

## **D<sup>4</sup>AR – A 4-DIMENSIONAL AUGMENTED REALITY MODEL FOR AUTOMATING CONSTRUCTION PROGRESS MONITORING DATA COLLECTION, PROCESSING AND COMMUNICATION**

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EDITORS: Kazi A S, Aouad G, Baldwin A

**Mani Golparvar-Fard, MAsc, MSc,**  
*Construction Management and Information Technology Group, Department of Civil & Environmental Engineering, University of Illinois, Urbana-Champaign*  
[mgolpar2@illinois.edu](mailto:mgolpar2@illinois.edu)

**Feniosky Peña-Mora, Sc.D., P.E., E.W. and J.M. Gutgsell Endowed Professor,**  
*Construction Management and Information Technology Group, Department of Civil & Environmental Engineering, University of Illinois, Urbana-Champaign*  
[feniosky@illinois.edu](mailto:feniosky@illinois.edu)

**Silvio Savarese, PhD, Assistant Professor,**  
*Department of Electrical and Computing Engineering, University of Michigan, Ann Arbor*  
[silvio@eecs.umich.edu](mailto:silvio@eecs.umich.edu)

**SUMMARY:** *Early detection of actual or potential schedule delay in field construction activities is vital to project management. This entails project managers to design, implement, and maintain a systematic approach for construction progress monitoring to promptly identify, process and communicate discrepancies between actual and as-planned performances. To achieve this goal, this research focuses on exploring application of unsorted daily progress photograph logs available on any construction site as a data collection technique. Our approach is based on computing- from the images themselves- the photographer's locations and orientations, along with a sparse 3D geometric representation of the as-built site using daily progress photographs and superimposition of the reconstructed scene over as-planned 4D models. Within such an environment, progress photographs are registered in the virtual as-planned environment and this allows a large unstructured collection of daily construction images to be sorted, interactively browsed and explored. In addition, sparse reconstructed scenes superimposed over 4D models allow site images to be geo-registered with the as-planned components and consequently, location-based image processing technique to be implemented and progress data to be extracted automatically. The results of progress comparison between as-planned and as-built performances are visualized in the D<sup>4</sup>AR (4D Augmented Reality) environment using a traffic light metaphor. We present our preliminary results on three ongoing construction projects and discuss implementation, perceived benefits and future potential enhancement of this new technology in construction, in all fronts of automatic data collection, processing and communication.*

**KEYWORDS:** *Progress monitoring, structure from motion, 3D site progress analysis, construction field imagery, image processing, augmented reality.*

**REFERENCE:** *Golparvar-Fard M, Peña-Mora F, Savarese S (2009) Application of D<sup>4</sup>AR – A 4-Dimensional augmented reality model for automating construction progress monitoring data collection, processing and communication, Journal of Information Technology in Construction (ITcon), Vol. 14, Special Issue Next Generation Construction IT: Technology Foresight, Future Studies, Roadmapping, and Scenario Planning, pg. 129-153, <http://www.itcon.org/2009/13>*

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## 1. INTRODUCTION

Early detection of actual or potential schedule delay or cost overrun in field construction activities is vital to project management (Halpin 2006). It provides the opportunity to initiate remedial actions and increases the chance of controlling such overruns or minimizing their impacts. Since schedule delays and cost overruns diminish profits of a project, it is easy to see why both project managers and project executives are perceptive to any deviation. This entails project managers to design, implement, and maintain a systematic and comprehensive approach for progress monitoring to promptly identify, process and communicate discrepancies between actual (as-built) and as-planned performances as early as possible. In this paper, monitoring is defined as *collecting, analyzing, recording, and reporting* information concerning key aspects of project performance at the appropriate level of detail required by project managers and decision makers.

Despite the importance of progress monitoring, systematic implementation of such framework can be challenging because: (1) Current progress monitoring is *time-consuming* as it needs extensive as-planned and as-built data extraction (Navon and Sacks 2007). Every day, superintendents and field engineers study 2D as-planned drawings, construction details as well as project specifications, review progress perceived by that date and study schedule and work breakdown structure to detect the work to be performed. Subsequently, they perform, monitor and supervise site activities and for the work performed, they collect site photographs and document daily construction reports; (2) The excessive amount of work required to be performed may cause human-errors and reduce the quality of manually collected data and since only an approximate visual inspection is usually performed, makes the collected data *subjective*; (3) Existing methods for monitoring such as weighted milestones and budget-based monitoring are also *non-systematic* and create a tendency to let project as-planned inputs serve as proxy measures for performance outputs which affects the quality of the results (Meredith and Mantel 2003). They may also create a time-lag between the time progress is reported and the time that progress is actually accomplished; (4) In addition, progress reports are visually complex, and they do not effectively represent multivariable progress information (i.e., schedule, cost, and performance) nor do they intuitively reflect information pertaining spatial aspects of the construction progress and their associated complexities (Kymell 2008, Poku and Arditi 2006; Koo and Fischer 2000); and (5) Current reporting methods *increase the time* required to *describe and explain* the progress situation in coordination meetings and in turn could delay the decision making process (observed by authors and reported in Golparvar-Fard et al. 2006). In summary, with current methods, it may be not be easy to understand the progress situation clearly and quickly.

Most of the current techniques for automating progress data collection (such as laser scanners, RFID and embedded sensors) are promising if one wishes to eliminate *labor-intensive* and *non-value adding* tasks associated with manual progress data collection. A drawback is the necessity to add new tasks that need to be performed before, during, or after utilization of such technologies at a construction site (El-Omari and Moselhi 2008, Kiziltas et al. 2008, Akinci et al. 2006). Barcodes and RFID sensors are excessively time consuming to set up and costly for many projects. Additionally they cannot be attached to many types of components or capture progress of partially installed components. Laser scanners are also expensive, require experienced people for operation, could document excessive noise within dynamic scenes, and require manual data processing and selection as well as a preparation time for warming up (Kiziltas et al. 2008). In addition, laser scanners only provide Cartesian coordinate information of the scanned scene. Working with such featureless data and without any *semantic* information of the scene (Kiziltas et al. 2008), geometric reasoning is challenging and induces estimation errors. Also none of these techniques (other than when site images are overlaid on laser scanners point clouds (El-Omari and Moselhi 2008) provide any reliable *visual information* about work sequence or site logistics. To address all these issues, in our approach we have taken all the aspects of progress monitoring into account: *collection, analysis, communication and reporting*. We have looked into the existing simple yet robust progress data collection and communication techniques available on any job site to see how we can effectively and efficiently build upon existing information and data collection techniques to address mentioned problems. Such information and techniques are categorized on two fronts:

(1) *As-planned progress data*: We consider using three-dimensional/ four-dimensional models as as-planned data repositories to facilitate accessing geometrical information, visualizing planned schedule and communicating progress. Visualization of the as-planned progress in 4D environment enables project participants and clients, regardless of their level of construction knowledge and expertise, to identify spatial layouts and explore construction processes (Hartmann et al. 2008, Hartmann and Fischer 2007, Woksepp and Olofsson 2006). In addition, 3D/4D models can provide a consistent visual base-line platform of as-planned information (Golparvar-Fard et al. 2009, Song, Pollalis, and Peña-Mora 2005) and act as an underlying structure for monitoring progress where deviations between the as-planned and as-built progresses could be visualized.

(2) *As-built progress data*: Considering current technical inefficiencies of available data collection technologies i.e., laser scanners, bar codes and RFID tags we investigate the idea of processing daily progress photographs to enhance *collection*, *analysis* and *communication* of as-built data. Digital photography together with internet has enabled construction management companies as well as sub contractors, project owners and architects to share progress photographs on a truly massive scale. Nowadays it is a common practice for jobsite images to be gathered periodically, stored in central databases, and utilized in communication and coordination of project tasks (Soibelman et al. 2008). Site photographs not only have the advantage of being understandable to those who are not well-versed in studying written material or numerical data analysis or even those who question verbal or written reports (Oglesby et al. 1989), but also allow a large amount of progress data to be understood and absorbed quickly. Just as the Chinese proverb says “A picture is worth a thousand words”, it could be imagined how daily site photograph logs, which consist of many site images, can help as comprehensive sources of as-built data. Furthermore photographs provide a visual value in understanding large amount of information, and could be automatically processed and converted into information regarding construction progress (Brilakis and Soibelman 2008, Golparvar-Fard and Peña-Mora 2007, Navon and Sacks 2007, Wu and Kim 2004, Abeid et al. 2003) and yet compared to other data collection techniques, do not burden efficiency of the project management processes by requiring significant data collection efforts.

In this paper, we focus on the application of progress site imageries as well as 3D/4D models for progress monitoring. First we review current progress monitoring practice and its deficiencies in detail as well as the state-of-the art technologies for automatic progress monitoring data collection and associated visualization techniques. Then we present our work on combing daily progress images and 3D/4D models to create the 4 Dimensional Augmented Reality (D<sup>4</sup>AR) models.

The D<sup>4</sup>AR models consist of a new image-based modeling technique for visualizing progress monitoring wherein progress discrepancies between as-planned and as-built construction performances are visualized through superimposition of 4D as-planned models over site photographs using different visualization techniques such as a traffic light metaphor. Our approach is based on computing, from the images themselves, the photographer’s locations and orientations, along with a sparse 3D geometric representation of the as-built scene using daily progress photographs and superimposition of the reconstructed scene over the as-planned 4D model. Within such an environment, progress photographs are registered in the virtual as-planned environment, allowing a large unstructured collection of daily construction images to be sorted, interactively browsed and explored. In addition, sparse reconstructed scenes superimposed over 4D models allow site images to be geo-registered with the as-planned components and consequently, a location-based image processing technique to be implemented and progress data to be extracted automatically. The result of progress comparison study between as-planned and as-built performances can subsequently be visualized in the D<sup>4</sup>AR environment. In such an environment, a construction project manager would be able to: 1) use the 4D as-planned model as a baseline for progress monitoring, compare it to daily construction photographs and study workspace logistics; 2) interactively and remotely browse and explore registered construction photographs in a 3D environment; 3) automatically analyze registered images and quantify as-built progress; 4) automatically measure discrepancies between as-planned and as-built performances; and 5) visually represent progress discrepancies through superimposition of 4D as-planned models over progress photographs, make control decisions and effectively communicate those with project participants.

