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RECURSIVE SEGMENTATION FOR AS-IS BRIDGE INFORMATION MODELLING

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Abstract: Prior studies reported that the time needed to manually convert a point cloud to an as-is geometric model using cutting edge modelling software is ten times greater than the time needed to obtain the point cloud. The laborious nature of manually modelling infrastructure such as bridges is the reason behind the significant cost of modelling which impedes the proliferation of the usage of Bridge Information Models (BrIM) in Bridge Management Systems. Existing commercial solutions can automatically recognize geometric shapes embedded in segmented point cloud data (PCD) and generate the corresponding IFC objects. Researchers have taken further studies and have additionally automated surface reconstruction through generating parametric surface-based primitives in order to automate the segmentation process. However, surface-based segmentation for bridge modelling is an unsolved problem, which is neither straightforward nor consistent, thus hinders the automation of BrIM.

This paper presents a top-down PCD detection solution that follows a knowledge-based heuristic approach for BrIM generation that can semi-automatically segment a bridge point cloud recursively. We leverage bridge domain knowledge as strong priors through a histogram-based algorithm to conduct the tasks of segmentation and classification. We implemented this solution and tested on one highway bridge. The experimental results indicated that the detection precision of this solution is 92%.

Keywords: As-is BrIM, laser scanning, point cloud data, recursive segmentation.

1 INTRODUCTION

The automatic generation of Bridge Information Models (BrIM) from point cloud data (PCD) is still an unsolved problem. Prior study reported that the time needed to manually convert a point cloud to an as-is geometric model using existing software is ten times greater than the time spent on scanning on-site (Trimble 2014). According to the Federal Highway Administration, more than one in nine bridges in the United States (US) were classified as structurally deficient in 2013. Assuming a similar number of bridges in the European Union (EU), and a two-year inspection cycle, there is a need for approximately 500,000 bridge inspections per annum across the EU and the US. BrIM are generally acknowledged in industry, through which bridge owners are able to manage lifecycle data related to bridges and individually-inspected bridge elements (Volk 2014). However, BrIM are not broadly utilized in the infrastructure asset management field despite the implementation of laser scanning-based survey techniques for inspection data collection over the past few years. This is mainly because the current practice for creating an as-is BrIM using modelling software is a laborious manual task, that is time-, cost- and

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knowledge-intensive. The general process of PCD-to-Building Information Models (BIM) or -to-BrIM is first segmenting PCD into sub- point clusters, then fitting the recognized point clusters with predefined 3D models and enriching their semantics. Whilst solutions for the latter task have existed, the former task (i.e. segmentation) and semantic enrichment are still unsolved and remain manual. Many major vendors, such as Autodesk, Tekla, and EdgeWise, provide state-of-the-art commercial solutions for BIM modelling. EdgeWise, for example, uses a combination of feature extraction, objection recognition and auto-completion algorithms to automatically recognize geometric shapes embedded in segmented point clusters and fit into point clusters 3D objects, although it especially focuses on buildings and industrial facilities. Based on the understanding of a given PCD, modellers use PCD processing (e.g. CloudCompare) or modelling software (e.g. EdgeWise) to manually select regions of interest using bounding boxes until the point cloud is split into subsets. Segmentation is crucial, as current technology is still struggling to manage the enormous content of point clouds. Segmentation simplifies and/or transfers the representation of the original PCD into sub- point clusters that are easier for modelling software to handle and to understand. To the best of our knowledge, the limitations of existing software packages for PCD detection are: (1) substantial human intervention is required for manual point cloud segmentation; (2) manual labelling is necessary in order to assign correct class labels to the segmented point clusters. The whole process of PCD-to-BrIM should be largely streamlined if and only if we could boost the level of automation on the detection process in current software tools.

We provide a literature review in section 2, the outline of our proposed solution is given in section 3. We present the research methodology and preliminary results in section 4, followed by a conclusion in section 5.

2 BACKGROUND

The main problem that we aim to solve in this paper is bridge point cloud detection, i.e. PCD-to-labelled clusters, which refers to the task of bridge point cloud segmentation and point cloud cluster classification. In other words, we aim to (1) segment an entire bridge PCD into sub- point clusters corresponding to bridge structural components making up the 3D bridge model and (2) assign semantic labels to the segmented point clusters. The review provided in this work focuses on related methods for PCD segmentation and classification, which can be generally categorized into two groups. The first group employs a bottom-up strategy, going from points to surfaces to clusters to assemblies and finally to a model. The cluster-level (or object-level) semantics are yielded through feature extraction when generating surface primitives. The second group employs a top-down strategy, going from a model to assemblies to clusters to basic features and finally to points. The cluster-level semantics are injected as priors. We summarize both strategies as follows.

