

Automated Construction Progress Tracking using 3D Sensing Technologies

by

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AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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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, Global Positioning System (GPS), Ultra Wide Band (UWB) indoor locating, hand-held computers, voice recognition, wireless networks, and other technologies in various combinations.

Three dimensional (3D) imaging technologies, such as 3D laser scanners (LADARs) and photogrammetry have shown great potential for saving time and cost for recording project 3D status and thus to support some categories of progress tracking. Although laser scanners in particular and 3D imaging in general are being investigated and used in multiple applications in the construction industry, their full potential has not yet been achieved. The reason may be that commercial software packages are still too complicated and time consuming for processing scanned data. Methods have however been developed for the automated, efficient and effective recognition of project 3D BIM objects in site laser scans.

This thesis presents a novel system that combines 3D object recognition technology with schedule information into a combined 4D object based construction progress tracking system. The performance of the system is investigated on a comprehensive field database acquired during the construction of a steel reinforced concrete structure, Engineering V Building at the University of Waterloo. It demonstrates a degree of accuracy that meets or exceeds typical manual performance. However, the earned value tracking is the most commonly used method in the industry. That is why the object based automated progress tracking system is further explored, and combined with earned value theory into an earned value based automated progress tracking system. Nevertheless, both of these systems are focused on permanent structure objects only, not secondary or temporary. In the last part of the thesis, several approaches are proposed for concrete construction secondary and temporary object tracking.

It is concluded that accurate tracking of structural building project progress is possible by combining a-priori 4D project models with 3D object recognition using the algorithms developed and presented in this thesis.

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Dedication

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Chapter 1

Introduction

1.1 Background and Motivation

Construction projects often suffer from not being on schedule which affects construction productivity in terms of time and cost. That is why project performance in the Architectural / Engineering / Construction and Facility Management (AEC & FM) industry needs to be assessed as thoroughly and as fast as possible in terms of quantities and elements put in place, tests conducted etc. Traditional practice for construction progress assessment involves intensive manual data collection and processing which is labor intensive, expensive and generally results in partial and sometimes erroneous information.

Using new technologies in construction has been shown in several research efforts to improve productivity in construction projects and as a result, save time and cost. Razavi et al. (2008) deployed a unique combination of GPS, RFID and hand held computing technologies to track key construction materials. The impact on project control and productivity has already been proved to be substantial, and the impact on the Canadian construction industry could be considerable if this technology becomes standard on large industrial projects. Some other similar achievements have occurred in the construction industry during the last decade. Earth moving activities have been changed fundamentally using GPS on earth moving equipment blades as feedback for three dimensional (3D) cut-and-fill models as a control signal, and isometric graphical interfaces for the operators (Cho et al., 2004, Kim and Haas, 2002, Seo et al., 2000).

Improved progress tracking, among other things, requires better three dimensional (3D) as-built status tracking. Until recently, accurate and comprehensive 3D as-built status tracking remained impractical since the available technology made it too time and labor intensive. However, developments made in 3D imaging technologies, specifically laser scanning and photogrammetry, and 3D/4D modeling in the last two decades make fast and accurate 3D as-built status tracking possible. Three dimensional (3D) laser scanners, also known as LADARs, are capable of capturing and recording the 3D status of construction sites with high accuracy in short periods of time and have thus the potential to effectively support progress tracking. 3D laser scanning technology has already been used for maintenance and construction projects on existing industrial plants to develop as-built

models, but there are limitations with current commercial software in terms of automated 3D image interpretation.

To address this challenge, this research has developed a system that combines 3D imaging, object recognition, and 4D modeling technologies to track construction project progress. The first novel system was developed (Bosché et al., 2008) for recognizing project 3D model objects in site laser scans. The automated progress tracking system developed here was built upon the automated object recognition system by adding construction schedule information as the fourth dimension. Given a laser scan of a construction site and its acquisition date, the system quasi-automatically recognizes the building elements that are expected to be built at that date and visible in the scan. Results from multiple scans obtained on the same date but from different locations can be aggregated, and the combined recognition results are used to automatically infer site progress status, and subsequently update the schedule. This system was tested with real life data acquired over the course of construction of the Engineering V Building at the University of Waterloo. Experimental results demonstrate the significant potential of this system for automated 3D progress tracking, which should result in improved construction productivity, as well as improved schedule and cost performance for the Canadian construction industry.

1.2 Research Objectives

The objectives of the proposed research are to:

- Develop an automated progress tracking system which uses existing 3D object recognition tools and 4D a-priori information.
- Develop an automated progress tracking system which is applicable for both concrete and steel structures' permanent elements as well as concrete construction secondary and temporary objects.
- Test these algorithms on a significant, longitudinal set of data from a reinforced concrete building test site.
- Develop an approach for automated earned value tracking for projects.
- Explore ways to automatically track some key temporary project assemblies such as scaffolding, shoring and formwork in order to refine the progress estimates.

- Save time and make cost savings for progress tracking.

Experiments with real life data obtained from a reinforced concrete building construction site were used to validate the algorithms; to demonstrate the feasibility of employing the system developed; and to facilitate its transfer to the industry.

In summary, the hypothesis to be examined is that automated structural building project progress tracking is feasible by combining a-priori 4D project models with 3D object recognition.

1.3 Research Scope

This research study was conducted within the following outlined scope:

- Tracking of volumetric progress classes only, but not linear progress or state change tracking
- Tracking of permanent structural elements as well as concrete construction secondary and temporary objects
- Object based and earned value based tracking
- Tracking of steel structures and reinforced concrete structures
- Commercial buildings and large industrial projects

1.4 Research Methodology

This research began with a problem statement and the definition of the preliminary scope and objectives. These led to a comprehensive literature review, which covered a wide spectrum of related information, including studies related to three dimensional imaging technologies, building information modeling, object recognition from three dimensional point clouds, construction planning, scheduling, and four dimensional models for project management, construction progress control, and previous research on automated construction progress tracking.

While field data collection was carried out at a construction site, design of the progress tracking algorithms was also being accomplished. Computational experiments for implementing the algorithms were then conducted. Object based tracking, earned value based tracking, and concrete construction temporary and secondary object's tracking approaches were validated using the data acquired from the construction site. Finally, all the knowledge, experiments, and lessons learned

were documented and presented along with the recommendations for further work. Figure 1.1 shows schematically the research methodology outlined and defined as follows:

Preliminary Stage

- **Problem Statement:** Identify the existing needs and problems in order to define the research idea, objectives and main scope.
- **Literature review**

Design and Implementation Stage

- **Design of the progress tracking and schedule updating algorithms:** The progress tracking and schedule updating algorithms as well as the different progress tracking approaches, i.e. object based progress tracking, earned value based progress tracking, concrete construction temporary object's progress tracking, were designed. The progress tracking and schedule updating algorithms were built upon the automated object recognition system developed by Bosché et al. (2008). This system makes it possible to recognize 3D model objects from site laser scans if a 3D model of the project is available. The designed algorithms calculate the progress and update the schedule using the recognition statistics obtained from the object recognition system.
- **Implementation of the algorithms:** The algorithms designed for progress tracking were implemented in the same software with the automated object recognition system.

Field Trials

- **Field data acquisition:** The automated progress tracking approach presented in this thesis was validated with real life data collected from the Engineering V Building, a reinforced concrete structure, which is located on University of Waterloo's main campus. The construction site was scanned using a time of light laser scanner over a period of time.

Evaluation

- **Analysis of field data to validate the tracking approach:** The collected data will be used to run and validate the progress tracking approach. The field data acquisition and data processing application are described in more detail in Chapter 3.

Conclusions and Recommendations, including Documentation

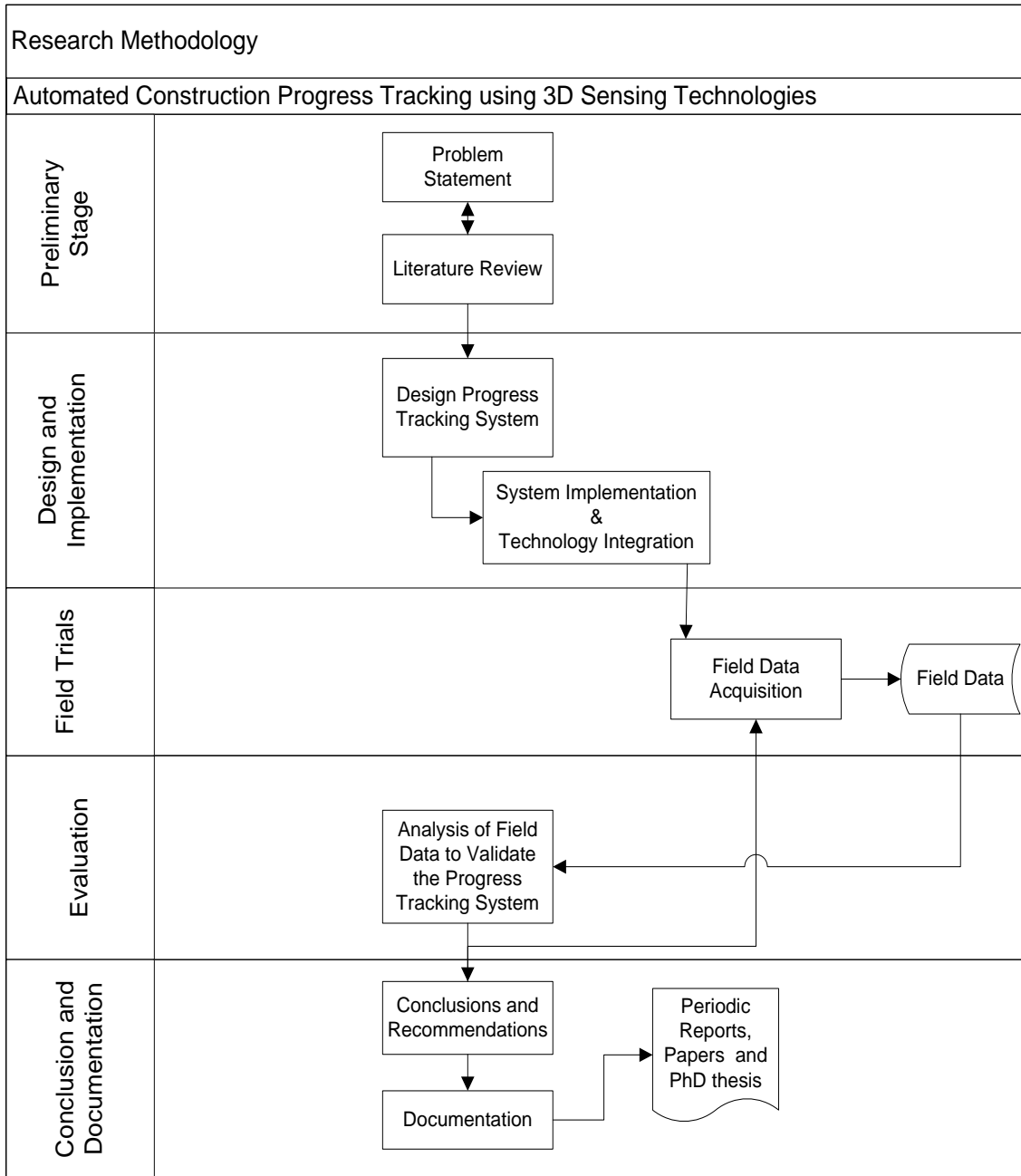


Figure 1.1 Research Methodology

1.5 Thesis Organization

This thesis is organized in seven chapters. Chapter one provides an overview of the research problem and describes the motivation, objectives, scope and methodology of the research. Chapter two provides background knowledge about three dimensional imaging technologies, building information modeling, object recognition from three dimensional point clouds, construction planning, scheduling, and four dimensional models for project management, construction progress control, and automated progress tracking systems. Chapter three presents the field implementation and data acquisition framework for the automated progress tracking system. The automated progress tracking system and the details of the developed object based tracking and earned value based tracking are presented in chapters four and five, respectively. Concrete construction secondary and temporary objects detection and progress tracking techniques are discussed in chapter six. Chapter seven then summarizes the research and presents possibilities for future work. The software implementation document is provided in Appendix E.

Chapter 2

Background and Literature Review

2.1 Need for automation in construction project management activities

Construction project management activities necessitate forward flow of design intent and feedback flow of project or facility state information (Figure 2.1) (Navon & Sacks, 2007 and Haas, 2009). Project planning and design activities that result in 3D design files, project specifications, and schedules may be combined in Building Information Models (BIMs). These constitute the primary information source for forward flow of design intent. Feedback flow of information, on the other hand, is usually derived from progress monitoring activities which are recently becoming more automated and integrated. The comparison of the as-built (feedback) and as-planned (forward) information enables an objective measure of the progress and more generally project performance.

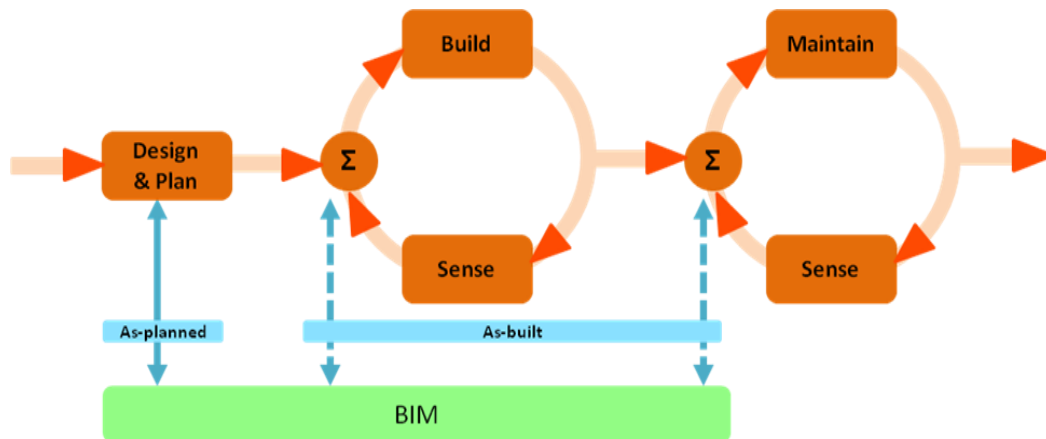


Figure 2.1 Information flow in the control loop

Multidimensional Computer Aided Design (CAD) modeling is one key technology for forward flow in current practice. BIMs are taking the place of CAD modeling as they provide more comprehensive information about the construction design. Three dimensional (3D) sensing technologies, on the other hand, such as total stations, Global Positioning Systems (GPS), Radio Frequency Identification (RFID), Ultra Wide Band (UWB) tags, 3D laser scanning technologies (also called LADAR or LIDAR), and modern photogrammetry are being investigated for providing

information for the feedback flow. Three dimensional laser scanning is a key technology for 3D sensing as it provides fast, accurate and comprehensive information about the scene being scanned.

Fully Integrated and Automated Technologies (Fiatech) Capital Projects Technology Roadmap (Figure 2.2) is a collective vision of how the construction process may be integrated with Information Technology tools. The capital projects industry (i.e. the industry that executes the planning, engineering, procurement, construction and operation of predominantly large-scale buildings, plants, facilities and infrastructure) provides the physical infrastructure that supports the economy. The current situation in the capital projects industry is that it falls somewhat behind other sectors in exploiting technological advances. However, the vision of the future for the capital projects industry is of a highly automated project and facility management environment integrated across all phases of the facility lifecycle. This integrated environment will enable all project partners and project functions to instantly and securely connect their operations and systems. Interconnected, automated systems, processes, and equipment will reduce the time and cost of planning, design, and construction (Fiatech, 2010).

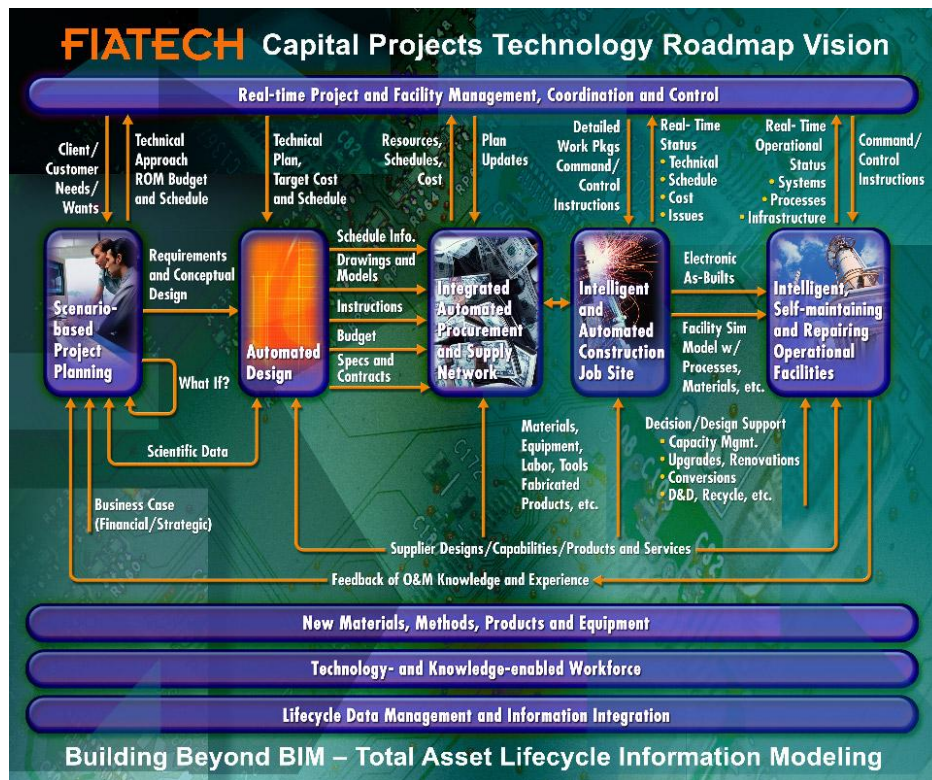


Figure 2.2 Fiatech Roadmap (Courtesy of Fiatech)

Another project on integrated and automated construction processes was initiated by the Building and Research Fire Laboratory (BRFL) at the National Institute of Standards and Technology (NIST). They investigated the challenges and evolving technologies which might be applicable for these processes. It is stated in their report (Palmer, 2009) that NIST is cooperating with the Construction Industry Institute (CII) to measure how combinations of industry best practices and automation and integration technologies impact task and project productivity. In fact, the construction industry has tried to employ many integration and automation technologies, but the success has been limited so far. One of the main reasons is the lack of a general conceptual framework and supporting reference model structure for the monitoring and controlling of the construction processes. To overcome this problem, NIST will adapt their open and scalable reference model structure to support monitoring and control of construction processes by using integration and automation technologies in the industry. To achieve this, NIST is developing standards for performance metrics to evaluate individual sensors (e.g., 3D imaging, calibrated camera networks, RFID, UWB tags), construction object recognition and tracking algorithms. In the scope of this NIST project, Cheok et al. (2008), for example, has started developing standards for performance metrics for 3D imaging systems. These standards are expected to lead to a better service of these technologies in the construction industry, and thus facilitate their adoption by the construction industry.

Project control tasks, such as construction structural (or civil trades) progress and productivity tracking and construction quality assessment and quality control (QA/QC) require 3D as-designed (as-planned) and as-built information organized at the object level. Three dimensional CAD Models and Building Information Models (BIMs) are being used more frequently for project and facility life cycle management. These tools have been key technologies for forward flow. BIMs are still typically built on a project's 3D model which is a 3D representation of the as-designed project dimensional specifications, and organizes 3D as-designed information at the object level. However, sensing technologies do not naturally produce object oriented data.

Three dimensional sensing technologies, such as total stations, Global Positioning Systems (GPS), Ultra Wide Band (UWB) tags, 3D laser scanning technologies, and modern digital photogrammetry that are being investigated for providing 3D as-built information for the feedback flow produce their data in various formats. Three dimensional laser scanning, a key technology for feedback information flow because it provides fast, accurate, comprehensive and detailed 3D as-built information about the scene being scanned, produces vast point clouds of data. When these are

processed properly, they make it possible to compare as-built data (point clouds) and as-designed 3D models, thus supporting more efficient and effective feedback control loops for project control tasks.

Three dimensional laser scanning technologies have already been used in the construction industry for several applications such as creating as-built drawings of industrial plants, and measuring deterioration of infrastructure such as bridges (Park et al., 2007), freeways (Biddiscombe, 2005, Yen et al., 2008, Jaselskis et al., 2005), monuments, and towers. However, their full potential has not been achieved yet, since the currently available commercial packages do not allow automated organization of the data at the object level – some manual and sometimes semi-automated approaches exist, but they are very time consuming, must be operated by experts, and are thus very expensive. However, a method developed by Bosché et al. (2008, 2009) can overcome these limitations, if a project's 3D model is available. This method will be explained in Section 2.4.

2.2 Three Dimensional (3D) Imaging Technologies

A 3D imaging system is a measurement instrument that is used to rapidly measure the 3D coordinates of densely scanned points within a scene. The information gathered by a 3D imaging system is provided in the form of “point clouds” with color and intensity data often associated with each point within the cloud. There are two well known approaches to obtain such clouds: laser scanning and photogrammetry.

2.2.1 Laser Scanning Technology

Three dimensional (3D) Laser scanning, also known as LADAR (Laser Detection and Ranging), is an advanced imaging technology which has been used in industry since the late 1970s. Because of the high cost and poor reliability of early devices, they were not widely utilized until the early 1990s. Technological developments related to computers, optics, and micro-chip lasers make it possible for today's LADAR technology to capture comprehensive and very accurate 3D data for an entire construction scene using only a few scans (Cheok et al., 2002). The 3D data captured is stored as dense range point clouds or point clouds, also referred to as range images and laser scans, respectively. Range images are arrays where a range value is stored in each cell, while laser scans are not organized coherently.

Laser scanners used in the Architectural / Engineering / Construction and Facility Management (AEC & FM) industry fall into two groups based on the technology they use: phase based scanners

and time-of-flight (pulsed) scanners (Jacobs, 2008). With both technologies, each range point is acquired in the equipment's spherical coordinate frame by mounting a laser on a pan-and-tilt unit that provides the spherical angular coordinates of the point. The range is however calculated using different principles. Phase based scanners measure phase shift in a continuously emitted and returned sinusoidal wave. Time of flight scanners send a laser pulse in a narrow beam toward the object and deduce the range by calculating the time taken by the pulse to be reflected off the target and back to the scanner. Phase based and pulsed laser scanners typically achieve similar point measurement accuracies (1.5 mm to 15 mm depending on the range). They differ in scanning speed and maximum scanning range. While pulsed scanners can measure ranges up to a kilometer, phase based scanners are limited to 50 meters. However, phase based scanners can achieve scanning speeds up to 1,000,000 points/second (FARO, 2011) while pulsed scanners can only typically achieve speeds of a maximum of 10,000 points/second.

Among other three dimensional (3D) sensing technologies, laser scanning is currently most likely the best adapted technology for sensing the 3D status of projects accurately and efficiently (Cheok et al., 2000). Shih et al. (2004) investigated the use of 3D laser scanning data to monitor project progress. They concluded that schedule-based scanning facilitates a detailed definition for partially completed construction work, and also provides as-built proof for geometric measurement and visualization. A formal methodology was developed in (Akinci et al., 2006) for active construction quality control using laser scanning, embedded sensors and integrated project models. In this work, the technological feasibility of acquiring frequent, complete and accurate three dimensional and material quality related as-built data from construction sites using laser scanning, embedded and other advanced sensor technologies was explored. The authors concluded that these reality capture technologies can be employed for accurate as-built data collection on construction sites, and they can be leveraged to improve quality control processes. Akinci et al. (2006) proposed a simulation-based framework to model information flow processes from a job site to a field office to measure and highlight existing deficiencies, and to model and demonstrate the effect of using laser scanners and radio frequency identification in streamlining the data collection process for the same project. Their simulation results showed that the time spent on non-value adding activities in the information flow can be reduced significantly by utilizing these automated reality capture technologies. Tang et al. (2010) investigated techniques developed in civil engineering and computer science that can be utilized to automate the process of creating as-built BIMs. In a similar research effort, Brilakis et al. (2010) emphasized that having access to an as-built model of an existing facility can enhance project

planning, improve data management, support decision making, and increase the productivity, profitability and accuracy of a construction project. They stated that as-built data can be collected automatically using laser scanners, but interpretation and merging of point clouds, stitching and object fitting are all performed manually. Therefore, they proposed an approach to automate the generation of as-built BIMs of constructed facilities by using hybrid video and laser scan data as input.

In a study by Greaves and Jenkins (2007), it is shown that the three dimensional laser scanning hardware, software, and services market has grown exponentially in the last decade, and the AEC-FM industry is one of its major customers. This shows that owners and contractors are aware of the potential of using this technology for sensing the 3D as-built status of construction projects. However, current usage of laser scanners in the industry often does not go beyond capturing existing 3D conditions and extracting a few dimensions, tie-in points and cross sections from the three dimensional point clouds of the construction, because current software for point cloud analysis requires time consuming manual data analysis to organize data at the object level. Recently released commercial tools based on algorithms such as those described in early work by Kwon et al. (2004), do allow manually guided, semi-automated fitting of pipe spools (assemblies) to selected volumes of point clouds, but there is still costly labor input required. Thus, most of the information contained in the laser scans is not extracted, so laser scans are not being used to their full potential. As explained above, as-built information needs to be recognizable at the object level to be used to its full potential, and information at the object level is a must for progress tracking purposes (and other control tasks).

2.2.2 Photogrammetry as an alternative technology

Traditionally, photogrammetry is defined as the process of deriving metric information about an object through measurements made on photographs of the object. It is a technique that establishes the geometric relationship between the image and the object accurately as it existed at the time of the imaging event. Once this relationship is correctly recovered, then accurate information about the object can be derived from its imagery (Mikhail, 2001). There are two main different types of photogrammetry applications: aerial photogrammetry and close-range photogrammetry. Aerial photogrammetry has been used as an accurate and cost effective mapping and surface reconstruction technique. Close-range photogrammetry, on the other hand, has been used in diverse applications such as architecture, engineering, automotive, aerospace, forensics, car accident reconstruction, biomechanics, chemistry and biology. Its applications in civil and construction engineering includes

deformation measurements (Niederöst et al., 1997), concrete crack measurements (Liang-Chien et al., 2006), pavement distress surveying (Ahmed et al. 2010), and project progress tracking (Golparvar-Fard et al., 2009, El-Omari et al., 2008).

Despite its presence as a robust and accurate image based approach for a long time, photogrammetry has been rarely used for civil and construction engineering applications. Because expensive metric cameras needed to be used or specific camera configurations were required in the past.

Moreover, in traditional photogrammetry, specific technical data such as lens distortion and three interior orientation parameters need to be known in advance. Additionally, a minimum number of control points need to be visible and measurable in two or more overlapping images, and then exterior orientation parameters should be calculated for a robust re-construction of a 3D CAD model from 2D images. Because of such requirements, photogrammetry has never been used extensively in construction industry.

However, there are some applications where the photogrammetric approach was successful although the camera positions are neither restricted to vertical positions nor located in one plane parallel to the imaged surface. Moreover, when cheap non-metric cameras were used as an alternative to expensive metric cameras, the output accuracy was acceptable (Fryer, 1985). But, even these applications still require several extensive computations, e.g., camera calibration, estimating interior and exterior camera orientation parameters, epi-polar stereo matching and 3D object reconstruction.

Photogrammetry is a well established mapping and surface reconstruction technique. Photogrammetric data is characterized by high redundancy through observing desired features in multiple images. Richness in semantic information and dense positional information along object space break lines add to the advantages of photogrammetry. The most important function of photogrammetry is not only the generation of accurate 3D models, but also it is an ideal technology when measuring features and phenomenon that are inaccessible. Nonetheless, photogrammetry has its own drawbacks; for example, where there is almost no positional information along homogeneous surfaces. A major existing obstacle in the way of automation in photogrammetry is the complicated and sometimes unreliable matching procedure, especially when dealing with convergent imagery with significant depth variations. Moreover it does not penetrate dark interior spaces of buildings.

2.2.3 Selecting the 3D imaging approach

Photogrammetry and laser scanning technologies have their own advantages and disadvantages. Selecting the best approach for a certain application depends on several factors: expertise and technology available, the budget and time available, the field and objects under investigation, and the availability of the required hardware and software. The ideal case would be to exploit advantages of both technologies which may not be affordable in most cases. Habib et al. (2004), El-Omari et al. (2008) proposed approaches integrating photogrammetry and laser scanning. In this research, the choice was to only use laser scanning technology for various reasons, including the ability to penetrate thorough dark interior spaces of buildings.

2.3 Previous Research on Object Recognition

Most object recognition methods that exist were developed for manufacturing control, involving recognition of single objects in controlled environments. For the need addressed in this thesis, the situation is different. Some detection methods have also been developed to recognize 3D objects in somewhat cluttered environments (e.g. spin images), but such feature tracking approaches would fail here because these features do not have the capacity of being discriminative. The approach in (Bosché, 2009) simplifies the search by considering that a good estimation of where to search for objects is given by finding three pairs of matching points to compute a coarse registration of the CAD model and the scan. The approach then enables a robust recognition of each object.

2.4 An object recognition method that uses 3D apriori information

2.4.1 Overview of the 3D object recognition approach used in this research

The recognition system is built upon the algorithm proposed by (Bosché and Haas 2008; Bosché et al. 2010 and Turkan et al. 2012) to recognize designed 3D model objects in laser scanned point clouds. The system is very robust with respect to occlusions sourced from either 3D model objects or non 3D model objects (e.g. temporary structures, equipment, people). It requires converting the input 3D model into triangulated mesh format (STL is currently supported) as a pre-step, and follows a three-step process: (1) Manual coarse registration (2) Model fine registration (3) Object Recognition. These steps are described as follows.

This system and its experimentally validated performance were published in (Bosché, 2009).

Project 3D CAD Model Format Conversion: The 3D information contained in project 3D CAD models must be fully accessible to practically use this object recognition system. However, 3D CAD models are generally stored in protected proprietary 3D CAD engine formats (e.g. DXF, DWG, DGN, etc.). Thus, the 3D CAD model must be converted into an open-source format. Among several open-source 3D data formats, STereoLithography (STL) format, which approximates the surfaces of 3D objects with a tessellation of triangles, was chosen. Because 3D CAD models can be converted into STL format faithfully, i.e. any surface can be accurately approximated with a tessellation of triangular facets. Also it enables simple and efficient calculation of the as-planned points (Step 2). There are several commercial software packages enabling this conversion. NuGraf software from Okino Graphics was used here (Appendix C).

1- Manual coarse registration: It is performed by manually matching n pairs of points selected in the 3D model and in the scan. There are a number of available commercial point cloud processing software enabling registration between point clouds and CAD models including Trimble Real Works (Trimble, 2007), Leica CloudWorx (Leica Geosystems, 2009), FARO Scene (2007). Trimble™ Real Works geo-referencing tool was used here (Appendix E). However, coarse registration is not very reliable as it provided only a few pairs of matched points. In order to achieve a more reliable and improved registration, an additional step, fine registration, can be implemented to check, and if necessary to improve, the quality of the registration.

2- Model fine registration: An optimization algorithm can be developed to start from a coarse registration and then locally search for a better one (in the registration space) (Besl and McKay, 1992). Such local optimization is referred to as fine registration. A robust Iterative Closest Point (ICP) algorithm was specifically developed for this system to perform the fine registration of a large site laser scan with a 3D model of the building under construction as subsequently described. The algorithm is very simple and generally used in real-time. It iteratively revises the transformation (translation, rotation) needed to minimize the distance between the points of two raw scans.

Selection of Data points: All data points can be used for registration. However, this might be time consuming depending on the point cloud size. Instead, a robust sampling algorithm is implemented in this approach which can be used to reduce the processing time without compromising the accuracy of the result.

Calculation of matching Model points: The model is considered to be in a format in which the surfaces of the objects are all triangulated (e.g. STL format). Then, for each scanned *Data point*, a

matching *Model point* is calculated as the closest of the orthogonal projections of the *Data point* on the objects' triangulated facets. This infers that points which have no orthogonal projection on any of the objects' facets are rejected. This corresponds to rejecting points at the borders of objects. Point matching algorithm is explained in detail below.

Error metric: The Mean Square Error (MSE) of the Euclidean distance between pairs of matched points is used as error metric. Additionally, for ensuring the robustness of the metric with respect to outliers, point pairs are rejected when:

(1)The Euclidean distance between two matched points is larger than a threshold τ_D . τ_D is adjusted at each iteration k with the formula:

$$\tau_{Dk} = \max \left(2\sqrt{MSE_{k-1}}; \epsilon_{const} \right) \quad [2.1]$$

where MSE_{k-1} is the MSE obtained at the (k-1)th iteration, and ϵ_{const} is a constant distance that can be interpreted as the maximum distance for which objects with dimensional deviation should be searched. In the results presented in this thesis, $\epsilon_{const}=50$ mm. This value is chosen to be (1) large enough not to fail to recognize objects due to sensor inaccuracies; (2) large enough not to fail to recognize objects that are built at a position up to 50 mm away from their expected position; but (3) small enough not to mismatch *Data* and *Model* points corresponding to different objects.

(2)The angle between the normal vectors to two matched points is larger than a threshold τ_A . In the results presented in this thesis, $\tau_A=45^\circ$, but a smaller value could be preferred.

Termination criterion: The iterative process is stopped when the MSE improvement between the current and previous iterations is smaller than 2 mm^2 .

Point matching algorithm: There are three main matching strategies which have been proposed for ICP algorithms: point-to-point (Besl and McKay, 1992), point-to-plane (Chen et al., 1992) and point- to-projection (Blais et al., 1995). The first two, especially the point-to-plane algorithm, generally result in more accurate registrations (Park et al., 2003 and Rusinkiewicz et al., 2001). The third algorithm, however, enables faster calculations (at each iteration). Among these three strategies, the point-to-plane approach typically converges in less iterations and the point-to-projection converges in the largest number of iterations.

The method in this research uses a point-to-point matching algorithm by combining point rejection and acceleration techniques. The algorithm calculates for each scanned *Data point*, P_D , a matching *Model point*, P_M that is the closest of the orthogonal projections of P_D on the CAD model's triangular facets. This procedure can be accelerated by implementing facet culling techniques that quickly narrow down the set of facets among which the closest projection lies.

Distance-based outlier rejection is commonly applied in ICP algorithms, and is applied here with the threshold τ_D . Thus, as illustrated in Figure 2.3, a frustum can be constructed for each *Data point*, centered on the point's scanning direction (ray), and with opening spherical angles equal to:

$$\alpha_\phi = \alpha_\theta = 2 \arctan (\tau_D / P_D \cdot \rho) \quad [2.2]$$

where $P_D \cdot \rho$ is the range of the given *Data point* P_D . This point's frustum has the following characteristic: If the distance between the point and its orthogonal projection on a facet is lower than τ_D , then the facet must intersect the frustum. Another important characteristic related to the problem here is that the facets of construction project 3D CAD models are naturally grouped into at least three hierarchical groups: single facet, object and model.

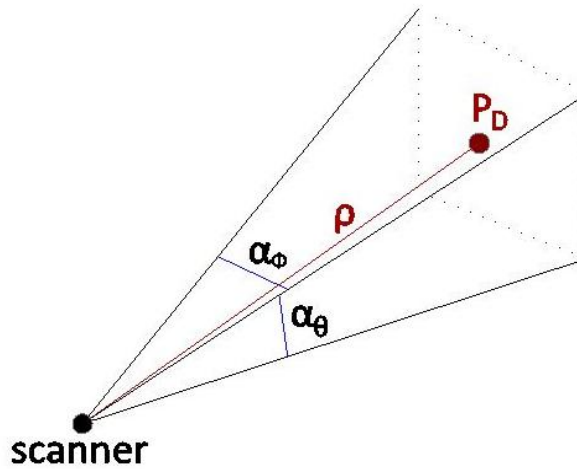


Figure 2.3 Frustum of a Data point, P_D

Based on these observations, the following method to accelerate the designed point-to-point algorithm was developed. First, a Bounding Volume Hierarchy (BVH) is calculated for the project 3D CAD model where each bounding volume is the frustum of a facet hierarchical group, as identified in Figure 2.4. Then, back-facing culling and frustum culling are performed to remove all the facets from the BVH on which no matching point can possibly be found. Finally, for each scanned Data point, its frustum is calculated as described above. The facets on which the matching Model point may be found (i.e. on which the orthogonal projection should be calculated) are identified by going through the model's BVH. They are the facets whose frustums intersect the Data point's frustum. The BVH, back-facing and frustum culling depend on the registration, i.e. location of the scanner, so must be recalculated each iteration of the fine registration algorithm. However, they enable a significant acceleration of the algorithm despite the necessary recalculations.

