Advanced Graph-Based Object Segmentation in Large-Scale 3D Point Clouds

Marcin Mazur[1], Marcin Daszuta[1], Dominik Szajerman[1][0000−0002−4316−5310], and Piotr Napieralski[1][0000−0003−1427−7791]

Institute of Information Technology, Lodz University of Technology, Poland
marcin.mazur.995@gmail.com, mxdaszuta@gmail.com,
dominik.szajerman@p.lodz.pl, piotr.napieralski@p.lodz.pl

Abstract. We present a novel framework for object detection and segmentation in large-scale 3D point clouds. Our approach integrates edge-aware feature extraction with graph-based clustering to achieve highly accurate semantic segmentation. Unlike conventional methods relying heavily on handcrafted features or extensive labeled datasets for deep learning, our framework leverages geometric consistency and topological constraints to achieve robust object partitioning. We demonstrate the efficacy of our method on benchmark datasets, achieving state-of-the-art precision in complex environments with incomplete data.

Keywords: 3D Point Cloud · Edge-Based Methods · Graph Neural Networks · Feature Extraction · Object Segmentation

1 Introduction

Point clouds are essential datasets for representing 3D objects and spatial environments [1]. These datasets consist of discrete points in a three-dimensional coordinate system, each carrying geometric information and often additional attributes such as color and intensity. Point clouds are widely used in numerous fields, including autonomous driving, robotics, cultural heritage preservation, and medical imaging [2].

The acquisition of point clouds relies on advanced sensing technologies, including:

- Photogrammetry-based image reconstruction;
- Light Detection and Ranging (LiDAR) systems;
- Red Green Blue - Depth (RGB-D) cameras (e.g., Microsoft Kinect, Intel RealSense);
- Synthetic Aperture Radar (SAR) imaging.

Different point clouds exhibit varying characteristics depending on the acquisition method, sensor resolution, and environmental conditions. Variability in density, noise levels, and occlusion effects pose challenges for automated analysis [3]. Among these challenges, one of the most significant is 3D Point Cloud

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Segmentation (PCS), which involves partitioning raw 3D data into semantically meaningful regions [4].

Segmentation methods fall into three primary categories:

– Semantic segmentation: Assigning class labels to each point (e.g., chair, table, floor);
– Instance segmentation: Identifying separate objects of the same class;
– Part segmentation: Dividing objects into meaningful subcomponents (e.g., legs, backrest of a chair).

Traditionally, point-cloud segmentation has relied on geometric features and statistical methods. Techniques such as region growth, edge detection, and model fitting have been widely used [5]. However, recent advances in deep learning, particularly graph-based neural networks and transformer-based architectures, have significantly improved segmentation accuracy [6].

With the increasing availability of large-scale annotated datasets such as S3DIS, ScanNet, and SemanticKITTI, machine learning-based methods have gained prominence. However, they come with computational costs, requiring extensive training data and high-performance computing resources.

This paper presents a novel edge-aware segmentation approach that integrates geometric feature extraction with graph-based clustering. Our method balances the efficiency of traditional techniques with the robustness of modern deep learning, offering improved segmentation performance in diverse environments.

2 Related Work

The proposed method entails the instance segmentation of 3D point clouds, a crucial and challenging task that aims to distinguish individual object instances in a 3D space. Our approach combines per-point semantic prediction with geometric constraints to extract candidate object instances efficiently. Unlike traditional deep learning-based methods requiring extensive labeled datasets, our method enables object instance extraction without large-scale supervised training.

Instance segmentation techniques for 3D point clouds are typically categorized into:

– Detection-based methods;
– Segmentation-based methods.

Jiang et al. [7] introduced the PointGroup architecture, which performs instance segmentation by leveraging both spatial distribution and semantic labels. Their two-stage approach first groups points into potential object clusters and then refines the segmentation using an offset-based learning mechanism.

