AN INTELLIGENT BIM-BASED AUTOMATED PROGRESS MONITORING SYSTEM USING SELF-NAVIGATING ROBOTS FOR DATA ACQUISITION

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

MUHAMMAD USMAN HASSAN

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF DOCTOR OF PHILOSOPHY
IN
CIVIL ENGINEERING

DECEMBER 2018

Approval of the thesis:

AN INTELLIGENT BIM-BASED AUTOMATED PROGRESS MONITORING SYSTEM USING SELF-NAVIGATING ROBOTS FOR DATA ACQUISITION

submitted by **MUHAMMAD USMAN HASSAN** in partial fulfillment of the requirements for the degree of **Doctor of Philosophy in Civil Engineering Department, Middle East Technical University** by,

Prof. Dr. Halil Kalıpçılar
Dean, Graduate School of **Natural and Applied Sciences** _____________________

Prof. Dr. İsmail Özgür Yaman
Head of Department, **Civil Engineering** _____________________

Asst. Prof. Dr. Aslı Akçamete Güngör
Supervisor, **Civil Engineering Dept., METU** _____________________

Examining Committee Members:

Prof. Dr. M. Talat Birgönül
Civil Engineering Dept., METU _____________________

Asst. Prof. Dr. Aslı Akçamete Güngör
Civil Engineering Dept., METU _____________________

Prof. Dr. Rifat Sönmez
Civil Engineering Dept., METU _____________________

Prof. Dr. Gökhan Arslan
Civil Engineering Dept., ESTU _____________________

Asst. Prof. Dr. Selen Pehlivan
Computer Engineering?? Dept., TEDU _____________________

Date: 14-Dec-2018

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last Name: Muhammad Usman Hassan

Signature :

ABSTRACT

AN INTELLIGENT BIM-BASED AUTOMATED PROGRESS MONITORING SYSTEM USING SELF-NAVIGATING ROBOTS FOR DATA ACQUISITION

Hassan, Muhammad Usman
Ph.D., Department of Civil Engineering
Supervisor: Asst. Prof. Aslı Akçamete Güngör

December 2018, 189 pages

Construction managers require a continuous flow of timely and accurate site status information that is acquired efficiently for successful project delivery. Current methods of data acquisition from the site are error-prone, laborious, and unable to provide timely information to project stakeholders for effective decision making. In this research, we developed a methodology for extraction of data points using BIM, acquisition of progress data using self-navigating robots, estimation of progress information using computer vision algorithms, followed by calculation and visualization of cost metrics. All these steps are performed without any human input in an automated manner to create a robust and efficient mechanism that is both accurate and cost-effective.

The developed methodology is named Context-Aware Progress Monitoring System (CAPMS) which consists of five distinct phases. In the first phase; as-built spatial and semantic information from BIM is extracted to calculate data points for element level data acquisition using the imaging sensor. Using this extracted element data, an algorithm creates an element-wise activity list for the formation of a 4D model. The second phase involves acquiring images using a BIM-based data acquisition device, which is verified by a robot, that navigates inside the structures and reaches elements to photograph them. The robot acquires images of building element and transmits them to the server for progress estimation from image data. In the third phase, a context-aware method is developed to estimate element status using computer vision algorithms. Contextual information obtained from schedule adds robustness to the developed methodology by reducing false positives. The states of the elements are used to estimate progress status and update cost-based progress metrics which we visualize on a dashboard in the fifth and final phase. The developed system has been validated by using the images obtained on two different construction sites with a robot and processing those images to determine accurate progress status in an automated manner.

Keywords: Automated Progress Monitoring, Robotic Construction Monitoring, BIM, Computer Vision

ÖZ

VERİ TOPLAMAK İÇİN OTONOM YÖNGÜDÜMLÜ ROBOT KULLANAN YAPI BİLGİ MODELLEMESİ TABANLI AKILLI BİR OTOMATİK İLERLEME TAKİP SİSTEMİ

Hassan, Muhammad Usman
Doktora, İnşaat Mühendisliği Bölümü
Tez Yöneticisi: Dr. Öğr. Üyesi Aslı Akçamete Güngör

Aralık 2018, 189 sayfa

İnşaat yöneticileri, başarılı proje teslimi için verimli bir şekilde elde edilen zamanında ve doğru saha durumu bilgisinin, sürekli akışına ihtiyaç duymaktadırlar. Sahadan veri toplamak için kullanılan mevcut yöntemler, hataya açık ve zahmetlidir; ve bu yöntemler, etkin karar vermek için proje paydaşlarına zamanında bilgi sağlayamamaktadır. Bu çalışmada, Yapı Bilgi Modellemesi (YBM) kullanılarak veri noktalarının çıkarılması, otonom yöngüdümlü robotlar kullanılarak ilerleme verilerinin elde edilmesi, bilgisayarlı görü algoritmaları kullanılarak ilerleme bilgilerinin tahmin edilmesi ve ardından maliyet ölçümlerinin hesaplanması ve görselleştirilmesini içeren bir metodoloji geliştirdik. Tüm bu adımlar, hem doğru hem de uygun maliyetli sağlam ve verimli bir mekanizma oluşturmak için otomatik olarak herhangi bir insan girdisi olmadan gerçekleştirilmektedir.

Geliştirilen metodoloji, beş ayrı aşamadan oluşan Bağlam Bilinçli İlerleme Takip Sistemi (BBİTS-CAPMS) olarak adlandırılmıştır. İlk aşamada; YBM'deki nihai uzaysal ve semantik bilgiler, görüntüleme sensörü kullanılarak eleman düzeyinde veri toplamak için kullanılacak veri noktalarını hesaplamak üzere çekilir. Geliştirilen algoritma, çekilen bu veriyi kullanarak 4D modelinin oluşturulması için eleman-bazlı bir aktivite listesi oluşturur. İkinci aşama, yapıların içinde dolaşan ve onları fotoğraflamak için elemanlara ulaşan, bir robot tarafından doğrulanan, YBM-tabanlı

bir veri toplama cihazı kullanarak görüntülerin elde edilmesini içermektedir. Bu aşamada, robot, yapı elemanının görüntülerini almakta ve görüntü verisinden ilerleme tahmini için bunları sunucuya iletmektedir. Üçüncü aşamada, bilgisayarlı görü algoritmalarını kullanarak eleman durumunu tahmin etmek için bağlam-bilinçli bir yöntem geliştirilmiştir. İş programından elde edilen bağlamsal bilgiler, yanlış pozitifliği azaltarak geliştirdiğimiz metodolojiye sağlamlık katmaktadır. YBM elemanlarının hali, ilerleme durumunu tahmin etmek ve bir kontrol panelinde görselleştirdiğimiz maliyet tabanlı ilerleme ölçümlerini güncellemek için kullanılmaktadır. Geliştirilen sistem, bir robot ile iki farklı şantiyeden elde edilen görüntüleri kullanarak ve doğru ilerleme durumunu otomatik bir şekilde belirlemek için bu görüntüleri işleyerek geçerlenmiştir.

Anahtar Kelimeler: Otomatik İlerleme Takibi, Robotik Yapım İzleme, Yapı Bilgi Modellemesi, Bilgisayarlı Görü

Brig Khalid Hassan SI(M)

&

Nadeem Hassan (1970 - 2018)

ACKNOWLEDGMENTS

I am extremely grateful to my supervisor for her time, patience, guidance, effort and mentoring. She taught how to plan and organize a research from the beginning till the end. I am especially grateful for the time spent on improving my writings which has greatly helped me improved my written skills. I am grateful to my thesis committee members Prof. Dr. Talat Birgönül, Prof. Dr. Rifat Sönmez, Prof. Dr. Gökhan Arslan, and Asst. Prof. Dr. Selen Pehlivan for their time, comments and guidance. I want to thank my teachers from NUST especially Dr. Jamal Thaheem, Awais Jamil Ch. and Col Irfan for their grooming that helped me through this Ph.D.

I am grateful to my father Brig Khalid Hassan for his prayer and mentoring, it was his strong wish to see me finish my Ph.D. and it is one of the reasons I took up higher education; to my mother for her continuous support and motivation that made me pass through all the difficult stages; to my wife Sara for her standing steadfastly with me and my kids Ammar and Nuray for their unconditional love; to my brother Faheem, and my partner in Yapıdestek Can Yücel for providing with the resources when I needed them the most. In the end I thank my research friends Murat Altun and Onur Dogan for all the intellectual help that they have provided.

TABLE OF CONTENTS

ABSTRACT v

ÖZ… vii

ACKNOWLEDGMENTS x

TABLE OF CONTENTS xi

LIST OF TABLES xv

LIST OF FIGURES xvi

ABBREVIATIONS xxii

CHAPTERS

1. PROBLEM DEFINITION 1
   - 1.1. Error-prone 2
   - 1.2. Timely (Real-time) 4
   - 1.3. Time Consuming (Laborious) 5
   - 1.4. Flow of the Document 8
2. BACKGROUND STUDY & RESEARCH OBJECTIVES 9
   - 2.1. Data Acquisition Technologies 10
     - 2.1.1. Sensor Network 10
     - 2.1.2. Laser Scanning 11
     - 2.1.3. Multimedia 12
   - 2.2. Information Retrieval 14
     - 2.2.1. Object Recognition and Material Classification 16
     - 2.2.2. Context-Based Recognition 17
     - 2.2.3. Machine Learning 19
   - 2.3. Progress Estimation 20
     - 2.3.1. As-Planned 4D BIM 20
     - 2.3.2. As-Built vs. As-Planned Comparison 21
     - 2.3.3. Images based Progress Monitoring Solution 22

2.4. Data Visualization and Dashboard 23
2.5. Gaps in research 26
2.6. Research questions 29
2.7. Objectives, Scope, and Contribution of Research 31
2.8. Proposed Solution: Context-Aware Automated Construction Progress Monitoring System 32
2.9. Conclusion 37
3. ELEMENT-WISE AUTOMATED ACTIVITY AND POINT OF INTEREST (POI) EXTRACTION (EAPE) 39
3.1. Introduction 39
3.2. Methodology of EAPE 40
3.3. BIM-based POI List Creation 44
3.4. BIM-based Activity List and Schedule Creation 50
3.5. Daily POI Extraction 52
3.6. Validation on BIM of two different construction projects 54
3.7. Conclusion 56
4. BIM BASED DATA ACQUISITION PLATFORM 59
4.1. The need for Robots in Construction 59
4.2. Review of Robots in Construction 61
4.3. Method for BIM-based data acquisition 63
4.4. Navigation to POI and Imaging 65
4.4.1. Chassis and Drive Train 67
4.4.2. Imaging Sensor Distance and Tilt 68
4.5. Image Tagging and Transmission 72
4.6. Image Storage at Server 72
4.7. Experiment for Validation of Navigation Algorithm 73
4.7.1. Creation of BIM and Extraction of POI Information 73
4.7.2. Experiment Results and Discussion 76
4.8. Validation of Imaging on Site using BAAP 79
4.9. Conclusion 85
5. SCHEDULE BASED CONTEXT AWARE ELEMENT RECOGNITION (SCAER) 87

