# TOWARD AUTOMATED EARNED VALUE TRACKING

# USING 3D IMAGING TOOLS

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## Abstract

Accurate and frequent construction progress tracking provides critical input data for project systems such as cost and schedule control as well as billing. Unfortunately, conventional progress tracking is labor intensive, sometimes subject to negotiation, and often driven by arcane rules. Attempts to improve progress tracking have recently focused mainly on automation, using technologies such as 3D imaging, GPS, UWB indoor locating, hand-held computers, voice recognition, wireless networks, and other technologies in various combinations. However, one limit to date of these approaches is their focus on counting objects or milestones rather than value. In this paper, a 4D model recognition driven automated progress tracking system that transforms objects to their earned values is examined via analysis of data from the construction of a steel reinforced concrete structure and a steel structure. It is concluded that automated, object oriented recognition systems that convert each object to its earned value can improve the accuracy of progress tracking substantially and thus better support project systems like billing. The contribution of this study is an argument based on scientific results for refocusing future research onto automated earned value tracking which is ultimately what is needed in practice.

**Keywords:** Building Information Models (BIM), 4D, 5D, Construction Progress Control, Cost codes, Earned Value, Laser Scanning, Object recognition.

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## Introduction

Effective progress control is essential for successful delivery of construction projects (Hegazy 2002). Progress tracking is required as feedback for any progress control system. Hendrickson and Au (1989) point out that there are four basic approaches to progress tracking, including: (1) measuring units of work completed, (2) noting completion of predefined interim milestones, (3) subjective judgments of work complete by surveyors, inspectors, and managers that may need to be negotiated for agreement to be reached, and (4) cost ratio. The first three of these can be converted to earned value (defined later in this paper) which is the common basis for project billing. It is this aspect of progress tracking in which many contractors are most interested.

Attempts to improve progress tracking have recently focused mainly on automation, using technologies such as 3D imaging, GPS, UWB indoor locating, hand-held computers, voice recognition, wireless networks, and other technologies in various combinations. The following section summarizes the significant progress that has been made in 3D imaging based approaches to automated progress tracking while identifying remaining knowledge gaps. The following section reviews relevant concepts related to earned value. Then, the experimental results are presented and interpreted.

## Literature Review

### 3D Imaging-based Approaches to Automated Progress Tracking

Because they enable fast, dense, and accurate 3D data collection from construction sites, 3D imaging technologies, such as laser scanners and digital photogrammetry have been demonstrated to have potential for supporting a wide range of applications. They include progress measurement, as-builts creation, quality analysis, structural forensics analysis, and others (Bosché 2009; Cheok et al. 2000; Greaves and Jenkins 2007; Golparvar-Fard et al. 2009, 2012; Wu et al. 2010).

In pioneering research, Cheok et al. (2000) used 3D laser scanning technology to collect 3D images from a construction site in order to measure earthwork progress. Jaselskis et al. (2005) advanced this area of research by further developing laser scanning technology to measure the volume of soil and

1    rock, determine road surface elevations, and assist in the creation of as-built drawings. They found that

2    laser scanning technology can be used effectively to make safe and highly accurate construction progress

3    measurements.  Shih and Huang (2006) developed an internet based 3D scan information management

4    system (3DSIMS) which enables storage, display and analysis of laser scan data for construction progress

5    measurements. And, Teizer et al. (2007) used range cameras to track moving construction objects as

6    crude masses for safety applications.  These early advances focused on non-parametric objects or

7    volumetric progress data collection.  Another stream of research focused on two related applications of

8    3D imaging: (1) parametric object modeling, and (2) object recognition.

9         For example, Kwon et al. (2004) developed algorithms based on the Hough transform and

10   principle axis analysis to fit 3D point clouds to simple 3D parametric objects such as spheres, boxes, and

11   cylinders.  These algorithms are now used in commercial software packages that semi-automatically

12   convert 3D scans of industrial facilities into 3D CAD models of piping networks. Tang et al. (2010)

13   investigated several techniques such as Hough transform, object recognition using priori knowledge,

14   modeling curved surfaces using NURBS patches and some others that can be used for automatic

15   generation of as-built BIMs. Brilakis et al. (2010) analyzed new advances in disciplines such as computer

16   vision, videogrammetry, laser scanning and machine learning, and then demonstrated how they can be

17   used to generate as-built BIMs.  Adan et al. (2011) have developed a method to automatically convert 3D

18   laser scanned point clouds into a compact, semantically rich model for buildings, which, while still error

19   prone, represents a tremendous stride towards full automation.

