Feature Sampling and Balancing for Detecting Rock Bolts from the LiDAR Point Clouds

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ABSTRACT: Rock bolts play a crucial role in enhancing the stability of tunnel structures. However, designing bolt detection methods from LiDAR point clouds often faces the challenge of data imbalance. Despite this, the state-of-the-art deep learning-based detection methods adopt uniform sampling strategy for both bolt and background points without considering their unequal distribution, leading to a substantial loss of bolt features and overabundance of noise points. We propose a novel bolt feature sampling and grouping strategy by integrating principal component and surface curvature analysis to balance the noise background points and the bolt points. The balanced point features are fed into a newly designed deep neural network with a weighted loss function to accurately detect the position of rock bolts. The proposed method achieves state-of-the-art results on the Civil Tunnel dataset and Mining Tunnel dataset, outperforming the state-of-the-art 3D deep learning-based detection methods with uniform sampling strategy.

Keywords: Rock bolt detection, point cloud, LiDAR, neural network.

1 INTRODUCTION

Rock bolts are crucial for stabilizing rock faces in tunneling projects. Accurate determination of rock bolt positions is essential for constructing a smart monitoring system to ensure tunnel structure stability. In low light and dusty mining environments, 3D LiDAR laser scanning technology is commonly used for precise localization of rock bolt positions. Previous studies by Gallwey et al. (1998) and Saydam et al. (2021) have shown that LiDAR technology is effective in handling uneven illumination.

LiDAR scanning generates point cloud representations of the tunneling environment. Localizing rock bolts from these point clouds falls within the domain of 3D object detection in computer vision research. Recently, deep learning-based 3D object detection models such as PointNet (Qi et al., 2017) and PointRCNN (Shi et al., 2019) have been proposed, utilizing powerful 3D feature extraction backbones and object detection frameworks. However, these state-of-the-art models are not directly applicable to the problem of rock bolt localization due to the disparity in bolts sizes and point cloud sizes. LiDAR scans in mining environments typically consist of over 1 million points, with a single rock bolt comprising around 500 points (Saydam et al., 2021). This leads to over 99% of the points being background points and less than 1% being bolt points. When downsampling is applied without bias, very few bolt points remain, resulting in inadequate feature representation and poor detection performance. Therefore, an appropriate downsampling strategy that prioritizes bolt points and retains as many as possible is necessary to address rock bolt detection in mining environments.

Additionally, rock bolts occupy a minuscule area within the entire point cloud scan compared to general 3D objects. Even with a non-uniform downsampling strategy, the number of background points remains significantly larger than the number of bolt points. Binary classification of each point in the point cloud is essential for rock bolt detection. However, even with 10% bolt points in a LiDAR scan, deep learning models face challenges in learning effectively, as they can predict all points as background to achieve 90% accuracy. Consequently, a loss function that accounts for the minority class is required to improve the performance of deep learning models in rock bolt detection.

This paper aims to address the challenges faced in detecting rock bolts in mining environments. A new approach is proposed, which eliminates uniform downsampling and introduces a novel bolt feature sampling and grouping strategy based on principal component and surface curvature analysis. This strategy allows for the retention of a maximum number of bolt points while discarding most background points. Furthermore, a deep neural network is employed, considering the balanced bolt and background point features, and a specially designed loss function is introduced to tackle the data imbalance problem between bolt points and background points. The method is evaluated using the widely used PASCAL criteria for 3D object detection methods.

The contributions of our work can be summarized as follows.

1. We propose a novel bolt feature sampling and grouping strategy that replaces the uniform down sampling step to generate more bolt points in the training data.
2. We present a new loss function that effectively addresses the data imbalance problem in bolt detection.
3. We demonstrate that our method outperforms the current state-of-the-art method CFbolt on both the Civil Tunnel dataset and our newly collected dataset from an underground mine.

The manuscript is structured as follows: Firstly, the novel strategy for sampling and grouping bolt features is presented. Next, the deep learning framework incorporating two loss functions to address the data imbalance problem is introduced. The manuscript then provides a comprehensive analysis of experimental results, including evaluation of the framework's performance on bolt detection datasets and an ablation study. Finally, the conclusions of the study are presented.

