Defining quality metrics for photogrammetric construction site monitoring

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ABSTRACT: Point clouds are becoming a quasi-standard as a representation for capturing the existing context, for construction progress monitoring and quality control. While it is possible to create and track sites with a reasonable amount of effort using photogrammetry, different recording strategies and computational power lead to different properties of the point cloud. While the needed specifications are based on the concrete type of analysis and will vary from recording to recording, the overall properties of the reconstruction toolchain are immanent to assess the performance of further processing. Within this paper we will present different criteria for the quality and evaluation of point clouds in respect to construction sites. These indicators together form a benchmark and can be used to evaluate a given toolchain and estimate the properties of a resulting point cloud.

1 INTRODUCTION

Capturing construction sites in their as-built state has become a central point in the automation of construction site management and quality control. In the past this was achieved with a high amount of manual labour and untraceable results. Within the digitalization process of multiple disciplines in the construction industry, new opportunities to increase the degree of automation occur. Processed and presented in the right way, the captured data will provide useful information, not only to the main contractor due to a good overview over the progress but also to architects and engineers working in existing context and even insurance companies. The primary step is capturing and documenting the site of interest. Although laser scanned point clouds are of high quality, the expense to create them is rather high. If needed for visualization, colour needs to be added later via images. Capturing images and the photogrammetric reconstruction of point clouds by the combination of Surface from Motion (SfM) and Multiview reconstructions (MVS) are a cheaper and more widely used alternative.

As different automation processes will use the captured data as a basis, the point cloud must suffice specific requirements. Factors as coverage, recording interval, colour schemes, resolution, speed, trueness, precision, observational error and robustness must be taken into consideration. In the workflow of photogrammetric 3D reconstruction, these parameters can be influenced directly, e.g. coverage (our definition in section 4.3) by changing the position of images, or indirectly, depending on the chosen toolchain and reconstruction parameters. Considering 3D reconstruction is a highly computational intensive task and a tradeoff must be made in speed versus quality. For practitioners and early adaptors, this means that using a finished solution may result in insufficient results or unnecessary expenses.

This work will define several indicators and factors that will help the users to evaluate their toolchain. After a brief summary of related research in Section 2, Section 3 will introduce the processes of SfM/MVS that are the algorithm classes used by most applications. In Section 4 we will introduce metrics and deduct how they can be measured before summarizing and suggesting further research topics in Sections 5 and 6.

2 RELATED WORK

In recent years, multiple advances for monitoring construction sites via laser scanners or images were developed. Using the base idea of comparing a geometric representation of a construction site and matching it with a captured point cloud (Fischer and Aalami, 1996) lead to several detection algorithms for planed building elements (Scan-vs-BIM). First approaches went from a simple point to surface with a linear thresholded (<50mm) recognition of objects (Bosché et al., 2008) over machine learning recognition (Kim 2015) to rasterized point projections onto the geometric model (Rebolj et al., 2017).

While all these publications tend to apply slightly different use cases, the first hurdle for a successful identification is registration of the captured point cloud to the geometric representation. For the relative registration of the geometric model, two base approaches exist in literature: feature-based recognition and the reduction of distances between the alignments (optimization). An Iterative Closes Point (ICP) (Besl and McKay, 1992) showed good results (Bosché, 2010; Masuda et al., 1996) after a successful manual initial alignment. It also worked well in combinational approaches (Huang and You, 2013). A generalized approach for surface to pointcloud was deducted by Segal (Holz et al., 2015; Segal et al., 2009). All these approaches need initial alignment or filtering since the ICP is a non-convex method. This problem leads to a global alignment when dealing with noisy construction site captures (Braun et al., 2016; Tuttas et al., 2017).

The SfM/MVS based approach was identified as less accurate but much cheaper (Golparvar-Fard et al., 2011) compared to laser scanning and lead to a discussion of quality (Toth et al., 2013).

To predict the quality of site captures, recent developments showed two different approaches: deducing the quality of the recording based on the result of the identification process (Rebolj et al., 2017) or using pure point cloud related properties and toolchains (Angel Alfredo Martell, 2017; Dyer, 2001; Haala et al., 2013). Following up on these publications, we present simple metrics of quality and emphasize on developing robust independent criteria.