The bottom-up strategy begins by processing PCD as a point-level input, followed by the generation of higher level features, e.g. surface normal (Rusu et al 2009), surface patches (Zhang et al 2014a) etc. These higher level features enable the extraction of more informative geometric and semantic information of the objects embedded in the PCD for further analysis. The reason that surface-based methods concentrate on generating planar surfaces are mainly due to the high occurrence of planar elements in a construction context (Pătrăucean et al 2015). These methods either assume access to well-labelled training datasets that facilitate supervised learning or to very high-quality PCD. These assumptions, however, are neither realistic nor correct because of (1) non-availability of large numbers of large-scale PCD datasets and (2) the issues of clutter and occlusions. Prior studies developed local representations (Dimitrov and Golparvar-fard 2015) to overcome the latter problem. Local representations (or local descriptors) usually handle small surfaces which are less complex for computation. As a result, these methods are fairly robust to clutter and occlusions. However, small regions of support in the local representation methods are usually susceptible to noise. By contrast, global representations (or global descriptors) (Rusu et al 2009) taking the entire object as region of support, are relatively robust to noise. However, they suffer in occluded and cluttered scenes, making them difficult to reach global optimum results. There are some promising bottom-up works in the as-built/-is BIM literature. However, additional detection steps are required in order to generate specific instance labels (Xiong et al 2013; Zhang et al 2014) and conversion from surface- to volume-based clusters is necessary (Anagnostopoulos et al 2016), as BIM are mainly represented using volumetric primitives (Tang et al 2010).

The top-down strategy is a heuristic for the problem of object detection which begins with a big-picture view of the problem, then breaks it down into a few easier sub- problems. The given input for the task of PCD detection is a whole structure. We segment the entire PCD into sub- assemblies that make up the structure, then to sub- clusters that make up each assembly, based on engineering knowledge. Some studies integrate existing PCD and/or as-built/-design BIM as input information (Liu et al 2012). Using available prior modelling data can be regarded as, building top-down rules which, in turn, simplify the process of PCD-to-labelled clusters. However, very few existing structures have complete as-built/-design models, let alone as-is ones. Knowledge-based methods are more robust, as object classes (Dore & Murphy 2014), contexts (Koppula et al 2011), and domain-specific knowledge (Riveiro et al 2016), can provide the most probable model candidate from a defined library by matching the training features to the testing features (Zhang et al 2014b) or by encapsulating the expert knowledge in the form of rule sets (Belsky et al 2014). However, these studies either require a large number of training data or they do not meet the goal of BIM modelling.

Point cloud detection using surface-based primitives does not satisfy the requirements of BrIM generation. A more direct solution, such as volumetric segmentation does not exist (gap in knowledge). The objectives of this work are two-fold: we will develop a robust solution, which can (1) segment an entire bridge PCD into component-level point clusters, and (2) assign semantic labels to these point clusters. We will conclude our work by answering two research questions: (1) What accuracy can the proposed solution achieve for the task of bridge PCD segmentation? (2) What accuracy can the proposed solution achieve for the task of labelling the segmented bridge PCD clusters?

