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AUTOMATED RETRIEVAL OF PROJECT THREE-DIMENSIONAL CAD OBJECTS IN RANGE POINT CLOUDS TO SUPPORT AUTOMATED DIMENSIONAL QA/QC

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SUMMARY: *In construction, dimensional quality is critical but is very difficult to achieve, especially with built-in-place elements. As a result, dimensional Quality Assessment / Quality Control (QA/QC) must systematically be conducted, which often delays the value-adding work. Current methods for dimensional QA/QC are labor intensive, time consuming and therefore expensive. Comprehensive dimensional QA/QC approaches are thus often discarded for strategic ones, which may provide misleading dimensional QA/QC results, and result in future rework or failures. In the research presented here, the authors take advantage of new technologies available to the Architectural Engineering Construction & Facility Management industry – 3D Computer-Aided Design (CAD) engines, 3D positioning technologies and 3D laser scanners – to develop a method for automated retrieval of 3D CAD model objects in 3D laser scanner range images. This approach for automated CAD object retrieval allows for the automated and accurate segmentation of the as-built cloud corresponding to each project 3D CAD object, and it is robust with respect to occlusions. The quality of the output data is such that it is possible to use it to perform automated defect detection for dimensional QA/QC. In this paper, the authors first present the developed approach and demonstrate its efficiency through a simple experiment. Then, the authors discuss in more detail how the retrieval output data can be used to support automated dimensional QA/QC.*

KEYWORDS: *Three-Dimensional Data, Laser Scanner, CAD Model, Automated Object Retrieval, Dimensional Quality Control.*

1. INTRODUCTION

1.1 Quality in the Construction Industry

Quality is one of the three main performance criteria tracked in construction, and more generally in the Architectural Engineering Construction & Facility Management (AEC/FM) industry. Good quality reduces rework and work delays, ultimately ensuring on-time payment, adequate company cash flow, as well as expertise recognition. To achieve good quality, specifications must first be provided that translate the quality that the owner expects in the end-product (e.g. a new building, a renovated infrastructure) into qualitative or quantitative goals. Failure to reach those specified goals leads to either rework at the expense of the installer or contractor, or financial penalties. Quality specifications can be classified into two groups: material quality specifications and workmanship quality specifications. Material quality specifications refer to intrinsic characteristics of materials. Workmanship quality specifications refer to the quality of both the manual work performed by the workers and the products resulting from this work (Hendrickson, 2003). Specifications can also be categorized into measurable vs. non-measurable specifications. For instance, “sufficient space between A and B” is a non-measurable specification, while “must have a length of 5 meters with plus or minus 10 millimeters” is a measurable specification. Non-measurable quality specifications constitute a major source of misunderstanding, confusion, disagreements, and disputes between the different stakeholders involved. They must thus be avoided. Non-measurable specifications put aside, an important aspect of measurable specifications is that they are constrained by the tools available to perform the required measurements so that each type of specification generally implies the use of a specific tool.

In order to ensure that quality specifications are met, different project stakeholders may conduct inspections. These inspections can be classified in two groups: “quality control” and “quality assurance”. “Quality control” (QC) and “quality assurance” (QA) refer to the planned set of procedures intended to ensure that a construction project adheres to a defined set of quality requirements. A difference may however be distinguished between the two as QA generally focuses on the procedures occurring during the construction of the project (or each sub-element) while QC focuses on the procedures occurring once the project (or each sub-element) has been built. Overall, companies may refer to the Quality Assurance System as the system encompassing all their QA/QC procedures. ISO 9000 is an international standard that many companies use to ensure that their quality assurance system is in place and effective. It must nonetheless be noted that QA and QC are not homogeneously defined across the different industries and even across the AEC/FM industry, and QA is even sometimes used to mean QC and vice versa. Therefore, the authors indicate that they will consider the definitions above in the present paper.

QA/QC of measurable specifications may require different types of testing methods such as on-site measurement or failure testing of sampled material. In any case, it is rarely and in fact often costly and impossible in terms of time to conduct a comprehensive QA/QC of an entire project (or sub-element). As a result, QA/QC of measurable specifications is often performed strategically using random samples of data and quality is inferred using statistical tools. Accordingly, measurable specifications generally don’t include a single threshold but tolerances around a most appropriate value (Hendrickson, 2003; Pyzdek and Keller, 2003).

Although owners expect their delivered products (new building or infrastructure, renovation, etc…) to perform according to their needs, construction project specifications historically do not focus on the characteristics of delivered products but on those of building processes. These are referred to as process based specifications. There is however a shift towards performance based specifications that more appropriately define the functional characteristics of the end-product.

In (Boukamp and Akinci, 2007), the authors present a method for automatically processing construction specifications in order to support QA/QC tasks in construction and ultimately allow automated defect detection. The authors focused their work on the automated extraction of adequate specifications and corresponding measurement procedures from information originating from different specification sources for each controlled product. While the work they present focuses on the automated extraction of QA/QC specifications and procedures for each built project element, major research results have yet to be obtained in the automated measurement of as-built dimensions required by these procedures.

1.2 Dimensional Specifications and QA/QC

Among workmanship quality specifications are dimensional specifications. Measurable dimensional specifications are the focus of this paper. Measurable dimensional specifications can be categorized into shape (e.g. length, diameter, flatness, “levelness”, “plumbness”, etc.) and pose (location and orientation) specifications. Note that measurable dimensions are generally process-based.

As with most other measurable specifications, dimensional QA/QC is performed with sampled measurements. However, current measurement tools such as measurement tapes present some limitations in terms of accuracy. Additionally, these tools generally require being manipulated by humans who also need to go to the exact location of measurement, which constitutes another source of error (and hazard). These potential errors may thus often lead to situations where the obtained measurements are within tolerances but the product does not in fact meet the specifications, which may later result in costly rework.

In (Boukamp and Akinci, 2007) the authors suggest the use of new technologies for performing comprehensive, accurate and automated dimensional QA/QC. Such new technologies include total stations and laser scanners. These two technologies allow for accurate 3D measurements from remote locations which results in time and safety improvements.

Total stations are already being used on construction sites and offer significant advantages over conventional measurement tools. However, their manipulation still requires skilled surveyors as well as time. On the contrary, laser scanners allow the acquisition of dense point clouds instead of sparse ones. This requires less supervision as these dense point clouds can later be analyzed in office to extract the search dimensions. In fact, laser scanned data is so dense that it could be analyzed not only to extract specific dimensions, but also to retrieve entire project 3D elements. Such information would be far more valuable to the management team as it could be used for multiple applications outside dimensional QA/QC such as progress tracking or productivity tracking.