3 PROCESS OF RECONSTRUCTION

3.1 *Structure from Motion*

The structure from motion pipeline provides us with the first step to create a 3D model from taken images. It eliminates the need of a calibrated camera where the extrinsic and intrinsic parameters are fixed and known. In all taken images, points of interest are calculated and their correspondence is determined. Rejecting flawed correspondences, each camera is registered relative to the initial match. With the help of the bundle adjustment, the overall error is reduced significantly as multiple images will be refitted to the current model.

The main goal of the SfM is to generate the initial camera configurations of a scene captured by one or more cameras with multiple images. Since on construction sites, the images are quasi random, it is the first step in retrieving correct 3D information. The correspondences exist as a point cloud deduced for the camera alignment. They already have partial geometric information of the dense reconstruction. The camera alignment is the basis for all common reconstruction pipelines used in construction site monitoring.

3.2 *Multi View Stereo*

Multi-view stereo algorithms vary significantly in their principles. Seitz categorized the existing methods by six major properties (S. M. Seitz et al., 2006).

1. Scene representation
   Voxels, volumes or levelset methods represent the approximate surface, polygon meshes as facets and depth maps as 2D representation.
2. Photo consistency
   Two main competitors: Determined by the discretization and projection in scene (reconstruction grid) or image space (pixels of the image).
3. Visibility model
   The model verifies, if the view needs to be considered during calculation. This is especially important with larger scenes.
4. Shape prior
   During the reconstruction, assumptions for the shapes are imposed e.g. approaches that minimize surfaces.
5. Reconstruction algorithm
   Different types are used: calculating the cost of voxels, evolving a surface iteratively, enforced consistency in depth maps and merging them into a 3D scene, fitting a surface to an extracted set.
6. Initialization requirements
   Needed initialization may be bounding boxes, fore-/background separation. Image-space algorithms restrict the disparity or depth values.

These properties will later define the quality of different algorithms and in case of 1.) if a point cloud is a suited output. In the next section we will look at current applications available and group them regarding to these fundamental properties.

3.3 *Applications*

In the construction industry, only a few selected software solutions are commonly used. Most tools support SfM and MVS and do not need a complementary part. For practitioners the ease of use and the cost can play an important part in their selection of the toolchains. Table 1 lists a selection of applications and their pipelines. When benchmarking different solutions comparing the output of interim results of each reconstruction step helps to identify their limitations. Working with a dataset (construction site 48°08'50.6"N 11°31'33.4"E, 25th of June 2017, 1087 images) showed that not all software solutions are able to handle the big amount of data from a construction site sufficiently well and that some need a considerable amount of computational resources.

Application	License	SfM	MVS
Agisoft Photoscan	c	✓	depth-map
Pix4DMapper	c	✓	PDE (whitepaper)
ContextCapture	c	✓	polygon mesh
VisualSFM	nc	✓	patch expansion
Colmap	o	✓	depth-map
Sure	nc	✗	extracted set
openMVS	o	✓	depth map

Table 1: Selection of available software solutions for 3D reconstruction from multiple unsorted images. Licenses are commercial (c), non-commercial (nc), and open source solutions. Agisoft (Dmitry Semyonov, 2011), Pix4DMapper (Strecha et al., 2003), ContextCapture (Acute3D, 2018), Visual SFM (CMVS) (Furukawa and Ponce, 2007 - 2007), Colmap (Schönberger et al., 2016), Sure (Rothermel et al., 2012) openMVS (Demetrescu et al., 2011).

4 METRICS

4.1 *Baseline*

For the definition of the quality criteria of a point we will make several assumptions. First, while most of these criteria will also work with all point clouds we will only reference to MVS generated point clouds. Some measurements cannot be performed with the point cloud alone and need a ground truth. For us, there are two possible ways to provide this ground truth. We either generate the point cloud from a synthetically generated set of images (Eickeler and Jahr, 2017; Rebolj et al., 2017) or use actual data (e.g. captured by laser scanning) for the ground truth. With synthetic data generated from a model, it is hard to verify the process of reconstruction due to the assumptions made in the camera model. Opposed to synthetic data, a ground truth from a laser scanner will always have measurement errors and deviations.

