Multi-Sample Image-based Material Recognition and Formalized Sequencing Knowledge for Operation-Level Construction Progress Monitoring

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ABSTRACT

This paper presents a new method for operation-level monitoring of construction progress using image-based 3D point clouds and 4D Building Information Model (BIM). Previous research on comparing point clouds to 4D BIM has proven the practicality of performing progress monitoring by occupancy-based assessment: detecting if BIM elements are present in the scene. Nonetheless, without appearance information, operation-level monitoring – formwork vs. concrete surfaces for concrete placement– is still challenging. By leveraging the interconnectivity of site images and BIM-registered point clouds, this paper presents a new method for densely sampling and extracting 2D patches from all site images from which BIM elements are expected to be visible. Our method reasons about occlusions in the scene and classifies the material in each image patch. By formalizing the sequencing knowledge of construction operations for progress monitoring purposes and using histogram-based representation for possible types of construction materials, our method can accurately detect the current state-of-progress for BIM elements in presence of occlusions. We introduce a new image dataset for material recognition, and present promising results on operation-level progress monitoring on an actual concrete building construction site. Our method addresses the challenges of working with non-detailed BIM or high-level work breakdown structures.

INTRODUCTION

Progress monitoring or detection of performance deviation is a vital component of construction project control as it is closely related to efficient and effective decision-making process. There has been many efforts to improve the traditional monitoring practices by using 4D Building Information Modeling (BIM). Examples on using laser scanning include (Turkan et al. 2014, Bosché et al. 2013, Kim et al. 2013, and Turkan et al. 2012) and on 3D image-based reconstruction methods include (Han and Golparvar-Fard 2014, Golparvar-Fard et al. 2012, 2011, 2009 and Ibrahim et al. 2009).

The challenges in common are dealing with occlusions, working with non-detailed BIM, or lack of detail in the underlying work breakdown structure of the construction schedule. Golparvar-Fard et al. (2012) measures the expected visibility per element from the camera convex hull and Han and Golparvar-Fard (2014) propose an appearance-based material recognition in efforts to deal with static and dynamic occlusions. The latter also detects construction progress at operation-level as material classification enables reasoning about the current state of the progress by *sequencing knowledge* – e.g., detection of formwork indicates work-in-progress (WIP). Figure 1 illustrates an example of operational details that can help infer different stages of operational work. Nonetheless, the approach by Han and Golparvar-Fard (2014) still requires formalizing such sequencing knowledge.

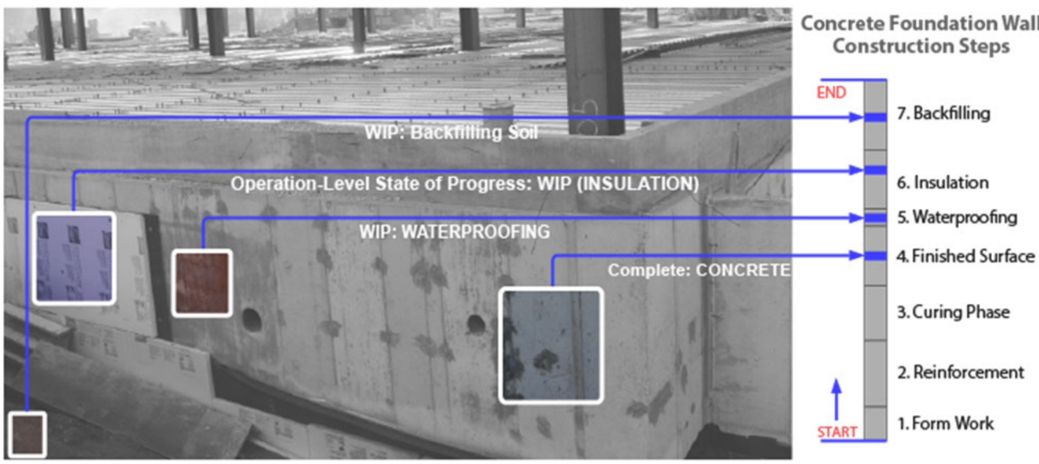


Figure 1. Example of operational-details for constructing a concrete foundation wall and how monitoring can benefit from detecting appearance information.