5.1. Introduction and Background Information 87
5.1.1. Contextual Information 88
5.1.2. Color Space 91
5.2. Proposed Methodology 95
5.3. Learning Material Signatures 96
5.3.1. K-Means Clustering 98
5.3.2. Material Tagging 99
5.4. Identification of Materials within Image 103
5.5. Prediction of Element State 106
5.5.1. Context Awareness based on the Logic of Scheduling 106
5.5.2. Prediction based on Probability of Presence 108
5.6. Parameter Tuning 109
5.6.1. K Clusters 109
5.6.2. Threshold 110
5.6.3. Color Space 111
5.7. SCAER Validation Using Site Images 113
5.7.1. Evaluation Metrics 114
5.7.2. Sampling 115
5.7.3. Material Recognition from Site Images 118
5.7.4. False Positive and Confusion 125
5.7.5. Element State Prediction Recall 127
5.8. Conclusion 128
6. PROGRESS SIMULATION AND VISUALIZATION 131
6.1. Framework for Progress Visualization using Dashboard in CAPMS 131
6.2. Simulated structure and activities tracking 135
6.2.1. Day 1: Rebar Installation, Imaging and Analysis 138
6.2.2. Day 2: Formwork Installation, Imaging, and Analysis 141
6.2.3. Day 7: Removal of Formwork, Imaging, and Analysis 143
6.2.4. Day 9: Masonry Work Completion, Imaging, and Analysis 145
6.2.5. Day 11: Final Site Status and Dashboard 147
6.3. Discussion on Cost Metrics 149
6.4. Conclusion 150

7. CONCLUSION 151
7.1. Review of Developed Methodologies 152
7.2. Case for Robot as Employees 154
7.3. Contribution to Field of Knowledge 156
7.4. Drawbacks of Context-Aware Progress Monitoring System 157
7.5. Site Requirements 158
7.6. Future Work 159
REFERENCES 165
APPENDICES
A. SIMULATED STRUCTURE SCHEDULE 183
CURRICULUM VITAE 189

LIST OF TABLES

TABLES

Table 1 Comparison of MLS and TLS accuracies and point cloud densities [39]. ...12
Table 2 Rating criteria for progress monitoring system by Kopsida et al. [14].........26
Table 3 Performance evaluation of progress monitoring systems derived from Kopsida et al. [14]. 27
Table 4 Custom Activity Code List (CACL). 36
Table 5 Example Categories with their Revit IDs. 42
Table 6 POI Detected from BIM...50
Table 7 Partial sample output for POI extraction..50
Table 8 Activity ID Breakdown 51
Table 9 Sample extracted activity list for BIM elements..52
Table 10 Sample extracted daily POI list..54
Table 11 POI Extracted from ESDB and CHB BIM. 56
Table 12 Robot components and characteristics...66
Table 13 Camera tilt and EOI distance for imaging. 69
Table 14 Material and numeric material identifier list...101
Table 15 Column-wise statistical metric of $CADi$ Matrix. 105
Table 16 Column-wise statistical measures for $CAD1$ Matrix................................106
Table 17 Decision Table. 114
Table 18 Activity monitoring list for ESDB. 117
Table 19 POI list extracted from virtual structure BIM. 137
Table 20 Comparison with other research on progress monitoring. 157

LIST OF FIGURES

FIGURES

Figure 1 A typical pile of daily construction progress report, (b) Sample daily progress report with incomplete information filled in by site supervisor [13]. 3
Figure 2 Process of site data collection in a large construction company [2]............. 7
Figure 3 Labor productivity of construction industry vs manufacturing industry [28]. 8
Figure 4 Components and flow of automated progress measurement mechanism.... 10
Figure 5 ROBIN All-in-one Vehicle, Backpack, and UAV LiDAR System [36]. 11
Figure 6 A point cloud containing millions of points of an under construction structure [48]. 15
Figure 7 Semantic labeling on geometric primitives [79]. 19
Figure 8 Color-coded progress status information using augmented reality [110]. .. 24
Figure 9 Multi-system construction dashboard proposed by Kuo et al. [114].......... 25
Figure 10 Research questions from problem definition schema.............................. 31
Figure 11 Construction Information Loop [121]. 33
Figure 12 Vision for Context Aware Automated Progress Monitoring System (CAPMS). 34
Figure 13 Server Client Architecture of CAPMS. 35
Figure 14 Revit Element Classification System [126]... 41
Figure 15 Process flow for EAPE. 43
Figure 16 Process Flow for Activity List and POI Creation. 44
Figure 17 Sample POIs for varying categories. 45
Figure 18 POI extraction process flow. 45
Figure 19 Dynamo visual programming interface [128]. 46
Figure 20 Dynamo code for level-wise POI extraction from BIM. 47
Figure 21 Function for POI extraction from each level. 48
Figure 22 Validation of (a) extracted POIs for wall elements and (b) 3D model used for the test. 49
Figure 23 Category and Related Activity List 51

Figure 24 Daily POI extraction by image acquisition platform using Pull request. ..53
Figure 25 (a) Rendering of Educational Science Department Building and (b) Revit 3D Model for Classroom Hall Building (Courtesy of METU). 55
Figure 26 S-curve applied to construction transformation from conventional to automation [132] where building component manufacturing (BCM), large-scale refabrication (LRP), single task construction robots (STCR), robot-oriented design (ROD), automated robotic on-site factories (A/ROF), and automated deconstruction (AD). 61
Figure 27 (a) SAM100 world's first commercially available robot [137], (b) Tybot robot for rebar tying [138]..63
Figure 28 (a) Effibot will follow workers carrying heavy items [139], (b) Built robotics dozer to carry out works automatically [140]. 63
Figure 29 Boston dynamics robot for monitoring [136]. 63
Figure 30 Process flow within BAAP framework. 65
Figure 31 BAAP in different forms (a) Terrestrial robot (b) Drone (c) Helmet mounted camera. 65
Figure 32 Robot Views from Different Angles..67
Figure 33 Robot Chassis and Components. 67
Figure 34 Robot camera orientation and scene representation. 69
Figure 35 Camera-tilt at (a) 0°, (b) 180°, (c) 30°, and (d) 140° to capture the EOI. 70
Figure 36 Imaging of elements above the robot with very low ϴ < 20°....................71
Figure 37 Imaging of element in front of robot. camera Point forward. 40° < ϴ < 90°. 71
Figure 38 Imaging of elements below the robot with ϴ > 90°. 71
Figure 39 Images tagged with POI, Activity ID, angle and distance of acquisition..72
Figure 40 (a) Image storage according to POI at server end, (b) Image storage within according to activities. 73
Figure 41 3D model of navigation test site created on Autodesk Revit. 74
Figure 42 Extracted POI locations for robot navigation validation. 74
Figure 43 Navigation vector calculation from POI coordinates. 75
Figure 44 Error at POI 1...76

Figure 45 Error at POI 2. 77
Figure 46 Error at POI 3. 77
Figure 47 Combined plot of error at POI 1, POI2, and POI3. 78
Figure 48 Box and whisker plot for percentage error w.r.t length. 79
Figure 49 Process flow for conduct of field test. 80
Figure 50 Number of pictures taken of subject materials taken at given tilt and distance values. 81
Figure 51 Poor Image Examples (a)-(b) Acquired at 30% misses EOI and captures roof slab, (c)-(d) Images acquired at 90% captures clutter on the floor next to wall. 82
Figure 52 (a) Poor quality pictures w.r.t angles and distances, (b) recall for images at angle-distance combination. 83
Figure 53 Images acquired with all tilt angles. 84
Figure 54 Material wise recall for image with good tilt angles. 85
Figure 55 Markov chain transition probabilities and transition matrix [148]. 89
Figure 56 Transition state diagram for various element states 91
Figure 57 RGB color space. 93
Figure 58 Hue Saturation Value (HSV) color space [154]. 94
Figure 59 CIE L*a*b color space model [155]. 94
Figure 60 Process flow for Schedule-based Context-aware Element Recognition (SCAER) 95
Figure 61 Flowchart of the learning algorithm 97
Figure 62 Training image for a demonstration of the learning algorithm. 98
Figure 63 Result of K-means clustering on test image: (a) Cluster 0, (b) Cluster 1, (c) Cluster 2, (d) Cluster 3. 100
Figure 64 Process flow for material prediction in acquired image 103
Figure 65: Image acquired for prediction of material using prediction algorithm. 104
Figure 66 False positives affecting results vs false positives not affecting results.. 107
Figure 67 Critical vs noncritical false positives represented on BIM elements. 107
Figure 68 Element state prediction process. 109
Figure 69 K value vs. % recall error chart. 110
Figure 73 % Recall error variation with change in min distance threshold. 111

Figure 74 % Prediction error for different values of mean. 111
Figure 75 Color model combination for feature vector. 112
Figure 76 Percent error for different color space combinations. 112
Figure 77 Images of under construction (a) Educational Science Department Building, (b) Classroom Hall Building. 113
Figure 78 Test locations marked according to activity on floor. 115
Figure 79 Sample size for (a) Category (b) Expected State; where, DR: Door, MW: Masonry Work, CN: Concrete, FW: Formwork, RF: Reinforcement. 118
Figure 80 (a) Concrete column images using robot at 45 degrees (b) Extracted column from the image. 119
Figure 81 Correctly detected concrete from column POIs......................................119
Figure 82 (a) Image with formwork (FW) with (b) extracted formwork from the image. 120
Figure 83 Correctly detected formwork POI. 121
Figure 84 (a) Image with masonry and concrete (b) Extracted masonry from the image. 122
Figure 85 Correctly detected concrete from masonry POIs....................................122
Figure 86 (a) Image with reinforcement (b) Extracted reinforcement from image. 123
Figure 87 Correctly detected POI for reinforcement. 123
Figure 88 (a) Image with formwork (b) Extracted formwork from the image. 124
Figure 89 Correctly detected door in frames acquired for each POI. 124
Figure 90. False positive of CN with all other materials for different minimum threshold values..125
Figure 91 False positives of FW with all other materials for different minimum threshold values..126
Figure 92 False positive MW with all other materials for different minimum threshold values...126
Figure 93 False positives of RF with other materials for different minimum threshold values...127
Figure 94 Percent recall for materials in the project. 128
Figure 95 Project management dashboard. 132