Before measuring deviations between captured data and ground truth, the MVS generated model needs to be perfectly aligned. While we can do this with the help of control points, the most suitable alignment (registration) method needs to be determined and the relation to the considered metric must be investigated. This is of particular interest if we take scaling and warping into account. In this regard, we must compare between two different concepts: the alignment via control points with an affine transformation, and the alignment with a ridged transformation to the minimal error. While the first method may induce additional error by distorting the point cloud and fitting the control points to their reference, it may also reduce the error introduced by warping.

Because we cannot assume evenly distributed density, it is not possible to align both point clouds with a point-to-point ICP algorithm and compare the results of the error. Therefore, we will use the generalized ICP approach with point-to-plane matching with a meshed version of the ground truth (or the model itself). Since laser scans are usually much denser than the point cloud generated from an MVS, the introduced error is smaller than the resolution of the tested point cloud (nyquist criteria (Shannon, 1948)).

All criteria will be defined without any relation to the underlying analytical process for Scan-to-BIM, the object recognition. It is our understanding that if we considered these processes, we would bias and tailor the results to any chosen algorithm. Hence, we will only consider metrics that are self-contained within the point cloud, the process of creation or those that we are able to deduce by comparing the reconstruction with the ground truth.

Starting from process parameters that are only partly applicable to all named pipelines in Section 3.2, we will look at the point cloud as an isolated entity and then follow with the comparisons.

4.2 *Process criteria*

Evaluating the process of point cloud creation is meaningful on its own for comparing the resulting quality. Using different configurations and software tools we want to establish some properties for tools first before continuing to investigate point clouds as isolated data structures. This will help to identify possible errors in the image space.

4.2.1 *SFM Accuracy*

As all pipelines need to find the original camera configuration with SfM, we define the mean error and the variance of the camera positions as our first process criteria. Taking the ridged transformation matrix H where R is a 3 x 3 rotation matrix and $\boldsymbol{t}$ the translation vector of the camera.

$$H = \begin{bmatrix} R & \boldsymbol{t} \\ \mathbf{0}^T & 1 \end{bmatrix} \tag{1}$$

With this we define the absolute mean error and the variance as our first two process indicators.

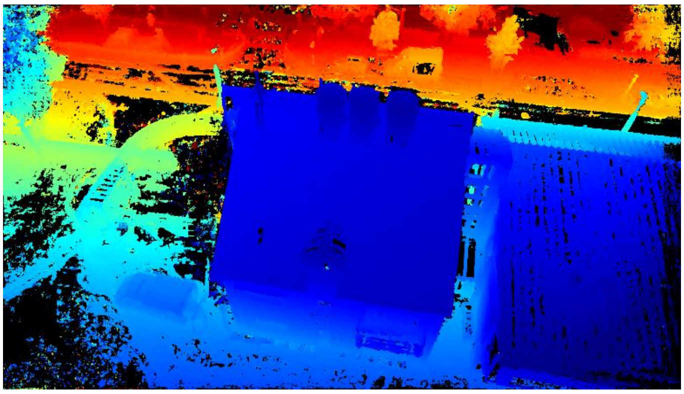
$$\overline{\Delta H} = \frac{1}{n}\sum_{i=1}^{n} |H_{sfm,i} - H_{t,i}| \tag{2}$$

$$\mathcal{V}_H{}^2 = \frac{1}{n}\sum_{i=1}^{n} |\Delta H_i| - \overline{\Delta H} \tag{3}$$

H_{sfm} is the calculated alignment and H_t the recorded camera positions. For construction sites, the camera positions are not determinable. However for smaller objects, datasets that provide the exact camera positions and orientations exist, (S. M. Seitz et al., 2006).