This paper builds on our prior work on progress monitoring using D^{4}AR (4-dimensional augmented reality) models (Golparvar-Fard et al. 2012) and appearance based model for operation-level progress (Han and Golparvar-Fard 2014). These works use image-based point clouds to infer the current progress. The latter uses image-sampling for material recognition on back-projected BIM onto the 2D image planes. This paper presents an integrated method based on material recognition and formalized sequencing knowledge similar to Koo et al. (2007) and Echeverry et al. (1991) with emphasis on physical interaction among building elements. The proposed method can infer state of progress for building elements that are partially visible or invisible in an as-built model, and correctly detects state of progress when BIM or Work Breakdown Structure (WBS) are not detailed –e.g., BIM does not contain formwork, or one activity of "FRPS foundation walls" contains operation details of placing a concrete element.

BACKGROUND

D^{4}AR – 4D Augmented Reality – Models. In our previous work, Golparvar-Fard et al. (2009) proposed the D^{4}AR models for progress monitoring and 3D visualization of as-built model using an unordered set of daily construction images with BIM. The method consists of four steps: 1) 3D as-built point cloud generation using images; 2) 4D as-built point cloud generation as incrementally add new images that capture; 3) Superimposition of BIM and 4D point cloud; and 4) Visualization of progress using the generated D^4AR model. To address issues of partial visibility and occlusion, a multiple one-vs.-all Support Vector Machine (SVM) classifier built upon a Bayesian model was used and compared with the expected progress visibility in Golparvar-Fard et al. (2012). Because this method analyzes progress purely based on spatial relationship between the point cloud and BIM, further analysis on different textures and different types of materials were needed.

Material Recognition for Progress Monitoring. Construction material recognition using images for identifying building elements was first introduced by Brilakis et al. (2005). Dimitrov and Golparvar-Fard (2014) also proposed an image-based material recognition using machine learning algorithms. Utilizing Leung and Malik (2001) filter bank with 48 filters (8 derivative filters, 4 low-pass Gaussian filters, and 36 oriented filters at 6 orientations, 3 scales, and 2filters), they model the material appearance by a joint probability distribution of responses from a filter bank and principal Hue-Saturation-Value color values in a Bag-of-Words model. Generated material histograms are classified using multiple one-vs.-all SVM classifiers with $\chi 2$ kernel. For validation, an image database with 20 typical construction material categories and about 150 images per category is assembled. An average of 97% for 200×200 pixel and 91% for 30×30 pixel image patches are reported. Han and Golparvar-Fard (2014) builds on this work to infer progress using 30 × 30 pixel image patches sampled from images that observe BIM elements. This paper uses the same approach and adds formalized sequencing knowledge discussed below.

Formalizing Sequencing Knowledge. Most of the construction activities have dependencies, requiring certain sequences for installment. Levitt and Kunz (1985), Navinchandra et al. (1988), and Echeverry et al. (1991) was among the first to formalize construction sequencing knowledge for construction planning. They identify four governing factors for activity sequencing:

1*) Physical relationships among building components* – e.g., spatial restriction, gravity support, inter-component relationship, and weather protection; 2) *Trade interaction* – e.g., different ways of trades affecting each other during construction phase; 3) *Path interference* – e.g., moving around the job site for any displacement; 4) *Code regulations* – e.g., safety regulation.

Koo et al. (2007) further develops this idea for formalizing sequencing rationale for project control, finding alternative sequences for changes. They introduce a constraint ontology for this rationale so that a computer system can infer the role and status of activities. For instance, the physical relationship factor has “supported by,” “connected to,” and “enclosed by” constraints with their default values, “enabling-inflexible” which defines the attribute and degree of flexibility. Building on prior works on formalizing sequencing knowledge and appearance-based progress monitoring method of Han and Golparvar-Fard (2014), our contribution in this paper is a method that reasons about the true state of progress for all building elements. In case of occluded elements, this is done by inferring state of progress using other elements "physically related to them" for which the state of progress is directly detected using the proposed appearance-based classification method. For low levels of detail in BIM or WBS, the formalized sequencing ontology helps infer the correct state of progress.

