Towards automated construction progress monitoring using BIM-based point cloud processing

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ABSTRACT: On-site progress monitoring is essential for keeping track of the ongoing work on construction sites. Currently, this task is a manual, time-consuming activity. The research presented here, describes a concept for an automated comparison of the actual state of construction with the planned state for the early detection of deviations in the construction process. The actual state of the construction site is detected by photogrammetric surveys. From these recordings, dense point clouds are generated by the fusion of disparity maps created with semi-global-matching (SGM). These are matched against the target state provided by a 4D Building Information Model (BIM). For matching the point cloud and the BIM, the distances between individual points of the cloud and a component's surface are aggregated using a regular cell grid. For each cell, the degree of coverage is determined. Based on this, a confidence value is computed which serves as basis as for the existence decision concerning the respective component. Additionally, process- and dependency-relations are included. First experimental results from a real-world cases study are presented and discussed.

1 INTRODUCTION

The traditional, manual construction progress assessment with human presence is still dominating. The main reason is the lack of reliable and easy to use software and also hardware for the demanding circumstances on construction sites. Automating construction progress monitoring promises to increase the efficiency and precision of this process. It includes the acquisition of the current state of construction, the comparison of the actual with the target state, and the detection of variations in the schedule and/or deviations in the geometry.

A Building Information Model (BIM) provides a very suitable basis for automated construction progress monitoring. A BIM is a comprehensive digital representation of a building comprising not only the 3D geometry of all its components but also a semantic description of the component types and their relationships (EASTMAN et al., 2011). The model is intended to hold all possible information for all project participants. In addition to the building itself, it also stores process information, element quantities and costs.

A Building Information Model is a rich source of information for performing automated progress monitoring. It describes the as-planned building shape in terms of 3D geometry and combines this with the as-planned construction schedule. Accordingly, the planned state at any given point in time can be derived and compared with the actual construction state. Any process deviation can be detected by identifying missing or additional building components.

The actual state can be monitored either by laser scanning or by photogrammetric methods. Both methods generate point clouds which hold the coordinates of points on the surface of the building parts but also on all objects which occlude them.

The main steps of the proposed monitoring approach are depicted in *Figure 2*. The minimum information which has to be provided by the BIM is a 3D building model and the process information for all building elements. From this, the target state at a certain time step *t* is extracted. Subsequently the target stat is compared to the actual state, which is captured by photogrammetric techniques in this study. Finally, the recognized deviations are used to update the schedule of the remaining construction process.

The paper is organized as follows: Section 2 gives an overview on related work in the field. The proposed progress monitoring procedure is explained in detail in Section 3 and first experimental results are presented in Section 4. The paper concludes with a summary and discussion of future work.