20        A progress and schedule control system called Photo-net was introduced in (Abeid and Arditi

21   2003; Abeid et al. 2003). This web based system links digital movies of construction activities with CPM

22   scheduling for progress control, and enables project staff/managers to follow the progress at a

23   construction site in real time. Golparvar-Fard et al. (2007) proposed an approach for visualizing

24   construction progress monitoring using time-lapse photographs and 4D project models. The approach

25   requires manual comparison of as-planned models of construction projects with their actual progress

26   photographs, and determining project progress from time-lapse photographs captured by on-site cameras.

In the same paper, Golparvar Fard et al. establish several visualization techniques to represent the project performance. These techniques involve several metaphors including quadrangle colour scheme that can be used for visualization of Earned Value Analysis (EVA) metrics such as Schedule Performance Index (SPI) and Cost performance Index (CPI). Later one, Golparvar-Fard et al. (2009a) proposed a new framework for EVA to facilitate progress monitoring through superimposition of four-dimensional (4D) as-planned model over time-lapsed photographs for manual interpretation of deviations.

Ibrahim et al. (2009) proposed a first system that aims to *automate* progress assessment of work packages by employing computer vision techniques as well as to automate generation of work packages, i.e. planning assignment. The computer vision module of their system makes it possible detecting building elements using an as-planned 3D model of the building projected on 2D time-lapsed photographs, in combination with model matching and change detection algorithms. Zhang et al. (2009) developed a similar Integrated Building Information System built on 2D computer vision technology to automate progress measurement of work at construction sites. A computer vision module enabled the detection of the construction of building components using a 3D as-planned model of the building projected onto 2D images, and a model-based fitting approach to detect deviations.

The latest achievement in 2D image-based progress tracking has been introduced by Golparvar-Fard et al. (2009b) who developed an image based system called $D^4AR$ – Four Dimensional Augmented Reality – for progress monitoring using daily photographs taken from a construction site. This system does not rely on time-lapsed images acquired from a fixed location, but a series of images acquired by management at different locations on site. The relative orientations of the photographs as well as a sparse 3D point cloud of the site are computed using a sparse matching algorithm combined with a bundle adjustment procedure. In (Golparvar-Fard et al. 2010) the system was improved with a volumetric occupancy reconstruction algorithm to obtain an as-built site occupancy array. That was then superimposed over an as-planned site occupancy array derived from the project 4D model (IFC-based BIM) in order to estimate the as-built progress and compare it to the as-planned progress. In (Golparvar-

Fard et al. 2012 and 2011), the system was further improved by measuring construction progress at schedule activity level.

Golparvar-Fard's approach and the one pursue by the authors (see sections below) have been developed fairly concurrently and clearly present many similarities. The main differences between the two approaches are: Golparvar-Fard's approach is based on digital photogrammetry and space voxelisation, meaning that acquisition is cheap, but 3D reconstruction is sensitive to brightness, surface characteristics and picture overlapping, and data analysis can only detect deviations larger than 5cm (voxel size used by the authors). On the other hand, the proposed approach uses raw laser scanned data (i.e. directly 3D data), meaning that acquisition is more expensive, but it is much less sensitive to environment characteristics, does not require data overlap and deviations as low as 1cm can be detected. It is anticipated that both approaches will continue to evolve in parallel. Both have their strengths and weaknesses which will be better quantified based on further research.

The approaches for semi-automated and automated progress tracking described above are based on single sources of data. El-Omari and Moselhi (2011) proposed a control model using data fusion that integrates several automated data acquisition technologies including bar coding, Radio Frequency Identification (RFID), 3D laser scanning, photogrammetry, multimedia and pen-based computers to collect data from construction sites to generate progress reports, thus supporting efficient time and cost tracking. Data fusion for automated progress tracking is an active area of research.