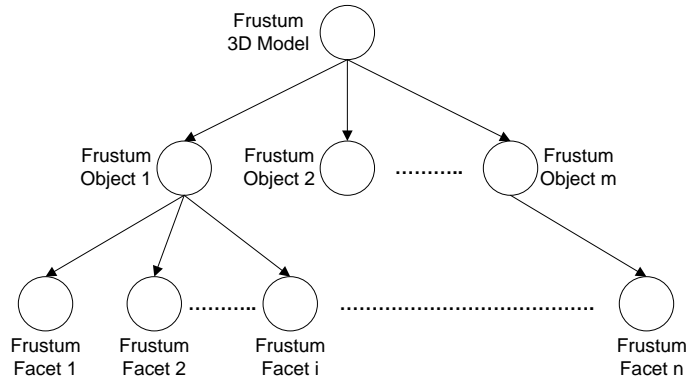


Figure 2.4 Facet hierarchical groups in a 3D CAD model

(3) Object Recognition: At the end of the registration process, the project 3D model and the investigated scan are optimally registered. Further, it is known from which CAD model object the Model points which were matched at the last iteration come from. As a result, each CAD object can be assigned temporary as-designed (Model) and corresponding as-built (Data) point clouds. The analysis of the as-built point cloud can then lead to the recognition of the object itself using the recognition metric defined in (Bosché et al., 2009). For each object, its recognized surface, $Surf_R$, is calculated based on the number of recognized points, their distances to the scanner and the scan's angular resolution. If $Surf_R$ is larger than or equal to $Surf_{min}$, then the object is considered recognized; it is not otherwise. Both $Surf_R$ and $Surf_{min}$ are calculated as a function of the scan's angular resolution. Thus the object recognition metric used here is invariant with the scan angular resolution and the

distance between the scanner and the object. Detailed information can be found in (Bosché et al., 2009)

2.5 Planning, Scheduling, and 4D Models for Project Management

2.5.1 Construction Planning

Construction planning is one of the most challenging phases in the project development cycle (Hegazy, 1999, 2002 and 2006). Effective and good planning is vital for the successful execution of a construction project, and it requires high knowledge and expertise. It is essential to have a good team to perform this difficult task efficiently. The creative and highly experience based nature of this task restricts it to human planners, with little or no help provided by even the fastest computer available (Hegazy, 2002). Construction planning involves the choice of technology, the definition of work tasks, the estimation of the required resources and durations for individual tasks, and the identification of any interactions among the different work tasks. The project budget and the schedule are developed based on the construction plan (Hendrickson, 2000). Construction planning is not an activity restricted to the period after the award of the construction contract. It is also essential during the facility design. Furthermore, re-planning would be needed if problems arise during construction.

Using three dimensional imaging technologies during the construction phase could be beneficial if re-planning is required. As discussed in section 2.1, three dimensional laser scanning technology is one of the key technologies for the feedback information flow in the project cycle as it provides fast, accurate, very comprehensive and detailed 3D as-built information. Having such data would permit identifying any discrepancy between as-planned and as-built data, thus it would give early warning if any problem starts occurring during the construction. Therefore, re-planning could be performed on time to avoid the impact of these problems on the overall schedule, and this would save time and accordingly cost. It might also have an impact on reducing the time required for site visits and saving on travel costs. Because, the planner could do his/her job (re-planning) in the office using the provided comprehensive as-built data (i.e. laser scans) instead of repeatedly walking the site to confirm details. This would save time, and accordingly cost especially if the construction site is located in a remote place.

Planning Steps: Planning involves three main steps: (1) Defining Work Breakdown Structure (WBS), (2) Creating logical relations among tasks, (3) Drawing the Project Network.

A project's work breakdown structure (WBS) is essentially a breakdown of the whole project into numerous tasks that can be managed and controlled separately in order to manage the whole project (Oberlender, 2000). The WBS is created as a logical hierarchical decomposition of the project into different levels of detail, from a broad level, down to a very detailed level (work packages) (Hegazy, 2002). The degree of breakdown varies according to the project size. The smallest element in the decomposition is the "activity" or "task". As shown in Figure 2.5, WBS elements are linked to the contractor's organization breakdown structure (OBS), which defines the different responsibility levels in the organization. The figure also shows that work packages are linked with the company's code of accounts system and the databases of resources, unit cost, and productivity data.

The WBS identifies the tasks and activities that must be performed, but does not provide the order in which they must occur. Therefore, once the WBS of the project is defined, the planning team then establishes the activity interdependencies and identifies logical relationships among activities. The next step after identifying the logical relationships among activities is to represent these activities in a network diagram.

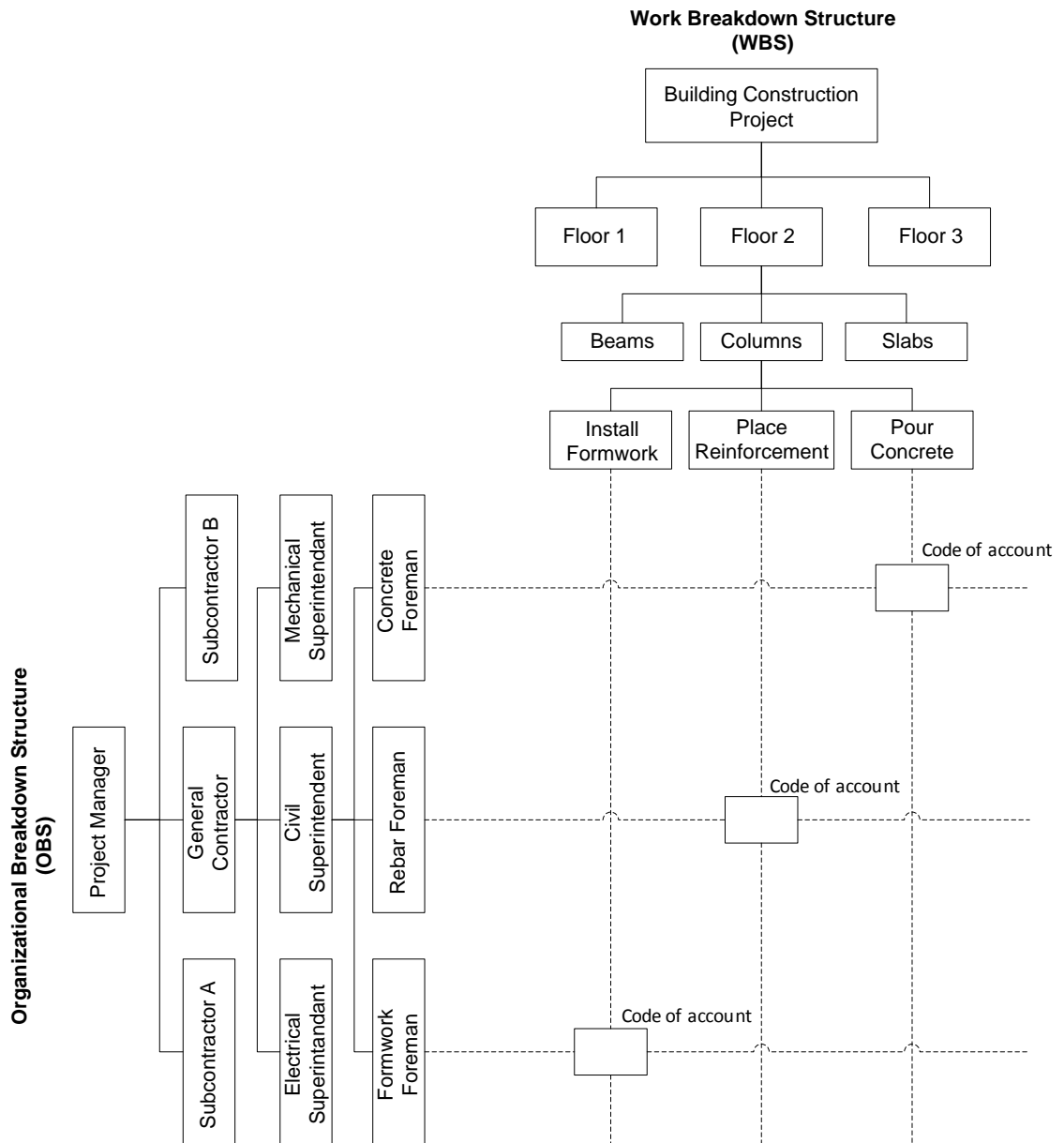


Figure 2.5 An Example of a Work Breakdown Structure (adapted from Hegazy, 2002)

2.5.2 Construction Scheduling

A construction schedule helps to improve management activities, and serves as a good communication tool among project participants (Hegazy, 2002). Project scheduling assigns dates to project activities, and matches the resources of equipment, materials and labor with those activities over time (Hendrickson, 2000). Scheduling also determines the start and finish times of activities, as well as critical and non-critical activities. So it is possible to calculate slack time for an activity which may be used in case of a delay in the project (Hegazy, 2002 and 2006). Good scheduling would eliminate problems due to production bottlenecks, facilitate timely procurement of necessary materials, and insure the completion of a project as early as possible. On the other hand, poor scheduling would result in labor and equipment waste due to waiting for the availability of needed resources or the completion of preceding tasks (Hendrickson, 2000; Hegazy et al. 2011).

CPM Scheduling:

The most common scheduling technique used in construction management is the critical path method (CPM), often referred to as critical path scheduling. This method calculates the minimum completion time for a project along with the possible start and finish times for the project activities (Hegazy, 2002; Hegazy and Menesi 2010). Computer programs and algorithms for critical path scheduling are widely available, and they can efficiently handle projects with thousands of activities. The duration of the critical path is the sum of the activities' durations along the path (Hendrickson, 2000), and it represents the minimum time required to complete a project. In case of a delay along the critical path, additional time would be required to complete the project (Hegazy 2002 and 2006).

2.5.3 Four Dimensional (4D) CAD Models/BIM for Project Planning

A 4D CAD model/BIM links components in the project 3D CAD model with construction schedule activities. The resulting 4D model allows project stakeholders to view the planned construction of a facility over time on the screen and to review a 3D CAD/BIM model for any day, week, or month of the project. An example is shown in Figure 2.6 (Turkan et al. 2010), from the construction site subsequently described in Chapter 3.

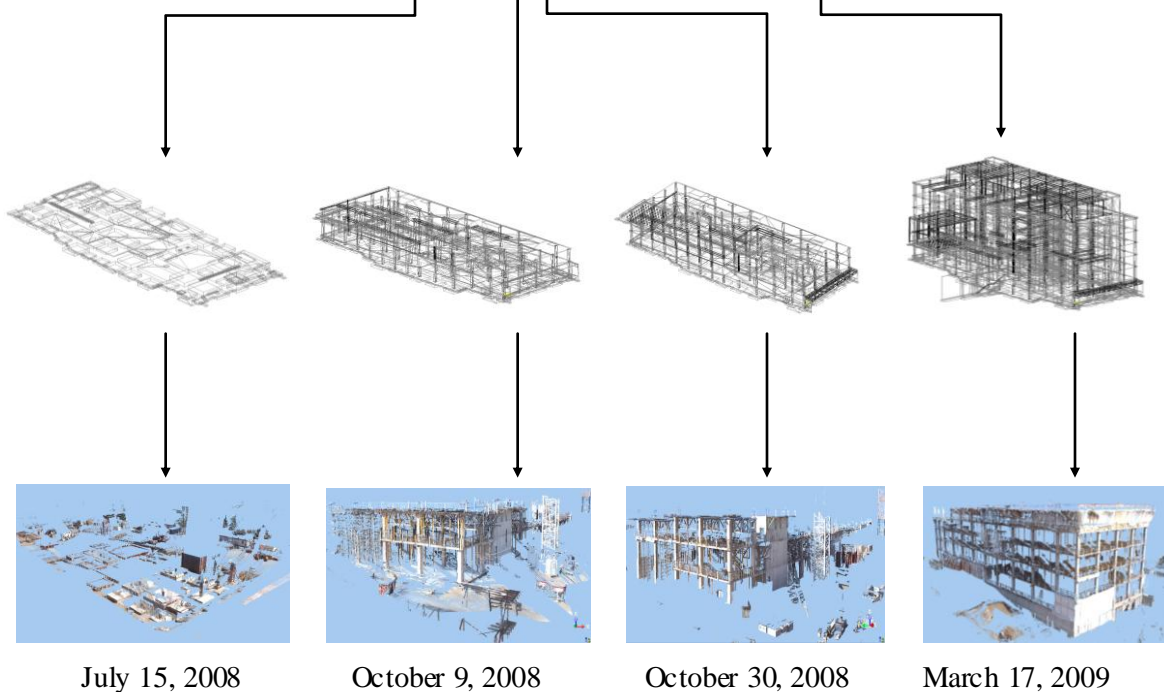
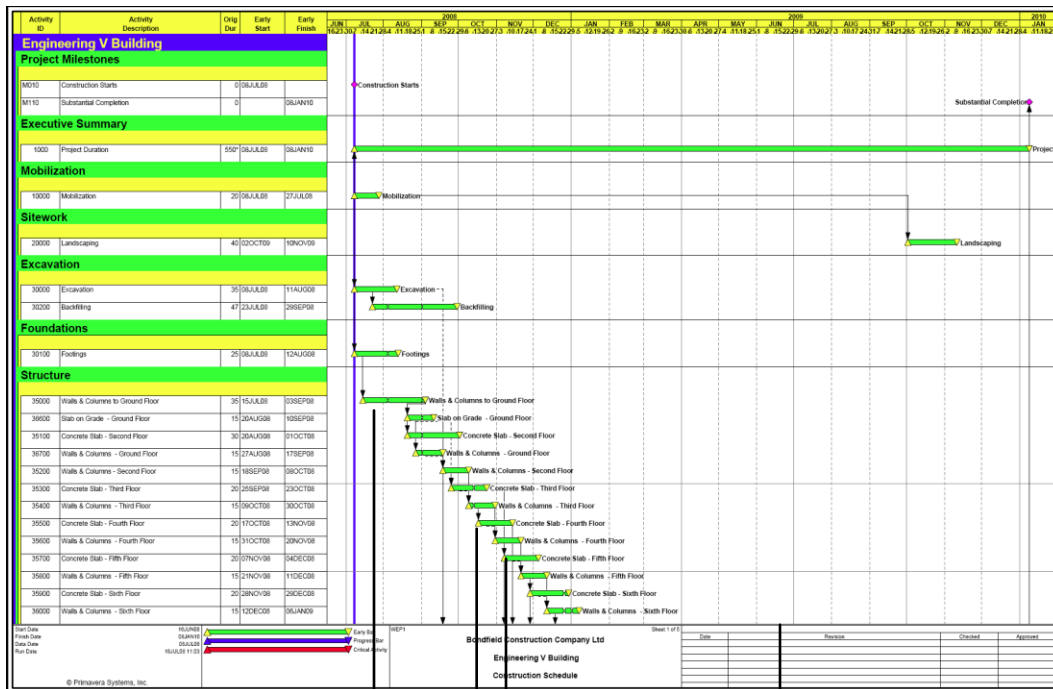


Figure 2.6 Four Dimensional Model

A 4D model enables the project team to visualize time constraints as well as opportunities which can help to improve project schedule, and to identify where the major challenges may occur. During the construction phase, potential spatial conflicts may arise between building components. These conflicts are very hard to identify when coordination is performed using 2D or 3D layouts. The use of 4D models greatly enhances this coordination process. (Hartmann et al., 2008) (Webb et al., 2004)

2.6 Construction Progress Control

Construction sites are very dynamic environments where a number of operations are performed at the same time. Because of all the material delivery and workers gathering to complete their assignments, construction sites become congested soon after the project execution starts (Hegazy, 2002). Progress control is essential for successful delivery of construction projects. Measuring work progress, cost and schedule control, and schedule updating are the main aspects of a progress control system.

2.6.1 Cost and Schedule Control

Earned Value Technique:

The Earned Value technique is very adaptable to the cost and schedule performance analysis in a project (Hegazy, 2002). It combines measurements of technical performance (i.e., accomplishment of planned work), schedule performance (i.e., behind/ahead of schedule), and cost performance (i.e., under/over budget) within a single integrated methodology (El-Omari and Moselhi 2011; Sumara and Goodpasture 1996). Most contractors' cost reporting systems report the quantity completed and how much has been spent. These reports are sufficient for tracking individual cost accounts. However, it is difficult to summarize the results from many cost accounts and look at parts of the project or trends. Instead, converting the quantities (cubic yards, tons etc.) to the "Earned Value" of the quantity completed allows tracking the overall project progress. Earned value can be reported in labor hours, labor cost or total cost. For example, if a ton of steel was estimated at 5 hours/ton, then each ton of steel has a value of 5 hours. Earned value is calculated multiplying quantity completed with the estimated unit rate, or multiplying total estimated cost with percent work completed. Thus, earned value allows combining the progress of different types of works, such as cubic yards of concrete with square feet of forms, tons of rebar, feet of pipe, feet of cabling, etc. More detailed definition of the technique is given below.

Earned value method evaluates project progress in an objective manner using three measures (PMBOK, 4th Edition) (Figure 2.7) which are defined as follows:

Budgeted Cost of Work Scheduled (BCWS): measures the work that is planned to be completed in terms of the budget cost. BCWS S-curve can be plotted by accumulating the budget cost on the schedule that shows the planned percent complete.

Budgeted Cost of Work Performed (BCWP) - Earned Value: measures the work that has actually been accomplished to date in terms of the budget cost. BCWP S-curve can be plotted by accumulating the budget cost on the schedule that shows actual percent complete.

Actual Cost of Work Performed (ACWP): measures the work that has actually been accomplished to date in terms of the actual cost. ACWP S-curve can be plotted by accumulating the actual expenditures on the schedule that shows the actual percent complete.

The significance of these three values is that they directly show the schedule and cost performances of the project at its different reporting periods. The following performance indicators are calculated based on these three values: (1) Cost variance (CV) = BCWP-ACWP, CV>0 indicates cost savings, (2) Schedule variance (SV) = BCWP-BCWS, SV>0 indicates schedule advantage, (3) The cost performance index (CPI) = BCWP/ACWP, CPI>1.0 indicates cost savings, and (4) The schedule performance index (SPI=BCWP/BCWS), SPI>1.0 indicates schedule advantage.

Earned value analysis is the most commonly used method of performance measurement in the industry. It provides an early warning of performance problems when properly applied (Abba, 2001).

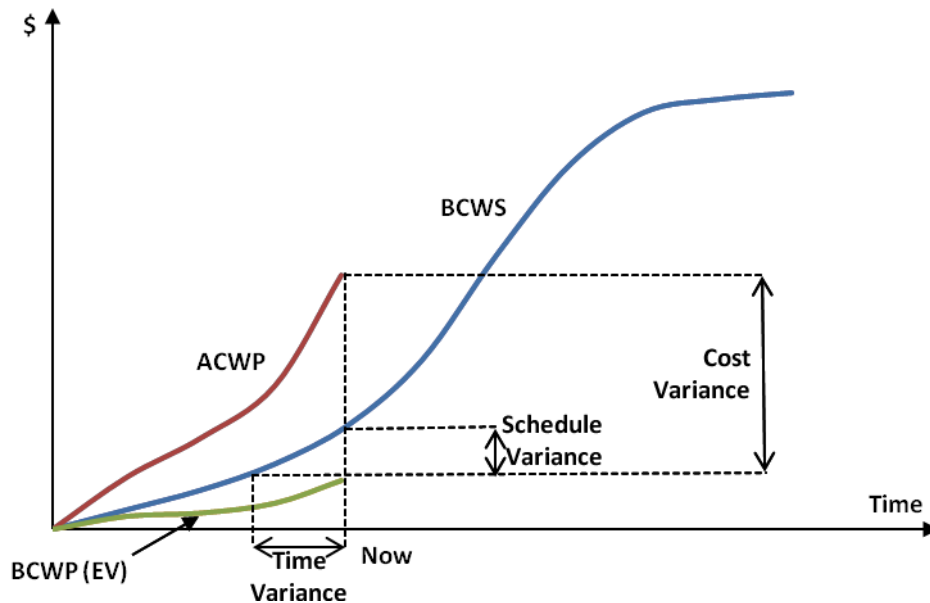


Figure 2.7 Typical EVM Chart (adapted from Hegazy, 2002)

2.7 Previous research on automated construction progress tracking and control

Most research on automated project progress tracking, in contrast to manually based quantity collection efforts, aims to automate the measurement of physical quantities in-place by using spatial sensing technologies. This is feasible for many categories of work such as earth moving, structural erection, and masonry, because products of these construction processes are tangible physical objects. For non-volumetric progress such as painting, tests, and surface treatments, other automated approaches to progress tracking are being investigated by many researchers. An intuitive way to assess the progress would be to geometrically compare the as-built condition with the planned condition. This concept has been supported by a number of research studies (Cheok et al. 2000; Bosché and Haas 2008; Golparvar-Fard et al. 2009)

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 (Cheok et al. 2000; Greaves and Jenkins 2007; Golparvar-Fard et al. 2009; 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 rock, determine road surface elevations, and assist in the creation of as-built drawings. They found that laser scanning technology can be used effectively to make safe and highly accurate construction progress measurements. Shih and Huang (2006) developed an internet based 3D scan information management system (3DSIMS) which enables storage, display and analysis of laser scan data for construction progress measurements. And, Teizer et al. (2007) used real-time 3D imaging to track moving construction objects as crude masses for safety applications. These early advances focused on non-parametric objects or volumetric progress data collection. Another stream of research focused on two related applications of 3D imaging: (1) parametric object modelling, and (2) object recognition.

For example, Kwon et al. (2004) developed algorithms based on the Hough transform and principle axis analysis to fit 3D point clouds to simple 3D parametric objects such as spheres, boxes, and cylinders. These algorithms are now used in commercial software packages that semi-automatically convert 3D scans of industrial facilities into 3D CAD models of piping networks. Tang et al. (2010) investigated the techniques developed for automatic generation of as-built BIMs. Brilakis et al. (2010) analyzed new advances in disciplines such as computer vision, videogrammetry, laser scanning and machine learning, and then demonstrated how they can be used to generate as-built BIMs. Adan et al. (2011) have developed a method to automatically convert 3D laser scanned point clouds into a compact, semantically rich model for buildings, which, while still error prone, represents a tremendous stride towards full automation.

A progress and schedule control system called Photo-net was introduced in (Abeid and Arditi 2003; Abeid et al. 2003). This web based system links digital movies of construction activities with CPM scheduling for progress control, and enables project staff/managers to follow the progress at a construction site in real time. Wu et al. (2010) proposed another image-based approach to estimate project status information automatically from construction site digital images. They developed an object recognition system to recognize construction objects of interest successfully from their construction site digital images. The approach exploits advanced imaging algorithms and a three dimensional computer aided design perspective view to increase the accuracy of the object

recognition, and thus enables acquisition of project status information automatically. Golparvar-Fard et al. (2009a, b) developed an image based system called D⁴AR – Four Dimensional Augmented Reality – for progress monitoring using daily photographs taken from a construction 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. Zhang et al. (2009) developed an 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 into 2D and a model-based fitting approach.

The approaches for 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.

Bosché and Haas (2008), and Bosché (2009) introduced algorithms for automatically recognizing 3D BIM objects in laser scan point clouds. 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.

It is true that progress related to inspections, tests, calibrations, etc., are non-spatial, so there is much opportunity for future research efforts to automate progress tracking in these areas. Already, some progress has been made with rugged, hand held computers that can be used to automate the data entry process to some extent and to reduce transcriptions errors introduced by having to transcribe hand-written reports into project control computers.

Chapter 3

Data Acquisition

The automated construction progress tracking approach presented in this thesis (see Chapter 4 to Chapter 6) is validated with real life data collected from a concrete building construction site. This chapter gives information about the construction site, the data collected, field data acquisition, i.e. laser scanning, and data processing.

3.1 Construction Site



Figure 3.1 Engineering V Building, University of Waterloo main campus

Engineering V Building (Figure 3.1) is located at the University of Waterloo's main campus. The 176,000-square-foot (16,000-square-metre), six story building is a reinforced concrete structure, and is connected to the existing engineering complex by an enclosed pedestrian bridge. The \$55 million project was completed in 2010.

The data collected includes a 3D model, a schedule and a set of field laser scans obtained for the construction of the Engineering V building. The design company produced the 3D CAD model with two levels of detail (i.e. Level 1: Building structure 3D model, Level 2: All 3D column elements in

the model, all 3D beam elements in the model etc. defined as single layers) in *Autodesk Revit™* (a BIM standard), with 1,573 3D elements including columns, beams, walls and concrete slabs (Figure 3.2). The original construction schedule, including twenty activities related to the erection of the building structure, was produced by the general contractor with three levels of detail (i.e. Level 1: Building Project, Level 2: Floor 1, Floor 2, etc. Level 3: Walls & Columns-Floor 1, Concrete Slab – Floor 1, etc.) in Primavera. The complete construction schedule is presented in Appendix A.

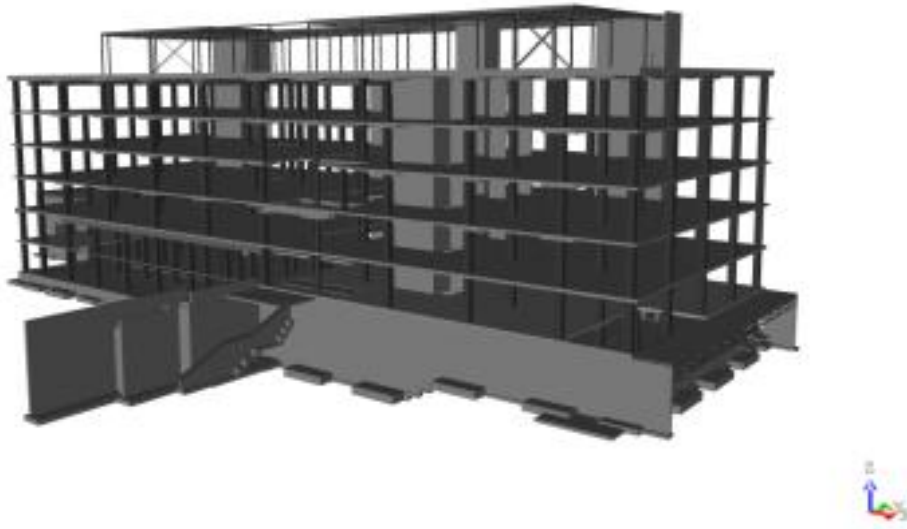


Figure 3.2 Engineering V Building, 3D CAD model

3.2 Field Data Acquisition (3D Laser Scanning)

The construction site was scanned using a *Trimble™ GX 3D* laser scanner (Figure 3.3) from July 2008 until May 2009 (Figure 3.5). Since it is recommended not to use this scanner with external temperatures under zero degrees Celsius, no scan was performed between November 2008 and March 2009¹. The scans contain between 250,000 and 2,600,000 points each, with horizontal and vertical resolutions of 582 μ rad x 582 μ rad. Figure 3.4 shows one of the scans conducted on May 9, 2009. The full scanning schedule is provided in Appendix B.

¹ For regular project use, a warming hut could be used.



Figure 3.3 Scanning at E5 Building construction site on September 26, 2008



Figure 3.4 Scan acquired on May 9, 2009

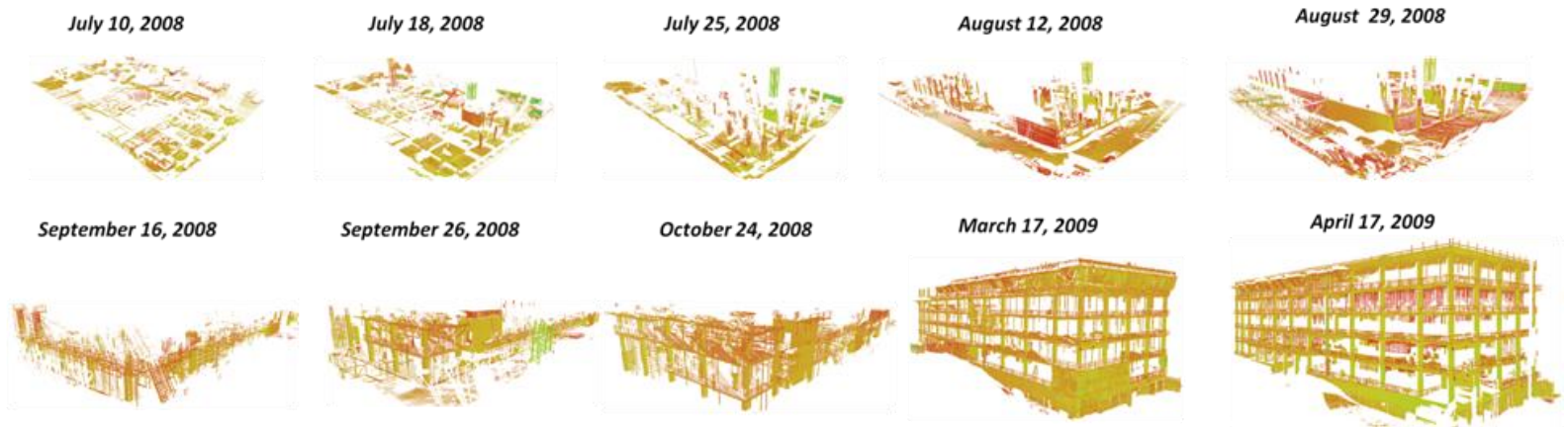


Figure 3.5 Engineering V Building 3D Laser Scan Images

The *Trimble™ GX 3D* Scanner is an advanced surveying and spatial imaging sensor that uses high speed laser and video to capture coordinates and image data (Trimble™, 2007) (Figure 3.6). It uses time-of-flight technology which means that the scanner simply shoots a laser pulse at the object and measures the time taken for the pulse to return to the scanner. Given that the speed of light is constant, the distance from the scanner to the surface of the object can be calculated quite easily. The *Trimble™ GX 3D* scanner allows collecting millions of points for photo-realistic resolution, or it is possible to collect exactly the number of points needed. Main technical properties of the scanner are given in Table 3.1.

Table 3.1 Characteristics of Trimble™ GX 3D Scanner

Laser Type		Pulsed; 532nm; green
Distance	Range	2 m to 200m
	Accuracy	1.5 mm @ 50 m; 7 mm @ 100 m
Angle	Range	Hor: 360°; Vert: 60°
	Accuracy	Hor: 60 μrad; Vert: 70 μrad
Maximum Resolution		Hor: 31 μrad; Vert: 16 μrad
Acquisition Speed		up to 5000 pts/s



Figure 3.6 Trimble GX 3D Laser Scanner

3.3 Data Processing

As explained in Section 2.4, the system used here requires converting the 3D CAD model into triangulated meshes, with a distinct mesh for each model element. The system currently supports the ASCII STL and OBJ formats which are widely available in common CAD and BIM software. In this

thesis, STL format was chosen to be used for various reasons including its computational efficiency. The conversion procedure from CAD to STL format is detailed in Appendix C.

The schedule provided in Primavera format was converted into Planner format (an open source project management software) since the Planner is the only format currently supported by the automated progress tracking system. After this conversion, the schedule file is augmented with an additional field for each activity that states the IDs of the corresponding 3D model objects to generate a four dimensional (4D) schedule of the project. In Figure 3.7, three dimensional (3D) model object IDs can be seen under the “Notes” tab.

WBS	Name	Start	Finish	Work	Priority	Complete	Cost	Notes
1	Construction Starts	Jun 16	Jun 16					
2	Mobilization	Jun 16	Jul 25	30d	500	0%		
3	Excavation	Jun 16	Aug 1	35d	500	0%		
4	Footings - Section 1	Jun 23	Jul 3	9d	500	0%	275,276,277,278,279,280,281,282,283,284,285,286,287,288,289,290,291,292,293,294,295,296,297,298,299,300,...	
5	Footings - Section 2	Jul 4	Jul 16	9d	500	0%	369,376,377,378,379,380,381,383,384,389,390,397,398,399,400,404,405,406,409,410,411,412,413,414,415,416,...	
6	Footings - Section 3	Jul 17	Jul 28	8d		0%	457,458,459,460,461,462,463,464,465,466,467,468,469,470,471,472,473,474,475,476,477,478,479,480,481,482,...	
7	Walls & Columns to Ground Floor - Section 1	Jul 4	Jul 14	7d	500	0%	385,386,391,392,393,394,395,396,401,403,408,505,506	
8	Walls & Columns to Ground Floor - Section 2	Jul 17	Jul 25	7d		0%	507,508,509,511,512,513,514,515,516,517,518,519,533	
9	Walls & Columns to Ground Floor - Section 3	Jul 29	Aug 6	7d		0%	534,598,846,858,859,860,861,862,867,868,968,1571,1572	
10	Backfilling Section 1	Jul 15	Jul 17	3d	500	0%		
11	Backfilling Section 2	Jul 28	Jul 29	2d		0%		
12	Backfilling Section 3	Aug 7	Aug 8	2d		0%		
13	Slab on Grade - Ground Floor - Section 1	Jul 21	Jul 28	6d	500	0%	387,402,407,494,496,497,498,500,540,545,571,599	
14	Slab on Grade - Ground Floor - Section 2	Aug 4	Aug 8	5d		0%	600,840,841,842,843,844,845,847,848,849,851,865	
15	Slab on Grade - Ground Floor - Section 3	Aug 13	Aug 19	5d		0%	866,870,871,878,879,880,881,899,970,971,1573	
16	Walls & Columns - Ground Floor - Section 1	Aug 5	Aug 12	6d	500	0%	29,37,42,48,54,64,70,80,85,96,99,109,115,120,122,128,129,131,137,143,149,155,161,167,173,179,185,191,197,2...	
17	Walls & Columns - Ground Floor - Section 2	Aug 15	Aug 21	5d		0%	333,335,337,339,364,365,366,367,370,520,521,522,523,524,525,526,527,528,529,530,531,532,535,536,537,538,...	
18	Walls & Columns - Ground Floor - Section 3	Aug 26	Sep 1	5d		0%	596,597,617,618,619,620,621,671,722,723,724,725,726,727,728,729,730,731,732,733,734,735,736,737,738,739,...	
19	Concrete Slab - Second Floor - Section 1	Aug 19	Aug 27	7d	500	0%	548,549,550,551,552,553,554,572,573,574,575	
20	Concrete Slab - Second Floor - Section 2	Aug 28	Sep 5	7d		0%	576,882,883,884,885,886,887,888,889,890,891	
21	Concrete Slab - Second Floor - Section 3	Sep 8	Sep 16	7d		0%	892,893,894,895,896,897,898,934,994,1539,1563,1565	
22	Walls & Columns - Second Floor - Section 1	Sep 3	Sep 10	6d	500	0%	39,44,50,56,66,72,87,97,101,111,121,124,130,133,139,145,151	
23	Walls & Columns - Second Floor - Section 2	Sep 12	Sep 18	5d		0%	157,163,169,176,181,188,193,199,205,211,218,224,230,236,242,256,265	
24	Walls & Columns - Second Floor - Section 3	Sep 23	Sep 29	5d		0%	271,319,321,327,331,334,336,338,340,373,622,626,631,636,641,646,675,1545	
25	Concrete Slab - Third Floor - Section 1	Sep 17	Sep 25	7d	500	0%	322,323,382,555,556,557,558,559	
26	Concrete Slab - Third Floor - Section 2	Sep 26	Oct 6	7d		0%	560,561,562,563,564,565,577,1548	
27	Concrete Slab - Third Floor - Section 3	Oct 7	Oct 15	7d		0%	1549,1550,1551,1552,1553,1554,1566	
28	Walls & Columns - Third Floor - Section 1	Oct 2	Oct 9	6d	500	0%	31,33,40,45,51,57,60,67,73,76,82,88,91,98,102,105,112	
29	Walls & Columns - Third Floor - Section 2	Oct 13	Oct 17	5d		0%	117,125,134,140,146,152,158,164,170,175,182,187,194,200,206,212,219	
30	Walls & Columns - Third Floor - Section 3	Oct 22	Oct 28	5d		0%	225,231,237,243,246,250,257,260,266,272,372,623,628,633,638,643,648,1546	
31	Concrete Slab - Fourth Floor - Section 1	Oct 16	Oct 24	7d	500	0%	601,602,603,604,605,606,607,608,609,610,611,612,613,614	
32	Concrete Slab - Fourth Floor - Section 2	Oct 27	Nov 4	7d		0%	615,616,652,653,654,655,656,657,658,659,660,661,662,663	
33	Concrete Slab - Fourth Floor - Section 3	Nov 5	Nov 13	7d		0%	664,665,666,667,668,669,670,672,673,674,675,676,677,1567	
34	Walls & Columns - Fourth Floor - Section 1	Oct 31	Nov 7	6d	500	0%	28,32,35,41,46,52,58,62,68,74,78,83,89,93,95,103,107,113	
35	Walls & Columns - Fourth Floor - Section 2	Nov 11	Nov 17	5d		0%	118,126,135,141,147,153,159,165,171,177,183,189,195,201,207,213,220,226,232	
36	Walls & Columns - Fourth Floor - Section 3	Nov 20	Nov 25	5d		0%	238,244,248,252,258,262,267,273,374,624,629,634,639,644,649,651,1547,1555,1558	

Figure 3.7 Four dimensional (4D) construction schedule

The developed system for automated progress tracking requires the 3D point clouds and the 3D CAD model to be registered in the same coordinate system to extract useful data for progress tracking as explained in detail in Section 2.4. This is done performing a manual coarse registration between the point cloud and the 3D model as a first step which requires the user to find at least three pairs of corresponding points in the scan and the 3D model. There are a number of commercial point cloud processing software packages enabling registration between point clouds and CAD models. *Trimble™ Real Works* geo-referencing tool was used for the analysis presented in this thesis since it is currently available at the University of Waterloo Infrastructure Sensing and Analysis Laboratory. The coarse registration procedure with Trimble Real Works geo-referencing tool is detailed in Appendix E.

