Automatic identification of irregular rock blocks from 3D point cloud data of rock surface

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Abstract. The block size is an important index for determining the integrity of rock masses, as well as the evidence for estimating the rock mass classification. However, obtaining the block size information of exposed rock is a time-consuming, labor-intensive and high risk work. This paper proposed a new method to automatically identify the rock block and calculate the block size based on the 3D point cloud data of rock surface. The proposed method includes four steps: (1) automatic identification of rock discontinuity and extraction of information based on several machine learning algorithms, (2) Rough extraction of block discontinuities combination by distance filtering and angle filtering, (3) accurate identification and extraction of blocks by applying mutual projection of centroid and adding angle repair coefficient, (4) calculation of block size by filling in the concavity outline of point cloud for single block. An automatically statistic and analyzed program is compiled by matlab language based on massive point cloud of block information. The method is applied in controllable boxes model and real road cut slope, making comparison with the results of former research and calculated results by specialized point cloud processing software. It reveals that the proposed method is applicable with high calculating accuracy and efficiency.
1. Introduction

Plenty of the large-scale infrastructure construction in the world are rock engineering, the acquisition of basic data is the primary part in engineering construction. The methods of obtaining data determine the efficiency of investigation works and the reliability of the research materials. The discontinuity of rock masses includes bedding, joint, interlayer, fracture, shear zone and fault (Palmström et al. 2001), which are distributed inside the rock masses. The discontinuity have great influence on the mechanical property, and accurate and quick collection of the discontinuity information is the basis and premise of the stability analysis of engineering rock masses (GU and Wang, 1981). The rock mass usually has three or more than three groups of dominant discontinuities, these discontinuities intersect with each other and formulate a single block. The key block theory (Goodman and Shi, 1985) is increasingly developed and perfected as a new method of rock engineering stability analysis (Tang, 2012; Kulatilake et al., 2011). The block size is an essential calculated parameter in blasting design (Shim et al., 2009), classification of rock masses (Cai et al., 2004; Cai, 2011), stability analysis of slope and tunnel excavation (Goodman, 1995; Pantelidis, 2009).

With the development of computer technology, many scholars combined the 3D network simulation technology of rock discontinuity with the block theory to conduct the block searching and block visualization (Azarafza et al., 2018; Lin et al., 1987; Stavropoulou, 2014). The most frequently used methods include the index estimating method and simulation method. In the index estimating method, the block size is approximately represented by the average size of the block. This method is simple and efficient, but the accuracy of the calculated results are not high enough. In simulation method, the discrete network model of discontinuity is simulated and the block can be extracted from the model (Azarafza et al., 2016; Monsalve et al., 2019; Pan et al., 2019; Wang et al., 2003) according to the collected information of rock discontinuity (e.g. Orientation, trace length, spacing). Though the two methods have been widely used, the final accuracy of the results are not high enough for the primitive data collecting methods and the data collector’s lack of experience.

The remote sensing technology like Light Detection and Ranging (LIDAR), Unmaned Aerial Vehicle (UAV) have been widely applied in the area of engineering geology and geotechnical engineering, such as geological logging of rock mass structure (Deb et al., 2008; Kong et al., 2019; Slob et al., 2005; Deliormanli et al., 2014), deformation monitoring of slope and tunnel (Mukupa et al., 2016), stability analysis of rock mass (Havaej et al., 2015) and investigation on dangerous rock mass and landslides (Runqiu and Xiujun., 2008; Wang et al., 2018). The technology can obtain the point cloud information of rock surface from a long distance, effectively avoid the hidden danger, poor efficiency and incomplete collected information in manual measurement and eliminate the user bias. The collected information can be stored permanently and provides a database of 3D point cloud for later study on comparing the reliability and accuracy of new method (Lato et al., 2013). After obtaining the 3D point cloud data with high accuracy, the researchers have done a lot of study on extracting discontinuity information by using point cloud. Several methods like plane fitting (Feng et al., 2001), local normal vector calculation (Riquelme et al., 2014), plane detection of boundaries (Chen et al., 2017; Drews et al., 2018) have been applied to extract the orientation information, in order to
avoid the drawbacks of traditional orientation statistics, Shanley and Mahtab (1974) proposed the discontinuity grouping based on cluster analysis, subsequent study have been focus on machine learning algorithms, such as K-means algorithm (Chen et al., 2016, Li et al., 2019), Fuzzy C-Means algorithm (Hammah and Curran, 1998, Xu et al., 2012), Kernel density clustering algorithm (Riquelme et al., 2014), global optimization algorithm (Cui and Yan, 2020) and density peaks clustering algorithm (Rodriguez and Laio, 2014). These algorithms have been applied in rock discontinuity grouping and statistic.

By applying LIDAR, Dong et al. (2020) obtained large range of rock structure information and fit the plane of block boundary, to identify the large-scale single dangerous rock block and estimate the volume of the block. Mavrouli et al. (2014) manually extracted the rock discontinuity information by using Polyworks based on 3D point cloud data, and determinate the discontinuity grouping. The average block size can be roughly calculated by measuring the distance between adjacent discontinuities in the same group. Chen et al. (2017) assume that arbitrary three discontinuities which are intersected with each other to formulate the candidate block, and automatically extract the real block by using the Floodfill algorithm. However, in the their study works, Mavrouli et al. (2014) can only identify the discontinuity visually and manually with poor efficiency. Chen et al. (2017) can realize the automatic identification of rock block, but the method can only identify regular block which are very few in nature consist of three sets of discontinuities which are intersected with each other.

In this paper, a new method with low cost and high accuracy is proposed to automatically extract the information of discontinuity and calculate the block size of irregular block. The method have been applied in two cases and make comparison with the methods in previous study. The results by using different methods in the two cases have been discussed and analyzed.