Han et al. [8] proposed an occupancy-aware segmentation method that utilizes voxel-based representations. Their model employs multi-task learning to predict occupancy signals and embedding representations, allowing effective object instance identification in cluttered 3D environments.

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In another approach, Engelmann et al. [9] and Liu et al. [10] investigated Gaussian Instance Center Networks (GICN) for semantic instance segmentation. These models estimate the probability distribution of instance centers within a scene, leading to improved object localization and segmentation accuracy.

Pham et al. [11] presented a multi-task pointwise network capable of performing joint semantic and instance segmentation directly on reconstructed 3D maps. Their work highlighted the advantages of leveraging deep learning models for instance-level classification.

An alternative approach is to separate semantic and instance segmentation tasks and later fuse their outputs. The JSNet framework [12] follows this paradigm, integrating PointNet++ [13] and PointConv [14] to extract and refine features. However, these methods often suffer from high computational costs, requiring powerful GPUs and large training datasets to achieve optimal performance.

Recent advancements have explored more efficient architectures, such as Dynamic Graph CNN (DGCNN) [15], which enhances geometric feature extraction by incorporating graph-based representations. Unlike conventional deep learning techniques that rely on structured grids, DGCNN dynamically constructs neighborhood graphs, making it more adaptable to point cloud sparsity. Shogo et al. [16] demonstrated that replacing PointNet++ with DGCNN significantly improved segmentation flexibility and accuracy while reducing dependency on labeled datasets.

While deep learning-based frameworks have shown promising results, they remain resource-intensive. Our proposed method addresses these limitations by integrating geometric reasoning with graph-based clustering, reducing reliance on annotated datasets while maintaining competitive segmentation accuracy.

3 Methodology

The aim of the method is to label points within a point cloud distinguishing groups which represent particular objects like chairs, desks, lamp or other elements, that may be scanned in indoor areas. To achieve this goal, we bring the point cloud to the set of edges which are easier to operate and interpret in 3D space. Additionally, it was observed, that through geometrical characteristic of edges, it is possible to retrieve objects contours. Therefore, in order to apply proper algorithm allowing points' grouping into edges, the axis aligned point clouds are required.

3.1 Designating points on the edges

The first step of the method is to designate points in the clouds that belong to the edges. It is achieved by taking each 3D point and creating covariance matrix from its local neighborhood. The eigenvalues of this matrix can be used to calculate geometric features which describe local dimensionality of the point.

Weinmann et al[17]. presented the following concept of linearity feature:

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$$L_\lambda = \frac{\lambda_1 - \lambda_2}{\lambda_1} \tag{1}$$

Where:

L_λ - linearity feature
λ_1, λ_2 - first two eigenvalues of pointclouds' covariance matrix,
fulfilling condition $\lambda_1 \leq \lambda_2 \leq \lambda_3 \leq 0$

Afterwards, the points with values below a specified threshold are discarded resulting in the point cloud having points that lay on the edges of the objects only.

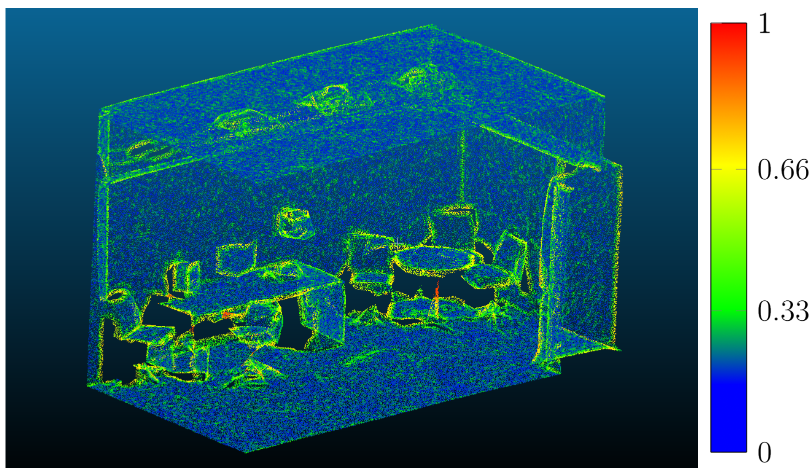

Fig. 1. Designated linearity for point cloud (CloudCompare preview)