3 PROPOSED SOLUTION

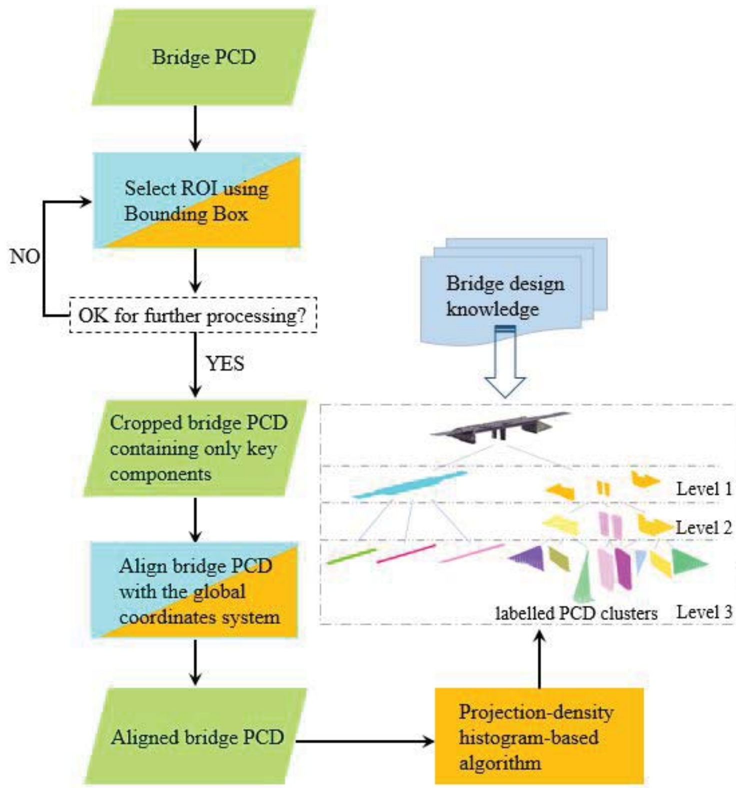
We propose a top-down knowledge-based solution. The top-down strategy has not attracted much attention in the literature. However, it looks appropriate to solve the detection problem in this work. This is because, 73% of the existing Highway Bridges and 86% of the planned future bridges in England are simply slab and beam & slab bridges (Kim et al 2016). The level of variance of these bridges is relatively low compared to other bridges, such as arch bridges, suspension bridges, etc. Structural components of slab and beam & slab bridges are distinct 3D solid objects with no free forms and the taxonomy of bridge components for any given context is finite and well defined. More specific, the key components of slab and beam & slab bridges are given in Table 1.

Table 1: Key components for bridge type (Kim 2016)

Bridge Type	**Key Components**	
	Superstructure	Substructure
Slab	deck	pier, pier-cap
Beam & Slab	deck, beam/girder	pier, pier-cap

We use density-histograms to conduct a recursive segmentation. The workflow of the top-down solution is demonstrated in Figure 1. The recursive segmentation algorithm tends to segment a given bridge PCD into three semantic segmentation levels (LV), namely:

- LV1, deck assembly and support (i.e. pier) assembly
- LV2, slab cluster, pier-cap/beam cluster (if exist) and pier clusters
- LV3, individual sub- point cloud clusters for each component



NOTE: The green rhombi represent input and output of each step, the blue blocks represent steps employing existing algorithms and tools while the orange block represent step using original algorithms. The blocks with half blue half orange represent steps involving both existing and new developed methods.

Figure 1: Framework of the proposed top-down solution

Both the structure-level and cluster-level semantics are injected as input in a hierarchical procedure and serve as detection guidance.

First, we use the Bounding Box function to clean the raw PCD and remove the irrelevant points (e.g. traffic, trees, and vegetation) for a given task of BrIM generation. The cropped bridge PCD contains only the key components.

Second, we roughly align the major axes of the bridge with the global coordinate system x-y-z (Figure 2). The alignment is crucial since most of the features that need to be extracted in the further steps are in a canonical coordinate frame. The most important tool for pose normalization is Principal Component Analysis (PCA). The performance of PCA is largely affected by noisy points, this is another reason why the raw data should be cleaned in previous step. The alignment is not perfect as the bridge itself normally has a certain degree of curvature in both horizontal and vertical directions. PCA transforms and aligns the bridge in such a way that the horizontal axis of the deck assembly is quasi-parallel to the global x-axis.

Third, we project the aligned bridge PCD onto the 2D YZ plane followed by generating a simple 1D density multi- bin histograms through which the number of points is tallied within bins along the Z-axis (Figure 3). The objective of the projection (2D representation) and the density-histograms generation (1D representation) is to reduce dimensionality and to yield more informative features from bridge 3D points for the following task of segmentation. Non-trivial "peak" signals derived from density-histograms are leveraged as discriminative features in each segmentation level. Specifically, for LV1, the empirical experiments showed very muddy results of density-histograms on Y-axis. This is because, compared with the vertical parts, many more deck assembly points are captured when laser scanning. Therefore, we first segment the deck assembly. Specifically, the "peak-gap-peak" feature on the Z-axis is used to split the deck assembly from the pier assembly (Figure 3). For LV2, local minimum density-histogram values are extracted to estimate the sub- horizontal clusters (i.e. slab and/or pier-caps) and the sub- vertical clusters (i.e. piers). The semantics of the constituent components are given from bridge design rules. They are integrated in each segmentation level so that we understand what we detect in the PCD. For example, one can infer an element to be "pier-cap" on the basis of the evidence that we find smaller peaks in-between deck assembly and pier assembly. We implement iteratively the similar processes until the entire bridge PCD is segmented into component-level semantic clusters in LV3. Finally, the detected bridge PCD is returned to its original position by using the transpose of the rotation matrix derived from PCA.

