Application of the Edge Upsampling Network to Soft-Edge Regions in a 3D-Scanned Point Cloud

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Abstract. Large-scale 3D scanning data based on point clouds enable accurate and fast recording of complex objects in the real world. The edges in a scanned point cloud usually describe the complex 3D structure of the target object and the surrounding scene. The recently proposed deep learning-based edge upsampling network can generate new points in the edge regions. When combined with the edge-highlighted transparent visualization method, this network can effectively improve the visibility of the edge regions in 3D-scanned point clouds. However, most previous upsampling experiments were performed on the sharp-edge regions despite that 3D-scanned objects usually contain both sharp and soft edge regions. In this paper, to demonstrate the performance of the upsampling network on soft-edge regions, we add more polygon models that contain soft edges by adjusting the models in the training set so that the network can learn more features of soft-edge regions. Additionally, we apply the upsampling network to real 3D-scanned point cloud data that contain numerous soft edges to verify that the edge upsampling network is equally effective at the upsampling task on soft-edge regions. The experimental results show that the visibility of the complex 3D-scanned objects can be effectively improved by increasing the point density in the soft-edge regions.

Keywords: Point upsampling · 3D-scanned point cloud · Transparent visualization

1 Introduction

The development of 3D scanning technology in recent years has made it possible to precisely record complex objects in the real world. To observe the internal structure and external contours of complex objects more intuitively, we proposed opacity-based

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edge highlighting [1], which combines the edge-highlighting technique with transparent visualization based on stochastic point-based rendering (SPBR) [2, 3] to highlight 3D edges, which substantially improves the transparent visibility of complex objects. However, the points in the 3D-scanned point cloud data are not always dense and uniform along the edges, and the point density in the edge regions tends to be low due to errors in the measurement and edge extraction process. Yu et al. [4] proposed a deep learning-based upsampling network for sparse point cloud data. However, this approach is usually applied to the upsampling task of overall point clouds. Therefore, to improve the visibility of edge regions, we proposed a deep learning-based network [5] for upsampling edge points. This network can improve the transparent visualization visibility of edge regions in complex 3D-scanned objects. In fact, in real 3D-scanned objects, the edges are usually divided into sharp edge and soft-edge regions. In our previous work [5], we applied the proposed network mainly to sharp edges and obtained excellent results. In addition, we also made a preliminary discussion on the possibility of applying the proposed network to soft edges. This paper is a further development of our previous work. We focus on applying the proposed network to 3D-scanned point cloud data that contain numerous soft-edge regions and demonstrate the applicability to soft edges. By adjusting the models in the training set, the network can learn more features of the soft-edge regions to generate more understandable soft edges and improve the visibility.

2 Methods

2.1 Opacity-Based Edge Highlighting of Soft Edges

To extract 3D edges, i.e., high-curvature areas, of the target point cloud, we adopt the statistical method [6–8], which uses an appropriate eigenvalue-based 3D feature value. For a local spherical region centered at each point, the variances and covariances of point distributions are numerically calculated, and the local 3D structure tensor [9] is defined. Then, the 3D feature value is calculated using the tensor's three eigenvalues, and the value is assigned to the centered point. The 3D edges are extracted by collecting points with large feature values. In our work, we adopt change-of-curvature as the feature value f: $f = \lambda_3/(\lambda_1+\lambda_2+\lambda_3)$ with $\lambda_i (i = 1, 2, 3, \lambda_1 \geq \lambda_2 \geq \lambda_3 \geq 0)$, the three eigenvalues of the 3D structure tensor.

Recently, we proposed opacity-based edge highlighting applicable to 3D scanned point clouds [1]. The idea is to execute transparent visualization of the target point cloud and assign larger opacity to the extracted 3D edges regions. We can increase the edge opacity by locally increasing the point density using upsampling and applying stochastic point-based rendering (SPBR) [2, 3], in which regions with higher point density are visualized with larger opacity.