METHOD

Operational-level Progress using BIM and Site Images. By incorporating image sampling and material classification, Han and Golparvar-Fard (2014) proposes a method to infer the operational-level state of progress using element's classified material types. For instance, if a formwork was detected for a concrete element, it is fair to state that the element is still WIP. The method consists of two parts: 1) sampling from site-registered images in the D^{4}AR model by back-projecting BIM on relevant images, and 2) material classification from sampled 2D patches using machine learning algorithms described above for inferring the state of progress for the expected BIM elements. Given a 4D BIM, construction schedule, and daily site photologs, a D^{4}AR model is generated as discussed previously. The following briefly explains the remaining steps and Figure 2 illustrates the whole process, including the formalized sequencing knowledge. For details on the underlying algorithm, readers are encouraged to refer to Han and Golparvar-Fard (2014).

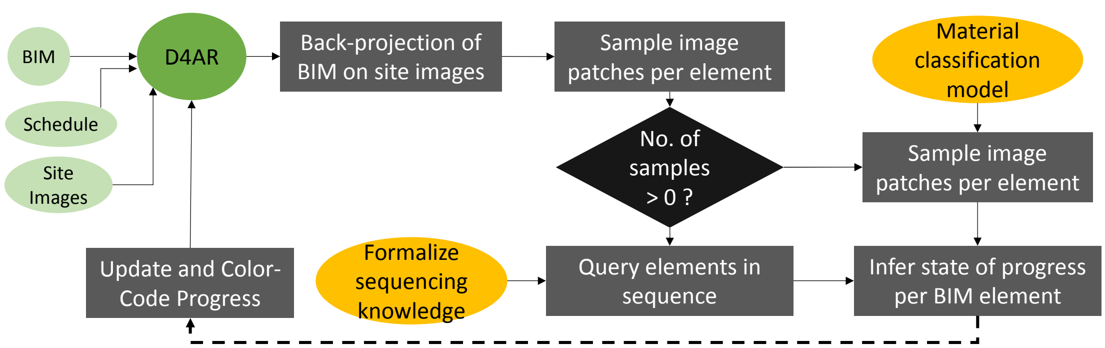


Figure 2. Overall workflow of the proposed method

1) Back-projection of BIM onto Images and Generation of Depth Maps

In the SfM step discussed above, we can retrieve camera projection parameters, which can be used for transforming 3D points to 2D image plane (see steps 4-6 in Figure 4). When back-projecting 3D points of the 4D BIM, we only use one face that has the maximum 2D area per element for a sampling purpose, in order to make sure that we conduct material recognition over flat surfaces only. This strategy provides the largest area for extracting patches and minimizes the risk of taking samples from edges and corners which themselves may become strong visual features and increase chances of material misclassification. A depth map per image is created to make sure we extract patches only from the visible areas of elements – e.g. we prefer not to sample images from the occluded areas of an element and state that the queried patches belong to that BIM element. Figure 3 describes the overall steps for back-projection and depth map generation and Figure 4 shows an outcome of these steps.

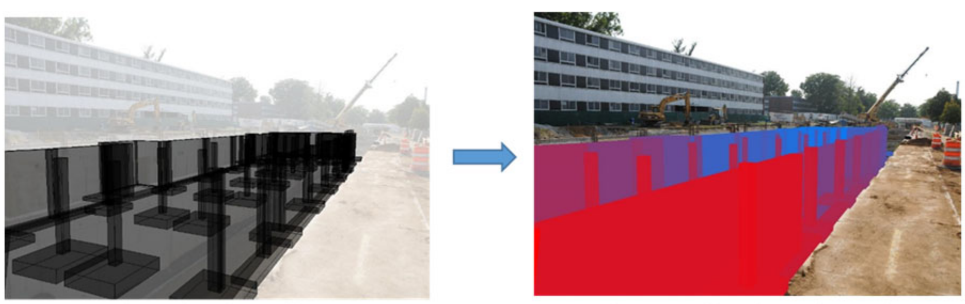
2) Sampling Image Patches and Material Recognition

Using the depth maps created, φ image patches of $\delta \times \delta$ pixels are randomly sampled per element per image, grouped by each element, and then classified for inferring progress using statistical distribution of the material classes and the scores from SVM classifiers. See Figure 5 and 6 for exact steps for the process and illustration.

