boldsymbol{\mu}}_k$ and $\hat{\boldsymbol{\Sigma}}$.

2.4 Evaluation of discriminant criterion

The prior probability p_α is allocated by the proportion of training samples of collectivity $\boldsymbol{G}_\alpha$ to all samples, i.e.,

$$p_\alpha=\frac{n_\alpha}{n_1+\cdots+n_k},\quad \alpha=1,\cdots,k \tag{12}$$

where p_α is the prior probability of collectivity $\boldsymbol{G}_\alpha$, and n_α is the number training samples belonged to collectivity $\boldsymbol{G}_\alpha$.

2.5 Evaluation of discriminant criterion

To estimate the reliability of discriminant criterion above, the re-substitution method was used to calculate the mis-discrimination rate [16]. All the training samples were regarded as the new samples and re-substituted into the discriminant criterions. The rate of misjudgment can be evaluated as the value of the number of mis-discrimination samples divided by the number of all samples.

3 BDA model for identification of goaf risky

3.1 Flow chart of building model

The process to build the Bayes discriminant model can be divided into five steps: 1) determining the impact factors influencing the goaf risky; 2) dividing risky levels of goafs; 3) building the BDA model by using training samples; 4) testing of BDA model; 5) application of BDA model. The flow chart of building model is shown in Fig. 1.

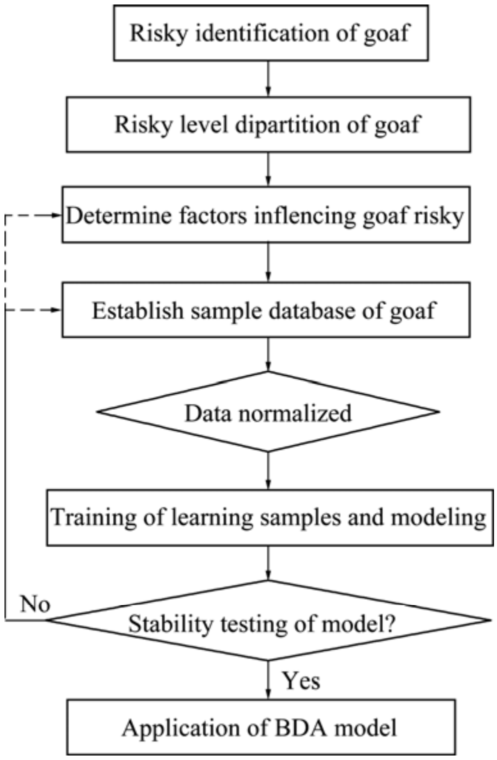

Fig. 1 Flow chart of building BDA model

3.2 Risky level dipartition of goaf

The characteristics of goaf disaster area and related studies show that the rock movement will not develop normally to the surface when the ore body buried deeper than 4 to 5 times the mining area. When the development of rock movement reached the surface, caving zone, fracture zone and bending zone (referred to as the "three zones") will form in upper rock mass of goaf (shown in Fig. 2). With the expansion of the scope of mining, the fracture zone and range of three zones will gradually change. When only the fracture zone occurs, the risk is low. When the fracture zone gradually develops, bending zone may occur, but the risk is also low; with the further development, the roof rock at footwall of fracture zone will collapse, which may cause a underground harm and can be regarded as a greater hazard. When caving zone appears and gradually expands, there are significant hazards. The serious risk of disaster is affected by many factors. Generally, caving zone and fracture zone have been extremely developed and goaf spans the space, resulting in complete collapse of bending zone, which will bring a great harm to the underground and surface of goaf.

Therefore, according to the severity of the dangerous consequences scale (Table 1), the instability of the goaf is divided into four risk levels: the first grade I (normal risk hazard), grade II (greater harm hazard), grade III (major hazard) and grade IV (large damage hazard), which means that the collectivity number of Bayesian discriminant analysis model has four.

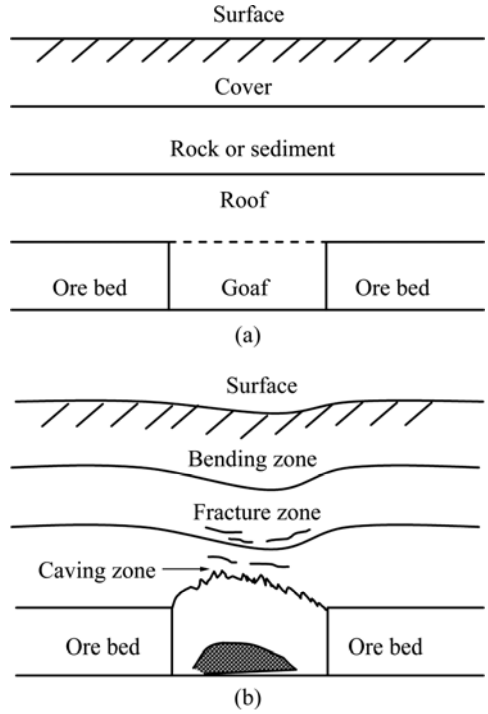

Fig. 2 Schematic diagrams of goaf initial state (a) and goaf hazard state (b)