The difficulty in highlighting the soft edges is that there are no sharp peak regions of the feature value f. The value of f gradually increases around the soft edges, and a "feature-value gradation" appears. In such soft-edge regions, introducing a definite feature-value threshold is not easy, aiming at distinguishing the edge regions from the remaining non-edge regions. Therefore, we rather consider an intermediate area where the feature-value gradation occurs. Then, we make the feature-value gradation correspond to the "opacity gradation" based on the opacity formula of SPBR [1]. In the created image, the opacity gradation appears as a "brightness gradation" that shows the existence of the soft edges.

The contribution of the current paper is proposing a deep learning-based high-quality upsampling of the soft-edge regions. For sharp edges, upsampling by simple copying the original points works well [1]. However, for soft edges, we need more careful upsampling so that the delicate opacity gradation can be correctly reflected in the edge-highlighting visualization.

2.2 Proposed Upsampling Network

In our work, we aim to upsample the edge regions in 3D scanned point clouds. In our training phase, we adopt training strategies similar to [4], which use polygon data to generate high-precision point cloud data for training. However, in contrast to our previous work [5], we add 10 polygon mesh models containing numerous soft edges to the training set and remove 10 models that only contain sharp edges to achieve better upsampling performance in the soft-edge regions. Specifically, we cut each polygon mesh data used for training to generate numerous local patches. To generate training point cloud data with a uniform point distribution and fine detail retention, Poisson disk sampling (PDS) [10] is used to generate points on these patches as ground truth $\mathcal{T}$. Then, the ground truth data are downsampled to generate sparse input point cloud data $\mathcal{P} = \{p_i \in \mathbb{R}^{3\times 1}\}_{i=1}^{N}$ with N points. As illustrated in Fig. 1, the network consists of a generator and a discriminator, and the discriminator guides the generator training. Continuous adversarial training alternating between the two models eventually makes

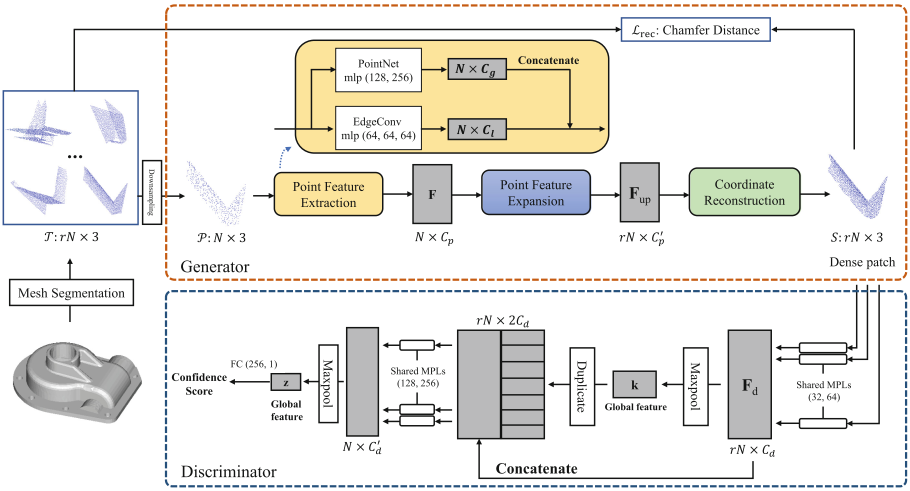

Fig. 1. Architecture of the proposed upsampling network. Note that N is the number of points in input patch $\mathcal{P}$, and r is the upsampling rate. Given a sparse input patch $\mathcal{P}$ with N points, we generate a dense patch S with rN points in the generator, which consists of feature extraction, feature expansion, and coordinate reconstruction. The goal of the discriminator is to distinguish whether its input is produced by the generator.

the generator better able to perform the upsampling task. Specifically, for each input point cloud data $\mathcal{P}$, the goal of the generator is to produce dense and uniformly distributed point clouds $S = \left\{s_i \in \mathbb{R}^{3\times 1}\right\}_{i=1}^{rN}$, where p_i and s_i are the coordinates of 3D points, and r is the upsampling rate. The discriminator finds the fake data generated by the generator. Please see our previous work [4] for a detailed network structure.