Figure 1 shows a comparison between traditional representations of construction as-planned and as-built data and how D<sup>4</sup>AR associates these two sets of information to visualize progress discrepancies and workspace logistics in single imagery. To that extent, we present reconstruction of the as-built scene, superimposition over as-planned model and visualization of the discrepancies, and discuss guidelines for automatic measurement of progress. The resulting system is robust and reliable in practice. Finally we have included preliminary results of generating these models for three ongoing construction projects, ranging from \$32M to \$62M for a period of two to two and a half years, and conclude with a discussion of limitations and future works.

## **2. PROGRESS MONITORING: CURRENT PRACTICE CHALLENGES AND CURRENT EMERGING TECHNOLOGIES**

Well-depicted baseline, systematic data collection, rigorous comparison of the as-planned and as-built progress, and effective presentation of measured deviations are key ingredients for effective project control. Unfortunately many challenges undermine the ability to implement these objectives in practice. Next we examine some of these challenges:

## Typical Representations of As-Built Progress

## Typical Representations of As-Planned Progress

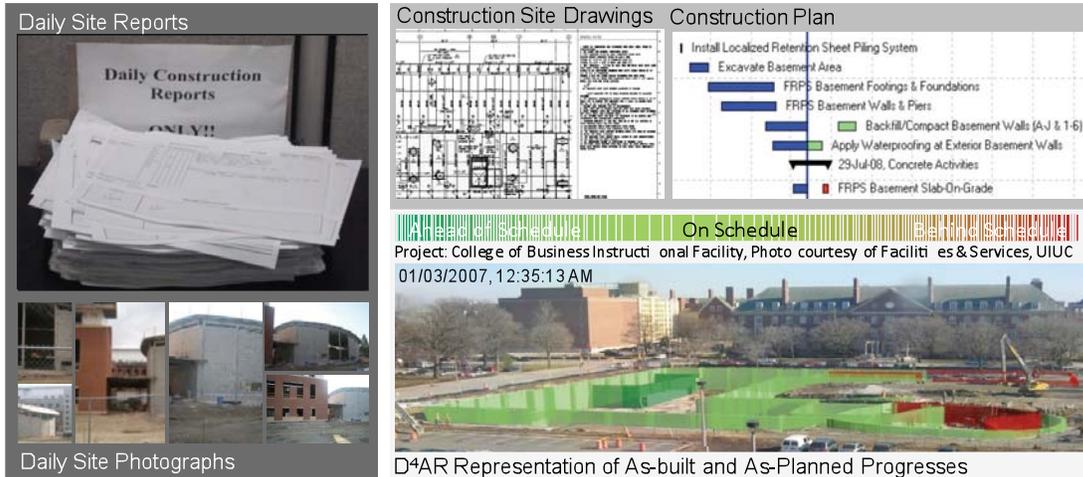


FIG. 1: A comparison between traditional representations of construction as-planned and as-built data and how D<sup>4</sup>AR associates these two sets of information to visualize progress discrepancies and workspace logistics in single imageries.

### 2.1 Challenges in current practices

(1) Current progress monitoring is time-consuming and labor-intensive: Currently many construction projects are not systematically monitored, i.e., there is no monitoring plan for when and how to monitor progress, making it very difficult to take corrective actions on a timely basis. Current methods require manual data collection and extensive as-planned and as-built data extraction from construction drawings, schedules, budget information and field reports produced by superintendents, subcontractors, trades foremen and project managers (observed by authors and also reported by Navon and Sacks 2007). Occasionally, field personnel collect progress data from a construction site at certain time intervals, analyze and deliver them to project manager in different formats (e.g., as-planned data such as construction drawings, spreadsheets, bar charts, CPM or as-built data such as daily/weekly progress reports, progress graphs, site photographs and videos). Such discrete reporting does not explicitly convey problems in a timely manner, since project managers need to devote a significant amount of time and effort to sort out, prioritize and interpret these data (Golparvar-Fard et al. 2009, Song, Pollalis, and Peña-Mora 2005). Figure 2 shows an example of existing mechanisms of reporting perceived progress in a coordination meeting at one of the projects under study.

(2) Quality of manually collected and extracted progress data may be low: Progress data— usually manually acquired by field staff— is dependent upon what they are able to measure on the construction site. Usually, the information collected tends to be based on their interpretation of what needs to be measured, the way it needs to be measured and the way it needs to be presented, and therefore it may not reveal the actual impact of site circumstances on the construction project. More importantly their approach may affect quality of the collected data and make it more susceptible to data error since the ability of measuring progress is based on the expertise of the field staff and the tools that are available to them. Figure 3 represents a sample of a daily progress report from one of the projects under study. As seen in this case, there is only a percentage documented per activity without further details.

(3) Existing methods of measuring progress are non-systematic and metrics are subjective: Accurate measurement of the progress performance usually poses the most difficult data gathering problem as there may be a tendency to let project inputs serve as proxy measures for output (Meredith and Mantel 2003). For example, a concrete subcontractor reports to the project manager that they have completed 60% of the roof work. Does it mean 60% of the planned area/volume of concrete pouring is finished? Is it 60% of the planned concrete that has been used? Or is it 60% of the planned labor-hours that have been spent? Is it 60% of the originally planned work or the actual requirement that is complete? If the item being referenced is a small work unit, it may not have a significant difference. However, in the case where the references are to the whole task or project, assumption of input/output proportionality could be very misleading (Meredith and Mantel 2003). This issue is found in the most commonly used monitoring methods: (a) *Monitoring physical progress in percentile*: used in most construction fields and heavily reliant upon experience and knowledge of the project management personnel. This metric is subjective and inefficient in presenting progress due to its abstract nature of

representing physical progress since the actual progress is determined by evaluation of the field staff; (b) *Budget-based monitoring*: based on the percentage of the budget paid to contractors according to the schedule-based inspections. This method of monitoring creates time-lag between progress estimations and schedule updates. In addition, judgments are often subjective and misleading, especially if field staff makes any erroneous decisions on the volumes of material consumed or the actual physical progress made. This in turn affects the robustness of the method (Shih and Wang 2004). Without a comparative analysis in the construction plan, resources, and cost data, inaccurate assumptions and measurements on the progress could be made. Consequently, mistakes such as over paying and overlooking of an expected delay might occur.



*FIG. 2: An example of existing progress reporting techniques. Construction drawings and work schedules are hung on a construction site trailer's wall to communicate progress with contractors and subcontractors. Progress is visualized in two-dimensional drawings using annotations and color-coding. The date on which progress is made is also annotated on different sections. Different work plans are hung over each other.*

(4) Progress monitoring reports are visually complex: Control over the decision making for corrective actions and schedule revisions usually takes place in progress coordination meetings. A wide range of individuals (e.g., from the owners and architects to subcontractors and trades foremen) with different areas of expertise and interests often attend these meetings. In these face-to-face interactions, progress information needs to be easily and quickly communicated among the participants. However, none of the existing reporting methods (e.g., progress S curves, schedule bar charts, photographs, and textual reports) easily and effectively present multivariable information (e.g., schedule, cost, and performance) in a holistic manner nor do they intuitively reflect information pertaining to the spatial aspects of construction progress and their associated complexities (Poku and Arditi 2006, Koo and Fischer 2000). Existing representations cause a significant amount of information to be inefficiently presented in the coordination meetings; as a result, extra time needs to be spent in describing existing problems and explaining the context in which problems occurred rather than understanding the causes of the problems, evaluating alternatives to solve the problems and discussing corrective actions (based on field observations and as observed in Golparvar Fard et al. 2006). Therefore with the current methods, it is not easy to understand progress of a project clearly and quickly.

## 2.2 Emerging field data capture technologies

For more than a decade, researchers have been pointing out deficiencies in current construction site data collection practices (e.g., manual data collection, need for systematic collection and processing of as-built data to produce useful and real-time progress information (Kiziltas et al. 2008, Bosche and Haas 2008, Navon and Sacks 2007, Navon 2006, Akinci et al. 2006; Chen and Wong 2002, Echeverry and Beltran 1997). According to (Navon and Sacks 2007) these research efforts have been motivated by: (a) an increasing need for real-time feedback and monitoring information, (b) rapid and cost effective technological development in automated data

collection technologies for construction. The main technologies designed and implemented for automatic data collection are barcode and Radio Frequency Identification (RFID) tags, Global Positioning System (GPS), Laser scanners and embedded sensors:

- Barcode and RFID tags have been used to capture and transmit data from a tag embedded or attached to construction products (Kiziltas et al. 2008, Navon and Sacks 2007, Ergen et al. 2007, Jaselskis and El-Misalami 2003, Echeverry and Beltran 1997). Unlike barcodes, RFID tags do not require line-of-sight, close proximity, individual reading and direct contact (Kiziltas et al. 2008). Active RFIDs also have higher reading ranges and allow data to be stored on them; however their performances are reduced in proximity of metals and liquids in particular when RFID is used at higher frequencies (Kiziltas et al. 2008). Although RFIDs and barcodes potentially eliminate non-value adding tasks associated with project management processes, they require frequent installation and maintenance. Additionally they cannot be attached to many types of components and they do not capture progress of partially installed components.