Chapter 4

Four Dimensional (4D) Progress Tracking

Efficient and effective construction progress tracking is critical to construction management. Current manual methods, which are mainly based on foremen daily reports or quantity surveyor reports, are time consuming and/or error prone. Three dimensional (3D) sensing technologies, such as 3D laser scanners (LADARs) and photogrammetry are now being investigated and have shown potential for saving time and cost for recording project 3D status and thus to support some categories of progress tracking. Although laser scanners in particular and 3D imaging in general are being investigated and used in multiple applications in the construction industry, their full potential has not yet been achieved. The reason may be that commercial software packages are still too complicated and time consuming for processing scanned data. Methods have however been developed for the automated, efficient and effective recognition of project 3D CAD model objects in site laser scans. A novel system is thus described herein that combines 3D object recognition technology with schedule information into a combined 4D object recognition system with a focus on progress tracking. This system is tested on a comprehensive field database acquired during the construction of the structure of the Engineering V Building at the University of Waterloo (Chapter 3). It demonstrates a degree of accuracy for automated structural progress tracking and schedule updating that meets or exceeds typical manual performance.

4.1 Construction progress tracking

Typical practice for progress tracking mostly depends on foremen daily or weekly reports which involve intensive manual data collection and entail frequent transcription or data entry errors. These reports are then studied by field engineers and/or superintendents along with 2D as-planned drawings, project specifications and construction details to review the progress achieved by that date. After that, they study the construction schedule to identify the work planned to be done by that date. This requires a significant amount of manual work that may impact the quality of the progress estimations (Kiziltas et al., 2005). On building projects, progress numbers may even be simply the claims made by the subcontractors, negotiated with or summarily verified by the general contractor. In essence, current manual methods for progress tracking have limitations in studying project progress precisely, objectively, and quickly.

Attempts to improve progress tracking have recently focused mainly on automation using technologies such as 3D imaging. Bosché et al. (2006, 2009) and Bosché and Haas (2008) introduced a quasi-automated approach for model object recognition by fusing 3D CAD modeling and time stamped 3D laser scanned data. This latter work forms the basis for the further research developments presented herein.

4.2 New Approach

The approach presented in this chapter combines three dimensional (3D) point clouds with project 3D CAD model and schedule information to track construction progress. On one hand, 3D laser scan data provides current site conditions. On the other, the 3D CAD model combined with schedule information (the project 4D model), provides designed (as-planned) spatial characteristics of the facility under construction over time (Figure 4.1). Using such a 4D model, a time-stamped 3D CAD model can thus be formed automatically for a given date.

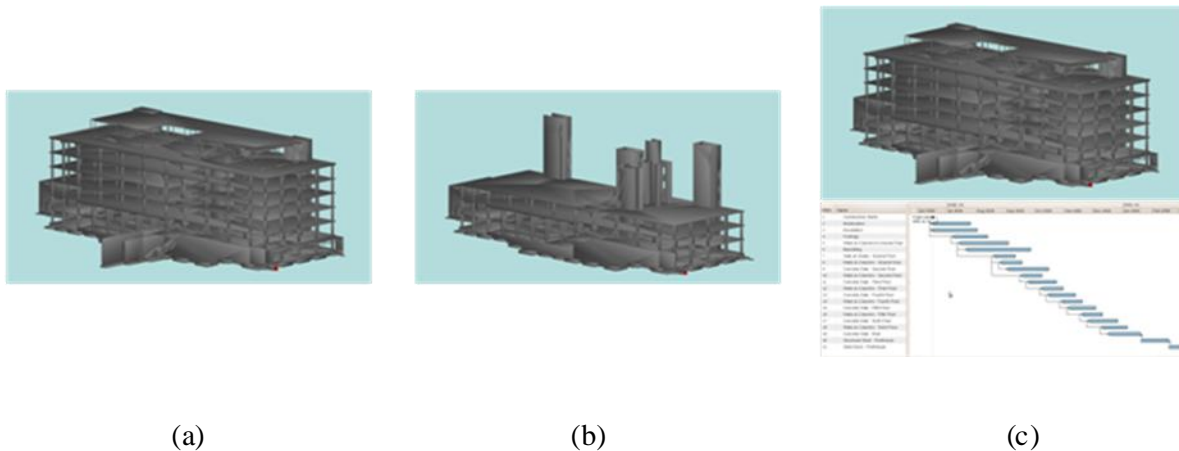


Figure 4.1 (a) 3D model, (b) time-stamped 3D model and (c) 4D model.

The proposed system for automated progress tracking and schedule updating requires the 3D point clouds and the 4D model to be registered in the same coordinate system to be able to extract useful data for progress tracking. Once registered, as-built objects can be recognized, progress estimated, and the schedule updated all automatically (Figure 4.2).

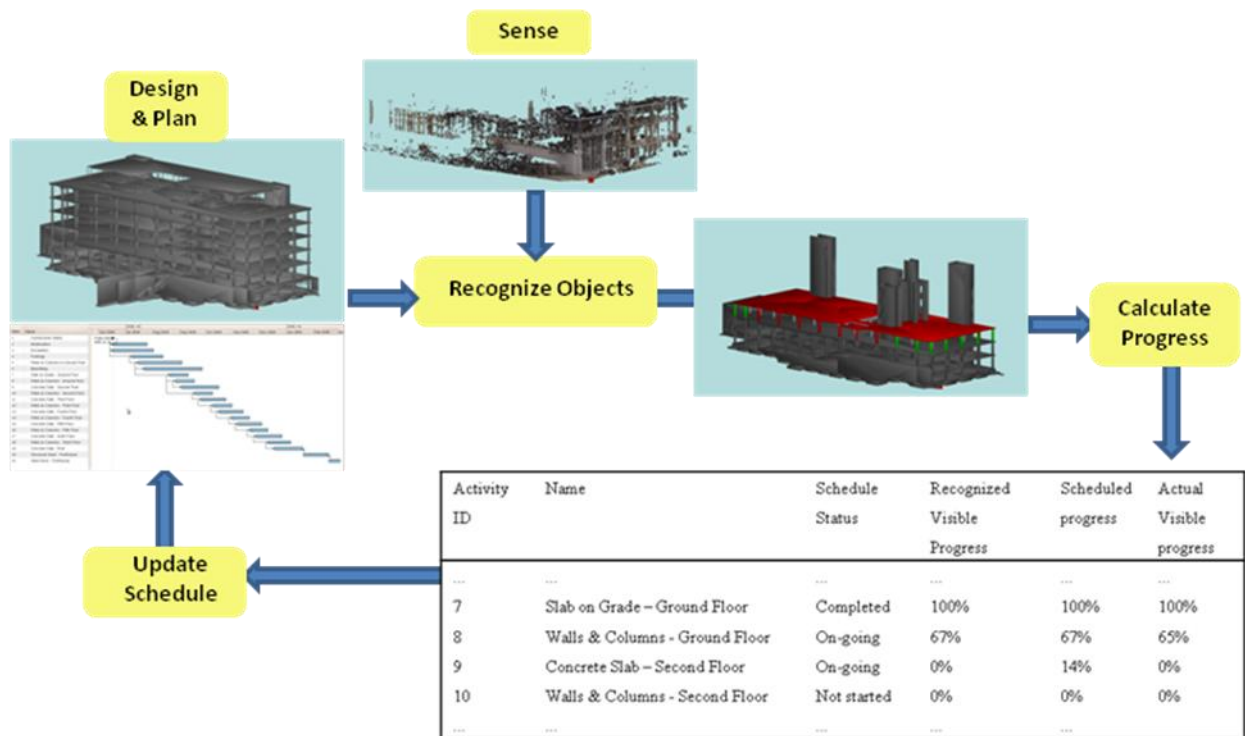


Figure 4.2 Procedure for automated progress calculation and schedule update

4.2.1 Three dimensional (3D) object recognition

The recognition system is built upon the algorithm proposed by Bosché et al. (2009) to recognize designed 3D model objects in laser scanned point clouds. The approach is robust with respect to occlusions sourced from either 3D model objects or non 3D model objects (e.g. temporary structures, equipment, people). The approach requires converting the input 3D model into triangulated mesh format (OBJ and STL are currently supported) as a pre-step, and follows a three-step process:

1. *Manual Coarse Registration* performed by manually matching n pairs of points selected in the 3D model and in the scan;
2. *Model fine registration* implementing a robust Iterative Closest Point (ICP) algorithm;
3. *Object Recognition* using a robust surface-based recognition metric.

The coarse registration step (step 1) is currently performed manually, while the model fine registration and object recognition steps (steps 2 and 3) require that the user define only a few input parameters (though default parameter values generally achieve high recall and precision rates).

Turkan et al. (2010) empirically demonstrated how the use of a time-adjusted 3D model improves the system's performance. While the time-adjusted 3D models used by Turkan et al. (2010) were manually defined from the complete model, the original system of Bosché (2009) has been improved in (Bosché et al., 2010) to enable the user to import true project 4D models (Figure 4.1). Therefore, the system automatically constructs the right time-adjusted 3D model – which is to be compared to the laser scan – based on the laser scan's acquisition date.

4.2.2 Three dimensional progress calculation

Construction progress at date *ScanDate* is calculated by the system based on the object recognition results from the analysis of scans acquired on that date. The system only estimates progress for the activities that are *on-going*, i.e. with scheduled start dates earlier than *ScanDate* and scheduled end dates later than *ScanDate*, as a first step. This means that all objects that are built during activities with end dates earlier than *ScanDate* are considered already built, and similarly the objects built during activities with start dates later than *ScanDate* are considered not built. This is done by the algorithm assigning 100% recognized progress to the activities with the end dates earlier than *ScanDate*, and 0% recognized progress to the activities with start dates later than *ScanDate*. This assumption is made under the premise that, if the system is used frequently enough, then only on-going activities need to be assessed.

For each on-going activity, the system compares the number of recognized objects with the number of expected objects, i.e. scheduled and visible from scanner's location(s). If the number of expected objects for the activity is equal to zero, then the recognized progress is assigned as 0%. Otherwise, the recognized progress for the on-going activity *i* at date *ScanDate* is calculated as:

$$Recognized_Prog_i = \frac{|Obj_{recognized} \cap Obj_{expected}_i|}{|Obj_{expected}_i|} \times 100 \quad [4.1]$$

where $Obj_{expected}_i$ is the set of expected objects for activity *i*, and $Obj_{recognized}$ is the set of recognized objects and $|\bullet|$ is the cardinality operator.

It is possible that the objects recognized on *Scan day 1* may not be recognized on *Scan day 2* due to temporary occlusions, scanning from a different location, etc. This would lead to lower recognized progress estimation for *Scan day 2* than *Scan day 1*. To prevent such situations; when calculating

recognized progress for *Scan day 2*, its recognized progress estimation value is compared with the one of *Scan day 1*, and the higher value is assigned as recognized progress of *Scan day 2*. This is not optimal and keeping track of the recognition of each individual object would be much more appropriate. Nonetheless, the chosen heuristic leads to sufficiently good results and demonstrates the potential impact of the system.

Scheduled progress for each activity is calculated using the following formula:

$$Scheduled_Prog_i = \frac{|ScanDate - StartDate_i|_s}{|EndDate_i - StartDate_i|_s} \times 100 \quad [4.2]$$

where $StartDate_i$ and $EndDate_i$ are the start and end dates of the activity i , and $|Date_B - Date_A|_s$ is the duration (e.g. number of seconds) between $Date_A$ and $Date_B$.

It is important to emphasize here that the system calculates the recognized visible progress by considering only the objects visible from the scanner's location(s).

The schedule is updated based on the estimated progress. First, scheduled progress is calculated for all *on-going* activities using Equation 4.2. Then, for an on-going activity i :

If $Recognized_Prog_i \neq Scheduled_Prog_i$, $EndDate_i$ is delayed (or brought earlier) according to $Recognized_Prog_i - Scheduled_Prog_i$. Finally, the non-started activities are updated based on the predecessor-successor relationships.

The resulting updated schedule can then be used: (1) by management to identify deviations and then implement corrective actions, but also (2) for the analysis of scans acquired at future dates.

4.3 Experiments

A set of experiments has been conducted using real life data to evaluate the performance of the proposed approach. The data collected includes a 3D BIM, construction schedule, and frequent laser scans of the corresponding site. Obtaining this data was the result of a significant and cooperative effort from the different partners of the project, i.e. the owner (the University of Waterloo), the general contractor (Bondfield Construction Company Limited), the design company (RJC), and the UW Construction group research team.

4.3.1 Data

The data is composed of a 3D model, a schedule and a set of field laser scans obtained for the construction of the Engineering V building on the University of Waterloo main campus (a six-story building with cast-in-place concrete structure). The design company produced the 3D CAD model with two levels of detail (i.e. Level 1: Building structure 3D model, Level 2: All 3D column elements in the model, all 3D beams in the model etc. defined as single layers) in *Autodesk Revit™*, with 1,573 3D elements including columns, beams, walls and concrete slabs (Figure 4.1a). The original construction schedule, including 20 activities, was produced by the general contractor with three levels of detail (i.e. Level 1: Building Project, Level 2: Floor 1, Floor 2, etc. Level 3: Walls & Columns-Floor 1, Concrete Slab – Floor 1, etc.) in *Microsoft Project* (Figure 4.3).

The construction site was scanned using a *Trimble™ GX 3D* laser scanner from July 2008 until May 2009. Since it is recommended not to use this scanner with external temperatures under zero degrees Celsius, no scan was performed between November 2008 and March 2009. For regular project use, a warming hut could be used. The *Trimble™ GX 3D* scanner uses time-of-flight. Its main technical properties (Trimble™, 2007) are given in Table 3.1 in Chapter 3.

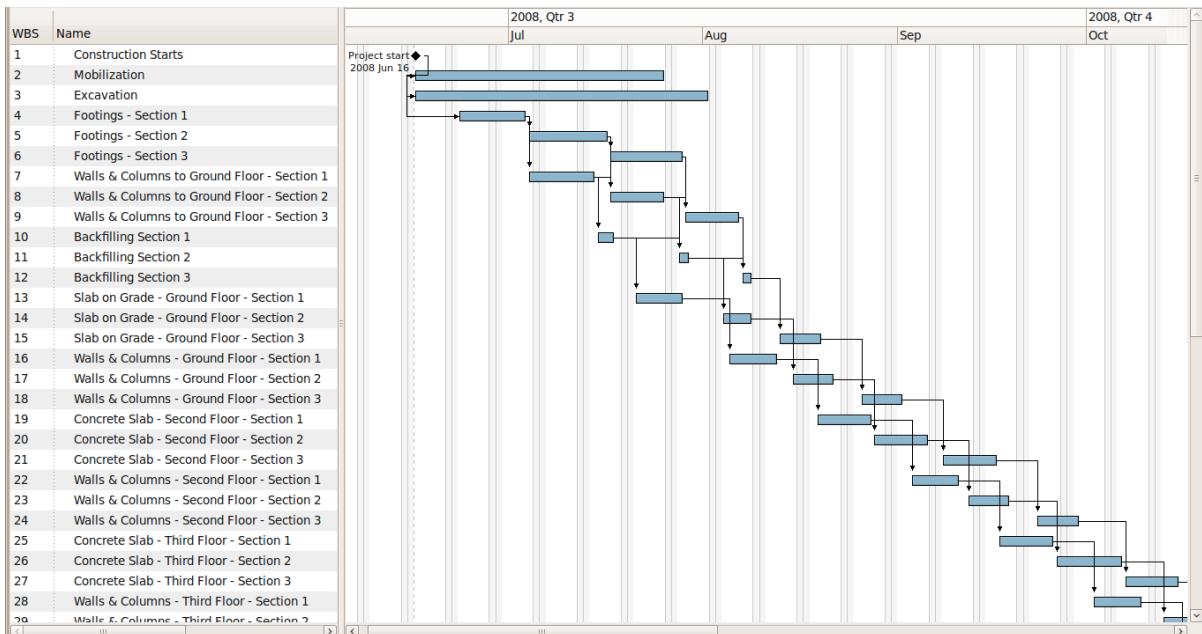


Figure 4.3 Construction schedule of the Engineering V building

The experimental results presented in the following section were obtained using seven different scans conducted on five different dates (Table 4.1). The scans contain between 250,000 and 1,200,000 points each, with horizontal and vertical resolutions of 582 μ rad x 582 μ rad. Figure 4.4 shows one of the scans conducted on August 29, 2008.

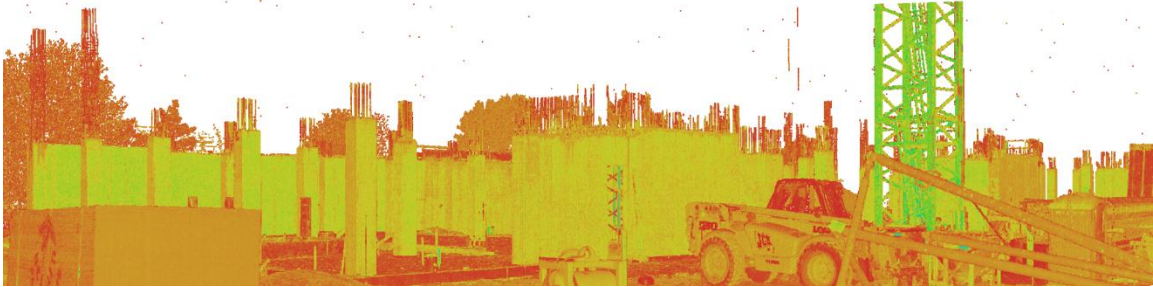


Figure 4.4 Scan acquired on August 29, 2008

As mentioned in Section 4.2.1, the approach used here requires converting the 3D CAD model into triangulated meshes, with a distinct mesh for each model element. The system currently supports the ASCII STL and OBJ formats which are widely available in common CAD and BIM software. Then, the schedule provided in Microsoft Project format, is augmented with an additional field for each activity that states the IDs of the corresponding 3D model objects.

Table 4.1 Object recognition performance

Scan ID	Scan Date	Recall rate	Precision rate
1	August 12, 2008	100%	96%
2	August 19, 2008	98%	96%
3	August 21, 2008	98%	95%
4	August 26, 2008_ST1	100%	98%
5	August 26, 2008_ST2	98%	95%
6	August 29, 2008_ST1	97%	96%
7	August 29, 2008_ST2	97%	94%
Overall		98%	96%

4.3.2 Results

The proposed approaches for 3D object recognition and 3D progress tracking were used to process the data. The following results were obtained:

3D Object Recognition: Table 4.1 shows the object recognition performance of the approach by using recall and precision rates. The precision is the percentage of recognized 3D elements that are actually in the scan(s), and the recall is the percentage of 3D elements present in the scan(s) that are actually recognized. High recall rate indicates that most building 3D elements present in scans are recognized, and high precision rate shows how well the recognition is done without recognizing elements that are not present in the scans. Therefore, it can be said that the proposed object recognition approach achieves very good performance (98% recall and 96% precision on average). A more detailed analysis of these results shows that, for both recall and precision, the small errors (i.e. false negative rate and false positive rate, respectively) generally result from objects with only a few points acquired in the scan, or temporary objects with a few points wrongly recognized as coming from one building 3D element. It is possible to further decrease these two errors by increasing the object recognition threshold that is expressed as a minimum recognized surface, $Surf_{min}$ (m^2). For each object, its recognized surface, $Surf_R$, is calculated based on the number of recognized points, their distances to the scanner and the scan's angular resolution. If $Surf_R$ is larger than or equal to $Surf_{min}$, then the object is considered recognized; it is not otherwise. Both $Surf_R$ and $Surf_{min}$ are calculated as a function of the scan's angular resolution. Thus the object recognition metric used here is invariant with the scan angular resolution and the distance between the scanner and the object. The reader is referred to (Bosché, 2009, Bosché et al., 2009) for more detail.

As described in Section 4.2, the approach requires having a 4D model of the structure to automatically recognize its objects from their laser scans, and calculate its progress. In this project, the 4D model did not include information about rebar or formworks. Thus, object recognition and progress estimation couldn't be performed to that level of detail.

3D Progress Tracking: Table 4.2 and Table 4.3 present the progress tracking results for the scan data acquired between August 12, 2008 and August 29, 2008 using the original project schedule and the constantly automatically updated project schedule, respectively. Three different types of progress are given in Table 4.2 and Table 4.3: The Recognized Visible Progress, The Scheduled Progress, and The Actual Visible Progress as defined in Equations [4.1], [4.2], and [4.3], respectively.

Table 4.2 shows the progress tracking results (on-going activities only) for the scans acquired between August 12th, 2008 and August 29th, 2008 using the original schedule of the construction project without updating, and Table 4.3 shows the progress tracking results for the same scan data set using the constantly updated schedule. In Table 4.3, the original schedule is used to obtain the progress tracking results for the first scan (acquired on August 12th, 2008), while all the other results are obtained using the updated schedules, i.e. schedules output from the analysis of the previous scans.

Table 4.2 Progress tracking using the original construction schedule

Scan Day	ID	Activity Name	Start Date	End Date	Recognized Visible Progress	Scheduled progress	Actual Visible Progress
2008-08-12	7	Slab on Grade - Ground Floor	2008-07-20	2008-08-19	67%	67%	65%
	8	Walls & Columns - Ground Floor	2008-08-04	2008-09-01	21%	32%	20%
	9	Concrete Slab – 2nd Floor	2008-08-18	2008-09-16	0%	0%	0%
2008-08-19	7	Slab on Grade - Ground Floor	2008-07-20	2008-08-19	67%	100%	100%
	8	Walls & Columns - Ground Floor	2008-08-04	2008-09-01	48%	57%	48%
	9	Concrete Slab – 2nd Floor	2008-08-18	2008-09-16	0%	3%	0%
2008-08-21	7	Slab on Grade - Ground Floor	2008-07-20	2008-08-19	100%	100%	100%
	8	Walls & Columns - Ground Floor	2008-08-04	2008-09-01	49%	67%	50%
	9	Concrete Slab – 2nd Floor	2008-08-18	2008-09-16	0%	10%	0%
2008-08-26	7	Slab on Grade - Ground Floor	2008-07-20	2008-08-19	100%	100%	100%
	8	Walls & Columns - Ground Floor	2008-08-04	2008-09-01	60%	71%	65%
	9	Concrete Slab – 2nd Floor	2008-08-18	2008-09-16	0%	27%	0%
2008-08-29	7	Slab on Grade - Ground Floor	2008-07-20	2008-08-19	100%	100%	100%
	8	Walls & Columns - Ground Floor	2008-08-04	2008-09-01	71%	86%	72%
	9	Concrete Slab – 2nd Floor	2008-08-18	2008-09-16	0%	40%	0%

In Table 4.2, it can clearly be seen that the recognized visible progress values are quite different from the scheduled ones. This could lead to the conclusion that the project is behind schedule. Some of the results presented in Table 4.3 tend to show that these differences were in fact mainly due to the use of a non-updated schedule. For instance, the difference was decreased from 9% (57% - 48%) to 0% (48% - 48%) for Activity 8 and from 3% (3% - 0%) to 0% (0% - 0%) for Activity 9 on August 19, 2008. This shows that using updated schedules, which are generated automatically by the system, improves the system's performance in the case that a project is behind schedule. However, there is still 8% difference between the scheduled and recognized progress values for Activity 8 on August 21, 2008, 14% difference for Activity 9 on August 26, 2008, and 10% and 17% differences for Activities 8 & 9 on August 29, 2008, respectively (Table 4.3). Multiple reasons may explain these values. First, the project was observed to be indeed a bit behind schedule. Then, the scans did not provide data on all objects related to the on-going activities (visibility issue). Therefore, the complete tracking of their progress could not be achieved. This signifies the importance of capturing a set of scans which covers all the necessary information for progress tracking. In other words, this suggests the need for *planning for scanning*, including a planned schedule. Another reason may be found in the progress estimation formulas. In any case, this shows the importance of having all objects present in the scans, i.e. good planning for scanning is essential prior to the project start to ensure having all the objects to be tracked in the scans so that more precise progress estimates can be made by the system. Thus, any difference between recognized and scheduled progress could then lead to the only conclusion that the project is either behind or ahead of schedule.

Despite these issues, the recognized visible progress appears similar to the actual visible progress (this relates to the very high recall and precision rates of the object recognition algorithm). Therefore, it can be concluded that, if the scans did contain data about all the objects related to on-going activities, then the recognized visible progress would have been similar to the expected progress (when using the constantly updated schedule with the current system).

Table 4.3 Progress tracking using the constantly updated construction schedules

Scan Day	ID	Activity Name	Start Date	End Date	Recognized Visible Progress	Scheduled progress	Actual Visible Progress
2008-08-12	7	Slab on Grade - Ground Floor	2008-07-20	2008-08-19	67%	67%	65%
	8	Walls & Columns - Ground Floor	2008-08-04	2008-09-01	21%	32%	20%
	9	Concrete Slab – 2nd Floor	2008-08-18	2008-09-16	0%	0%	0%
2008-08-19	7	Slab on Grade - Ground Floor	2008-07-20	2008-08-19	100%	100%	100%
	8	Walls & Columns - Ground Floor	2008-08-04	2008-09-01	48%	48%	48%
	9	Concrete Slab – 2nd Floor	2008-08-22	2008-09-22	0%	0%	0%
2008-08-21	7	Slab on Grade - Ground Floor	2008-07-20	2008-08-19	100%	100%	100%
	8	Walls & Columns - Ground Floor	2008-08-04	2008-09-01	50%	58%	50%
	9	Concrete Slab – 2nd Floor	2008-08-22	2008-09-22	0%	0%	0%
2008-08-26	7	Slab on Grade - Ground Floor	2008-07-20	2008-08-19	100%	100%	100%
	8	Walls & Columns - Ground Floor	2008-08-04	2008-09-02	67%	67%	65%
	9	Concrete Slab – 2nd Floor	2008-08-22	2008-09-22	0%	14%	0%
2008-08-29	7	Slab on Grade - Ground Floor	2008-07-20	2008-08-19	100%	100%	100%
	8	Walls & Columns - Ground Floor	2008-08-04	2008-09-03	71%	81%	72%
	9	Concrete Slab – 2nd Floor	2008-08-22	2008-09-26	0%	17%	0%

4.4 Conclusions

An automated construction progress tracking system which integrates 4D modeling and laser scanning is tested with the data collected from a concrete superstructure construction site in this chapter. Progress tracking is a critical management task for construction projects, and the current manual tracking methods such as using foremen daily reports, are time consuming and/or error prone. The system used here automates and increases the accuracy of this time-consuming management task by calculating construction progress and updating project schedule automatically. Experimental results show that the system's performance is promising. However, the existence also of incomplete input scan data explains why these were less than perfect results, and indicates the importance of ensuring that a set of scans captures all necessary data for progress tracking, i.e. planning for scanning needs to be addressed. Another reason may be found in the progress estimation formulas. The current approach takes occlusions into account when calculating the recognized progress, but this does not necessarily lead to appropriate results. For instance, the system will recognize 100% progress in the case where 4 out of 10 objects of an activity are built and visible in the scan(s), and the 6 others are not built yet and are invisible in the scan. However, there are also cases when taking occlusions into account gives more appropriate results. This shows the importance of having all objects present in the scans, i.e. *planning for scanning*. The system already enables calculating updated schedules, and the experimental results presented in this chapter show that using updated schedules instead of the original project schedule gives better progress estimation results. Better results; i.e. recognized progress corresponds to expected progress; can be expected with comprehensive field data. Thus, as future work, the system will be tested using a significant field database, acquired during the construction of the structure of the Engineering VI Building at the University of Waterloo. Furthermore, it is acknowledged that the current estimations of the scheduled and recognized progresses have some limitations (i.e. all objects are given the same weight in the calculation of the recognized progress, regardless of the earned value associated with them or the complexity to build them). Although these are sufficient to prove the feasibility of using the approach of Bosché (2009) to monitor progress, this limitation is addressed by combining the system with Earned Value Theory which is discussed in Chapter 5.

Chapter 5

Automated Earned Value Tracking

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. Significant progress has been made. However, one limit to date of these approaches is their focus on counting objects or milestones rather than value. In this chapter, an a priori 4D model driven, 3D object recognition based, 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 billing. The contribution of this part of the thesis is an argument based on scientific results for refocusing future research onto automated earned value tracking which is ultimately what is needed in practice.

5.1 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 chapter) 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 gaps in the knowledge that remain. The following section reviews relevant concepts related to earned value. Then, the experimental results are presented and interpreted.

5.2 Three Dimensional (3D) Imaging Based Approaches to Automated Progress Tracking

Bosché and Haas (2008), and Bosché (2009) introduced algorithms for automatically recognizing 3D BIM objects in laser scan point clouds. 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. Taking the example of steel erection, Earned value (EV) can be calculated by the product of the tons of steel erected (i.e. quantity completed) and the budgeted cost per ton of steel. EV is the budgeted cost of the work completed and what can be billed. So, the percentage of objects completed is not normally equal to percentage of value earned.

Clearly, for an automated progress tracking system to be useful in practice, it must track earned value (EV). In this chapter, we propose a 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.

5.3 Earned Value for Construction Progress Control

The Earned Value (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). EV analysis is performed using the data stored in cost accounts to evaluate project progress performance. Cost accounts (CA)

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 labour input for each type of work in the project for a given period of time. A typical \$50 M project can have hundreds of cost accounts. Each may apply to one or more schedule activities, and the structure of costs 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 2.7):

- *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 directly show 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 3D and 4D object recognition systems will facilitate more objective and timely EV analysis. Those systems are described next. Then, the conversion to earned value is explained.

5.4 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 5.1).

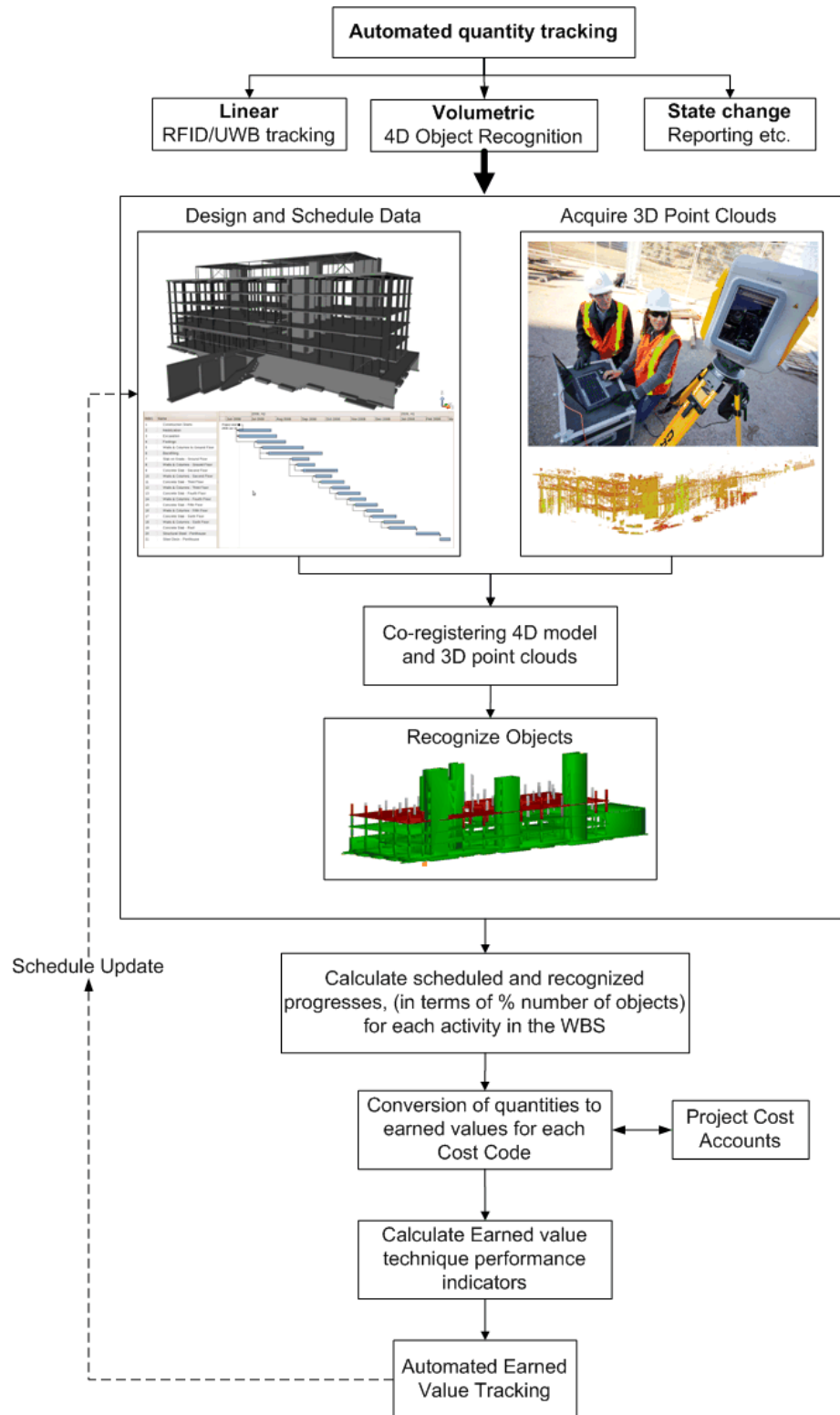


Figure 5.1 Conceptual view of the components of the system for Volumetric Progress Classes

Three dimensional (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). It is necessary to first convert the 3D model into triangulated mesh format. Then a three-step process is followed (as detailed in section 2.4):

- *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,
- *Fine registration* implementing a robust Iterative Closest Point (ICP) algorithm, and
- *Object Recognition* using a robust surface-based recognition metric.