Figure 96 Schedule update from POI and dashboard update.................................133
Figure 97 Cinfo dashboard with (a) updated Gantt chart tracking, (b) Day of last activity, (c) S-curve (d) KPI (e) Cost Metrics (f) Progress bar (g) Daily monitoring list...135
Figure 98 Floor plan for the virtual structure...136
Figure 99 No of elements from each category in the simulated structure. 138
Figure 100 Schedule summary of the virtual structure...138
Figure 101 Activities completed at the end the first day of construction. 139
Figure 102 SCAER output for Day 1 of inspection..139
Figure 103 Dashboard view after completion of rebar installation work. 140
Figure 70 Site status at the end of Day 2 of construction. 141
Figure 71 SCAER Output for Day 2 of inspection. 141
Figure 72 Dashboard view after completion of formwork installation work. 142
Figure 104 Virtual site view at the end of Day 7 of construction...........................143
Figure 105 SCAER output at the end of Day 7 of inspection.................................143
Figure 106 Dashboard view after completion of concrete work.............................144
Figure 107 Rendered Site status at the end of Day 9 of construction.....................145
Figure 108 SCAER output at the end of Day 9 of inspection.................................145
Figure 109 Dashboard view after completion of masonry work. 146
Figure 110 Activities completed at the end of Day 11 of construction. 147
Figure 111. SCAER output at the end of Day 11 of inspection.............................147
Figure 112 Dashboard at project completion...148
Figure 113 Estimated vs. Actual progress metrics comparison..............................149
Figure 114 POI error and KPI error comparison. 150
Figure 115 Robot can negotiate unsafe routes..155
Figure 116 Cluttered site creates robot navigation difficulties...............................158
Figure 117 Reinforcement image processed to attain rebar diameter [108]............160
Figure 118 (a)-(b) SCAER for detection of MEP in masonry images....................161
Figure 119 (a)-(b) Boom loader detected (c)-(d) crane detected by K-means clustering in SCAER...161
Figure 120 Loaded truck image with extracted (b) Truck (c) Loaded Formwork...162

Figure 121 (a) Insulation stockpile image with extracted (b) XPS stockpile (b) Glass wool stockpile. 162

ABBREVIATIONS

API	Application Programming Interface
AR	Augmented Reality
BAAP	BIM based Image Acquisition Platform
CACL	Custom Activity Codes List
CCD	Charged Couple Device Sensor
CHB	Classroom Hall Building
CN	Concrete Work
DR	Door
EAPE	Element-wise Activity and POI Extraction
EOI	Element of Interest
ESDB	Education Science Department Building
FW	Formwork
GPS	Global Positioning System
HD	High Definition
HSV	Hue Saturation Intensity
LAN	Local Area Network
MLS	Mobile Laser Scanner
MW	Masonry Work
$P_{P\|C}$	Probability of Planned state given Confirmed state
RFID	Radio Frequency ID
SfM	Structure for Motion
PL	Plaster
RF	Reinforcement
RGB	Red Green Blue
TLS	Terrestrial Laser Scanner
UWB	Ultra-Wide Band
WD	Window
WSN	Wireless Sensor Network

CHAPTER 1

PROBLEM DEFINITION

The construction industry is immensely complicated by nature since project execution, consisting of several phases, requires a diverse array of specialized services and involves numerous participants [1]. The dynamic nature of building and infrastructure projects coupled with its ad-hoc work organization makes communication and smooth flow of information between stakeholders a more significant challenge. The construction projects are temporary in natures and therefore unsuitable for adaptation of standard industrial monitoring solutions. Construction project organization itself is usually formed as ad-hoc groupings, that do not evolve into the formation of long-term relationships beyond the scope of the project [2] making data communication and dissemination a more significant challenge in comparison with manufacturing or retail industry. The construction industry is unlike manufacturing or service sector, which operate in a static environment with teams that work with one another for long periods, creating working relationships that allow smooth flow of information across different levels of management. Construction companies complete their projects in a relatively short duration of time, with the teams that are explicitly created for the project and dissolved as soon as the project reaches its conclusion. Management of construction projects is, therefore, an arduous task compounded by communication and human interaction related complexities. The common practice of data acquisition in construction information management is based on manual and monotonous data acquisition, immethodical analysis and complicated reports [3]. This inefficient approach toward information management is one of the reasons why construction projects are very often late [4] and exceed their budgets thus failing to achieve their objectives.

Construction projects need a smooth flow of information for construction management system to perform efficiently. The data originating from construction sites can be related to finance, quality and progress domains [5]. Financial data includes Quantity Takeoff (QTO) rates, reimbursements, contractor payments, taxes, procurement details, and different cost-related information. Quality records contain test results, specifications, checklists, Key Performance Indicators (KPI), noncompliance lists and audit results. Progress data typically identifies work carried out on construction sites. It contains information ascertaining where, when and how work is being performed including deviations and delays. Progress monitoring is considered to be the most complex task due to several interdependencies of activities [6], and thus the highest challenge a project manager has to encounter. Timely collection of site progress data, its interpretation, and communication in an efficient manner is a critical factor in the success of a project [7] and therefore a significant concern for construction companies. Ideally, a progress monitoring measurement system should be measurable, consistent, timely, understandable, verifiable, cost-effective and suitable for decision making [8].

1.1. Error-prone

Traditionally data collection on the progress of construction projects done using manual or visual inspections is infrequent, error-prone [9], time-consuming, [10] inconsistent and produces a large amount of paperwork [11] (see Figure 1). A survey [12] had shown that more than 63% of site operatives do not keep a record of exactly when work took place. In the same study, more than 62% of workers did not keep a record of linkage between activities that showed the impact of delay on overall project's performance. Sometimes site staff lacks experience in proper site information handling, being unaware of the importance of keeping accurate information. It is also observed that site operatives are not even concerned with the value of activity linkages and the effect of delay in one critical activity over the whole project [12].

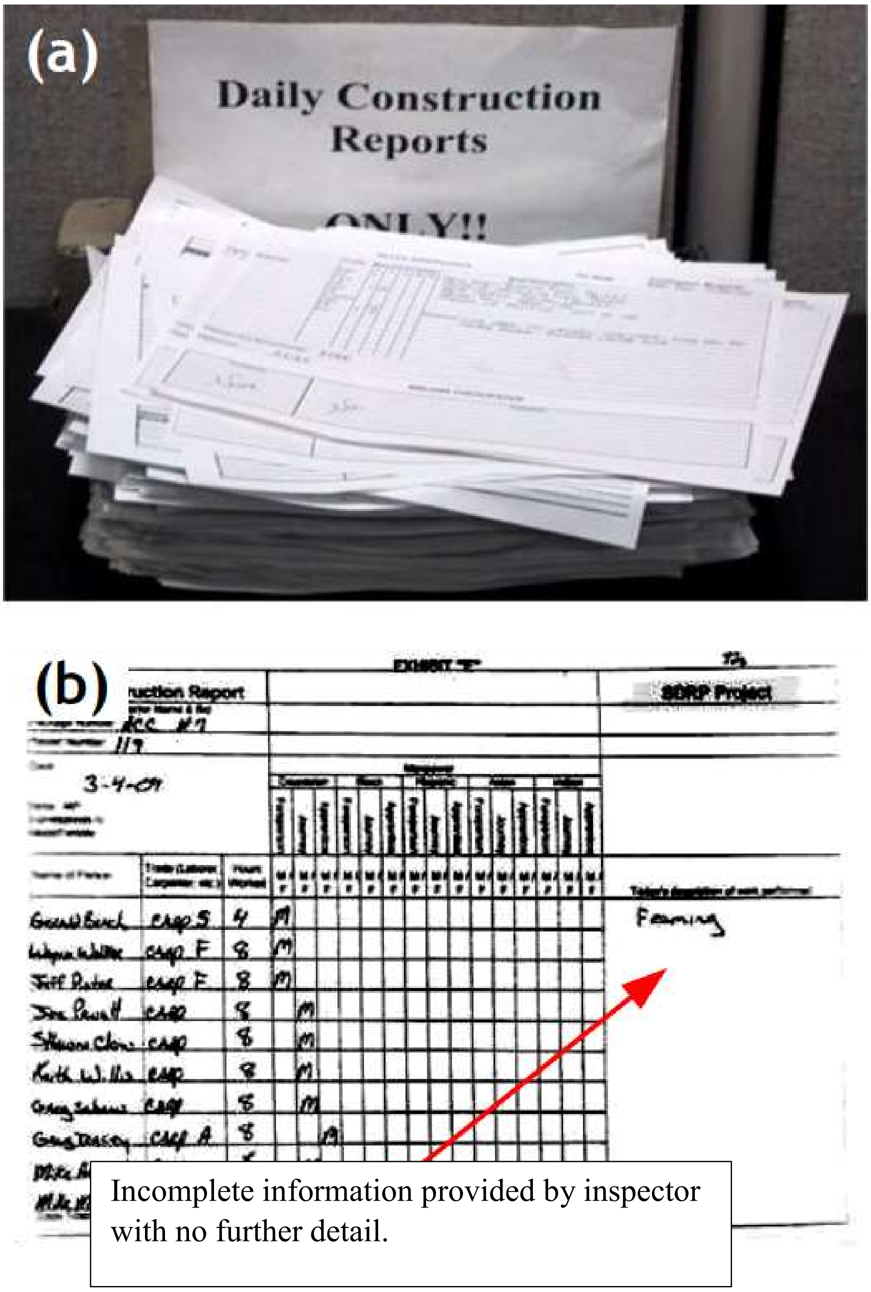


Figure 1 A typical pile of daily construction progress report, (b) Sample daily progress report with incomplete information filled in by site supervisor [13].