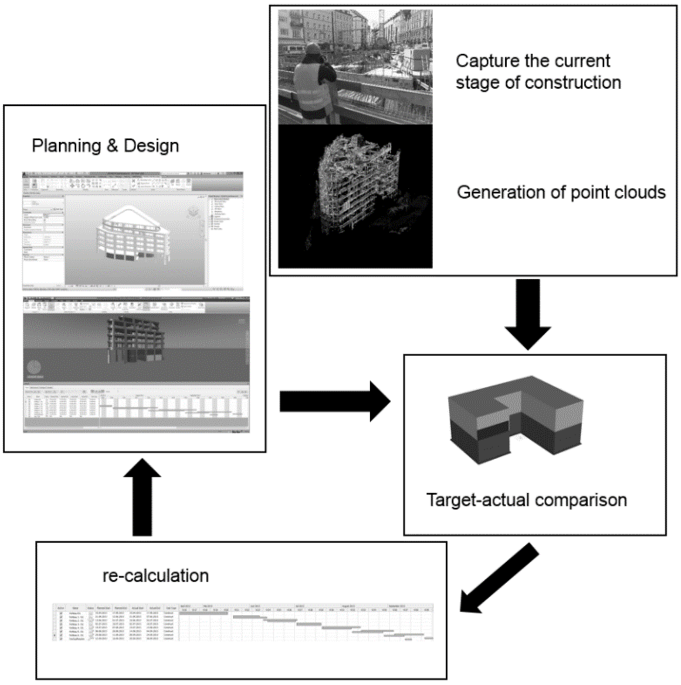

Figure 1: construction progress monitoring schema

2 RELATED WORK

2.1 *Monitoring and object verification*

As mentioned in the previous section, as-built point clouds can be acquired by laser scanning or photogrammetric methods. Golparvar-Fard et al. (2011a) compare the accuracy of both techniques in different case studies regarding as-built documentation and visualisation. Bosche (2010) describes a method for object recognition based on laser scanning. The generated point clouds are co-registered with the model with an adapted Iterative-Closest–Point-Algorithm (ICP). The object recognition is performed based on a threshold on the ratio of the covered area to the entire surface of object. The 3D model must be decomposed to a triangular mesh.

Turkan et al. (2012) use this method for the detection of objects as input for their approach to derive the construction progress and adjust the schedule. Kim et al. (2013a) also use laser scanning data. In addition, RGB values of the points are recorded. First, they extract points of concrete structures using the color values in HSV color space with the aid of a supervised classification. The co-registration is performed by means of ICP, what demands the conversion of the model into a point cloud. Finally, the points are assigned to specific component types through a supervised classification algorithm.

In Son & Kim (2010) also the HSV color space is used to detect metal structures. A stereo camera system is used as recording device. Kim et al. (2013b) update the set schedule of a bridge structure by the detection of finished components in images of a fixed camera. Golparvar-Fard et al. (2011b) use unstructured pictures of a construction site to create a point cloud. The orientation of the images is performed using a Structure-from-Motion process (SFM). Subsequently, dense point clouds are calculated. For the comparison of as-planned and as-built, the scene is discretized into a voxel grid. The construction progress is determined in a probabilistic approach. As an alternative configuration for recording image data show Kluckner et al. (2011), the data received in a construction site scenario using a UAV. A dense cloud of points is determined by a global optimization.

Our approach can be distinguished from the mentioned methods that the accuracy of the photogrammetric point clouds are explicitly calculated, that control points are incorporated in the process and that the “as-built”-“as-planned” comparison is performed in a very direct way.

2.2 *Process information and dependencies*

Process planning is often executed independently from conceptual and structural design phases. Current research follows the concept of automation in the area of construction scheduling.

Tauscher describes a method that allows automating the generation of the scheduling process at least partly (Tauscher, 2011). He chooses an object-oriented approach to categorize each component according to its properties. Accordingly, each component is assigned to a process. Subsequently, important properties of components are compared with a process database to group them accordingly and assign the corresponding tasks to each object. Suitable properties for the detection of similarities are for example the element thickness or the construction material. With this method, a "semi - intelligent" support for process planning is implemented.

Huhnt (2005) introduced a mathematical formalism which is based on the quantity theory for the determination of technological dependencies as a basis for automated construction progress scheduling. Enge (2009) introduced a branch and bound algorithm to determine optimal decompositions of planning and construction processes into design information and process information.

These innovative approaches to process modelling form a very good basis for the automated construction monitoring, but have so far not been applied in this context.

3 CONCEPT

The developed methodology comprises the following steps:

During the design and planning phase, the building model and the process is modelled. During construction, the site is continuously monitored by capturing images. These are processed to create point clouds (Section 3.1), which are compared to the as-planned building model (as-built – as-planned comparison), what is described in Section 3.3. Process and spatial information can help to further improve the detection algorithms (Section 3.2).

3.1 *Recording*

The generation of the point cloud consists of four steps: Data acquisition, orientation of the images, image matching and co-registration.

Image acquisition: Photogrammetric imaging with a single off-the-shelf camera is chosen as data acquisition since it is inexpensive, easy to use and flexible. When using a camera, some acquisition positions such as on top of a crane can be arrived more easily than when using a laser scanner. In addition, a major requirement is that the image acquisition process shall be conducted without any disturbance of the construction process. During the acquisition process the construction site should be covered as complete as possible. At least parts which have changed should be imaged, together with some images which can link them to unchanged parts on or beyond the construction site for making the orientation process possible.

