Quality Enhancement Technique for Similarity-based Polygonization from a Point Cloud

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Abstract:

This paper presents a novel technique for enhancing the polygonization of point cloud data by using geometric similarity. Our method is an extension of our previous work, which uses local shape matching and aligns polygons with similar shapes into a point cloud by using the Iterative Closest Point (ICP) algorithm. In this paper, we propose to input the polygon data as template polygons and to add a fitting operation in the alignment step. Our technique makes it possible to use various polygons as input keys. It also enables the creation of a more detailed product model from a coarse point cloud by filling up missing data points, regions, and defects. This enhancement is especially effective on the point clouds of civil infrastructures, whose parts are similar in shape but slightly different in size. This paper shows the results of our method applied to the point clouds of a harbor facility and a monorail structure acquired from a mobile mapping system (MMS).

Keywords: Point cloud, Polygonization, CIM, Geometric similarity, MMS.

1. INTRODUCTION

Maintenance of civil infrastructures is important for prolonging their service lives. Many civil infrastructures are approaching their end of service, and efficient methods for their maintenance are required. In the case of new civil infrastructures, construction information modeling (CIM) (Yabuki, 2012) consolidates all life-cycle information of structures into 3D models. Ideally, the CIM framework could be utilized for efficient maintenance of existing civil infrastructures. However, 3D models are required for CIM, and existing structures do not have such models. Even if 2D drawings exist, it is difficult to translate them into 3D models, and the 3D models may be different from the existing buildings due to building modifications over time. For these reasons, methods to efficiently create 3D models of existing civil infrastructures are needed.

The use of laser scanning technology is one of the possible solutions to obtain 3D data of existing civil structures. Laser scanners can acquire the surfaces of objects as a set of colored points. These point clouds, which provide the “as-is” geometric information of objects, could be used for any CIM application that can be converted to polygon data.

Creating polygons from point clouds is known as surface reconstruction and is one of the emerging topics in geometric modeling (see survey by Burger et al., 2014). However, these methods usually create a single polygon from a point cloud. Generally, product models consist of several parts and additional post processing such as segmentation is required. Also, target civil infrastructures are usually large and difficult to polygonize at once. The problem may be resolved by grid clustering. However, these clusters should be assembled at the end or an unexpected artifact may appear on the boundary of the clusters. In addition, memory overflow may prevent direct polygonization of large structures.

An alternative approach is to decompose a point cloud into meaningful regions. For example, Adan et al. (2013) proposed a method for classifying point clouds of an indoor environment into a wall, floor, ceiling, or clutter based on machine learning. To define a region, Matsuoka and Masuda (2014) proposed a method to remove road points in the point cloud of a city according to height. The main advantage of these methods is the decomposition of points into simple components with a lower number of points. This enables easier polygonization. However, the components of a civil structure are usually unique and it is difficult to use similar approaches due to the shortage of training data.

Recently, Hidaka et al. (2015) proposed an efficient method to create a 3D model from a point cloud of civil infrastructures by using geometric similarity. In this method, a point cloud is decomposed into similar regions by local shape matching (Mori et al., 2006). For each similar part, only one representative point cloud is polygonized, and the created polygons are used for representing other similar parts. This method is efficient for creating polygons for civil infrastructures that have many identical or similar parts. Additionally, defects of the polygons may be repaired by replacement of the representative parts. This is efficient for polygonization of point clouds with missing regions. However, when the representative polygon lacks important features, the quality of the output polygon becomes worse.