2. Methodology

The proposed methodology includes four main steps (Fig.1.):

Step 1: Automatic extraction of discontinuity information which forms the block boundary by using the machine learning algorithms.

Step 2: Combination of arbitrary two discontinuities in order to calculate the distance and angel of the discontinuities, the data will be deleted if it is above the threshold.

Step 3: Accurate extraction of blocks by applying mutual projection of centroid and adding angle repair coefficient.

Step 4: Fill in the concave outline of point cloud of single block in order to calculate the block size.
2.1. Identification of discontinuity in rock masses

2.1.1. Calculation of point cloud normal vector

The calculation on normal vector of point clouds is the basis of automatic identification of rock discontinuity by numerous current algorithms. The current commonly used methods of calculating the normal vector of point clouds include Delaunary Triangulation method (Amenta and Bern, 1999) and local plane fitting method (Hoppe et al., 1992). When the Delaunary Triangulation method is applied to the rock surface which are relatively flat, the results reveal to be accurate. However, when the rock surfaces turn to be rough, the results vary a lot for the effect of the noise points. With increasing improvement of the local plane fitting method, the K Nearest Neighbor algorithm (KNN) (Riquelme et al., 2014) can form a subset of planes by randomly searching a sample point and its k neighborhood points as shown in Fig. 2. The subset can be regarded as the plane generated from the sample point (the plane pass through its centre of gravity). The calculated normal vector of the plane is approximately expressed as the normal vector of the point. The plane through the centre of gravity can be formulated as:

\[ a(x_i - \bar{x}) + b(y_i - \bar{y}) + c(z_i - \bar{z}) = 0 \]  

(1)

Where \(a, b, c\) are the normal vector of fitting plane and \((x_i, y_i, z_i)\) is the 3D coordinate of the subset of neighborhood points, \((\bar{x}, \bar{y}, \bar{z})\) is the centre of gravity for subset of neighborhood points.

The normal vector of point could be gained by least squares method which transforms to calculate the eigenvector corresponding to the minimum eigenvalue of covariance matrix (Singular Value Decomposition). This solution has strong robust to the noise of data, the key point is making decentralization on the data. The normal vector calculated by the least squares method can be found in the following equation:
\[
\min \sum_{i=1}^{N} (ax_i + by_i + cz_i)^2 = \min S
\]  

A feature matrix( \(\lambda_1, \lambda_2, \lambda_3\) ) and corresponding eigenvectors( \(V_1, V_2, V_3\) ) could be gained by decomposing the generated matrix via applying matlab. The normal vector of the point can be regarded as the eigenvector corresponding to the minimum eigenvalue \(\lambda_3\). In order to clear the sharp points, the deviation efficient \(\eta\) is defined in the following equation:

\[
\eta = \frac{\lambda_3}{\lambda_1 + \lambda_2 + \lambda_3}
\]

Where \(\eta_{\max}\) is defined as the maximum deviation which the neighbor domain subset of the sample points can endure, then the points in the subset is determined to be on the same plane only when \(\eta < \eta_{\max}\). The dip direction (\(\alpha\)) and dip angle (\(\beta\)) of the fitting plane can be calculated via the following equation:

\[
\alpha = \tan^{-1}\left(\frac{a}{b}\right) + N
\]

\[
\beta = \tan^{-1}\left(\frac{c}{\sqrt{a^2 + b^2}}\right)
\]

Where \(a, b, c\) are the normal vector of fitting plane. \(N=0^\circ\), if \(a \geq 0\), and \(b \geq 0\); \(N=360^\circ\), if \(a \geq 0\), and \(b < 0\), for other conditions, \(N=180^\circ\).

Fig 2. Subset of neighborhood points and computing node on the fitting plane

2.1.2. Grouping of dominant discontinuity
Considering the similarity and parallel of normal vector of point cloud in the same discontinuity set, the normal vector of all points will be conduct the stereographic projection in lower hemisphere in the Schmidt net, and make statistics and dominant grouping on point set of rock discontinuities. Several commonly used algorithms have been introduced to determinate the point set of the dominant discontinuity sets, such as k-means algorithm, Fuzzy C-means clustering algorithm. The common characteristic of these algorithms is the initial guess on the number of the clustering sets and centre, which usually caused man-made deviation. In order to accurately conduct the automatic discontinuity grouping, this paper applied the DPC algorithm (Gao et al., 2019; Rodriguez and Laio, 2014) which can quickly search and partition the point set of the best local density in global scope without giving the number of the clustering.
sets and centre in advance. The point set of each partition can be extracted independently. The basic principles of the DPC algorithm is assuming that the local density of the neighbor points around clustering centre is less than the density in the clustering centre, and the distance between the clustering centre is maximum. From the previous study, the local density is calculated by the following equation when there is quite a lot of data point:

$$\rho_i = \sum \chi(d_{ij} - dc)$$  \hspace{1cm} (6)

Where \(d_{ij}\) is the distance between point \(i\) and point \(j\), \(dc > 0\), \(dc\) is the truncation distance (the percentage of the average number of each data point’s neighborhood points taken up the total number of data points), the function \(\chi(x)\) is defined as below:

$$\chi(x) = \begin{cases} 1, & x < 0 \\ 0, & x > 0 \end{cases}$$  \hspace{1cm} (7)

The distance of point \(i\) with maximum local density can be determined in Eqs.(8):

$$\delta_i = \begin{cases} \max(d_{ij}), & \rho_{\text{maximum}} \\ \min_{j\rho_j > \rho_i}(d_{ij}), & \rho_{\text{non-maximum}} \end{cases}$$  \hspace{1cm} (8)

Select the larger point between \(\rho_i\) and \(\delta_i\) as the clustering centre by using the visual decision diagram. Afterwards distribute all the points in descending order of local density \(\rho_i\) to the nearest same sets, and complete the normal vector grouping of points. The orientation of the clustering centre can be used to represent the dominant orientation of the discontinuity. When the cluster is done, the points which are far away from the cluster centre can be filtered by distribution probability density function (Fisher, 1953; Kulatilake, 1985), based on all the orientation of planes meet the characteristic of spherical normal Fisher distribution. This step can increase the accuracy and efficiency of the calculation.