Site records contain errors related to their accessibility, legibility, continuity, and consistency [12]. Accessibility issues relate to the excessive amount of time required to extract information from site records due to the large volume of data. Legibility is related to the difficulty to read due to poor handwriting, incorrect terminologies and poor command over technical jargons. Continuity problems are related to missing records which may be lost or not taken in the first place and consistency is the problem when multiple records do not match or follow a sequence. Monitoring cannot be done on hard to reach areas, and photographic evidence cannot be attained thus the completeness of acquired data is negatively impacted. The site information may, therefore, lack details necessary to extract relevant information about the progress from the dairies since the worker did not record it in the first place. Site records can be misleading at sometimes giving information that a manager can interpret into a work performed at a particular location while it has not completed or vice versa. Some researchers [14] have assumed that current practices do not correctly represent data understandably coming from the site.

Accurate as-built information plays a vital role in performance analysis, corrective action planning and later operation and maintenance of projects. As-built progress data provides a measure of progress attained and can be compared with the as-planned schedule to determine deviations and delays. It enables site management to take a proactive decision and reduce cost overrun as well as delays that can be caused by deviations from schedule. The accuracy of data is the key since managers make decisions on data provided to them, erroneous data will lead to poor choices. Project managers have to spend a lot of time dealing with inaccurate and out of date information, which is an output of old-school methods of information acquisition, transmission, processing, and dispersal that doesn't belong to the 21st century.

1.2. Timely (Real-time)

Attaining accurate and timely knowledge of the status of a construction project is a challenging problem faced by project management and job site personnel [15]. There is no real mechanism to bring as-built information to project stakeholders in real time [16]. A time-space gap between the site and office consequently delays the data. Duration of activities is typically in days while site teams provide progress reports on the weekly or monthly basis [2], that handicaps project manager's ability to monitor schedule, cost and KPI reducing his capability to manage uncertainty [17] inherent to construction projects.

Project managers require a robust system that provides information in a timely and comprehensive manner so that they can make decisions quickly and efficiently [18]. An effective method to filter and extract information from a large amount of data, pouring in from the site through different mediums, is required to ensure knowledge of site operation is available as and when a manager is taking decisions. Actual and potential progress deviations are costly but preventable [19], the longer it takes to detect a defect, the more expensive and difficult it becomes to fix that defect while avoiding compromise of project objectives. Today's construction methods are not providing data at the frequency that guarantees timely corrective actions. Therefore, it is not surprising that construction projects are very often late [4] and exceed their budgets. The lack of adequate information and a shortage of record is one of the reasons behind the delayed identification of progress impeding issues. Time taken to determine deviation from the schedule and to undertake countermeasures on site is proportional to mitigation cost. Thereby real-time information will enable appropriate countermeasures that will reduce monetary loss [20] caused by delays, reworks, claims, and disputes. Construction giants are investing on state of the art Management Information Systems (MIS) and Enterprise Resource Planning (ERP) systems to assist project management teams, however, the utility of such a system is subject to timely acquisition of timely information.

1.3. Time Consuming (Laborious)

The efficient data acquisition process is utmost necessary for successful project delivery, but the current practice does not provide an elaborate mechanism to attain site data articulately [13]. Current information acquisition and processing techniques are not only time consuming and labor-intensive but are also compromising the performance of project leadership team. This inefficiency across project teams is, in large measure, due to laborious processes involved in as-built data collection and analysis. Data acquisition for construction progress monitoring is labor-intensive work and requires the extraction of data from drawings and databases [21], involving many calculations that take away precious man-hours from intellectual work to mundane, repetitive tasks. Standard practice for field engineers and superintendents is to walk around the site, take notes and site pictures to document progress which is a fatiguing, time consuming and dangerous process on a live construction site. The site inspections result in the creation of a large volume of site records which contain thousands of drawings and notes taken by numerous operatives with a wide array of experience, knowledge and skill level. A survey of Management Information System (MIS) showed that the need for data entry is impeding the success of the whole system [22].

A study [23] of five large construction companies has concluded that companies are storing thousands of images without any standard retrieving mechanism making image search and retrieval cumbersome, thereby diminishing the utility of complete imaging exercise. A field engineer must filter, sort and annotate images, therefore, evaluating images according to their context and contents remains manual which is both time-consuming and full of errors. Figure 2 [2] shows a portion of a process model for a study done on a company with sophisticated information management system where the author observed that significant part of data collection is manual (e.g., activity reporting, person hour record, etc.). The information fed into the computer using manually attained data reduces the overall efficiency of the system, defeating the whole purpose of digitization. Workers spend their energy for manual collection of data, and submit it to the management team, who extract information from different forms of data relayed to them. Various studies have taken place on information retrieval from images; however, to use this information, image has to be detected first.

Management time is much more valuable in monetary terms when compared with site staff. A manager manhour can cost anywhere between three to ten times what a company would pay to its field staff depending upon the geographic location of the project, as the disparity between blue collar and white collar earning is much more in the east as compared to the west. Project managers are spending considerable amount of time dealing with delayed, missing, inaccurate, and inconsistent information. McCullouch (1997) noted that managers spend, on average, 30–50% of their time to record and analyze site data due to manual nature of monitoring and controlling methods and thus, they are distracted from other vital tasks [14]. Project management teams are spending 77% of their time in meetings on descriptive and explanative tasks and only 12% and 11% of the time is spent on evaluative and predictive tasks respectively [24]. Managers getting well organized, ready to use data directly from the site will save costly manhours, prevent mental fatigue that decrements intellectual capabilities and provides time for brainstorming resulting in well-thought decisions that would have long-lasting consequences on project deliverables.

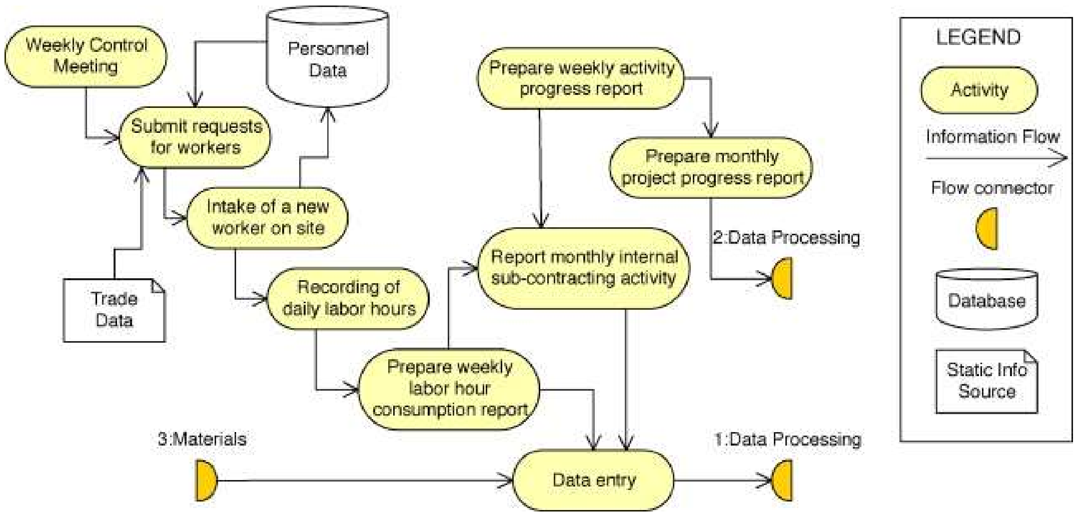


Figure 2 Process of site data collection in a large construction company [2].

Data is costly to acquire, costlier to convert into information and even costlier to transform into a digital format that can be manipulated using computer software [2]. A significant portion of this cost is direct workforce cost paid per hour of work done on data. The complexity and vast size of data generated from construction sites [25] make information management on construction sites all the more difficult [26]. The construction industry is losing too many man-hours on non-value adding tasks thus showing a continuous decline in productivity while the productivity index of all farm industry has increased considerably [27] as can be seen in Figure 3.

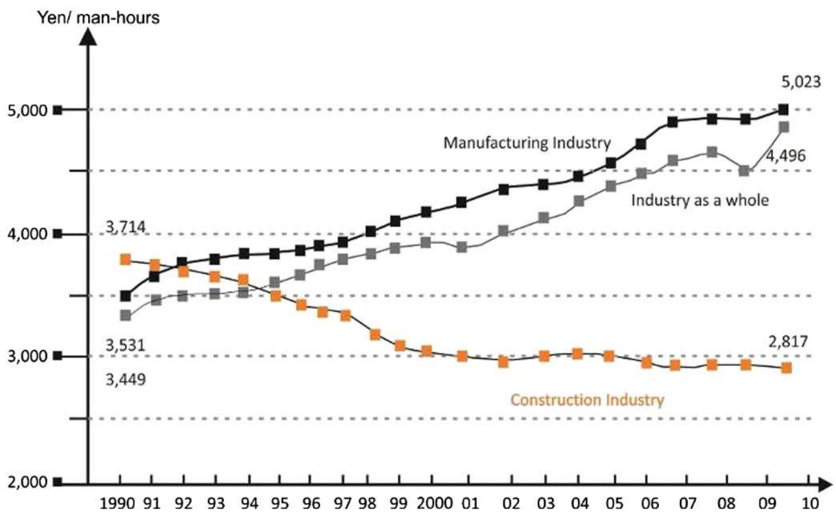


Figure 3 Labor productivity of construction industry vs manufacturing industry [28].

1.4. Flow of the Document

This document explains methodologies that form the developed automated progress monitoring system, followed by a simulation of the proposed system on a virtual structure. Chapter 2 discusses various components of automated progress monitoring system namely data acquisition, information retrieval, progress estimation, BIM and data visualization. Chapter 3 presents an algorithm developed to extract location for image acquisition from BIM through an Element-Wise Activity and Point of Interest Extraction methodology. Chapter 4; presents an automated data acquisition platform and a robot developed as its realization. Chapter 5 presents the computer vision algorithm to get element state from images taken on the site by developing a Schedule Based Context-Aware Element Recognition (SCAER) Algorithm. Chapter 6 discusses simulation of a Context-Aware Progress Monitoring System (CAPMS) on a virtual structure and progress metrics update using outputs from automated methodologies followed by a conclusion.

CHAPTER 2

BACKGROUND STUDY & RESEARCH OBJECTIVES

Embedded intelligence is not a new concept in building community and with the advent of cheap sensors and computing resources to handle big data, it has gained immense popularity [29]. Information technology plays a pivotal role in ensuring projects' success by providing project managers tools that increase their efficiency and assist them in making decisions. After formulation of comprehensive BIM, building data can be incorporated with other information system data to streamline tasks. With the advent of new software packages, data processing has become facile but still involves a large amount of human intervention making such applications time consuming and less feasible for task monitoring. The data technologies that fit in the roles of the collecting, organizing, and analysis of as-built data are classified according to Omar et al. [8] as those that collect as-built data like geospatial method or those organizing acquired data and analysis of as-built data. An automated progress monitoring system would comprise of the steps shown in Figure 4 where data acquisition systems that refer to geospatial sensing technologies and information retrieval involves data processing operations to extract information, progress estimation that is an out of a comparison between as-built and as-planned data and visualization of results. This chapter discusses research on each step of progress monitoring shown in Figure 4, with focus on computer vision.

