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Improving microseismic event and quarry blast classification using Artificial Neural Networks based on Principal Component Analysis

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ABSTRACT

The discrimination of microseismic events and quarry blasts has been examined in this paper. To do so, Principal Component Analysis (PCA) and Artificial Neural Networks (ANN) have been used. The procedure proposed has been tested on 22 seismic parameters of 1600 events. In this work, the PCA has been used to transform the original dataset into a new dataset of uncorrelated variables. The new dataset generated has been used as input for ANN and compared to Logistic Regression (LR), Bayes and Fisher classifiers, which classify microseismic events and quarry blasts. The results have shown that PCA is effective for rating variables and reducing data dimension. Furthermore, the classification result based on PCA has been better than those based Ref. [22] and without PCA methods. Moreover, the ANN classifier has obtained the best classification result. The Matthew's Correlation Coefficient (MCC) results of the PCA, Ref. [22] and without PCA based methods have reached 89.00%, 73.68% and 82.04%, respectively, thus showing the reliability and potential of the PCA based method.

1. Introduction

Microseismic monitoring, an efficient regional monitoring tool that takes advantage of microseismic signals from rock deformation, has been widely used in disaster monitoring and mining hazard prediction [1,2]. Its main technical concerns include monitoring planning, data processing and microseismic event location [2]. Microseismic event and quarry blast classification is a key issue in microseismic data processing [3–5].

Many microseismic monitoring systems have been equipped with automatic microseismic data classification modules, such as that of the Institute of Mine Seismology (IMS), that of the Engineering Seismology Group (ESG) and that of the Seismological Observation System (SOS). Nevertheless, microseismic data are often adversely influenced by background and stationary noises [6], discontinuous transmission media and transmission distance, which make the classification results of these monitoring systems unreliable. Therefore, microseismic classification is still conducted mainly visually by experts in practice. Manual discrimination is time consuming and subjective due to the fact that depends on the analysts' experience [7]. Therefore, large volume of microseismic data requires a reliable and automatic microseismic identification method.

In this paper, an algorithm based on Principal Component Analysis (PCA) and Artificial Neural Networks (ANN) has been proposed. In addition to previous works, this paper has introduced some new parameters into microseismic classification and has considered the correlation between variables. The performance of the PCA-ANN method has been applied to 22 seismic parameters of 1600 events selected from the Yongshaba mine (China) and compared to Logistic Regression (LR), Bayes and Fisher classifiers. The results have shown that the PCA is effective in rating variables and reducing data dimension. Moreover, it has been shown that the parameters E_0, E_p, E_s, M_0, M_w, P, P_p, P_s, σ_a, f_c, r_0 and $\Delta\sigma$ (see Section 3) are paramount for microseismic classification. The ANN classifier has obtained a better classification result than the LR, Bayes and Fisher classifiers. The Matthew's Correlation Coefficient (MCC) results of the PCA, Ref. [22] and without PCA based methods have reached 89.00%, 73.68% and 82.04% respectively, thus showing the reliability and potential of the PCA based method.

2. State of the art

In order to distinguish seismic events from man-made explosions, such as quarry blasts, underwater explosions and nuclear tests, different

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parameters and classification techniques have been proposed. These methods select some parameters to replace seismic data. Then, these parameter-vectors are used as input in statistical or machine learning methods for classification. The parameters commonly used include amplitude peak ratio of seismic phases [8–10], spectral ratio of seismic phases or average amplitude in low and high frequency bands for a specific phase [9–13]. The statistical and machine learning methods are Gaussian maximum-likelihood classifier [14,15], neural networks [4,16–19], self-organizing map [20,21] and Bayes classifier [7,22,23].

Most of the above researches focused on the classification of earthquake and man-made explosions. Nonetheless, usually the microseismic event has a higher frequency than that of an earthquake and is more likely to quarry blast. This makes hard to distinguish microseismic events from quarry blasts using waveform spectrum analysis. Malovichko [24] selected time of occurrence, similarity of the seismic signals to the neighboring waveforms, ratio of high-frequency and low frequency radiation, and radiation pattern as microseismic discrimination factors. Later, he applied a multivariate maximum likelihood Gaussian classifier technique for the classification. Vallejos and McKinnon [19] examined the identification of seismic records in two seismically active mines in Ontario (Canada). They considered LR techniques and neural network classification techniques. Finally, 13 seismic parameters provided by the ESG system were selected as classification features. Ma et al. [23] proposed two feature-extraction approaches: source parameters and waveform characteristics. They applied Bayes discrimination analysis to the characteristic parameters extracted. Zhao et al. [25] selected the repetition of waveforms, tail decreasing, dominant frequency and occurrence time of day as discrimination features. They obtained a high correct discrimination rate for the statistical model by applying the Fisher discrimination analysis. Dong et al. [22] applied Fisher classifier, naive Bayesian classifier and LR to discriminate microseismic events from quarry blasts. The origin time of seismic records (t), seismic moment (M_0), total radiated energy (E_0), S-wave to P-wave energy ratio (E_s/E_p), corner frequency (f_c) and static stress drop ($\triangle\sigma$) were selected as discrimination factors. Dong et al. [26] improved the Dong et al. [22]. To do so, they used logistic and log-logistic distributions to establish probability density functions for the origin time of blasts and the Origin Time Difference (OTD) of neighboring blasts in the time domain. All the aforementioned microseismic event and quarry blast classification methods obtain good results in general terms. However, all of them share same features that they have not considered the importance of each parameter in microseismic classification and the correlations between variables which usually leads to poorer results.