**CONSTRUCTION INSPECTION REPORT**

Store No.	3374	New	Schedule	Site	Bldg.	
Store Name			Contract Time	141 days	187 days	
Store Division	Midwest		Days Elapsed	175 days	84 days	
Project Location						
Project Address						
City, State	Sugar Grove, IL		Extensions	days	days	
GO/PRO Date	3/29/2006		Days Left	-34 days	103 days	
Date	11/28/05		Site Start	08/06/05	Building Start	09/05/05
Time	8:00		Site Complete	10/31/05	Building Complete	03/03/06
Report #	2					send to Arch. File clerks send to Arch. File clerks (new or remodel)

WEATHER: Clear  Overcast  Rain  Temperature Range 50°  
 Dry  Muddy  Snow

WORK FORCE:

Site	Refig. / Fixt.	Masonry/Concrete	Electricians	Plumbers	HVAC	Ceiling
Iron	<input checked="" type="checkbox"/>					
	Sprinkler	Stud / Drywall	Roofers	Carpenters	Painters	Flooring
		<input checked="" type="checkbox"/>	CANCELLED		CANCELLED	

**WORK PERFORMED**

Subcontractor	% Completed	Comments
1. Site	95%	
2. Foundation	100%	
3. Masonry/Precast	80%	
4. Iron	99%	
5. Roof	70%	
6. Sprinkler		
7. Electrical	20%	
8. Plumbing	35%	
9. HVAC		
10. Stud/Drywall	15%	
11. Painting	10%	
12. Ceiling		
13. Refrigeration	10%	
14. Fixturing		

**MILESTONE EVENTS**

Event	Scheduled Compl Date	Actual Date	Compl	Comments
1. Pre-cast Start	10/6/05	10/18/05		
2. Roof Start	11/17/05			
3. Mechanical, Refrigeration & Electrical Rough-in Start	11/11/05			
4. Slab Start	11/22/05			Non-colored concrete
5. Deck Spray Start				
6. Building Secured				
7. VCT Start				
8. Fixture Start				
9. Energy Mgmt. Complete				
10. Merchandising Start				

FIG. 3: A sample of a real project progress/inspection report (some information is removed for confidentiality). As shown from the "Work Performed" section, it is very difficult to figure out how much real progress has been perceived or to figure out if schedule-based or monetary progress has been made.

- Laser scanners have been used for construction quality control (Akinci et al. 2006, Jaselskis et al. 2006), condition assessment (Gordon et al. 2004), component tracking (Bosche and Haas 2008, Teizer et al. 2005) and progress monitoring (El-Omari and Moselhi 2008, Bosche and Haas 2008, Su et al. 2006). Although laser scanners are promising to automate data collection, still they are expensive and there is a set of challenges in implementing such technology on construction sites. These limitations include discontinuity of the spatial information, mixed pixel phenomenon (Kiziltas et al. 2008) as well as scanning range and sensor calibration. For example, any moving object in line of sight of the scanner would not allow the point cloud of the under-study object to be captured. In addition, the moving object creates additional effort of the user to manually have the noisy point cloud fixed. Furthermore as the laser scanner gets away from the objects, level of details within the captured components are reduced. Laser scanners also require regular calibrations as well as warm up time. They are not easily portable

and cannot efficiently be used for scanning indoors. These limitations are a part of time consuming process of data collection; nevertheless since the type of data they provide only contains Cartesian coordinate information of the scanned scene, processing such data is time consuming and also they do not carry any *semantic* information, such as which point belongs to what structural components. Working with this type of featureless data makes geometric reasoning based on this data tedious and error prone (Kiziltas et al. 2008). Also none of these techniques provide any visual reliable information about work sequence, site logistics or construction crews. Recently El-Omari and Moselhi (2008) presented a new approach for progress data collection by using 3D laser scanners and photogrammetry. The method was shown to be less time-consuming and has higher cost savings compared to single application of laser scanners. Their suggested approach minimizes access limitations of scanner placement but still the processing time required for each scan may considerably be high and the registration of images and 3D point cloud needs further adjustments. Also laser scanners may not give the possibility of aligning site images - taken from arbitrary viewpoints- with the 3D point cloud; yet in El-Omari and Moselhi (2008) the common points between laser scanner's 3D point clouds with images have been selected manually. Manual selection of common points between each image and point cloud (as experienced by the authors) makes such an approach difficult to use.

- GPS, Geographical Positioning Systems as a location tracking tool also need line-of-sight between the receiver and the satellite; therefore it cannot normally operate indoors, limiting the project context that could be monitored. Behzadan et al. (2008) suggests using WLAN technique as a tracking technique for indoor locations but they also report difficulties in using WLAN set ups on actual construction sites, and they relate these inefficiencies to ongoing works (i.e., changes in soil, structure, plant and equipment, site layout). These inefficiencies necessitate WLAN system to be calibrated after regular intervals to maintain a high level of accuracy. Such regular calibration requirements may make such a system difficult to manage.
- Other techniques such as wearable computers (PDAs) along with speech recognition and touch screens have also helped in capturing construction site data electronically (Reinhardt et al. 2000), but current systems still need full time observer(s) to input and process the information (Navon and Sacks 2007) and have not minimized the time required to process the data.

Also, none of these techniques besides (El-Omari and Moselhi 2008) - in which photographs are used to provide more information about the context of the scene- provide visual and reliable information about work sequence logistics, site layout or construction crew. Our approach addresses all the aspects of progress monitoring: *collection, analysis, communication and reporting*. We have looked into the existing simple yet robust progress data collection and communication techniques available on construction sites to see how we can effectively and efficiently use such information to address mentioned problems. Such information is categorized on two fronts: as-planned visualization as a baseline of progress monitoring, and as-built data collection and visualization techniques. In the section that follows some of the previous works which have led to this research are briefly introduced.

### **2.3 As-planned visualization as baseline for progress monitoring**

Visualization technologies have been widely adopted in construction, from visualizing control data (e.g., Korde et al. 2005, Songer and Heys 2003) to visualizing building products, to facilitate constructability reasoning or workability of the operation methods selected for construction (e.g., Hartmann et al, 2008, Kamat and Martinez 2008). The three main categories of these technologies that have been implemented to contribute to visualization of progress information are:

#### *4D models as a progress monitoring baseline for simulating as-planned progress*

These models are mainly developed for detecting spatial and temporal conflicts, understanding construction logistics, coordinating construction with subcontractors and trades and visualizing planned progress to owners (Hartmann et al. 2008, Kamat and Martinez 2008, Hartmann and Fischer 2007, and Staub-French and Khanzode 2007). These kind of pre-construction time-based models enable project participants and clients, regardless of their construction knowledge, to understand spatial constraints and explore construction alternatives before construction starts. While these models may not take into account every incident that might occur to the building under construction, they could be used as proper baselines for as-planned information of a project in our proposed research. These 4D models not only provide a realistic visual platform of the as-planned database, but also will serve as an underlying structure for monitoring progress where deviations between the as-planned and as-built progress status could be visualized.

### *Color/tone variations and motions for visualization of progress discrepancies*

In this context, Song, Pollalis, and Peña-Mora (2005) introduced a project dashboard wherein a 3D-model visual representation was used to represent progress. Multiple project data sets were applied to geometric attributes (e.g., shape, faces and edges) of a building model by means of color- tone variations and motion. The results of this study suggests that consistent application of colors allows progress metrics to be represented easily and also eliminates visual complexities which are caused by complexities associated with large-scale and sophisticated building product models. The preliminary results of using color-tone variations form a suitable baseline for visualizing progress metrics and we expand our proposed research methodology and system upon this concept.

### *Augmented reality for visualization of progress*

Within this category, Lee and Peña-Mora (2006) suggested overlaying as-planned models on photographs and conceptually formed a method for visualization of construction progress where deviations between planned and as-built performance models were conceptually represented in an AR (Augmented Reality) environment (such as ones developed by Behzadan et al. 2008; Wang and Dunston 2005). Using traffic light and weather metaphors, progress was manually visualized in comprehensive single imageries. The findings from all these studies on as-built data collection, as-planned modeling and visualization of progress monitoring form a stepping stone (Golparvar-Fard et al. 2007, Golparvar-Fard and Peña-Mora 2007) upon which the proposed framework for interactive visualization of construction progress monitoring with the D<sup>4</sup>AR model is developed.

## **2.4 Progress Photography for As-built visual model**

Site photographs are becoming valuable sources of accurate project information (Soibelman et al. 2008). Nowadays, it is a common practice among all parties involved in projects (from construction managers to subcontractors and from clients to architects) to take digital photographs from construction sites to create a complete progress photo-log and utilize the log for coordination, communication as well as supplementary documents to potential claims. Cameras, especially if equipped with zoom lenses, can cover extensive areas of a construction site. They also have the capability of providing real-time positioning information about multiple entities concurrently and are capable of self-calibrating and minimizing positioning errors when multiple cameras are installed (Brilakis and Soibelman 2008). All of these facts indicate that cameras and project photographs have evolved into a significant and irreplaceable part of project documentation and thus provide solid participations for their usage as visual, real-time as well as easy-to-obtain and low-price data capturing technology which does not need any expertise. The availability of such rich imagery of large parts seen under different viewing conditions presents enormous opportunities for progress monitoring, study of workspace logistics, quality assurance/ control, safety, as well as construction productivity. From the stand point of progress monitoring, these site photographs present the ultimate data set, which should give the ability to model a significant portion of as-built geometry at high resolution respective to conditions where enough photographs are being taken. This will also enable 3D visualization of as-built scene, progress data collection, localization, communication and recognition that can impact a construction project at large. Previous research efforts in using photographs for the purpose of progress monitoring goes back to Oglesby et al. (1989) wherein it was suggested that the application of site photographs allows analysts to focus on the details of the work face while being away from site tensions and confusions and perform time-studies on time-lapsed photographs for productivity improvement. However, lack of advanced technologies for automation, had made the process time-consuming and unattractive to some extent. More recently Abeid et al. (2003) presented Photo-Net II wherein time-lapse digital movies of construction activities were linked with critical path activities. In Photo-Net II, time-lapse photography has been used as a source of spatial as-built information; however, as-planned spatial information has not been integrated into the system. In addition, Golparvar-Fard et al. (2009) also recently presented an Augmented Reality (AR) system wherein 3D models are superimposed over time-lapsed photographs. In that environment, 3D models were semi-automatically superimposed over one image using control points and same camera configuration was applied to all subsequent images, allowing progress deviations to be visualized over time-lapsed images. Fig 4 shows an example of such augmented photographs where the 3D model is superimposed over the photograph and different schedule deviations are visualized using a traffic light color spectrum.