The work presented in Bosché and Haas (2008) and Bosché (2009) is the basis of the one presented in this paper. In (Bosché and Haas 2008 and Bosché 2009), algorithms for automatically recognizing 3D BIM objects in laser scan point clouds are introduced. Full scale tests using data obtained during the construction of a green field power plant project achieved very promising results (Bosché et al. 2008). Further developments were presented in (Bosché et al. 2009) for visualization of the 3D status of a project and automation of construction dimensional quality control. In (Turkan et al. 2010; Bosché et al. 2010; Turkan et al. 2011), the 3D object recognition system described above was enhanced by linking the 3D BIM and the construction schedule, effectively creating a 4D object recognition system. With the

addition of object recognition conflict resolution and latency rules, the system automates the feedback

loop for schedule updating with high accuracy.  It was validated with data acquired over the course of

construction of a six story concrete structure.

However, this system, and those described above, calculate scheduled and recognized progress by

giving equal weight to all objects in the BIM, regardless of the earned value associated with objects.

Earned Value (EV) is the budgeted cost of the work completed and what can be billed; the percentage of

objects completed is not normally equal to percentage of value earned. Taking the example of steel

erection, EV can be calculated the product of the tons of steel erected (i.e. quantity completed) and the

budgeted cost per ton of steel.

Clearly, for an automated progress tracking system to be useful in practice, it must track EV.  In

this paper, we propose a 5D progress control system which links the output of the automated object

recognition system described in (Bosché 2009; Turkan et al. 2011) to project cost accounts in order to

facilitate more objective and timely EV analysis for automated progress control.

**Earned Value for Construction Progress Control**

The EV technique is the most commonly used method for cost and schedule control as it

combines technical performance, schedule performance, and cost performance within a single framework

(El-Omari and Moselhi 2011; Sumara and Goodpasture 1996).  EVA is performed using the data stored in

cost accounts to evaluate project progress performance. Cost accounts (CAs) are Work Breakdown

Structure (WBS) components used for project accounting (PMBOK® Guide 2008).  Each CA is assigned

a unique code, or account number, that links directly to the account system of the organization

(Hendrickson and Au 1989).  CAs store actual expenses, original cost estimates, material quantity, and

labor input for each type of work in the project for a given period of time.  A typical $50 M project can

have hundreds of CAs.  Each may apply to one or more schedule activities, and the structure of cost codes

typically varies from project to project even for a single contractor.  Still, contractors typically state a

clear preference for EV progress tracking over design object oriented quantity (progress) tracking for

buildings and industrial facilities.

In the EV method, project progress is evaluated in an objective manner using three measures (PMBOK® Guide 2008) (Figure 1):

- *Budgeted Cost of Work Scheduled (BCWS):* measures the work that is planned to be completed in terms of the budgeted cost.

- *Budgeted Cost of Work Performed (BCWP) - Earned Value:* measures the work that has actually been accomplished to date in terms of the budgeted cost.

- *Actual Cost of Work Performed (ACWP):* measures the work that has been accomplished to date in terms of the actual cost.

The significance of these three values is that they distinguish the schedule and cost performances of the project at successive reporting periods. The following performance indicators are calculated based on these three values:

- *Cost variance (CV)*: CV = BCWP-ACWP, with CV>0 indicating cost savings,

- *Schedule variance (SV)*: SV = BCWP-BCWS, with SV>0 indicating schedule advantage,

- *The cost performance index (CPI)*: CPI = BCWP/ACWP, with CPI>1.0 indicating cost savings, and

- *The schedule performance index (SPI)*: SPI =BCWP/BCWS, with SPI>1.0 indicating schedule advantage.

Earned Value is the most commonly used method of progress measurement in the industry. It provides an early warning of performance problems when properly applied (Abba 2001). Integrating this well-accepted and commonly used technique with automated 4D object recognition systems will facilitate more objective and timely progress analysis.  The resulting proposed system is now described.

**Proposed System**

**Automated Object Based Construction Progress Tracking**

In the approach used here (Bosché et al. 2010; Turkan et al. 2010), 3D point clouds are acquired by terrestrial laser scanning periodically through the project in order to provide time-lapsed data on the

as-built status. A 4D model provides data on the as-designed (i.e. as-planned) status of the construction project over time.

Once the 3D point clouds and the 4D model have been registered in the same coordinate system, as-built objects can be recognized, progress estimated, and the schedule updated, all automatically (Figure 2).