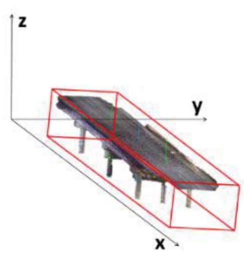


Figure 2: Aligned Bridge PCD

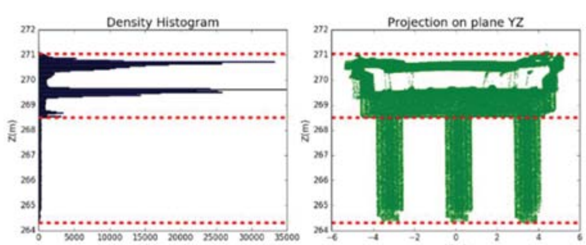


Figure 3: Density Histograms on Z-axis for LV1

As a whole, we aim to segment a bridge point cloud into semantic point clusters. The key question that this work answers is "To what degree can the detection process be automated?" Thus, certain criteria were defined that set the scale for the Degree of Automation (DoA) that can be achieved at the end of the process (Table 2). In this work, we only consider elements that are detectable with very high importance in slab and beam & slab bridges. The DoA scale of elements identification is Category 1 (scope of this work).

Table 2: Element identification evaluation categories (Kedar 2016)

		Element importance				
		Very High	High	Medium	Low	-
Elements Detectability	Detectable	Category 1	Category 2	Category 3	Category 3	Category 4
	Partially detectable	Category 2	Category 3	Category 3	Category 4	Category 4
	Non detectable	Category 5	Category 5	Category 5	Category 5	Category 5

4 Research Methodology & Preliminary Results

We collected extensive laser scan data for ten Highway Bridges around Cambridgeshire, UK, using the FARO Focus 3D X330. Also, we have properly registered all of the ten bridge raw scans using the FARO Scene software. Based on our bridge engineering knowledge and BrIM modelling experience, we prepared our ground truth data for these bridges. The ground truth data consists of two parts: (1) the manually segmented PCD clusters using CloudCompare; (2) the manually created BrIM using Autodesk Revit 2016 (Figure 4).

We recorded the scanning and registration time, and both the manual segmentation and manual modelling time. Each segmented cluster was represented within a ground truth bounding box (GTBBox) (Figure 4). We can see clearly from Table 3, the time spent on completing each BrIM is approximately ten times greater than the scanning time.

We have developed an open-source software platform named Gygax (https://github.com/ph463/Gygax) to implement our proposed solution. Ggyax is coded in C# and Visual Studio 2015 Windows Presentation Foundation (WPF). It provides powerful processing libraries that contain basic tools needed for PCD processing and visualization. Figure 5 illustrates the Graphic User Interface (GUI) of Gygax. Figure 6 shows the experimental results on one bridge data set. The bridge point cloud was finally segmented into sub- clusters for each semantic component that was encoded in a different colour.

Each point cluster was represented within a bounding box (AutoBBox). Both the centres of AutoBBox and GTBBox were computed. The component is detected if the centre of AutoBBox is inside its corresponding GTBBox. The overall performance metrics of the proposed solution are: precision, recall and accuracy under the following three scenarios:

- Scenario 1: False Negative (FN), i.e. GTBBox is there, AutoBBox is not there
- Scenario 2: False Positive (FP), i.e. GTBBox is not there, AutoBBox is there