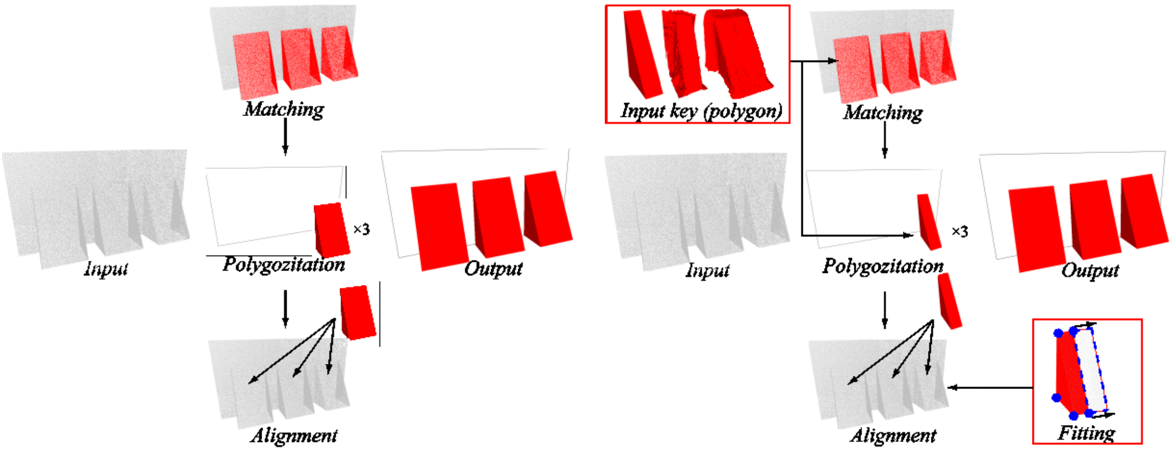
In this paper, we present a novel technique for enhancing the polygonization of point cloud data by using geometric similarity. The proposed method is an extension of the previous method, which accepts various input data as representative parts (such as CAD data). This enables users to control the quality of polygons by the input sources. This paper also introduces some improvements that allow template shapes to be accepted. The proposed method was implemented and its usability was verified by adopting different point clouds of infrastructure facilities scanned by mobile mapping systems (MMS). This paper discusses the results, and advantages and limitations of the proposed method.

2. METHOD

2.1 Overview

Our proposed method is based on our previous method (Hidaka et al., 2015). In the previous method, shown in Figure 1(a), a point cloud of a civil infrastructure is segmented by the similarity of shapes, and each part is polygonized. This method consists of three major steps. First, the input point cloud is decomposed into meaningful parts that are clustered by local shape matching. Second, only one representative cluster of points is selected and polygonized. Finally, the created polygons are arranged in the input point cloud based on the result of matching by the Iterative Closest Point (ICP) algorithm (Besl and McKay, 1992).

Our proposed method, shown in Figure 1(b), follows the same steps as the previous method. The difference is the use of polygon data acquired from other sources (e.g. CAD systems or photogrammetry systems (Agarwal et al., 2011)) as representative polygons (i.e. template polygons). The use of different input sources creates the following challenges. First, the different densities of points may affect the accuracy of the shape matching. Second, the fitting of key polygons from different sources to similar parts is required. Third, the ICP results may involve a small tilt due to the segmentation result. The proposed solutions to these issues are described in the following subsections.



(a) The previous method (b) The proposed method

Figure 1. Overviews of the previous method (Hidaka et al., 2015) and the proposed method

2.2 Sampling of input polygon for shape matching

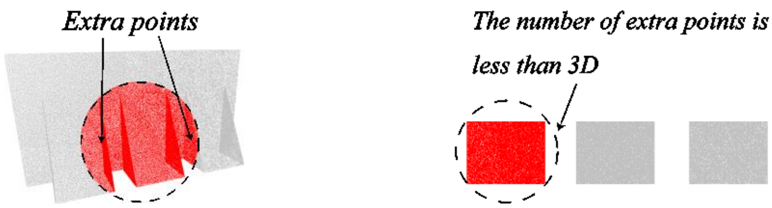
It is important to maintain similar density of point clouds for the efficient shape matching. The density of point cloud created in other applications is different from a point cloud scanned by a laser scanner. In the case of CAD polygons, their vertices are usually very few and their descriptors are different from the input point cloud, even though their geometries are almost the same. Our method uses Poisson disk sampling (PDS) (Cook, 1986) to obtain dense points from surfaces. PDS is a random sampling method that selects a point $\mathbf{p}_i$ and removes a point $\mathbf{p}_j$ whose distance to $\mathbf{p}_i$ is less than D, which is a user-defined density parameter. The method iterates until all points are sampled or removed. Figure 2 shows a result of the method.

(a) Polygon (b) Sampling result

Figure 2. Poisson disk sampling of a polygon

2.3 Projection of point clouds onto 2D space for shape matching

In the previous method, bounding spheres are used for defining local regions. Consequently, unnecessary points are included in the region, as shown in Figure 3(a). Our method resolves this issue by considering the region as a 2D problem. The method first projects the point clouds of the keys and the input source onto the 2D plane and computes the 2D descriptor (Mori et al., 2006) for the region inside the circle, as shown in Figure 3(b).