*3D Object Recognition:*

The 3D object recognition system that recognizes designed 3D model objects in laser scanned point clouds is built upon the algorithm defined by Bosché and Haas (2008) and Bosché (2009). The system is very robust in terms of occlusions sourced from either 3D model objects or 3D non-model objects (e.g. temporary structures, equipment, people). The system requires the 3D model be loaded in a triangulated mesh format. Then a three-step process is followed:

1. *Coarse Registration of the 3D model and a 3D point cloud into the same coordinate system* performed by manually matching *n* pairs of points selected in the 3D model and the scan,

2. *Fine registration* implementing a robust Iterative Closest Point (ICP) algorithm, and

3. *Object Recognition* using a robust surface-based recognition metric.

The approach is almost entirely automated. Only the first step, coarse registration, is currently performed manually – though a recent article reports on efficient semi-automated coarse registration methods (Bosché, 2011).

Furthermore, object recognition results are improved by importing a project 4D model. This enables the system to automatically construct the 3D model of what is expected to be seen at any point in time as defined by  the schedule . This particularly enables occlusions defined by the schedule-defined 3D model more exactly correspond to those observed in the sensed laser scans, ultimately improving the object recognition performance (Turkan et al. 2010; Turkan et al. 2011).

Finally, recognition results are used to update the schedule (see following Section). In turn, more correct as-planned/schedule-defined 3D models can be generated, resulting in a self-reinforcing feedback loop for progress tracking.

1	In more detail, once a set of laser scans have been fine-registered with the project BIM model, the

2	system computes for each object: (1) the surface that should be recognized based on the scanner's

3	location and taking into account model internal occlusions (as-planned surface, $S_{ap}$); (2) the surface that is

4	occluded by external object (as-built occluded surface, $S_{ab,occl}$); and (3) the recognized surface (as-built

5	recognized surface, $S_{ab,rec}$). "Recognisability" (advanced visibility criterion) and Recognition are then

6	concluded taking these three values into account. An object is considered "recognizable" if $S_{ap} - S_{ab,occl} \geq$

7	$S_{min}$, with $S_{min}$ user-defined but typically set to values such as $50cm^2$. Then, an object is considered

8	recognized if it is "recognizable" and $S_{ab,rec} \geq S_{min}$. Note that the value $S_{ab,rec} /(S_{ap} - S_{ab,occl})$ defines the

9	percentage of recognizable surface that is recognized, and could therefore be used to track partial activity

10	completion such as for brick wall construction. While the system currently visually reports (through

11	color-coding) this recognition percentage, the system currently does not use it for progress estimation;

12	only the binary recognition result is used. There are multiple reasons for this decision, but mainly the fact

13	that early or late construction (i.e. work conducted ahead or behind schedule) can impact the recognition

14	percentage and thus lead to wrong conclusions on progress. Nonetheless, the use of recognition

15	percentages will be further investigated – note that Golparvar-Fard (2012) make use of this percentage in

16	their framework.

17	*Progress Calculation and Schedule Update:*

18	The system calculates construction progress automatically based on the object recognition results

19	from the analysis of scans acquired at any date *ScanDate*. The system estimates progress only for the

20	activities that are on-going, i.e. with scheduled start dates earlier than *ScanDate* and scheduled end dates

21	later than *ScanDate*. This implies that all objects that are built during activities with end dates earlier than

22	*ScanDate* are considered already built, and similarly, the objects built during activities with start dates

23	later than *ScanDate* are considered not built. This assumption is made on the hypothesis that if the system

24	is used frequently enough, then only on-going activities need to be assessed. The system can, however, be

25	altered to search more actively for schedule deviations, particularly early works (by using a 3D model

26	obtained for a later date in the schedule).

1    The system proposed in (Bosché 2009; Turkan et al., 2010, 2011) compares the number of

2    recognized objects with the number of expected objects, i.e. scheduled and "recognizable" from the

3    scanner's different locations. Finally, the recognized and scheduled progress for the on-going activity $i$ at

4    date *ScanDate* are calculated as:

5
$$Recognized\_Prog_i^{ScanDate} = \frac{\sum_{o \in \pi_i} r_o v_o}{\sum_{o \in \pi_i} v_o} \quad [1]$$

6    where $o$ is the object index, $\pi_i$ is the list of objects scheduled to be built during activity $i$, $r_o$ is the binary

7    value of recognition (a percentage could be used instead if partial construction is actively tracked), $v_o$ is

8    the binary value of visibility.