The approach is thus mostly 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). 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 the schedule (or time) which results in fewer occluded objects that may confuse the object recognition system (Turkan et al. 2010; Turkan et al. 2011).

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

Three Dimensional Progress Calculation and Schedule Update:

The system calculates construction progress automatically based on the object recognition results from the analysis of scans acquired at any date *ScanDate*. The system estimates progress only for the activities that are on-going, i.e. with scheduled start dates earlier than *ScanDate* and scheduled end dates later than *ScanDate*. This implies that all objects that are built during activities with end dates earlier than *ScanDate* are considered already built, and similarly, the objects built during activities with start dates later than *ScanDate* are considered not built. This assumption is made on the hypothesis that if the system is used frequently enough, then only on-going activities need to be assessed. The system can, however, be altered to search more actively for schedule deviations, particularly early works.

The system compares the number of recognized objects with the number of expected objects, i.e. scheduled and visible from scanner's location, for each on-going activity. (A proper staged combination of scanning positions should reveal all objects in practice). Finally, the recognized and scheduled progress for the on-going activity i at date $ScanDate$ are calculated as:

$$Recognized_Prog_i^{ScanDate} = \frac{\sum_{o \in \pi_i} r_o v_o}{\sum_{o \in \pi_i} v_o} \quad [5.1]$$

where o is the object index, π_i is the list of objects scheduled to be built during activity i , r_o is the binary value of recognition, v_o is the binary value of visibility.

$$Scheduled_Prog_i^{ScanDate} = \frac{|ScanDate - StartDate_i|_{time}}{|EndDate_i - StartDate_i|_{time}} \quad [5.2]$$

where $StartDate_i$ and $EndDate_i$ are the start and end dates of the activity i , and $|ScanDate - StartDate_i|_{time}$ and $|EndDate_i - StartDate_i|_{time}$ are the times that have elapsed between $ScanDate$ and start day of the activity i , and start and end dates of activity i , respectively.

The estimated progress results are used to update the schedule. Scheduled progress for all on-going activities is calculated using Equation 5.2 as the first step. Then, for an on-going activity i , if $Recognized_Prog_i^{ScanDate} \neq Scheduled_Prog_i^{ScanDate}$ then $EndDate_i$ is delayed (or brought forward/advanced) based on the difference between $Recognized_Prog_i^{ScanDate}$ and $Scheduled_Prog_i^{ScanDate}$. The resulting updated schedule can be used: (1) by management to identify deviations and then implement corrective action, but also (2) for the analysis of scans acquired at future dates.

In (Bosché et al. 2009; Turkan et al. 2011), the authors also calculate the actual progress to objectively evaluate the performance of the object recognition system:

$$Actual_Prog_i^{ScanDate} = \frac{\sum_{o \in \pi_i} a_o v_o}{\sum_{o \in \pi_i} v_o} \quad [5.3]$$

where o is the object index, π_i is the list of objects built during activity i , a_o is the binary value of actual presence of the object in the data, v_o is the binary value of visibility. This progress is calculated

manually for experimental and developmental purposes by visually observing object recognition results together with the scan data.

It should be noted here that the system calculates the recognized visible progress by considering only the objects visible from the scanner's location(s). Moreover, as can be seen in equations (5.1) and (5.2), the scheduled and recognized progress parameters are calculated by applying equal weight to all BIM objects, regardless of the earned value associated with them or the complexity needed to build them. Although these estimated values are adequate to prove the feasibility of using the approach to monitor progress, they are not in themselves adequate for progress tracking in terms of earned value. Additional steps to track earned value are described in the following sections.

5.5 Earned Value Calculations Using the Object Recognition System's Output

As described previously, EV analysis is performed using the information stored in individual project cost accounts. Planned and actual progress data in terms of quantities put in place and/or job hours, as well as budgeted and actual expenses are stored in individual project cost accounts. The approach proposed here uses the automated object recognition system's output and links the project cost accounts to the 4D BIM. The linking is performed manually here, but it will be automated in the future by linking the object recognition algorithms to BIM through IFC files where all cost information can be encapsulated. A conceptual view of the proposed approach is given in Figure 5.1.

The output data from the 4D object recognition system provides the following information: (a) whether the object is expected to be there or not, and (b) whether it is recognized or not. Separately, each object's quantity (in terms of volume or weight) can be calculated using the project BIM. Since each object belongs to a project cost account, linking can be achieved using the object IDs. Finally, earned value measures and project performance indicators can be calculated for the project using the material quantity, budget cost, and actual expenses data stored in the cost accounts.

Progress tracking algorithms which use the 4D object recognition system's output (Bosché et al. 2010; Turkan et al. 2011) are modified for earned value analysis by multiplying each object's recognition result (binary value) with the object's value per unit (equations (5.4) and (5.5)). For example, quantities of steel and reinforcing bars are in tons, while concrete is typically in cubic meters, and formwork is in square meters.

$$Recognized_Prog_i^{ScanDate} = \frac{\sum_{o \in \pi_i} r_o w_o v_o}{\sum_{o \in \pi_i} w_o v_o} \quad [5.4]$$

$$Actual_Prog_i^{ScanDate} = \frac{\sum_{o \in \pi_i} a_o w_o v_o}{\sum_{o \in \pi_i} w_o v_o} \quad [5.5]$$

where o , π_i , r_o , a_o , v_o are the same as in Equations 5.1 and 5.2, and w_o is the value per unit. It should be noted here that the “Recognized” progress used in our system corresponds to the “Actual” used in the EV theory, and “Actual” progress used in our system (Figure 5.4 and Figure 5.5) is calculated manually to assess the performance of the proposed system.

5.6 Experiments

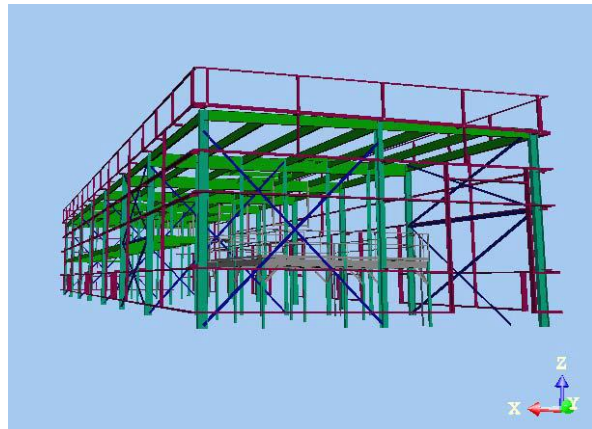
5.6.1 Data Collection

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 3.1.

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 5.2).



(a) Laser Scan acquired on July 22, 2007



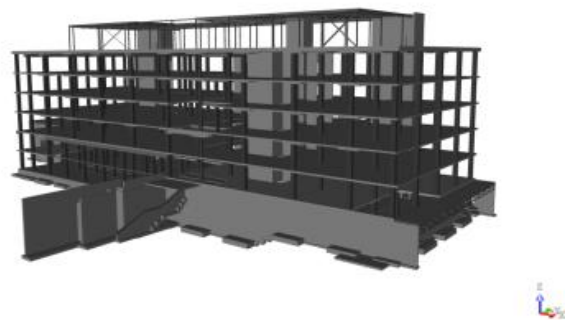
(b) 3D CAD model containing 612 objects

Figure 5.2 Portland's Energy Center

The Engineering V Building has a steel reinforced concrete structure. The 176,000-square-foot (16,000-square-metre), six story 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 5.3). 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™ 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.



(a) Laser Scan acquired on May 5, 2009



(b) 3D CAD model containing 1573 objects

Figure 5.3 Engineering V Building, University of Waterloo

5.7 Analysis of Results

5.7.1 Portlands Energy Center Project (steel structure)

3D Object Recognition: Table 5.1 presents the object recognition performances of the five laser scans of the building (Bosché, 2009). As can be seen in the table, high 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. It was shown in (Turkan et al. 2011) that using project 4D models (a combination of the project 3D model and schedule) improves the object recognition algorithm’s performance (98% recall and 96% precision rates on average). While schedule data was not available for the Portlands project, it is a good case study for a steel structure, and so it is used for the analysis presented in the following section.

Earned Value Tracking: The building 3D CAD 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 high 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 Earned Value. 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.

Table 5.1 Overall object recognition performances

Scan ID	Scan Date	Recall rate (objects)	Precision rate (objects)
1	July 15, 2007	83%	93%
2	July 15, 2007	77%	93%
3	July 22, 2007	85%	93%
4	July 22, 2007	87%	93%
5	July 22, 2007	84%	82%
Portlands project overall performance using 3D model		83%	93%
1	August 12, 2008	100%	96%
2	August 19, 2008	98%	96%
3	August 21, 2008	98%	95%
4	August 26, 2008_ST1	100%	98%
5	August 26, 2008_ST2	98%	95%
6	August 29, 2008_ST1	97%	96%
7	August 29, 2008_ST2	97%	94%
8	September 8, 2008_ST1	98%	97%
9	September 8, 2008_ST2	97%	96%
UW E5 Building overall performance using 4D model		98%	96%

Table 5.2 presents the object recognition results that were obtained for the scan captured on week n, and the link established between the 4D BIM and project cost accounts. As can be seen in the table, linking is established through the model object IDs. The object quantities (in tons) were calculated manually using commercial CAD software. Once this is done, the planned, recognized, and actual quantities of each object in terms of tons were calculated by multiplying each object's quantity with the object recognition results (binary value) using excel sheets. Finally, the planned, recognized, and actual progress totals (tons of steel) for that scan day were calculated using equations 5.2, 5.4 and 5.5. This process was repeated for the other four scans as well, and the steel structure building's construction progress in terms of earned tons of steel installed is presented in Figure 5.4. As can be seen in the figure, the recognized and actual progress values are very similar. This correspondence results from the good performance of the object recognition system. Table 5.3 presents the recall and precision rates in terms of EV. As can be seen in the Table, the results have improved significantly

when using EV (99% recall and 100% precision on average) instead of using the number of objects (83% recall and 93% precision on average in Table 5.1). Thus, it can be concluded that the non-recognized objects were indeed minor in nature (i.e. those with lower values) and do not have considerable impact on project progress in terms of EV.

Table 5.2 Object – Cost Account Association for the scan captured on week n

Cost Account	Object ID	Planned	Recognized	Actual	Quantity (tons)	Planned (tons)	Recognized (tons)	Actual (tons)
C01	1	1	0	1	0.34	0.34	0.00	0.34
C01	2	1	1	1	1.33	1.33	1.33	1.33
C01	3	1	1	1	0.34	0.34	0.34	0.34
C01	4	1	1	1	0.14	0.14	0.14	0.14
C01	5	1	0	1	0.10	0.10	0.00	0.10
C01	6	1	0	0	0.10	0.10	0.00	0.00
C01	7	1	1	1	0.04	0.04	0.04	0.04
C01	8	1	1	1	0.04	0.04	0.04	0.04
C01	9	1	1	1	0.01	0.01	0.01	0.01
C01
C01
C01
C01
C01	612	1	1	1	0.08	0.08	0.08	0.08
Total					94.60	94.41	76.48	77.1

However, there is a significant difference between planned and recognized, as well as planned and actual progress values. These differences are sourced from using the complete project 3D model. It was thus expected that improved results would be obtained when using project 4D models, as detailed in the following section.

5.7.2 Engineering V Building Project (reinforced concrete structure)

3D Object Recognition: The object recognition results for the laser scans obtained from the Engineering V building construction site is also presented in Table 5.1. As can be seen in the table, using a 4D model, excellent object recognition performance is achieved (98% recall and 96% precision on average) (Turkan et al. 2011). Of course, 4D models are not always available.

Earned Value Tracking: The Engineering V Building is a reinforced concrete structure. Although each concrete construction project is unique, the following sequences of activities are common for construction of any cast-in place concrete structures with reinforcement: (1) erect formwork, (2) place

reinforcement, (3) place concrete, (4) strip forms. These activities require a variety of resources such as concrete, rebar, formwork, worker hours, equipment hours etc. Earned value analysis for such a construction project requires data from all these resources. Not all of this information was available for the Engineering V Building. Therefore, cubic yards of concrete required for each activity were calculated from the Building's 3D CAD model to illustrate the proposed approach.

Analysis similar to that performed for the Portlands project was performed for the Engineering V project. The 4D BIM was linked with the project cost accounts through the model object IDs, and the object quantities (footings, columns, beams, and concrete slabs) were calculated manually in terms of cubic yards using commercial CAD software. As with the previous experiment, the planned, recognized, and actual progresses in terms of cubic yards for each scan day were calculated using equations 5.2, 5.4 and 5.5, the results of which are presented in Figure 5.5.

Again, very similar recognized and actual progress results were obtained for all the scans. This is simply the result of the object recognition system's high performance as mentioned earlier. Table 5.3 reports the recall and precision rates in terms of EV for the Engineering V Building. As with the Portlands project, the results demonstrate improvement of the system's performance when using EV instead of the "number of objects" approach. Recall and precision rates improved from 98% and 96% (Table 5.1) to 100% and 100% (Table 5.3), respectively.

On the other hand, the differences between planned and recognized progress values are considerably large, especially with the scans acquired on later dates (i.e. August 26, 2008, August 29, 2008 and September 8, 2008). A variety of factors might explain these differences. First, the project fell slightly behind schedule, and one of the purposes of the system is to be able to detect this. Another potential reason could be that due to visibility limitations, the scans did not provide data on all objects related to on-going activities. It is important to note here that 'Planned Progress', as opposed to 'Actual Progress' and 'Recognized Progress', does not take visibility into account. It is calculated simply as a percentage of the planned activity duration. Therefore, complete tracking of the on-going activities' progress could not be achieved. This signifies the importance of capturing a set of scans which cover all the necessary information for progress tracking. In other words, this suggests the need for *planning for scanning*. It is critical to plan scanning locations prior to the project start in order to capture every object to be tracked in the scans so that better progress estimates can be determined by the system. Only after ensuring that all objects under investigation have successfully

been scanned can any difference between recognized and scheduled progress lead to a conclusion about whether the project is behind or ahead of schedule.

Another important point is that the 4D object recognition system also reports occlusion level (of the model objects from the scanner’s point of view) for each model object, but it does so at the object level. In future work, this information can be aggregated to the activity level, and used to provide some level of confidence in the reported progress by giving the percentage for objects that were occluded. In other words, future investigations may reveal whether a correlation exists in the discrepancy between ‘planned progress’ and ‘actual/recognized progress’ using the occlusion level information of each activity.

Table 5.3 Overall tracking performances in terms of **earned value**

Scan ID	Scan Date	Recall rate (earned value)	Precision rate (earned value)
1	July 15, 2007	99%	100%
2	July 15, 2007	98%	99%
3	July 22, 2007	99%	99%
4	July 22, 2007	98%	100%
5	July 22, 2007	99%	100%
Portlands project overall performance using 3D model		99%	100%
1	August 12, 2008	100%	100%
2	August 19, 2008	100%	100%
3	August 21, 2008	100%	100%
4	August 26, 2008_ST1	100%	99%
5	August 26, 2008_ST2	100%	100%
6	August 29, 2008_ST1	99%	100%
7	August 29, 2008_ST2	100%	100%
8	September 8, 2008_ST1	100%	100%
9	September 8, 2008_ST2	99%	100%
UW E5 Building overall performance using 4D model		100%	100%

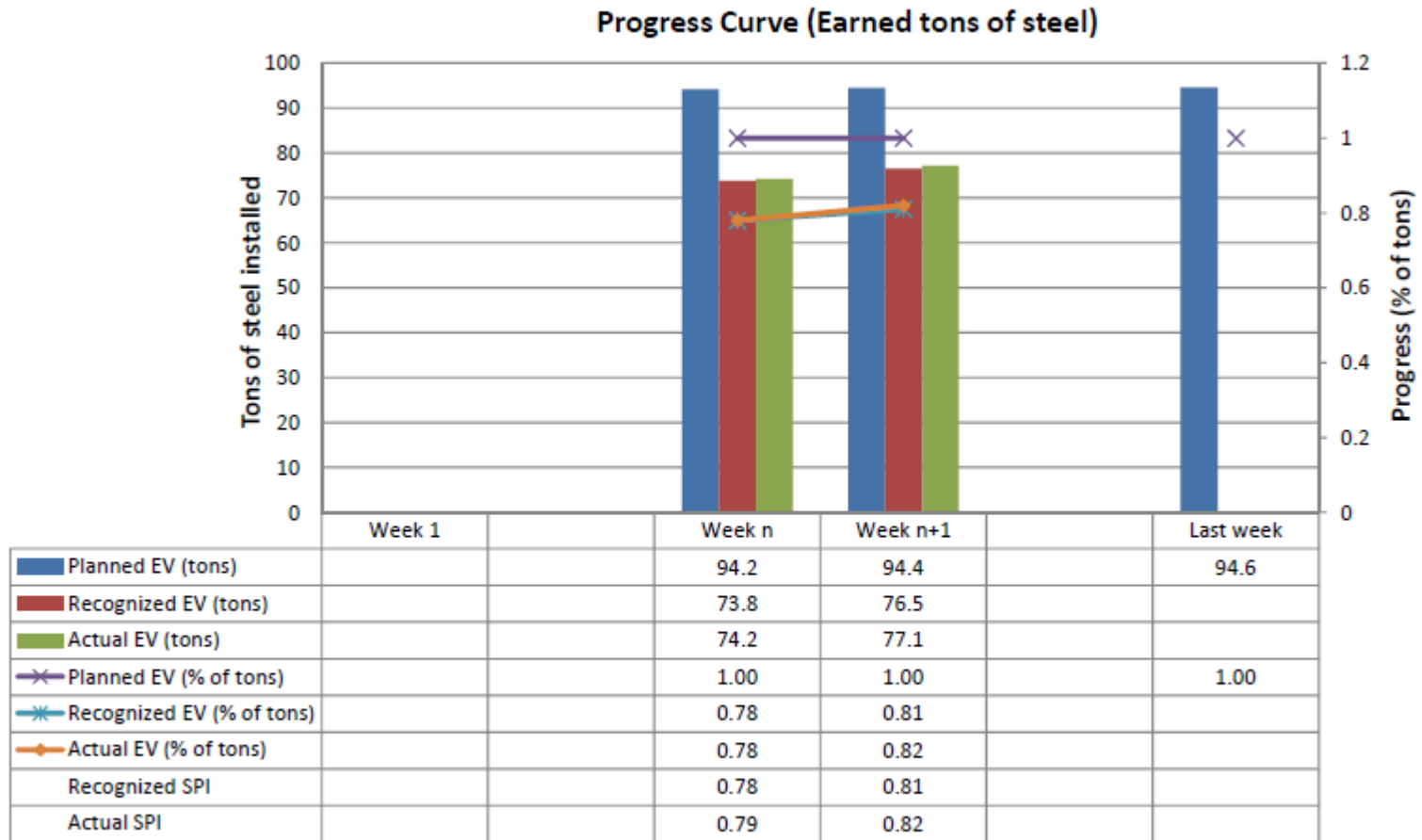


Figure 5.4 Portland's Project - Progress Chart (Earned tons of steel)

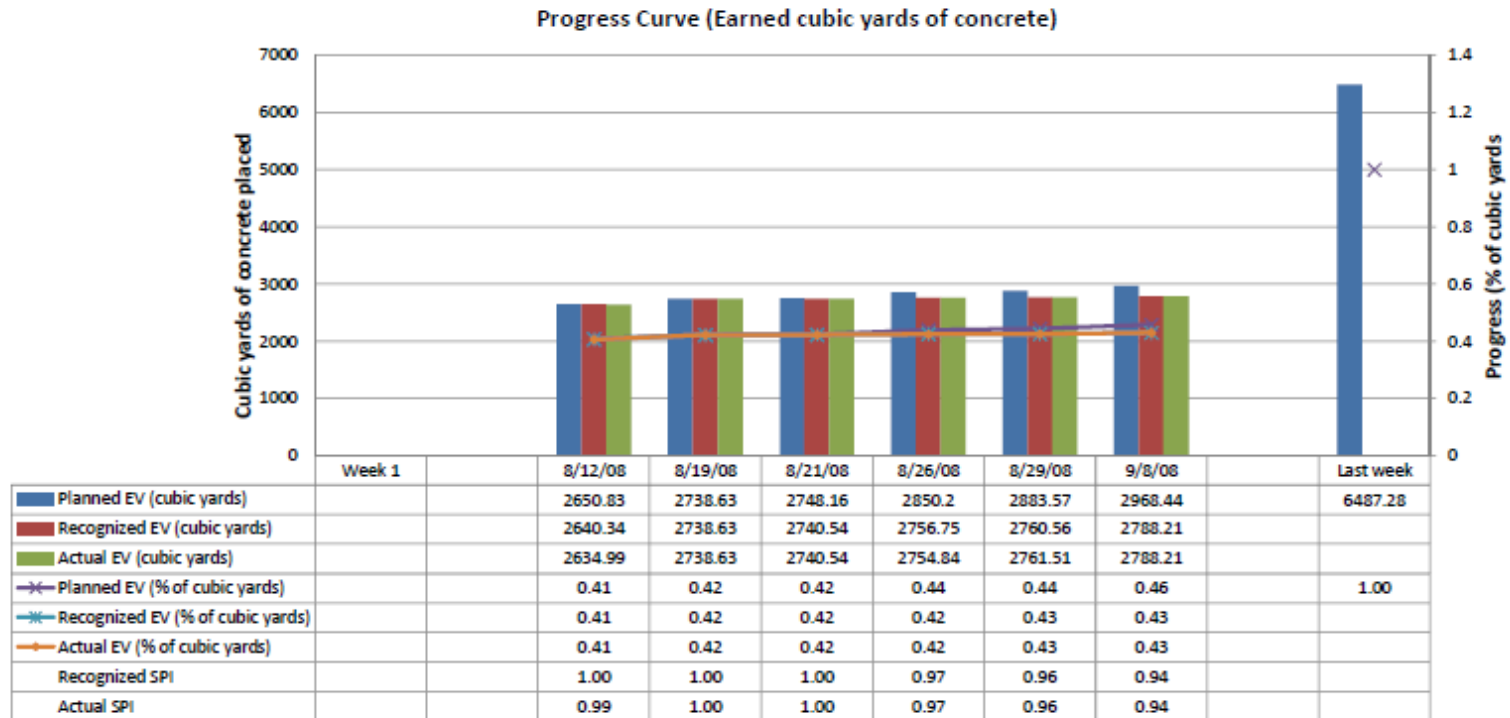


Figure 5.5 Engineering V Project - Progress Chart (Earned cubic yards of concrete)

5.8 Conclusions

In this chapter, 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. 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. It should be noted that 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 also be pointed out that 'value' is assessed in terms of 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 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.

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 to compensate for them. The next step would be to measure "percent built as-planned" automatically.

Moreover, the experiments here are focused on permanent structure objects only, not on the secondary or temporary structure objects. In order to have a more complete project progress tracking, methods need to be developed to detect and track these objects, and this is discussed in Chapter 6.

Chapter 6

Concrete Construction Secondary and Temporary Objects Tracking

Accurate, frequent and complete progress tracking is critical to project management. The automated object based 4D tracking and earned value based progress tracking systems, presented in Chapter 4 and 5 respectively, are focused on the permanent structure elements only, such as columns, beams and slabs. However, comprehensive progress tracking requires information to be gathered from a variety of sources such as concrete, rebar, formwork, labor hours. In this chapter, several techniques are proposed for automated recognition and progress tracking of secondary and temporary construction objects from 3D laser scan point clouds.

6.1 Introduction

Efficient and accurate progress tracking of construction projects is vital for successful project management as it allows corrective decisions to be made in a timely manner. Traditional progress tracking methods require manual data collection and extensive data extraction from different construction documents which distract project managers from the important task of decision making.

Recent research efforts to improve progress tracking are mainly focused on employing technologies such as three dimensional (3D) imaging including digital photogrammetry (Golparvar-Fard et al. 2010; 2011; 2012; Ibrahim et al. 2009; Wu et al. 2010; Zhang et al. 2009) and 3D laser scanning (Bosché and Haas 2008; Bosché et al. 2009; Turkan et al. 2012). However, none of these systems report progress of secondary or temporary structures, i.e. their focus is mainly on tracking permanent structure's progress. Nonetheless, secondary and temporary structures' progress would add veracity and detail to the progress tracking process. Furthermore, temporary construction objects such as formwork, scaffolding, and shoring are the largest cost components of a concrete building's structural frame. Together with the secondary objects such as rebar, total cost of temporary and secondary objects constitute a significant portion of a concrete building's structural frame's cost. Therefore, it is important to track these elements to increase the accuracy of progress tracking and also better support billing.

The automated object recognition system, which is detailed in section 2.4, combines 3D imaging technologies and 3D a-priori information (Bosché and Haas, 2008). This system and its experimental

validation is presented in (Bosché and Haas, 2008; Bosché et al., 2009; Bosché 2009). The automated object recognition system was further explored, and combined with schedule information in order to automate progress tracking by focusing only permanent structural elements (Turkan et al. 2010; 2012). It may be feasible to identify and therefore track formwork, shoring, scaffolding and rebar by leveraging the advantages of this automated object recognition system. Moreover, other techniques such as applying simple feature metrics to the negative spaces defined by design objects, foreshadowing rules, volumetric occupancy reconstruction algorithms may be used to detect secondary and temporary construction in 3D point clouds.

Therefore in this chapter, several techniques are proposed to detect concrete construction secondary and temporary objects from 3D laser scan point clouds. The following section reviews relevant information related to secondary and temporary construction objects. Then, the proposed techniques for secondary and temporary object detection from 3D laser scan point clouds are explained. Finally, the experimental results are presented and interpreted.

6.2 Secondary and Temporary Construction Objects

Formwork is a temporary support structure that is fabricated and installed to support the permanent structure objects. Formwork by itself is the largest cost component of a concrete building's structural frame. Vertical shores and scaffolding are used with formwork to support concrete girders, beams, floor slabs, roof slabs, bridge decks, and other members until these members gain sufficient strength to be self supporting. On the other hand, reinforcing bar, commonly called rebar, is used as a tensioning device in reinforced concrete and reinforced masonry structures holding the concrete in compression. Thus, it can be considered as a secondary construction object that supports the primary object, i.e. concrete.

Temporary and secondary structures together constitute the major part of the total installed cost of concrete structures (Hurd, 2005; Jarkas and Horner 2011). Thus, their efficiencies accelerate the construction schedule, which can result in reduced interest cost during construction and early occupancy for the structure. Also increased job site productivity, improved safety, and reduced potential for errors (Hurst, 1983; Peurifoy and Oberlender, 2011).

Nevertheless, a thorough examination of the literature revealed a dearth of research into using 3D imaging technologies for automated detection and tracking of secondary and temporary construction objects. Lee et al. (2010) developed an algorithm for calculating the quantity of formwork installed

from construction site images. Their algorithm requires a user to select a reference form area in the image which has reasonable color and size. The algorithm then searches for the forms in the image by gradually extending the searching area from the selected form area to the neighboring areas. Although high recognition values were reported in this work as much as 90%, there are issues with sunlight, shadow, obstructions etc., since image based techniques are used.

6.3 Techniques for Concrete Construction Secondary and Temporary Objects Recognition and Tracking

Several techniques for concrete construction secondary and temporary object detection from 3D laser scan point clouds are proposed in Table 6.1. The first three are built upon the automated object recognition system developed by Bosché and Haas (2008), and can be used for detecting formwork, rebar and pipe insulation. The first technique proposes changing the system's default point matching range in order to detect these objects. The second one suggests modifying the original 3D BIM by creating new design objects for formwork or rebar or pipe insulation, and then using the system's default point matching range. The third one proposes using the system's default point matching range if formwork or rebar or pipe insulation is already in the original 3D BIM. In this thesis, only the first technique out of these three is validated for detecting formwork and rebars using real life data.

Visual editing techniques require the user to identify each object visually from the 3D point cloud. This approach can be used for detecting all types of secondary and temporary objects such as formwork, rebar, pipe insulation, scaffolding and shoring. However, it requires a significant amount of manual input. Thus, it would be time consuming and error prone when handling large datasets.

The last three techniques presented in Table 6.1 are for detecting scaffolding and shoring from 3D point clouds. The first of the last three is application of simple feature metrics to the negative space volumes defined by design objects (example the cubic space surrounded by four columns). The negative space volumes can be defined using commercial point cloud processing software. Then, by counting the number of points in the defined space volumes and using simple feature metrics, it is possible to identify scaffolding and shoring with high degree of confidence.

The next technique is to use foreshadowing rules for shoring detection. For example, by assuming partition walls are design objects in the 3D BIM, and if a few of them are identified before they can possibly exist, then it can be assumed that they are shoring. Similar rules can be developed.

Table 6.1 Techniques for Secondary and Temporary Object Detection from 3D Point Clouds

ID	Technique	Type of Secondary / Temporary Object			
		Formwork	Rebar/pipe insulation	Scaffolding	Shoring
1	Change the default point matching range of the system	✓	✓		
2	Create new design objects and use the default point matching range of the system	✓	✓		
3	Use the default point matching range of the system if formwork/rebar/insulation is in BIM	✓	✓		
4	Visual editing (context, corrections, etc.)	✓	✓	✓	✓
5	Apply simple feature metrics to negative space volumes			✓	✓
6	Develop and use foreshadowing rules				✓
7	Use volumetric occupancy reconstruction algorithms			✓	✓

The last technique presented in the table is to use volumetric occupancy reconstruction algorithms for shoring and scaffolding detection. These algorithms have already been used in the AEC-FM context for detecting model objects from 3D point clouds (Golparvar-Fard et al., 2010). The algorithms can be used to obtain occupancy arrays for formwork and scaffolding. Then by superimposing over an as-planned site occupancy array derived from the project 4D model (3D BIM including formwork and scaffolding + schedule), the shoring and scaffolding progress can be estimated and compared it to their as-planned progress.

Being able to detect secondary and temporary objects would enhance progress tracking capabilities for steel reinforced concrete structures. As mentioned in the previous section, total cost of temporary and secondary objects constitute a significant portion of a concrete building's structural frame's cost. Thus, tracking their progress accurately and frequently is crucial for project's success.

6.4 Experiments

In order to evaluate the performance of the proposed secondary and temporary construction object detection techniques presented in Table 6.1, a set of experiments were conducted using the set of 3D

laser scan point clouds obtained from the Engineering V Building site (Figure 6.1). The 3D laser scans were taken using Trimble® GX 3D laser scanner (Trimble, 2007) that uses time-of-flight technology (detailed in Chapter 3). The experimental results are presented in the following section.

6.4.1 Automated Formwork Recognition and Tracking

In Table 6.1, four different techniques including visual editing are proposed for recognizing formwork from 3D laser scan point clouds. Except for the visual editing, the other three techniques involve the automated object recognition system which is detailed in section 2.4. The first of the three techniques suggests modifying the system parameters, i.e. changing the point matching distance for object recognition. The second one proposes modifying the original 3D BIM by adding model objects for formwork, and then using the default system parameters for point matching. Finally, the third one proposes using the default system parameters if the formwork is already in the original 3D BIM. Here, due to limited resources, only the first technique that proposes changing point matching distance of the automated object recognition system is validated with real life data.



Figure 6.1 Temporary objects at E5 Building site – July 25, 2008

The default point matching distance of the system is set at 50 mm. However, the system gives options to users to select the point matching distance from the values between 10 mm and 50 mm (Figure 6.2). Using the Engineering V Building 3D laser scans obtained from different dates, each of these values was tested for 50 different columns of formwork (Table 6.2). None of the columns' formwork is recognized when the point matching distance is set between 10 and 25 mm, while all of them are recognized when the point matching distance is set between 30 and 50 mm. This result can be explained with the fact that the thickness of the formwork is about 30 mm (confirmed using Trimble Realwork's measurement tool).

Consequently, it is feasible to recognize formwork in 3D laser scan point clouds by modifying the automated object recognition system (Bosché and Haas, 2008; Bosché et al., 2009). Column formworks and columns themselves can be differentiated by running the system twice: first using a point matching distance between 10 – 25 mm, and then between 30-50 mm. The difference between the two runs would then give the number of column formwork. Once the formwork objects are recognized, their progress can also be tracked. For this, the construction schedule would need to be altered by adding activities for temporary objects, so that their progress can be calculated using the 4D automated progress tracking system presented in Chapter 4.

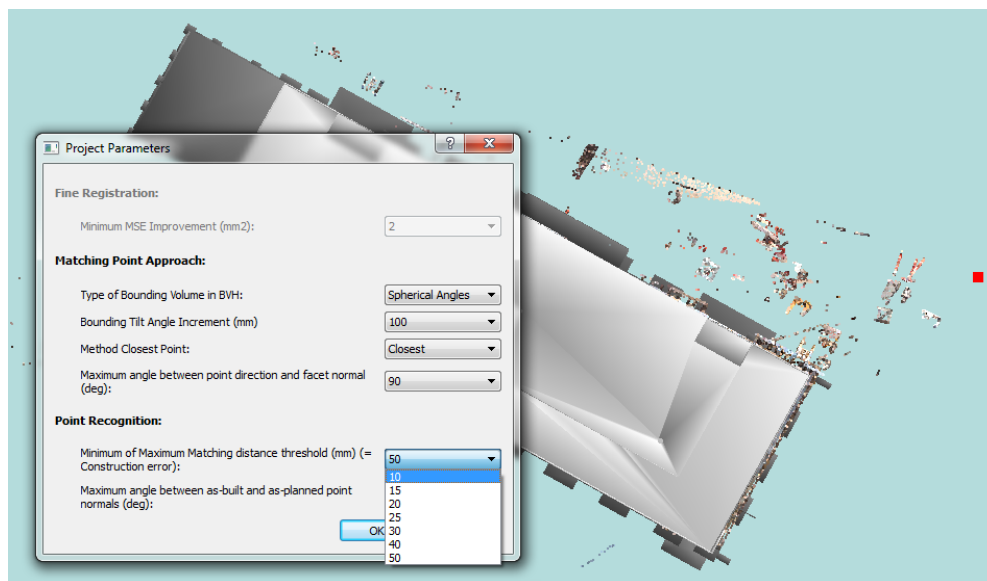


Figure 6.2 Maximum matching distance values for point recognition

Table 6.2 Formwork Detection using different point matching distances

Scan Date	Object ID	10mm	15mm	20mm	25mm	30mm	40mm	50mm
July 15, 2008	1	-	-	-	-	✓	✓	✓
	2	-	-	-	-	✓	✓	✓
July 18, 2008	3	-	-	-	-	✓	✓	✓
	4	-	-	-	-	✓	✓	✓
July 22, 2008	5	-	-	-	-	✓	✓	✓
	6	-	-	-	-	✓	✓	✓
	7	-	-	-	-	✓	✓	✓
July 25, 2008	8	-	-	-	-	✓	✓	✓
	9	-	-	-	-	✓	✓	✓
	10	-	-	-	-	✓	✓	✓
	11	-	-	-	-	✓	✓	✓
	12	-	-	-	-	✓	✓	✓
	13	-	-	-	-	✓	✓	✓
	14	-	-	-	-	✓	✓	✓
	15	-	-	-	-	✓	✓	✓
July 29, 2008	16	-	-	-	-	✓	✓	✓
	17	-	-	-	-	✓	✓	✓
	18	-	-	-	-	✓	✓	✓
	19	-	-	-	-	✓	✓	✓
August 5, 2008	20	-	-	-	-	✓	✓	✓
	21	-	-	-	-	✓	✓	✓
August 12, 2008	22	-	-	-	-	✓	✓	✓
	23	-	-	-	-	✓	✓	✓
	24	-	-	-	-	✓	✓	✓
	25	-	-	-	-	✓	✓	✓
August 19, 2008	26	-	-	-	-	✓	✓	✓
	27	-	-	-	-	✓	✓	✓
August 21, 2008	28	-	-	-	-	✓	✓	✓
	29	-	-	-	-	✓	✓	✓
August 29, 2008	30	-	-	-	-	✓	✓	✓
	31	-	-	-	-	✓	✓	✓
September 8, 2008	32	-	-	-	-	✓	✓	✓
	33	-	-	-	-	✓	✓	✓
September 16, 2008	34	-	-	-	-	✓	✓	✓
	35	-	-	-	-	✓	✓	✓
	36	-	-	-	-	✓	✓	✓
	37	-	-	-	-	✓	✓	✓
September 19, 2008	38	-	-	-	-	✓	✓	✓
	39	-	-	-	-	✓	✓	✓
September 26, 2008	40	-	-	-	-	✓	✓	✓
	41	-	-	-	-	✓	✓	✓
October 17, 2008	42	-	-	-	-	✓	✓	✓
	43	-	-	-	-	✓	✓	✓
	44	-	-	-	-	✓	✓	✓
	45	-	-	-	-	✓	✓	✓
October 24, 2008	46	-	-	-	-	✓	✓	✓
	47	-	-	-	-	✓	✓	✓
October 30, 2008	48	-	-	-	-	✓	✓	✓
	49	-	-	-	-	✓	✓	✓
November 6, 2008	50	-	-	-	-	✓	✓	✓

6.4.2 Shoring Detection using feature metrics for negative spaces

In Table 6.1, four different techniques are proposed for detecting shoring in 3D laser scan point clouds: (1) apply simple feature metrics to the negative spaces defined by design objects; (2) foreshadowing rules; (3) visual editing; and (4) occupancy cubes. Here only the first technique, applying simple feature metrics to the negative spaces defined by design objects, is tested using real life data. Trimble Realworks[®] segmentation tool (Figure 6.3) is used to define the negative spaces in 3D laser scan point clouds. The segmentation tool allows user to select a set of points from the point cloud by defining boundaries using its polygonal framing function (Figure 6.4). This procedure is detailed in Appendix G. For the experiments presented here, the negative space volume is defined as the cubic space surrounded by four columns (Figure 6.5).