In the paper presented here, the authors propose an approach for automatically retrieving project 3D CAD model objects in laser scanned point clouds. The authors have confidence in the efficiency and robustness of the proposed method and that it is complementary to the work presented in (Boukamp and Akinci, 2007) for the future development of automated dimensional quality control systems. But, again, keep in mind that this 3D CAD model object retrieval approach has many other applications outside dimensional QA/QC.

In Section 2, new technologies for three-dimensional (3D) information acquisition and processing are presented that can positively impact the efficiency of obtaining dimensional QA/QC results and the robustness of these results. In Section 3, the new automated approach for retrieving 3D CAD model objects in construction 3D laser scans is presented. This approach takes advantage of these new technologies. A laboratory experiment is presented in Section 4 that demonstrates its efficiency. It will then be shown in Section 5 that its output data can be used for extracting dimensional information that can be directly compared with construction specifications for detecting defects. The paper ends with a discussion of the impact of different types of measurement errors on the dimensional QA/QC results that could be obtained using the proposed approach.

2. NEW 3D TECHNOLOGIES AND THEIR IMPACT ON QA/QC PRACTICES

2.1 New Technologies:

In the past half-century, many significant 3D technologies have emerged in the AEC/FM industry such as: 3D CAD engines, 3D positioning systems, and 3D laser scanners and point cloud management software. These technologies are presented below. Section 2.2 discusses how these technologies could impact dimensional QA/QC practices.

3D CAD Models: 3D CAD engines allow for the design of project 3D models. Project 3D models have been shown to increase design quality, communication and management among stakeholders, and decrease the number and impact of changes occurring during the project life cycle (Brucker and Nachtigall, 2005). Furthermore, 3D CAD models are now used as the central components of more complex AEC-FM management models such as Building Information Models (BIM).

3D CAD models do not constitute a basic library, but a spatially organized library of the project 3D elements. The relative location and orientation of 3D project elements is meaningful as it is intended to be exactly the same in the 3D CAD model as in reality, once built.

3D Positioning Technologies: Global positioning technologies, such as GPS for location and digital compasses for orientation, enable management to track the pose of any type of important resource in real-time for applications as diverse as productivity tracking, lay-down yard management or safety. These technologies are maturing very rapidly. For instance, current GPS technologies can already achieve sub-foot accuracy in location estimation (using Real Time Kinematics (RTK) technology), and digital compasses can achieve accuracies of half a degree in orientation estimation. Further, by geo-referencing 3D CAD models, field and office data can be referenced to each other.

3D Laser Scanners and Point Cloud Management Software:

Similarly to total stations, 3D laser scanners, also referred to as Laser Detection and Ranging (LADAR), are laser beams mounted on a frame that can be oriented in three dimensions through pan and tilt rotations. The difference is that LADAR technologies allow for very rapid and automated scans of zones instead of individual points at a time. Laser scanners can be built based on two different technologies using either pulsed or continuous signals. They are generally referred to respectively as time-of-flight and phase-based scanning technologies. The advantage of the continuous signal used in phase-based laser scanners is that it allows magnitudes faster scanning. However, it provides slightly lower accuracy and cannot be used for long range scanning (≥70m). On the other hand, the pulsed technology used in time-of-flight laser scanners allows accurate scanning at distances of 300m and above. Typical specifications of both types of laser scanners are presented in Table 1. Accuracies claimed by vendors are often argued about as they are generally obtained in best-case situations, which are rarely encountered by the users. Nonetheless, laser scanning technologies have a definite potential for being extensively used in the AEC/FM industry, in applications such as: as-built archiving and life-cycle asset management (Akinci, 2004, Bains and Carney, 2007), pre-fabrication quality control (Danko, 2007), and heritage archiving (Kacyra, 2007). Previous research publications also suggest using 3D laser scanners for automated project performance tracking such construction progress tracking and quality control (Gordon et al, 2003; Akinci et al, 2006; Navon, 2007; Boukamp and Akinci, 2007).

In order to process the dense point clouds created by laser scanners, point cloud management software are intensively being developed. These software packages provide many different features such as three-dimensional measurements, point cloud comparison for volume change measurements, and surface matching and comparison for clashes and defect detection. They also include packages for comparing point clouds to CAD objects so that they could be used to perform dimensional QA/QC. These dimensional analysis packages however present an important limitation that is detailed in Section 2.2 and 3.

TABLE 1: Examples of typical specifications of time-of-flight and phase-based laser scanners

Model		**Time-of-flight**	**Phase-based**
Laser Type		Pulsed; 532 nm	Continuous; 785 nm
Distance	**Range**	Up to 200 m	Up to 70 m
	Accuracy	1.5 mm at 50 m; 7 mm at 100 m	3mm at 10m
Angle	**Range**	Pan: 360 deg Tilt: 320 deg	Pan: 360 deg Tilt: 320 deg
	Accuracy	Pan: 60 µrad Tilt: 70 µrad	Pan: 13 µrad Tilt: 150 µrad

2.2 Impact on current QA/QC Practices

The process of dimensional QA/QC is aimed at comparing as-built dimensional information to specified values. 3D CAD models have been described as a spatially organized library of project 3D elements. A 3D CAD model can be considered as the “as-planned 3D project”. Project specifications provide information about acceptable deviations between this “as-planned 3D project” and the “as-built 3D project”. 3D laser scanners offer a fast and unique way to acquire comprehensive and accurate 3D point clouds from the as-built project, and 3D (geo)-referencing technologies allow the registration of as-built and as-planned data. Therefore, registering 3D laser scanned point clouds with project 3D CAD models opens the possibility of automatically analyzing the dimensional differences between the as-planned and as-built data and comparing the observed deviations with the dimensional specifications in order to detect defects.