Project: College of Business Instructional Facility, Photo courtesy of Facilities & Services, UIUC

01/03/2007, 12:35:13 AM

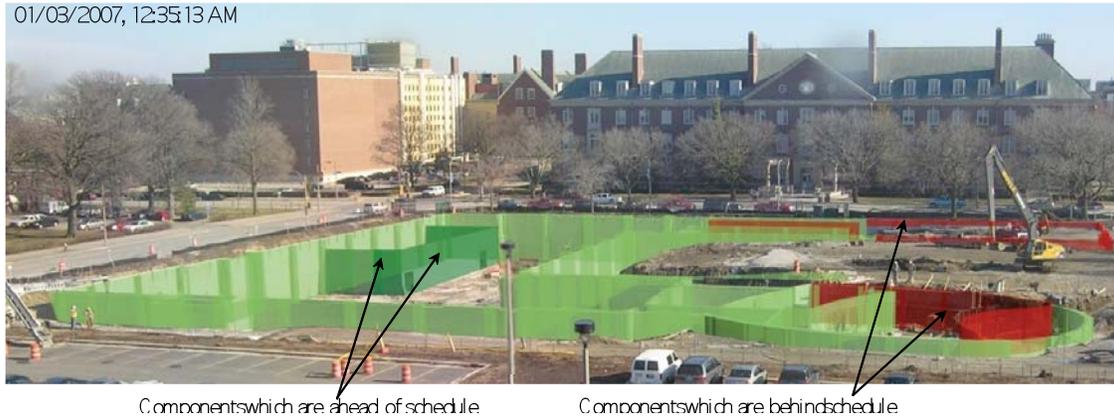


FIG. 4: The as-planned 3D model of UIUC College of Business Instructional Facility project is superimposed over the site image, visualizing progress as of 01/03/2007 using traffic light metaphor color spectrum. Photo courtesy of College of Business, UIUC; used by permission. (Image best seen in color).

Such images are fairly easy to obtain, are inexpensive and easily understandable; however, time-lapse photography has a series of limitations for progress monitoring. Time-lapsed photos only show what is not obstructed by objects such as construction machinery or scaffolding. Once the building envelope is placed, the application of time-lapsed images is limited, since it will be impossible to track progress inside the building. In addition they only show what is within range and field-of-view of the camera. Various illumination, shadows, weather and site conditions also make it difficult to use time-lapse photography for performing consistent image analysis on such imagery. Figure 5 shows some of these effects within a limited time-lapsed dataset. As shown in Figure 5-a, the slab has casted a shadow over interior structural components and have made it difficult to see inside. Also in Figure 5-b, the shadow casted by the adjacent building or the fog in Figure 5-c have almost made it impossible to understand the scene, and in turn make it very difficult to use a consistent image processing technique for all images or different parts within a single image. Even in normal conditions only a limited area of a time-lapsed photo will be associated with each construction component (may be even less than 50 square pixels). Developing image processing techniques that can operate on such limited-size patches is a major challenge.

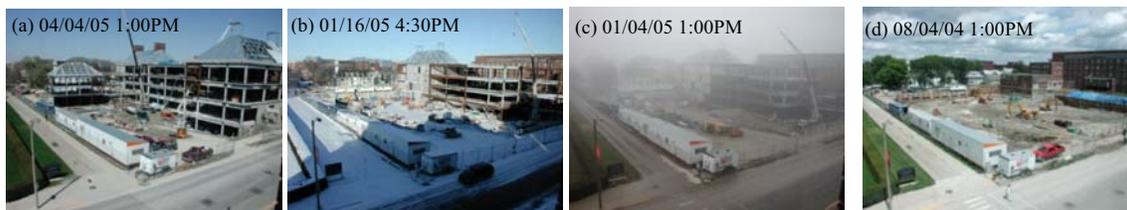


FIG. 5: Time-lapsed progress Photographs taken during construction of Institute of Genomics Biology, UIUC; Photographs courtesy of Information, Tech & Communication Services, College of ACES; used by permission.

In Golparvar Fard et al. (2009), Leung et al. (2008) and Abeid et al. (2003), installation of multiple cameras on a construction site is suggested; however again each camera will have the mentioned limitations and such a limited number of views cannot overcome limitations of occlusion, obstruction and weather conditions. Given the benefits and limitations of time-lapse photography even where multiple cameras are installed, comprehensive visualization of progress will not be possible. This motivated the authors to look into a larger visual dataset, i.e., the unordered set of progress imagery that is casually being taken on construction sites. These images are usually taken by construction managers, owner representatives, contractors and subcontractors and have the capacity to enable complete visualization of a construction site. Furthermore they have minimal redundant occlusions since photographers usually have the tendency of taking photos from particular components on the site as opposed to their potentially occluding peripheries. This makes site photo-logs even more attractive especially because such

datasets can enable a more comprehensive 3D visualization of as-built scene, localization, communication and recognition that can ultimately impact a construction project at large.

To date, the application of this site imagery for a complete as-built reconstruction and progress recognition is almost unexploited. Site photographs are usually not organized according to the locations they are taken from, are uncalibrated and are also widely variable and under various illumination, resolution, and image quality. Developing computer vision and image processing techniques that can effectively operate on such imagery is a major challenge. One key challenge is image registration, i.e., figuring out correspondences between images, and how they relate to one another in a common 3D coordinate system. This procedure is commonly called *Structure from Motion (SfM)*. While substantial research has been done in these areas over the last decade (Snavely et al. 2008, Akbarzadeh et al. 2006, Brown and Lowe, 2005, Hartley and Zisserman 2004, Triggs et al. 1999) many challenging aspects are still unsolved. For instance, there is a necessity to work with images that are capturing sites whose appearance is constantly changing due to progress or excessive movement of objects (e.g., construction crew and machinery). Furthermore, progress photographs taken at a project are either from specific activities under progress and/or are taken in a panoramic manner and therefore they may not carry enough information about perspective (since panoramic images form a plane) for a more global reconstruction of the as-built construction scene. In the sections that follow, we first present some of the state-of-the-art steps towards solving this problem. Then we present our preliminary results in reconstructing and localizing the as-built scene and registration of progress images.

### 3. OVERVIEW OF RESEARCH WORKS LEADING TO D<sup>4</sup>AR MODEL

Within the last decade, there have been significant increases in capabilities of computer vision and image processing techniques in feature detection, localization and registration of images. One of the key issues has been to discover the presence of corresponding features across multiple views in the same scene. Once a set of feature correspondences are known between these images, camera positions and orientations could be calculated. These techniques are still under consistent developments in computer vision, computer graphics and multimedia applications domains. In the following, some of the works that have further inspired development of the D<sup>4</sup>AR model are introduced:

#### *Feature Detection and Correspondence*

Image matching is a fundamental aspect for reconstructing a 3D (either sparse or complete) structure from multiple images in computer vision domain. First step for this task is extracting distinctive invariant features from images to be used to perform reliable matching between different views of an object or scene. These features should be *invariant* to image *scale* and *rotation* changes, and as shown by Moreels and Perona (2008), Tuytelaars and Mikolajczyk (2008), Mikolajczyk et al. (2005), Tuytelaars and Van Gool (2004) and Lowe (2004), allowing robust matching across a substantial range of distortion, change in 3D viewpoint, addition of noise, and change in illumination. The features need to be highly distinctive, in the sense that a single image can be correctly matched with high probability against a large database of images. Mikolajczyk et al. (2005) review some of these techniques and evaluated their performances. In our research, we have used Lowe's SIFT features - Scale Invariant Feature Transforms (Lowe 2004)- which is widely used in the computer vision community and achieves good performances over an acceptable range of viewpoint changes. Recent methods have taken advantage of these properties (Savarese and Fei-Fei 2007, Snavely et al. 2007, Rothganger et al. 2006, Niebles et al. 2006, Brown and Lowe 2005). Figure 6 shows some of these features that are identified in a construction image.

#### *Structure from Motion*

Structure from Motion (*SfM*), aims to reconstruct the unknown 3D scene structure and estimate unknown camera positions and orientations from a set of feature correspondences among an image set (Ma et al. 2006, Akbarzadeh et al. 2006, Hartley and Zisserman 2004, Faugeras et al. 2004, Pollefeys 2004, Triggs et al. 1999, Tucco and Verri 1998, Tomasi and Kanade 1992). Bundle adjustment has been shown to be a critical tool for obtaining a robust 3D reconstruction from a large number of sparse images. Experiments conducted by Snavely et al. (2007) and Bown and Lowe (2005) show bundle adjustment is robust with respect to changes in image resolution, time, focal length variability, and illumination changes. While these techniques have been applied for image-based walkthroughs and virtual touring, our paper marks the first successful demonstration of *SfM* technique being applied to geospatially photographs that are capturing a dynamic construction scene over the time span of its construction.