9
$$Scheduled\_Prog_i^{ScanDate} = \frac{\left| ScanDate - StartDate_i \right|_{time}}{\left| EndDate_i - StartDate_i \right|_{time}} \quad [2]$$

10   where $StartDate_i$ and $EndDate_i$ are the start and end dates of the activity $i$, and $\left| ScanDate - StartDate_i \right|_{time}$

11   and $\left| EndDate_i - StartDate_i \right|_{time}$ are the times that have elapsed between *ScanDate* and start day of the

12   activity $i$, and start and end dates of activity $i$ respectively.

13   The estimated progress results are used to update the schedule. For an on-going activity $i$, if

14   $Recognized\_Prog_i^{ScanDate} \neq Scheduled\_Prog_i^{ScanDate}$ then $EndDate_i$ is delayed (or brought forward/advanced)

15   based on the difference between $Recognized\_Prog_i^{ScanDate}$ and $Scheduled\_Prog_i^{ScanDate}$. The resulting

16   updated schedule can be used: (1) by management to identify deviations and then implement corrective

17   actions, but also (2) for the analysis of scans acquired at future dates.

18   In (Bosché et al. 2009; Turkan et al. 2011), the authors also calculate the actual progress to

19   objectively evaluate the performance of the object recognition system:

20
$$Actual\_Prog_i^{ScanDate} = \frac{\sum_{o \in \pi_i} a_o v_o}{\sum_{o \in \pi_i} v_o} \quad [3]$$

1   where $o$ is the object index, $\pi_i$ is the list of objects built during activity $i$, $a_o$ is the binary value of actual

2   presence of the object in the data, $v_o$ is the binary value of visibility. Actual progress is calculated

3   manually for experimental purposes by visually the scan data.

4       It should be noted here that the system calculates the recognized visible progress by considering

5   only the objects visible from the scanner's location(s). Also, it is important to point out that the level of

6   detail in BIM has a direct impact on the system's accuracy. In order to obtain meaningful results using the

7   proposed system, the BIM is detailed at element level such as columns, beams. The BIM used in this

8   research does not contain temporary or secondary elements since the primary focus of this paper is on

9   building skeleton elements only. Nonetheless, such information could bring additional value for (1)

10  tracking progress at finer levels; and (2) more accurately recognize objects by taking into account the

11  occlusions of those temporary or secondary elements on the primary elements of interest. In fact, the

12  current system is able to address this to some level, but can certainly be confused. The system could

13  recognize the formwork, but this needs to be modeled in the BIM. Another solution would be using a

14  combination of 3D and RGB information to address such situation. This is feasible since Laser Scanners

15  now commonly output color information for each scanned point and objects like formworks does not look

16  like concrete. Combinations of object detection and recognition techniques could be investigated.

17      Moreover, as can be seen in equations (1) and (2), the scheduled and recognized progress

18  parameters are calculated by applying equal weight to all BIM objects, regardless of the EV associated

19  with them or the complexity needed to build them. Although these estimated values are adequate to prove

20  the feasibility of using the approach to monitor progress, they are not in themselves adequate for progress

21  tracking in terms of EV. Additional novel steps to track earned value are described in the following

22  sections.

23  **EV Calculations**

24      As described previously, EV analysis is performed using the information stored in individual

25  project CAs. Planned and actual progress data in terms of quantities put in place and/or job hours, as well

11

1 as budgeted and actual expenses are stored in individual project CAs. The approach proposed here uses

2 the output of the automated 4D model recognition system and links with the project CAs to form a 5D

3 model recognition system. The linking is performed manually here, but it will be automated in the future

4 by linking the object recognition algorithms to BIM through IFC files where all cost information can be

5 encapsulated. A conceptual view of the proposed approach is given in Figure 2.

6  The output data from the 4D object recognition system provides the following information: (a)

7 whether the object is expected to be recognized, and (b) whether it is recognized. Separately, each

8 object's quantity (in terms of volume or weight) can be calculated using the project BIM. Since each

9 object belongs to a project CA, linking can be achieved using the object IDs. Finally, EV measures and

10 project performance indicators can be calculated for the project using the material quantity, budget cost,

11 and actual expenses data stored in the cost accounts.