3. Methodology

This section describes the improved method for microseismic event and blast classification. Fig. 1 illustrates the process of the methodology.

(1) Set of inputs: it is worth noting that the classification problem has been turned into a binary problem. The microseismic events have been labeled with a 1, while the blasts have been labeled with a 0. The variables E, N, D, $\triangle r$, t, N_s, M_0, M_w, E_0, E_s/E_p, r_0, $\triangle\sigma$, σ_a and $\triangle\sigma_d$ introduced by Vallejos and McKinnon [19] and AV, f_c, E_p and E_s described in Ref. [22] have been selected as microseismic classification features. In addition, P, P_p, P_s and P_s/P_p have also been chosen as classification input features, where $P = 4\pi c R \frac{\Omega_0}{F_c}$ is the total potency of P- and S-waves, P_s/P_p is the S-wave to P-wave potency ratio, c is the velocity of the wave in rock (m/s), R is the distance from the seismic source (m), Ω_0 is the low-frequency plateau of the frequency spectrum of a seismic waveform in the displacement. F_c is the radiation pattern parameter: for a P wave F_c is 0.52, while for an S wave F_c is 0.63 [27].

(2) Principal Component Analysis (PCA): PCA has been applied to study the importance of each parameter to microseismic classification. Furthermore, the original data has been transformed into a new dataset of uncorrelated variables with dimensionality reduction, which results in less number of input variables for the ANN classifier and reduces the classification computing time.

(3) Application of machine learning classifiers: ANN has been selected to classify microseismic events and quarry blasts. The results of LR, Bayes and Fisher classifiers have been provided for comparison.

(4) Assessment: evaluations of the prediction performances by means of a variety of quality parameters (see Section 3.2), and discussions of the advantages and limitations for these classifiers.

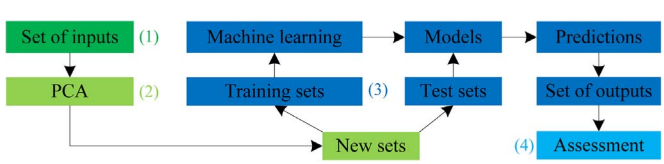

Fig. 1. Steps involved in the PCA based machine learning methodology. The green, light-green, blue and light-blue correspond to step (1), (2), (3) and (4), respectively. (1) Set of inputs; (2) Principal component analysis (PCA); (3) Application of machine learning classifiers; (4) Evaluations and discussions. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.1. Principal Component Analysis

PCA is one of the most useful statistical methods to transform a large dataset of interrelated variables into a smaller dataset of uncorrelated variables, namely Principal Components (PCs). The PCs can be expressed in terms of linear combination of the original variables, which retain the maximum information from the original data. In order to avoid the asymptotic effect, the input data should be normalized. The commonly used normalization strategies are Min-Max scaling and Z-score standardization, however, the Principal Component Analysis will ignore the variable information with low standard deviation. Therefore, the latter strategy is selected to eliminate the effect of standard deviation and it is defined as follows [28]:

$$x'_{ij} = (x_{ij} - \overline{x_j})/\sigma_j \tag{1}$$

where x'_{ij} is the ith value of the standard score of the j-variable ($i=1, 2, \ldots, n$ and $j=1, 2,\ldots, m$), x_{ij} is the ith value of the j-variable, and $\overline{x_j}$ and σ_j are the mean value and the standard deviation of the j-variable, respectively.

The eigenvalues and eigenvectors of correlation matrix $\mathbf{R}$ can be obtained from the Eqs. (2) and (3) as follows:

$$|\mathbf{R} - \lambda \mathbf{I}| = 0 \tag{2}$$

$$\mathbf{R}\ \mathbf{e} = \lambda \mathbf{e} \tag{3}$$

where $r_{ij} = \left(\sum_{k=1}^{n}(x'_{ki} - \overline{x'_i})(x'_{kj} - \overline{x'_j})\right)/\left(\sqrt{\sum_{k=1}^{n}(x'_{ki} - \overline{x'_i})^2 \sum_{k=1}^{n}(x'_{kj} - \overline{x'_j})^2}\right)$ is the ith value and jth variable of the $\mathbf{R}$-matrix, λ is the eigenvalue ($\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_m \geq 0$), $\mathbf{e}$ is the eigenvector, and $\mathbf{I}$ is the identity matrix.

The ith value and jth variable of the principal component load matrix and the jth variance of PC_j are given as:

$$l_{ij} = \sqrt{\lambda_j}\, e_{ij} \tag{4}$$

$$\text{Variance}_j = \lambda_j / \sum_{j=1}^{m} \lambda_j \tag{5}$$

Then, the principal component PC_j can be reconstructed by:

$$PC_j = l_{j1}x_1 + l_{j2}x_2 + \ldots + l_{jm}x_m \tag{6}$$

The first, PC_1, corresponding to λ_1 represents the linear combination of the variables, and accounts for the maximum variability in the data. While the second, PC_2, represents the maximum variability which is not accounted by the PC_1. This procedure is repeated m-times to obtain the principal components PC_3, PC_4,…, PC_m.