Input: Camera parameters <f, k_1, k_2, R, T> for $c \subseteq Photolog$ & BIM elements (E^i)
Output: Depth map and back-projections of max $Face$ for all E^i onto all images

1. **for** each element E^i
2. **for** each $face^m \in E^i$
3. **for** each vertex $v^k \in face^m$
4. $P^k_{cam} = (Rv^k + T) \,/\, P^k_{cam}.z$ ← transform v^k into camera coordinate & perspective division
5. $r(P^k_{cam}) = 1.0 + k_1\|P^k_{cam}\|^2 + k_2\|P^k_{cam}\|^4$ ← undo radial distortion
6. $P^k_{image} = f \times r(P^k_{cam}) \times P^k_{cam}$ ← transform onto image plane
7. $argmax_{Face}\ A(Face) := \{Face \in E^i \mid \forall j: A(face^m) \leq Area(Face)\}$ ← face with max 2D back-projected area for element E^i
8. $d^i = \|c^i_F - c^j_C\|$, c^j_C :center location for camera j and c^i_F :center of $Face$ in 3D
9. sort(B) for all (E^i) by d^i for depth map
10. **return** depth map and plot only $Face$ for all (E^i) as in sort(B)

Figure 3. Back-projection and depth map of BIM onto an image.



Back-projection of BIM　　Depth map of back-projected BIM

Figure 4. Back-projection and depth map of back-projected BIM elements.

3) Inferring State of Progress per Element

A frequency histogram per element is generated based on the outcome of material classification. Its x-axis contains all existing material types and its y-axis