Once the volume boundaries are defined, the total number of 3D image points in that volume is calculated automatically by the segmentation tool. Separately, the corresponding volume in the 3D BIM is calculated using commercial BIM software. Number of points per cubic meter is then calculated dividing the total number of points by the negative volume value which is in cubic meters.

$$\text{NumberofPointsperCubicMeter}=\text{TotalNumberofPoints}/\text{TotalVolume}(in\text{CubicMeters}) \quad [6.1]$$

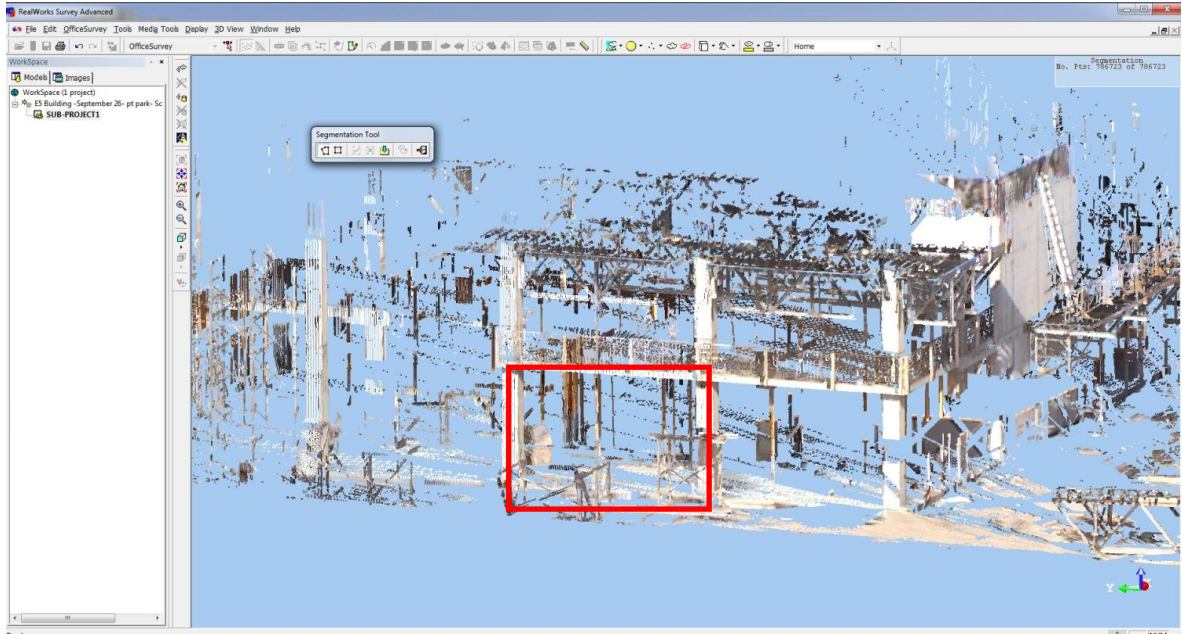


Figure 6.3 Trimble Realworks segmentation tool

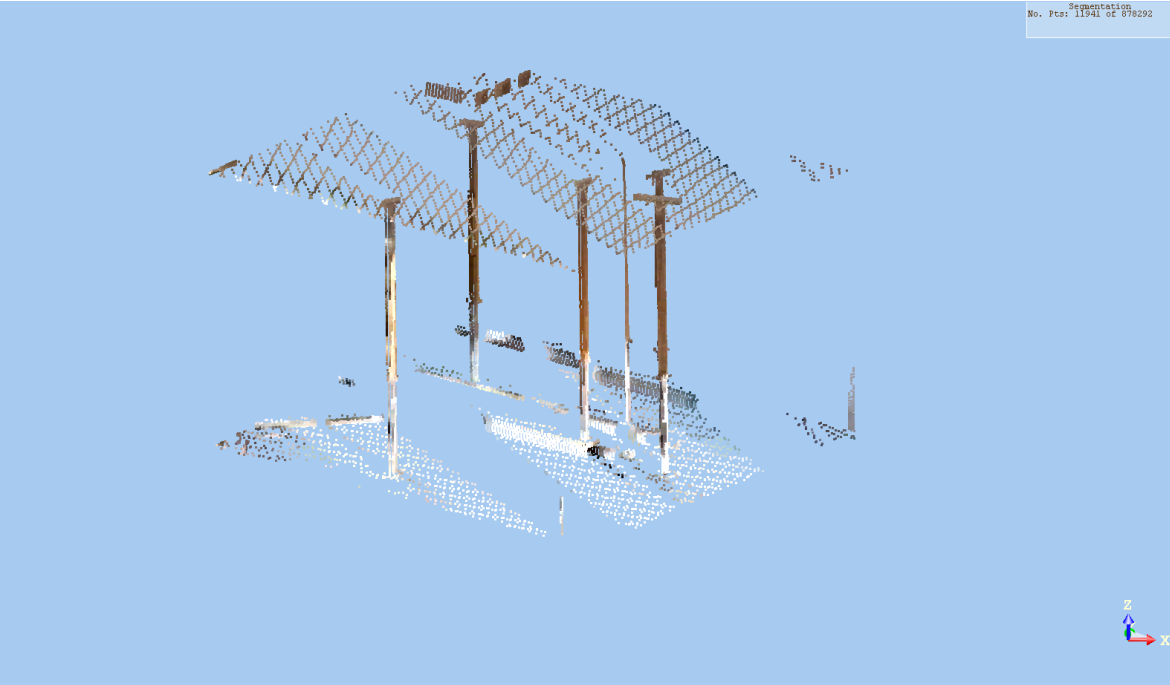


Figure 6.4 Shoring in the inter-column volume

Based on visual observations, 50 negative spaces that at different times had shoring and no shoring were selected from the 3D laser scan point clouds of the Engineering V Building, and tested (Table 6.3) using the technique detailed above. Table 6.3 presents the number of points per cubic meter for the following cases: 1) shoring exists; 2) shoring does not exist in the corresponding negative space volume. Figure 6.6 was drawn using the information presented on Table 6.3. From the Table 6.3 and Figure 6.6, it can be concluded that the number of points per cubic meter changes between 20 and 40 (column 4 in Table 6.3) if there is no shoring, and 60 and 100 (column 3 in Table 6.3) if there is shoring in the selected negative space volume.

$$\begin{aligned}
 \text{NegativeSpaceVolume} = \{ & \text{LeftWall} \langle \text{NumberOfPoints} \rangle \text{RightWall} \} \\
 & \cup \{ \text{FrontWall} \langle \text{NumberOfPoints} \rangle \text{BackWall} \} \\
 & \cup \{ \text{Ceiling} \langle \text{NumberOfPoints} \rangle \text{Floor} \} \quad [6.2]
 \end{aligned}$$

However, it can be argued that it is possible to obtain false positive results for both cases that shoring exists and shoring does not exist in the selected negative space volume. Construction sites are very dynamic environments where a number of operations are performed at the same time. Because of all the material delivery and workers gathering to complete their assignments, construction sites become congested soon after the project execution starts. Therefore, the selected negative space volumes may be occupied by people, equipment, materials etc., and this may result having a number of points per cubic meter in the range defined for the case that shoring exist. On the other hand, there might be cases that a negative space volume is classified as that it does not contain shoring although it does. This may be due to visibility issues sourced from the laser scanner's position. Both of these types of false positive results can be prevented by checking the 3D point cloud visually.

Here, a simple feature metric was used here in order to detect shoring in 3D laser scan point clouds. Based on this metric, algorithms can be developed in order to detect shoring from laser scan point clouds automatically. In this case, a simple threshold value application would achieve 100% accuracy. Furthermore, it is feasible to track their progress by incorporating the object detection results into the automated progress tracking system presented in Chapter 4.

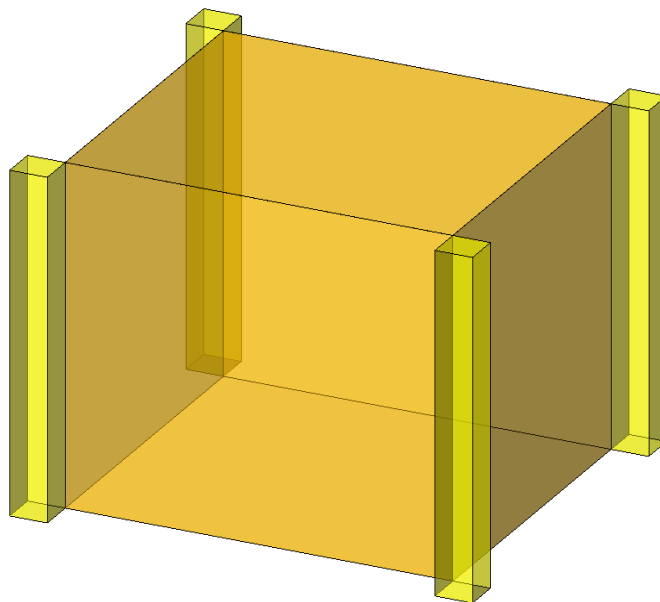


Figure 6.5 Empty space volume boundaries

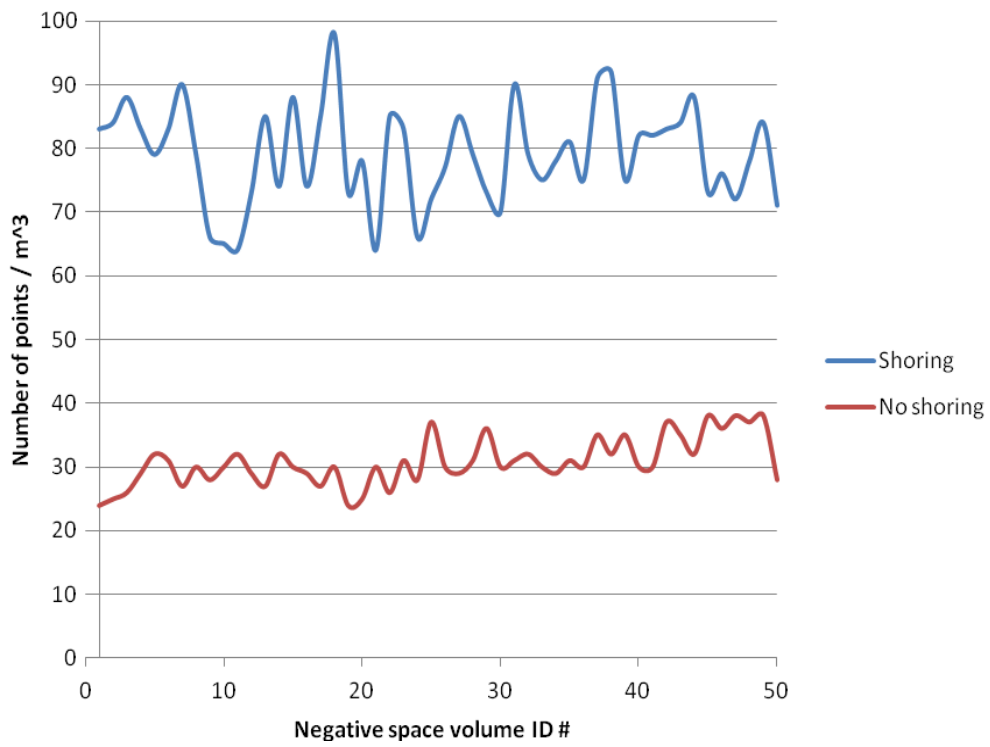


Figure 6.6 Distribution of number of points per meter cube in the volumes that have shoring and no shoring

Table 6.3 Number of points in the inter-column volumes

Scan Date	Negative space ID #	Number of points / m ³	
		Shoring	No shoring
2008-09-08	1	83	24
	2	84	25
2008-09-11	3	88	26
	4	83	29
2008-09-16	5	79	32
	6	83	31
	7	90	27
	8	79	30
2008-09-19	9	66	28
	10	65	30
	11	64	32
	12	73	29
2008-09-26	13	85	27
	14	74	32
	15	88	30
	16	74	29
	17	85	27
2008-10-09	18	98	30
	19	73	24
	20	78	25
	21	64	30
	22	85	26
2008-10-17	23	83	31
	24	66	28
	25	72	37
	26	77	30
	27	85	29
2008-10-24	28	79	31
	29	73	36
	30	70	30
	31	90	31
	32	79	32
2008-10-30	33	75	30
	34	78	29
	35	81	31
	36	75	30
	37	91	35
	38	92	32
	39	75	35
	40	82	30
2008-11-06	41	82	30
	42	83	37
	43	84	35
	44	88	32
	45	73	38
2009-04-17	46	76	36
	47	72	38
	48	78	37
	49	84	38
	50	71	28

6.4.3 Automated Rebar Recognition and Tracking

As discussed in section 6.1, secondary objects such as rebars constitute an important portion of the total cost of a building's structural frame. Therefore, it is important to track their progress. If rebars can be detected from 3D laser scan point clouds automatically, then the automated progress tracking system presented in Chapter 4 can be used to track them.

The same techniques as the ones for formwork are proposed for detecting rebars in 3D laser scan point clouds (Table 6.1): (1) modifying the system parameters, i.e. changing the point matching range for object recognition; (2) modifying the original 3D BIM by adding model objects for formwork, and then using the default system parameters for point matching; (3) using the default system parameters if the formwork is already in the original 3D BIM; and (4) visual editing. Only the first technique, changing the point matching range for object recognition, was tested with real life data obtained from Engineering V Building. In retrospect, it would have made sense to apply the approach used for shoring in empty space volumes (inter-column) to rebar in solid volumes (columns). Time and resources permitting, this approach is recommended for future research.

As explained in section 6.4.1, the object recognition system (Bosché et al., 2008; Bosché, 2009) allows a user to select the point matching range from the values between 10 mm and 50 mm. All the point matching distances that were set in the system were tested for 50 different columns' rebars using the 3D laser scan data captured from Engineering V Building site (Figure 6.8). None of the columns' rebar was recognized with any of the point matching distances (10 mm – 50 mm). This result corresponds with the 50 mm concrete cover to the rebars (Figure 6.7). However, it is feasible to expand the point matching distance range of the object recognition system by altering its relevant algorithms. Then, it should be possible to recognize a column's rebar using a matching distance larger than 50 mm. In future work, this hypothesis should be further explored.

Also, an obvious fifth approach would be to count the 3D point cloud points inside a column using much the same process as was used for shoring. This will be tried in future research.

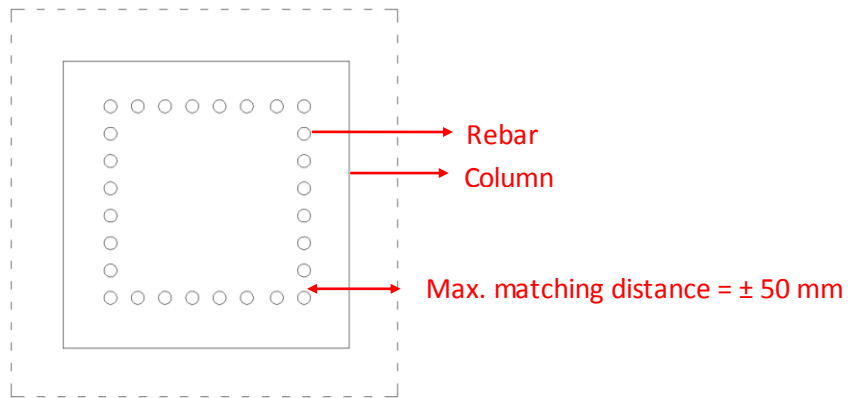


Figure 6.7 Rebar Detection



Figure 6.8 Column rebar at Engineering V Building Site

6.5 Conclusions and Recommendations

In this chapter, several techniques for concrete construction secondary and temporary object detection from 3D laser scan point clouds are proposed. Two of these techniques were validated for formwork, rebar and shoring using real life data obtained from the Engineering V Building construction site.

The first technique leverages the advantages of the automated object recognition system of Bosché et al. (2008). It requires changing the point matching range for object recognition and then applying a difference operation between the sets of recognition results obtained with different point matching ranges. This technique was used for formwork and rebar detection. Experimental results have shown that it is feasible using the automated object recognition system for formwork by using the high point matching ranges that were defined in the system (30 mm – 50 mm). On the other hand, rebar recognition was not possible using any of the defined point matching ranges within the current system. However, it should be possible to detect rebars by altering the relevant system algorithms. The second technique is an application of a simple metric to negative spaces defined by design objects (cubic spaces surrounded by four columns were used here) for shoring detection from laser scan point clouds. The experimental results have shown that it is feasible to identify the spaces that have shoring and no shoring using this simple metric. The negative spaces were selected manually, using commercially available point cloud processing software. However, algorithms can be developed based on the simple metric explained above, so that shoring can be identified from 3D laser scan point clouds automatically.

In future research, it is recommended that techniques to detect secondary and temporary concrete construction objects from 3D point clouds automatically should be further explored. Moreover, case studies should be conducted to measure the improvement in progress tracking when secondary and temporary objects included in the process.

Chapter 7

Conclusions and Recommendations

7.1 Conclusions

This thesis presented an automated construction progress tracking system that integrates 3D object recognition technology with 4D modeling. Progress tracking is a critical management task for construction projects, and the current manual tracking methods such as using foremen daily reports, are time consuming and/or error prone. The system used here automates and increases the accuracy of this time-consuming management task by calculating construction progress and updating project schedule automatically. The only manual step required is to register laser scan data with the 3D BIM in the same coordinate system by choosing at least three pairs of corresponding points both in the scan and the model. The object recognition system (Bosché and Haas, 2008) used is very accurate and robust to occlusions sourced from both 3D model and temporary construction objects. Compared to the system originally proposed in (Bosché and Haas, 2008), the progress tracking system presented herein uses a 4D BIM (combination of 3D BIM and schedule data) to improve recognition of BIM objects from their laser scans. Once the object recognition step is completed, progress estimates are made for each activity, and the schedule is updated automatically based on the progress estimates. The performance of the system is investigated on a comprehensive field database acquired during the construction of a steel reinforced concrete structure, Engineering V Building at the University of Waterloo. It is shown through multiple experiments that the progress tracking system achieves promising results, especially when the full feedback loop is implemented.

Second, the automated 4D object recognition system is linked to project cost accounts to facilitate more objective and timely Earned Value analysis for automated progress control. The Earned Value tracking is the most commonly used method in the industry. 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. Experimental results demonstrated reasonably accurate, automated estimation of a project's structural erection progress in terms of Earned Value.

Third, several techniques for concrete construction secondary and temporary object detection from 3D laser scan point clouds are presented, and validated for formwork, rebar and shoring detection using the data obtained from the Engineering V Building construction site. The

experimental results have shown that it is feasible to detect formwork and rebar by leveraging the advantages of the automated object recognition system. It is also shown that shoring detection from 3D point clouds is possible by using simple feature metrics to negative spaces defined by design objects.

Finally, it is also important to identify the cost saving potential of employing this system on construction projects. If fully implemented on a construction site to track progress, it may save contractors substantial dollars since it gives an object measure for the project's progress and feeds an updated schedule back into the system. This enables the contractor to make corrective decisions and take actions to avoid the impact of delays on the overall schedule and the budget. Moreover, investing in 3D laser scanners is becoming increasingly cost effective which makes it easier for contractors to spend on this technology.

In summary, the following main conclusions can be stated:

- Using 4D BIM (combination of 3D BIM and schedule data) improves recognition of BIM objects from their laser scans
- Accurate and automated structural building project progress tracking and schedule updating is feasible by integrating 3D object recognition and 4D modeling technologies
- Experimental results show that the system's performance is promising
- Automated Earned Value analysis can be performed by linking the automated 4D object recognition system with project cost accounts
- Secondary and temporary construction objects such as rebar, formwork and shoring can be identified and retrieved automatically by leveraging the advantages of the 4D object recognition system as well as some other techniques such as using simple feature metrics in negative space volumes

7.2 Contributions

This research has contributions in three major areas: (1) Contribution to the construction industry (2) Contribution to the body of knowledge of sensing in civil engineering, and (3) Contribution to the body of knowledge in automation in construction. A brief discussion on these three areas of contribution follows.

1. This study promoted adoption of 3D imaging technologies by the construction industry through presenting their benefits in terms of labor time reduction, schedule and cost performance improvement.
2. This study enriched the existing body of knowledge in the area of sensing in civil engineering by: (a) successful deployment of 3D laser scanning technology in construction projects, and (b) development of a novel construction progress tracking system that integrates 4D modeling and laser scanning. The developed system automates and increases the accuracy of this time consuming management task.
3. This research contributed to the body of knowledge in automation in construction by developing and implementing an automated construction progress tracking and schedule updating system that integrates 3D object recognition algorithms with 4D schedule data. This novel system implements an automated progress feedback loop, and uses new and unique logical inferencing algorithms.

7.3 Suggestions for Future Work

This thesis investigated the impact of using 3D imaging technologies for automated construction progress tracking, with a particular focus on steel reinforced concrete construction buildings. A number of recommendations for future research are listed below:

- Experimental results indicates the importance of ensuring that a set of scans captures all necessary data for progress tracking, i.e. planning for scanning needs to be addressed. Thus, it is suggested to test the system's performance using a comprehensive set of data obtained over the course of a construction project.
- In its current form, the system only estimates progress for the activities that are on-going. This means that early work cannot be detected by the current system. Therefore, in future work, it is suggested to improve the progress estimation formulas of the system in order to detect early work.
- The automated earned value approach presented uses the automated object recognition system's output and links the project cost accounts to the 4D BIM. The linking is done manually here, but this should become automated in the future by linking the object

recognition algorithms to BIM through IFC files where all cost information would be provided.

- 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 to compensate for them. The next step would be to measure “percent built as-planned” automatically.
- It is recommended that techniques for secondary and temporary concrete construction objects detection from 3D point clouds should be further explored. For example, negative space volumes can be generated automatically using special algorithms based on simple metrics. And, case studies should be conducted to measure the improvement in progress tracking when secondary and temporary objects included in the process.

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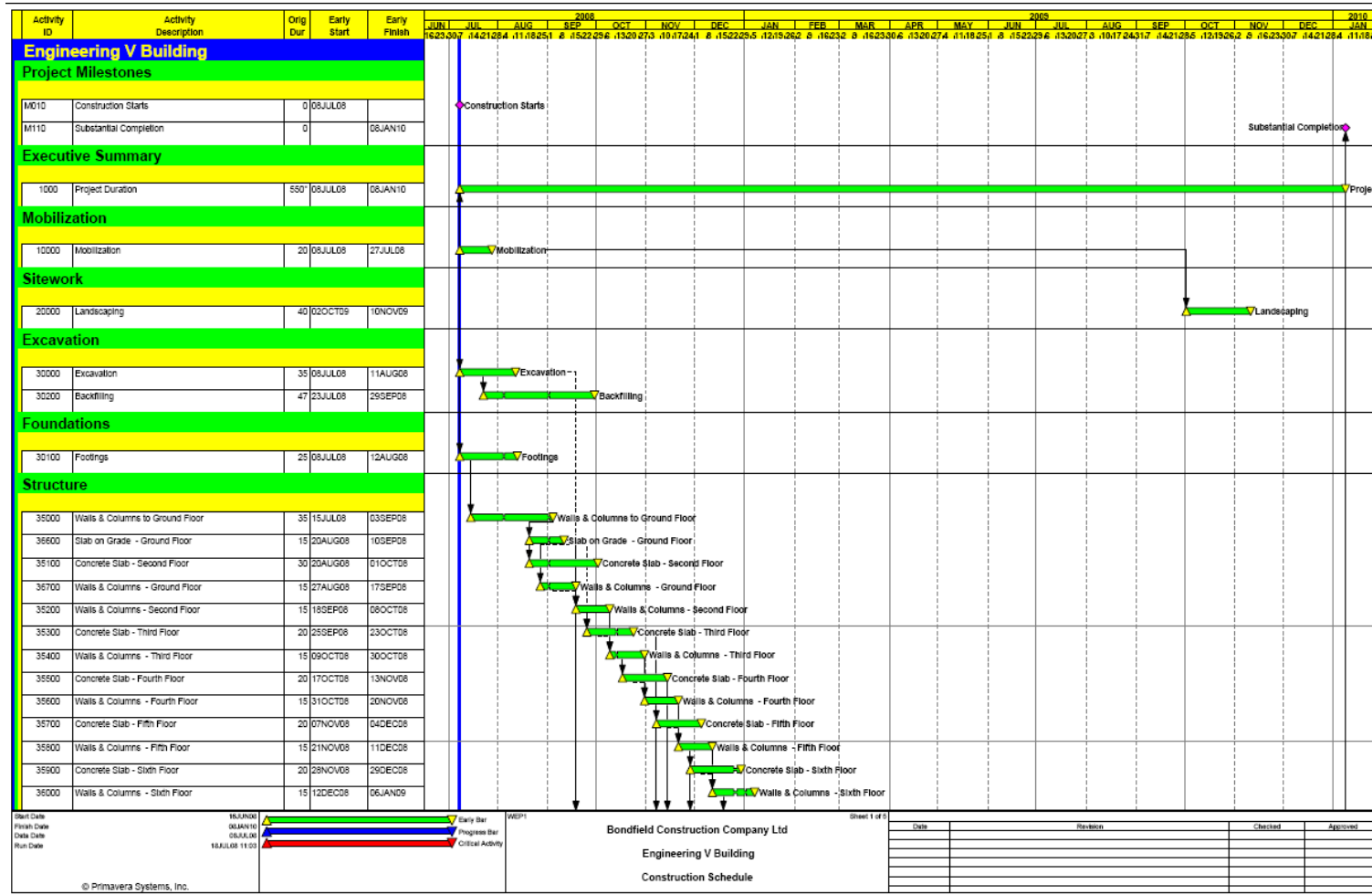
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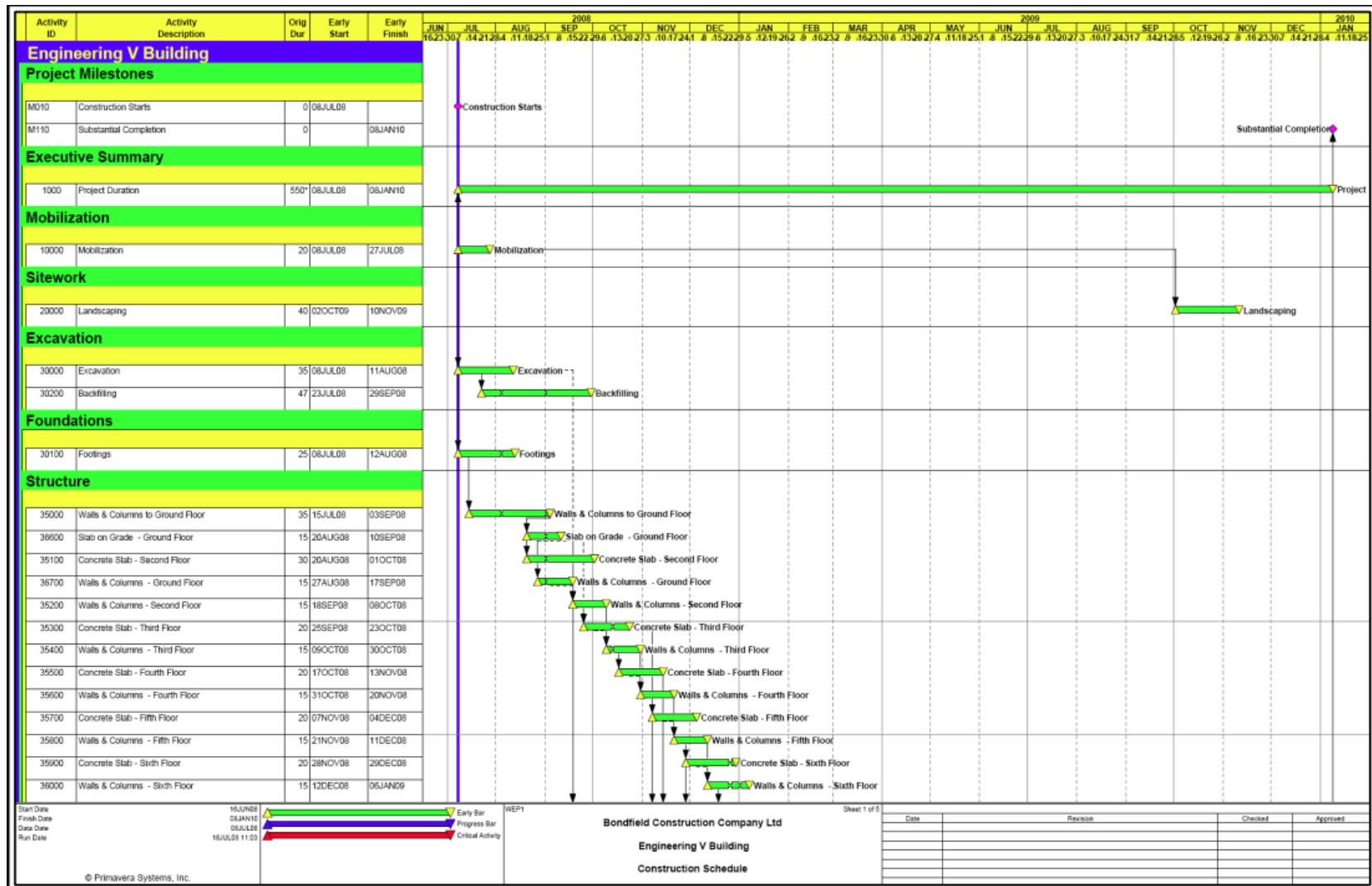
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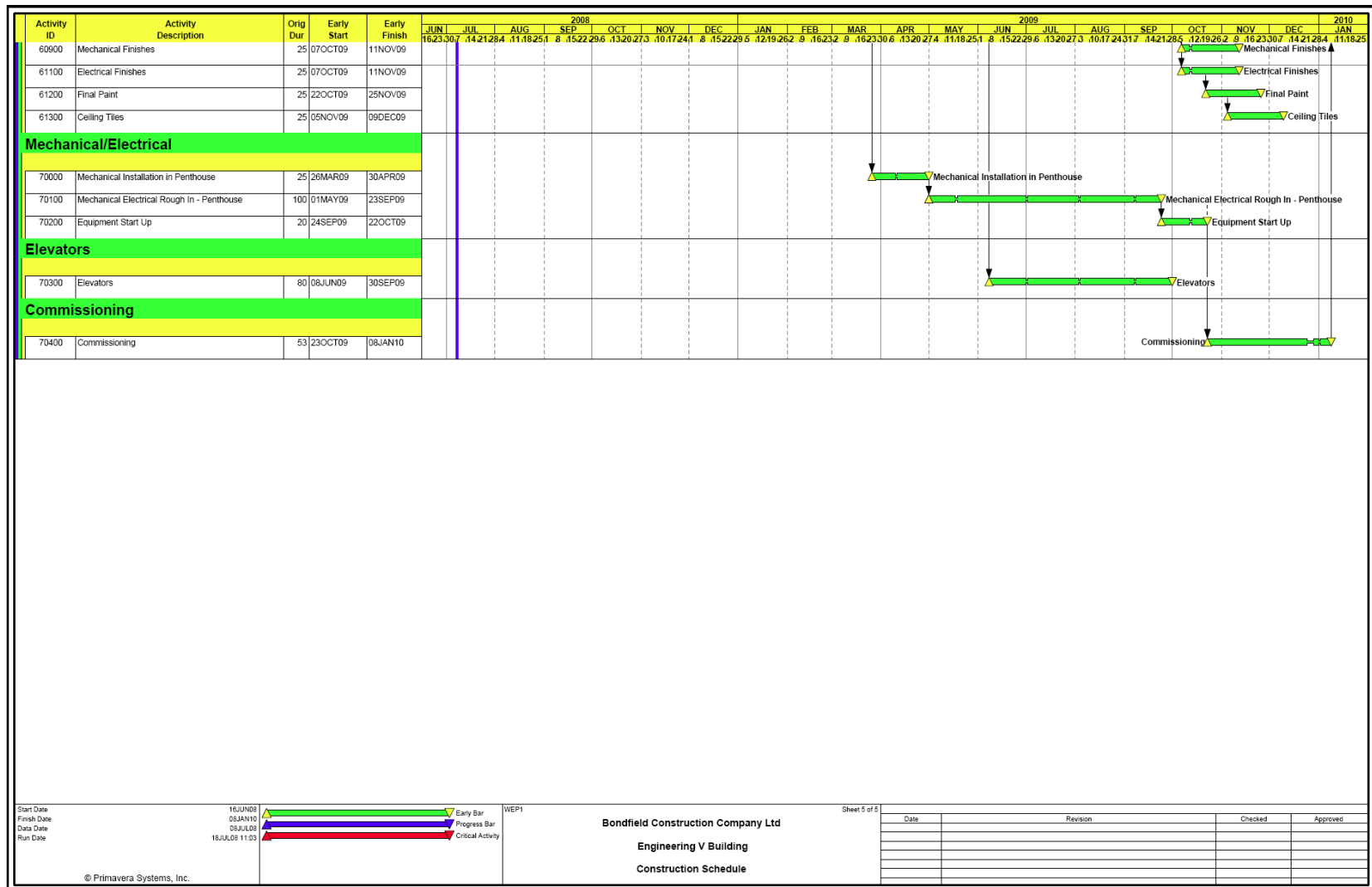
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Appendix A