3.2 Walls, ceiling and floor detection

Surfaces not directly visible to the scanner appear in the point cloud as missing data or gaps (*Fig. 1*). Those are surrounded from algorithm perspective by undesired edges. Meaning, that contours of these gaps are considered as edges, based on linearity feature. These gaps are mostly visible on the floor and walls because objects in the interiors are mostly placed next to them. In further processing, it may cause unintended results during edge analysis.

In order to remove edges detected around gaps, is to remove not needed surfaces like walls, ceiling and floor. To achieve it, method proposed by Ioannis Anagnostopoulos et al. [18] has been employed, with some adjustments explained further.

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Due to existing differences between the data sets in use, the criteria for detecting walls had to be changed. The vertical planes are considered walls when they touch the floor *(2)* and have the minimum distance to the cloud bounding box *(3)*.

$$|Z_{max} - Z_{min}| < T \tag{2}$$

Where:

Z_{max} - the highest z coordinate number of a plane
Z_{min} - the lowest z coordinate number of a plane
T - the smallest distance of a detected surface to the borders of a pointclouds' bounding box

$$T = \frac{ax + by + cz + d}{\sqrt{a^2 + b^2 + c^2}} \tag{3}$$

where:
a, b, c, d - bounding box's closest plane coefficients
x, y, z - coordinates of the center point retrieved from the detected plane

Afterwards detected walls, ceiling and floor are stored as classified objects and removed from the original cloud.

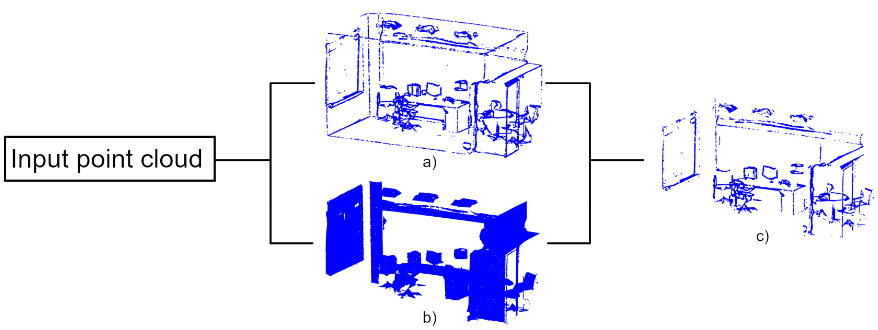

Fig. 2. a) Cloud cropped based on linearity b) Cloud without walls, ceiling and floor c) Common part of clouds a) and b)

As a consequence of the previous steps two clouds are generated. Moreover, the common parts can be extracted from those clouds as shown in *Fig. 2*. The resulting cloud consists mostly of the edges belonging to objects that are not part of the structure and are separated in 3D space.

3.3 3D points classification

First step in order to treat point cloud as a set of edges is to group points by their local structure.

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The process starts from creating a voxel grid from a point cloud. Then set of points within bounds of each voxel is taken into consideration. Using Singular Value Decomposition, a best line for each set of points in a voxel is designated. This describes the orientation of the given set of points in voxels. All points in those point cloud fragments are assigned to a certain group based on the minimum angle between orientation of the voxel points and each of the vectors to which the classification groups are assigned.

Those vectors are designated by using equally distributed points on a Fibonacci sphere that has its centre in the beginning of the coordinate system and radius equal to 1. The method distinguishes 9 of those vectors.

In case of the entire set of points in given voxel not fitting within range of $R_{voxel}/3$ then this set is recursively divided into smaller voxels with the resolution of $R_{voxel}/2$ and the check continues until all points are classified or the max depth is reached *Fig 3*.