Orientation: The orientation process is performed using a structure-from-motion system like VisualSfM (Wu 2013) for an automatic generation of tie points. By means of the algorithm, also the relative orientations of the cameras are determined. For the following reasons we also introduce (manually) measured control points:

- Having two control points, a distance is introduced and the missing scale is known then.
- With the help of control points we can combine image groups which could not be orientated relatively to each other by the usage of only the automated measured correspondences.
- Control points are preferably in the same coordinates system as the one which is used for the construction work itself. If this is ensured, the point cloud is already co-registered to the model (assuming it is having also the same coordinate system).

This process can be automatized by using markers for control points, which are automatically measured in the images.

Finally, a bundle block adjustment is accomplished to determine the exterior orientation of all images and the corresponding standard deviations.

Image matching: Using either calibrated parameters or parameters from self-calibration (i.e. determined simultaneously with the orientation parameter) distortion free images are calculated. In this study, a calibration device has been used to calibrate the camera in advance.

As next step, stereo pairs (image pairs which are appropriate for image matching, i.e. they shall be overlapping and shall have approximately an equal orientation) have to be determined. This can be done based on conditions on the baseline or by using the tie point distribution, what allow to identify overlapping images.

Every image of each stereo pair is rectified. That means artificial camera orientations are calculated so that the camera axes of the pair are orientated normal to the base and parallel to each other. The rectified images are resampled from the original images. These images can then be used for dense-matching. For every pixel, a corresponding pixel in the other image is searched and the disparity is determined. The disparity is the distance of two pixels along an image row. To determine this, semi-global-matching (SGM) has been established in the last years (Hirschmüller 2008). Different implementations are available, e.g. SGBM in the openCV-library or LibTSGM (Rothermel et al. 2013). By means of the disparity (what corresponds to the depth of the point) and the exterior orientation of both images, the 3D point can be triangulated.

To get a more robust estimation of the points, to reduce clutter and to estimate the accuracy of the depth, not simply all 3D-points of all stereo-pairs are combined but overlapping disparity maps are merged and only 3D-points are triangulated which are seen in at least three images. The following procedure follows the approach of Rothermel et al. (2013). First, an image has to be selected to become a master image. For every pixel of the undistorted master image, the disparities are interpolated from all n disparity maps the master image is involved in. Now for every pixel, n disparity values are available. An interval for the distance D from the camera center to the 3D-point is determined by adding/subtracting an uncertainty value s from the disparity value. For every pixel, the depth values are clustered into one group if the intervals are overlapping. For calculating the final depth, the cluster having the most entries is chosen. The final value and its accuracy are determined by a least-square adjustment as described by Rothermel et al. (2013). The final 3D-point coordinates (X, Y, Z) are then calculated by

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = R^T \cdot (n \cdot D) + \begin{bmatrix} X_0 \\ Y_0 \\ Z_0 \end{bmatrix} \qquad (1)$$

with rotation matrix R (from object to camera coordinate system), unit vector n from perspective center to pixel and camera position X_0, Y_0, Z_0. By applying the law of error propagation, the accuracy of the coordinates are calculated, using the standard deviations estimated in the bundle block adjustment (R and X_0, Y_0, Z_0) and the determination of the depth (D), respectively.

As last step, the point clouds of all master images are fused. For every point, the coordinate, the RGB-color, the accuracy in depth, the accuracy for the coordinates and the ID of the reference image are stored. With the latter information, the ray from the camera to the point can be retrieved. This is a valuable information to apply visibility constraints for comparing target and actual state.

Co-registration: If the model coordinates as well as the control point coordinates are in a common construction site reference frame, a co-registration is not necessary. Otherwise, corresponding features which can be determined unambiguously in the model and the images have to be measured to calculate the transformation parameters. Of course, only building parts which have been proofed to be built correctly can be used for that. This has to be performed only once in an early time step, since the parameters are constant during the construction process.

3.2 *Technological dependencies and checkpoint components*

In principle, a building information model can contain all corresponding process data for a building. In the version 4 of the standardized data model Industry Foundation Classes (IFC), the *IfcProgress* entity was introduced to represent all process information and dependencies for a building element with direct relations to corresponding elements (BuildingSmart 2014). This entity gives the possibility to combine geometry and process data in a convenient way.

In current industry practice, construction schedules are created manually in a laborious, time-consuming and error-prone process. As introduced by Huhnt (2005), the process generation can be supported by detecting technological dependencies automatically. These dependencies are the most important conditions in construction planning. In the following, the concept of the technological dependencies is illustrated with the help of a simple two story-building (Figure 2).