2 METHOD

2.1 Bolt feature sampling and grouping

In order to mitigate the issue of excessive pruning of bolt points resulting from uniform down sampling, a novel approach has been devised. Specifically, we propose to sample features via principal component analysis (PCA), as introduced by Abdi and Williams (2010), in combination with curvature analysis. Subsequently, these sampled features are grouped together based on predetermined criteria. By employing this method, we aim to ensure that a greater proportion of important bolt points are retained and subsequently utilized for downstream processing.

To extract features from the point cloud data for bolt detection, we utilize a technique inspired by prior work. Specifically, we create several spherical structures around each point in the point cloud, with radii chosen as 8cm, 10cm, and 12cm, in accordance with the definition proposed by (Brodu &

Lague, 2012). For each point within a sphere of radius r, we apply principal component analysis (PCA) and extract the first normalized eigenvalue, denoted as λ_1^r. The resulting feature descriptor of PCA for each point is $[\lambda_1^{8cm},\ \lambda_1^{10cm},\ \lambda_1^{12cm}]$, which is subsequently used to train a linear classifier (Balakrishnama & Ganapathiraju, 1998) to differentiate between bolt points and background points. In addition, we take into account the curvature characteristics of bolt points, which differ from those of background points. To incorporate curvature information into our feature extraction process, we also calculate the curvature on each sphere with radii of 8cm, 10cm, and 12cm. The resulting feature descriptor of curvature, normalized and represented as $\{k^{8cm},\ k^{10cm}, k^{12cm}\}$ is then used to train another linear classifier to differentiate between bolt points and background points. By combining the results of these two classifiers, we can effectively identify potential bolt points within the point cloud data.

The potential bolt points are first combined to form a merged set. Next, the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm is utilized to identify and group the potential bolts from these potential bolt points. To ensure a high-quality training dataset, potential bolts that contain less than ten real bolt points are removed as they do not capture the entire structure of a bolt. It should be noted that this selection criteria is relatively loose and may result in some remaining false positive bolts. However, this issue is further addressed in Section 2.3. The resulting potential bolts are then uniformly downsampled to reduce the number of points and subsequently fed into the neural network for further processing.

2.2 Neural network framework

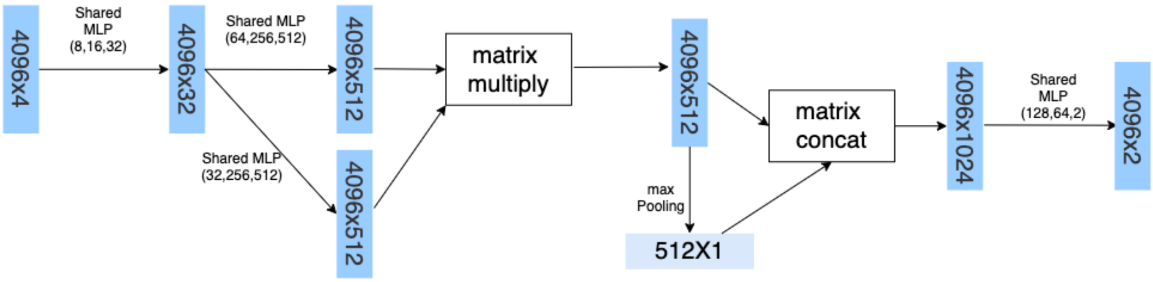

Figure 1. The proposed neural network structure.

To improve the accuracy of rock bolt detection, we have designed a novel artificial neural network (ANN) specifically tailored for this task. Our network architecture draws inspiration from the CFBolt and PointNet models but has been optimized for our purposes. Specifically, we increased the input point number from 1024 to 4096 and streamlined the network structure to better address the bottleneck in bolt feature sampling and grouping down-sampling.

The input dimension for each potential bolt is $[4096 \times 4]$, where 4096 is the maximum number of points the network can accept and 4 is the (x, y, z) coordinates of each point, along with one intensity value. This intensity value represents the return strength of a LiDAR laser beam and provides additional information that distinguishes bolt positions from background. The shared MLP is used to increase or decrease the dimensions, while "matrix multiply" and "matrix concat" are element-wise multiplication and concatenation operations, respectively. The network architecture is depicted in Figure 1.