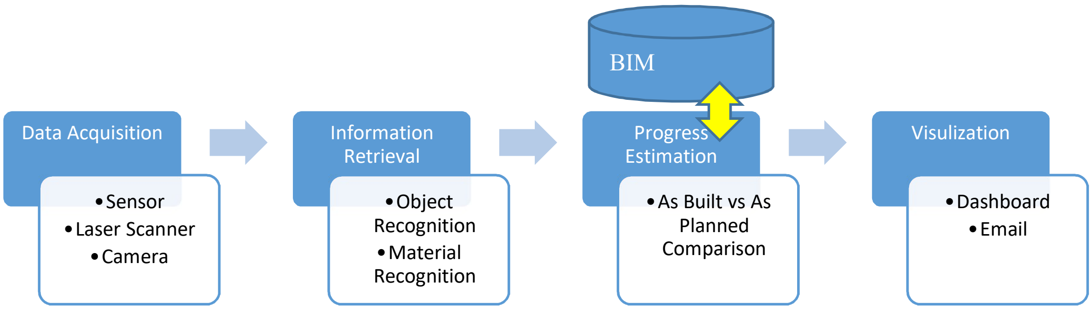


Figure 4 Components and flow of automated progress measurement mechanism.

2.1. Data Acquisition Technologies

The advent of low-cost data acquisition technologies will enable accurate and efficient automated progress status determination. Companies around the world are adopting advanced, cutting-edge tools that may be web services, voice-based tools or handheld computing devices to boost productivity. Automated progress measurement relies on data collected through various devices. These devices can either be fixed or mobile. Digital cameras, laser scanners, handheld computers, and voice acquisition systems are mostly mobile or fixed with a rotation mechanism.

2.1.1. Sensor Network

Wireless sensor networks (WSN) are mostly fixed, consisting of spatially distributed sensors, monitoring physical and environmental conditions. WSN consists of a base station and nodes with a gateway that connects nodes to the wired world, creating an embedded acquisition and relay framework. Geospatial tools include barcode readers, Geographical Positioning Systems (GPS) and Radio-Frequency Identification (RFID), UWB Tags and Geographical Information System (GIS) [2]. They are mostly used for augmenting management [30], resource tracking [31][2] or for inspections to retrieve onsite data [32]. Sensors are low in cost and can be easily tagged, however, they may require special power and mounting equipment. GIS[33] has demonstrated that sensing technologies can automate construction progress monitoring. Attempts have been made to provide mobile devices to workers to support faster and reliable data collection, [34] however, providing mobile devices to site workers is not a feasible option considering the risk of theft and damage as well as extra equipment a worker has to carry.

2.1.2. Laser Scanning

Since the beginning of 21st-century research has been focused on the development of 3D data collection and modeling techniques with particular attention to geometric aspects for which Laser Distance and Ranging (LIDAR) has been handy. Laser scanners are either Airborne Laser Scanners (ALS), Terrestrial Laser Scanner (TLS), or Mobile Laser scanners. ALS can provide geo-reference point clouds by laser measurement from an aircraft and orientation of this measurement between reflecting objects and sensor using differential GPS technology. TLS is fixed at a position and measures time of flight (ToF) of a laser beam generated by laser scanner to reflect from an object and reach the detector present in the scanner. TLS can measure the distance of a point in the proximity of a sensor with millimeter accuracy at a rate of one million points per second, to create a dense point cloud. MLS (see Figure 5) is a modification of ALS as it has a laser scanner, GPS, Inertial Motion Unit (IMU) but it is mounted on ground-based vehicle's cart or human being at times [35].

Figure 5 ROBIN All-in-one Vehicle, Backpack, and UAV LiDAR System [36].

Laser scanners produce accurate point clouds but fail to provide a semantic understanding of the scene. Majority of laser scanners are expensive, bulky and power-hungry requiring special operator training and at times placement of targets to work place. The absence of semantic information and a large amount of data produced by laser scanners make a computationally expensive setup that would make it impossible to provide data in real-time without lag. MLS are lighter in weight and don't require setup, centering and leveling at every station. MLS provides quicker results but compromises on point cloud density and absolute accuracy (see Table 1). It can, therefore, be safely said that MLS is a complimenting current surveying technique rather than replacing them [37]. TLS is still a key player in the laser scanning industry due to its comparatively lower cost, durability, and ease of use. As mentioned, MLS cost way above TLS but are useful when a large area has to be covered making static devices impractical due to many sensor station setups involved [38].

Table 1 Comparison of MLS and TLS accuracies and point cloud densities [39].

	MLS (backpack)	MLS (Vehicle)	TLS
Accuracy (Absolute)	30mm	20mm	<10mm
Accuracy (Relative)	3-5 mm	3-5 mm	3-5mm
Point Density	60,000 pts/m at 2m	6,000 pts/m2 at 2m	250,000 pts/m2 at 2m

2.1.3. Multimedia

Multimedia includes digital images, videos and audio recordings collected to confirm activity completion that has been in vogue since the 1990s to assist in delay analysis. Multimedia tools allow visualization of information and red flagging of problem areas [40]. Imaging comprising of both still and video capture is a promising form of as-built data. In recent years, Digital Imaging has evolved from monochrome to Ultra HD, from photosensitive films to charge coupled device (CCD), and their application in civil engineering has increased significantly. With the advent of high definition low-cost cameras, imaging has become an economical and speedy source of accurate data acquisition from the site. Over the last decade, cameras have become cheap with increased data storage capacity and also have built-in Bluetooth and data connectivity.

Photography has become a rich medium of data acquisition on site because of its ability to collect semantically rich information quickly and economically. Site images are acquired for documentary purposes [41]. Every construction site has cameras and keeps an archive of pictures as evidence of progress, identification of deviation from design and dispute resolution attained according to specifications. Images have evolved into a significant and irreplaceable part of project documentation, thus justifying the ever-growing rate of imaging information acquisition in the AEC/FM industry [23]. Images are used for settling on-site disputes, training of workers, root cause analysis of incidents and as a marketing tool to show the quality of work. Imaging can be either still or video, which is essentially a number of frames acquired by image per second. Videos contain data obtained at higher frequency thereby holding a considerable amount of information while consuming large amounts of storage space. Video transmission over Wi-Fi and Bluetooth is time-consuming, and live stream software have built-in lag depriving the user of real-time information. Image stitching is a data efficient process to attain and combining images in a manner that is not as memory consuming. Image stitching is the process of modifying and blending image in a manner so that photographs align seamlessly [42]. It has been used in the construction industry mainly to visualize anomalies [43][44] such as cracks or creation of panoramas from images [45]. The volume of images stored on a site database is increasing rapidly, and it is becoming increasingly difficult to browse and extract images manually for utilization in construction project management tasks [46].

The current state of the art methods for automated progress monitoring is relying on data acquisition technologies which include sensing, laser scanning, and imaging to attain site information and generate 3D point clouds. In comparison, laser scanners produce more accurate point clouds than their alternative digital cameras, but scanners fail to provide a semantic understanding of the scene. Cameras, on the other hand, are lower in cost and contain color data that can be used in a variety of ways to ascertain site information. It can be inferred that if there are no occlusions, i.e., Line of Sight to the element is without any obstruction; site image processing is more effective and viable for construction progress monitoring. To benefit from the advantage of both laser scanning and 2D imaging system, 3D laser scans were merged with digital images to estimate quantities and amount of work [47]. However, this method involves manual selection of common points between images and laser scans, requiring a significant amount of manual processing.

2.2. Information Retrieval

Data acquisition devices provide data that may be in the form of change in voltage or current in case of analog sensors, point clouds in case of laser scanners, and RGB images when cameras are used. Enhanced Information Technology (IT) devices are great tools for continual improvements on site, which resulted in increased productivity and better project management. However, they require initial expenditures, training, software, O&M which may limit their use on site. Until or unless investment made on enhanced IT tools has a high return on investment, contractors, who are already repulsive towards technology, will never adopt them.

The point clouds (see Figure 6 [48]) generated by laser scanners already have 3D information and don't require a lot of further processing for comparison of as-planned with spatial as-built data. However, point clouds are not object-oriented but rather a set of scattered points. The processing of point cloud to attain object level information is a computationally expensive process. The point cloud can also be generated from site pictures using Photogrammetry [49], which though computationally expensive, is the process of attaining structural and shape characteristic of an object in the form of 3D point cloud [50]. The 3D point cloud can be created using video streams [51], building façade modeling [52], distinctive features [53] and Structure from Motions (SfM) coupled with Multi-View Stereo (MVS) images [54]. 3D reconstruction and modeling provide a reconstructed 3D scene for a particular day. However, they cannot restore the context and content of the photo [55].

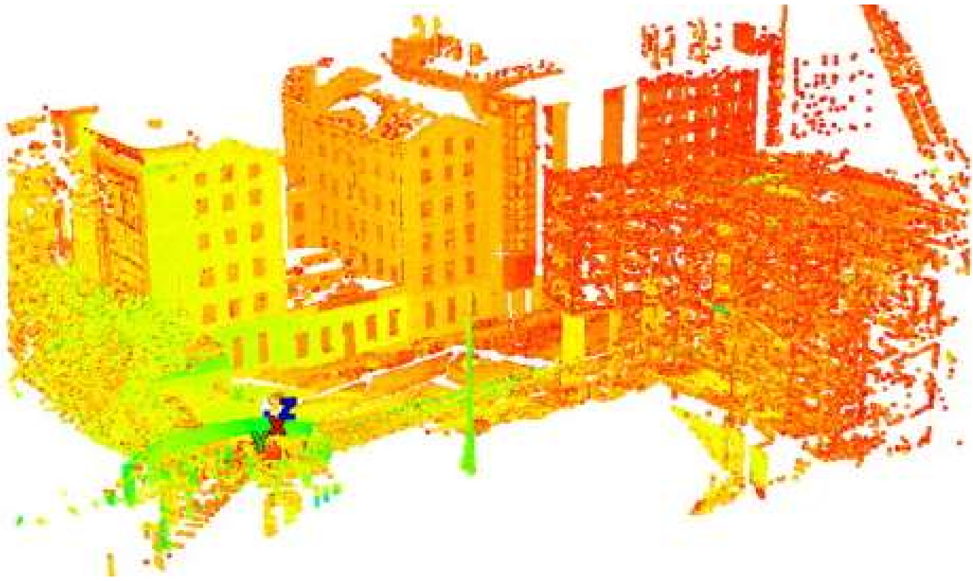


Figure 6 A point cloud containing millions of points of an under construction structure [48].