2.1.3. Cluster segmentation

In order to extract the discontinuity information, the region growing algorithm (Hu et al., 2019) is applied after the density cluster. The seed region is growing to an extended region according to the growing rule and the extracted cluster of point cloud is performed segmentation. Firstly, select one seed point randomly from one cluster of point cloud to conduct the nearest searching and generate a sub region, calculating the distance between all the neighbor points and the seed point. If the distance is less than the threshold (the threshold is usually set as 3 to 5 times of the accuracy of the collected sample), then all the points met the condition are identified as new seed points and conducted nearest neighbor searching to calculate the distance, and this step will be repeated until extended region stops growing, the extended region is the required extracted discontinuity. Next, delete the points set belong to the extracted discontinuity, and select one point randomly from the rest of point cloud in the cluster to repeat the same process according to the growing rule. We defined the value of mincluster which is the minimum number of point cloud included in the discontinuity, if the number of points included in the region is greater than the mincluster, this region will be identified as extracted discontinuity, and the points set will be deleted from the original data to be identified. Otherwise, all the points set in this region will be returned to be original data. If the mincluster is set too large, the discontinuity with small outcropping plane, can not be identified, while the mincluster is set
too small, lots of noise will be wrongly identified as discontinuities, which will affect the final results.

2.1.4. Extraction of discontinuity

The rock surface affected by weathering usually cause the uneven discontinuity of the rock masses in the nature. The geological compass is traditionally applied to measure the orientation, only small area of the measured result is used to approximately represent the actual orientation. The proposed method in this section is optimal plane fitting method, which can use the complete point cloud data of the outcrop plane to fit the plane and calculate the orientation, this method has considered the effect of the sharp points on the fitting plane and broken the limitation of manual measurement. The commonly used plane fitting method includes the Least Squares method (Wang et al.,2001) and Random Sample Consensus (RANSAC) method (Fischler and Bolles,1981; Ferrero et al.,2008). Fig.3. shows the comparison of fitting results by the least squares and RANSAC methods, the least squares has considered the effects of all points on the fitting line while RANSAC automatically ignored the noise around. The experimental results prove that the fitting results applied by the least squares method to extract discontinuity are not as good as the ones applied by RANSAC method. This attributes to the interference of the sharp point in the least squares method while RANSAC method can automatically denoise. Hence we finally choose RANSAC method to accurately extract the discontinuity considering RANSAC can directly use the advantage of the original point cloud data and strong robustness, the plane fitting method of RANSAC can generate more objective estimations. In general, we think the proposed method of RANSA could be more reliable than the manual measurement.

![Fig 3. Comparison of fitting results by RANSAC and Least Squares methods](image)

2.2. Pre-processing of irregular rock block

The natural rock block is usually formulated by three groups of mutually cut discontinuities with different spacing and direction or more than three groups, which caused the irregularity of the rock block. The proposed method automatically identifies all the point sets of the rock blocks, and fill in the outlines generated by each point set. Hence information of the rock blocks can be obtained. Considering the irregularity, we have to simplify the block identification algorithm in order to increase the calculating efficiency. In this section, we compiled the pre-processing program of partial merger of discontinuities with same normal vector on irregular rock block, by applying the visual graphic cursor commands named “datacursormode” as shown in Fig.4. This program could merge the point cloud data of the discontinuities with similar normal vector on the same block by extracting the 3D data of one point and
automatically index the subset of the discontinuity which the point belongs to. Finally the outcropping polygonal irregular block only includes three subsets of the discontinuities.

![Visual interface of pre-processing on irregular blocks](image)

**Fig 4.** Visual interface of pre-processing on irregular blocks

### 2.3. Rough combination of blocks

The shape of the rock masses and the discontinuities of the combinations varies a lot for the complexity of the rock discontinuity. In this paper we select the final combination of the discontinuities of the block by the filtering exclusive method. The euclidean distance between the point sets of the two planes in the discontinuity combinations can be calculated by Eqs. (9), after making arbitrary pairwise combinations of all the discontinuities.

$$\text{dist}(p_{m}, p_{n}) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2}$$

(9)

where \(p_{m}\), \(p_{n}\) are the coordinates of point sets of the two planes in the discontinuity combination. \(x_i, x_j, y_i, y_j, z_i, z_j\) are the 3D coordinate value of arbitrary point on the two planes.

In order to filter the invalid discontinuity combinations we compare the threshold \(D\) with \(\text{dist}\), the value of threshold \(D\) is determined by the minimum spacing of discontinuity sets. when the minimum \(\text{dist}\) in the discontinuity combination is greater than the minimum threshold \(D\), then eliminate the combination; when the minimum \(\text{dist}\) in the discontinuity combination is less than the minimum threshold \(D\), then retain the discontinuity combination and conduct further filter.

We can also conduct the angle filter of the discontinuities, the angle of normal vector of arbitrary discontinuity combination can be calculated by Eqs. (10), according to the extracted information of the discontinuities in section 2.1.4.

$$\theta = \arccos |n_m \cdot n_n|$$

(10)

where \(\theta\) is the angle of the discontinuities, and \(n_m, n_n\) are the normal vectors of the two planes. If the angle is greater than or less than certain extent, the discontinuity combination could be eliminated as well. The angle of discontinuity usually ranges from 25° to 155° under the natural state, if the \(E\) (absolute value of the cosine value of the angle) is under 0.9, then retain the discontinuity combination, otherwise eliminate the combination and continue filtering the rest of the discontinuity combinations. The pseudo-code of the the combination of adjacent discontinuity is listed in Appendix A.