12  Progress tracking algorithms based on the 4D object recognition system presented above (Bosché

13 et al. 2010; Turkan et al. 2011) are modified for EVA by multiplying each object's recognition result

14 (binary value) with the object's value per unit (equations (4) and (5)). For example, quantities of steel and

15 reinforcing bars are in tons, while concrete is typically in cubic meters, and formwork is in square meters.

16
$$Recognized\_Prog_i^{ScanDate} = \frac{\sum_{o \in \pi_i} r_o w_o v_o}{\sum_{o \in \pi_i} w_o v_o} \quad [4]$$

17
$$Actual\_Prog_i^{ScanDate} = \frac{\sum_{o \in \pi_i} a_o w_o v_o}{\sum_{o \in \pi_i} w_o v_o} \quad [5]$$

18 where $o$, $\pi_i$, $r_o$, $a_o$, $v_o$ are the same as in Equations 1 and 2, and $w_o$ is the value per unit.

19  It should be noted here that the "Recognized" progress used in our system corresponds to the

20 "Actual" used in the EV theory, and "Actual" progress used in our system is calculated manually to assess

21 the performance of the proposed system.

22

23

## Experiments

### Data Collection

The proposed approach is demonstrated with real life data acquired from two different construction sites: the Portlands Energy Centre located in downtown Toronto, and the Engineering V Building located on the University of Waterloo's main campus. The Trimble GX 3D laser scanner that uses time-of-flight technology was used to acquire 3D laser scans for both projects. The main technical properties of the scanner are given in Table 1.

Portlands Energy Centre is a 550-megawatt natural gas-fuelled power plant located in downtown Toronto. The project was completed in 2008 (Portland Energy Centre Newsroom 2008). The data used here was obtained from the construction of a steel structure building that is a part of the power plant. The data includes a 3D CAD model of the building provided by the construction company SNC Lavalin, and five laser scans acquired from different locations on two different days, each one week apart from the other (Figure 3).

The Engineering V Building has a steel reinforced concrete structure. The 176,000-square-foot (16,000-square-metre), six storey building was completed in 2010 (Truemner and Morris 2010). The data obtained from the Engineering V Building project includes 3D laser scans, a 3D BIM provided by the architect, and a construction schedule provided by the contractor (Figure 4). The scans were acquired over a period between July 2008 and May 2009. Since it is not recommended to use the laser scanner below 0°C without special equipment (Trimble[TM] GX 3D Laser Scanner Datasheet 2007), and alternative procedures were not available to the authors at the time, no scans were performed between November 2008 and March 2009. The experimental results presented in the following section were obtained using nine different scans conducted on six different dates.

### Analysis of Results

### Portlands Energy Center Project (steel structure)

*3D Object Recognition:* Table 2 presents the object recognition performances of the five laser scans of the building (Bosché, 2009). As can be seen in the table, good recall and precision rates were

achieved with the system. A high recall rate indicates that most building 3D elements present in the scans

are recognized, and a high precision rate indicates that most recognized building 3D elements are in the

scans. Therefore, it can be said that the object recognition approach achieves very good performance of

83% recall and 93% precision on average. However, it is worth noting here that these results were

obtained using the complete 3D model of the structure – as no schedule information was obtained for this

construction project – which results in a significant difference between number of expected (scheduled)

objects and number of recognized objects. Despite the lack of a schedule, the authors believe that the

Portlands project is a good case study for a steel structure, and so it is used for the analysis presented in

the following section. Another reason that affects the precision and recall values is the completeness of

the point cloud. It is a challenging task to capture data from all 3D elements, especially the ones in

smaller sizes which results in an incomplete point cloud and thus lower recall and precision values.

However, in the case of the Portland project's experiment, it was observed that two scans acquired from

opposite corners of the buildings enabled the acquisition of data from each main 3D object contained in

the building BIM.

*Earned Value Tracking:* The Portland building's 3D BIM model contains 612 objects, including

large objects such as columns and beams, and small objects such as wall panel braces or hand rail tubes.

Although good recall and precision rates were achieved with the 3D Object recognition system in this

case (Bosché, 2009), using the number of objects planned and recognized does not adequately represent

the object recognition systems' performance in terms of EV. Indeed, some objects are more `valuable'

than others with respect to project progress and success. For instance, large columns and beams bring

more 'value' than small objects such as wall panel braces or hand rail tubes. It is so because more

material generally implies higher cost. In practice, structural steel work is billed based on tons of steel

erected. Thus, the steel work that has actually been accomplished to date in terms of budgeted cost, i.e.