Scenario 3: True Positive (TP), i.e. GTBBox is there, AutoBBox is there

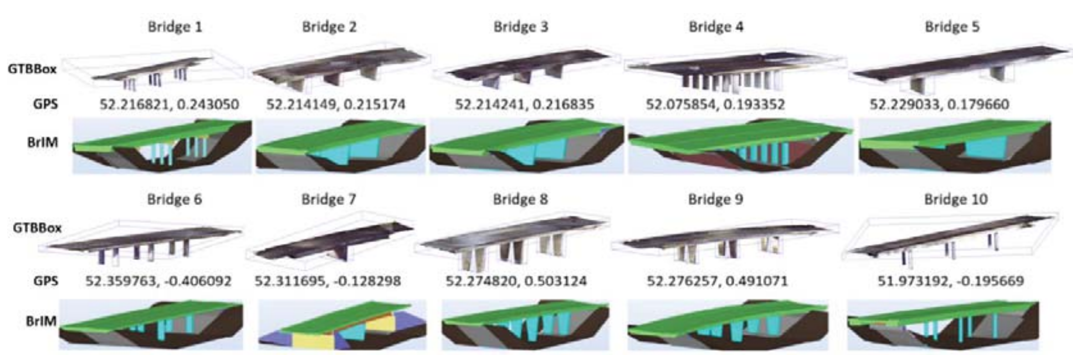


Figure 4: bridge PCD clusters in GTBBox and the BrIM

Table 3: Bridge modelling using Autodesk Revit 2016

Bridge ID	On-site Scanning time (h)	# of scans (FARO)	Registration time (h)	Clean-up & Segmentation time (h)	# of points for modelling	As-is Modelling time (h)
1	3.5	18	14	1.5	26,650,420	50
2	3.3	17	8	1	12,567,781	31
3	3.2	19	12	1	15,664,533	30
4	4	25	14	1.5	11,391,402	26
5	3.2	16	6	1.2	10,190,169	22
6	2.5	17	8	1.5	19,998,887	25
7	2	14	6	2	13,643,711	27
8	2.3	16	6	1.7	19,767,176	23
9	2.2	16	24	2.5	21,897,480	20
10	2	16	8	1.3	20,389,248	22
Avg.	2.82	17.4	10.6	1.52	17,216,081	28

NOTE: The original size of the point cloud is down sampled for modelling.

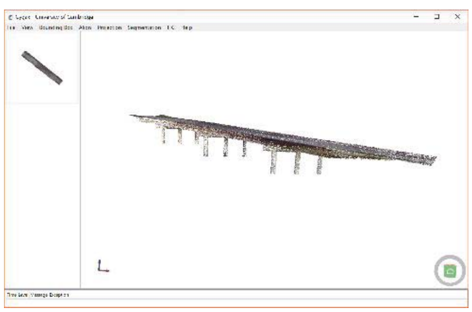


Figure 5: Gygax GUI

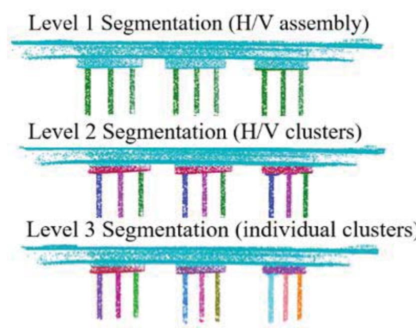


Figure 6: Recursive Segmentation Results

The results suggest that the precision of the detection is 92%, with 92% recall, and 85.7% accuracy. All of the segmented bridge point clusters in LV3 were detected except pier-cap 1. The assembly and cluster labels in all the segmentation levels were 100% correctly assigned. The accuracy of AutoBBox is also evaluated by False Volume Added (FVA) and True Volume Loss (TVL) (Figure 7). In LV3, the FVA for pier-cap 1 was 119m3 while the TVL for slab was 144m3. The relative TVL comparison suggested that pier-cap 3 had an abnormal TVL (23%).

5 CONCLUSION

We presented a top-down solution to conduct the bridge PCD detection and we tested the solution on one bridge point cloud. The overall detection results showed good performance. However, segmentation errors exist due to a slight slab vertical curvature. Note that errors within a certain degree is practically inevitable as strict orthogonal alignment does not exist in real-world bridges. Limited adjustments are acceptable and will be proceed so that the issues will not fundamentally affect the IFC conversion in the future.

The biggest direct impact of the proposed solution is that it will largely facilitate modellers to complete bridge PCD segmentation. Top-down detection solution overcomes the bottlenecks that most bottom-up solutions encounter and will greatly expedite the process of PCD-to-labelled clusters. Additionally, this solution also enhances the possibility to apply Design for Manufacturing and Assembly (DfMA) to bridge repair and rehabilitation. The bridge point cloud data analysed in this work is available at https://1drv.ms/f/s!AnTX_oS8DysbtEfFRbNKFi32RZG1.

Figure 7: FVA & TVL for each component

6 ACKNOWLEDGMENTS

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