Table 1 Scale of risky of serious consequences

Level	Risky	Consequence characteristic
I	Negligible	Personnel no damage, no loss of system
II	Critical edge	Less staff damage, less loss of system
III	Dangerous	Serious injury, significant damage system
IV	Disastrous	Death, retirement system

3.3 Determine of impact factors influencing goaf risky

The risky of goaf is influenced by many factors, which can be divided into several aspects, including rock properties of goaf, geological conditions, exploitation technical factors and treatment methods. After comprehensive analysis, nine specific indexes influencing the stability of goaf risky (shown in Table 2) [17], uniaxial compressive strength of rock ($\boldsymbol{X}_1$), elastic modulus of rock ($\boldsymbol{X}_2$), rock quality designation ($\boldsymbol{X}_3$), area ratio of pillar ($\boldsymbol{X}_4$), ratio of width to height of pillar ($\boldsymbol{X}_5$), depth of ore body ($\boldsymbol{X}_6$), volume of goaf ($\boldsymbol{X}_7$), dip of ore body ($\boldsymbol{X}_8$) and area of goaf ($\boldsymbol{X}_9$), were selected as discriminant indexes.

3.4 Training of learning samples and modeling

From Ref. [17], the actual data of 40 goafs were used as training samples to establish a Bayes analysis model to identify the risky of goaf. The BDA model is shown in Fig. 3.

Table 2 Original data of 40 training goaf samples

No.	X_1/MPa	X_2/MPa	X_3/%	X_4	X_5	X_6/m	$X_7/10^4$ m^3	X_8/(°)	$X_9/10^4$ m^2	Risky level
1	130	35000	64	0.15	2.4	385	484.5	80	16.2	II
2	90	22000	55	0.13	1.8	260	178.9	85	8.0	IV
3	115	23000	70	0.16	1.9	216	128.0	78	3.7	III
4	124	26000	62	0.15	1.7	300	181.3	82	5.5	IV
5	113	27000	58	0.22	1.9	230	67.2	75	6.1	II
6	141	21000	62	0.23	2.0	300	115.0	82	4.3	II
7	146	28000	65	0.18	2.4	475	191.0	75	3.4	III
8	135	32000	66	0.17	2.3	250	170.9	80	5.8	III
9	108	29000	64	0.15	1.7	100	88.3	71	6.2	III
10	45	11000	48	0.12	1.2	200	29.2	12	7.3	IV
11	53	14000	56	0.14	1.6	120	30.5	13	5.0	III
12	58	17000	60	0.18	2.3	50	108.4	15	12.3	II
13	190	36000	82	0.24	2.2	60	17.5	21	5.7	II
14	172	34000	84	0.22	2.0	30	28.0	18	13.2	III
15	164	39000	86	0.23	1.8	20	37.0	5	15.0	II
16	155	38000	80	0.20	1.6	20	23.4	23	2.8	IV
17	181	35000	85	0.21	1.9	50	10.5	20	2.2	II
18	35	18000	46	0.18	1.5	120	85.5	19	9.4	IV
19	147	34000	75	0.26	0.8	80	64.0	58	12.0	II
20	240	39000	81	0.25	0.9	65	86.4	22	7.2	II
21	270	35000	77	0.23	1.0	60	46.3	18	3.7	III
22	135	18000	55	0.17	0.7	80	27.4	48	4.6	II
23	166	26000	65	0.12	0.4	50	78.3	65	5.8	IV
24	174	28000	68	0.15	0.5	90	196.0	70	5.4	III
25	65	15000	65	0.24	1.5	75	12.6	10	4.3	II
26	240	37000	76	0.21	1.2	60	153.5	15	26.7	IV
27	58	17000	40	0.23	1.6	65	371.0	12	35.2	III
28	60	20000	56	0.22	1.7	70	59.2	14	29.6	II
29	85	21000	60	0.27	1.6	75	60.0	15	12.0	II
30	80	22000	65	0.23	1.5	72	80.5	16	17.0	III
31	110	25000	66	0.29	2.7	300	41.5	30	4.5	I
32	140	28000	70	0.30	2.9	240	70.8	20	16.8	I
33	170	36000	78	0.32	3.0	150	35.0	40	8.2	I
34	90	22000	54	0.33	3.4	60	47.6	85	3.6	I
35	95	24000	58	0.34	2.9	190	48.0	15	7.5	I
36	100	28000	61	0.31	2.8	70	54.0	25	9.0	I
37	180	39000	75	0.29	2.9	85	60.5	38	12.2	I
38	270	42000	80	0.35	3.1	120	88.0	65	18.5	I
39	250	47000	85	0.32	4.4	140	132.0	25	19.5	I
40	310	55000	88	0.31	3.2	160	121.0	70	8.8	I