EV, will be bigger when larger objects are built.

Table 3 presents the object recognition results that were obtained for the scan captured one given

week (week n in Figure 5), and the link between the 4D BIM and project cost accounts established

14

1  through the model object IDs. The object volumes (in cubic meters) were calculated manually using

2  commercial CAD software, and multiplied with steel density (7.85 ton/cubic meter) to calculate each

3  object's quantity. Once this is done, the planned, recognized, and actual quantities of each object in terms

4  of tons were calculated by multiplying each object's quantity with the object recognition results (binary

5  value) using excel sheets. Binary planned and recognized object recognition values are automatically

6  produced by the 4D automated progress tracking system, and exported on excel sheets. Finally, the

7  planned, recognized, and actual EV totals (tons of steel) for that day were calculated using equations 2, 4

8  and 5. This process was conducted using all five scans acquired on two different scanning dates, and the

9  steel structure's construction progress in terms of earned tons of steel installed is presented in Figure 5.

10  As can be seen in the figure, the recognized and actual progress values are very similar. This

11  correspondence results from the good performance of the object recognition system. Table 4 presents the

12  recall and precision rates in terms of EV. As can be seen in the Table, the results have improved

13  significantly when using EV (99% recall and 100% precision on average) instead of using the number of

14  objects (83% recall and 93% precision on average in Table 2). This indicates that the non-recognized

15  objects were minor in nature (i.e. those with lower values) and do not have considerable impact on project

16  progress in terms of EV.

17       However, Figure 5 also indicates a significant difference between planned and recognized (and

18  actual) progress values. These differences are sourced from using the complete project 3D model. It was

19  thus expected that improved results would be obtained when using project 4D models, as detailed in the

20  following section.

21  **Engineering V Building Project (reinforced concrete structure)**

22       *3D Object Recognition:* The object recognition results for the laser scans obtained from the

23  Engineering V building construction site is also presented in Table 2. As can be seen in the table, using a

24  4D model, excellent object recognition performance is achieved (98% recall and 96% precision on

25  average) (Turkan et al. 2011). Of course, 4D models are not always available. Furthermore, the WBS and

26  the level of detail in BIM can both impact the 4D model, and consequently the accuracy of progress

1    tracking. For example, if a general contractor's schedule is available, only the major activities associated

2    with building elements can be recognized and tracked using the proposed system. On the other hand, if a

3    detailed schedule is provided, it may be possible to track progress in more detail, such as temporary

4    structures' progress. Also, it is important to note that the current system is not capable of detecting

5    elements that are ahead of schedule, because those elements will not be present in the 4D model. As a

6    result, physical progress on those elements will not be reported. This situation can be handled by altering

7    system algorithms to search more actively for schedule deviations.

8        *Earned Value Tracking:* The Engineering V Building is a reinforced concrete structure. Although

9    each concrete construction project is unique, the following sequences of activities are common for

10   construction of any cast-in place concrete structures with reinforcement: (1) erect formwork, (2) place

11   reinforcement, (3) place concrete, (4) strip forms. These activities require a variety of resources such as

12   concrete, rebar, formwork, worker hours, equipment hours etc. Earned value analysis for such a

13   construction project requires data from all these resources. Not all of this information was available for

14   the Engineering V Building. Therefore, cubic yards of concrete required for each activity were calculated

15   from the Building's 3D CAD model to illustrate the proposed approach.

16       Analysis similar to that performed for the Portlands project was performed for the Engineering V

17   project. The 4D BIM was linked with the project CAs through the model object IDs, and the object

18   quantities (footings, columns, beams, and concrete slabs) were calculated manually in terms of cubic

19   yards using commercial CAD software.  As with the previous experiment, the planned, recognized, and

20   actual progresses in terms of cubic yards for each scan day were calculated using equations 2, 4 and 5, the

21   results of which are presented in Figure 6.

22       Again, very similar recognized and actual progress results were obtained for all the scans. This is

23   the result of the object recognition system's high performance as mentioned earlier. Table 4 reports the

24   recall and precision rates in terms of EV for the Engineering V Building. As with the Portlands project,

25   the results demonstrate improvement of the system's performance when using EV instead of the "number

1    of objects" approach. Recall and precision rates improved from 98% and 96% (Table 2) to 100% and

2    100% (Table 4) respectively.