In practice, the implementation of this approach is complex because 3D CAD model and 3D scanned data use completely different data representations, respectively combinations of 3D forms and point clouds. Furthermore, dimensional specifications generally relate to the basic parameters of the primitive forms used for building the project 3D model (e.g. length, width, height of a parallelepiped). In order to detect defects, corresponding values should be extracted from the as-built data, which requires retrieving from the as-built point clouds the different primitives used to build the 3D CAD model. Current point cloud management software allows the fitting of 3D shapes such as primitives on point clouds, but only after the user manually segments the points that should be used in the fitting process. The reason why the segmentation is performed manually is that automated unsupervised segmentation of complex data sets such as construction site scans gives poor results. Despite the human intervention, the manual segmentation of construction site scans remains very complex, demanding skilled engineers and therefore very expensive. Thus, the efficient detection of construction defects will be possible using 3D laser scanned data only if the process of segmenting scanned point clouds can be improved and, if possible, automated. Section 3 presents an automated approach for retrieving CAD objects in registered

3D images. The authors are confident this will provide the missing link to a future automated defect detection process.

3. AUTOMATED 3D CAD MODEL RETRIEVAL IN CONSTRUCTION 3D IMAGES

In Section 3.1, existing object recognition approaches are reviewed and their applicability to the investigated problem analyzed. In Section 3.2, the new automated method for retrieving 3D CAD model objects in 3D images is presented as well as its expected advantages. The output of this approach is the accurately segmented as-built point cloud where each point cloud segment is the retrieved as-built point cloud of one object constituting the project 3D CAD model.

3.1 Previous Approaches to the Object Recognition Problem

The object recognition problem is an old problem that has been extensively investigated in many different fields. In this type of problem, a library of the search objects is given *a priori*, and sensed data is compared to this library to retrieve the objects. Complexity generally results from noise, occlusions, different data representations, etc. Most approaches to this problem aim at converting the representation of the sensed data into the one of the objects in the library and then compare the two data sets to infer the retrieval of the objects. Most approaches additionally require the segmentation of the sensed data prior to perform the comparison. The problem with these methods is that the data segmentation must be performed automatically and is unsupervised (the number of clusters to identify is unknown). Unfortunately, automated unsupervised segmentation of complex data sets such as construction site laser scans generally leads to poor segments. Some approaches, such as the one presented in (Johnson and Hebert, 1999), do not require any automated data segmentation but this is at the expense of a complexity proportional to the size of the sensed data set. Further, all current object recognition methods present a complexity that is proportional to the size of the library of search objects as they search each object at a time.

3.2 New Approach

The limitations of existing automated object recognition approaches in situations such as the one investigated here have led the authors to the formulation of a completely new approach for more robust, efficient, and automated 3D CAD object retrieval in 3D images. The authors propose to use the project 3D CAD model and scan registration information to build an as-planned point cloud that can be directly compared to the as-built one to infer the retrieval of each object present in the project 3D CAD model.

In more details, (geo)-referencing information is first used to reference the project 3D CAD model in the laser scanner's spherical coordinate frame. Then, for each as-built range point, a corresponding range point is calculated using the project 3D CAD model as a virtual as-planned world. The point cloud resulting from this virtual scan is the as-planned point cloud, where each as-planned point corresponds to exactly one as-built point. As-built point features include at least three spatial coordinates that are sometimes enhanced with reflectivity and color information. Similarly, as-planned point features include three spatial coordinates as well as any additional information that can be extracted from the project 3D CAD model when calculating each as-planned point (e.g. material). In fact, one additional as-planned point feature that can be systematically extracted from the project 3D CAD model is the “CAD object” from which each as-planned range point is obtained. With this feature, if two corresponding as-built and as-planned points are found spatially similar, it can be inferred that the as-built point corresponds to the object “CAD object” from which the as-planned point was obtained.

The challenge of this approach consequently lies on the calculation of the as-planned point cloud. A method for this calculation is presented in Section 3.2.2. Then, Section 3.2.3 presents the metrics used for the automated comparison of as-built and as-planned clouds in order to infer the retrieval/recognition of all project 3D model objects. Finally, Section 3.2.4 summarizes the expected advantages of this approach.

3.2.1 Project 3D CAD Model Format

First of all, it must be noted that, in order to calculate the as-planned point cloud, it is necessary to have full access to the 3D CAD model data. Since most 3D CAD engines have proprietary data formats, an open-source format must be used. The chosen open-source format must lead to the least possible loss of information from the original CAD model in its native format. In (Bosche and Haas 2006) the authors identify one good candidate format that meets this information preservation requirement: the STereoLithography (STL) format. Detailed information about this format that approximates volume envelopes by tessellations of triangles can be found in (3D Systems Inc., 1989).

It might be argued that, if access to proprietary formats was granted, this conversion would not be necessary anymore. However, it will be shown in the following section that polygon tessellation-based formats such as the STL format present an additional advantage over native CAD engine formats with respect to the proposed approach.

3.2.2 Calculation of the As-planned Point Cloud

Once the STL-formatted project 3D CAD model is registered in the laser scanner's spherical frame, the as-planned range point cloud is calculated as follows: For each as-built range point, the corresponding as-planned range point is assigned the same pan and tilt angles. Then, its range is calculated by finding the closest STL triangle intersected by the ``ray" traced in the direction defined by these pan and angle angles.

The identification of the closest STL triangle intersected by a ray requires calculating the intersection of the ray with each STL triangle and identifying the intersection point that is the closest to the scanner's origin. The calculation of the intersection of a ray with a STL triangle is a constrained version of the calculation of the projection of a 3D point on a 2D plane in a given direction. This problem is fairly straight-forward so that the solution will not be detailed here. Note nonetheless that, if the 3D CAD model was not represented with a polygon tessellation-based format but with a native CAD format, this intersection calculation would become much more complex.

At this stage, the complexity of this as-planned point cloud calculation is high as the calculation of each as-planned point requires the calculation of the intersection of a ray with all STL triangles composing the 3D CAD model. This complexity can be significantly reduced. In the spherical coordinate frame of the scanner, it is possible to calculate the bounding pan and tilt angles of each STL triangle. Then, the direction defined by the two angles pan_0 and $tilt_0$ can only intersect a STL triangle whose bounding pan and tilt angles surround the pan_0 and $tilt_0$ values. This is illustrated in Fig. 1, where the ray defined by the scanning direction of the as-built point P can not possibly intersect the STL triangle 2 because the bounding angles of this STL triangle do not surround this direction. On the contrary, this ray could possibly intersect the STL triangle 1. This implies that the closest intersected STL triangle can be rapidly identified by only calculating the intersection of a ray with all the STL triangles whose bounding pan and tilt angles surround pan_0 and $tilt_0$.