From the retained discontinuity combinations, select arbitrary two discontinuity combinations.
to conduct the second grouping, if the two discontinuity combinations share one same plane, then a candidate block generates. Otherwise eliminate the new combinations. Only the combinations sharing the same plane can be retained. Through the simple filter, it can eliminate 90% of the invalid discontinuity combinations which can save the time and increase the efficiency of the calculation.

2.4. Accurate extraction of blocks

From section 2.3. we have select the proposed discontinuity combinations of blocks, but they are not the actual discontinuity combinations of blocks. Thus we propose to apply mutual project of centroid and add angle repair coefficient in order to accurately extract the real blocks. By assuming the internal part of the computer as the location of the rock mass, while the external part of the computer as the location where the scanning takes place, we regard plane 1, plane 2 and plane 3 together as one real block as shown in Fig.5, the suppositional combination of block consist of plane 2, plane 3 and plane 4 and the suppositional combination of block consist of plane 2, plane 4 and plane 5 remain to be the proposed blocks. Therefore it is proposed to apply mutual projection of centroid and add angle repair coefficient in order to accurately extrac real rock block.

2.4.1. Mutual projection of centroid

As shown in Fig.5, the centroid coordinates of arbitrary two planes are projected to the third plane (e.g. P1 is projected to Plane 3 and turn to be P5; P2 is projected to Plane 3 and turn to be P6) on the retained block combinations after filter, and the midpoint of the connection between the two projected points which is P8. The centroid coordinates is defined as Eqs.(11), and the centroid is projected by Eqs.(12).

\[
\begin{align*}
    x_0 &= \frac{\sum x_i}{n}, \quad y_0 = \frac{\sum y_i}{n}, \quad z_0 = \frac{\sum z_i}{n} \\
    Ax_m + By_m + Cz_m + D &= 0 \\
    y_m &= \frac{B}{A} (x_m - x_0) + y_0 \\
    z_m &= \frac{C}{A} (x_m - x_0) + z_0
\end{align*}
\]

where \((x_i, y_i, z_i)\) is coordinate of the point set of arbitrary plane, the \((x_0, y_0, z_0)\) is the centroid coordinate before being projected, \((x_m, y_m, z_m)\) is the coordinate of the projected point, and \(A, B, C, D\) are the normal vector of the projected plane.

In order to identify the real block of the rock mass, each combination of the three adjacent planes will be conducted three rounds of the mutual projection and meet the condition which is the midpoint is on the third plane, or the minimum Euclidean distance between the point and the third plane is within the threshold. As shown in Fig.5, it is obvious that P8 is included in the point set of plane 3, so plane 1, plane 2 and plane 3 formulate the real block. However, P9 is not included in the point set of plane 3 and far away from the boundary point of the plane 3. Hence the combination consist of plane 2, plane 3 and plane 4 is identified as invalid block. For plane 2, plane 4 and plane 5, though they meet the conditions of the threshold of the distance
between projection points, each plane of the combination has been included in the other real blocks, so the combination consist of plane 2, plane 4 and plane 5 is identified as fake block. Both of the invalid blocks and fake blocks shall be eliminated. The pseudo-code of the mutual projection of centroid is listed in Appendix B.

![Diagram of projection points and planes](image)

**Fig 5.** Example for identification of real block and fake block by the centroid projection method

### 2.4.2. Angle repair coefficient

It could be know that the projected point will be projected directly on the edge of the plane, if the angle between the arbitrary two planes in the combinations is around 90°. However, the projected point will deviate from the outline of the plane, if the angle of two planes are especially large or small when the projected point is projected on the third plane. So in this section we propose to use the angle repair coefficient \( \varphi \) to make the projected point close to the projected plane. For example shown in Fig.6, assuming plane 2 and plane 3 are mutually vertical, the angle between plane 1 and plane 3 is \( \alpha \), the steps of the method are the following:

1. Project the centroid of arbitrary two planes on the third plane, and gain the 3D coordinates of the projected points. (e.g. P1 is projected to P5, P2 is projected to P4 which locates on the extended part of Plane 3.)

2. Calculate the absolute values \( \varphi \) of the cosine value of the angles between the selected arbitrary two planes and the third plane respectively.

3. Calculate the minimum distance \( d_{min} \) between the projected point and the point set of the third plane (the distance between P5 and P9), and calculate the slope K (between the two points, the slope of the connection between P5 and P9).

4. Obtain the distance between P5 and P6 based on the value of \( d_{min} \) multiplying \( \varphi \), then obtain the coordinate value of P6 based on the coordinate value of P5 and direction vector K.

5. Calculate the 3D coordinate value of the midpoint P8 of the connection of the repaired two projected points. Then compare the threshold with the minimum distance between P8 and the third plane, to judge whether the discontinuity combination forms the real block.
2.5. Calculation of the block size

From the identified combinations of the block discontinuities, we use the built-in functions of Matlab named Alphashape to fill the concave outline of point cloud on each single block, and the volume of the block can be estimated. With the volume of the block, the block size can be calculated by Eqs.(13):

\[
\text{blocksize} = \sqrt[3]{V_{\text{polygon}}}
\]  

(13)

where \( V_{\text{polygon}} \) is the volume of the block.