3         On the other hand, Figure 6 seems to indicate that the differences between planned and

4    recognized progress values are larger, especially with the scans acquired on later dates (i.e. August 26,

5    2008, August 29, 2008 and September 8, 2008). A variety of factors might explain these differences.

6    First, the project fell slightly behind schedule, and one of the purposes of the system is to be able to detect

7    this. Another potential reason is that due to visibility limitations, the scans did not provide data on all

8    objects related to on-going activities. It is important to note here that 'Planned Progress', as opposed to

9    'Actual Progress' and 'Recognized Progress', does not take visibility into account. It is calculated simply

10   as a percentage of the planned activity duration. Therefore, complete tracking of the on-going activities'

11   progress could not be achieved. While an improved method for calculating 'Planned Progress' could be

12   investigated, this also signifies the importance of capturing a set of scans which cover all the necessary

13   information for progress tracking. In other words, this suggests the need for *planning for scanning* (both

14   spatially and timely). It is critical to plan scanning locations prior to the project start in order to capture

15   every object to be tracked in the scans so that better progress estimates can be determined by the system.

16   Only after ensuring that all objects under investigation have successfully been scanned can any difference

17   between recognized and scheduled progress lead to a conclusion about whether the project is behind or

18   ahead of schedule. Also, the WBS can play an important role in *planning for scanning*. Depending on the

19   level of detail provided in the WBS, scanning procedure can be planned accordingly to capture all the

20   details provided with the WBS. For example, if the formwork activity is provided in the WBS, scanning

21   schedule can be planned to capture formwork and this would add more detail to progress tracking (The

22   writers would like to acknowledge that this idea was suggested by one of the anonymous reviewers of the

23   paper).

24        As described earlier, the 4D object recognition system also reports "recognizability" (i.e.

25   occlusion) level for each model object. In future work, this information could be aggregated to the activity

26   level in order to fine-tune the estimations of planned progress In fact, Golparvar-Fard et al. (2011 &

2012) investigated and reported the impact of occlusion level on reporting physical progress at construction schedule activity level. They introduced an algorithm that uses a Bayesian probabilistic model to automatically monitor changes and assess progress of as-planned elements by comparing with as-built elements. Their algorithm similarly takes occlusions into account and recognizes if building elements are missing because of occlusions or because of changes. The difference with the system presented here is that the present system makes an early binary decision on the "recognizability" of an object and does not take the amount of "recognizable" surface in its final recognition decision (although this can be visually inspected by the user) and consequent progress calculations. Golparvar-Fard's system, on the other hand, uses some equivalent "recognizability" value but uses it directly into the progress calculation algorithm. While this may enable better progress estimations and the identification of partial progress at the object level, we note that partial object recognition values can be sensitive to many external factors, and thus may sometimes be unreliable for inferring partial progress. Future experiments with both systems should be able to clarify this.

## Conclusions and Recommendations

In this paper, a system is proposed that links an automated 4D object recognition system with project cost accounts to facilitate more objective and timely Earned Value analysis for automated progress control. The linking is currently performed manually by relating automated object recognition results with project cost accounts and object quantities on excel sheets. Preliminary experiments were conducted with data obtained from two different construction sites to test the system's performance for automated earned value tracking of volumetric work. Linear objects such as electric cables or state changes such as painting cannot be tracked by the system.

Experimental results are presented that demonstrate reasonably accurate, automated estimation of a project's structural erection progress in terms of EV. It should be pointed out that 'value' is assessed in terms of material cost; however, there might be cases wherein a cheap item is of tremendous value to a project, i.e. value in terms of cost does not always reflect criticality. The experimental results also

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demonstrate the necessity of ensuring that all objects that need to be tracked are present in the scans, i.e. the need for good planning of the scanning process. Current research is focused on "planning for scanning" and on automated EV tracking for piping and HVAC work.

Future research may focus on many related questions. For example, while it is possible to achieve project as-built status close to 100% as-designed, in practice many projects experience late changes due to change requests, design errors or refinements, site problems and other factors. This can lead to a much lower correlation between as-designed and as-built status for some work areas such as piping and HVAC. Research should be conducted to quantify these discrepancies automatically and compensate for them. The next step would be to measure "percent built as-planned" automatically.

## Acknowledgements

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