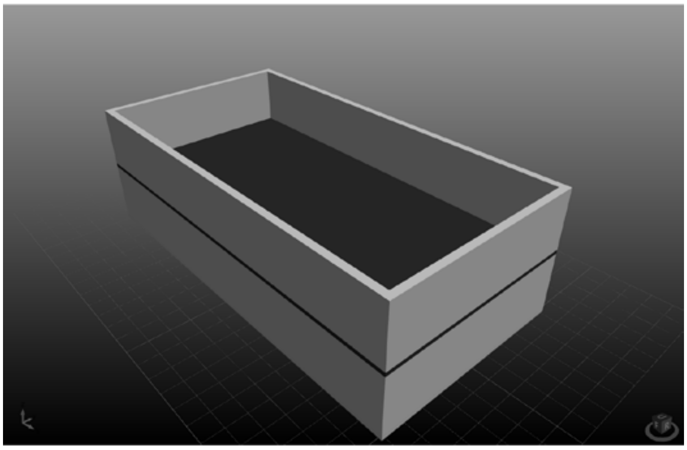

Figure 2: Sample building used to illustrate technological dependencies.

The specimen building has four walls and a slab for each floor. One example for deriving dependencies from the model is the following: The walls on the second floor cannot be built before the slab on top of the first floor is finished. The same applies for this slab and the walls beneath it. These dependencies are defined as technological dependencies. Other dependencies which have to be taken into account for scheduling, such as logistical dependencies, are defined by process planners and thus cannot be detected automatically.

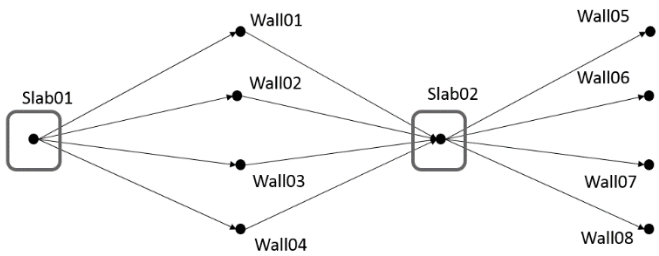

Figure 3: The technological dependencies for the sample building depicted in Figure 3 in a precedence relationship graph

A good solution for representing and processing these dependencies are graphs (Enge 2009). Each node represents a building element, the edges represent the dependencies. The graph is directed since the dependencies apply in one way.

Figure 4 shows the technological dependencies of the sample building in the corresponding precedence relationship graph.

The graph visualizes the dependencies and shows that all following walls are depending on the slab beneath them. In this research, these objects are denoted as *checkpoint components*. They play a crucial role for helping to identify objects from the point clouds (see following Section 3.3).

In graph theory, a node is called articulation point, if removing it would disconnect the graph (Deo 2011). As defined in this paper, all articulation points represent a checkpoint component. These points are very interesting for supporting object detection, since all objects left of them (in a left-to-right oriented graph) are depending on them. In other words, all objects have to be finished before the element linked to the articulation point can be started to be built.

3.3 *Comparing as-built and as-planned state*

The “as-planned” – “as-built” comparison can be divided into several stages. This includes the direct verification of building components on the basis of the point cloud and the indirect inference of the existence of components by analyzing the model and the precedence relationships to make statements about occluded objects.

3.3.1 *Matching point cloud and object surfaces*

For the direct verification, a measure is needed which allows to decide if certain points confirm the existence of a building part or not. To this end, we introduce the measure M based on the orthogonal distance d from a point to the surface of the building parts, taking into account the number of points and their accuracy σ_d.

$$M = \frac{1}{\mu_d} \cdot \sum_i \left(\frac{1}{d_i \cdot \sigma_{d_i}} \right) \qquad (2)$$

$$\text{with } d_i = \begin{cases} d_i = d_i & \text{if } d_i > d_{\min} \\ d_i = d_{\min} & \text{if } d_i \le d_{\min} \end{cases}$$

For the calculation of M, every object’s surface is treated individually and points within the distance Δd before and behind this surface are extracted from the point cloud. This surface is then divided into quadratic raster cells of size x_r for which M is calculated individually. The value μ_d denotes the mean value of the distances of all points to the surface within one raster cell. The condition additionally defined in Equation 2 by the minimum distance d_{min} limits the maximum weight of a single point (which would be very high for close points). We compare M against a threshold S to decide if the raster cell is confirmed as existent through the points. S can be calculated by defining minimum requirements for a point configuration which is assumed to be sufficient (see example in Section 4).