4.2.2 *Depth maps, deviation, and noise ratio*

Many state-of-the-art reconstruction pipelines use depth maps fusion (see table 1) to generate a point cloud. These maps can easily be compared to the derived depth-map from the ground truth. For this we must create the depth mapping as colour coded view. We use the camera projection matrix from the SfM for this process. A depth map extracted from MVS is shown in Figure 1. After generating the ground truth and normalizing the depth map, the images can be subtracted, and the intensity map evaluated. The variance of this intensity map $\mathcal{V}_{\mathrm{dm}}{}^2$ is an indicator for the expected accuracy of the point cloud, as it shows the difference before the fusion step. Comparing the Fourier transform in a desired spectrum will compare the spatial resolution of the depth-maps. It is possible to determine the maximal reliable resolution of the resulting point cloud and compare them to the SNR (signal to noise ratio) of the images.



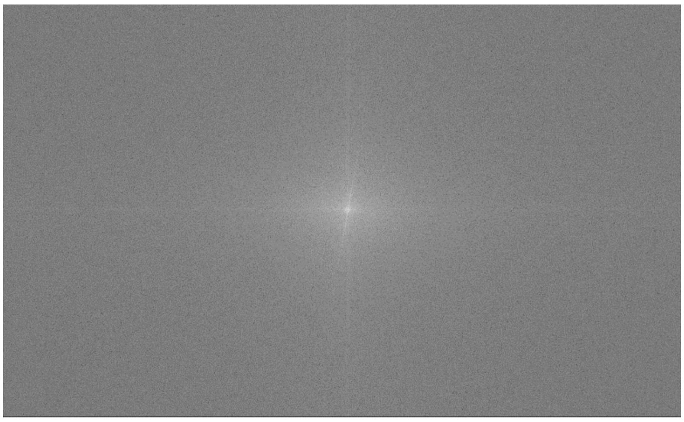


Figure 1,2: The upper figure shows a depth map from colmap as example. This depth-map has the same resolution as the input images. Figure 2 is the Fourier transform of the same image. A high amount of high frequency spectrum can be seen. The lower image is the result of a low-cut filter. The image set and ground truth was provided by Prof. Nüchter & Helge Lauterbach, Chair of Computer Science VII – Robotics and Telematics, University Würzburg (Helge and Nuechter, 2018).

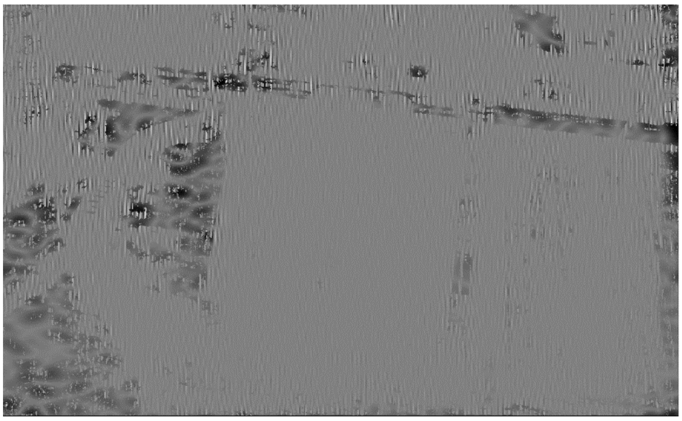


Figure 3: While higher contours result in higher noise there is also a high frequency interference in the X direction of the depth-map.

4.3 *Coverage*

The definition of coverage is problematic as we assume knowledge over the following process itself. Normally coverage defines a percentage of the covered ground or volume normed to the overall ground. In current recordings we normally record the image itself, but also the camera parameters and the rough location of where the image was taken and. If (Helge and Nuechter, 2018)recordings are to be taken, this is done by capturing all faces of the building. From the additional data we can determin a rough scale with the differential data of the GPS-Tracker. With this information (and if a higher accuracy is needed, the results from the SfM pipeline) we can deduce the coverage. The process is to fit a closed spline to the projected locations. This spline needs to be offset to the center by the recorded focal length. The coverage can be presented in the length of this offset spline s_c [m] or the inner area A_c [m²].