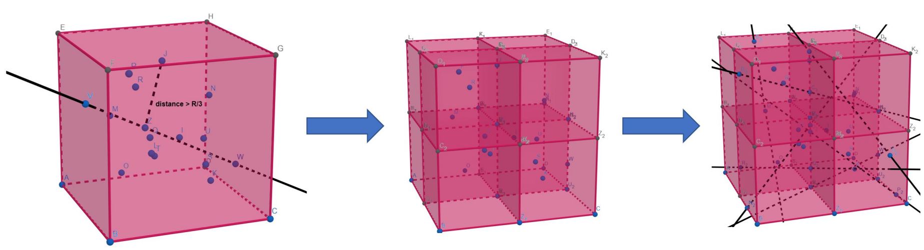

Fig. 3. Voxel classification stages in order from left to right, The best fitting line adjustment regarding point distribution within a voxel, distance comparison from point in a voxel to the best fitting line, splitting step into smaller voxels in case the distance being greater then $R_{voxel}/3$ and the best fitting line adjustment within smaller voxels.

The result is a dictionary, where a key is a group number and a value is the set of points. As seen on *Fig 4.* straight lines share usually one group with only small gaps. The density of different groups is highest in the corners where algorithm had to adjust the size of voxel. In consecutive stages, such organized points allow to separate edges from each other.

3.4 Adjacency graph

The essential step for this method to work is computing adjacency graph [20]. Such graph, allows further analysis in regard to qualification of point sets into particular edges and further analysis of edge characteristics, like direction or connections with other edges. This graph will be then used till the end results being received.

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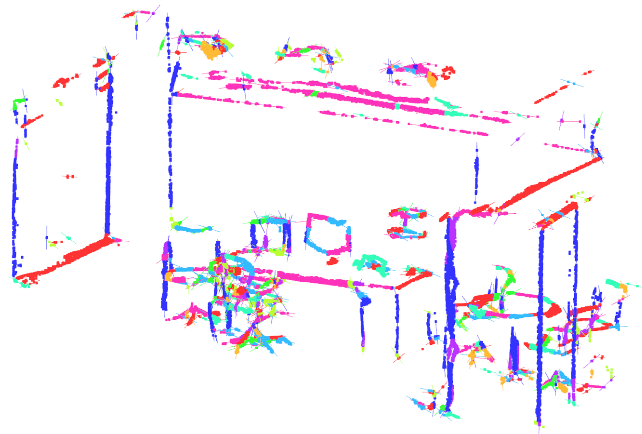

Fig. 4. Classified points

Adjacency graph is a graph of adjacent voxels. Voxels are acquired from the voxel grid that is created based on the cropped point cloud. There can be 3 types of adjacency with respect to voxels enumerated: 6-, 18-, or 26-adjacency. This method involves 18-adjacency as it provides the best results.

18-adjacent voxels are neighbouring one other when they share a face or an edge. To fulfill this condition the adjacent voxels centers need to be within range of $\sqrt{2} * R_{voxel}$. Where R_{voxel} is a voxel resolution that was used to create voxel grid.

3.5 Voxel Edges

Voxel edges play a fundamental role in our method, enabling the organization of point cloud data into structured segments. The process begins with the creation of a voxel grid, in which the point cloud is discretized into cubic units (voxels). Each voxel is assigned to a specific group based on the classification of its contained points.

To establish voxel edges, adjacent voxels belonging to the same group are connected, forming structured edge representations. Since a single voxel may belong to multiple groups, overlapping edges can occur, leading to discontinuities. To resolve this, we apply a series of filtering and merging techniques:

- Edge Filtering: Edges that are subsets of larger edges are removed to eliminate redundancy.
- Edge Merging: Edges with a single adjacent neighbor are combined to improve continuity.
- Graph-Based Merging: If two neighboring edges share only two adjacent voxels, they are merged into a single entity, ensuring structural coherence.

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– Artifact Removal: Small disconnected edges are reassigned to the largest neighboring edge to prevent segmentation artifacts.