3.3.2 *Graph-based identification*

To further improve the process of comparing actual and target state, checkpoint components and especially articulation points from the precedence relationship graph which represents the technological dependencies help to infer the existence of objects which cannot be detected by point cloud matching due to occluded objects. Those objects are present on the construction site but are occluded by scaffolding, other temporary work equipment or machines.

Identifying articulation points in a graph can be achieved with the following method:
Loop over all existing nodes in the graph and perform the following routine:

- Remove node
- Depth first search (DFS) to check whether the graph is still connected
- Add node

This routine helps to automatically detect checkpoint components.

4 CASE STUDY

For a case study, we chose a 5 story office building currently under construction in the inner city of Munich, Germany. In regular time intervals, the building was captured by means of the photogrammetric methods explained in Section 3.1. A snippet of a point cloud created by the procedure is depicted in Figure 4. The accuracy of the points is in the range of one to a few centimeters. Points with a standard deviation larger than 5 cm have been removed. For co-registration 11 corresponding points were measured in the images and the model on building parts which were already built.

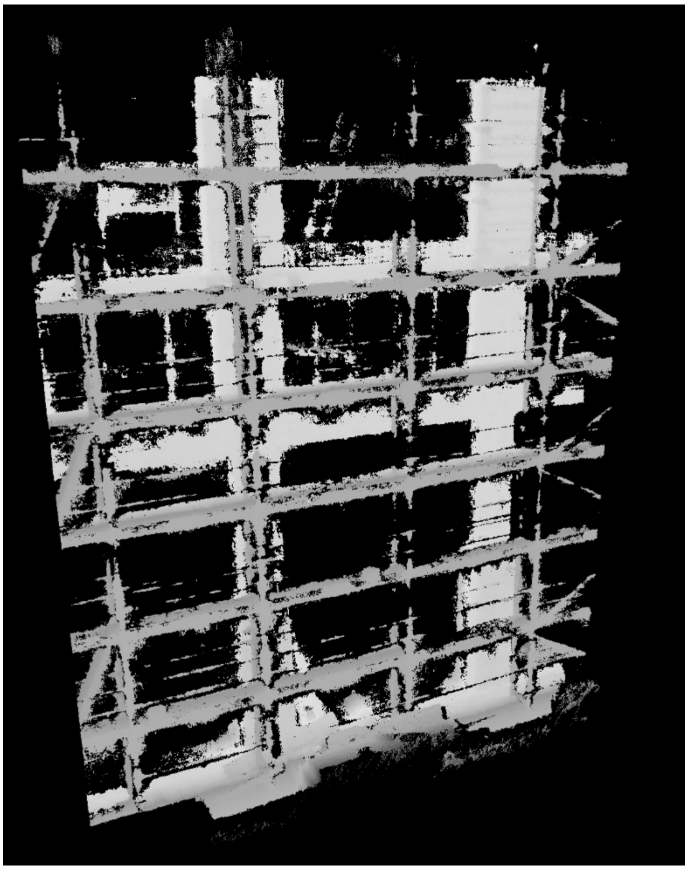

Figure 4: point cloud of monitored building

For the experiment, the model surfaces are split into raster cells with a raster size of x_r = 10 cm. Points are extracted within the distance Δd = 5 cm. As minimum requirement for S, a point density of 25 points per dm^2 is defined, with all points having an accuracy of σ_d = 1 cm and a distance of d = 2 cm to the model plane.

In Figure 5, thirteen building parts with the confirmed raster cells (in dark grey) can be seen. White numbers with black background indicate existing building parts, black numbers are used for parts which are not yet existing.