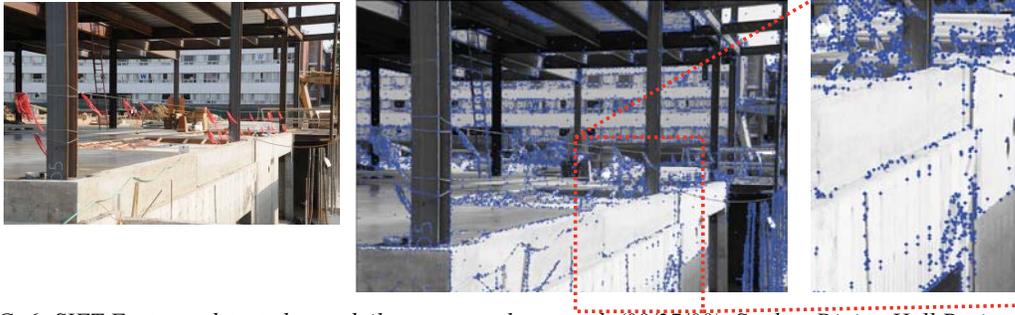


FIG. 6: SIFT Features detected on a daily progress photograph (08/27/08), Student Dining Hall Project – Photograph is taken right after concrete was placed in the First Floor Slab; Photographs courtesy of Turner Construction Company; Champaign, IL; used by permission.

#### *Image based modeling and rendering*

Image based modeling is the process of generating 3D models from a set of input photographs. In the computer graphics domain, SfM and model-based reconstruction are named under image-based modeling techniques. Notable examples of such works are the semi-automated Façade system of Debevec et al. (1996) which was used to create fly-through of University of California Berkeley campus and the Phototour of (Snavely et al. 2006) which was used to create virtual tours among thousands of online images. Image based rendering techniques can be used for synthesizing new views of a scene from a set of photographs (e.g., Avidan and Shashua 1997, Szeliski 1996, Seitz and Dyer 1996 and Chen and Williams 1993). Perhaps among the many works done in these areas, our approach needs to be closer to *Phototour* (Snavely et al. 2006) and *Sea of Images* (Aliaga et al. 2003) where a large collection of images are taken throughout architectural spaces. In our work, images are casually acquired on the site (as in Snavely et al. 2006), rather than being taken from fixed locations or on a guided robot (as in Aliaga et al. 2003). In our approach we do not need to render the complete scene structure (as in Debevec et al. 1996), rather we only need to render images on camera frusta. In this manner, we bypass the more challenging tasks of full photorealistic or non-photorealistic rendering of the as-built site.

#### *As-planned Model*

The application of 4D technology in construction site simulation, for the purposes of process evaluation and communication, has been under development for some time. Forerunners to this field were the works of Williams (1996) and Collier and Fischer (1996). In a 4D system, combined description of schedules and geometries of a particular scheduled event in a chronological manner helps to visualize construction process (McKinney et al. 1998). Techniques such as (Kamat and Martinez 2008, and Behzadan and Kamat 2007) also exist where construction operations are simulated and visualized in 4D virtual or Augmented Reality (AR) environments. The latter techniques focus on visualization of construction operations and require location tracking techniques which is obtained either by GPS or WLAN (Behzadan et al. 2008). Because our approach does not require GPS or any other instrument for location tracking, it has the advantage of being applicable to the existing image databases that are already being collected on a daily basis on almost every construction site. Our proposed feature correspondence estimation and sparse reconstruction of the as-built scene goes beyond what is possible in mentioned location-based systems since it does not need any additional work (no setup or calibration time) from field superintendents as they usually take photos from ongoing construction on a daily basis.

## **4. OVERVIEW OF THE D<sup>4</sup>AR MODEL**

Our system like other Augmented Reality (AR) applications requires accurate information about camera extrinsic parameters (i.e., *relative* location and orientation), and intrinsic parameters (i.e., focal length and distortion of the lenses) of each construction site camera. In addition the superimposition of the reconstructed scene over as-planned model requires *absolute* locations of the cameras. However in our system, we do not rely on the camera itself or any other equipment such as GPS or wireless location trackers for detecting location, orientation, or geometry. Rather, we compute such information from the images themselves using computer vision techniques. In this section, the steps towards reconstruction of the as-built scene and superimposition of 3D model over photographs are presented as follows:

## 4.1 Reconstructing cameras and sparse as-built scene

We first detect a set of robust features in each image, then match these features across images, and finally run a robust *SfM* procedure to recover camera intrinsic and extrinsic parameters. We use EXIF tag of image files to initialize our estimate on focal length. However using EXIF tag is not necessary when this information is inaccurate. This component of the system allows photographs being taken from any type of camera to be applicable for sparse reconstruction. In this system, *SfM* only provides the relative position of each camera, while we are interested in absolute coordinates. Therefore we calculate the transformation between as-planned and as-built models using a method similar to that of (Golparvar-Fard et al. 2009). We registered an as-built 3D set of points to a set of as-planned 3D model points that minimizes the sum of squared residual errors between the set and the model. Each of these steps is described in the following subsections:

### *Keypoint detection and matching*

The first step in reconstruction of the as-built scene and geo-registration of progress images is to find feature points in each image that could be used to estimate the initial structure of the scene. In our work, we use the SIFT keypoint detector (Lowe 2004), because of its good invariance to scale changes and view and illumination transformations as well as its widespread application in the computer vision domain. For a detailed study of feature detectors and descriptors, the reader can look into Moreels and Perona (2008), Tuytelaars and Mikolajczyk (2008), Mikolajczyk et al. (2005), Tuytelaars and Van Gool (2004) and Lowe (2004) wherein different feature detectors and descriptors are compared with each other. A small image of 500x500 pixels typically gives about 1,500 to 2,000 SIFT features. As a proof of concept for keypoint detection and matching, we run SIFT detection on a subset of 160 daily progress photographs. This data set of images was taken on the Student Dining and Residence Hall construction project of Turner Construction Company in Champaign, IL. A field engineer carried a high-resolution SLR camera (Nikon D300) for this task. The choice of a high resolution camera was only based on the possibility for further enhancement of the algorithm so the quality of the images could be synthetically reduced (in our experiment reduced to about 3 Mega Pixels) and the keypoint detection could be tested on synthetically lowered resolution images. Figure 7 shows these points on a subset of images on the same dataset.

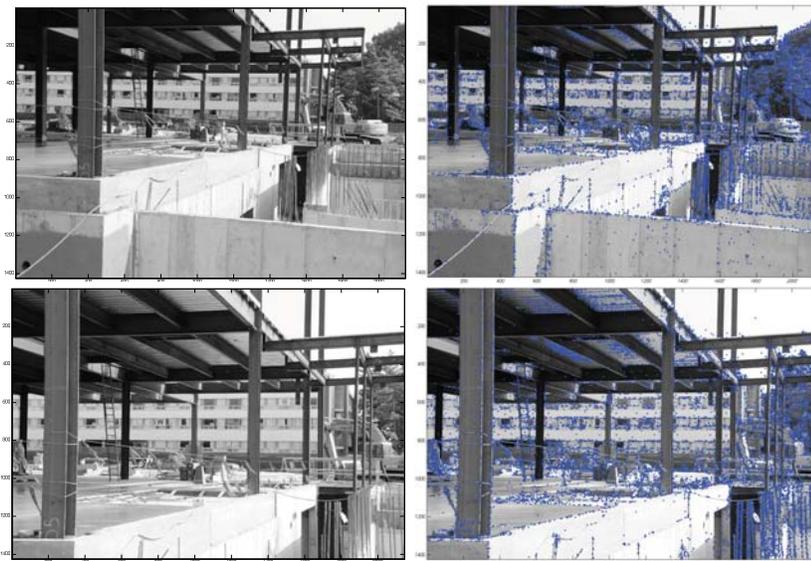


FIG. 7: SIFT Features shown on two daily progress photographs taken on 08/27/08, Student Dining Hall Construction Project; Photographs are taken right after concrete was placed in the First Floor Slab; Photographs courtesy of Turner Construction Company; Champaign, IL; used by permission.

Once the features have been detected over the dataset, we need to detect how many of these features are matched in each image pair. We use SIFT descriptors to match keypoint between each image pair. Each SIFT descriptor is a 128-dimensional feature vector. Using (Lowe 2004) approach, once keypoints are identified, the gradient of intensities is captured over a window of pixels centered around a keypoint. Then these pixels are categorized to a 4x4 sample windows wherein each sample window and histogram of intensity gradients are stored in 8 cardinal directions (4x4x8 directions = 128 dimensions). Descriptors are matched across two images by computing a

distance function between corresponding histograms of intensity gradients. Features are matched by using a nearest neighborhood matching strategy. As experienced by Snavely et al. (2006), if the number of features is large enough a  $k$ - $d$  tree matching scheme (Arya et al.1998) may be used instead; this is particularly effective when the dimension of the data is large (as in our case). Overall this improves the efficiency of the matching algorithm. To minimize computation load, we also use ANN's priority search algorithm and instead of classifying false matches by thresholding the distance to the nearest neighbor, we use the ratio test described by Lowe (2004): for a feature descriptor in image  $i$ , we find the two nearest neighbors in image  $j$ , with distances  $d_1$  and  $d_2$ , then accept the match if  $d_1/d_2 < 0.6$ . If more than one feature in image  $i$  matches the same feature in image  $j$ , we remove both of such matches, as one of them is a false match. Figure 8 shows the keypoints across the same image pair used in Figure 8 and visualizes matches through connecting these features by solid lines. In this image pair, 2071 matches are found in which some false matches are also formed and visualized in lower image in Figure 8.