By refining voxel edges through these steps, our method enhances object continuity while maintaining segmentation accuracy. These refinements ensure that segmented objects retain their structural integrity, improving the robustness of instance segmentation in complex point clouds.

3.6 Finding graph cycles

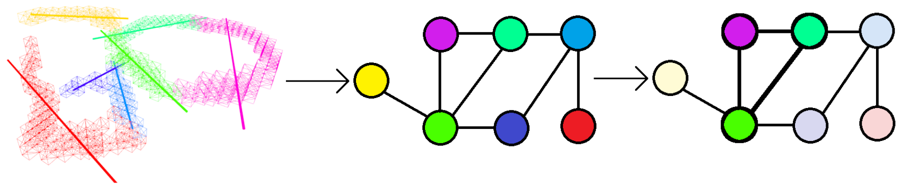

Fig. 5. Visualisation of steps in retrieving the smallest cycles during a graph analysis

It was observed, that through the edge adjacency, it is possible to consider distinguished edges as parts of graph. Therefore, decision was made to continue point cloud processing through a graph analysis. Such approach introduce additional characteristics and features which allow to retrieve more data regarding edge relations and connections. One of such features are graph cycles. In filtered edge set, it was seen that some particular graph cycles of certain traits, represent contours of objects' parts. Good example is a top of a table. In order to do that Voxel Edges are treated as graph nodes, whereas connections between neighbours as graph edges. Graph analysis is presented in Fig. 5

For each node the shortest closed chain (graph cycle) is searched. During the processing all non-unique cycles are discarded. As a result, the cycles that share at least 2 nodes are merged together with the exception of the case when two cycles have the same number of nodes. Then the cycle which after merging is of bigger volume is being discarded. Where, the volume is calculated based on simulated bounding box for a particular set of points within a graph cycle.

Voxel Edges belonging to founded cycles are being merged.

4 Experiment

Proposed solution was evaluated and tested on public S3DIS data set. This particular point clouds collection is widely used to do the comparison of seg-

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mentation methods. It consists of 6 large-scale indoor areas, covering more than 6000 square meters. Additionally, S3DIS has 13 classes of objects already isolated, which enables comparison precision of instance segmentation. Therefore, the measure which was chosen to compare results with other methods is precision (mPrec) and recall (mRec) measure . Precision quantifies the number of positive class predictions that actually belong to the positive class and recall quantifies the number of positive class predictions made out of all positive examples in the set of data. Both measures are widely used in instance segmentation comparison [8].

Additionally, comparison was made in 2 environments. Firstly, proposed method was compared with other approaches with access to color data per every point. In second test, the same experiment was performed in the environment without access to color data. Proposed approach does not use any data regarding scanned color within a point in dataset. The only fundamental data is geometric features retrieved from points entropy. Therefore, it is possible to do comparison in two different environments, where for the most of other methods, color is an important part of analysis.

4.1 Results

The following step is the presentation of test results and comparison with the ground truth. As per the visual example Fig. 6, it can be noticed that prediction has several differences considering the ground truth. However, segmentation is still consistent with entropy of the most important objects scanned in a very complex point cloud. It is worth mentioning, that this point cloud consist of many chairs tucked in tables and objects placed on chairs, what additionally hinders geometrical analysis.

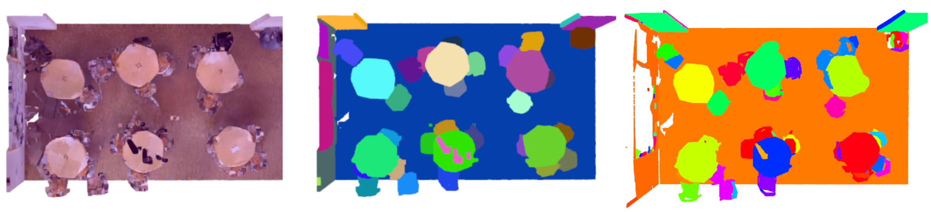

Fig. 6. Example of comparison between predicted instance segmentation and ground truth. In order from left: original point cloud, ground truth, predicted segmentation

Fig. 7 shows the additional visual comparison for the ScanNet v2 dataset. As in the previous example, the original point cloud, ground truth segmentation, and the result predicted by the proposed method are presented from left to right.