4.4 *Resolution & Details*

4.4.1 *Point cloud density*

The probably most mentioned quality metric in the context of point clouds in construction is the point density. A valid argument considering that most of the progress tracking algorithms use the point density to identify building elements. However, opposed to these concepts, we consider a higher point density only as valuable if the information content is increasing. In our studies we realized that with enough computational power increasing the density is possible but no additional information could be deducted ergo there is no need for a high number of points on a flat surface. We therefore propose a normal weighted density that will increase or decrease with the change of the normal vectors. These will reduce the weighted density in high contour areas and increase the density on flat surfaces without any further information.

$$\rho_W = \frac{1}{i}\sum_{i=0}^{i}\sum\nolimits_{\boldsymbol{p},\boldsymbol{n}\in ND} d(\boldsymbol{p}_i,\boldsymbol{p})\left(c(\boldsymbol{x}) + \frac{\partial \boldsymbol{n}_i}{\partial \boldsymbol{n}}\right) \quad (4)$$

In equation 4, i is the number of points in the point cloud, $\mathbf{p}_i$ the current point and $\mathbf{n}_i$ complementary normal. ND is a set of k nearest neighbors to $\mathbf{p}_i$. Again, $\boldsymbol{p}$ nominates the point and $\boldsymbol{n}$ the normal. The weighting function c is used to control the influence of the normals on the density. This definition also evaluates a higher density on boundaries and strong contours like corners.

4.4.2 *Resolution*

The resolution cannot be measured from a point cloud itself, but we can estimate the maximal possible resolution using the spatial bandwidth. This bandwidth was used for example in a method by Steeb (Steeb, 2005) and applied to point cloud by Graham (Graham, 2011).

$$f(x,y) = kf(kL_x, jL_y)sinc(2\pi B_x x - k\pi) \cdot sinc(2\pi B_y y - j\pi) \quad (5)$$

With:

$$B_x = \frac{1}{2L_x}, B_y = \frac{1}{2L_y}$$

B_x and B_y are the spatial bandwidth that maybe interpreted as line pairs per millimeter, the optical measurement of resolution during recording. However, this formulation must be handled with care and evaluated within local boundaries because the distribution of points from SfM and MVS is not uniform.

4.5 *Error and Robustness*

4.5.1 *Warping*

Warping, a geometrical distortion from rotation of single elements, of the 3D reconstruction is important when analyzing deviation in construction. The error of the reconstruction adds to the building errors of the construction site. If we want to identify warping in comparison to the ground truth, we can use a projective transformation matrix. The needed points can be found using corner detection on both datasets. While there are different algorithms for corner detection, we achieved good results with a *Harris Corner Detector (Harris and Stephens, 1988)*. We consider the non-euclidean factors as warping.

$$H_w = \begin{bmatrix} 0 & \mathbf{0} \\ \boldsymbol{v}^T & \vartheta \end{bmatrix} \quad (6)$$

4.5.2 *Spread of points*

Each point cloud that is recorded spreads around the real value. We determine the natural spread by considering the largest i patches. The patch is then reduced and isolated to isolate the patch from any other geometric entity. We fit a plane to this patch with PCA and measure the distance to this plane. This distribution δ_{ps} can be evaluated to define the minimal and maximal spread s_{ps} of the point cloud as FWHM (full width half maximum). Figure 4 shows an example for a photogrammetric reconstruction with Photoscan.

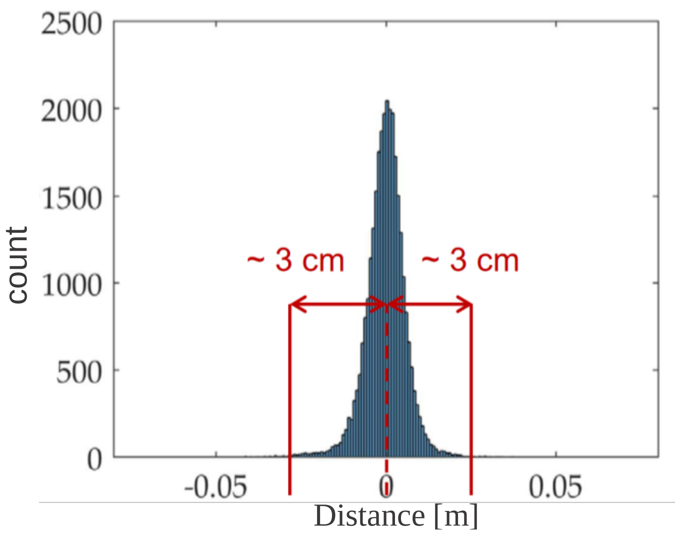


Figure 4: Distribution of distances of the selected points to the estimated plane. The width is a guiding indicator for the precision of the point cloud.