Engineering V Building Original Construction Schedule

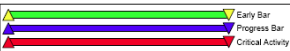






Start Date
Finish Date
Data Date
Run Date

16JUN08
08JAN10
08JUL08
18JUL08 11:03



WEP1

Bondfield Construction Company Ltd
Engineering V Building
Construction Schedule

Sheet 5 of 5

Date	Revision	Checked	Approved

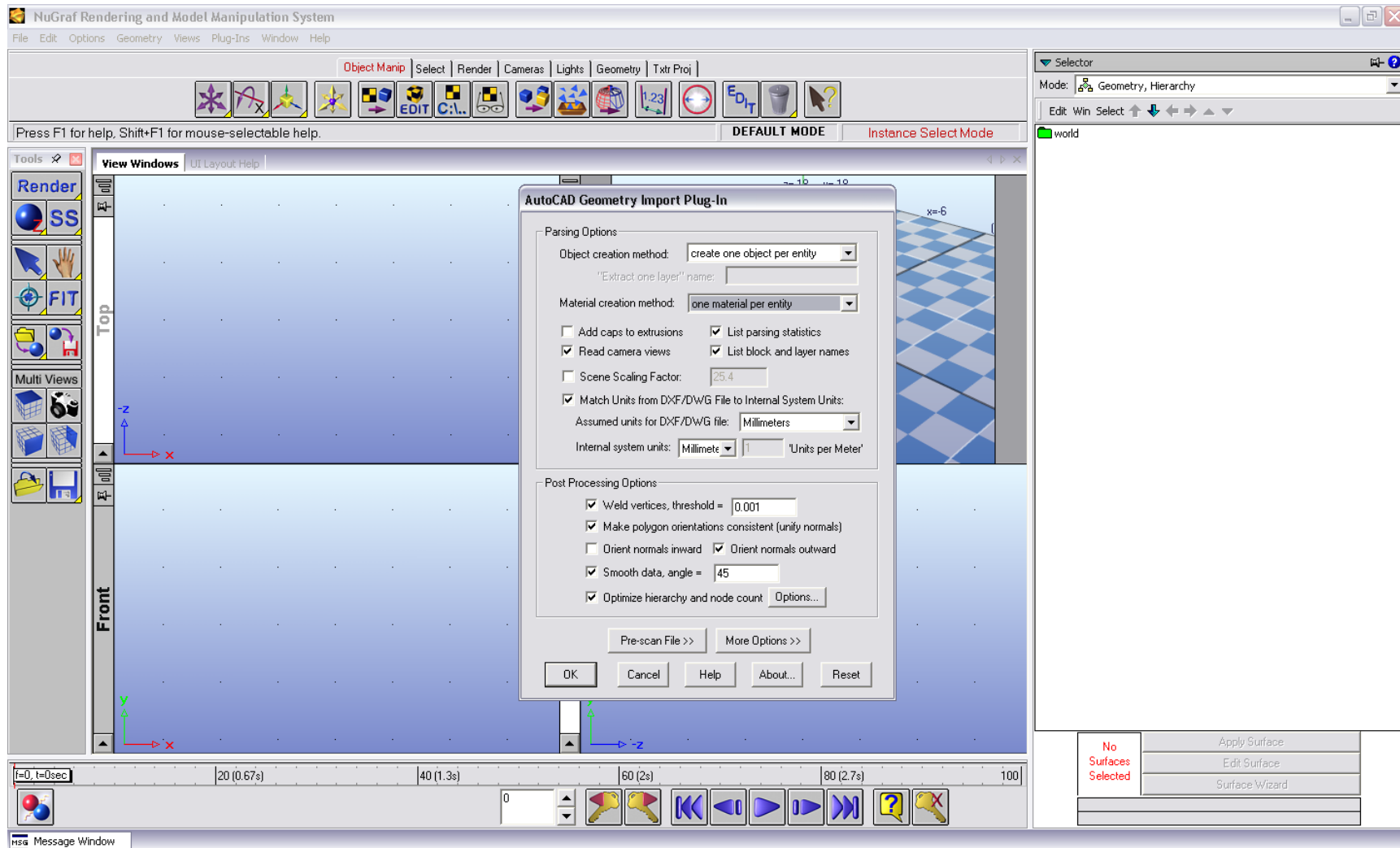
Appendix B

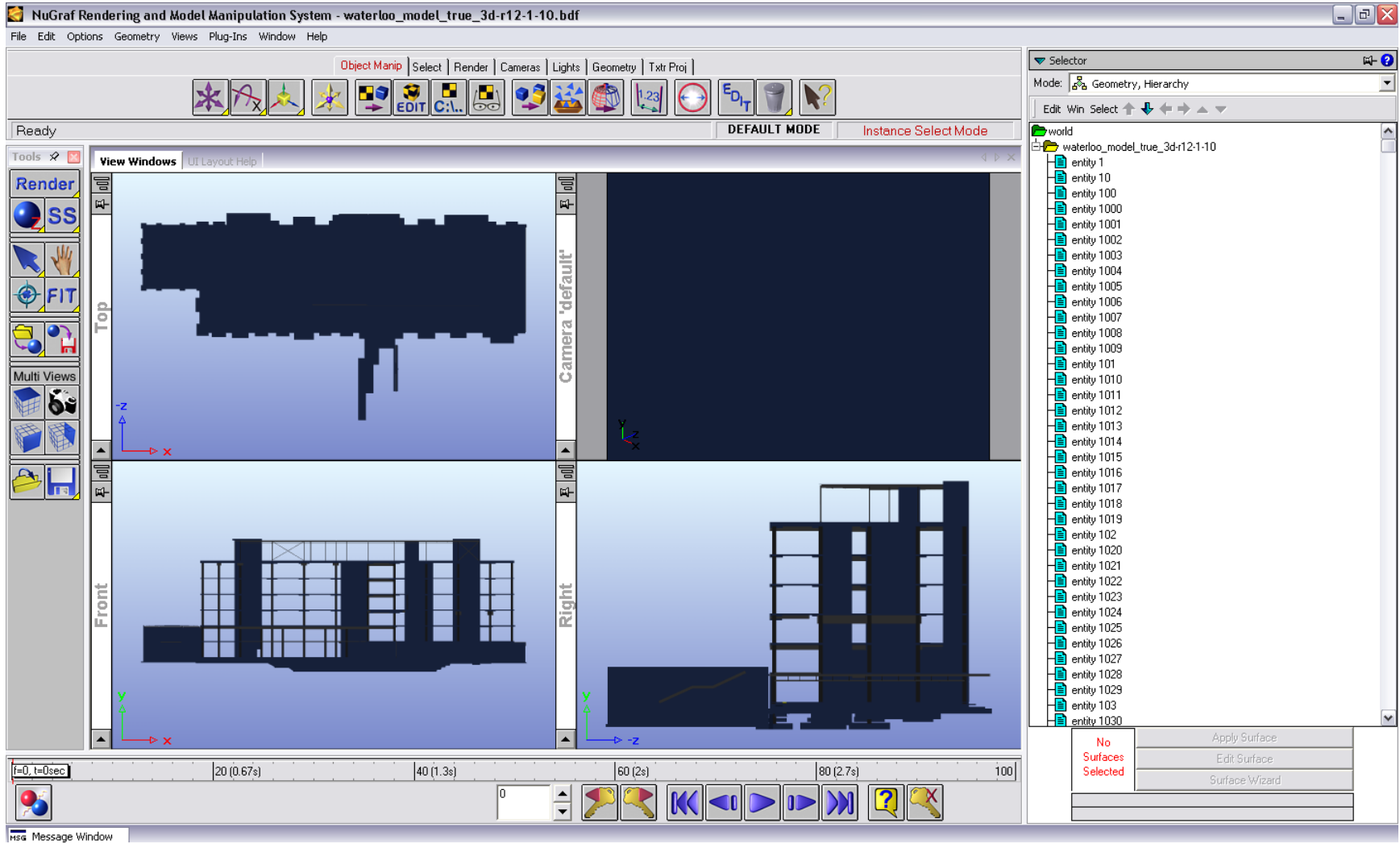
Engineering V Building Scanning Schedule

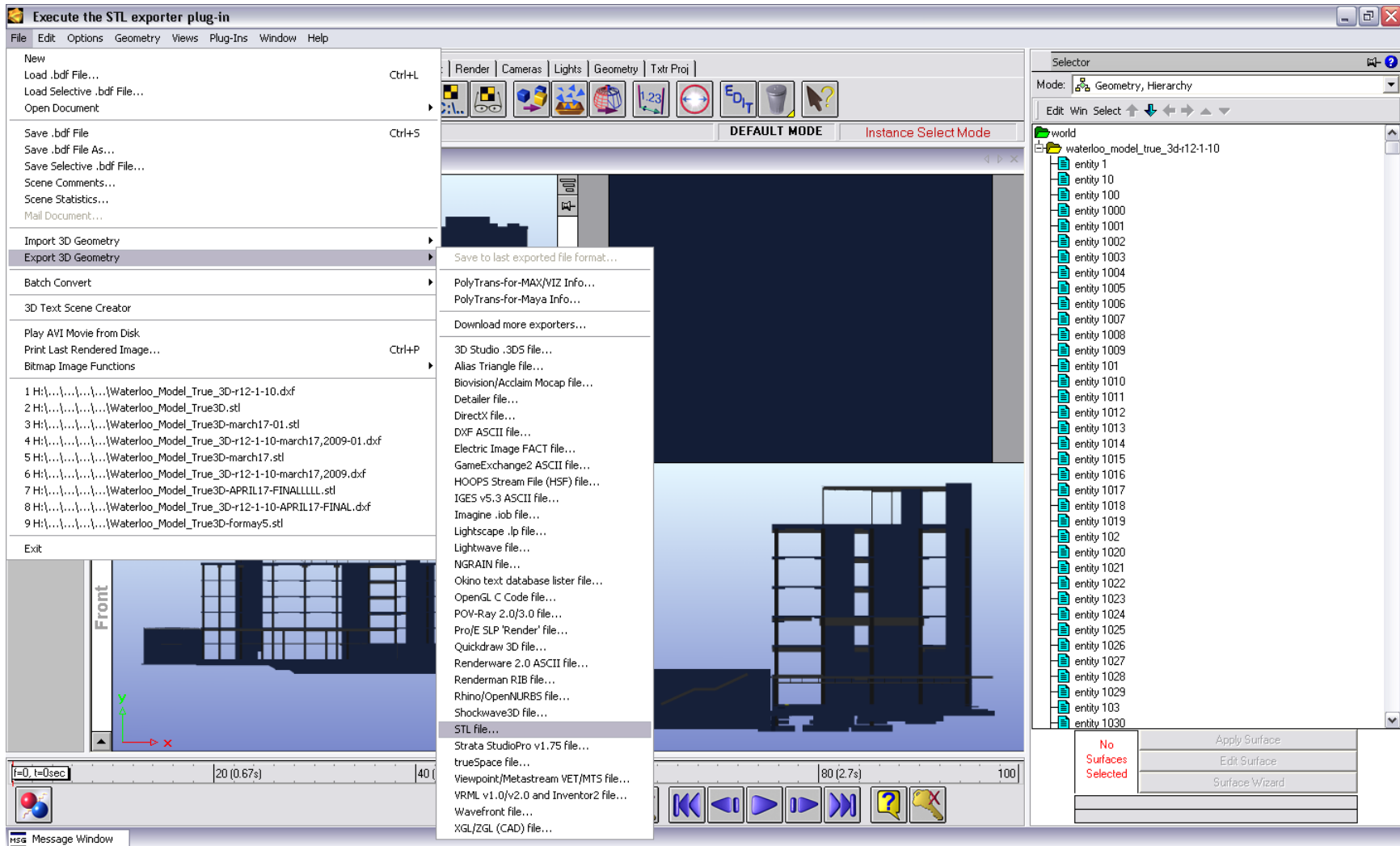
Scan ID	Scan Date	Horizontal Resolution	Vertical Resolution	Number of points in the scan
1	2008-07-10	582 μ rad	582 μ rad	1,068,522
2	2008-07-15	582 μ rad	582 μ rad	1,114,090
3	2008-07-18	582 μ rad	582 μ rad	1,061,056
4	2008-07-22	582 μ rad	582 μ rad	841,003
5	2008-07-25	582 μ rad	582 μ rad	1,935,082
6	2008-07-29	582 μ rad	582 μ rad	637,550
7	2008-08-01	582 μ rad	582 μ rad	448,447
8	2008-08-05	582 μ rad	582 μ rad	468,411
9	2008-08-12	582 μ rad	582 μ rad	1,081,922
10	2008-08-19	582 μ rad	582 μ rad	759,415
11	2008-08-21	582 μ rad	582 μ rad	777,672
12	2008-08-26 Scan 1	582 μ rad	582 μ rad	774,565
13	2008-08-26 Scan 2	582 μ rad	582 μ rad	914,516
14	2008-08-29 Scan 1	582 μ rad	582 μ rad	702,536
15	2008-08-29 Scan 2	582 μ rad	582 μ rad	1,344,998
16	2008-09-08 Scan 1	582 μ rad	582 μ rad	498,340
17	2008-09-08 Scan 2	582 μ rad	582 μ rad	842,481
18	2008-09-11	582 μ rad	582 μ rad	550,820
19	2008-09-16	582 μ rad	582 μ rad	627,781
20	2008-09-19	582 μ rad	582 μ rad	543,187
21	2008-09-26	582 μ rad	582 μ rad	786,723
22	2008-10-09	582 μ rad	582 μ rad	926,707
23	2008-10-17	582 μ rad	582 μ rad	1,055,607
24	2008-10-24 Scan 1	582 μ rad	582 μ rad	1,163,219
25	2008-10-24 Scan 2	582 μ rad	582 μ rad	1,801,467
26	2008-10-30	582 μ rad	582 μ rad	1,041,192
27	2008-11-06	582 μ rad	582 μ rad	1,679,618
28	2009-03-17 Scan 1	582 μ rad	582 μ rad	2,020,283
29	2009-03-17 Scan 2	582 μ rad	582 μ rad	1,031,206
30	2009-04-17 Scan 1	582 μ rad	582 μ rad	1,597,087
31	2009-04-17 Scan 2	582 μ rad	582 μ rad	960,578

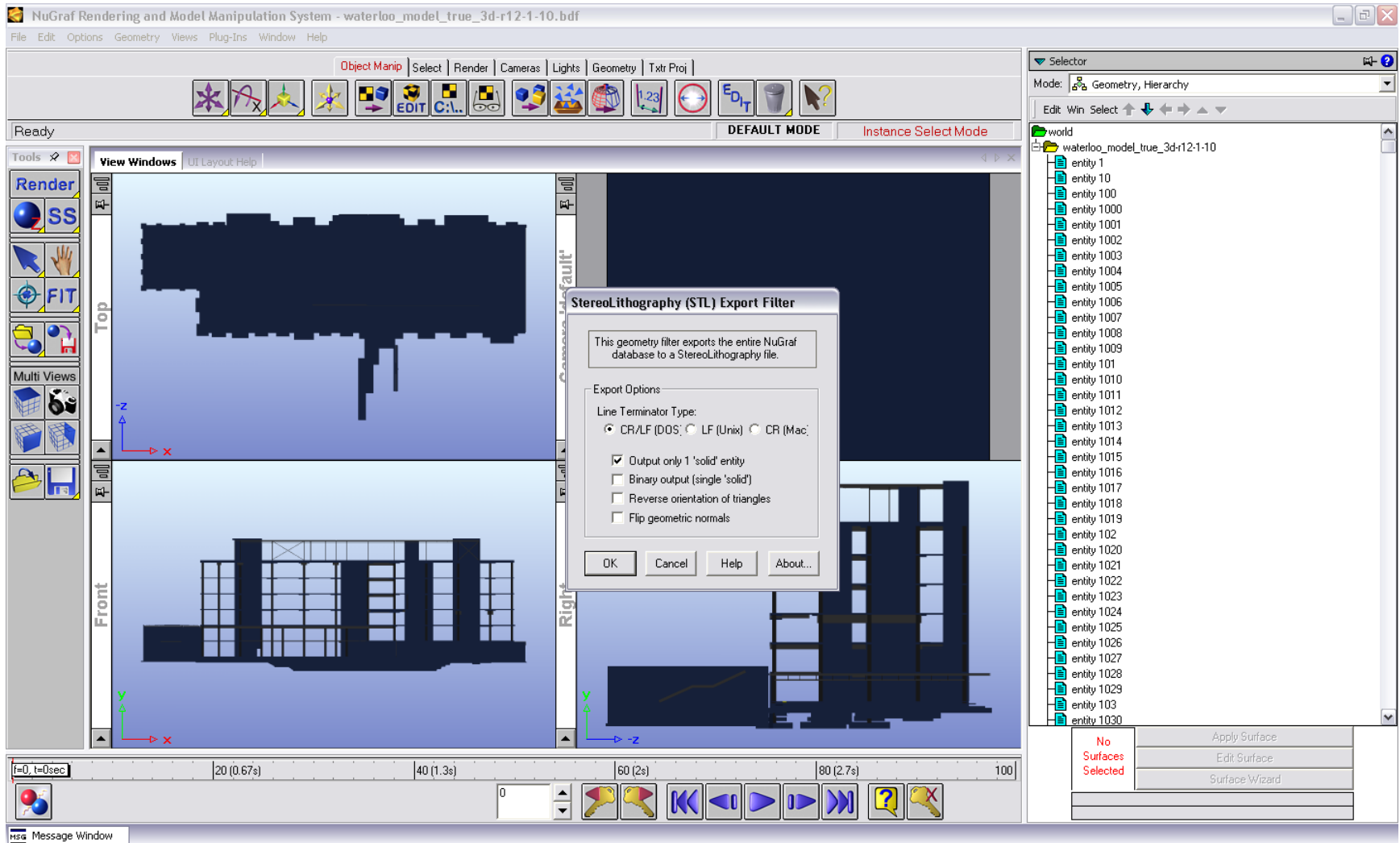
32	2009-04-17 Scan 3	582 μ rad	582 μ rad	1,448,095
33	2009-05-05 Scan 1	582 μ rad	582 μ rad	971,056
34	2009-05-05 Scan 2	582 μ rad	582 μ rad	734,027
35	2009-05-05 Scan 3	582 μ rad	582 μ rad	2,600,541
36	2009-05-05 Scan 4	582 μ rad	582 μ rad	1,815,218

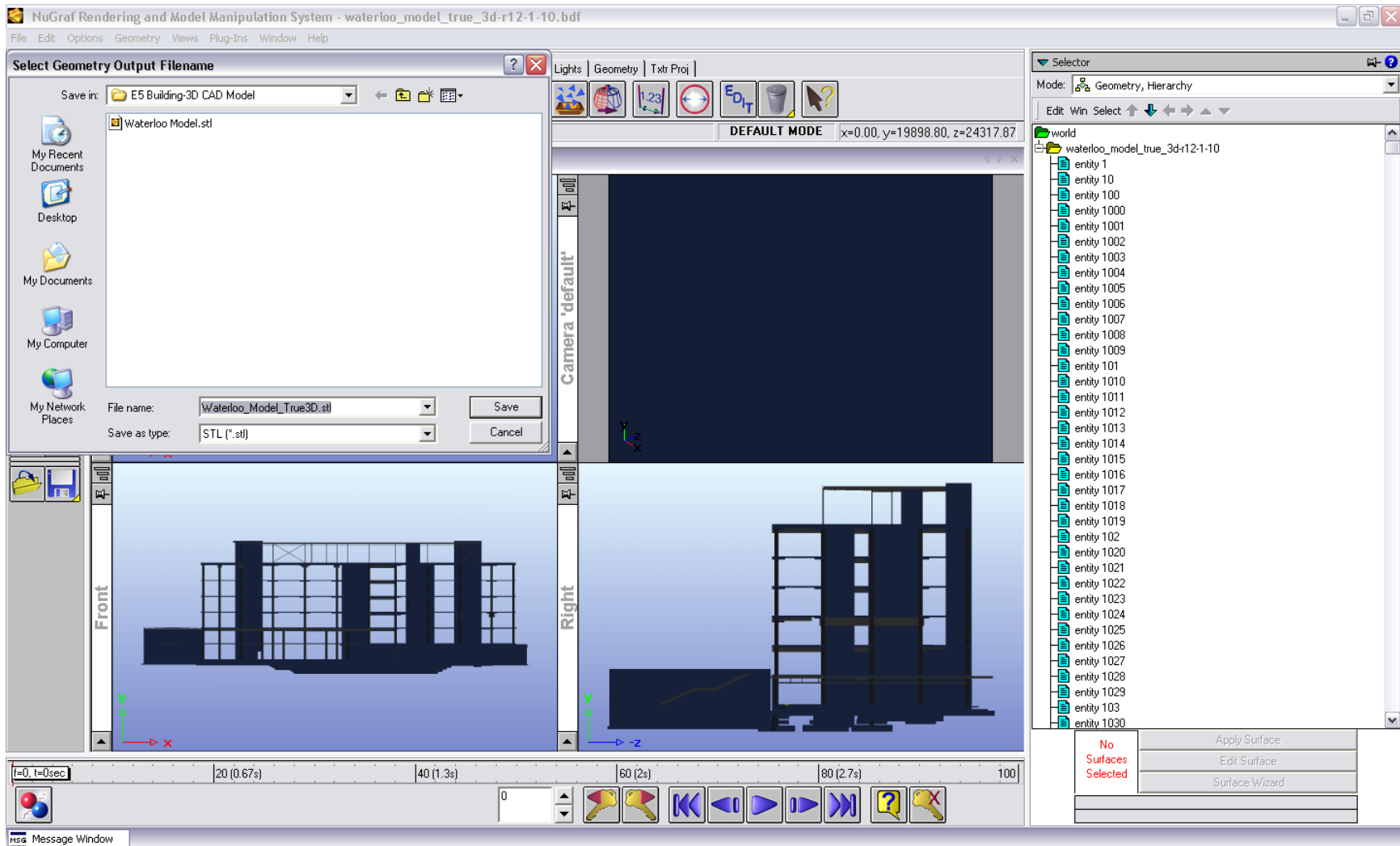
Appendix C STL Conversion using NuGraf software

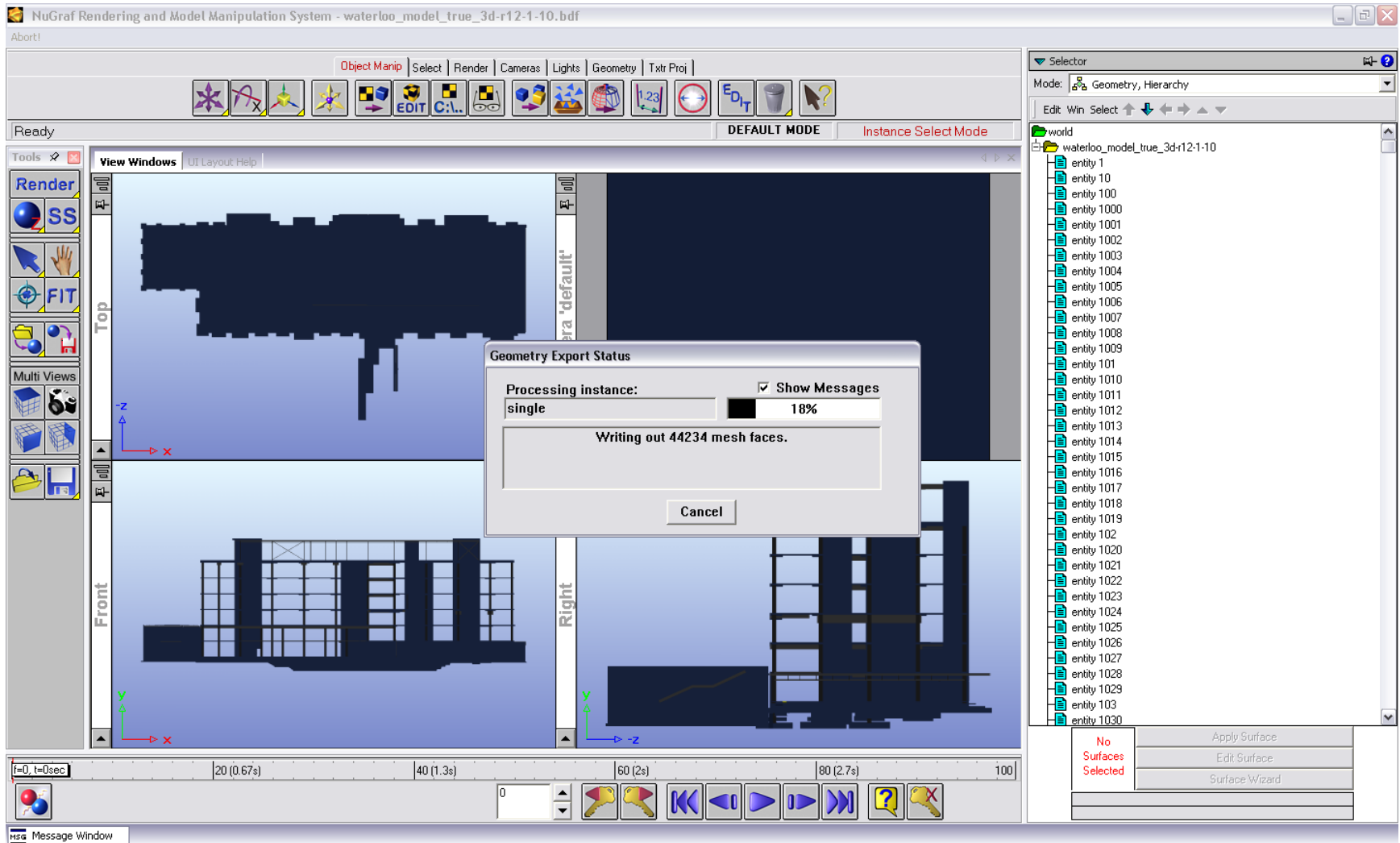












Appendix D

Engineering V Building Model in STL format

```
solid entity_1_0
  facet normal -0.140203 0.802621 0.579777
    outer loop
      vertex 99.9851 -200.013 300.015
      vertex 99.9814 -200.012 300.012
      vertex 99.974 -200.017 300.017
    endloop
  endfacet
  facet normal -0.139869 0.801951 0.580785
    outer loop
      vertex 99.9851 -200.013 300.015
      vertex 99.974 -200.017 300.017
      vertex 99.9791 -200.019 300.021
    endloop
  endfacet
endsolid entity_1_0
solid entity_10_0
  facet normal -0.137613 0.802789 0.580166
    outer loop
      vertex 100.023 -200.003 300.009
      vertex 100.021 -200.006 300.013
      vertex 100.029 -200.008 300.018
    endloop
  endfacet
  facet normal -0.140037 0.801656 0.581151
    outer loop
      vertex 100.023 -200.003 300.009
      vertex 100.029 -200.008 300.018
      vertex 100.032 -200.004 300.013
    endloop
  endfacet
endsolid entity_10_0
solid entity_100_0
  facet normal 0 1 0
    outer loop
      vertex 34522.6 6929.86 25350
      vertex 34523.5 6929.86 25350
      vertex 34523.5 6929.86 21500
    endloop
  endfacet
  facet normal 0 1 0
    outer loop
      vertex 34522.6 6929.86 25350
      vertex 34523.5 6929.86 21500
      vertex 34522.6 6929.86 21500
    endloop
  endfacet
  facet normal 0 1 0
    outer loop
      vertex 33923.5 6929.86 21500
      vertex 33923.5 6929.86 25350
      vertex 34522.6 6929.86 25350
    endloop
  endfacet
  facet normal 0 1 0
    outer loop
      vertex 33923.5 6929.86 21500
      vertex 34522.6 6929.86 25350
      vertex 34522.6 6929.86 21500
    endloop
  endfacet
  facet normal 0 0 1
    outer loop
      vertex 34522.6 6929.86 25350
      vertex 33923.5 6329.86 25350
      vertex 34523.5 6329.86 25350
    endloop
  endfacet
  facet normal 0 0 1
    outer loop
      vertex 34522.6 6929.86 25350
      vertex 34523.5 6329.86 25350
      vertex 34523.5 6929.86 25350
    endloop
  endfacet
```

(...continue until solid entity_1573_0)

Appendix E Data Processing

E.1 Coarse registration

As explained in Section 3.3, Trimble™ Real Works software geo-referencing tool was used for the coarse registration step of the data analysis presented in this thesis. This step requires user to select at least three corresponding points between the CAD model and the scan point cloud. The points should be well distributed in the model, and be easily identifiable in the scan file for more accurate results. It consists of the following steps:

- 1- Well distributed points are chosen throughout the CAD model, and their coordinate values are recorded (Cartesian coordinates).
- 2- The scan point cloud is loaded in Trimble RealWorks, and registration tool is activated (Figure E.1). There are three different options for registration. Geo-referencing option was chosen here (Figure E.2).

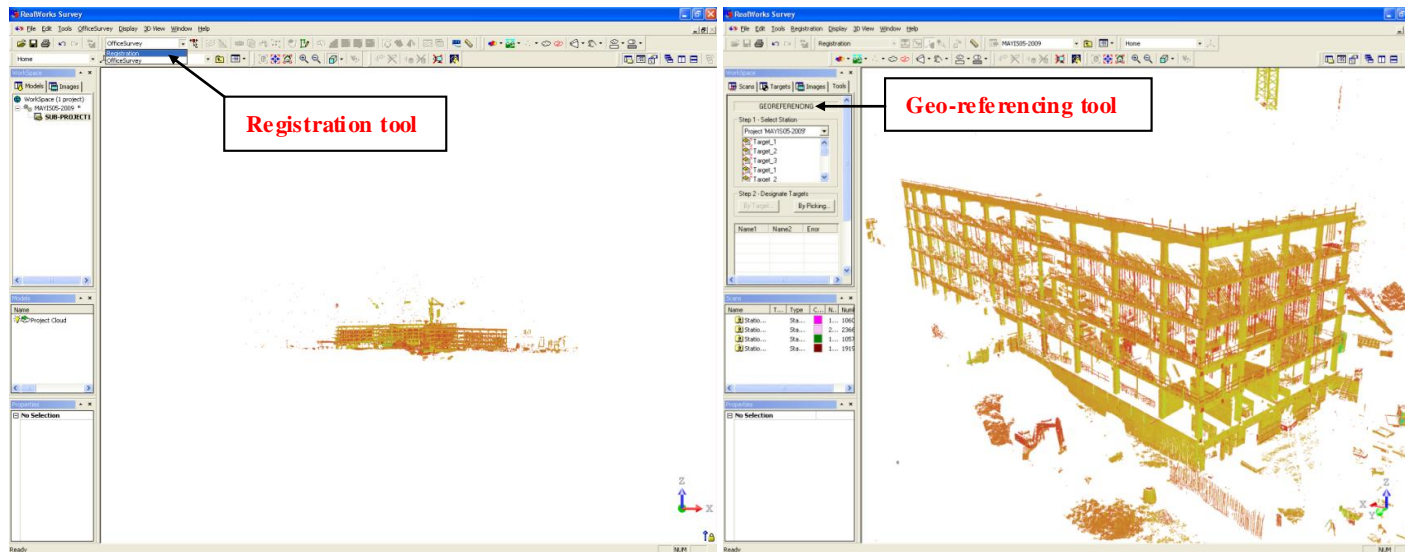


Figure E.1 Trimble® RealWorks® Registration Tool

Figure E.2 Trimble® RealWorks® Georeferencing Tool

- 3- Using the geo-referencing tool, corresponding points are selected in the scan point cloud, and Cartesian coordinate values obtained from the CAD model is assigned to them (Figure E.3). The geo-referencing tool calculates an approximate value of RMS (a value of 50-60 mm is determined to be acceptable here). The spherical coordinates of the selected points are recorded when an acceptable value of RMS is obtained. At the end of this step, the scan point cloud is registered faithfully in the CAD model's Cartesian coordinate system (Figure E.4).

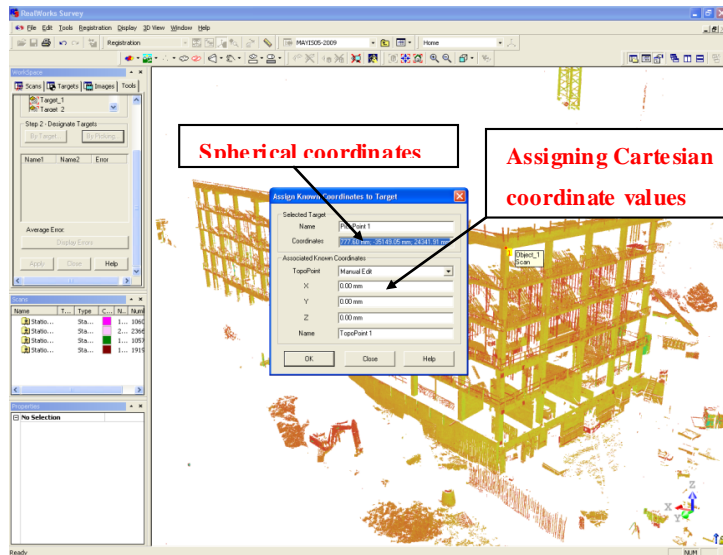


Figure E.3 Conversion from spherical to Cartesian coordinates

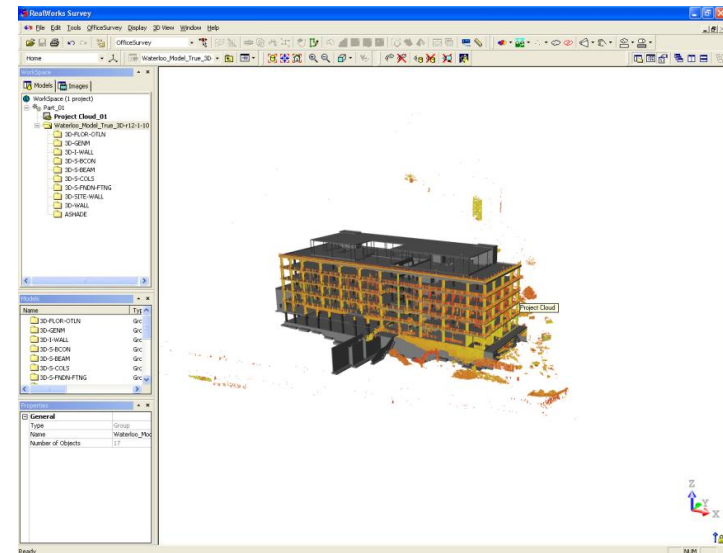


Figure E.4 Registered scan point cloud and CAD model

The coarse registration is optimized using Microsoft Excel Solver tool. Translation (x, y, z), rotation (yaw, pitch, roll), and minimum square error values obtained at the end of the optimization are used as input coarse registration parameters in the system.