To get more precise explanation of the results, the mean precision of predictions was shown in the tables below Tab 1 and Tab 2. It was divided into distinguished object classes. Presented comparison is considered in environment

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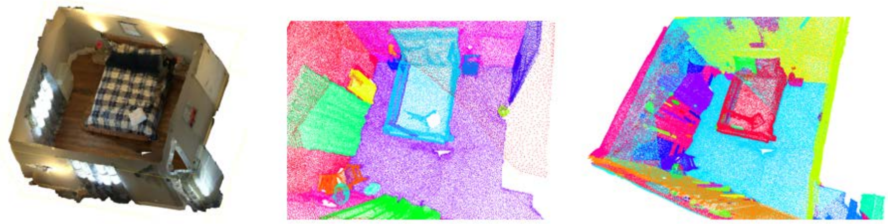

Fig. 7. Visualisation of the Result of point cloud segmentation for ScanNet v2 collection.

excluding color data, since proposed method does not use color data. Therefore, such comparison will give the best insight, regarding improvements in geometrical analysis of pointclouds.

Table 1. Mean precision (mPrec) per class w S3DIS without color data

Method	Beam	Board	Bookcase	Ceiling	Chair	Clutter	Column	Door	Floor	Table	Wall	Window
JSNET[12]	0.0	68.3	56.1	95.5	85.3	42.3	23.5	53.4	91.5	53.6	66.4	80.4
CNN[16]	10.0	86.9	64.3	55.9	90.0	52.8	21.3	87.5	95.8	89.1	87.3	90.9
Proposed	81.1	0.0	71.3	94.1	85.1	85.5	99.9	81.2	97.1	81.8	75.8	94.9

Table 2. Mean recall (mRec) per class w S3DIS without color data

Method	Beam	Board	Bookcase	Ceiling	Chair	Clutter	Column	Door	Floor	Table	Wall	Window
JSNET[12]	0.0	66.7	40.1	85.3	74.4	28.7	10.8	25.0	97.0	33.8	68.6	71.1
CNN[16]	0.0	4.8	18.4	37.3	37.2	20.6	6.5	33.9	51.2	27.5	41.6	34.4
Proposed	81.1	0.0	71.3	94.1	85.1	85.5	99.9	81.2	97.1	81.8	75.8	94.9

In both tables we see differences regarding different types of objects.

In case of precision measure, proposed approach has visibly better results, especially for beam, clutter and column classes. Improvement reached even 70 % considering beam class. It is crucial to mention, that final result is set of labeled points assigned to single objects, not sets of objects (semantic segmentation). The above results are considered regarding the complexity and similarities in certain classes and the influence of these characteristics on segmentation into

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single instances, without a class recognition. Considering recall results, it is visible that achived values are for the most of classes, lower comparing to other methods. However, mRec value is highly influenced by additional division of objects, which is caused by low level of scan accuracy in some areas of point clouds. It disturbs the continuity of scanned objects and disallows to treat them as a part of a bigger objects. An example is presented in the Fig. 8. Where, the same distinguished chair parts are considered as a one object in the ground truth segmentation. In fact, this can be treated as a positive side effect of the proposed solution, which allows to recognise object's important parts.

Fig. 8. Example of chair divided into 2 separate objects (blue - sitting part, red - basis)

4.2 Quantitative comparison

The comparison of this method with the other proposals is shown in table 3 and 4. The selected methods are considered to show the best precision in the case of the S3DIS data set in both environments: with and without color data [8].

There is a wider spectrum of approaches in the environment including color data, which allows one to make a comparison with more methods. Therefore, such results are also shown within the analysis.