3. Application of the proposed method

In this section, we applied the proposed method in two cases and analyzed the results by comparing with the manual measurements and the results in previous study. The application in case 1 is to verify the reliability of the proposed method by using the method on the boxes model, the results have been compared with the manual measurements. In case 2, the proposed method is applied on the road cut slope in USA and make a comparison with two methods from previous study and specialized software. Since the number of points cloud is enormous, it applies Octree algorithm to re-sample the data and define the minimum granularity as 8, which greatly increased the calculation efficiency.

3.1. Method Validation

The experiment of scanning the boxes model was conducted in the Geohazards Laboratory of Shaoxing University, total 21 boxes have been built to simulate the layered slope model. The boxes include seven 30cm×30cm×30cm, seven 45cm×45cm×45cm, five 60cm×60cm×60cm for cube boxes and two 40cm×30cm×30cm for cuboid boxes. The case study applies the Topcon GLS-2000 3D Laser Scanner to obtain the data in 2 scan positions. Totally 560,424 points were scanned by point cloud registration, the scanning accuracy is 2mm. Fig.7(a) shows the field of scanning the boxes model, Fig.7(b) presents the generating graph of the original data and Fig.7(c) presents the results of pre-processed 3D point cloud data. The size parameters have been known, hence the calculated results can be directly compared with the manual
measurements, to verify the reliability of the proposed method.

![Indoor experiment of boxes model (a) scanning the scene. (b) original 3D point cloud data of scanned boxes model with RGB information. (c) Pre-processed 3D point cloud data.](image)

**Fig 7.** Indoor experiment of boxes model (a) scanning the scene. (b) original 3D point cloud data of scanned boxes model with RGB information. (c) Pre-processed 3D point cloud data.

3.1.1. Orientation

We determined the dominant parameters of the boxes model, the identified parameters of the plane are $k=20$, $d_j=0.06$, $\text{mincluster}=50$; the identified parameters of block are $d=0.05$, $\epsilon=0.9$. The orientation of the planes has been plotted in pole graph by stereographic projection in lower hemisphere as shown in Fig.8(a). Three sets of dominant orientation have been identified which are set 1, set 2 and set 3 marked in different colors shown in Fig.8(b). Totally 23 planes have been extracted, for Plane 11, Plane 15, Plane 17, Plane 19, respectively includes more than two boxes. All the automatically extracted planes of the boxes model marked in number have been shown in Fig.8(c). The orientation calculated by the proposed method and manual measurement have been shown in Table 1. The deviation of dip direction is within 2% while the deviation of dip angle is within 1%. The maximum deviation is found on Plane 17, mainly because that Plane 17 includes 4 boxes but it was just been identified as one plane which is , which caused accumulated deviation. The rest of the planes are normal and the deviation ranges from 0.12 to 1.02, which are acceptable.
Fig 8. (a) pole graph of plane orientation by stereographic projection in lower hemisphere; (b) identified three sets of dominant planes with different color; (c) extracted planes marked in numbers.

Table 1. Comparison of calculated orientation between classical and proposed method

| Plane Set id | Cluster id (number of points) | Plane orientation by classical method (dip direction/dip angle) | Plane orientation by proposed method (dip direction/dip angle) | Deviation (%) | Δ|DD| | Δ|DA| |
|--------------|------------------------------|---------------------------------------------------------------|---------------------------------------------------------------|---------------|---|---|---|
| Set 1        | 1 (3471)                     | 332.01/88.75                                                 | 333.03/89.49                                                 | 1.02          | 0.74 |
| Set 1        | 3 (1849)                     | 332.14/89.12                                                 | 332.63/89.60                                                 | 0.49          | 0.48 |
| Set 1        | 5 (930)                      | 151.28/89.43                                                 | 151.71/89.82                                                 | 0.53          | 0.39 |
| Set 1        | 7 (582)                      | 153.85/88.39                                                 | 154.07/87.85                                                 | 0.22          | 0.54 |
| Set 2        | 11 (1767)                    | 60.96/89.57                                                  | 60.18/89.27                                                  | 0.78          | 0.30 |
| Set 2        | 13 (1517)                    | 242.92/89.58                                                 | 242.60/89.46                                                 | 0.32          | 0.12 |
| Set 2        | 14 (828)                     | 62.75/88.32                                                  | 62.10/88.08                                                  | 0.65          | 0.24 |
| Set 2        | 16 (350)                     | 62.25/89.62                                                  | 61.91/89.45                                                  | 0.34          | 0.17 |
| Set 3        | 17 (2897)                    | 209.42/0.82                                                  | 208.07/0.18                                                  | 1.36          | 0.64 |
| Set 3        | 19 (833)                     | 305.28/1.74                                                  | 304.73/1.97                                                  | 0.55          | 0.23 |
| Set 3        | 21 (547)                     | 348.77/0.87                                                  | 348.59/0.65                                                  | 0.18          | 0.22 |
| Set 3        | 23 (335)                     | 234.28/0.91                                                  | 233.74/0.47                                                  | 0.54          | 0.44 |
3.1.2. Block size
In the boxes model experiment a total number of 9 blocks have been automatically extracted and respectively marked in different color as shown in Fig.9. Then import the extracted plane combination of the block to the specialized point cloud processing software Geomagic wrap (3D systems, 2019) for encapsulating and calculating the volume as well as the block size. The calculated results have been compared with the results applied by the proposed method which are presented in Table 2. It reveals that the calculated results by the two methods are very close, the deviation is around 1%. The maximum deviation is found on block 7 because the left part of block 7 is hidden by block 6. It is noted that although the entire plane of some block has been extracted, actually only part of the plane is used in the block calculation. For example, block 1 is consist of Plane 3, Plane 13, Plane 17 as shown in Fig.8(c), although Plane 17 is entirely extracted, part of Plane 17 marked in purple as shown in Fig.9 has not taken part in the calculation.