Input: Depth map and back-projections of max $Face$ for all E^i onto all images
Output: The observed material $argmax_{\eta}\, f(\eta)$ for each element $E^i \subseteq B$

```
for each E^i ⊆ B
  for all Face_j^i from all images that observe
      randomly extract φ sample patches of δ × δ pixels within each Face
      for each φ
         η = Ψ(φ); classify Material and return the class with highest score
argmax_m f(m) := {m| ∀η: f(η) < f(m)}; maximum frequency of material
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Figure 5. Extraction of sample patches and material classification.

represents the frequency of appearance. The class with the highest frequency is chosen to infer the state of progress. For instance, if a concrete class has the highest frequency the element is completed. On the other hand, if a formwork class has the highest frequency, the element is WIP.

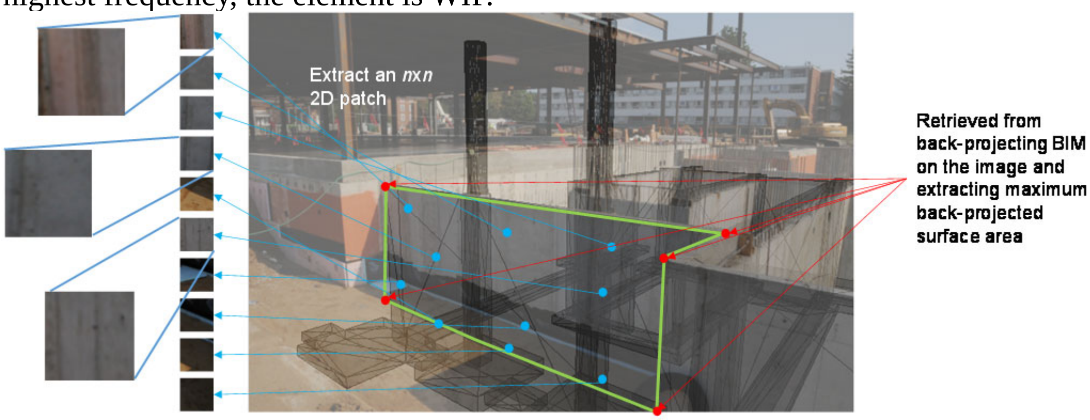

Figure 6. Extraction of sample 2D image patches for material classification.

Formalizing Sequencing Knowledge

Sequencing workflow for concrete element is discussed in Han & Golparvar-Fard (2014) but formalizing sequencing knowledge further extended to other types of elements and to the overall structure is needed. Since analyzing progress deviation analyzes preceding construction sequences for a given schedule activity –both operational and non-operational– we can reason about physical relationships and code regulations for back-tracking of as-built status. For instance, by physical relationship, we can assume that there already is a footing if a column is detected as complete. An example of code regulations would be fireproofing spray on beams and columns. Because we model fire-proofing as part of material classification and we know that it is sprayed over structural building components, we can infer the state of progress using shape and texture from the D^{4}AR model and the proposed material classification method. Because we already know the physical sequences from the 4D BIM, we do not need to take into account for other roles, flexibilities as Koo et al. (2007). Figure 7 illustrates this concept and Table 1 summarizes formalized sequencing knowledge for progress monitoring purposes.

Table 1. Formalized Sequencing Knowledge.

Types	Example
Physical Relationship	Footing "supported by" column
Code Regulation	Steel beam with fireproofing spray (different texture)

EXPERIMENTAL RESULTS AND DISCUSSION

The 4D BIM and 160 2-mega pixel daily site photos from construction of four-story concrete building project in Champaign, IL is used for preliminary experiments. An as-built point cloud is generated using all photos and superimposed with a BIM consisting of 141 elements to form the D^{4}AR model. For material classification, the Construction Material Library with about 3,000 images for 20 different construction materials is used (http://raamac.cee.illinois.edu/materialclassification).

Using the same dataset, Han and Golparvar-Fard (2014) achieved 91% accuracy on material classification validation. Figure 8 shows histograms for three different building elements. x-axis, corresponding materials to the numbers can be found at Han and Golparvar-Fard (2014) indicates the material classes and y-axis indicates the appearance frequency of patches. For instance, the class #5 (concrete) in the first two graph has the highest frequencies and infers that these elements are concrete elements and therefore "completed". For the third graph, class #6 (wood) has the highest frequency and the expected element from the BIM indicates that the element is concrete. From this information, together with sequencing knowledge we can infer that the current state is WIP as we can classify the appearance of the element resembles formwork at this stage.

Together with sequencing knowledge ontology, the state of progress for all 141 BIM elements can be accurately classified. As can be seen in Figure 7, footings and portions of columns are not visible because of the occluding wall. Moreover, footings after backfilling will not be visible anymore. Reasoning about physical relationship among connected building elements can solve this occlusion problem. This information about connectivity among objects (e.g., a column is connected to a beam) can be extracted from an Industry Foundation Classes (IFC) BIM file. Extracting such information and reasoning about process by physical connectivity of elements will be incorporated into our future research and validated with case studies.