Progress information requires additional semantic information such as construction materials and their interconnectivity for structural and architectural elements, beyond geometric coordinates of the respective elements, which can be derived from appearance-based 2D imagery. Construction images, unlike laser scan point cloud, contain color, a source of rich and useful as-built information, has been focus of research to grasp their context and content for information retrieval purposes using image processing and computer vision techniques [46]. The term image and video processing include tasks to restore, enhance, filter, modify and extract information from images using signal processing techniques [26] — several image processing techniques that are used to describe images in mathematical terms to provide a numerical representation of the items within an image for identification based on similarity. Computer vision uses statistical methods to extract visual information using geometry and machine learning concepts. It requires an understanding of cameras and processes involved in the formation of images on a sensor to gain inference from pixel level information in multiple images using probabilistic techniques to infer shape and recognize objects.

Computer vision studies can be divided into three main categories [50]: three dimensional (3D) reconstruction, individual photo analysis, and as-built model generation. These techniques are based on the fact that images can be represented as a three-dimensional pixel matrix with each pixel in the image as one element in the matrix. Various mathematical concepts derived from algebra, statistics, and geometry like Mean, Median, Filtering, Fourier, and Wavelets transform. The visual appearance of a material depends upon illumination conditions, geometric structure, and the reflectance properties, that can be exploited using mathematical concepts to extract object characteristics. Several studies have been conducted on automatic information retrieval from images. Computer vision has found various applications in construction performance measurement for construction project management [9], [56]–[59], using object recognition and material detection, [23], [60]–[62], resource and equipment tracking, [63], [64], occupational health and safety monitoring [65] and project visualization [66]. In damage detection domain computer vision algorithms are used for surface defects and crack detection, [67], and pothole detection [68].

2.2.1. Object Recognition and Material Classification

There is a need for extraction of semantic information from images, and it has opened two main research avenues in the field of computer vision, namely object recognition and material recognition [69]. Object recognition relies on material invariant features and overlooks features that are material specific thus focusing solely on geometrical characteristics of an object. The visual characteristic of an object is, to a certain degree, dependent upon its constituent materials. Different classes of objects can be made of different materials, or different materials may be present in one instance of an object. There have been many advances in the subject of object recognition that include shape context [70], histogram oriented gradients (HOG) [71] and label transfer [72] that may not apply to material recognition. Most of these methods ignore material information while focusing on material invariant features [72].

Material classification is an essential aspect of the automated progress monitoring system or for the creation of semantically rich 3D models. Therefore, developing a system that ascertains material information from images is an essential aspect of visual recognition [70]. Automated material classification (also called *Recognition* in computer vision literature) not only provides appearance based information for progress monitoring purposes, but it also assists in segmentation for geometric modeling purposes. The author of this research also conducted a study [73] on the use of terrestrial laser scanning to identify common construction materials based on their reflectance properties. The experiments showed that each material has unique reflectance characteristics when defect-free areas are scanned. Reflectance characteristics were found to be independent of illumination conditions though dependent on moisture content. The RGB values signatures were also evaluated and compared with reflectance signatures. Reflectance signatures were observed to be a robust identification criterion.

Color as a parameter for material identification has been suggested by Kim et al. [74] for the identification of concrete and by Son et al. [75] for the classification of construction equipment. However, using color for the classification of different types of materials using the same algorithm has not been done in research. Color values have been used for Content-Based Image Recognition (CBIR) [26] by Dimitrov [69] to increase the robustness of their algorithm. Neto and Arditi [76] used Red, Green, and Blue (RGB) color space for identification of structural components of bridges, while Dimitrov [76] used HSV color space to increase the robustness of his algorithm. Color based image filtering process was used by Son and Kim [77] to extract structural components from images for comparison with the 3D model.

2.2.2. Context-Based Recognition

Certain objects or materials on a construction site can have a similar texture and color to other objects with a lower probability of presence. It is difficult to differentiate between planar surfaces with very similar color and texture like a wall versus side of a bookshelf in a laser scan point cloud. Contextual information is useful in solving such problems which can either come from within the image, or it can be derived from non-image sources, where the latter comprises of geographical information of the image and the time at which the image is obtained [78]. In laser scanning point clouds, researchers have leveraged spatial relationships between objects to filter out ambiguous results. This approach generates a knowledge database containing a semantic label of geometric primitives (see Figure 7) which are used for the validation of recognized object [79]. Semantic Nets [80] are used for specific relationship between entities, e.g., walls and doors are always orthogonal to each other and doors are present inside walls. If a floor is recognized, then the valid orthogonal entities are walls and doors, and there is no chance of ceiling being orthogonal to floor thus reducing the search space for making the algorithm efficient. This approach of using geometric primitives to identify objects is also called Reverse Engineering [81]. A stepwise detection has been suggested by Pu and Vosselman [82] that detects recognizable objects and using characteristic features like size, shape, orientation, and relationship detects objects that are difficult to identify in the first stage without prior information.

Prior knowledge is also used to reduce the search space by utilizing knowledge of a specific facility [83] which can be attained directly from BIM floor as well as knowledge of construction sequencing. Context-based recognition is concept of using sensed data in its natural representation for object recognition purposes, by using expected or as-planned world to create an as-built point cloud [82]. The range point cloud is calculated from 3D CAD in laser scanner coordinate reference, and for each as-built range point, a point is calculated in the virtual world. The object that calculated point constitutes in the virtual world can be the inferred as that object in the as-built point cloud for the scanned point.

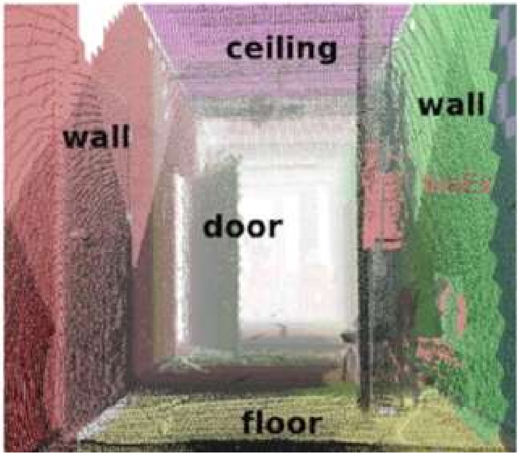


Figure 7 Semantic labeling on geometric primitives [79].

2.2.3. Machine Learning

Object recognition and material classification strategies are usually coupled with machine learning techniques for training and testing purposes. Pattern recognition is a process of recognizing patterns based on specific characteristics of a material using machine learning algorithms. It is a mature field in image processing, however, its application in civil engineering is recent [84]. Image recognition algorithms are dependent on machine learning algorithms to provide robust results. Machine learning algorithms have been used in image processing domain for handwritten digit recognition [85], process monitoring and early fault detection [86] and object recognition for the robot using laser range finders [87]. In the civil engineering field, we use machine learning algorithms for material based image retrieval [26], structural components detection [88] and crack [89][90] and surface defect detection [90]. Support Vector Machines (SVM) was used by Zhu and Birlikas [62] for concrete detection in construction site images. Son et al. [74] created a combination of color space and machine learning algorithm in two non-RGB color spaces for optimal results. Popular features like filter response, have been coupled with Multi-Layer Perceptron (MLP), Radial Basis Function and Support Vector Machine (SVM), which have shown promising results but have not performed very well with images collected from construction sites.

2.3. Progress Estimation

Automated progress monitoring has recently been the focus of research community, and several studies have been conducted on progress monitoring by comparison of as-built and as-planned data. A significant chunk of this research has been the measurement of physical quantities of different materials like earth cut and fill, masonry and structural erection using spatial sensing technologies. Intuitively progress can be assessed by comparison of as-built with as-planned models based on geometrical characteristics of their respective elements. As-built data is attained through various geospatial sensing methods while the Building Information Model (BIM) has provided as-planned information in a concise and extractable database. In the following section, BIM will be discussed as a source of as-planned data for progress monitoring and performance measurement.

2.3.1. As-Planned 4D BIM

BIM provides a framework for collaboration in a multidisciplinary environment that brings together all stakeholders of Architecture, Engineering, and Construction (AEC) industries allowing retrieval of 3D model characteristics by users during the project life cycle [91], [92]. BIM has found use in the design and preconstruction stages of a project as well as construction stages though to a lesser extent. BIM allows design integration, prototyping, simulation, cost estimation, retrieval and maintenance of building data [93]. In operation and construction stage, the role of BIM has been restricted to a static repository [91], [94] thus under utilizing its capabilities. BIM came with a promise of introducing information technology to the construction industry by revolutionizing information flow. The construction industry is still lacking behind in technology adaption, and BIM is still in its infancy [95]. The reason being additional manhours are required to develop BIM and contractors in the construction stage don't have the budget or the expertise [94] to take such an initiative.

BIM is a 3D model that can be converted to a 4D model by incorporating schedule and *nD* model by combining many design details required at each project stage. 4D BIM is a powerful tool to communicate construction plans and milestones [41] which are useful in tracking and monitoring of construction projects [96]. A 4D BIM contains various views and locations that replicate as-built views of a planned project which should be similar in appearance to as-constructed photos of time in a project. 4D BIM assists in grasping the content and contexts of a picture when matched with a viewpoint in the model using photo registration techniques like the one suggested by Park et al. [50]. Photo registration may not be required to match a photo with a viewpoint in 4D BIM incase photo is attained at pre-determined location and view.

4D BIM is a useful technology combining 3D elements along with their corresponding activities to assist construction management teams by effective visualization of a range of management levels (i.e., project, task, and operational level) [54]. 4D BIM can leverage progress monitoring algorithms by reducing the expected materials space based on real expectations at a particular location. There are two significant areas of improvement namely, advanced construction progress monitoring and efficient schedule data preparation. Research studies have been done on development and update of 4D models that include the use of RFID technology for high rise steel building construction [32] or use of unordered photographs for 4D as-built model development [18]. The laser has also been suggested for the 4D model update by Turkan et al. [58] to update site information using a feedback loop automatically.