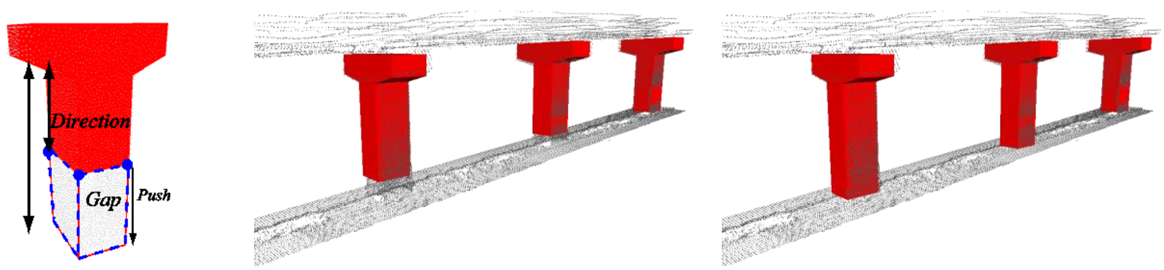


(a) Problem of clustering by spheres (b) Tighter segmentation by 2D projection

Figure 3. Defining regions by 2D projection

2.4 Key polygon fitting to point clouds

Because the key polygon is not exactly the same as similar regions in the point cloud, a fitting operation is applied to obtain accurate polygonization results (Figure 4). The fitting operation is specialized for simple civil structures. We assume the key shape can be approximated to the target point clouds by simple extruding operations. Given the key polygon and similar point clouds, we first determine the extruding surface of the key polygon by comparing the input data. Next, we find the extruding direction based on the difference of these data. Figure 4 shows examples of the push method. Gaps are enclosed by dashed lines and the directions for the push are indicated by arrows (Figure 4(a)). Figures 4(b) and 4(c) show the before and after examples of fitting, respectively. The fitting result shown in Figure 4(c) shows better accuracy than does Figure 4(b).



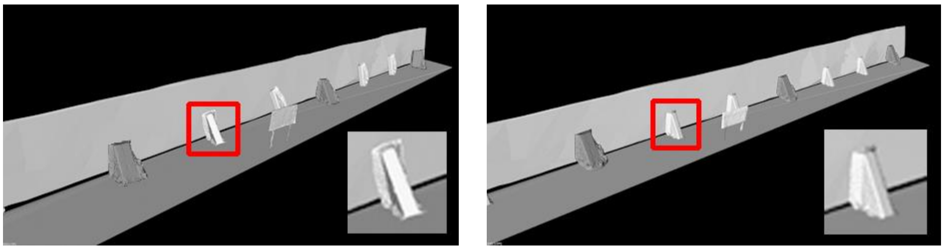
(a) Algorithm (b) Before fitting (c) After fitting

Figure 4. Fitting operation

This approach has two main advantages. The first advantage is that users can approximate key polygons that do not need to be very precise. In the previous method, it is presupposed that the shapes of parts are identical. Hence, the quality of a polygon becomes worse when the parts' shapes are dissimilar. Because all identical parts must be prepared, the fitting operation improves the accuracy by repairing any dissimilarities. The second advantage is the guaranteed quality of the parts. The segmentation method in the previous method sometimes includes unnecessary points and this affects the quality of polygons, whereas man-made polygons are well formed or do not contain noises. Such clean data are robust against incomplete MMS data, which often involve noises and missing data.

2.5 Constrained ICP for alignment

It is known that the ICP algorithm finds alignment in a least square sense and the result involves small tilt as shown in Figure 5(a). We modified this step based on the characteristic of civil infrastructures that they are generally built vertically. Our method uses 2D projection of the point clouds onto the horizontal plane introduced in Date et al. (2014) and applies ICP to these projected points. This can reduce the degrees-of-freedom of the transformation to as many as 4 (3 for translation and 1 for rotation). The transform matrix calculated by this modified ICP is then applied to the 3D key polygon for arrangement. Figure 5(b) shows the alignment result by constrained ICP; the part pose is clearly improved.



(a) Alignment by 3D ICP (b) Alignment by constrained ICP

Figure 5. Alignment by constrained ICP

3. RESULTS

The proposed method explained in the previous section is implemented by using the Point Cloud Library and is then applied to two MMS data examples.