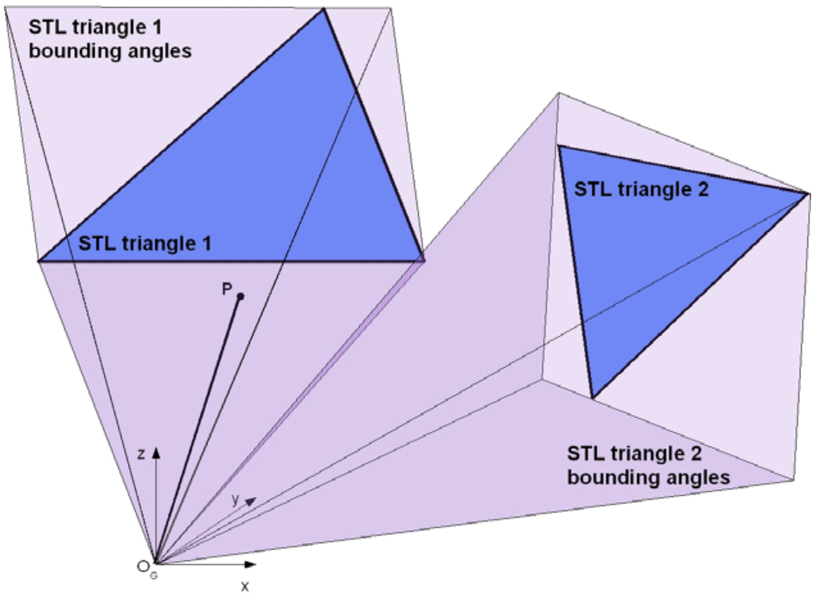

FIG. 1: Impact of Referencing CAD Models in the Laser Scanner's Frame.

3.2.3 Range Point Matching And Object Retrieval Metrics

Once the as-planned range point cloud has been calculated, it is possible to sort the as-planned points by their "CAD object" feature (the object from which each of them was obtained). This results in an as-planned point cloud for each object constituting the project 3D model. Each object for which no as-planned range point was obtained is simply assigned an empty point cloud. Then, each CAD object as-planned point can be compared to its corresponding as-built point. This comparison, which requires a *point matching metric*, results in the retrieval of each individual as-planned point. After matching each CAD object as-planned point, the recognition of the object can finally be inferred. This requires a second metric, the *object retrieval metric*.

Range Point Matching Metric. Each as-planned point corresponds to exactly one as-built point, and these two points have the same pan and tilt angles. Their matching can thus only be estimated based on the only remaining common feature, the range coordinate (although, if additional common features exist, they could and should be used). The range point matching metric used here considers the difference in the two ranges and compares it to a given threshold. For instance, an as-planned range point can be considered positively matched to its corresponding as-built point (or retrieved) if the absolute difference in their ranges, $\Delta Range$, is lower than the distance threshold, $\Delta Range_{min}$. $\Delta Range_{min}$ must be estimated *a priori* and it can be argued that it should take into account context-specific factors. While in the experiments presented in Section 4 $\Delta Range_{min}$ is manually *a priori* estimated, the authors discuss in (Bosche and Haas 2007) means to automatically estimate it and even customize it for each point using as-planned point intrinsic characteristics such as the as-planned range and its acquisition reflection angle (angle between the point acquisition direction and the normal to the STL triangle from which the as-planned point is obtained).

Object Retrieval Metric. Once the matching of the as-planned points of each CAD object with their corresponding as-built points has been assessed, the recognition of this CAD object can be inferred. For this, a straight-forward and commonly used object recognition/retrieval metric is used: the calculation of the object as-planned point cloud retrieval rate, $R_{\%}$, which is the ratio of the number of retrieved (matched) as-planned range points to the total number of as-planned range points. $R_{\%}$ can be compared to a pre-defined threshold $R_{\%min}$ to infer the object recognition/retrieval. However, as is, this metric would not be robust in the following two situations:

- *Object as-planned point cloud containing only a few points.* For instance, if an object as-planned point cloud contains two points and if one point is retrieved, then 50% of the as-planned point cloud is retrieved. Clearly, such a situation – that can occur when the object is far or very occluded, or when the range point cloud density is low – should not lead to the recognition of the object, despite the high point cloud retrieval rate.
- *Object occluded by non-CAD objects.* This may result in objects having unreasonably low retrieval rates although many points are actually retrieved. For instance, in the case where 5% of an as-planned point cloud containing 2000 points is retrieved, the retrieval rate is very low, but there are still 100 retrieved points and it could be argued that the object should be considered retrieved.

The first situation can be handled by adding to the retrieval metric the condition that an object can only be considered for retrieval if its as-planned range point cloud contains a minimum number of points, defined by a threshold P_{nmin}. The second situation can be handled by adding to the retrieval metric the condition that, if the number of recognized as-planned points is higher than a given threshold R_{nmin}, this is sufficient to consider the object retrieved (no need to calculate the as-planned cloud retrieval rate, $R_{\%}$). This final CAD object as-planned point cloud retrieval metric is summarized in Fig. 2.

Like for the *range point matching metric*, the authors discuss in (Bosche and Haas, 2007) methods to automatically estimate the values of the P_{nmin}, R_{nmin} and $R_{\%min}$ thresholds by taking into consideration context-specific factors such as: the scan point density and the distance between the scanner and each search object. In the experiments presented in Section 4 these thresholds are however manually *a priori* estimated.