2.3 Loss function for addressing data imbalance

In Section 2.1, we applied bolt feature sampling and grouping to reduce data imbalance, which limited the number of points per potential bolt to 4096. However, this did not completely balance the positive and negative samples, which can lead to bias towards the majority class and poor performance on the minority class. Therefore, we proposed a novel loss function to further address the data imbalance problem.

Inspired by the focal loss (FL) (Lin et al., 2017) and dice loss (DC) (Sudre et al., 2017), we designed a weighted loss function that assigns more weight to misclassified examples and down-weights the loss assigned to well-classified examples. This helps to focus the model's attention on the harder-to-classify examples, such as those in the minority class, and increases intra-class similarity and inter-class separability. Furthermore, to reduce the impact of the majority class and improve sensitivity to small objects like bolts, we measure only the similarity between predicted and ground truth bolt points, following the dice loss. The resulting loss function is given as follows:

$$Loss = FL + 0.5\,DC. \tag{1}$$

in which the FL is calculated by:

$$FL = -\alpha(1-p)^{\gamma} log(p) - (1-\alpha)p^{\gamma} log(1-p). \tag{2}$$

The α is set to 0.8 for balancing the bolt points and non-bolt points, and γ is set to 2 for balancing hard training and simple training samples. And the DC is calculated by:

$$DC = 1 - Dice(Pred, GT), \tag{3}$$

$$Dice(Pred, GT) = 2\frac{|Pred \cap G\,T|}{|Pred| + |GT|}, \tag{4}$$

in which $Pred$ and GT are the predicted bolt and the ground truth bolt. Our newly designed loss function have successfully boost the bolt detection performance by addressing data imbalanced problem (See Section.3 for detail).

3 EXPERIMENT

3.1 Datasets

Civil Tunnel (Saydam et al., 2021): Civil Tunnel dataset contain 84 rock bolt partial scans collected from a real civil tunnelling project site in Sydney, New South Wales, Australia. The number of bolts captured in each scan ranged from 10–20. There are 1,266 rock bolts in the dataset.

Mining Tunnel: We further collected 14 full rock bolt scans from a real mining tunnelling operation in New South Wales, Australia. The average number of bolts captured in each scan is around 200. There are 2917 rock bolts in the dataset. The surface of each scans in this dataset are rugged.

In comparison to the Civil Tunnel dataset, the Mining Tunnel dataset exhibits a more rugged surface with increased noise levels. Additionally, the number of bolts present in each Mining Tunnel scan is significantly higher than that of the Civil Tunnel dataset. This can be visually observed in Figure 2. Moreover, Mining Tunnel scans consist of complete scans, which contain more background points and potential branches, whereas Civil Tunnel scans are partial scans. Therefore, the Mining Tunnel dataset presents a more challenging scenario for the proposed rock bolt detection algorithm.

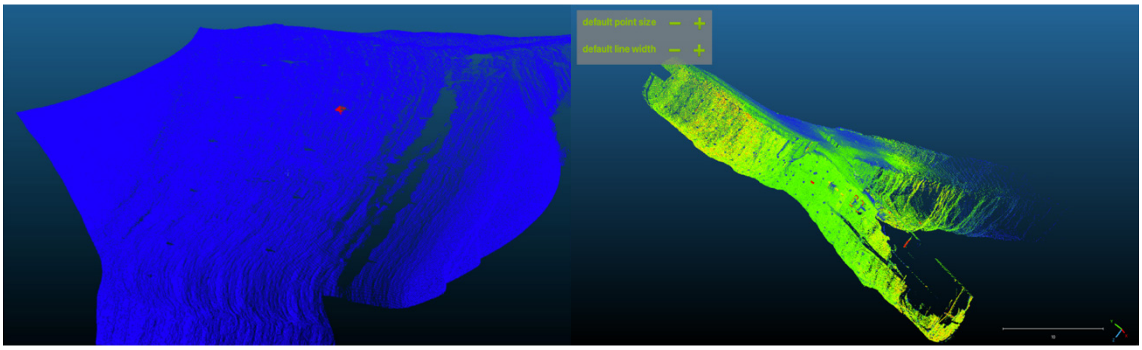

Figure 2. Visual example of the scans from Civil Tunnel (left) and Mining Tunnel (right). The Civil Tunnel scan is a partial scan, but Mining Tunnel scan is a full scan. The scan resolution is 6.3mm at 10m distance.