2.3 Steps to Highlight the Soft Edges

Based on the ideas explained in Sects. 2.1 and 2.2, our proposed method to highlight the soft edges is formulated as follows.

STEP 1: Extract points that are assigned a feature value larger than a given minimal value, which defines the boundary of a soft-edge region. **STEP 2:** Execute the deep learning-based upsampling for the extracted edge points. **STEP 3:** Merge the original 3D-scanned points, which include points of the non-edge regions, with the upsampled edge points. **STEP 4:** Apply SPBR to the integrated point cloud to create an edge-highlighted transparent image of the target 3D-scanned point cloud.

3 Experiments

In this section, we show the visualization experiments of our method. We demonstrate that our deep learning-based upsampling network works well to highlight the soft edges of 3D-scanned point clouds based on the opacity-gradation effect.

3.1 Transparent Edge-Highlighting Visualization of Japanese Armor

Here, we show experimental results of applying our method to the Japanese armor with many soft edges. Figure 2 shows the visualization result for our 3D-scanned data of a Japanese armor helmet that contains many soft edges. Figure 2a shows the opaque point-based rendering without edge highlighting. Figure 2b shows the edge-highlighting transparent visualization by using the original opacity-based edge highlighting [1]. In Fig. 2b, the soft edges are visible as the opacity gradation areas, but the edge highlighting is not very clear (see the enlarged image in the rectangle). In the original opacity-based edge highlighting method, the opacity gradation is realized based on simple copying or duplication of edge points. Although this copying is recognizable as quasi-upsampling, many of the added points are rejected through point occlusion. Therefore, the edge-highlighting does not work well. Figure 2c shows the result of our method. The opacity gradation is realized based on our deep learning-based upsampling well. Since the added points are different from the original ones, the opacity gradation becomes more evident, not diminished by the point occlusion. Therefore, edge-highlighting becomes more effective than Fig. 2b (compare the enlarged images in the rectangles).

Figure 3 shows the visualization result for our 3D-scanned data of a Japanese armor suit, which has both soft and sharp edges. The point cloud has several sharp edges that appear as the horizontal lines at the jointing parts of rectangular plates. Besides, there are varieties of soft edges. Figure 3a shows the opaque point-based rendering without edge highlighting. Figure 3b shows the edge-highlighting transparent visualization by using

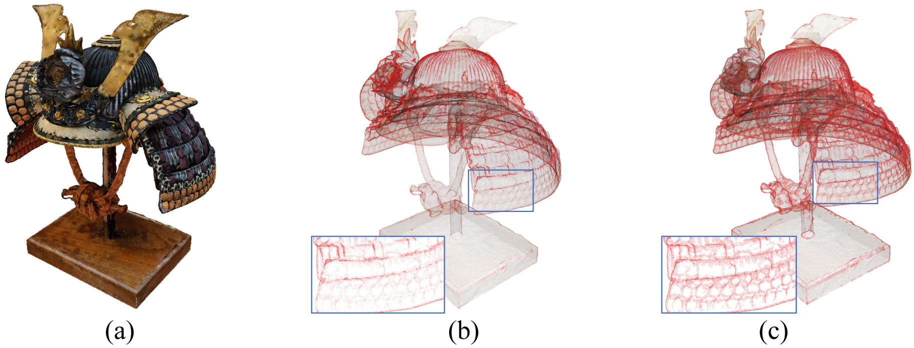

Fig. 2. Experimental results for 3D-scanned data of the Japanese armor helmet (10 million points). **(a)** shows the opaque point-based rendering without edge highlighting; **(b)** shows the transparent edge-highlighting visualization based on the original opacity-based edge highlighting [1]; **(c)** shows the transparent edge-highlighting visualization based on our method.