![Extracted blocks with different color](image)

**Table 2.** Comparison of calculated block size by different methods

| Plane id | Block id | Block size by Geomagic wrap (m) | Block size by proposed method (m) | Deviation (%) |
|----------|----------|--------------------------------|----------------------------------|---------------|
| 3, 13, 17 | 1        | 0.6249                         | 0.6245                           | 0.06          |
| 1, 12, 17 | 2        | 0.6692                         | 0.6780                           | 1.30          |
| 6, 11, 18 | 3        | 0.3940                         | 0.3917                           | 0.58          |
| 2, 10, 23 | 4        | 0.5732                         | 0.5925                           | 3.35          |
| 8, 11, 21 | 5        | 0.3385                         | 0.3441                           | 1.66          |
| 5, 14, 20 | 6        | 0.3784                         | 0.3760                           | 0.62          |
| 4, 16, 19 | 7        | 0.3274                         | 0.3542                           | 8.20          |
| 9, 15, 22 | 8        | 0.2802                         | 0.2834                           | 1.17          |
| 7, 15, 19 | 9        | 0.2591                         | 0.2598                           | 0.28          |

3.2. Real Case Study
The real case study is from an exposed road cut slope (Lato et al., 2013) located in Ouray,
Colorado, USA. It is referred to the open database from www.3d-landslide.com/projects/discontinuity. Fig.10(a) shows the field of the road cut slope and Fig.10(b) shows the generating graph of points cloud data analyzed on the road cut slope. The case study applies Optech Ilris 3D Laser Scanner to collect data in 4 scan positions in 2004, totally 1,515,722 data points have been obtained, the accuracy of the points is 2 cm. The results of the proposed method have been made comparison with the results of Riquelme et al.(2014) and classical method.

3.2.1. Orientation
According to the methods introduced in Section.2, we determined the dominant parameters of plane identification as $k=20$, $d_0=0.07$, mincluster=30. Since the scanning scope extended and the scanning accuracy decreased, the block identified parameters are determined as $d=0.25$, $\varepsilon=0.9$. The automatic identified results are shown in Fig.11(a), 5 sets of dominant discontinuities have been identified and marked in different colors. In order to analyze the extraction results of the discontinuities in details, we accurately locate 5 sets of dominant discontinuities as shown in Fig.11(b)-(d) including 18 corresponding discontinuities which were also in the study of Riquelme et al.(2014) and make comparison between them. The orientations obtained by the proposed method and Riquelme et al.(2014) are concluded in Table 3. It reveals that the results of proposed method are very close to the results of Riquelme et al.(2014). The deviation of the results between the two methods is $1^\circ$ when the plane is smooth, even if for the rough plane, the deviation of most measured orientation by two different methods is only $5^\circ$. These deviation are within the reasonable range in the application of real case study, which can further demonstrate that the plane information extracted by the proposed method could represent the outcrop information of the discontinuities of real slope.

![Fig 10](image-url)  
Fig 10. (a) Image of scanned survey site in Ouray, Colorado, USA; (b) 3D point cloud model re-sampled by Octree and the marked green area for block identification
Fig 11. (a) Results of automatically identified dominant discontinuities with different color. (b)-(d) Results of discontinuity segmentation from Set 1 to Set 5

Table 3. Comparison of calculated orientation by different methods

| Discontinuity id | Plane orientation using classical method | Plane orientation by Riquelme et al. (2014) | Plane orientation using proposed method | Riqueleme ea al.(°) | New proposed method (°) |
|------------------|------------------------------------------|--------------------------------------------|------------------------------------------|---------------------|-------------------------|
|                  | 249.18/40.23                             | 246.24/39.02                               | 247.99/39.44                            | ∆D | ∆D | ∆D | ∆D |
| 11               | 264.23/57.02                             | 256.86/52.30                               | 252.95/50.69                            | 7.37 | 4.72 | 11.2 | 6.33 |
|                  | 263.97/41.91                             | 70.26/35.80                                | 249.92/35.85                            | 13.7 | 6.11 | 14.0 | 6.06 |
| J 1              | 252.58/36.53                             | 252.68/35.48                               | 251.50/34.10                            | 0.10 | 1.05 | 1.08 | 2.43 |
| 14               | 248.71/36.98                             | 249.74/35.91                               | 249.94/35.89                            | 1.03 | 1.07 | 1.23 | 1.09 |
| 15               | 254.77/29.86                             | 70.47/35.92                                | 250.33/35.71                            | 4.30 | 6.06 | 4.44 | 5.85 |
| 16               | 249.85/35.94                             | 255.12/35.72                               | 255.82/32.06                            | 5.27 | 0.22 | 5.97 | 3.88 |
| 17               | 338.68/82.35                             | 339.47/83.25                               | 328.27/87.64                            | 0.79 | 0.90 | 10.4 | 5.29 |
| 21               | 347.47/79.01                             | 166.33/76.58                               | 340.98/82.12                            | 1.14 | 2.43 | 6.49 | 3.11 |
| J 2              | 341.04/89.50                             | 160.20/89.86                               | 158.12/82.01                            | 0.84 | 0.36 | 2.92 | 7.49 |
| 22               |                                          |                                            |                                          |                    |
3.2.2. Block size

The outcrop of rock masses varies in different sizes and shapes for the complexity of discontinuity. The proposed method is available to normally operate for the outcropping block in similar size. The interested region of green point cloud as shown in Fig. 10(b) is enclosed by the selected red line, which is 12m long and 6m wide. Based on the identified parameters of dominant block, this study has automatically extracted 14 discontinuities and 3 block, which are automatically marked in different colors as shown in Fig. 12(a)-(b). It can be found in Fig. 10(a) that it is unavailable to do the manual measurement in the field as the lowest position of the outcrop in the discontinuity is approximately 20m above the ground. Therefore this case study applied the Geomagic wrap to calculate the block size. A comparison of the calculated volume between the proposed method as shown in Fig. 13(a)-(c) and Geomagic wrap software as shown in Fig. 13(d)-(f). The corresponding coefficients of the cluster equation are presented in Table 4. The comparison of the deviation of the calculated block size by proposed method and Geomagic wrap software is presented in Table 5. The deviation of the block size is within 2% when the outcrop is relatively complete and in similar size.