2.3.2. As-Built vs. As-Planned Comparison

The general strategy for progress monitoring is to register and compare the information attained from scans and images to as planned BIM in a common coordinate system. Registration of 3D is done by careful selection of a set of features between 3D reconstructed models to be matched with 4D BIM, making the process difficult to automate because of the robustness issue. 3D registration of laser scanning point clouds with BIM can be used to check the quality of data as well as perform automated monitoring. The registration can be performed manually[97] or in a quasiautomated manner [98]. 3D registration is followed by object recognition and comparison of as-planned with an as-built model in a common frame of reference. The deviation of as-built from the as-planned model will give a measure of progress on site; the deviation can be either caused by delay, incorrect placement, or early completion of activities. Real-time assessment and documentation of construction activities and 3D models created by laser scanners were investigated by Cheok et al. [48]. While Jaselskis et al. [99] used laser scanning as an accurate mean for effective progress monitoring on transportation projects, Turkan et al. [58], [100] and Bosche et al. [101] focused on recognition of 3D elements for project performance measurement, an information which could also be useful for progress monitoring. These methodologies involving laser scanning provide sufficient enough information to create BIM [83], but in order to create a semantically rich model containing additional object-oriented information that may come from sensors or cameras. An integrated system using enhanced IT technologies involving laser scanning, images, RFID, and barcodes was proposed by El-Omar and Moselhi [102] for data acquisition from construction sites for monitoring purposes.

2.3.3. Images based Progress Monitoring Solution

Research effort on use of the photograph for site management goes way back to 1989 [103] where time-lapse pictures were used for productivity enhancement. Manual image based real-time progress review systems including Photo-Net II was developed by Abeid and Arditi [104] that links site time-lapse images to the critical path. Lueng et al. [105] proposed an online collaboration tool that consists of IP cameras and can be used to monitor construction by stakeholders while corroborating vital decisions.

Rebolj and Podbreznik [78] first published the concept of automated construction progress monitoring using image processing in 2005 [106], giving bright prospects for the future of research in the construction industry. Afterward, image processing-based progress monitoring has been the focus of research, and several image-based approaches have been proposed for construction progress measurement. Wu et al.

[107] proposes one such approach to estimate site progress from construction site digital images based on object recognition using image processing and 3D CAD. Golparvar et al. [18] used unordered daily site photo logs for progress measurement on the construction site by the construction of a sparse 3D schedule and comparing it visually with planned data. Son and Kim [77] suggested a technique for automated 3D structural component registration and modeling where the researchers divided monitoring into image acquisition, progress identification, and 4D model update steps which are valid for any image processing-based monitoring system. Abudayyeh [108] introduced a system comprising of a microphone and video camera to record events related to activity progress. Other approaches suggested in the literature use fixed cameras installed on high rise structures, and video and audio stream from smartphone cameras [109].

2.4. Data Visualization and Dashboard

Besides efficient data acquisition and timely analysis, an efficient progress visualization system is also essential [6]. Augmented reality and data dashboard are effective for progress visualization. While augmented reality provides very efficient virtual walkthrough (see Figure 8) and visual cues for site progress estimation, they suffer from AR registration errors and heavy computation. Dashboard provides performance metrics as a bird eye view of progress in a computationally efficient manner.

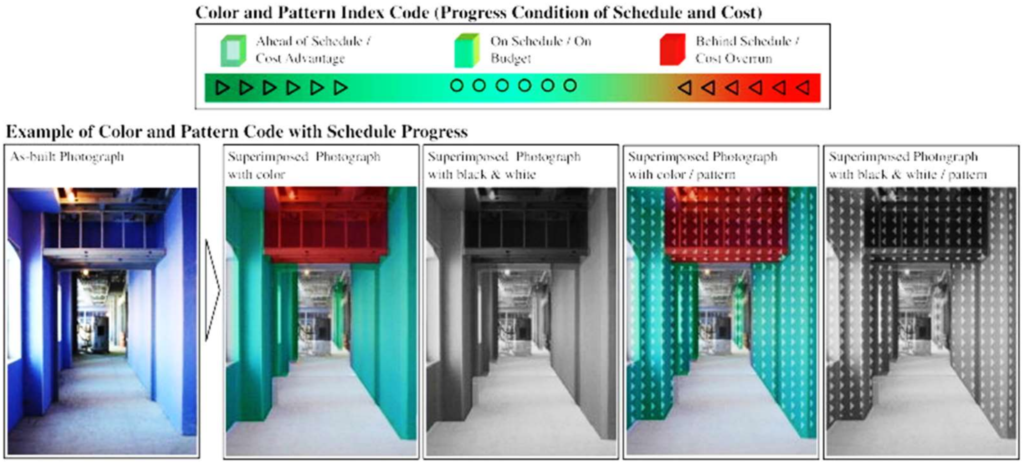


Figure 8 Color-coded progress status information using augmented reality [110].

Jaselkis et al. [111] provided a concept for remote project control utilizing audio visual equipment for data acquisition, thereby providing a framework for simultaneous monitoring of multiple projects. Leung et al. [112] proposed a web-based collaboration platform for site stakeholders to monitor construction and quality using data acquired through IP cameras. Tele-engineering techniques were used to attain site information and project data on large screen in auditoriums to give project insight to participants and get their feedback [5]. This provides an opportunity to attain expert opinion based on visualization of data acquired remotely when subject area specialists are not available locally.

Data dashboard is an information management tool [113] to track, analyze, and display KPIs and data points to monitor construction progress. Dashboard has various algorithms running in the background to acquire information in real-time to display information in the form of tables, gauges, and charts. Dashboard provides a central location for efficient data monitoring and performance evaluation of the project reducing long line of communication full of delays that challenges business execution. Dashboard provides quick analysis and informational analysis unlike advanced business intelligence tools; dashboards focus on birds eye view of project performance. Construction dashboard [5], similar to those in Figure 9, is proposed to enable information visualization using temporal, hierarchical, relational and spatial information views.

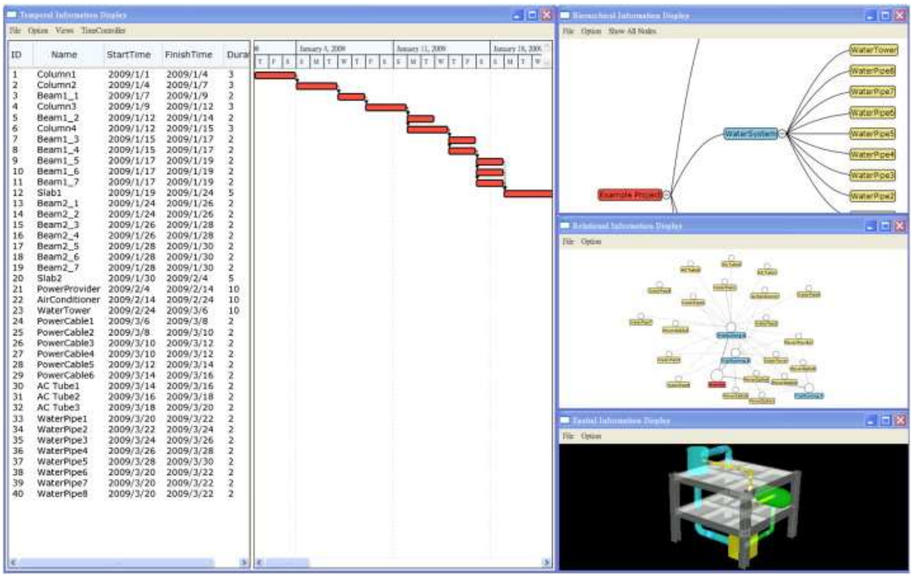


Figure 9 Multi-system construction dashboard proposed by Kuo et al. [114].

Dashboards perform information extraction and emphasizing function thereby fully exploiting its information capabilities and maximize construction performance. Dashboard provides high dimensional information in construction projects; they can be either strategic, analytical, or operational [113]. Operational dashboard is used to report business processes that frequently change and to track KPIs. Operational dashboards are used to monitor progress towards a target and are observed multiple times in a day. Strategic dashboards update at a less frequent interval as compared to operational dashboards and are used by top executives. Analytical dashboards are used for analysis of large chunks of data to investigate trends to forecast future progress, determine trends and discover insights. Analytical dashboards help stake holders establish their goals while operational dashboard assists in gauging daily progress by KPIs.

2.5. Gaps in research

Several data acquisition, information retrieval, and progress monitoring methods have been discussed above. The effectiveness of various acquisition methodologies can be judged by their utility, time efficiency, accuracy, automation level, and training requirements [6]. Table 2 shows the performance evaluation score sheet for criteria discussed for evaluation of progress monitoring systems utility; i.e., the suitability of the system on different applications like indoor, outdoor, architectural or structural monitoring. Time efficiency is the amount of setup time as well as the time required to extract useful information from the methodology. Accuracy governs the reliability of the system, the precision of the results and repeatability. The level of automation is the amount of user input and training is the competence level of personnel on site to deploy such a system.

Table 2 Rating criteria for progress monitoring system by Kopsida et al. [14].

.	**Good Performance**	**Mediocre Performance**	**Poor Performance**
Information	Semantic and Spatial	Spatial	Limited aspect
Time Efficiency	Real-time information	<1h	>1h
Accuracy	Precision in all steps	Precision in some steps	Error in all steps
Automation	Every step is automated	Only some processes are automated	None
Training	None	Easy to Learn	Specialized Personnel
Cost	<3,000	3,000-10,000	>10,000

Table 3 shows a comparison of various automated progress monitoring technologies discussed in this chapter with an ideal solution. Laser scanners are very accurate but are extremely expensive as well, and manual human input is required during registration and modeling. Laser scanners are also proprietary equipment with every manufacturer providing its black box software with little room for customization according to the user. When terrestrial laser scanners are used, the sensor setup and scan time per station is equal to or greater than ten minutes, which is a lot considering the number of stations required to scan a site. MLS is very expensive and beyond the reach of common building contractors. 3D reconstruction using images doesn't have the same accuracy as a laser scan and requires experienced user to function properly. Part of camera-based image reconstruction has not been fully automated, therefore, reducing its utility in a fully automated system. Static image-based systems are compromised by occlusions which will appear as the site progresses. The camera needs to be moved from time to time diminishing its utility and decreasing automation. Sensor network needs infrastructure investment to work despite their nominal cost of purchase. An experienced electrical technician is required on site to perform fixed sensor installation; however, handheld sensors don't need installation, but they do need a person to carry around. The data acquired from sensors don't give spatial information and lack semantics; it can work for a specific task and have very limited application. A perfect system will have full automation, low cost, no human training requirement and should have broad application.