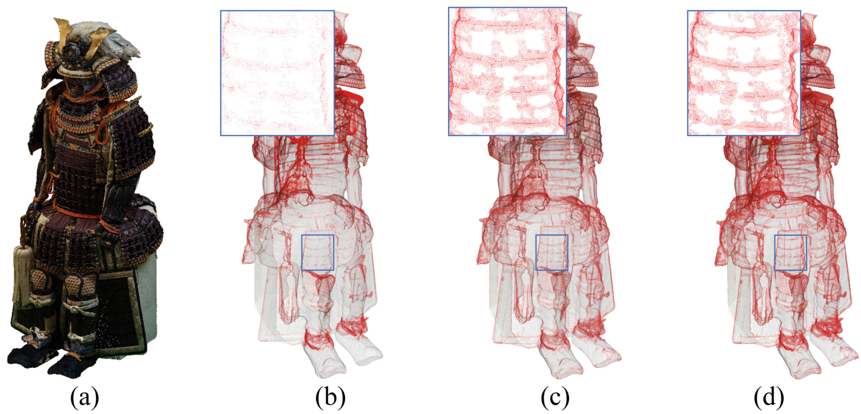

Fig. 3. Edge-highlighting visualization of the Japanese armor suite (10 million points). **(a)** shows the opaque point-based rendering without edge highlighting; **(b)** shows the edge-highlighting visualization based on the original opacity-based edge highlighting [1]; **(c)** shows the edge-highlighting visualization based on our method, and **(d)** shows the transparent edge highlighting visualization result of the upsampling network using the training set from our previous work.

the original opacity-based edge highlighting based on the point copying [1]. In Fig. 3b, the sharp edges are visible as thin horizontal lines but not very clear (see the enlarged image in the rectangle). Besides, the soft edges are not visible. Figure 3c shows the result of our method. We can observe the sharp edges clearer than Fig. 3b, and many soft edges are visible by the gradated colors (compare the enlarged images in the rectangles in Fig. 3b and Fig. 3c). Additionally, as shown in Fig. 3c and 3d, the result after adjusting the training set shows the soft-edge regions more clearly than the upsampling result obtained by using the training set in our previous work, and the generated new points are more clustered rather than diffused outside the edges.

As explained in Sect. 2.2, our improved deep learning-based network has learned soft-edge training data. The successful result of Fig. 3c proves that the training is also effective for sharp edges.

3.2 Edge Highlighting of Cultural Heritage Reliefs

In this subsection, we show experimental results of applying our method to the ancient reliefs of the Borobudur temple, the UNESCO world cultural heritage in Indonesia. Relief is a typical example of cultural heritage objects with sharp and soft edges. We should remark here that 3D scanned data of relief usually do not record any inside structure behind the relief surface. It means that we cannot distinguish the transparent visualization from opaque visualization. In such cases, our edge highlighting is available for photo-realistic edge-highlighting visualization.

Fig. 4. 3D-scanned point cloud (4,183,441 points) of a Borobudur relief panel.

Figure 4 shows a typical Borobudur relief panel. The sharp edges form the outlines of the human figures and other decorative objects. Besides, the soft edges mainly feature the details such as the tree branches and the human faces.

Figure 5a shows the edge-highlighting visualization of the data of Fig. 4 by using the original opacity-based edge highlighting based on the point copying [1]. Each drawn item is successfully characterized by the outlines expressed by the sharp edges. However, the details of each item are unclear because we cannot observe the soft edges clearly (see the enlarged image in the rectangle). Figure 5b shows the edge-highlighting result created by our method. The sharp edges are visualized clearly. Besides, we can observe the details with the help of the soft edges (compare the enlarged images in the rectangles in Fig. 5a and Fig. 5b).