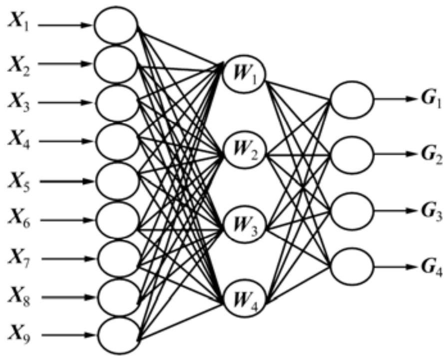

Fig. 3 Bayes discriminant model diagram

3.5 Data normalized

In the process of building BDA model, in order to make the model training more effective, the original sample data were normalized and the model input data will be in [0, 1] interval. For quantitative data, using the following formula:

$$\bar{x} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{14}$$

where $\bar{x}$ is normalized sample data; x is original sample data; $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of original data, respectively. In addition, there is no conversion for pillar area value and rock quality indicators can be directly divided by 100. Normalized sample data are shown in Table 3.

3.6 Test of BDA model

The prior probability is allocated by the proportion of training samples, and then p_1=10/40=0.250, p_2=13/40=0.325, p_3=10/40=0.250 and p_4=7/40=0.175. The normalized data are input into BDA model and discriminant functions can be obtained. It can be seen from Table 1 that the forecasting risky level of goaf is the same as the actual status except sample No. 30, and the ratio of mis-distinguish is 1/40=0.025. It can be

Table 3 Input data of 40 training goaf samples and discriminant results

No.	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	BDA level
1	0.345	0.545	0.64	0.14	0.500	0.802	1.000	0.938	0.364	II
2	0.200	0.250	0.55	0.13	0.350	0.527	0.355	1.000	0.182	IV
3	0.291	0.273	0.70	0.16	0.375	0.431	0.248	0.913	0.076	III
4	0.324	0.341	0.62	0.19	0.325	0.615	0.360	0.963	0.100	IV
5	0.284	0.364	0.58	0.22	0.375	0.462	0.120	0.875	0.118	II
6	0.385	0.227	0.62	0.23	0.400	0.615	0.220	0.963	0.064	II
7	0.404	0.386	0.65	0.18	0.500	1.000	0.381	0.875	0.036	III
8	0.364	0.477	0.66	0.17	0.475	0.505	0.338	0.938	0.109	III
9	0.265	0.409	0.64	0.15	0.325	0.176	0.164	0.825	0.152	III
10	0.036	0.000	0.48	0.12	0.200	0.396	0.039	0.088	0.155	IV
11	0.065	0.068	0.56	0.14	0.300	0.220	0.042	0.100	0.085	III
12	0.084	0.136	0.60	0.15	0.475	0.066	0.207	0.125	0.306	II
13	0.564	0.568	0.82	0.24	0.450	0.088	0.015	0.200	0.106	II
14	0.498	0.523	0.84	0.22	0.400	0.022	0.037	0.163	0.333	III
15	0.469	0.636	0.86	0.23	0.350	0.000	0.056	0.000	0.388	II
16	0.436	0.614	0.80	0.20	0.300	0.000	0.027	0.225	0.012	IV
17	0.531	0.545	0.85	0.21	0.375	0.066	0.000	0.188	0.000	II
18	0.000	0.159	0.46	0.18	0.275	0.220	0.158	0.175	0.218	IV
19	0.407	0.523	0.75	0.26	0.100	0.132	0.113	0.663	0.297	II
20	0.745	0.636	0.81	0.25	0.125	0.099	0.160	0.212	0.152	II
21	0.855	0.545	0.77	0.23	0.150	0.088	0.076	0.163	0.045	III
22	0.364	0.159	0.55	0.17	0.075	0.132	0.036	0.538	0.073	II
23	0.476	0.341	0.65	0.12	0.000	0.066	0.143	0.750	0.109	IV
24	0.505	0.386	0.68	0.15	0.025	0.154	0.391	0.813	0.097	III
25	0.109	0.091	0.65	0.24	0.275	0.121	0.004	0.063	0.064	II
26	0.745	0.591	0.76	0.21	0.200	0.088	0.302	0.125	0.742	IV
27	0.084	0.136	0.40	0.23	0.300	0.099	0.761	0.088	1.000	III
28	0.091	0.205	0.56	0.22	0.325	0.110	0.103	0.113	0.830	II
29	0.182	0.227	0.60	0.27	0.300	0.121	0.104	0.125	0.297	II
30	0.164	0.250	0.65	0.23	0.275	0.114	0.148	0.168	0.448	II
31	0.273	0.318	0.66	0.29	0.575	0.615	0.065	0.313	0.070	I
32	0.382	0.386	0.70	0.30	0.625	0.484	0.127	0.188	0.442	I
33	0.491	0.568	0.78	0.32	0.650	0.286	0.052	0.438	0.182	I
34	0.200	0.250	0.54	0.33	0.750	0.088	0.078	1.000	0.042	I
35	0.218	0.295	0.58	0.34	0.625	0.374	0.079	0.125	0.161	I
36	0.236	0.386	0.61	0.31	0.600	0.110	0.092	0.250	0.206	I
37	0.527	0.636	0.75	0.29	0.625	0.143	0.104	0.413	0.303	I
38	0.855	0.705	0.80	0.35	0.675	0.220	0.164	0.688	0.494	I
39	0.782	0.818	0.85	0.32	1.000	0.264	0.256	0.250	0.390	I
40	1.000	1.000	0.88	0.31	0.700	0.308	0.233	0.813	0.304	I