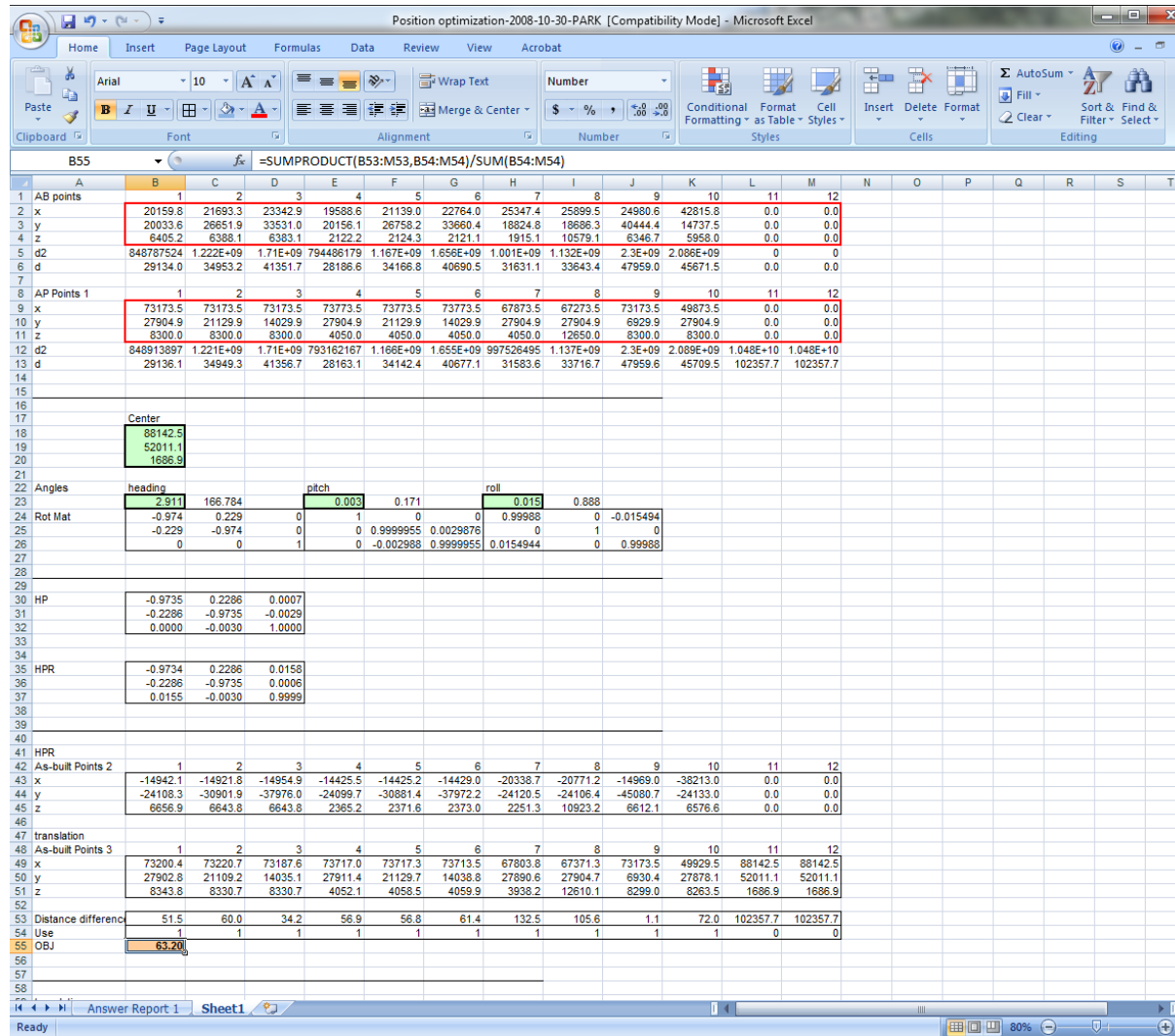


Figure E.5 Coarse registration optimization using MS Excel®

E.2 Data Structure

The data must be organized as follows (the folder names in the brackets < > can be chosen as wanted; the ones without must be written here)

- > Folder: <Project>
 - > Folder: As Built
 - > Folder <Scan> (for scan 1)
 - > File: ASCII File with point cloud 1 (.asc)
 - > File: ASCII File with scan 1 resolution (.asc)
 - > File: ASCII File with registration information (.asc)
 - > Folder <Scan> (for scan 2)
 - > File: ASCII File with point cloud 2 (.asc)
 - > File: ASCII File with scan 2 resolution (.asc)
 - > File: ASCII File with registration information (.asc)
 - > ...
 - > Folder: AsPlanned
 - > Folder: STL
 - > File: ASCII File with CAD model (.stl)
 - > Folder: Schedule
 - > File: Planner File with schedule information

Notes:

- The ASCII File containing the scan resolution information must contain “Resolution” in its name.
- The ASCII File containing the registration information must contain “Position” in its name.
- The ASCII File containing the point cloud must NOT contain “Resolution” or “Position” in its name.

The reason for these naming constraints is to speed up the retrieval of the necessary files.

Point Cloud File: This ASCII file is simply a list of points, one per line, and containing the following information: X, Y, Z, Refl, R, G, B, Nx, Ny, Nz which are described below.

- X, Y, and Z are the position values.
- Refl is the reflectivity value.
- R, G, and B are the color values.
- Nx, Ny, and Nz are the coordinates of the vector normal to the point (with respect to the local surface).

Resolution File: This is an ASCII file containing the following two lines:

%in mm @ 100

Resolution Pan: "Rx"

Resolution Tilt: "Ry"

- Rx is the horizontal resolution.
- Ry is the vertical resolution.

Registration File: This is an ASCII file containing the following information.

All angle are in degrees and distances in milimeters

MeanRegError: "RegError"

<Registration>

XDif: "Tx"

YDif: "Ty"

ZDif: "Tz"

RollDif: "Rroll"

PitchDif: "Rpitch"

YawDif: "Ryaw"

</Registration>

- RegError is the coarse registration error obtained from the manual coarse registration.
- Tx is the registration translation along the X axis obtained from the manual coarse registration.
- Ty is the registration translation along the Y axis obtained from the manual coarse registration.
- Tz is the registration translation along the Z axis obtained from the manual coarse registration.
- Rx is the registration Roll rotation angle obtained from the manual coarse registration.
- Ry is the registration Pitch rotation angle obtained from the manual coarse registration.
- Rz is the registration Yaw rotation angle obtained from the manual coarse registration.

Appendix F Progress Control Software

Open Project: The first step is to open a project. For this go to the menu “Project” and choose “Open”. A second will come up where you must pick the folder of the <Project> shown in the data structure.

Then the STL model is loaded, and is presented in the Tab “Project” as shown below.

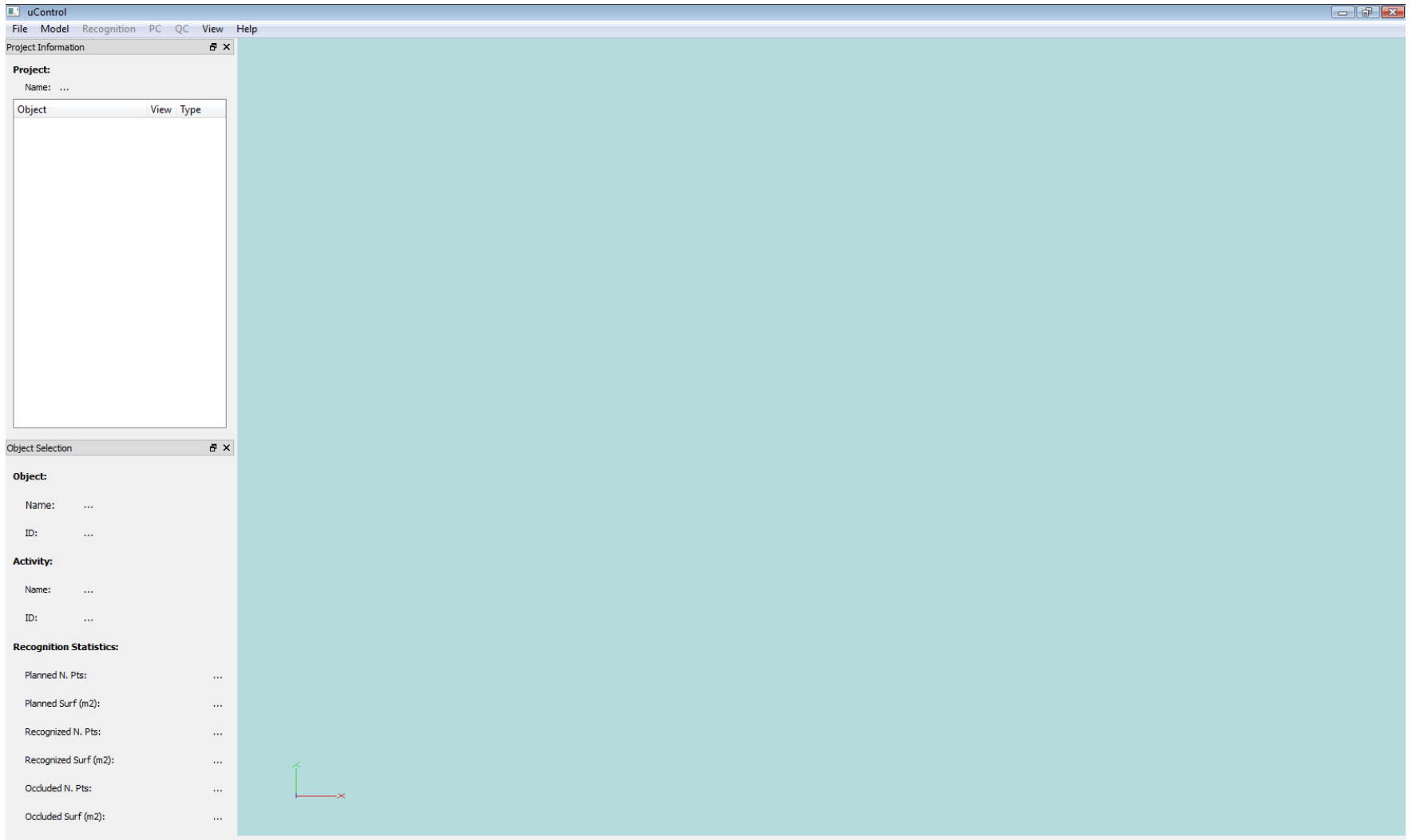
Pick Scan: The next step is to pick up the scan that you want to process. For this, go to the menu “Detection” and choose “1- Pick Scan”

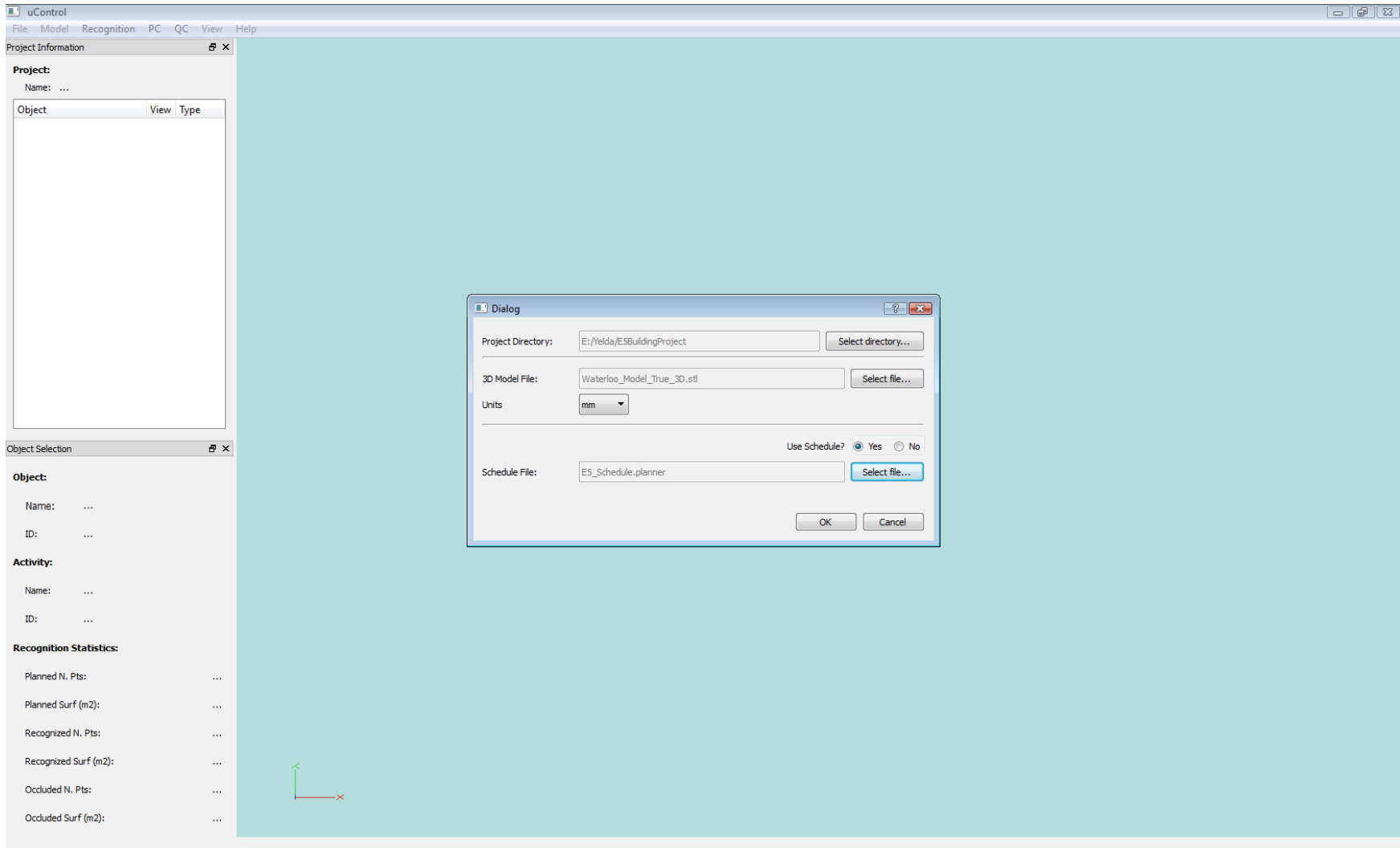
A window pops up where you have to choose the folder <Scan> as defined in the data structure. Note that this window should directly open on the folder AsBuilt, so that you can rapidly find the folder of the scan to be processed.

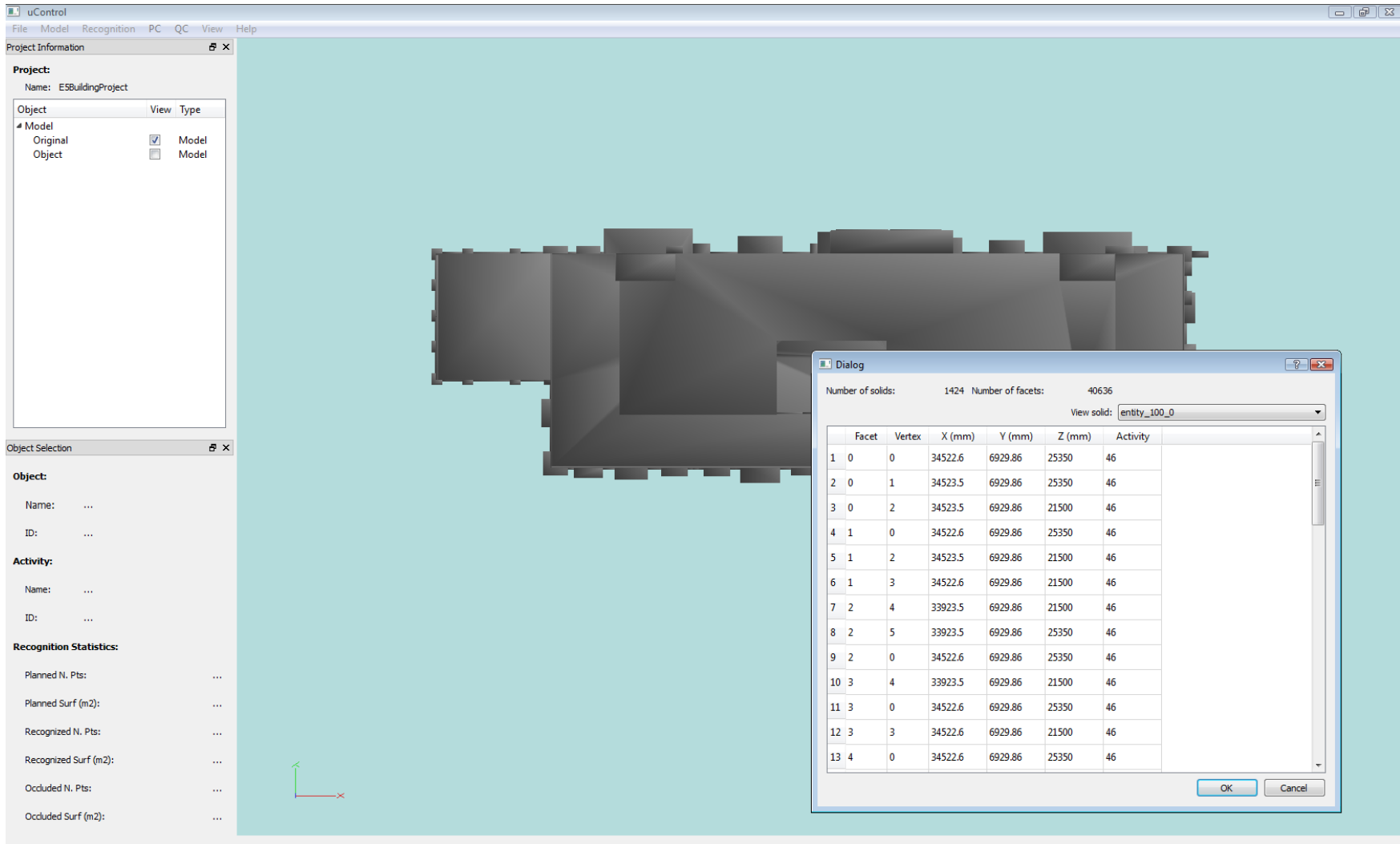
Then, a second window pops up asking you to pick a point frequency. This enables you to load all the points (pick “1”) or only 10% of the points (pick “10”), or 4% (pick “25”), etc.

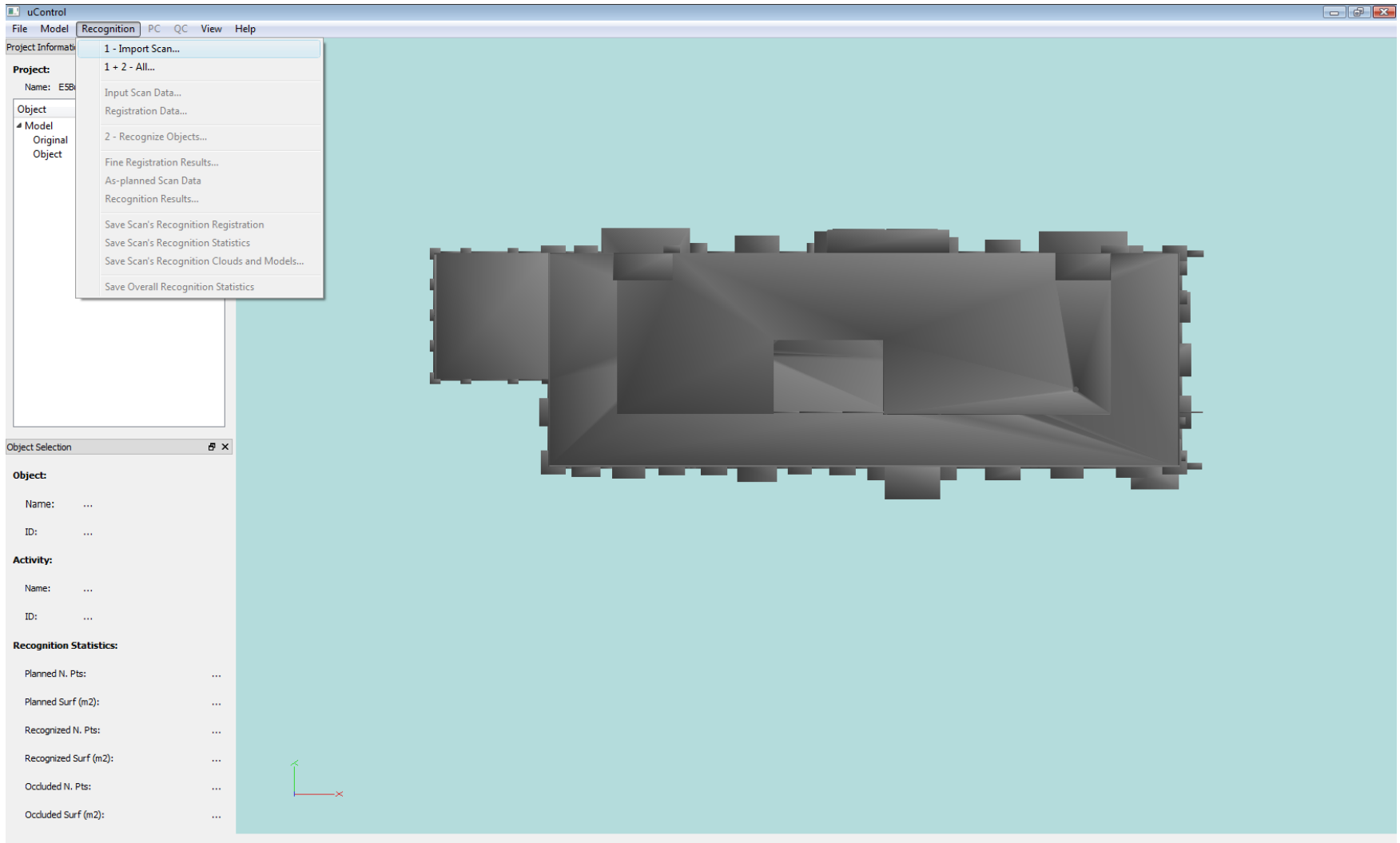
Finally, a last window pops up where the ASCII file containing the registration information is picked.

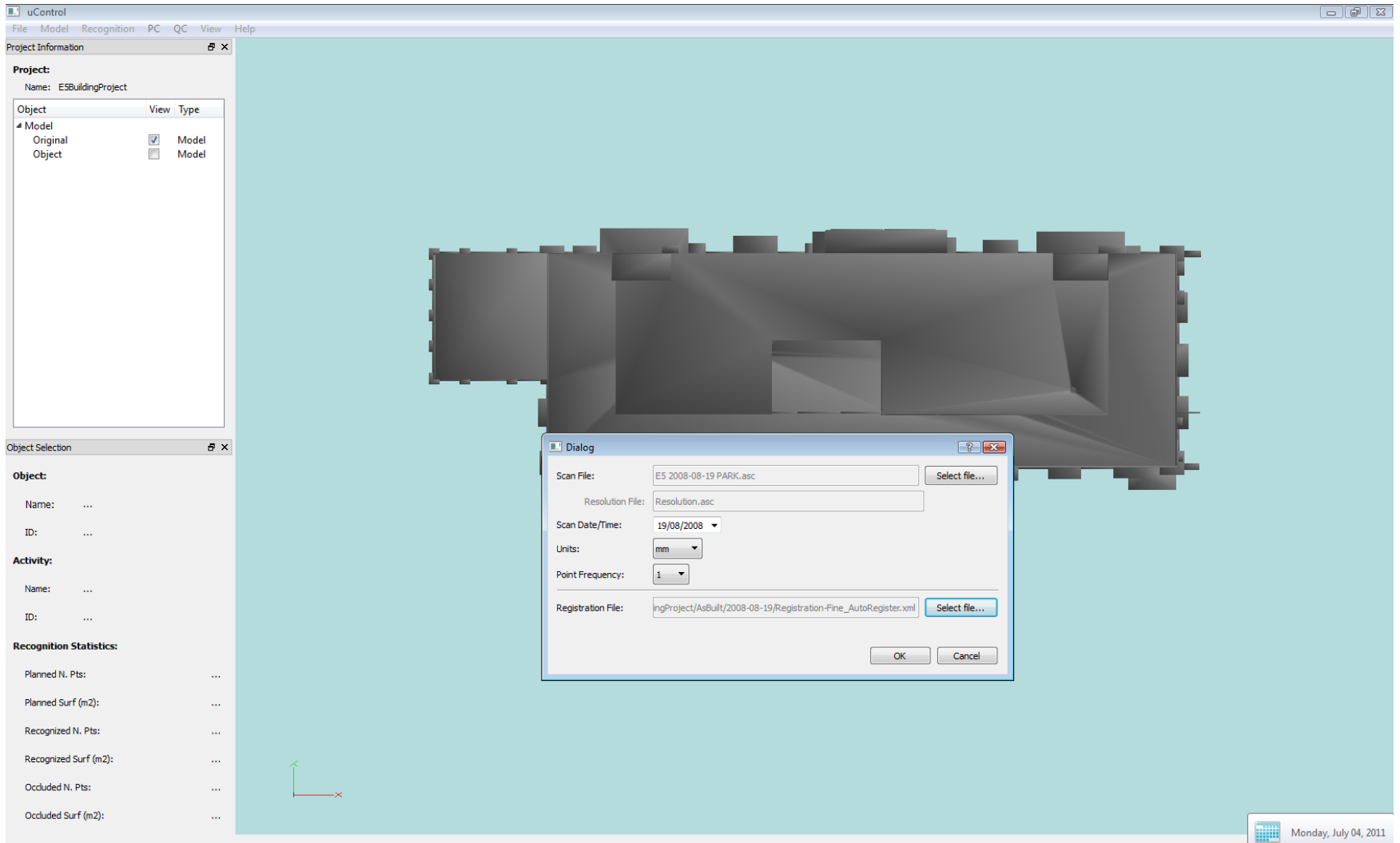
The scan, its resolution information, and its registration information are now loaded. Detailed information about the scan is presented in the tab “AB Scan”:











uControl
File Model Recognition PC QC View Help

Project Information

Project:
Name: ESBUILDINGPROJECT

Object	View	Type
Model		
Original	<input checked="" type="checkbox"/>	Model
Object	<input type="checkbox"/>	Model
2008-08-19		
AsBuilt	<input checked="" type="checkbox"/>	Scan

Object Selection

Object:
Name: ...
ID: ...

Activity:
Name: ...
ID: ...

Recognition Statistics:
Planned N. Pts: ...
Planned Surf (m2): ...
Recognized N. Pts: ...
Recognized Surf (m2): ...
Occluded N. Pts: ...
Occluded Surf (m2): ...

Dialog

Start date: 16.06.2008

Used calendar ID: 1

ID	Level	Umbr	Act. Name	Type	Dur. (hrs)	Start	End	Status	Prev. Prog	Sched. Prog	Recog.
1	1	1	Construction Starts	1	0	16.06.2008	16.06.2008	0	0.00	0.00	0.00
2	2	1	Mobilization	0	240	16.06.2008	25.07.2008	0	0.00	1.00	0.00
3	3	1	Excavation	0	280	16.06.2008	01.08.2008	0	0.00	1.00	0.00
4	4	1	Footings - Section 1	0	72	23.06.2008	03.07.2008	0	0.00	1.00	0.00
5	5	1	Footings - Section 2	0	72	03.07.2008	16.07.2008	0	0.00	1.00	0.00
6	6	1	Footings - Section 3	0	64	16.07.2008	28.07.2008	0	0.00	1.00	0.00
7	7	1	Walls & Columns to Gro...	0	56	03.07.2008	14.07.2008	0	0.00	1.00	0.00
8	8	1	Walls & Columns to Gro...	0	56	16.07.2008	25.07.2008	0	0.00	1.00	0.00
9	9	1	Walls & Columns to Gro...	0	56	28.07.2008	06.08.2008	0	0.00	1.00	0.00

OK Cancel

uControl
File Model Recognition PC QC View Help

Project Information

Project:
Name: ESBUILDINGPROJECT

Object	View	Type
4 Model		
Original	<input checked="" type="checkbox"/>	Model
Object	<input type="checkbox"/>	Model
4 2008-08-19		
AsBuilt	<input checked="" type="checkbox"/>	Scan

Object Selection

Object:
Name: ...
ID: ...

Activity:
Name: ...
ID: ...

Recognition Statistics:

Planned N. Pts: ...
Planned Surf (m2): ...
Recognized N. Pts: ...
Recognized Surf (m2): ...
Occluded N. Pts: ...
Occluded Surf (m2): ...