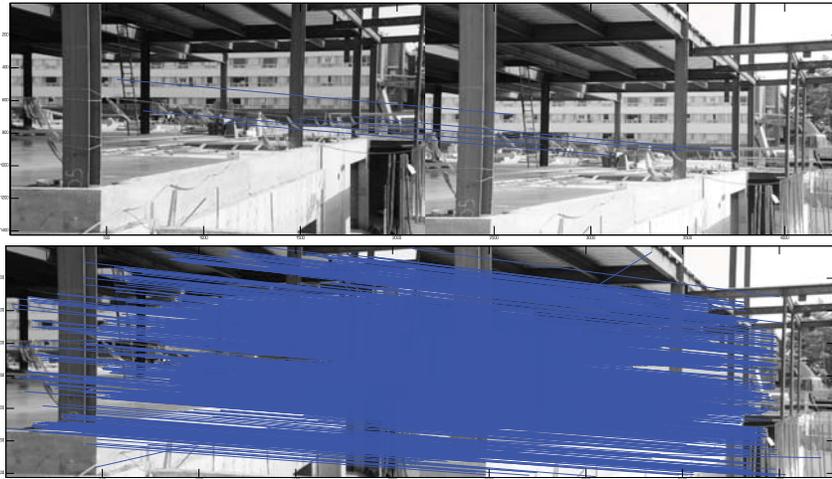


FIG. 8: Detected SIFT features matched over the same image pair of Figure 8. The upper image shows the first 5 matches found (lines in blue color) and the lower images shows the overall 2071 matches found. If looked closely a couple of mismatches diagonal to the stream of matches are visible.

Due to the sensitivity of the reconstruction algorithm to false matches, we further refine our process to remove such false matches. In our approach, once the matching features are detected in an image pair, we robustly estimate a fundamental matrix for the pair using RANSAC (Fischler and Bolles 1981). Fundamental matrix helps remove false matches as it enforces that corresponding features have to be consistent under view point transformation, that is:  $p_L^T F p_R = 0$  ( $p_L$  and  $p_R$  are point coordinates and  $F$  is the Fundamental matrix; See Fig 9). In our model, in each iteration of RANSAC, a fundamental matrix is computed using the eight-point algorithm of Hartley and Zisserman (2004), and then the problem is normalized to improve the robustness to noises (Hartley 1997).

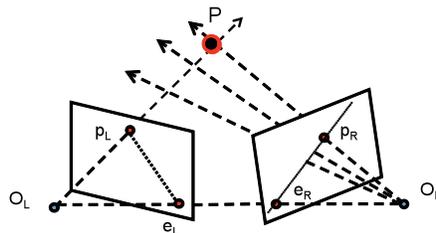


FIG. 9: Epipolar geometry of an image pair. In this figure  $O_L$  and  $O_R$  are the origin of cameras.

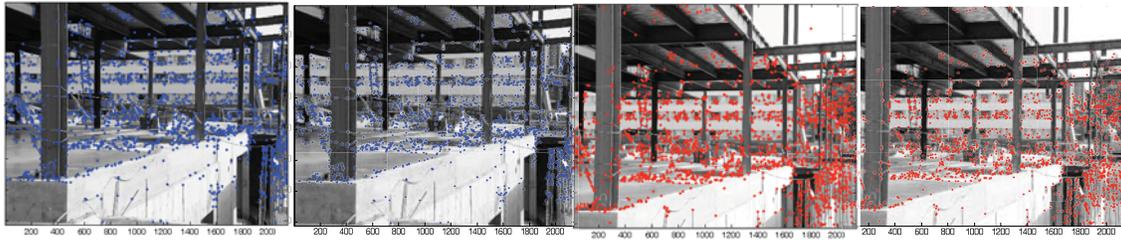


FIG. 10: Left to Right: Visualizing keypoint matching between a pair of images shown as (a) Image1-Before RANSAC, (b) Image1-After RANSAC, (c) Image2-Before RANSAC, (d) Image2-After RANSAC, number of matches have dropped from 2079 to 1800 and show a more accurate matching.

As suggested by Snavely et al. (2007), we set the RANSAC outlier threshold to be 0.6% of the maximum image dimension, i.e., 0.006 maximum of image width or height) (about 12 and 9 pixels for two dimensions of a 2144x1424 image). The Fundamental matrix returned by RANSAC is refined by running the Levenberg-Marquardt algorithm (Nocedal and Wright 1999) on the eight parameters of the Fundamental matrix, minimizing errors for all the inliers to the Fundamental matrix. We remove outliers to the recovered F-matrix (false matches) using the above suggested threshold. Figure 10 shows the keypoint matches in the same image pair as of Figure 8 and shows how the false matches are pulled out.

Since for lower numbers of matches in an image pair, even after fitting a Fundamental matrix through RANSAC iteration, the possibility of getting false matches is still high, we set a threshold to remove image pairs with number of matches less than the threshold. We set this threshold to be twenty matches which seems reasonable to opt out false matches. After finding a set of consistent matches between all image pairs, we organize these matches into *tracks*. A track connects matching keypoints across multiple images (Snavely et al. 2006). We keep tracks with a minimum of two keypoints for the next phase of the reconstruction procedure.

#### Structure from Motion

Now, we recover camera extrinsic and intrinsic parameters (extrinsic: rotation, translation; and intrinsic: focal length and distortion) for each image and a 3D location for each keypoint. The recovered parameters should be consistent, in that the re-projection error, i.e., the sum of distances between the projections of each keypoint track and its corresponding image features, is minimized. Similar to other SfM approaches, in our experiment this minimization problem is formulated as a non-linear least squares problem and solved using bundle adjustment. Here we briefly describe the required steps but the reader is encouraged to look into Snavely et al. (2007) and Triggs et al. (1999) for more details.

First, we estimate extrinsic and intrinsic parameters of a single image pair. Since bundle adjustment as other algorithms for solving non-linear problems is prone to getting stuck in bad local minima, it is strongly suggested by many researchers (e.g., Nistér 2004) to start with a good initial image pair and good estimates for camera parameters in the chosen pair. This initial pair for SfM should not only have a large number of matches but also a large baseline, so that the initial as-built scene can be robustly reconstructed. An image pair that is poorly described by a homographic transformation satisfies this condition. A 2D image homography is a projective transformation that maps points from one image plane to another image plane (Hartley and Zisserman 2004). We find the homography between all image pairs using RANSAC with an outlier threshold of 0.4% of maximum of image width and height, and store the percentage of feature matches that are inliers to the estimated homography. We select the initial image pair as that with the lowest percentage of inliers to the recovered homography, but with at least 100 matches (As also noted by Snavely et al. 2007). The extrinsic camera parameters for this pair are estimated using Nistér's five point algorithm (Nistér 2004), and then the tracks visible in the image pair are triangulated. A two-frame bundle adjustment for this initial pair is performed. Next, we add another photograph camera to the optimization. We choose the camera that examines the largest number of estimated tracks, and initialize the new camera's extrinsic parameters using the *Direct Linear Transform* (DLT) technique (Hartley and Zisserman 2004) within a RANSAC procedure. For this RANSAC step, we use an outlier threshold of 0.4% of maximum of image width or height. As mentioned previously we use focal length from the EXIF - Exchangeable image file format - tags of JPEG images (file type of almost all digital cameras) to initialize the focal length of the new camera and estimate the intrinsic camera matrix (see Snavely et al. 2007 more details).

Starting from this initial set of parameters, while the model is kept fixed, we run the bundle adjustment algorithm allowing only the new camera and the keypoints it observes to change. Finally, we add points observed by the new camera into the optimization algorithm only if it is observed by at least one existing recovered camera, and if triangulating the point gives a well-conditioned estimate of its location. We estimate the conditioning by considering all ray pairs that could be used to triangulate that point, and finding the pairs with maximum angle of separation. If this maximum separation angle is larger than a threshold, then the point is triangulated. Once the new points have been added, another global bundle adjustment is run to refine the entire as-built reconstructed scene. In our experiment, the minimum error solution using the sparse bundle adjustment library of Lourakis and Argyros (2004). This procedure is continued for all cameras until no camera is remained which observes enough 3D points to be reliably reconstructed. With such an approach, the algorithm may only determine and reconstruct a subset of the used images. Figure 11 shows the reconstructed sparse scene from the set of 160 images used from Student Dining and Residence Hall Projects of Turner Construction in Champaign, IL. Interestingly not only the scene, but also its peripheral structures (e.g., Garner Residence Hall building) on campus of University of Illinois in Champaign-Urbana is sparsely reconstructed.

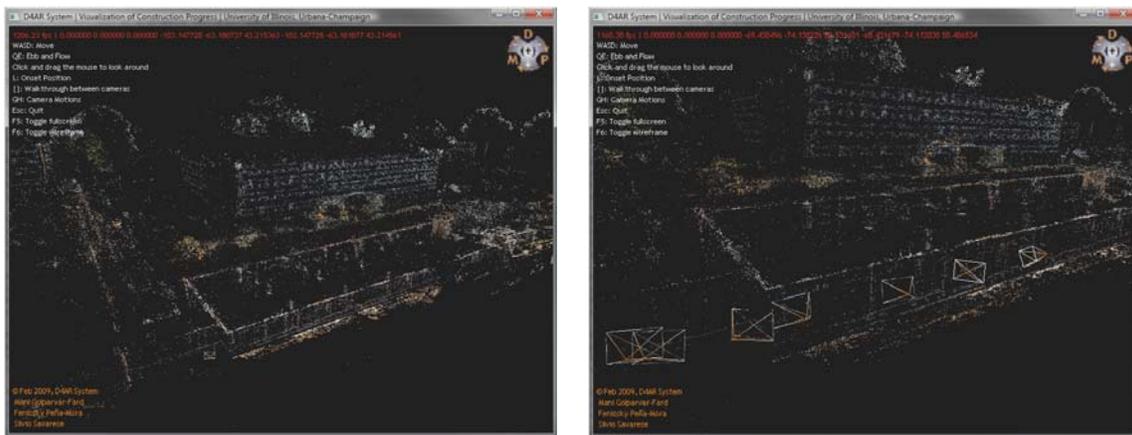


FIG. 11: The reconstructed sparse scene of Student Dining and Residence Hall construction project in Champaign, IL. The right image represents 7 camera frusta for which their images were used for sparse reconstruction of the as-built site.