The first example is the harbor breakwater near the Naruo river in Nishinomiya City, Hyogo, Japan. The number of points is 141,270. This structure has two types of ribs at regular intervals (Figure 6). Our experiment focuses on creating polygons of these parts from a single template polygon created by other sources (e.g. CAD, structure from motion (SfM)). Additionally, some unique objects including the wall, road, and signage board (Figure 7) are polygonized by the Poisson surface reconstruction algorithm (Kazhdan et al., 2006) prior to matching. Figures 8, 9, and 10 show the results of the experiments with different input sources. The correct result is confirmed and the statistics are shown in Table 1.

(a) (b) (c)

Figure 6. Photo of Example 1 (Harbor breakwater)

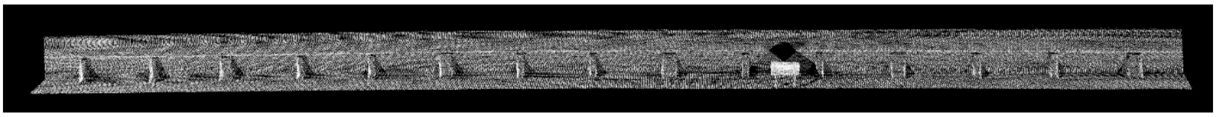
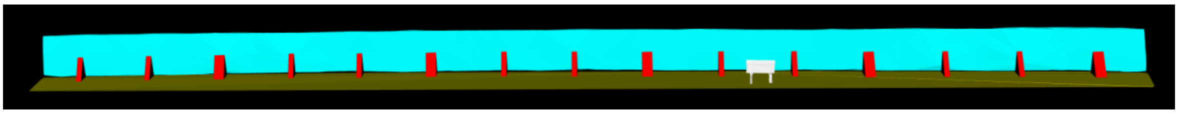
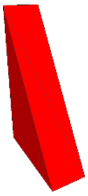


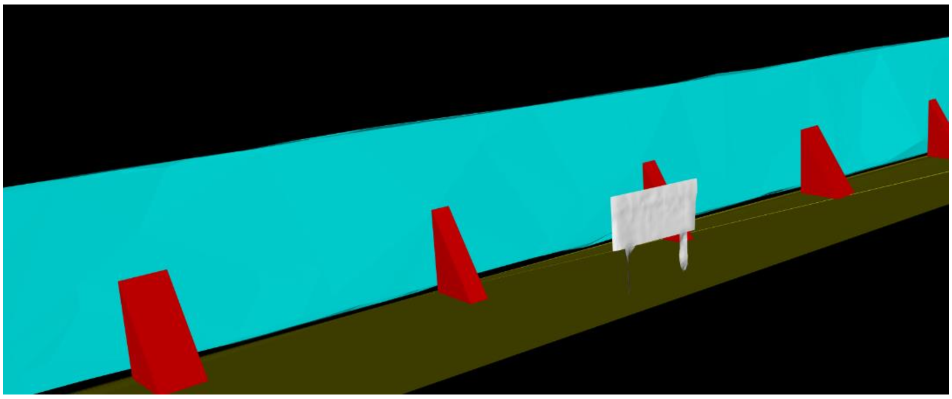
Figure 7. Point cloud data of harbor breakwater (141,270 pts.)



