Application of probabilistic clustering analysis to rockburst hazard assessment of rock mass

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Abstract. The team of researchers from the Institute of Mining, FEB RAS have developed the rockburts hazards assessment procedure which enjoys successful application in Russian mines. The main objective of the procedure is the continuous computer-automated geomechanical monitoring of rock mass behavior, identification of seismically active zone and determination of static and dynamic parameters for rockburst hazard prediction and assessment in the detected zones. This paper co-authors propose an algorithm to identify fracture source zones in rock mass and to calculate parameters of these zones by geomechanical monitoring data and using the methods and tools of nonparametric density estimate and probabilistic clustering analysis.

1. Introduction

The review of the current approaches to prediction of various dynamic events caused by confining pressure shows that they mostly rest upon the kinetic concept of solid fracture. Many scientists who adhere to this concept distinguish between some characteristic stages in the process of rock fracture, starting from inception of microcracks which grow from millimeter to centimeters and meters and finishing with formation of fractures from tens to thousands meters long, typical of rockbursts, induced earthquakes, etc. [1–4].

Researchers from the Institute of Mining, FB RAS have validated and proposed a monitoring procedure of seismically active areas in rock mass [1, 6]. The procedure is meant to determine a rockburst hazard index of a potentially hazardous zone identified and classified by the continuous automated seismic monitoring data.

Rock mass condition is recommended to assess using an integrated rockburst hazard index embracing a set of signs of rock susceptibility to dynamic events within the limits of a test area.

The key point in the seismic activity zone monitoring is identification of an uncontrollable area classifiable as a potential source of rock fracture. At the same time, the reviewed studies lack a sufficiently prepared and statistically justified identification procedure applicable within automated geomechanical monitoring systems. Furthermore, there is no problem solution on generation of a characteristic three-dimensional configuration, for instance, an ellipse, to describe geometry of a source zone.

In order to eliminate these constraints, it is necessary to develop mathematical methods for the statistically reasoned identification of acoustically active zones by geomechanical monitoring data, and to work out the procedure to generate a characteristic ellipsoid capable to describe geometry of the identified source zones at the preset accuracy.
2. Seismic monitoring data for fracture source identification

The practice of the clustering analysis of seismic monitoring data starts that before clustering, it is necessary to select subsets of data in the regions of high density of points standing for seismic events. The distribution density at each point is assessed using the distribution-free techniques of density estimation [7]. According to the above-mentioned model, solution of this problem allows separating values belonging to the regions with low and high density. The values from the low density regions are unambiguously assumed as the background emission.

The recorded seismic event with calculated coordinates \((x_i, y_i, z_i)\) is assumed to belong to the region with high density if the number of points located inside a sphere with the center point coordinates \((x_i, y_i, z_i)\) and some radius \(h\) is higher than a certain limit \(c\).

The main task in actual calculation of the wanted weight is selection of optimized values for \(h\) and \(c\). It is advised to find \(h\) using the least square-based cross-validation methods which minimize the integrated mean square root error of the estimate [8, 9].

The automation algorithm for optimized selection of \(c\) is presented in Figure 1. The proposed background emission filtration algorithm makes it possible to withdraw excessive data for further identification of seismically active zones and to place the background emission events in a separate group. In this case, it is also possible to study the background emission and its effect on prediction of dynamic events in rock mass [10].

![Figure 1. Selection algorithm for optimized value of \(c\).](image)

The clustering analysis is splitting of a chosen sampling of components (situations) into subsets named clusters such that a cluster is composed of similar components but components in different clusters considerably differ [11].

At first thought, on the basis of physical processes in rock mass under loading and deformation, it seems to be reasonable to use the hierarchical or graph approaches to describe fracture source zones [11]. These approaches use deterministic models as it is assumed that clustering involves splitting of the initial object set \(X\) into a number of non-overlapping subsets. Put it otherwise. These methods are the methods of ‘explicit’ clustering.

In the meanwhile, ‘fuzzy’ clustering techniques allow one and the same object to belong, simultaneously but at various probability, to a number (or even all) clusters. In many a situation, this is a more natural approach as it takes into account random processes intrinsic to animate nature objects, and their stochastic behavior [12].