Referring to the calculation time, all the calculation works in this study have been conducted by the Intel Core i7-8700 computer with 3.2 megahertz and 8G RAM storage. A comparison of calculation time between the new method and the method by Chen et al. (2017) have been listed in Table 6. It is proved that the calculation accuracy and efficiency are completely acceptable in the real case study. Though the cluster analysis takes the longest time in the computing process, cluster analysis by using the peak density search algorithm decreases the deviation by subjective judgment. This makes the calculated results more accuracy than the ones by k-means algorithm algorithm or Fuzzy C-means clustering algorithm.
Fig 12. (a) Results of identified extracted discontinuities with different color; (b) Results of identified extracted blocks with different color.

Fig 13. (a)-(c) Calculated volume of extracted identified block1, block2, block3 by proposed matlab program; (d)-(f) Calculated volume of block1, block2, block3 by geomagic software.

Table 4. Corresponding coefficients of the cluster equation

| Discontinuity id | A     | B         | C      | D         |
|------------------|-------|-----------|--------|-----------|
| Plane 1          | 0.7531| -0.0555   | 0.6554 | -18.6644  |
| Plane 2          | 0.7032| -0.1236   | 0.7001 | -17.0577  |
| Plane 3          | -0.8652| 0.1354   | -0.4827| 20.3283   |
| Plane 4          | -0.5012| 0.8546   | 0.1354 | 9.9363    |
| Plane 5          | -0.5580| 0.8278   | 0.0568 | 8.9292    |
| Plane 6          | -0.1269| 0.9694   | -0.2100| 3.9438    |
| Plane 7          | -0.5575| 0.8100   | -0.1812| 16.0190   |
| Plane 8          | 0.8240| -0.3575   | -0.4394| -18.7676  |
| Plane 9          | -0.5312| -0.2232  | 0.8172 | 10.5596   |
Table 5. Comparison of the deviation of the calculated block size by proposed method and Geomagic software

| Discontinuity id | Block id | Block size by Geomagic wrap (m) | Block size by proposed method (m) | Deviation (%) |
|------------------|----------|---------------------------------|----------------------------------|---------------|
| 3, 8, 12         | 1        | 2.2678                          | 2.3109                           | 1.90          |
| 2, 7, 13         | 2        | 2.2929                          | 2.2477                           | 1.97          |
| 1, 9, 10, 14     | 3        | 2.2269                          | 2.3080                           | 3.64          |

Table 6. Comparison of calculation time between the new method and the method by Chen

| Step                                | Computing time (s) | Proportion (%) |
|-------------------------------------|--------------------|----------------|
|                                     | New method | Chen et al.(2017) | New method | Chen et al.(2017) |
| Local normal vector calculation     | 14          | 86              | 5.1        | 25.3             |
| Cluster analysis                    | 166         | 55              | 61.2       | 16.2             |
| Discontinuity extraction            | 71          | 129             | 26.3       | 37.9             |
| Block identification and calculation| 20          | 70              | 7.4        | 20.6             |
| Total                               | 271         | 340             | 100        | 100              |

4. Discussion

4.1. Collection of the database

The quality of the collected data has great impact on the automatically identified information and the extracted results. In the process of generating the high quality of 3D point cloud, there are two major factors impacting its quality:

a) Data registration. During the process of the point cloud space division, the measurement deviation in point cloud registration generates as the different accuracy in the measurements, hence cumulative deviation generates in multi-station of point cloud registration.

b) Coordinates transformation. Centimeter-scale deviation generates when transform the geodetic coordinates after the point cloud space division is done, which is attributed to the different collecting investments of geodetic coordinates on the measuring position. It is recommended to use the RTK GPS device in the project application which requires high accuracy(i.e. centimeter-scale).

c) Environmental factors. The dust in the air, plants on the rock and the passing vehicles may cause the earlier echo of pulsed laser and skipping of effective information, thus the noise generates. The noise can be manually removed or automatically eliminated by setting the value
of threshold based on the reflection intensity of point cloud.

4.2. Parameter Setting

The initial parameter setting of different algorithms has influence on the final identified results during the automatic identification of the discontinuities and blocks.

a) Calculation of the normal vector of the points. When apply the K-Nearest Neighbor Algorithm to calculate the normal vector of the point, if the K is given to smaller value, the final fitting plane of the discontinuity will retain lots of noise, while the K is given to greater value, lots of the edge points of the discontinuity will be lost. After several times of testing, we found that K=20 is the most appropriate. Likewise, if the $\eta$ is given too small, many points belong to the discontinuity will be discarded in wrong, while the $\eta$ is given too high, some points far which are away from the fitting plane will be mixed in the point set of the plane as noise. After several times of testing, we found that $\eta=0.2$ is the most appropriate.

b) Discontinuity grouping. In the application of DPC algorithm to conduct the dominant grouping of discontinuities, the local density of the poles is affected by the cutoff distance, if $d_c$ is set too large, the program will identify the two discontinuities with similar orientation as one discontinuity, while $d_c$ is set too small may cause multi-groups of discontinuities . We commonly gain the median value of $d_c$ in the range of 0.5%-12% according to the analysis in previous study (Gao et al.2019).