3.2 Implementing detail

The implementation and testing of the proposed rock bolt detection algorithm were performed on a workstation equipped with an Intel XEON 6242R CPU and NVIDIA A6000 GPU. The datasets were split using k-fold splitting, with seventy percent of scans used for training and the remaining thirty percent used for testing. The neural network framework was implemented using PyTorch 1.7, with the Adam optimizer and an initial learning rate of 0.001. The batch size was set to 30, and the number of fine-tuning epochs was set to 200 for Civil Tunnel and 300 for Mining Tunnel datasets.

Table 1. Results on Civil Tunnel and Mining Tunnel.

Method	Dataset	Precision(%)	Recall(%)	F1(%)
CFBolt (Saydam et al., 2021)	Civil Tunnel	**98.0**	82.3	89.4
Ours		96.0	**88.1**	**91.9**
CFBolt (Saydam et al., 2021)	Mining Tunnel	65.2	45.5	53.6
Ours		**71.2**	**57.6**	**63.6**

The experimental results of our proposed approach are presented for Civil Tunnel and Mining Tunnel datasets, with visualization of some detection results in Figure 3.

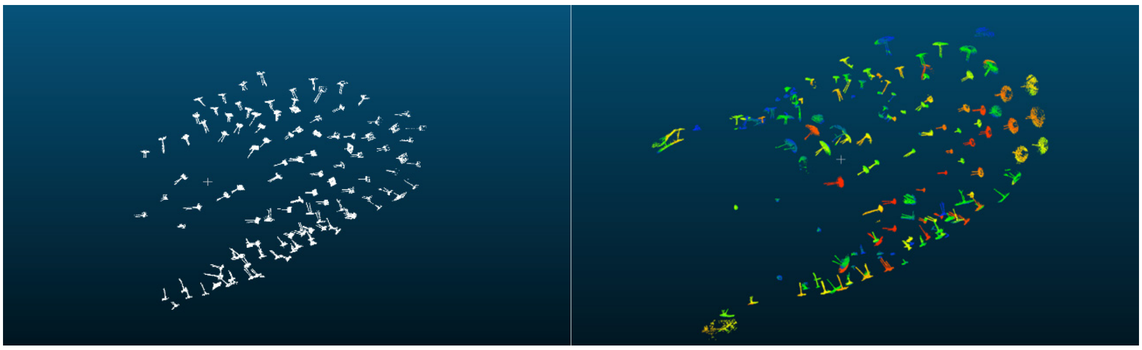

Figure 3. Examples of bolt detection result of the Ground Truth (left) and our method (right) on Mining Tunnel Dataset. Typical dimensions of the bolts range from approximately 20 - 30 cm.

Evaluation using the 2D/3D object detection protocol from KITTI (Geiger et al., 2012) with PASCAL criteria (Everingham et al., 2015) are presented in Table 1, and compared against the current state-of-the-art method CFBolt. The results show that our proposed method achieves F1 scores of 91.9% and 68.1%, respectively, with improvements of 2.5% and 10.0% on the Civil Tunnel and Mining Tunnel datasets. These findings demonstrate that the proposed bolt feature sampling and grouping down-sampling strategy, new network framework, and loss function are effective in addressing data imbalance issues and enhancing detection performance. Furthermore, our approach is particularly effective when scanning in real mining environments with rugged surfaces.

4 CONCLUSION

This study presents a novel approach for detecting rock bolts from 3D scans. To overcome the issue of data imbalance, we propose a bolt feature sampling and grouping strategy that utilizes multiple principal component and surface curvature features for down-sampling. Additionally, we design a new deep neural network framework and loss function to rebalance the network's learning process of bolt and background features. Our proposed method is evaluated on two bolt detection datasets, and the experimental results demonstrate its effectiveness in detecting rock bolts.

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