(a) Overall view

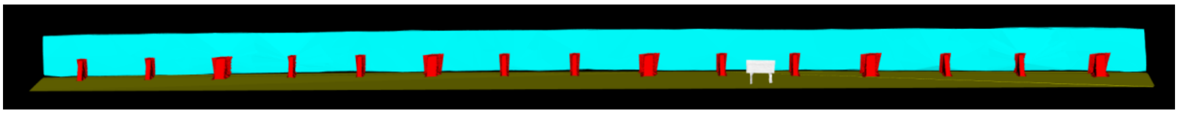


(b) Input key

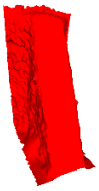


(c) Close-up view

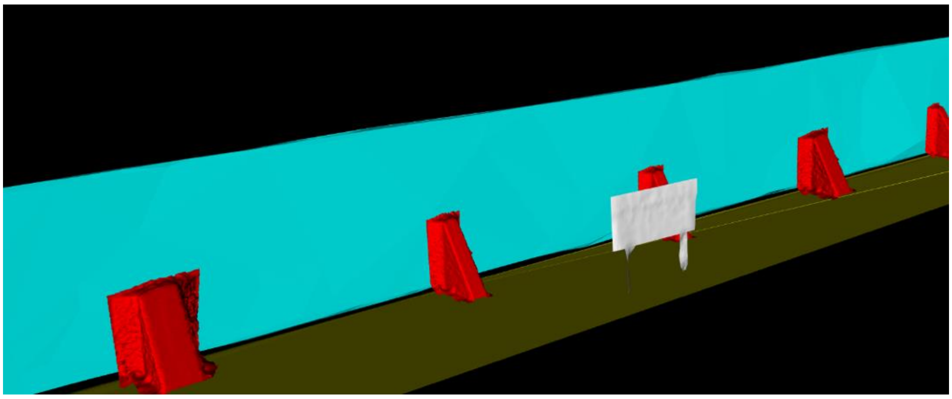
Figure 8. Result of using polygons created by CAD



(a) Overall view

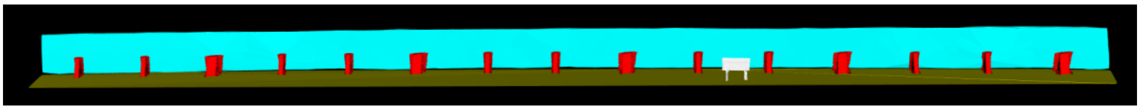


(b) Input key



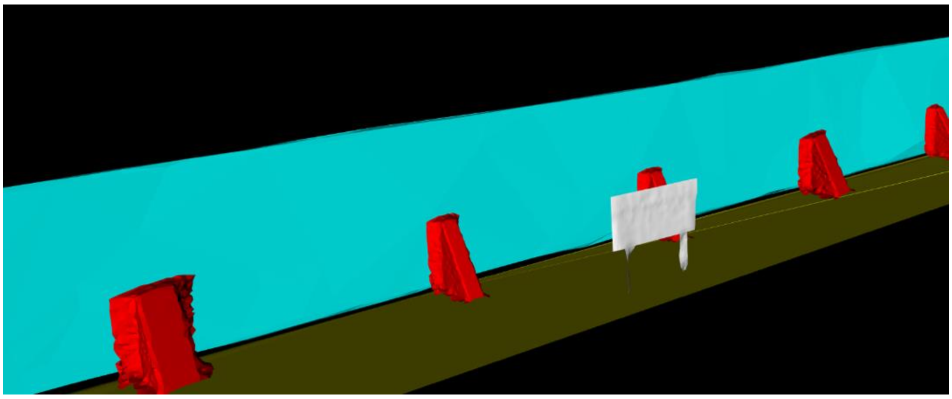
(c) Close-up view

Figure 9. Result of using polygons created by SfM



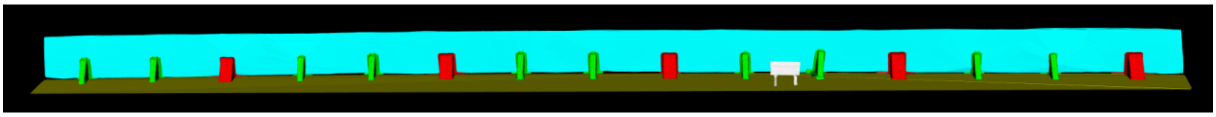
(a) Overall view

(b) Input key

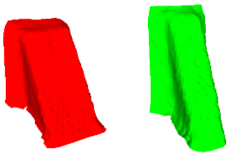


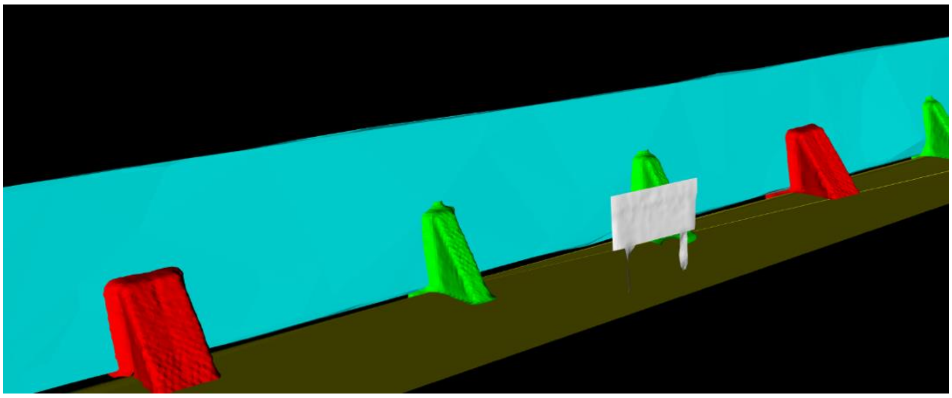
(c) Close-up view

Figure 10. Result of using polygons created by SfM (simplified)