Figure 6a shows the 3D-scanned point cloud of a famous Borobudur relief panel, where an ancient ship is drawn. The sharp edges express the outlines and the main structure of the ship. On the other hand, the soft edges should express the ocean waves (below the ship) and the clouds (upper right of the ship). Figure 6b shows the edge-highlighting by using the original opacity-based edge highlighting based on the point copying [1]. The sharp edges are visualized well, but the soft edges are not visualized clearly due to the insufficient local point density. The quasi-upsampling based on the

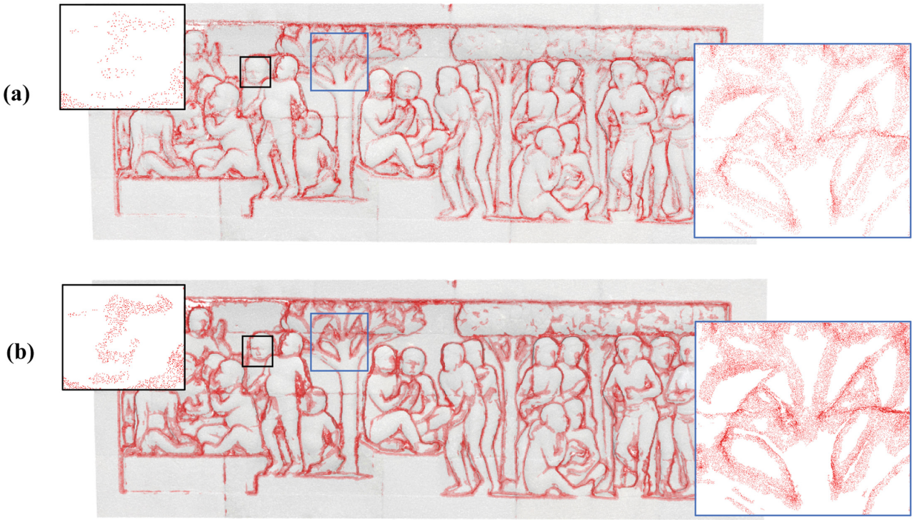

Fig. 5. Edge-highlighting visualization of the relief panel of Fig. 4. **(a)** shows the edge-highlighting visualization based on the original opacity-based edge highlighting [1]; **(b)** shows the edge-highlighting visualization based on our method.

point copying does not work well, especially around the soft edges. Figure 6c shows the edge-highlighting result created by our method. The soft-edge regions are given sufficient point density, and the soft edges are made clearly observable (compare the enlarged images in the rectangles in Fig. 6b and Fig. 6c).

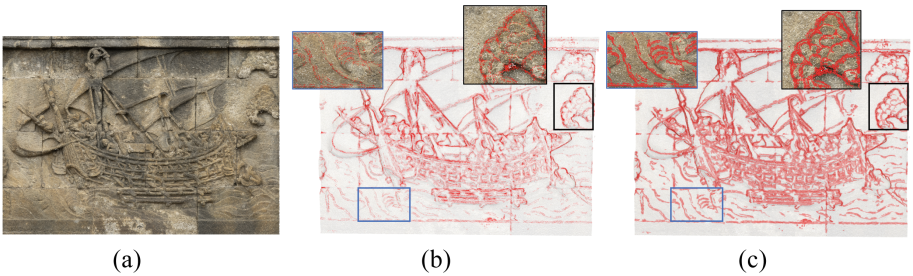

Fig. 6. Experimental results for 3D-scanned data of the Borobudur relief of the ancient ship (3,520,688 points). **(a)** shows the opaque point-based rendering without edge highlighting; **(b)** shows the edge-highlighting visualization based on the original opacity-based edge highlighting [1]; **(c)** shows the edge-highlighting visualization based on our method.

4 Conclusions

In this paper, we have proposed a robust edge-highlighting method applicable for 3D-scanned point clouds. By using our deep learning-based upsampling network, point density is made higher around the edge regions. The upsampling works well for both the soft and sharp edges. Applying the upsampling result to the opacity-based edge-highlighting makes the opacity gradation apparent. Then, the soft edges, which are usually difficult be highlighted, are successfully expressed. This feature of our method realizes comprehensible visualization of 3D scanned point clouds that record complex 3D shapes. We have demonstrated the effectiveness of our method by applying it to real 3D scanned data of cultural heritage objects.

In the future, we will consider adopting a multi-object training strategy that combines features of the original point cloud with features of the edge data to encourage the network to better distinguish between the edge and non-edge regions.

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