### Geo-Registration

The *SfM* procedure estimates *relative* camera locations. The final step of the location estimation process is to align the reconstructed scene with the as-planned model to determine the absolute geocentric coordinates of each camera. Although the as-built scene browser can work with relative coordinates, for geo-registration of the scene with as-planned model, the absolute coordinates are required. The estimated camera locations are related to the absolute locations by a global translation, rotation, and uniform scale transform. To determine the correct transformation, we use the closed-form solution of absolute orientation using unit quaternions (Horn 1987) similar to that of Golparvar-Fard et al. (2009) to register the as-built scene over the as-planned model. We register as-built 3D set of points to a set of as-planned 3D model control points that minimize the sum of squared residual errors between the set and the model. Figure 12 shows a screenshot of the expected alignment. In some cases the recovered as-built scene cannot be aligned to a geo-referenced coordinate system using a similarity transform. This can happen if the *SfM* procedure fails to obtain a fully metric reconstruction of the scene, or because of low frequency drift in the recovered point and camera locations. One way to rectify the recovered scene is to pin down a sparse set of ground control points or cameras to known 3D locations (acquired, from surveying instrument when visible location in some photographs before *SfM* step) by adding constraints to the *SfM* optimization (not tested yet by authors). Also a set of lines that are known to be orthogonal in the original model (self-calibration constraints) could be chosen to rectify the superimposition. In order to further refine the alignment, ICP-based (Iterative Closest Point) technique (Besl and McKay 1992) can also be used (Not tested by the authors - In future work).

### *As-built Scene Representation*

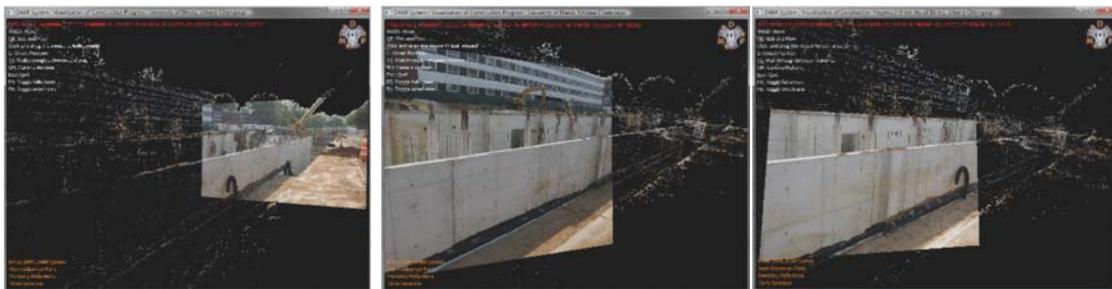
After the as-built scene is reconstructed and is superimposed over the 3D model, scene needs to be used for interactive explorations. The following data structure is used to represent the as-built reconstructed scene:

- A set of keypoints, in which each keypoint consists of a 3D location and a color that has been averaged out from all the site images that the keypoint is being observed from.
- A set of cameras, while the extrinsic parameters (translation and rotation), and intrinsic parameters (focal length and distortion in height and width directions) are known.
- A mapping between each point and all the cameras that observe the point. A list of number of cameras which observe the point, the location of the point in local coordinates of the image, and the SIFT keypoint index are all stored.

While this information is stored, cameras would be rendered as frusta. Once a camera is visited in this reconstructed scene, the camera frustum is texture-mapped with the full resolution image so the user can zoom in and thoroughly analyze progress, productivity as well as site logistics. Figure 13 shows two images of the reconstructed scene while the image under study is shown with respect to the reconstructed scene.



*FIG. 12: The alignment of the Student Dining and Residence Hall construction project 3D model with one of the construction progress images using Golparvar-Fard et al. (2009) approach. As shown some of the foundations and foundation short walls as well as piers that are not yet constructed, are superimposed over the image. Photograph courtesy of Turner Construction Company; Champaign, IL; used by permission.*



*FIG. 13: The registration of images within the sparsely reconstructed scene. Student Dining and Residence Hall construction project in Champaign, IL. Photographs courtesy of Turner Construction Company; Champaign, IL; used by permission.*

Once the registration of the 3D model with the reconstructed scene is performed, the reconstructed sparse scene is masked and only images with respect to the as-planned model are visualized. Figure 14 shows two images from Student Dining and Residence Hall projects wherein the as-planned model as of the day image was taken is superimposed over the image.

## 5. APPLICATION OF D<sup>4</sup>AR MODEL FOR PROGRESS MONITORING

Authors implemented D<sup>4</sup>AR system in Microsoft C++ .NET using Microsoft DirectX9 graphics library. The D<sup>4</sup>AR marks the first system that allows as-built construction spatial information to be visualized within the same framework of as-planned construction information. As shown, as-of-now, our system is only capable of reconstructing a sparse as-built scene and superimposition of the scene over a 3D model. As a proof of concept and to perceive how this model could be used in different aspects of the construction domain, many superimposed images have been generated and a set of them has been specifically used during the construction of two of our case studies. The first author of this paper has been a part of the onsite Turner Construction team for both Dining Hall and Residence Hall construction projects in Champaign, IL and has been generating such images for the project. In this section, the experiences of the authors on current and perceived applications of D<sup>4</sup>AR on those ongoing projects are discussed in full details.



FIG. 14: The registration of images with the construction progress images. Student Dining and Residence Hall construction project in Champaign, IL. Photographs courtesy of Turner Construction Company; Champaign, IL; used by permission.

### 5.1 Virtual walk through on the as-built scene

One of the major applications of this system is that it allows project managers, project executives, superintendents, subcontractors as well as owners and even architects to remotely access the under construction site (specifically if this system is offered through a web browser) and navigate through all the as-built scene, and browse through the collection of progress photographs in any given day. Such application can create significant benefits as follow:

1. *Remote Construction Control Decision Making:* It allows project managers, superintendents and other project participants to virtually walk on the construction site, as-of the time the scene has been reconstructed and position themselves in those positions that progress images have been taken. Such an interactive user walk-through allows progress to be discussed remotely without the need of any of those participants to be physically on the jobsite.
2. *Minimizes the time required to discuss the as-built scene:* Project managers and superintendents will spend less amount of time discussing or explaining progress. Rather, they can spend more time on how a control decision could be made, especially because the reconstructed as-built scene and geo-registered images allow workspace logistics, safety issues, progress and even productivity of workforce and machinery to be remotely analyzed. Such an as-built system could also be very beneficial in weekly contractor coordination meeting as the workspace could be navigated through the virtual world, especially once used in conjunction with large screen collaboration tools (e.g., such as smart board used in Golparvar-Fard et al. (2006) or even multi-touch screens (e.g., multi-touch interaction wall of Han (2006)))
3. *Significant cut in travel time and cost on project executives and architects* – Project Executives and architects can study the reconstructed scene and geo-registered images, instead of spending time and money to travel to the jobsite. The reconstructed scene with as-built progress images can be very beneficial, especially when the possibility of adding new photographs quickly to the system is considered. Even if a perspective of an interest is not registered within the reconstructed scene and is

not present in geo-registered image dataset, the user in the case of being owner and project executives can request the scene to be photographed. Those photographs taken can also be quickly geo-registered allowing a significant progress communication problem to be resolved.

## 5.2 Visualizing Deviation of progress

The main motivation of authors behind developing the D<sup>4</sup>AR system has been to come up with a system that geo-registers spatial as-built and as-planned models within the same environment allowing construction progress to be measured, analyzed and communicated. To that extent, authors have proposed the application of a traffic light color spectrum to be used for visualizing progress (Golparvar-Fard et al. 2009 and Golparvar-Fard et al. 2007). Figure 15 shows the application of the proposed color metaphor to visualize progress. As seen, the color spectrum (shown in Figure 4) has been used over the as-planned model to easily communicate deviations in progress. The presented image shows the actual progress made on construction of the College of Business Instructional Facility at the University of Illinois. As seen the concrete foundations have not been placed as of Dec 02, 2006 (the day photo was taken but schedule run date is November 13, 2006) and therefore forms for concrete walls are not set in place yet.

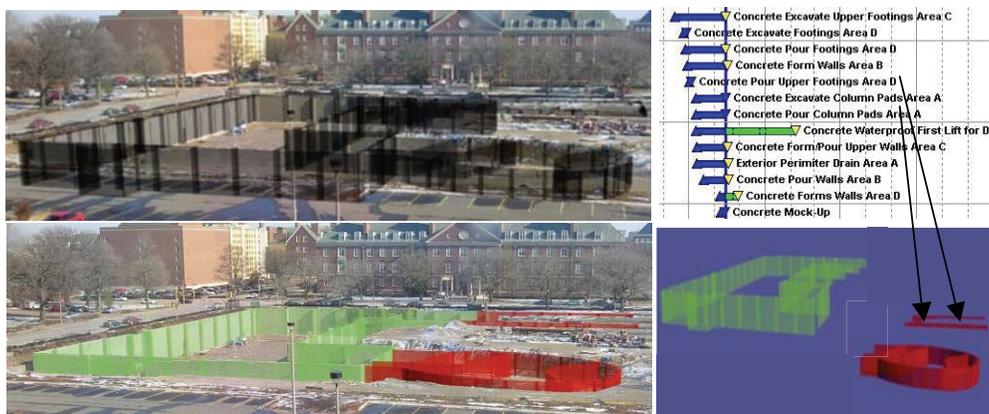


FIG. 15: The superimposed photo has been color-coded based on actual progress on the jobsite. As seen the concrete foundations have not been placed yet and therefore wall forms are not put in place yet. Photograph from construction of College of Business Instructional Facility at University of Illinois's campus, courtesy of College of Agriculture, Communication and Education, UIUC and Gilbane Construction Co; used by permission.