(a) Overall view





(b) Created polygons (c) Close-up view

Figure 11. Result of the previous method

Table 1. Statistics of the harbor breakwater

	Type of key data	#Vertices (#Sampled points)	#Faces	#Aligned parts	Time[s]
Proposed method	CAD model	6(1,420)	8	15	6.748
	SFM	85,106	169,066	15	18.743
	SFM (simplified)	540	999	15	6.612
Previous method		5,120	7,495	5	
		3,286	5,132	10	59.718

The second dataset is a railway structure of the Osaka monorail in Suita City and Ibaraki City, Japan. This structure consists of several types of piers. Although these piers are similar in shape, their heights are different to adjust for the heights of the rails (Figure 12). The number of points is 694,843. The points of the road and the rails were manually removed prior to the experiments, because the objective of this experiment was to polygonize the pier structure. Figure 14 shows the results of the experiment. We confirmed that equivalent result was computed from template polygons from different sources. Table 2 shows the statistics.

(a) (b)

Figure 12. Photo of Example 2 (Monorail)

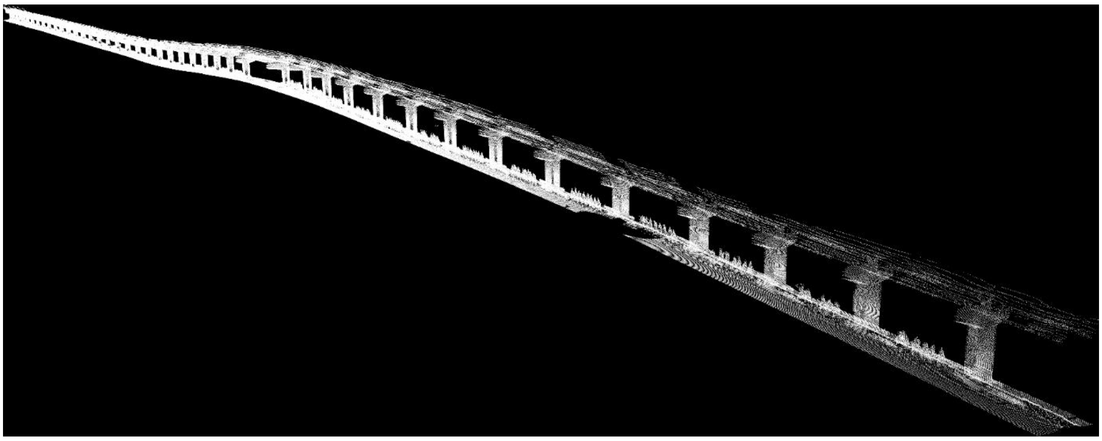


Figure 13. Point cloud of monorail (694,843pts.)