As shown, the proposed approach has the best mPrec result in both environments, with and without color data. mRec result is lower than in other methods. However, in colorless comparison it seems to be on moderate level. When we consider the environment with color data, mRec has low value. As was explained, the reason for such diversity is the division of objects into separate elements, which, in fact, gives additional information about the structure of an object.

5 Conclusions

In this paper, the novel method of segmenting point cloud objects based on edge detection and its evaluation was presented. Compared with the other approaches,

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Table 3. The comparison of mean precision and recall on S3DIS data set with color data

	mPrec	mRec
JSNET[12]	66.9	53.9
PartNet[19]	56.4	43.4
ASIS[21]	63.6	47.5
3D-BoNet[22]	65.6	47.6
OccuSeg[8]	72.8	60.3
Proposed	79.0	29.7

Table 4. The comparison of mean precision and recall on S3DIS data set without color data

	mPrec	mRec
JSNET[12]	58.26	47.7
CNN[16]	68.5	25.4
Proposed	79.0	29.7

it is in the minority of colorless instance segmentation methods and does not require training data set as in machine learning approaches. It is strictly based on geometrical analysis, which, on the other hand, makes it more flexible with regard to usage possibilities. It might be included as a form of augmentation to other methods or used in cases where RGB coded color is not inaccessible.

During experimental tests in both environments, with and without color data, it was proven that segmentation predicted by this solution could be considered as reliable, even in case of very complex and not accurate three-dimensional scans. Moreover, it is of quite good quality in case of precision measure (mPrec). Among colorless methods it can be considered as the highest result achieved. Due to vulnerability to incomplete scanning, the recall measure (mRec) could be seen as of lower quality than mRec received by methods using color data. Though, in colorless environment, we see that mRec results are moderate, where it should be noticed that the main comparison is done in this domain

With the above mentioned impediments, the presented solution, managed to give certain amount of additional information about the described space in point cloud, through dividing objects into separate parts. It could be well regarded as a positive adaptation to scans with missing areas. However, there are still some aspects to improve. For example, vulnerability to noise in point clouds. It highly influences the solution, since edge detection and evaluation involve the relation of the point's neighborhood and continuity in voxels. Thus, unexpected points in point cloud can cause some changes during further evaluation stages. What should be checked further are possible improvements in edge point detection accuracy, where each precision boost can enhance the final result. Another aspect considered, regarding the future research, is graph processing. It will be investigated if there are some better or more complex solutions of partitioning the graph into meaningful areas than the currently used search of cycles. For ex-

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ample, volumetric or shape-driven characteristics of 3D objects that could give additional data during object evaluation.

To sum up, the proposed approach is more flexible than the existing solutions regarding the lack of training requirement and in case of the most instance segmentation methods, lack of color analysis. It can be considered as currently the best solution, in case of mPrec measure regarding both environments. In mRec measure it can be considered as relevant for colourless solutions, where it should be noticed that, this area is the main concern of this paper. Although, still there is a room for improvements in immunity for point cloud scans imperfections, proposed method had proven significant contribution in this research area. Despite its promising results, the proposed method has certain limitations. Firstly, it is sensitive to noise and outliers in the input point clouds, which may lead to incorrect edge detection and ultimately impact segmentation accuracy. This is particularly evident in scenes with incomplete or low-density scans, where geometric continuity is disrupted. Secondly, the method assumes axis-aligned point clouds and relies on geometric regularities (e.g., edges and corners) that may not be present in more organic or irregular environments, such as natural outdoor scenes or complex vegetation. In such cases, additional preprocessing steps such as denoising or alignment may be required. Furthermore, the method does not incorporate semantic understanding of object classes. As a result, it may over-segment large objects or under-segment clustered items without a post-processing stage that refines instance boundaries. In future work, we plan to investigate the use of advanced graph partitioning techniques and incorporate shape priors or volumetric heuristics that can mitigate these limitations.

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