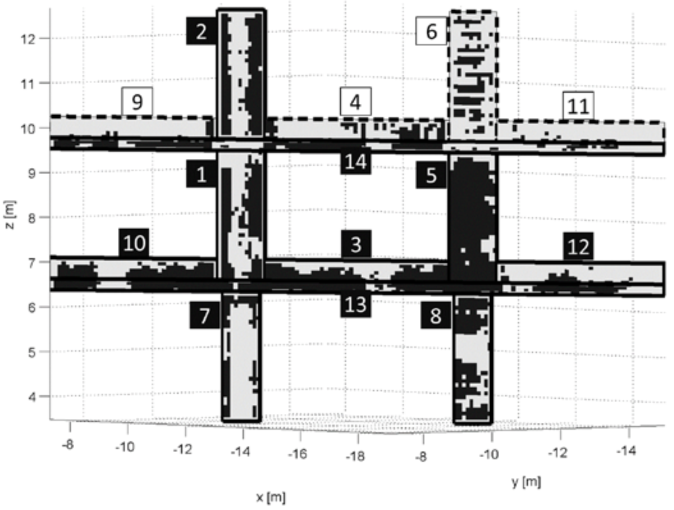

Figure 5: raster cells on object surfaces

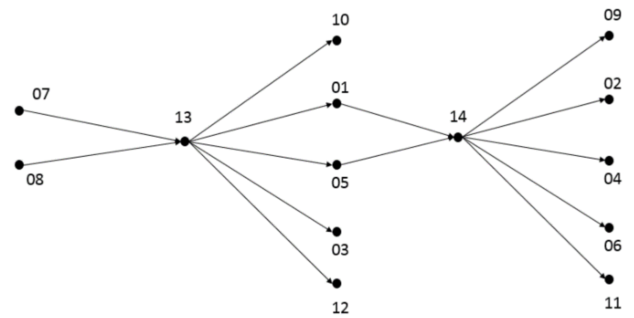

Figure 6: precedence relationship graph for building section in Figure 5

Existing parts			Non-existing parts	
5	85 %		9	7 %
13	72 %		11	7 %
3	54 %		4	27 %
8	50 %		6	29 %
10	49 %			
2	47 %			
1	46 %			
14	42 %			
7	26 %			
12	13 %			

Table 1: percentage of confirmed raster cells per element

As can be seen in Figure 5 and Table 1, not all elements can be confirmed unambiguously with the available data, shown in Figure 4, and the applied measure M. Column 7 has only 26% confirmed raster cells while column 5 has a rate of 85%. In this special case, the low rate for element 7 is due to a scaffolding in front of it. Column 5 can be identified very well, as there were no occlusions present. Another problem are false positives: Although column 6 does not yet exist, several raster cells were confirmed due to a formwork.

As discussed in Section 3.2, additional information can help to identify objects that cannot be detected but must be present due to technological dependencies. Figure 6 shows the corresponding precedence relationship graph for the shown building section.

The column with element-id 5 can be detected by the point cloud by 85% and thus is present with high probability. In contrast, column 7 has very few confirmed raster cells. Nevertheless, the technological dependencies can help to verify this element. Since object 5 is present, Element 13, 7 and 8 have to be also present, since they are depending on element 7.

5 DISCUSSION AND FUTURE WORK

This paper presents a concept for photogrammetric production of point clouds for construction progress monitoring and gives an outlook on the procedure for as-planned – as-built comparison based on BIM and the detailed use of additional information provided by the model and accompanying process data.

For the determination of the actual state, a dense point cloud is calculated from images of a calibrated camera. To determine the scale, control points are used, which requires manual intervention during orientation. For each point, the accuracy is calculated which is in the range of several centimeters. The evaluation measure introduced for component verification can provide unambiguous results only for components with very few occlusions and thus needs to be extended by additional features and visibility analysis.

Future research will target at achieving greater automation of image orientation, e.g. by automatically identifiable control points. The as-planned vs. as-built comparison can be improved by additional component attributes provided by the BIM, such as the color of the components. The rasterization is so far only implemented for flat component surfaces and must be extended to curved surfaces. The automated generation of precedence relationship graphs will be addressed by a spatial query language approach.

The proposed methods and concepts presented in Section 3 introduce new possibilities for an enhancement in progress monitoring. Currently, the effort for photogrammetric techniques and object detection is still very high and needs to be investigated further to improve those methods. Though, they can offer a variety of new possibilities for planners and

on-site personnel, including: (1) Time for photo-documentation can be reduced to a very low level, since the monitoring process is based on images.
(2) Automated process optimization can be pursued directly from the results of the process monitoring.