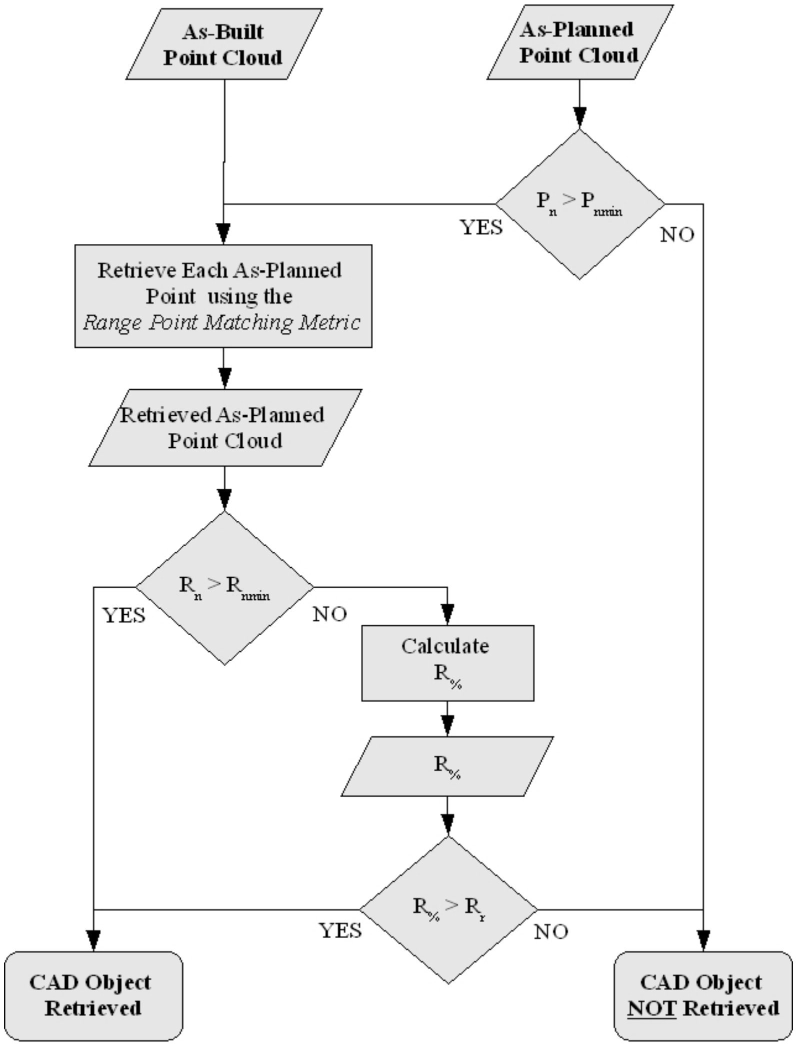

FIG. 2: CAD object retrieval metric.

3.2.4 Expected Advantages of this Approach

The proposed approach is expected to perform well with respect to:

Segmentation quality.

- **No reliance on segmentation algorithm**. This approach does not require any unsupervised data segmentation algorithm. Thus it does not suffer from the very limited results of such algorithms with unknown cluttered and occluded scenes such as construction sites.
- **Robustness to occlusions.**
  - **From other CAD objects**. The proposed approach builds an as-planned point cloud by performing a virtual scan with the registered entire 3D CAD model as the scanned world. Therefore, occlusions of a CAD object due to other CAD objects are expected to be the same in the as-planned and as-built scans, and the retrieval of objects using the retrieval rate will thus not be sensitive to this type of occlusions.
  - **From non-CAD objects**. In the case of occlusions from non-CAD objects (such as temporary structures like scaffoldings or simply random occluding objects), this method is expected to perform well in the sense that it is robust to avoid false positive matched points (matched points that should not be matched). Indeed, $\Delta Range_{min}$ would generally be set to low values such as 50mm. Therefore, all as-built points whose range is further away from the corresponding as-planned point than $\Delta Range_{min}$ are not matched. In the situation of a point

obtained from a set of scaffoldings in front of a wall, this threshold ensures that this point won't be matched with the as-planned one obtained from the wall, and overall that all the points obtained from the scaffolding will not be matched. Then, occlusions due to non-CAD objects will also have an impact on the retrieval rate. The adequate estimation of the P_{nmin}, R_{nmin} and $R_{\%min}$ thresholds based on context-specific factors can however ensure the retrieval of objects that are highly occluded by non-CAD objects (see discussion in Section 3.2.3).

Computational complexity. Contrary to other approaches, the complexity of the proposed approach does not increase with the number of search objects. Indeed, it has been shown that the search space of the object facets on which an as-planned point could be obtained can be reduced to all the STL triangles whose bounding pan and tilt angles surround the pan and tilt angles of the corresponding as-built point. Consequently, the complexity of this approach theoretically increases only with the number of scanned points.

However, it can be noted that the quality of this approach relies on the quality of the data registration. The impact of data registration error on the proposed object retrieval approach is discussed in Section 6.

4. EXPERIMENTAL RESULTS

In order to test the proposed object retrieval approach, an experiment is conducted using a simple structure made of five objects representing a column-slab structure, a time-of-flight Trimble™ GX 3D laser scanner – the characteristics of which are presented in the left column of Table 1, and the 3D CAD engine Bentley™ Microstation™. It must be noted that, in this experiment, data referencing is performed manually by matching a few corresponding points from the scan and CAD model.

Initially, a 3D CAD model of the column-slab structure is developed using the 3D CAD engine. This model is composed of the five CAD objects called: *column 1*, *column 2*, *column 3*, *column 4*, and *slab* (Fig. 3). Then, the structure is manually built with as much precision as possible with respect to the 3D CAD model. Finally, the entire scene is scanned with the laser scanner and the developed algorithm is run to automatically retrieve the 3D CAD objects in the scanned data. Fig. 4 shows the laboratory experimental setup with the column-slab structure and the laser scanner. Fig. 5 displays the scan containing 206,360 points, the size of each point being proportional to its associated sensed reflectivity. The algorithm used was developed in Visual Basic .NET language and uses here the following input parameter values:

- $\Delta Range_{min}$: An as-planned cloud point is considered retrieved if the difference between its range and the range of the corresponding as-built point is less than 30 mm.
- P_{nmin}: The retrieval of a CAD object is performed only if its as-planned point cloud contains more than 20 points.
- R_{nmin}: A CAD object is considered retrieved if at least 500 points of its as-planned point cloud are retrieved.
- $R_{\%min}$: If less than R_{nmin} points of a CAD object as-planned point cloud are retrieved, the object is considered retrieved only if at least 50% of the as-planned points are retrieved (retrieval rate).

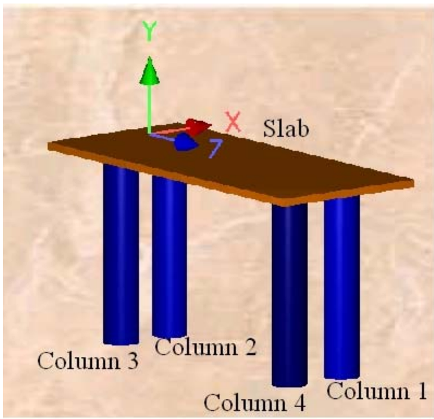

FIG. 3: 3D CAD model of the column-slab structure.