c) Discontinuity extraction. When segment and extract single discontinuity on point cloud of each cluster by using the region growing algorithm, the value setting of mincluster has influence on the final results. If the mincluster is set too large, the discontinuity with small outcropping plane, can not be identified, while the mincluster is set too small, lots of noise will be wrongly identified as discontinuities. The mincluster is determinate through extracting part of the noise region and checking the number of the point cloud in the region.

d) Plane fitting. The effects of fitting on point cloud of the single discontinuity by using RANSAC algorithm have influence on the final identified orientation of the discontinuity. We define the distance between the point and the plane as the determination of valid point or noise point ,if the point is within the distance it will be identified as valid point. According to previous study (Fischler and Bolles,1981),when the valid points reach 80%, the effects of fitting is the best.

e) Filter criterion. Combine arbitrary two discontinuities and calculate minimum distance and angle between the two discontinuities. If the minimum distance is greater than the threshold D or the absolute value of cosine value of the angle is greater than 0.9, the combination of discontinuities will be eliminated. The threshold D can be determined by using the point cloud processing software to measure the spacing of discontinuities.

4.3. Advantage of the proposed method

a) Identification of irregular block. The proposed method fully use the advantages of flexible operation on each independent point cloud, avoiding the programming difficulty caused by complex generated triangular meshes. Through applying the method of filling in the concavity
outline to extract the block, it solved the problem in this area of study which only regular parallelepiped block can be identified in the previous study.

b) Remote sensing survey. By applying the 3D laser scanning technology, the surface information of the rock could be obtained from long distance. The 3D laser scanning technology could solve the problems in traditional measurement technology such as time-consuming, high risk and high cost. For some high-steep and high-risk slopes, it’s impossible to adopt traditional measurement such as contact accurate measuring line and statistical window. The advantage of remote sensing technology turn to be prominent in field survey.

c) Estimation of the orientation. Traditional measurement of the orientation of rock discontinuity relies on compass, which can only estimate small part of the accessible discontinuity. The entire surface change of the rock discontinuity is easy to be ignored. This paper not only considers the the outcropping forms but also the roughness and undulation of the discontinuity by applying the RANSAC algorithm to fit the Plane. The proposed method is more reliable and accurate than the manual measurements on the estimation of the orientation.

5. Conclusion

A new method of automatic identification and extraction of block information is introduced based on 3D point cloud in this paper. The new method includes four main innovative improvements: (1) Realization of automatic identification and extraction of discontinuities by using several classical machine learning algorithms; (2) Introduction of the criterion of distance filter and angle filter in order to eliminate 90% of the combinations of block discontinuities which are invalid in the followed calculation, the calculation efficiency has been highly improved; (3) Accurate extraction of combinations of real block planes by applying mutual projection of centroid and adding angle repair coefficient; (4) Realization of filling the concave outline of point cloud by the built-in functions of matlab named Alphashape and compiling the software of automatic calculation on the volume and block size of the rock block.

The proposed method has taken full advantages of the 3D point cloud, which can realize the automatic calculation without processing the complicated triangular section meshes. The method is applied in two case study and the results have been compared with former research and software calculation. It has been proved that the method is accurate and applicable which can meet the requirements in practical projects. However the method has its limitation, as the application of the new method is based on the premise that extracted block is not hidden by other blocks and the rock blocks are in similar scale.

The further research will be focus on: (1) extraction of the roughness and linear outcrop of the discontinuities from 3D point cloud and high resolution images; (2) extraction of the internal information of outcropping rock masses by using digital borehole camera technology.
Acknowledgment
The authors gratefully thanks to Rockbench repository for providing the scanning data for the study. The authors would like to acknowledge the financial support by National Natural Science Foundation of China: [Grant Number 41831290], Zhejiang Provincial Natural Science Foundation of China: [Grant Number LGF18D020002], Key Scientific Research Project of Shaoxing University: [Grant Number 2020LG1015], Zhejiang Provincial Natural Science Foundation of China: [Grant Number LHQ20D020001].

Appendix A. The pseudo-code of extracting the combination of adjacent discontinuity

```plaintext
Input: Dp[N][planeid1,planeid2]: a N×2 matrix storing any pairs of planes; planeID1 and planeID2 is matrix storing the 3D points coordinate datasets of one discontinuity;
Output: C : Plane combination to meet filtering requirements
1.  C:=[]
2.  For i←1 to N do
3.    For each point belong to planeID1 do
4.      For each point belong to planeID2 do
5.        Calculate the distance between two plane point sets using Eq.(9) then
6.      End for
7.    End for
8.    If minimum distance<D // D is threshold of the minimum spacing of discontinuity sets
9.      Calculate the angle between planeid1 and planeid2 using Eq.(10) then
10.     If |cosθ|<0.9 // θ is threshold of the angle between two fitting planes
11.    C = C ∪ Dp[Ni]
12.  End if
13.  End if
14.  End for
15.  Output C
```

Appendix B. The pseudo-code of the mutual projection of centroid

```plaintext
Input: Dp[N][planeid1,planeid2,planeid3]: a N×3 matrix storing three planes; planeID1, planeID2 and planeid3 is matrix storing the 3D points coordinate datasets of one discontinuity;
Output: C : Combination of discontinuity of blocks
1.  C :=[]
2.  For i←1 to N do
3.    For each planeid do
4.      Calculate the centroid of each plane using Eq.(11) then
5.        Calculate the projection point of the centroid using Eq.(12)
6.      End for
7.    For i←1 to 3 do
8.      Calculate the distance from the center point of any two centroids to the third face
9.      If the distance<Ti,
10.     count←count+1
```

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11. End if
12. End for
13. If count=3
14. \( C_r = C_r \cup D_p[N_i] \)
15. End if
16. End for
17. Output \( C_r \)

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