Dynamic processes in rock mass are in a great measure governed by an ensemble of interrelated physical processes which are generally probabilistic in nature. Consequently, a deterministic approach...
to the analysis of the stochastic natural processes can only be recommended as an initial approximation.

We solve the problem connected with identification of fracture source zones using the modified FCM method—Gustafson-Kessel algorithm with fuzzy partitioning of data sets. As against the explicit method with two-element set \{0, 1\}, the fuzzy splitting approach uses the interval \[0, 1\]. In this algorithm, during clustering, optimization involves the center coordinates of the clusters, the fuzzy partitioning matrix and the norm-originating matrixes for all clusters. This makes it possible to define clusters of different geometry.

The most important parameter in this algorithm is the number of clusters. An optimal method to determine the number of clusters may be assumed the method of subtractive clustering advantageous, among other things, for no need to set an initial number of clusters [13].

We propose the following integrated algorithm of fracture source identification by seismic monitoring data:

1. Out of the whole set of recorded seismic events, the regions with low seismic activity related to the background emission are filtered using the nonparametric density estimate.
2. The number of clusters is determined using the subtractive clustering algorithm.
3. The clustering process by the Gustafson-Kessel algorithm is repeated many times until the stable result of partitioning of the initial set into the optimal number of clusters by assessment of distribution probability. Finally, for each event, the highest probability of belonging to each cluster is calculated.

The developed algorithm allows additional evaluation of the clustering quality. The process of partitioning is accomplished many times, and every time, for each event, the probability of belonging to a preset cluster preserves. Upon completion of the calculation, for each event, the higher probability (in terms of frequency) of belonging to each of the clusters is selected. In this manner, finally, we have both distribution of the events by probability of belonging to a cluster, and reliability of assignment of an object (event) to each of the clusters. Location and subsequent clustering of seismic signals enables formation of a domain of defects with identification of directions of fracture growth in space. Let this domain have a shape of an ellipsoid with its principal diagonals characterizing the ratio of the length, with and thickness of a broken layer and the orientation of this layer in space. The input data are assumed as the table of coordinates of the recorded seismic events assigned to clusters identified at the previous steps.

In order to detect a direction of the maximal distribution of coordinates, we assume that in this case, the projection of location points of events on the normal of the direction has maximal dispersion, and this is a characteristic of the length of a fracture source. In the orthogonal plane, we determine the thickness of the fracture sources as the direction with the minimal dispersion. Then, in the third direction oriented normally to the previous two directions, the dispersion of the points is assumed as the width of the fracture source.

The developed algorithm was tested through the analysis of seismic monitoring data obtained in 2017 at rockburst-hazardous mineral deposit Antei located in East Transbaikal [14]. The seismic events were recorded by the automated ground control system PrognozADS in one of the mine field sites.

All in all, 12477 seismic events were recorded in 2017. From the filtering outcome, 40.5% of the events were related with the background emission. The rest events were assigned in 3 clusters (active zones) by the clustering analysis. Cluster 1 contained 3662 events, cluster 2—1633 events and cluster 3—2067 events. The results obtained in shaping of characteristic ellipsoids of fracture sources are presented in Figure 2 (the coordinate center is reduced to the center of the identified source zone).
Figure 2. Output of algorithm of fracture source identification by seismic monitoring data. Vertical plane projection.

3. Conclusions
The use of the characteristic ellipsoid enabled more than 100 times reduction in the number of parameters of the source while ensured the analysis of the change in the volume and shape of the source zone both statically and dynamically.

The probabilistic clustering represents the ‘natural’ feature of the processes better than the classical clustering since it takes into account random processes intrinsic to real-life objects and their stochastic behavior, which is important for the boundary elements of cluster structures.

The use of the proposed approaches in geomechanical monitoring can facilitate automatization of hazard prediction in rock mass, greatly improves prediction quality and optimized the prediction process time. The developed algorithms and methods are applicable to automated geomechanical monitoring both in opencast and underground mining [15–17].

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