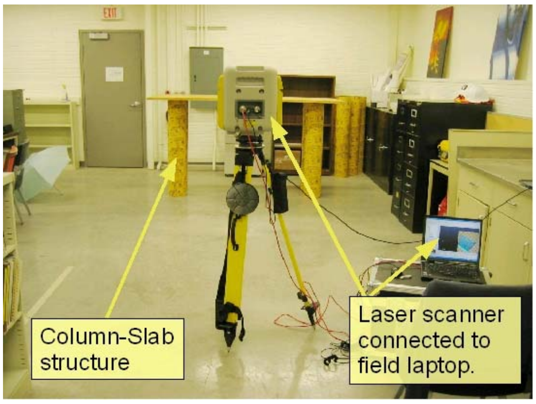

FIG. 4: Indoor setup with the scanned structure and the laser scanner.

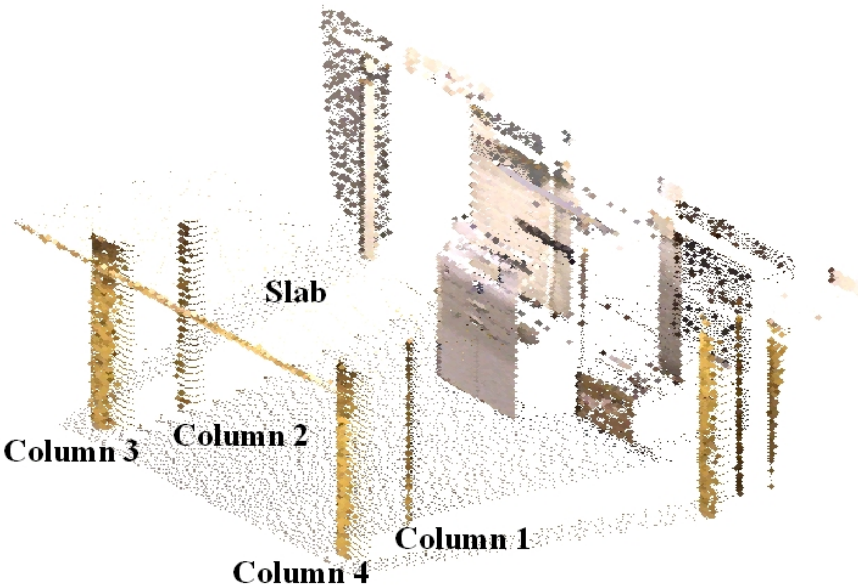

FIG. 5: 3D as-built point cloud. The size of each point is proportional to its reflectivity.

4.1 Results

The retrieval results are presented in Fig. 6 and Table 2. Fig. 6 displays the as-built, as-planned, and retrieved as-planned data at the different stages of the retrieval process. In this figure, only 10% of the total number of points of each cloud is actually displayed in order to increase picture clarity. Table 2 shows that all CAD objects from the 3D CAD model are retrieved. The retrieval rates of all CAD objects are high (at least 74%), including *column 1* and *column 2* despite the fact that 75% of their normally visible surfaces are occluded by *column 4* and *column 3* respectively. This demonstrates the robustness of this method with respect to occlusions due to other CAD objects. The very high retrieval rates of the four columns are the result of a high level of correspondence between the as-built and as-planned point clouds. This demonstrates not only the efficiency and robustness of the CAD object retrieval metric, but also the capacity of this automated method for segmenting accurate subsets of points from the as-built cloud corresponding to each 3D CAD object.

It can also be noted that the slab is retrieved with a high but slightly lower retrieval rate (74%). In Fig. 6, the figure presenting the retrieved as-planned point cloud shows that points were retrieved from the Slab face facing the laser scanner but not from the top face. This suggests that the *Slab* was not built at a proper height or that the altitude registration is not accurate. Indeed, in this example, a little error in the vertical registration would shift the as-built slab cloud vertically compared to the as-planned one, which would considerably alter the retrieval results of the slab without significantly altering the retrieval of the columns. The impact of registration errors is further discussed in Section 6. Another possible reason for this low retrieval rate can be found in Fig. 7 in which the size of each point is proportional to its associated sensed reflectivity. Reflectivity can be seen as an estimator of range acquisition uncertainty, and it can be noticed that most points obtained from the slab, especially from its top surface, have a very low reflectivity. The chosen $\Delta Range_{min}$ threshold might thus have been too low to retrieve these points. As mentioned earlier, the authors discuss in (Bosche and Haas, 2007) means to automate the estimation of $\Delta Range_{min}$ for each as-planned point by taking into account its intrinsic characteristics.