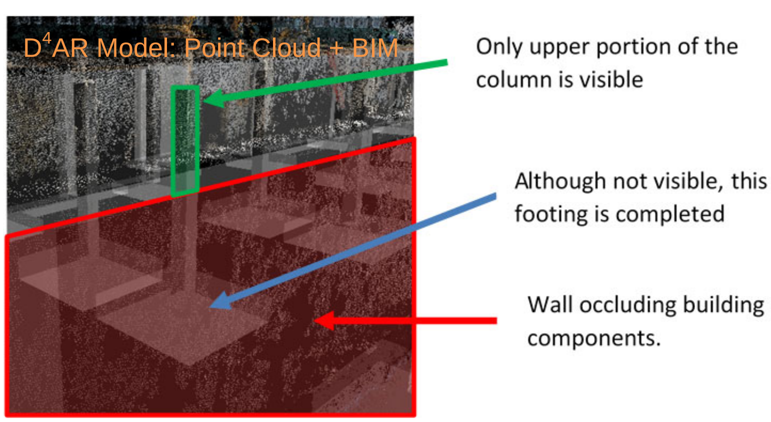

Figure 7. Inferring state of progress using sequencing knowledge.

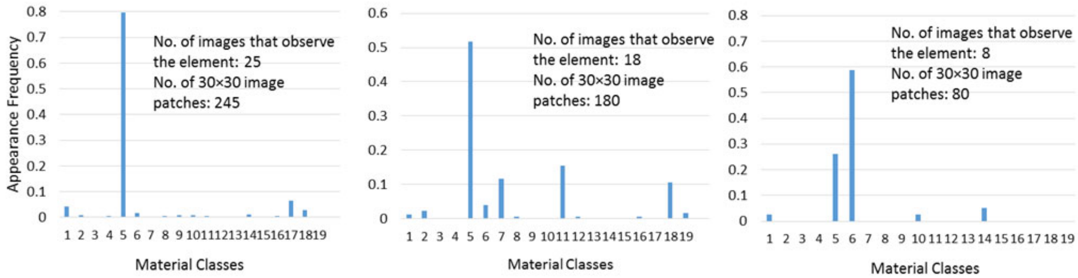

Figure 8. Example results of material frequency histograms.

CONCLUSION

This paper presents a method for multi-sample image-based material recognition and formalized sequencing knowledge for construction progress monitoring using 4D BIM and image-based point clouds. The preliminary results show promise on the feasibility of the proposed method for inferring the state of construction progress at operation-level. Formalizing sequencing knowledge and extracting the physical connectivity information from an IFC file can further improve the performance. Future work will focus on conducting more detailed experiments including various types of building skeleton and also on MEP systems.

REFERENCES

Bosché, F., Guillemet, A., Turkan, Y., Haas, C., and Haas, R. (2013). "Tracking the Built Status of MEP Works: Assessing the Value of a Scan-vs-BIM System." J. Comput. Civ. Eng., 10.1061/(ASCE)CP.1943-5487.0000343.

Brilakis, I., Soibelman, L., and Shinagawa, Y. (2005). “Material-based construction site image retrieval.” J. Comput. Civ. Eng., 19, 341-355.

Dimitrov, A., and Golparvar-Fard, M. (2014). “Vision-based material recognition for automated monitoring of construction progress and generating building information modeling from unordered site image collections.” Journal of Advanced Engineering Informatics, 28 (1), 37-49.

Echeverry, D., Ibbs, W., and Kim, S. (1991). "Sequencing Knowledge for Construction Scheduling." Journal of Construction Engineering and Management 117(1): 118-130.

Golparvar-Fard, M., Peña-Mora, F., Savarese, S. (2009). “Application of D^4AR - a 4-Dimensional augmented reality model for automating construction progress monitoring data collection, processing and communication.” ITcon, 14,129-153.

Golparvar-Fard, M., Peña-Mora, F., & Savarese, S. (2011). “Integrated Sequential As-Built and As-Planned Representation with D4AR Tools in Support of Decision-Making Tasks in the AEC/FM Industry.” J. of Construction Eng and Management, 137(12), 1099-1116.

Golparvar-Fard, M., Peña-Mora, F., and Savarese, S. (2012). “Automated Progress Monitoring Using Unordered Daily Construction Photographs and IFC-Based Building Information Models.” J. Comput. Civ. Eng., 10.1061/ (ASCE) CP.1943-5487.0000205.

Han K. and Golparvar-Fard M. (2014). "Automated Monitoring of Operation-Level Construction Progress Using 4D BIM and Daily Site Photologs." Construction Research Congress 2014, Atlanta, GA, May 21-23 (final paper approved).

Ibrahim Y.M., Lukins T.C., Zhang X., Trucco E., Kaka A.P. (2009), "Towards automated progress assessment of workpackage components in construction projects using computer vision", Advanced Engineering Informatics, 23 (1), 93-103.

Kim, C., Son, H., and Kim C. (2013). "Automated construction progress measurement using a 4D building information model and 3D data", Auto. Constr., 31, 75-82.

Koo, B., Fischer, M., and Kunz, J. (2007). "Formalization of Construction Sequencing Rationale and Classification Mechanism to Support Rapid Generation of Sequencing Alternatives." J. of Comput. in Civ. Eng., 21(6): 423-433.

Leung, T., and Malik, J. (2001). "Representing and recognizing the visual appearance of materials using 3D textons." Int. J. Comp. Vision, 43(1), 29-44.

Levitt, R. E., and Kunz, J. C. (1985). "Using Knowledge of Construction and Project Management for Automated Schedule Updating." Project Management J, 5, 57-81.

Navinchandra, D., Sriram, D., and Logcher, R. D. (1988). "GHOST: Project Network Generator." *J. Comp. in Civ. Eng.*, ASCE, 2(3), 239-254.

Turkan, Y., Bosché, F., Haas, C.T., and Haas, R. (2012). "Automated progress tracking using 4D models and 3D sensing technologies." Auto. Constr., 22 (1), 414-421.

Turkan, Y., Bosché, F., Haas, C. and Haas, R. (2013). "Tracking secondary and temporary concrete construction objects using 3D imaging technologies." IWCCE, 749-756.