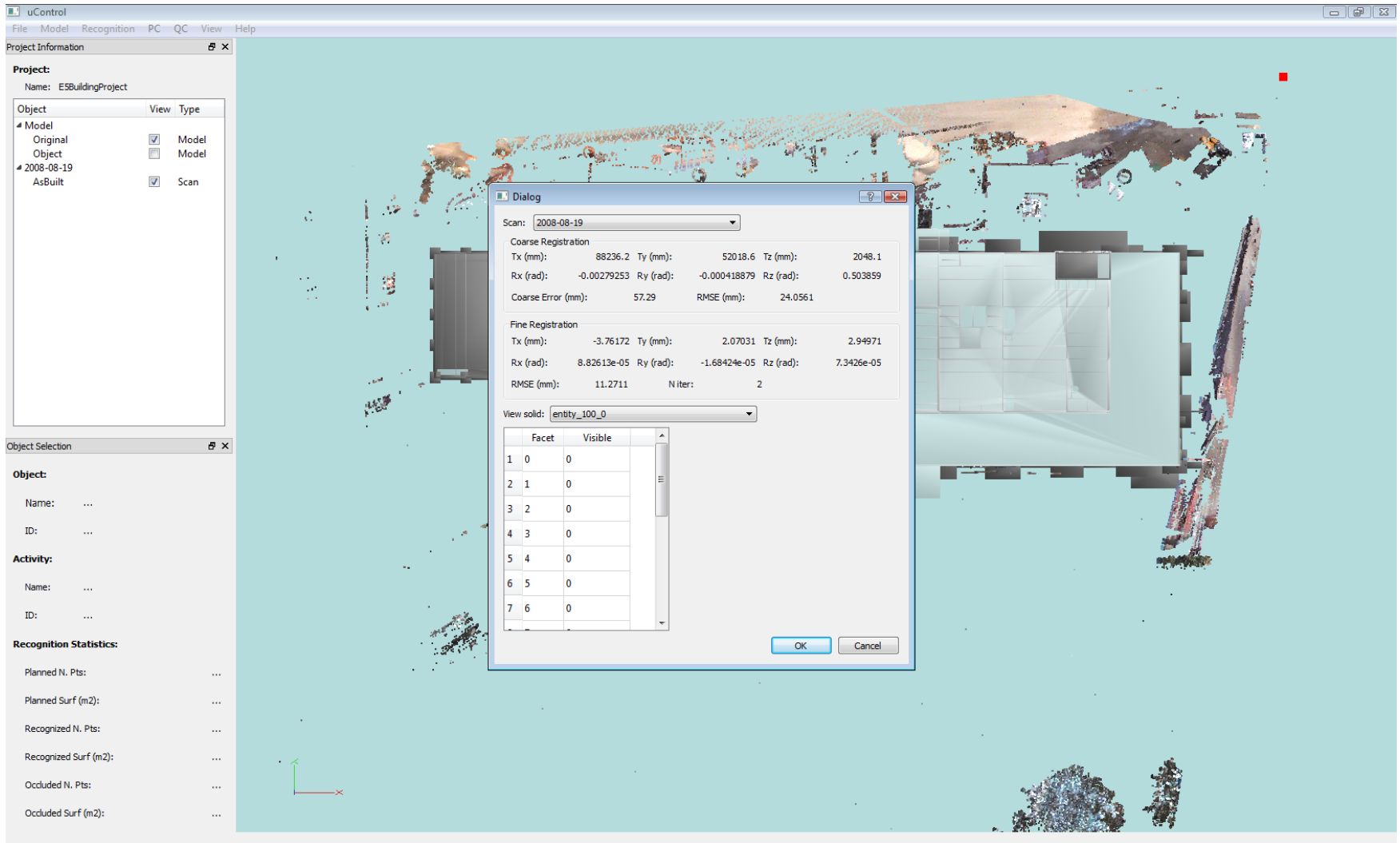
Dialog

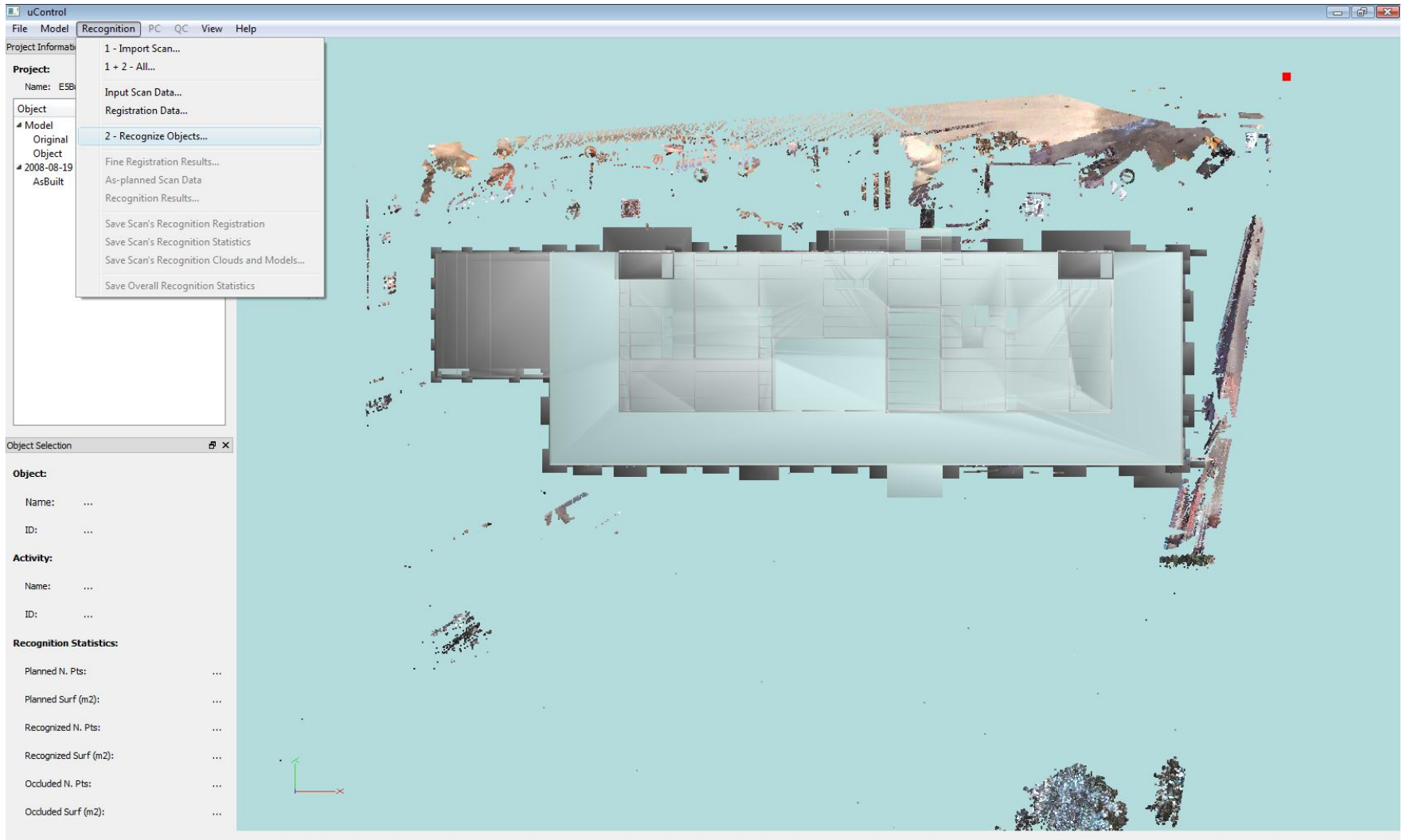
Scan: 2008-08-19 19/08/2008

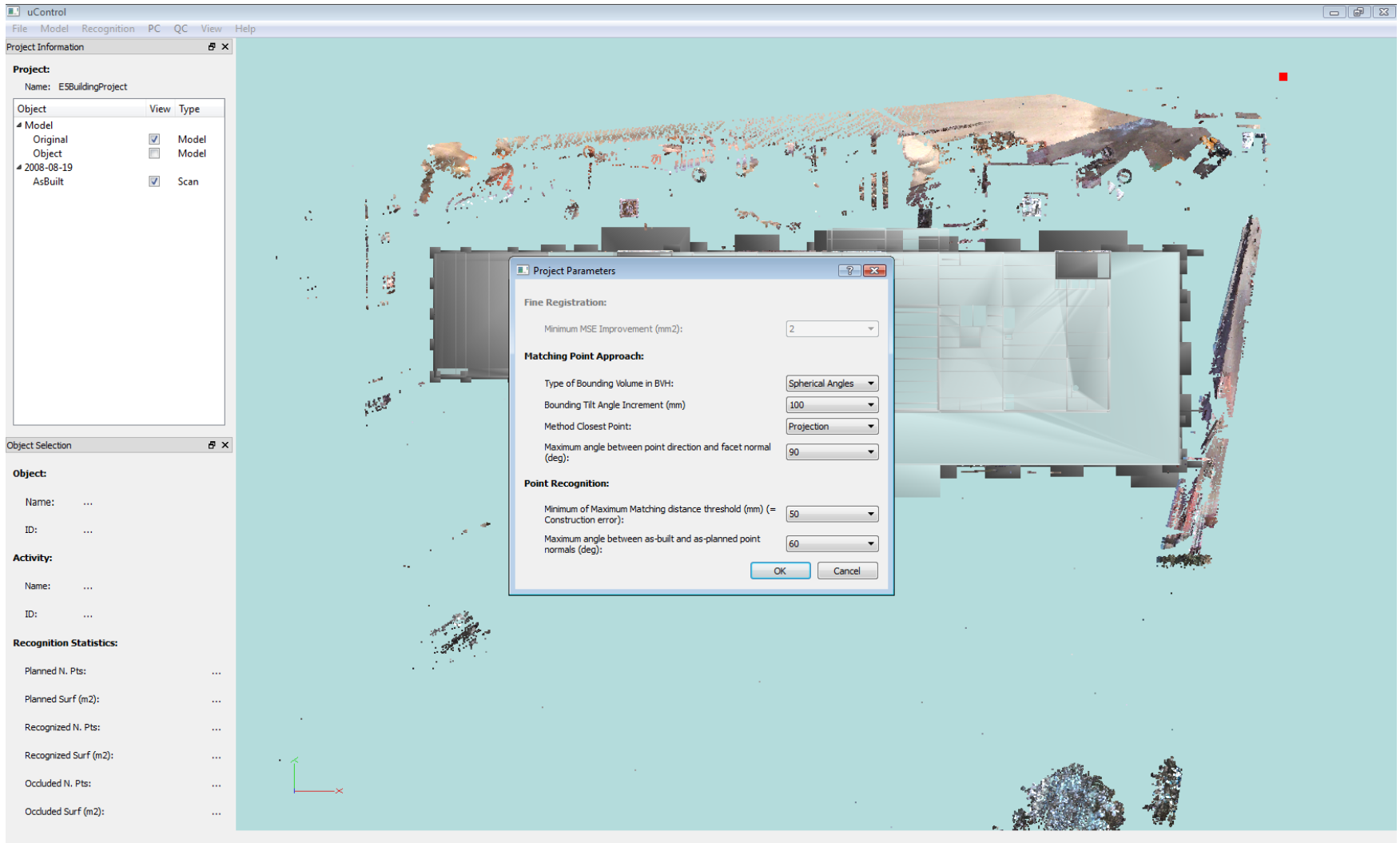
Number of points: 759415

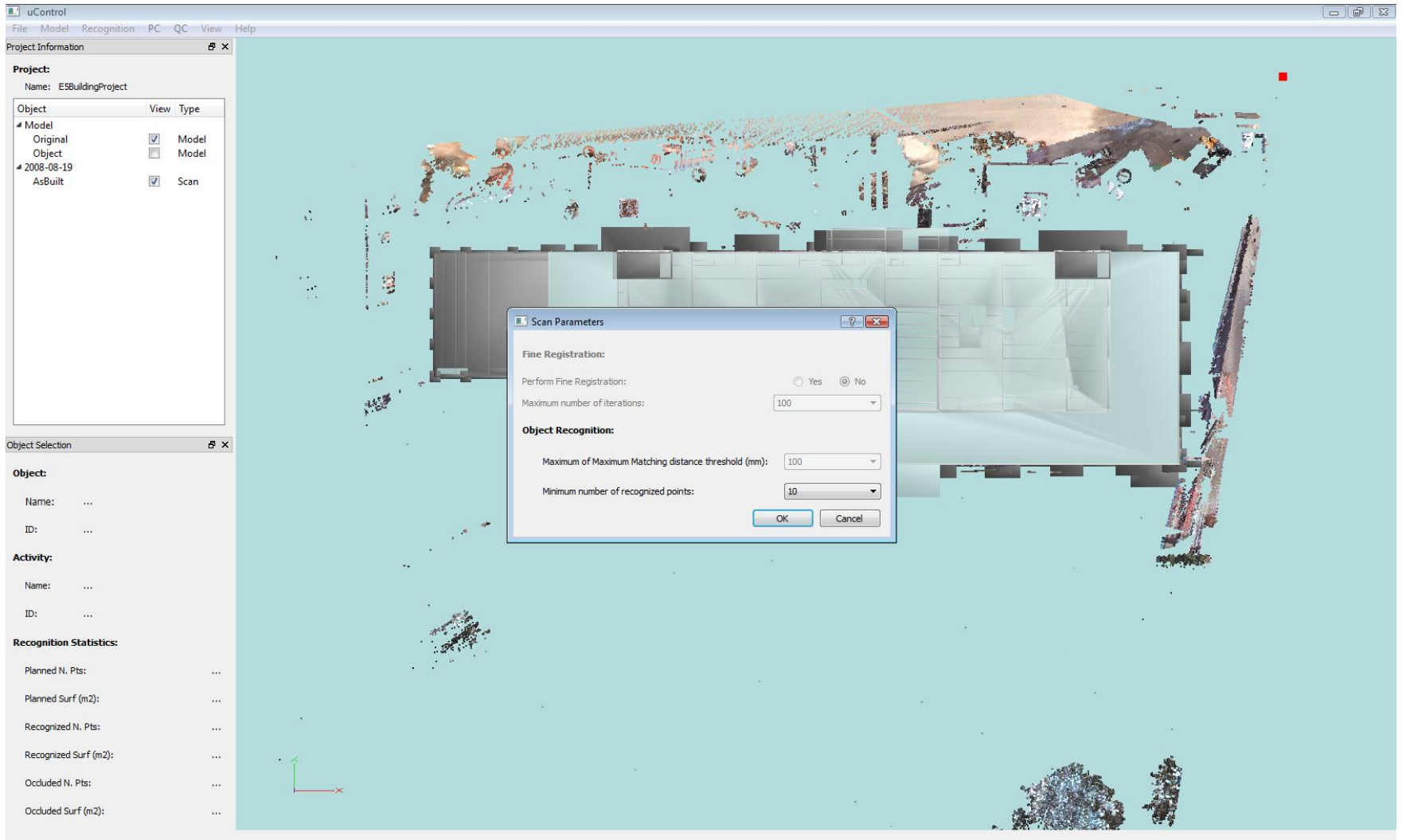
	Pt ID	X (mm)	Y (mm)	Z (mm)	Reflect.	R	G	B
1	0	74267.4	-43362.9	10237.2	0.0470...	45	64	89
2	1	74063.4	-44756.6	10284.8	0.0352...	24	39	63
3	2	74340.3	-42864.4	10066.2	0.0666...	24	39	63
4	3	73796.9	-46576.7	10322.5	0.0431...	52	51	74
5	4	73808.3	-46498.2	10259.8	0.0901...	52	51	74
6	5	74112.5	-44419.5	10026.4	0.0666...	86	91	112
7	6	74089.5	-44576.4	9982.7	0.0745...	86	91	112
8	7	73820.9	-46411.1	10072.4	0.0980...	109	102	127
9	8	74313.3	-43046.5	9684.59	0.1137...	109	102	127
10	9	74232.8	-43596.2	9674.45	0.0901...	109	102	127
11	10	74092.5	-44554.3	9690.94	0.0509...	96	106	116
12	11	74139.6	-44232.4	9610.22	0.0392...	105	94	93
13	12	74108	-44447.6	9567.2	0.0431...	105	94	93
14	13	73703.2	-47212.9	9664.99	0.0274...	89	92	91
15	14	70463	-69348.9	11293.2	0.0784...	93	81	67

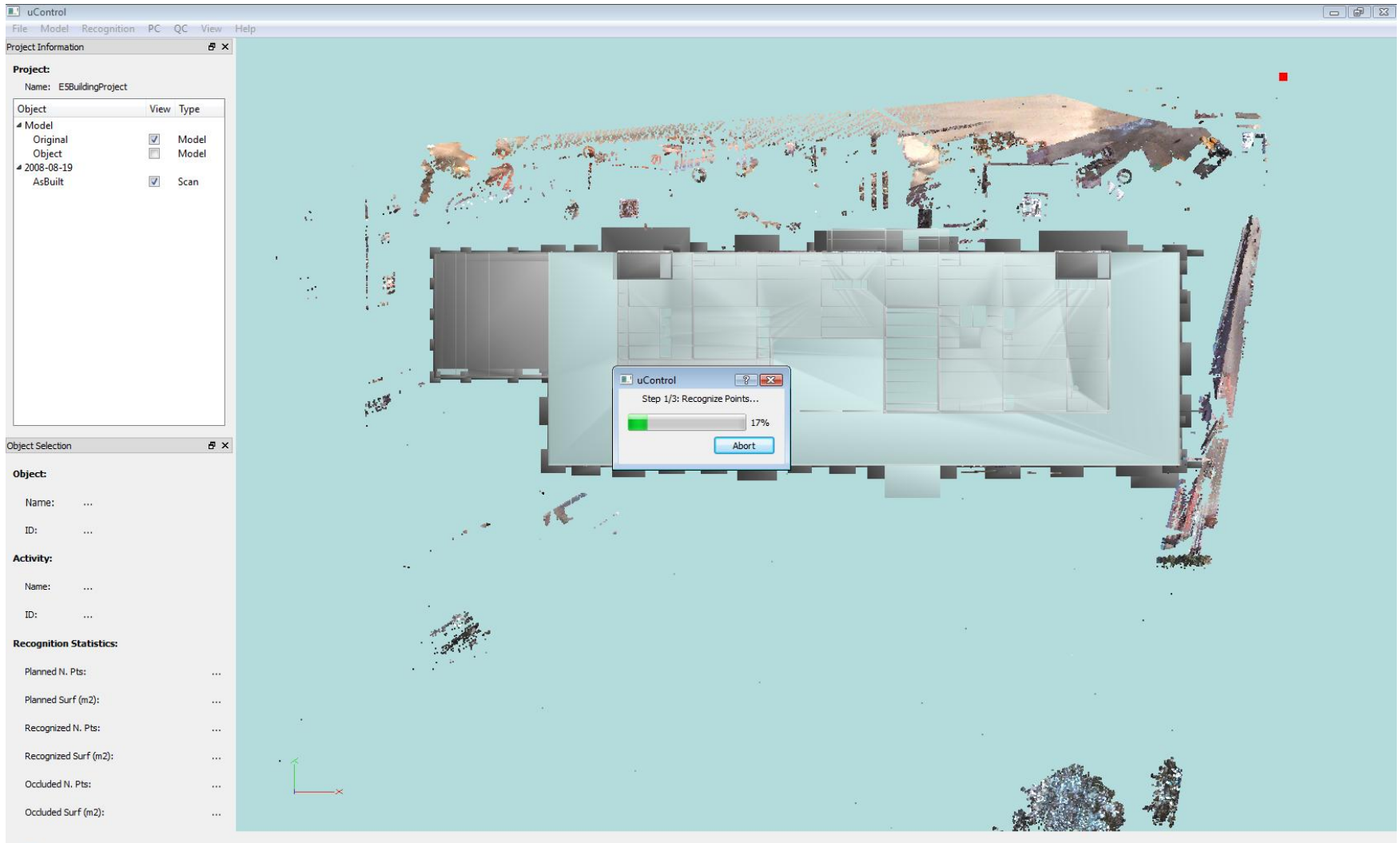
OK Cancel

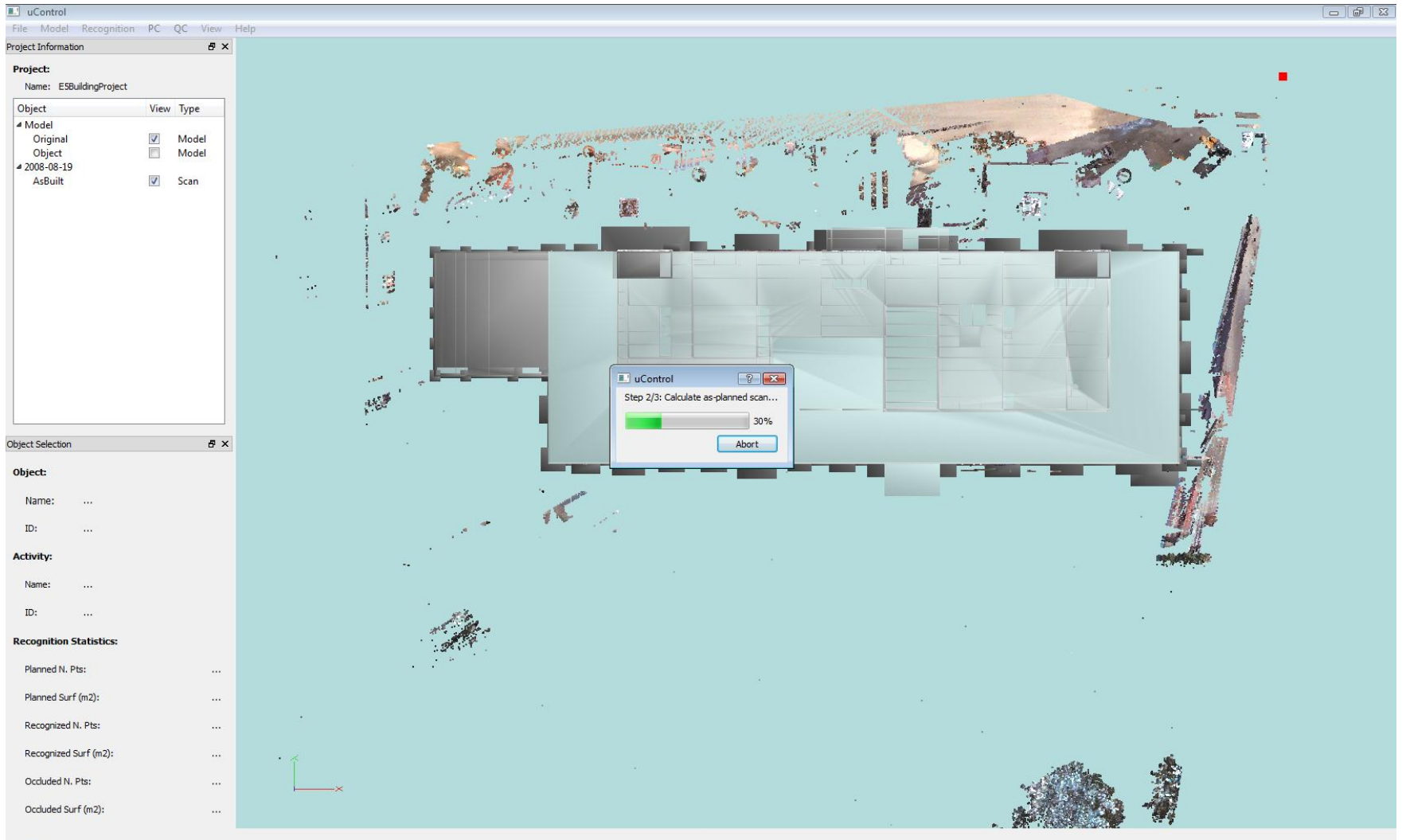


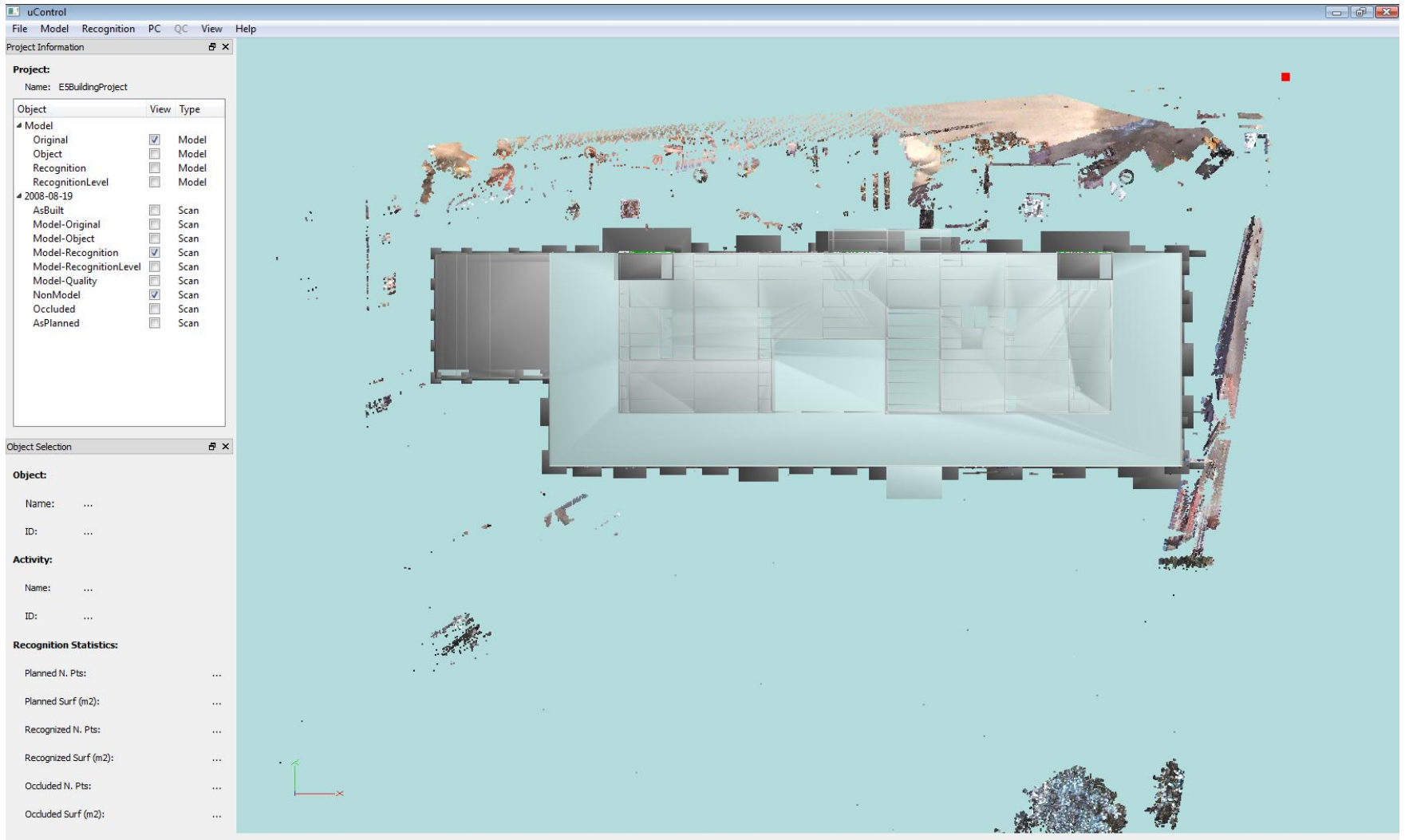


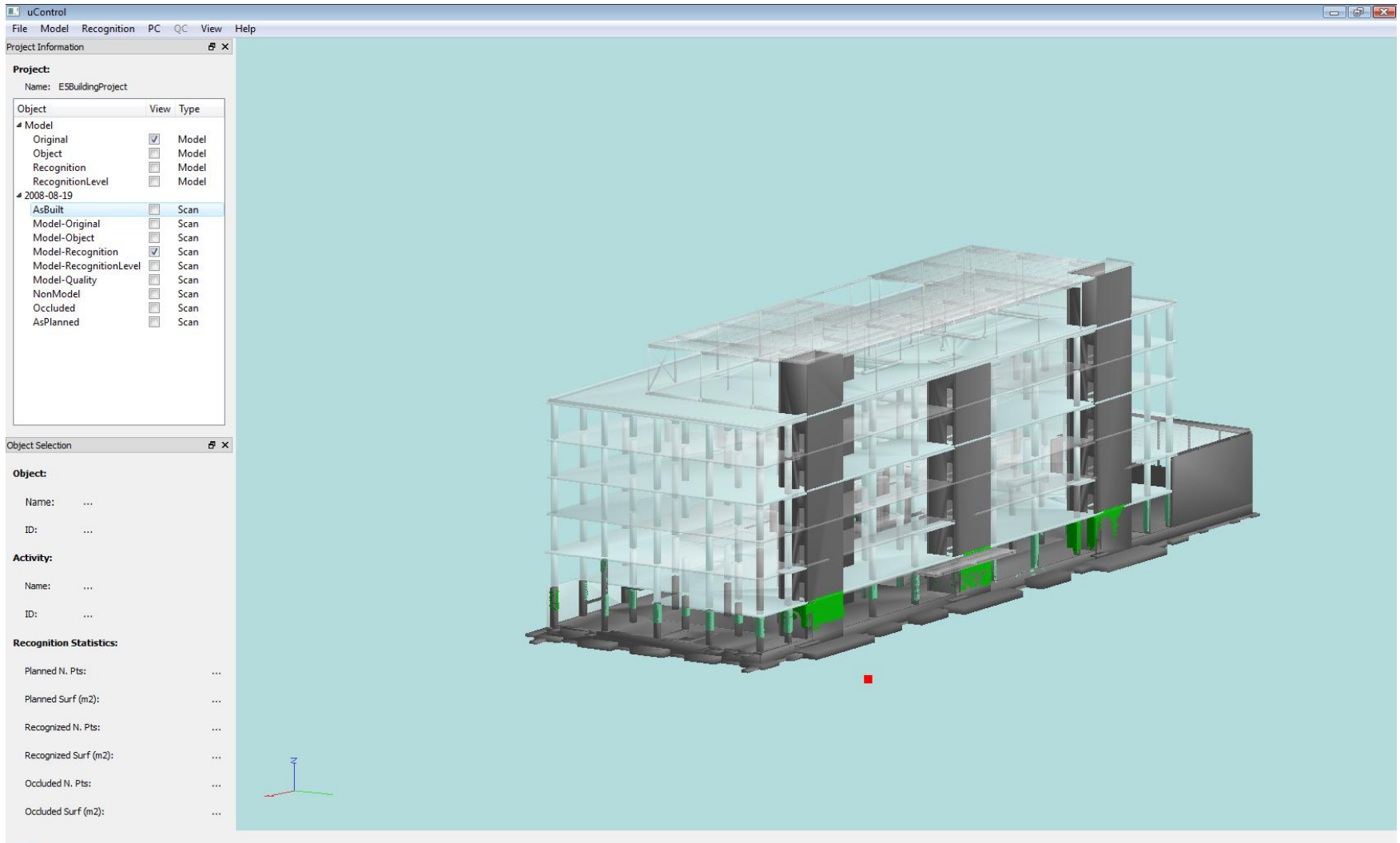


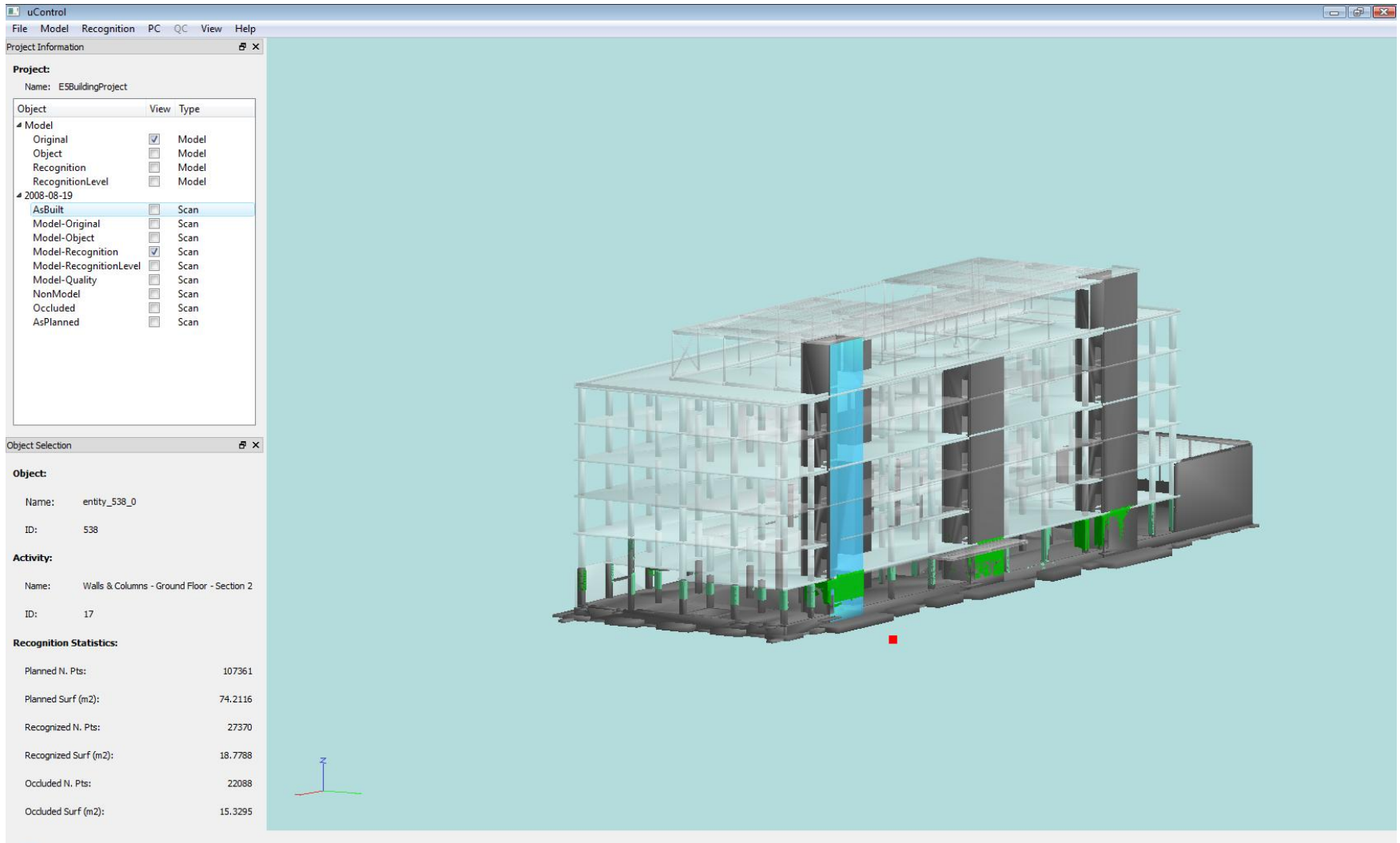


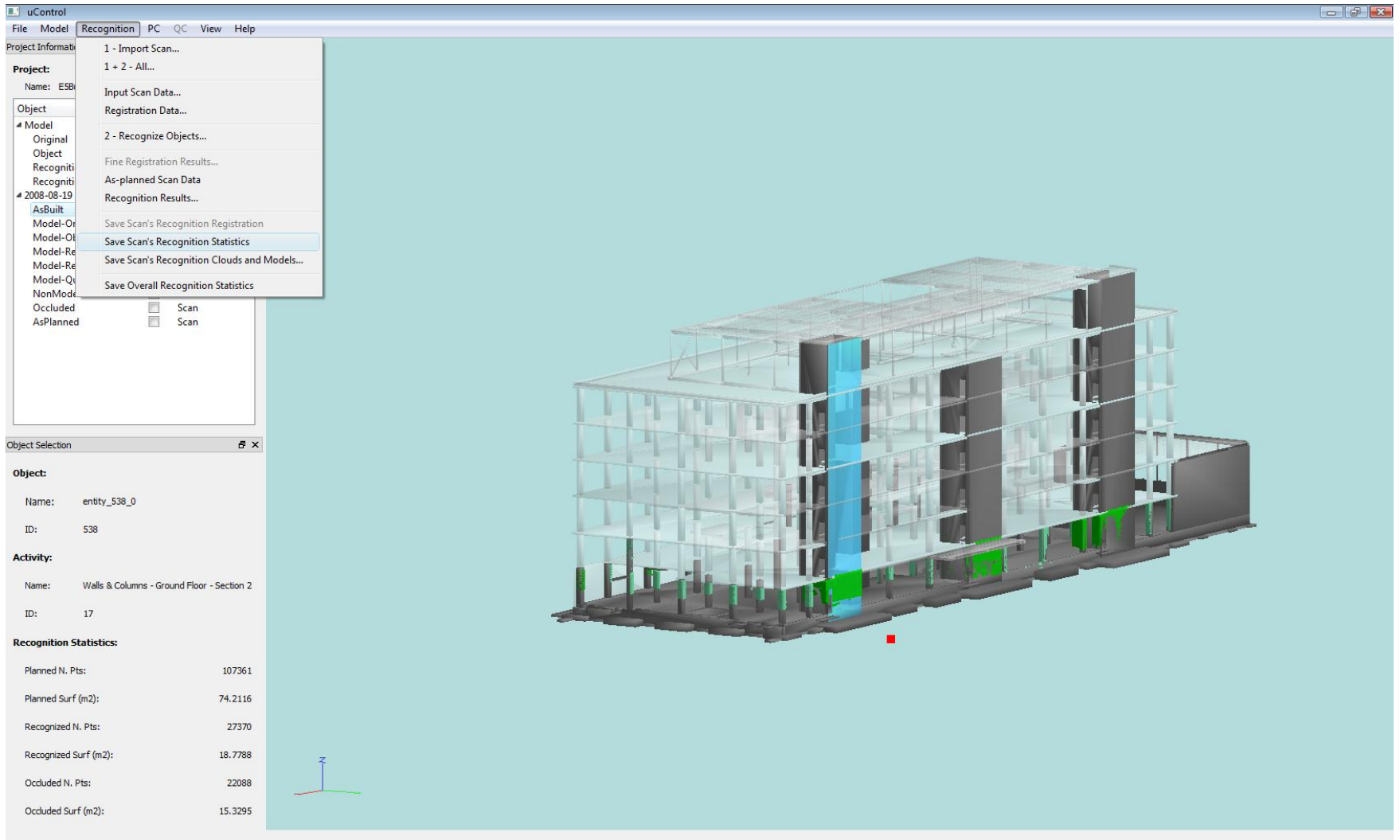


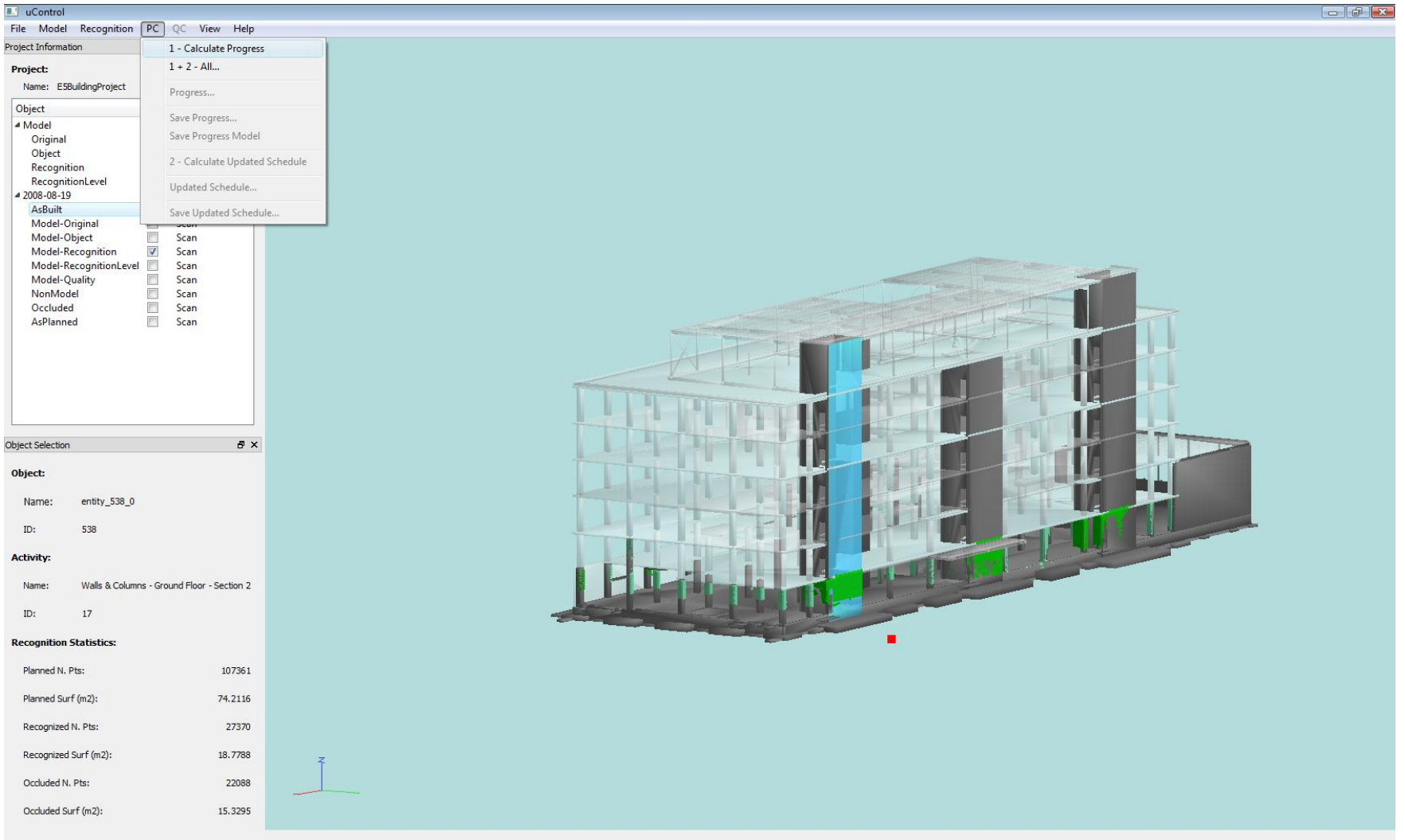


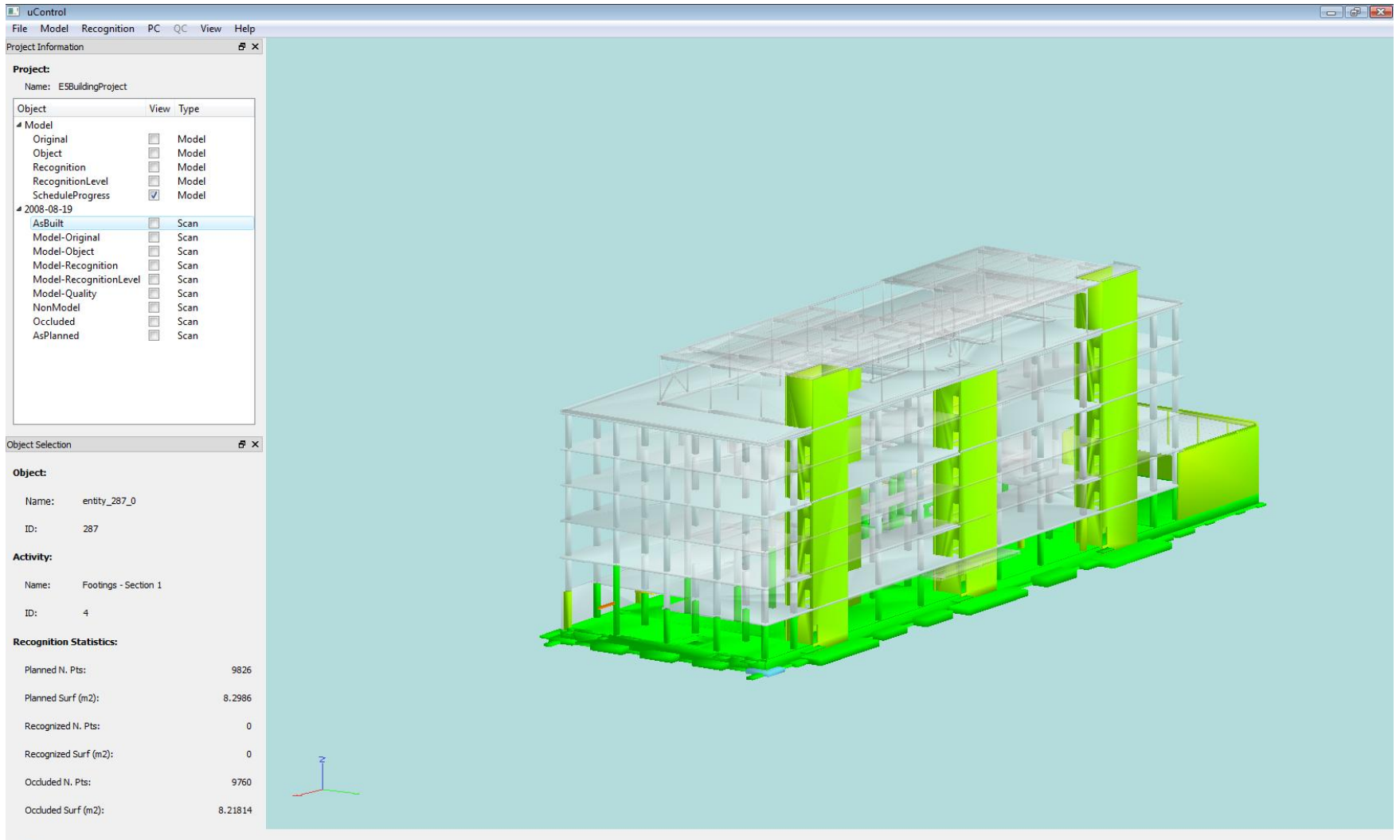












Appendix G Point Cloud Segmentation