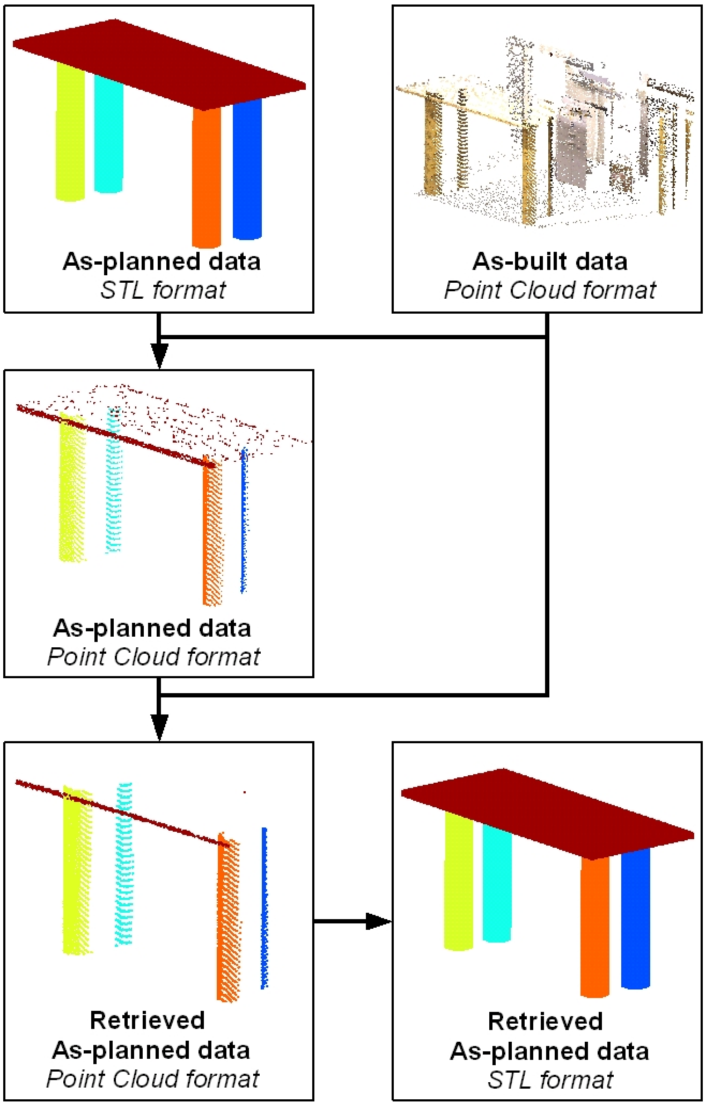

FIG. 6: As-built and as-planned data at different stages of the retrieval process in Experiment 1 (only 10% of the total number of points of each cloud is displayed to increase clarity).

TABLE 2: CAD model objects retrieval experiment results

Calculated Metric Value	**CAD Element**				
	Column 1	**Column 2**	**Column 3**	**Column 4**	**Slab**
$\mathbf{P_n}$	5,079	4,678	17,490	17,880	4,712
$\mathbf{R_n}$	4,423	4,411	16,403	16,120	3,479
$\mathbf{R_{\%}}$	87%	94%	94%	90%	74%
Detected ($R_{\%} \geq R_{\%min}$?)	YES	YES	YES	YES	YES
Average *ΔRange*	5 mm	7 mm	5 mm	18 mm	10 mm

5. USING THE 3D CAD OBJECT RETRIEVAL OUTPUT DATA TO SUPPORT AUTOMATED DIMENSIONAL QA/QC

Each 3D CAD object retrieved as-built point cloud could be used for performing automated dimensional defect detection. First, the differences between as-built and as-planned point ranges can be mapped to visually analyze the level of correspondence between the as-built and retrieved as-planned data, and therefore the dimensional quality. While this technique is not sufficient to perform automated dimensional QA/QC, it can be used to quickly identify the elements that seem to be inadequately built. For instance, Fig. 9 presents the as-built point cloud of the experiment presented in Section 4 with the color of each point set to *ΔRange* that ranges from –$\Delta range_{min}$ *to* +$\Delta Range_{min}$ (a negative value meaning that the point is found inside the object surface envelop, a positive value meaning that the point is found outside the object surface envelop). In this figure, a "greenish" color means that the as-built point is at most five millimeters away from the corresponding as-planned one. Blue and red colors mean that the as-built point is up to 30 millimeters away from the corresponding as-planned one. Along with the results presented in Table 2, it can be easily identified that *Slab* and *Column 4* require further investigation with respect to possible dimensional defect. For *Column 4*, it can be seen in Table 2 that the mean *ΔRange* is very high (almost two centimeters) despite a high retrieval rate $R_{\%}$, and in Fig. 9 its points are correspondingly shown in homogenous blue colors. For *Slab*, it can be seen in Table 2 that the mean *ΔRange* is about one centimeter, which may be considered acceptable, but its retrieval rate is very low, and in Fig. 9 no point is retrieved from its top surface despite "greenish" colors obtained for the points obtained from its front edge. On the other hand, in Table 2 *Column 1*, *Column 2* and *Column 3* present high retrieval rates, low mean *ΔRange* values, and in Fig. 9 they all appear with mostly "greenish" colors. As a result, these objects could be visually discarded for further dimensional control.

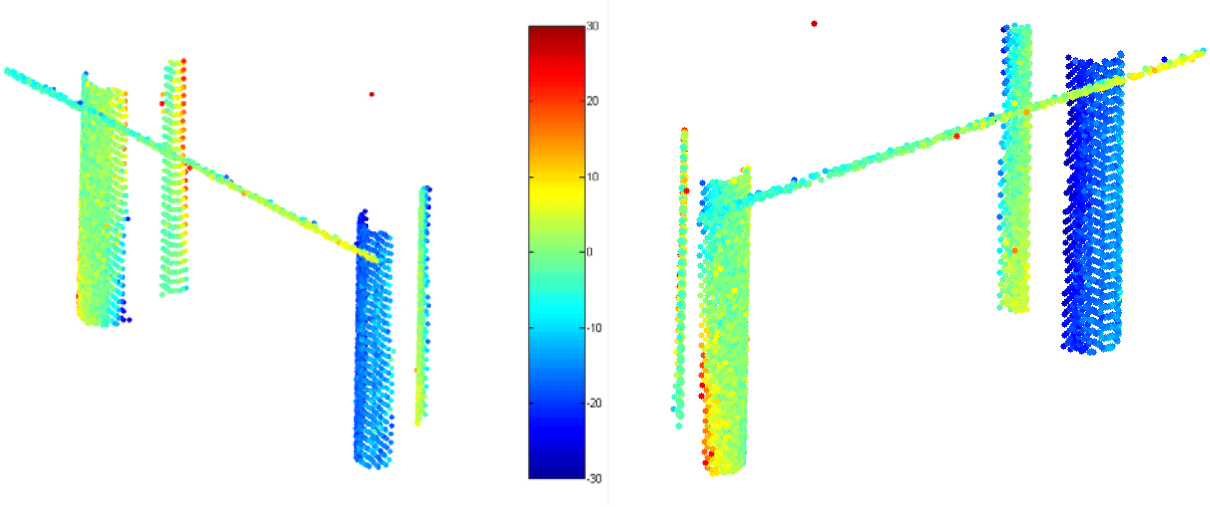

FIG. 9: As-built point cloud with point colors set to ΔRange viewed from the front-right side (left) and from the front-left side (right) of the structure . Scale values are in millimeters.