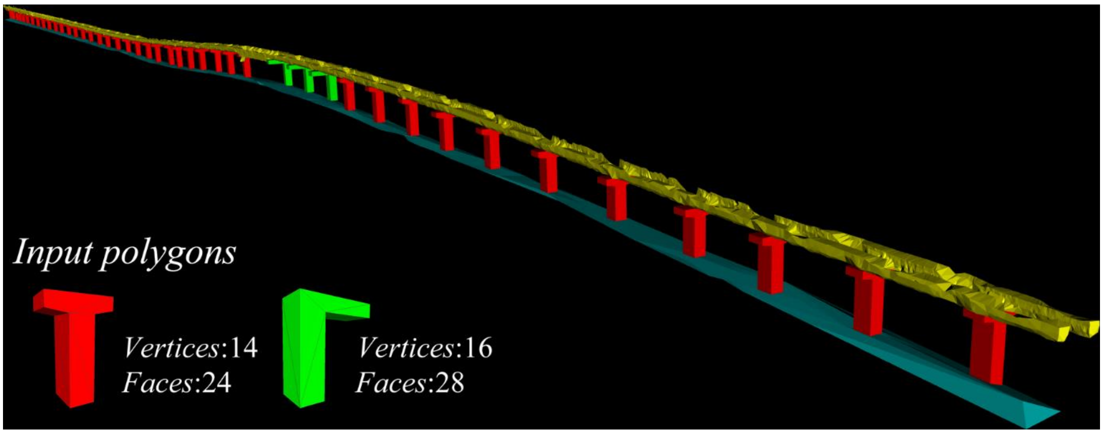


Figure 14. Result of mesh using polygons created by CAD

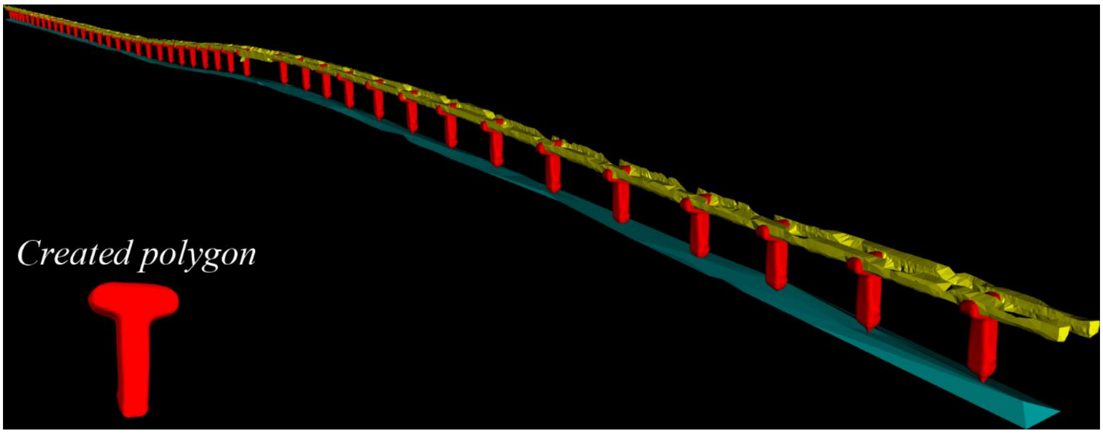


Figure 15. Result of the previous method

Table 2. Statistics (Monorail)

	Type of key data	#Vertices (#Sampled points)	#Faces	#Aligned parts	Time[s]
Proposed method	CAD model	14(7,349)	24	44	
		16(7,323)	28	3	37.110
Previous method		3,948	7,892	47	226.326

4. DISCUSSION

Figures 8, 9, 10, and 14 show that, although the representative parts were imported from difference sources such as CAD models and polygons created by SfM, equivalent results to the previous method can be obtained. These figures show that the framework can integrate various sources to obtain high-quality results. In particular, the quality of part arrangement was improved by introducing constrained ICP based on the assumption that civil structure parts are generally built vertically (Section 2.5). The proposed technique of part segmentation on 2D space (Section 2.3) also contributed to the improvement. The geometric fitting reduced the cost of creating key parts that are similar but not identical. Finally, the computation time was also improved by using templates as the key models, as shown in Table 2. This is due to the fact that the system does not need to find key shapes in the input cloud.

Nevertheless, our proposed method has three major limitations. The first limitation is that all of the key shapes to be used should be prepared in advance; otherwise, some unknown regions are polygonized by the previous method. For example, the monorail dataset used in this experiment contains plants that were not polygonized by the new method. The second limitation is that our method does not necessarily improve parts that can be created by sweeping their cross sections, such as the monorail rail structure in the second experiment. In this case, similar parts in the rail may be detected, but the realignment step may generate non-continuous output. The last limitation is that our fitting method does not handle all shapes. As the fitting operation becomes easier when shape correspondence is established, the conventional shape correspondence methods (e.g. Kim et al. 2011) can be used to resolve this issue. However, these methods works well with shapes that have distinctive features (e.g. heads, legs and hands of animals). Hence, as parts of civil structures do not have distinctive features, conventional methods failed to find correspondence in our experiment.

5. CONCLUSIONS

In this paper, our previous method to create polygons from a point cloud based on geometric similarity is improved. In our proposed method, polygons created in other applications are used as search keys. Additional enhancement methods are also discussed, such as a method to cover the gaps between polygons and point clouds by fitting. We implemented our proposed method by applying it to the point clouds of civil infrastructures. The results of case studies confirmed that meaningful parts could be decomposed and aligned, and the gaps between polygons and point clouds could be covered by a fitting operation.

Several future studies are being considered. For example, by generalizing the fitting, the method can be applied to more types of parts. In addition, adding the cross-section sweeping functionality can make the method more versatile.

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