concluded that the BDA model can be applied to identifying the goaf risky.

4 Actual engineering application of BDA model

Yaogangxian tungsten in Hunan province, China, is an old metal mine with more than mining 90 years, and there are a large number of goafs. The risky of goaf in Yaogangxian Tungsten Mine [4] was identified by using this BDA model above. The original data of mine goaf and discriminant results are shown in Table 4. The result of BDA model is identical with actual level, which also is the same with the result of ANN method [17]. It can be concluded that the BDA model can be applied in practical mine engineering to identifying the risky level. In fact, some goafs in the upper part of the ore has collapsed, making surface crack and deform. However, there is not catastrophic phenomenon. In the ore stope and tunnel of lower part, the phenomenon of partial roof collapse has occurred accidentally.

Therefore, the actual degree of danger is the level II, which is identical with the BDA model identification results. Table 5 also shows the results of 16 artificial neural networks (Artificial neural networks, referred to as ANN), which is also level II. Compared with artificial neural network method, the overall prior probability of every collectivity was fully considered in Bayesian discriminant analysis model. The Bayesian discriminant model has a fixed structure and the training process is simple and training is quick.

Table 4 Original data of Yaogangxian Tungsten Mine goaf

X_1/MPa	X_2/MPa	X_3/%	X_4	X_5
120	32000	70	0.28	4.2
X_6/m	$X_7/10^4$ m^3	X_8/(°)	$X_9/10^4$ m^2	Risky level
50	468.0	75	18.0	II

Table 5 Discriminant results of Yaogangxian Tungsten Mine goaf

X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	BDA level	ANN level
0.309	0.477	0.70	0.28	0.950	0.066	0.965	0.875	0.479	II	II

5 Conclusions

1) Based on the Bayes discriminant analysis theory and actual characteristics of goaf risky, a Bayes discriminant analysis (BDA) model for instability identification of goaf risky was presented.

2) The results show that this discriminant analysis model has high precision and can be used in practical engineering. Compared with the other prediction methods, BDA model has a stable structure and the discriminant process is very simple and convenient.

3) It is the preliminary attempt that Bayes discriminant analysis theory is applied to analysis of the identification of goaf risky in mines. In the future work, it is necessary to conduct depth-study in selecting the study sample and discriminant genes, and then enhance the practicality of BDA model.

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复杂采空区危险辨识的贝叶斯判别方法及应用

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摘 要：提出了复杂采空区危险程度辨识的贝叶斯判别方法。基于多元判别分析理论，将贝叶斯判别方法应用于金属矿山采空区危险程度的预测判别问题中，建立了相应的贝叶斯判别分析模型。该模型选用岩石单轴抗压强度、岩石弹性模量、岩石质量指标、矿柱面积比率、矿柱宽高比、矿体埋藏深度、采空区体积、矿体倾角和采空区面积 9 项指标作为判别因子，将采空区的危险性等级分为 4 级；以 40 个采空区实测数据作为学习样本进行训练，建立相应判别函数对待判样本进行分类。研究结果表明，贝叶斯判别模型的学习精度很高，回判估计的误判率为 0.025。利用学习后的模型对某金属矿山采空区实例进行了稳定性判别，判别结果和实际情况相符。

关键词：采空区；危险辨识；贝叶斯判别分析；金属矿山

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