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7 LITERATURE

Bosché, F. 2010. Automated recognition of 3D CAD model objects in laser scans and calculation of as-built dimensions for dimensional compliance control in construction. *Advanced Engineering Informatics* 24(1): 107-118.

Bosché, F. 2012. Plane-based registration of construction laser scans with 3D/4D building models. *Advanced Engineering Informatics* 26(1): 90-102.

Brilakis, I., Lourakis, M., Sacks, R., Savarese, S., Christodoulou, S., Teizer, J. & Makhmalba, A. 2010: Toward automated generation of parametric BIMs based on hybrid video and laser scanning data. *Advanced Engineering Informatics* 24(4): 456-465.

BuildingSmart, 2014, http://www.buildingsmart-tech.org/ifc/IFC2x4/rc2/html/schema/ifckernel/lexical/ifcprocess.htm

Daum, S. & Borrmann. A. 2013. Checking spatio-semantic consistency of building information models by means of a query language. Proc. of the International Conference on Construction Applications of Virtual Reality

Deo, N., 2011. Graph theory with applications to engineering and computer science. Prentice Hall

Eastman, C., Teichholz, P., Sacks, R. & Liston, K. 2011. *BIM Handbook: a guide to building information modeling for owners managers, designers, engineers and contractors*. Hoboken (New Jersey): Wiley.

ENGE, F. (2010). Muster in Prozessen der Bauablaufplanung. Ph. D. thesis.

Fischer, M. & Aalami, F. (1996). Scheduling with Computer-Interpretable Construction Method-Models. Journal of Construction Engineering and Management 122(4), pp 337-347

Golparvar-Fard, M., Bohn, J.; Teizer, J., Savarese, S. & Peña-Mora, F. 2011a. Evaluation of image-based modeling and laser scanning accuracy for emerging automated performance monitoring techniques. *Automation in Construction* 20(8): 1143-1155.

Golparvar-Fard, M., Peña-Mora, F. & Savarese, S. 2011b. Monitoring changes of 3D building elements from unordered photo collections. *Computer Vision Workshops (ICCV Workshops), 2011 IEEE International Conference on*: 249-256.

Hirschmüller, H. 2008. Stereo Processing by Semi-global Matching and Mutual Information. *Pattern Analysis and Machine Intelligence, IEEE Transactions on* 30(2): 328-341.

Huhnt, W. 2005. Generating sequences of construction tasks. In: Proceedings of 22nd of W78 Conference on Information Technology in Construction, Dresden, Germany: 17-22.

Kim, C., Son, H. & KIM, C. 2013a. Automated construction progress measurement using a 4D building information model and 3D data. *Automation in Construction* 31: 75-82.

Kim, C., Kim, B. & Kim, H. 2013b. 4D CAD model updating using image processing-based construction progress monitoring. *Automation in Construction* 35: 44-52.

Kluckner, S., Birchbauer, J., Windisch, C., Hoppe, C., Irschara, A., Wendel, A., Zollmann, S., Reitmayr, G. & Bischof, H. 2011. AVSS 2011 demo session: Construction site monitoring from highly-overlapping MAV images. *Advanced Video and Signal-Based Surveillance (AVSS), 2011 8th IEEE International Conference on*: 531-532.

Rothermel, M., Wenzel, K., Fritsch, D. & Haala, N. 2013. SURE: Photogrammetric Surface Reconstruction from Imagery. *LC3D Workshop, Berlin*.

Son, H. & Kim, C. 2010. 3D structural component recognition and modeling method using color and 3D data for construction progress monitoring. *Automation in Construction* 19(7): 844-854.

Tauscher, E. (2011). Vom Bauwerksinformationsmodell zur Terminplanung - Ein Modell zur Generierung von Bauablaufplänen. Ph. D. thesis.

Turkan, Y., Bosché, F., Haas, C. T. & Haas, R. 2012. Automated progress tracking using 4D schedule and 3D sensing technologies. *Automation in Construction* 22: 414-421.

Wu, C. 2013. Towards Linear-Time Incremental Structure from Motion. *3D Vision, 2013 International Conference on, Seattle, WA*: 127-134.