4.5.3 *Overall correctness*

It is possible to measure the overall distance of a point cloud to the ground truth. Before we can use the ground truth as reference model we had to align our reconstructed model (see paragraph 4.1) in a non-convex optimization. As an error estimate we took the overall normalized minimal distance during the fitting process (7 degrees of freedom). We follow the generalized approach (Segal et al., 2009). The minimal distances $s_{min}(p,q)$ and the distance distribution of $d(p,q)$, δ_{pq} define the overall fit of the model. The distribution can be regarded as a Weibull distribution. Sometimes specific areas can contribute unintentionally large to this metric. If further investigation is needed, the overlay with a color coding of the distances has proven to be an intuitive tool.

Metric	Description
$\overline{\Delta H}$	Camera alignment error
$\mathcal{V}_H^2$	Variance of the camera alignment
ρ_w	Weighted density of the point cloud
$\mathcal{V}_{dm}^2$	Variance of the intensity map difference
δ_{ps}	Distance distribution of the point spread
s_{ps}	Width of the point spread [min, max]
δ_{pq}	Distance distribution of the overall model to ground truth
$f(x, y)$	Recoverable Signal e.g. contour
H_w	Warping of the model
s_c, A_c	Coverage measure

Table 2: Listing of all metrics that were tend to in this paper.

5 CONCLUSION

In this paper, we summarize a list of quality measures that can be applied to different point clouds (see table 2). We concluded that there are three types of metrics for 3D reconstructed point clouds from images: process metrics (Paragraph 4.1), self-contained information (paragraph 4.2) and relative precision (paragraph 4.3). While the first two types can be used to classify the point cloud of the photogrammetric process, the latter needs a ground truth and is therefore only suited to evaluate the toolchain of the user. This is a serious limitation and this third category cannot be used to pose requirements on the point cloud consuming analysis. In practice knowing the properties of the reconstruction pipeline, will help to produce point clouds of similar quality. Going even further, policies for the reconstruction could serve as requirements. This can be regarded as a minimum reconstruction system requirement.

With this concept of point cloud and toolchain evaluation we can estimate the properties of a newly generated point cloud a priori. This information does not provide any benefit on its own and must be further related to the automation processes.

In progress of object detection used for Scan-vs-BIM on construction sites, the detection of elements is done by local density on the number of the points in the vicinity of the building element. The chosen thresholds and recognition criteria will directly impose a certain density of points for the correct as-built recognition. Since most of the time the cloud has a sufficient density for the chosen thresholds (Bosché vincinity ±5mm, Rebolji projected coverage of 0.5) an analysis with our proposed metrics needs to be made to establish a relation between our criteria and the performance of the object detection algorithm in question. By comparing the needed input quality for a successful detection with the output of the chosen reconstruction pipeline, we can investigate the metrics on their influence and define minimal requirements for the Scan-vs-BIM recognition. Separating these two steps is important for a generalized selection of processing parameters and the abstraction of the recognition process from the pipeline benchmark.

6 FUTURE WORK

We consider the definition of the criteria a first step in the benchmarking of algorithms and pipelines. The next step would be to create a selection of captures either with a mixture of synthetic data or/and precise measured data as ground truth.

With this benchmark, studies can be made that emphasize on the pipeline parameters, the needed processing size of the images and the selection of views during the capture. Further, defining the minimal requirements of proposed algorithms (see section 2) for Scan-vs-BIM and combining these insights with the input parameter analysis. This should lead to policies and best practices for the 3D reconstruction of construction sites for as-built recognition.

Other use cases like visualization, documentation, process tracking, quality management and digitalization of building stock to BIM should also be considered and opens up further requirement definitions.

Another research topic would be the use of these metrics for object recognition instead of the proposed algorithms (Bosché, Kim, Rebolji). Instead of solely using a local density it could be beneficial to relate to the weighted density, the coverage, and the resolution criteria $f(x, y)$.

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