One of the other observed applications of visualizing deviation is to facilitate onsite discussions. In the Student Dining and Residence Hall project, the authors came up with a D<sup>4</sup>AR superimposed image, highlighting the building foundation which was misinterpreted by the concrete subcontractor. This image has been used by the project manager to communicate the component under attention to concrete superintendent and foreman. The poor architectural/structural detailed-drawings respective to a continuous concrete footing miscommunicated the scope of work. The concrete subcontractor's foreman interpreted drawings in a way that a specific continuous footing is not a load-bearing component and therefore it does not need to be constructed along with the rest of the footings. Figure 16 shows the image where in the component which was not yet constructed as-of the day photo was taken (May 16, 2008) is highlighted. As seen, the strip footing highlighted in red (between two single footings) needs to be constructed while the foreman did not interpret it as a load bearing component from the drawing. After series of discussions using this image, concrete was placed and the strip footing was constructed.



The middle section highlighted in red color needs to be constructed.

FIG. 16: The superimposed photo visualizing the component which has been misinterpreted by the carpenter foreman. Student Dining and Residence Hall project, Champaign, IL. Photograph courtesy of Turner Construction Company; Champaign, IL; used by permission.

### 5.3 Automatic progress tracking

The D<sup>4</sup>AR system geo-registers construction site photographs with as-planned building components, and therefore serves as a rich baseline for automatic progress monitoring through consistent visual detection of progress and comparison with as-planned information. Figure 17 shows an IDEF-0 process model for automating progress monitoring through the D<sup>4</sup>AR system. As shown, first the digital as-planned model will be combined with progress metrics to provide a progress monitoring baseline. In this case, Earned Value Analysis (EVA) as a robust monitoring mechanism is proposed. Although EVA has some limitations as referred in Kim and Ballard (2000), all the construction work is planned, scheduled and budgeted in time-phased planning value increment, so it can constitute a performance measurement baseline (Abba 1997) which is useful for comparison. As-planned model wherein progress monitoring baseline is set will be used for comparison with the reconstructed as-built model. Once site images are all registered, progress will be analyzed and according to the analysis perform, as-planned model will be color-coded and superimposed over site images.

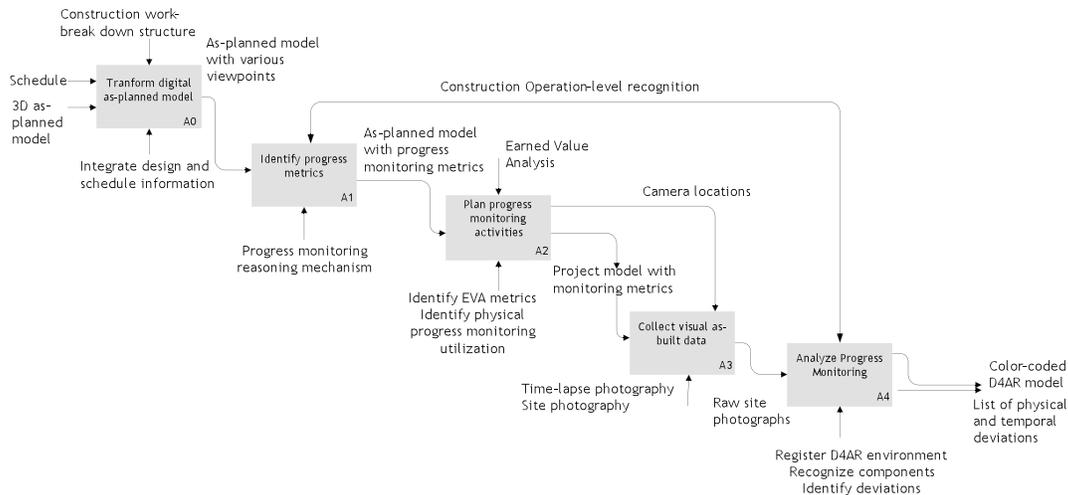


FIG. 17: IDEF0 representation of automatic progress monitoring using the D<sup>4</sup>AR model

Figure 18 presents step A4 of automatic progress monitoring system using the D<sup>4</sup>AR model in detail. Once the images and the 3D model components are geo-spatially and temporally registered, deviations could be measured using image recognition or processing techniques.

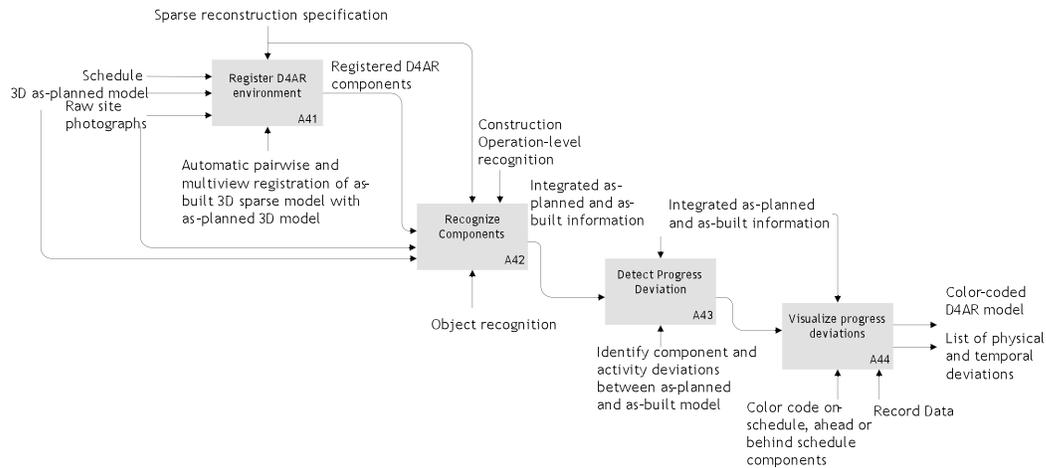


FIG. 18: IDEF0 representation of analyzing progress monitoring (Step A4 of the overall IDEF-0 representation of proposed D<sup>4</sup>AR system).

Figure 19 schematically visualizes how progress for a concrete wall given one geo-registered image could be analyzed. Now, one can imagine how a set of site images that contain photos of the same building component can minimize false-positive returns on any image processing technique. Furthermore, using a site photo-log minimizes redundant occlusion problems (which exists in case of using time-lapse cameras on a job site). Since these photos are normally taken closer to construction components, a larger patch containing more pixels would be available for analysis. This in turn boosts the accuracy of an automated progress detection system. The more number of image patches available for each component, the better the implemented image processing algorithm can be.



FIG. 19: Proposed Method of extracting image patches and performing image analysis for detecting progress. Photograph of College of Business Instructional Facility construction project, Champaign, IL; November 08, 2007, Gilbane Construction Company.

#### 5.4 Application of the D<sup>4</sup>AR System for Interior Progress Monitoring

One of the major applications of the D<sup>4</sup>AR is for tracking progress of interior components. If enough photographs are taken to connect exterior photographs' path to those of interior, this system could be efficiently used for tracking interior as well. As such, visualizing progress of MEP/FP (Mechanical-Electrical-Plumbing/Fire Protection) systems will also become possible. For such application, we perceive using short focal length lenses or wide angle lenses to allow short distances to be captured as well. This component of the research is still ongoing.

#### 5.5 Registering New Daily Site Photographs

New construction progress photographs can be incrementally added to the reconstruction (the as-built model) so as to update the model without the need to redo the reconstruction from scratch. First, a user can open a set of progress images, and drag and drop each image onto its approximate location on the as-built model. After each image has been dropped, the proposed system estimates the location, orientation, and focal length of the new photo by running a version of the *SfM* algorithm. In a similar fashion first, SIFT keypoints are extracted and matched to the keypoints of the cameras closest to the initial location; then the existing 3D points corresponding

to the matches are identified; and finally, these matches are used to refine the configuration of the new camera. After a set of photos has been dragged onto the environment, it generally takes in order of seconds to optimize the parameters for each new camera.

## 5.6 Augmented Reality Occlusion Removal

One of the perceived applications of geo-registered photograph is for occlusion removal. Occlusion within augmented reality systems changes the perspective of the virtual model and real world possibly causing confusion. A practical example of how occlusion may cause misperception is presented in Figure 20. As seen, the footing and pier highlighted appear in front of the temporary electricity box on the jobsite, but in reality they should be located behind the box. Note that the registration error in this image is minimal, especially when the accuracy of registration of the virtual foundation walls over actual foundation walls is perceived. Such occlusions may create confusion. We suggest two solutions for such cases:

- Since in the D<sup>4</sup>AR environment each component has the chance of being observed in a subset of images, user can study each component from different perspectives which will remove all potential confusions on depth and/or perspective.
- Since each image in the D<sup>4</sup>AR is geo-registered and intrinsic and extrinsic camera parameters are known, cameras are all calibrated. This information helps to extract geospatial information of certain components and allows occlusions to be removed through rendering the image patch associated with that component over the 3D model.



FIG. 20: As-built model superimposed over the progress photograph. Student Dining and Residence Hall construction project in Champaign, IL. Photograph courtesy of Turner Construction Company; Champaign, IL; used by permission.

## 6. CONCLUSIONS AND FUTURE WORKS

Visualization of as-built and as-planned construction can enhance identification, processing and communication of progress discrepancies. To that end, D<sup>4</sup>AR is proposed wherein application of unsorted daily progress photograph logs available on any construction site as a data collection technique is explored. Based on computing - from the images themselves - photographer's locations and orientations, along with a sparse 3D geometric representation of the as-built site using daily progress photographs and superimposition of the reconstructed scene over as-planned 4D models will be possible. Within such an environment, progress photographs are registered in the virtual as-planned environment which allows a large unstructured collection of daily construction images to be sorted, interactively browsed and explored. In addition, sparse reconstructed scenes are superimposed over 4D models allowing site imagery to be geo-registered with the as-planned components and also allowing a location-based image processing technique to be used and progress data to be automatically extracted. The D<sup>4</sup>AR system can perform as a robust tool for contractor coordination and communication purposes. Our preliminary results show perceived benefits and future potential enhancement of this new technology in construction, in all fronts of automatic data collection, processing and communication. There are still many technical challenges in developing a full systematic progress monitoring system and these are currently being explored within the research project highlighted in this paper.

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