Despite the information that can be obtained through this visual analysis, it does not provide dimensional information that can be directly compared to typical dimensional specifications. Again, the advantage of the method presented here is that each CAD object can be associated with an accurate as-built point cloud (as long as this object is part of the scanned scene). Then, it can be noted that most CAD objects are generally simple primitives (parallelepiped, cylinder, etc.) or intersections of primitives. Additionally, many algorithms already exist to fit primitives to point clouds, including in current point cloud management software. For instance, (Kwon et al, 2004) present two algorithms to fit parallelepiped and cylinders to point clouds. The output data of the proposed CAD object retrieval approach could be used as the input of a primitive fitting package that would automatically fit to the segmented point clouds the same primitives as the ones used for the corresponding objects in the CAD model. The parameters of these primitives, such as the length width and depth of a parallelepiped can then be used to compute the values that construction dimensional specifications generally refer to (e.g. column height, column verticality, cylindrical column radius, slab levelness, etc.) (CMHC/SCHL, 1996; ACI, 2006).

With respect to the experiment in Section 4, it can be seen in Fig. 9 that *Column 1*, *Column 2* and *Column 3* show colors that vary vertically, despite the overall "greenish" color. This suggests that these columns are generally well located horizontally but may in fact present some verticality defect. This could be easily deduced if, for each of these columns, a cylinder was fitted to its as-built point cloud and the direction of the cylinder axis was compared to the vertical axis. Similarly, *Column 4* appears in Fig. 9 with only "blue-ish" colors that are vertically homogeneous. This suggests that *Column 4* is not properly located horizontally (by about 20mm) but has a good verticality. Again, this analysis could be easily performed by fitting a cylinder to the acquired data and analyzing its main parameters, particularly here the column base center pose.

Further work must certainly be conducted on the automated fitting of primitives to point clouds given information from the 3D CAD model about the primitives to be fitted. This work should particularly investigate means to fit objects that are not simple primitives, but are intersections of primitives.

The authors also note that the use of laser scanners and these types of data processing algorithms could impact not only dimensional QA/QC practices but also the way dimensional specifications are defined. Current dimensional specifications and corresponding QA/QC methods are based on sparse discrete data – such as F-numbers used for estimating "flatness" and "levelness". The reason is that they were developed for use with tools such as measurement tapes, digital levels and total stations. If used with 3D laser scanners, these specifications and related QA/QC methods would not take advantage of the density of dimensional information contained in laser scans. In order to take advantage of 3D laser scanners and new 3D data processing algorithms such as the one presented in this paper, new types of dimensional specification QA/QC methods may need to be investigated.

6. IMPACT OF REGISTRATION ERRORS

In the proposed approach, errors in CAD model-scan registration/referencing could significantly affect the object retrieval as well as dimensional quality control results, to the point of misleading the decision maker. Ensuring that the registration is correct is therefore crucial.

In the case that global positioning technologies are used, registration quality depends on the quality of the geo-referencing information provided by the sensors. Geo-referencing information includes six parameters: longitude, latitude, and altitude for the location; heading, pitch and roll for orientation. Current geo-referencing technologies provide accuracies of at best several centimeters in location and half a degree in orientation. Future improvements in global geo-referencing technologies will likely improve these accuracies to levels acceptable for use with laser scanning technologies and the proposed CAD retrieval approach, however currently these accuracies are inappropriate. For this reason, local referencing must be used. This can be done by registering the scans to the facility tie points used for its construction. This registration is in fact very appropriate as it should lead to the best alignment of the as-built and as-planned data. In the case that such facility tie points do not exist, the registration can be performed by matching a few points in the 3D scan and 3D CAD model. This approach is not as good as the previous one because the choice of these few scan tie points may bias the whole registration quality (what if these points are actually not where they are expected to be?). In the experiment presented in this paper, registration was conducted using the last approach because no "facility" tie points were available.

In the case that registration is performed globally or locally without facility tie points, the resulting registration error can have a significant impact on the matching results. Being able to automatically correct registration error is critical. The authors propose a method for automated registration optimization (or registration error correction) that takes advantage of the proposed object retrieval approach. First of all, registration error can be considered as the difference between the geo-referenced poses (*northing*, *easting, altitude, heading*, *pitch*, *roll*) of the scan and the 3D CAD model. Then, it is assumed that the originally-used registration approach provides an acceptable registration estimation (the difference between the scan and model geo-references are low). It is thus proposed to perform a local search of a more optimal registration estimation. This local search is performed by considering the 3D CAD model properly registered and changing the geo-referenced registration estimation of the scan by pre-defined small increments (such as 10mm for altitude). A maximum likelihood estimator is calculated for each of these locally-varied registration estimations. It is calculated using the *ΔRange* values obtained for a fixed number of random points (at least 500) that are retrieved by using the object retrieval approach described in this paper. If one of these new registration estimations results in a value of the likelihood estimator that is higher than the value obtained with the original registration estimation, this new registration estimation is preferred. This process iterates until no local improvement is found.

While the original registration estimation would generally be based on a few tie points, this registration optimization then uses many more points (at least 500). As a result, it will not only correct the registration estimation, but it will also increase the level of confidence in the final registration estimation. Note, nonetheless, that this approach has only been tested a few times. Further experiments are therefore required to adequately evaluate its efficiency, robustness, as well as limitations. In any case, it must be emphasized that, like local registration performed without facility tie points, this registration optimization approach assumes that the best registration estimation occurs when the 3D CAD model and the scanned data are best aligned, which further assumes that the project was properly built. This is conflicting with the goal to perform dimensional QA/QC. As a result, this proposed registration optimization approach should only be used if there is only little confidence in the original registration or if that original registration was already performed using points from the actual elements under quality investigation. Overall, facility tie points should be preferred as they lead to high confidence in the registration and they are independent from the elements under quality investigation.

7. CONCLUSION

This paper presented a new automated method for CAD model objects retrieval from 3D images. This method shows overall better robustness with respect to occlusions due to other CAD elements, better segmentation of point sets, and lower complexity than currently available approaches. Then, it has been shown how the 3D CAD model objects retrieval output data can be used to identify dimensional defects in as-built objects, and ultimately perform automated dimensional QA/QC. Future research is nonetheless needed in adapting fitting algorithms such as those presented in (Kwon et al., 2004) to be able to automatically extract adequate information for comparison with typical dimensional specifications. Additionally, the last part of the paper emphasizes the impact of registration error in the approach results. Future work should thus also focus on further investigating the proposed method or developing new methods for automatically correcting registration error, which is critical to the proposed approach.

The authors would finally like to emphasize that the proposed approach for automated retrieval of 3D CAD objects in 3D images has applications not only in automated QA/QC, but also in fields such as: project advancement tracking, productivity tracking, 3D image database information retrieval, etc.

8. ACKNOWLEDGEMENT

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