Table 3 Performance evaluation of progress monitoring systems derived from Kopsida et al. [14].

	Sensors Networks	**Laser Scanners**	**Static Vision System**	**Vision Based Reconstruction**	**Ideal Case**
Information	Environmental Variables only	Spatial only	Semantic	Semantic and Spatial	Spatial and Semantic
Time Efficiency	Instant data	Time Consuming Scans	Time spent in acquisition	Time required for reconstruction	Real Time Data
Accuracy	Subjective	Accurate	Accurate for Simple tasks	Accuracy dependent on various factors	Accurate
Automation Level	Automated information acquisition	Manual Registration and Modelling Requirement	Automated acquisition and processing	Partially Automated with manual automation	Fully automated
Training Requirement	Trained personnel for installation	Trained personnel	None	Trained personnel for reconstruction	None
Cost	High initial cost of installation	Very costly	Consumer Hardware	Consumer Hardware	Commercial open source hardware

Gaps in literature were observed during the review which include the following

Indoor Localization; Most of the current practices are applicable on outdoor locations and use of technologies like GPS. Indoor progress measurement has been researched to a lesser extent because of the inability of fixed cameras to image indoor elements as Line of Sight will be affected and vision of camera will be blocked by newly constructed elements

Automated Data Acquisition; Over the past few years, research has focused on addressing current limitations through aligning the resulting 3D point cloud models with 4D BIM for progress measurement [16] and estimation of the pose of a camera within the BIM. Still, the user must manually upload images as the schedule is not automatically updated and a vast array of images is not computationally economical.

Image Localization and Tagging; Progress monitoring techniques whether they are automated or manual require images containing element level information in metadata for storage and quick retrieval. To the best of author's knowledge, no research exists on attaining images that are tagged to BIM elements and activity IDs without manual input by the camera operator.

As-built Verification; is a gap in image processing and modeling techniques. The project plan should be updated to reflect the progress of the project and ascertain delay in activities.

Validation on Site: Very limited studies have been validated on real site. Image processing algorithm works well in controlled environments but tends to give poor results when additional environmental variables are introduced.

2.6. Research questions

The high rate of defect, cost overrun and inefficiency as well ineffectiveness of strategic management initiatives suggests that conventional construction with the current level of technology adaption has reached the peak performance limit [115]. Improving site efficiency by use of technology is the focus of many studies after considering the way technology has revolutionized the manufacturing industry. The solution to these defects is Construction Automation (CA). New technologies are inferior in the beginning but improve with time to help achieve a higher level of performance overtime.

Automation is the way forward to attain accurate data promptly and efficiently, but there are specific challenges in applying automation techniques to the construction industry, which are different from challenges faced in other sectors like manufacturing. The need for automated data collection has been discussed widely [8]. Researchers in this field have observed that photo analysis along with other technology-oriented efficiency measures to improve project scheduling, monitoring and decision making processes can result in 5-6% reduction in overall project cost [116]. Different authors have suggested data acquisition technologies like (Radio Frequency ID (RFID) [117], Ultra Wide Band (UWB) [118], Global Positioning System (GPS) [119], Wireless Sensor Network (WSN) [120], Computer Vision [59] and Terrestrial Laser Scanning [73]. The technologies that can facilitate the acquisition of data, processing and visualization of the results have not yet been implemented to reduce the workload of project management teams.

In some cases research has been technology driven aiming to find a useful application of technology in construction instead of searching for technological solutions of construction problems [2]. Construction products are delivered in dynamic 'project' delivery mechanism, and typically construction sites are not hospitable to automation techniques. Automation is more suitable for a process rather than a project environment. Since, in process-based delivery mechanisms (e.g., manufacturing), the tasks are repetitive which aim to produce the very same product over and over again. The element of variation is non-existent in processes while in a project environment the product and delivery mechanism, as well as specification change in every iteration, thus making automation a difficult target to achieve. An additional requirement like installation, configuration, integration, commissioning, and resource training may make it difficult to attain short benefits thus making Return of Investment (ROI). Construction project does not go long enough to allow for full-scale integration of automation systems and concludes before the system starts giving its reward in the form of cost and manpower saving. The inertia to change and dynamic setup is one of the reasons why the construction industry is primitive and slow in adapting to new practices and innovative technologies.

Construction industries inability to fully exploit advances in automated information acquisition is impeding construction industry from taking full benefit of advancement in technology. Building Information Modeling (BIM) provides visualization, integration, and simulation related benefits that have great value in the design stage; however, in the construction stage, its benefits have not been fully exploited. This research will aim to achieve automation using BIM in a manner that doesn't put an extra administrative burden on site management. In doing so, the research will answer the following questions that are necessary for an efficient, timely and accurate progress management system with Figure 10 showing relationship between problems and research questions:

a. How can data points, for acquisition of images that are tagged to building elements, be determined for accurate and automated progress monitoring?
b. How can real-time and accurate construction site data be attained autonomously from the site?
c. How can accurate element level status be determined in an automated manner from site images without any human input? How accurately cost-based

progress metrics based on acquired material state information can be obtained from site images?

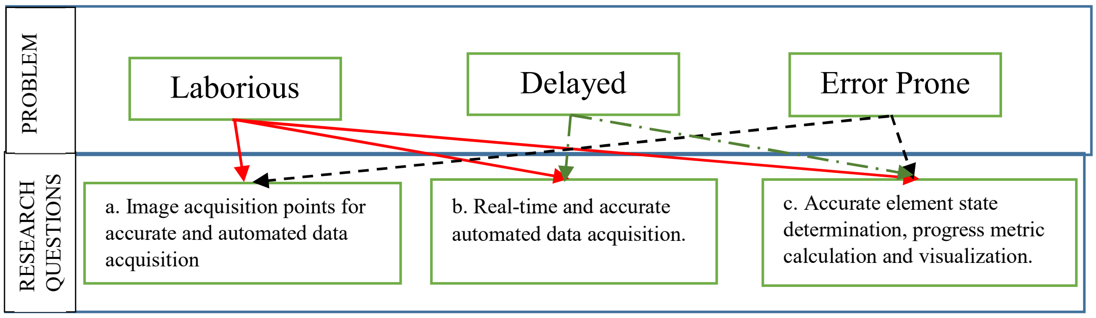


Figure 10 Research questions from problem definition schema.

2.7. Objectives, Scope, and Contribution of Research

The focus of this research is to develop and validate the performance of a fully automated system for progress monitoring by obtaining data from construction sites in near real-time using autonomous systems. The proposed system should require minimal or no human input and should not be disruptive to site activities. Accurate and expeditious provision of data to management will adjudge the performance of the proposed method. The objectives of this research are as follows,

- Develop a fully automated context-aware progress monitoring mechanism for structural and architectural works on building construction sites.
    a. Automatically extract coordinates for element image acquisition from BIM.
    b. Acquire site images using an autonomous device.
    c. Extract progress status from acquired images.
    d. Calculate performance metrics from acquired progress status.
- Validate the performance of the system and report its performance metrics.

The scope of this research is limited to shell and core building's opaque architectural and structural elements. The performance of developed methods is evaluated on building components that are omnipresent on building structures irrespective of their potential utilization, making this methodology valid for a vast array of construction projects. Imaging being utilized to determine progress and activities that can be visually monitored by the human eye are within the scope of this research. Internal or hidden changes in the state that a schedule adjudges as an activity is not evaluated.

2.8. Proposed Solution: Context-Aware Automated Construction Progress Monitoring System

A Context-Aware Automated Construction Progress Monitoring System (CAPMS) is proposed in order to address concerns related to inefficiency in construction progress monitoring due to manual methods. The goal of an automated system is to acquire data, convert it into information and deliver it to project leadership team in a timely manner [106]. Objective is to attain data in real-time that is not affected by human factors and is accurate and precise. The developed system focuses on main components of construction information loop (see Figure 11) that encompasses planning, construction progress, and reporting to stakeholders. Our purpose is to develop a system that is void of human involvement and provides timely information on construction progress to management team. The flow of information is a repetitive process throughout the lifecycle of the project. This cyclic process presents an opportunity for automation which is more effective for repetitive processes as compared to intellectual ones.

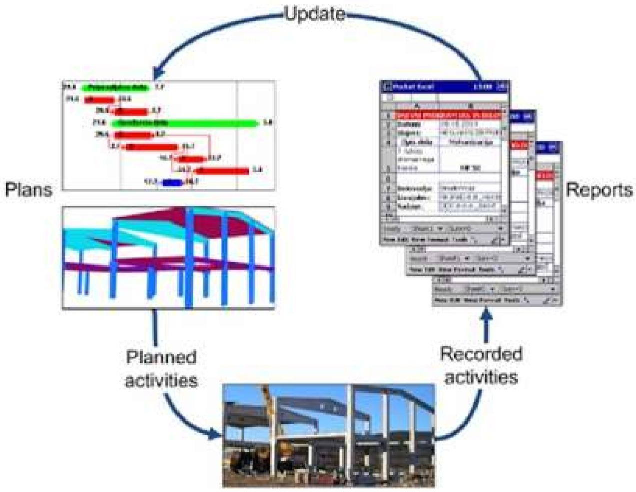


Figure 11 Construction Information Loop [121].

The developed system should cause minimum disruption on site with minimum cost of implementation and result into overall cost saving. Workers should be able to perform their tasks without any interruptions or delays. The sites should require minimum additional components that would add to the cost of construction or additional infrastructure that may require wiring, provision of DC power installed by spending extra man-hours since these will be non-value adding activities. There should be minimum training requirements for the worker and site management teams for implementation and integration of CAPMS.(see Figure 12) which comprises of 4D BIM containing element coordinates and the activities that are related to that element in a schedule. A daily monitoring list is extracted from 4D BIM activities that are expected to be completed till the day of inspection. The monitoring list containing the name of the activity and the coordinate of Point of Interest (POI) is sent to robot using post request over Wi-Fi. The robot traverses to the POI and takes images at different camera orientations controlled by onboard camera and servo motor. The images are then communicated to the server where they are processed using Schedule-based Context-Aware Element Recognition (SCAER) algorithm to determine the current state of the element.

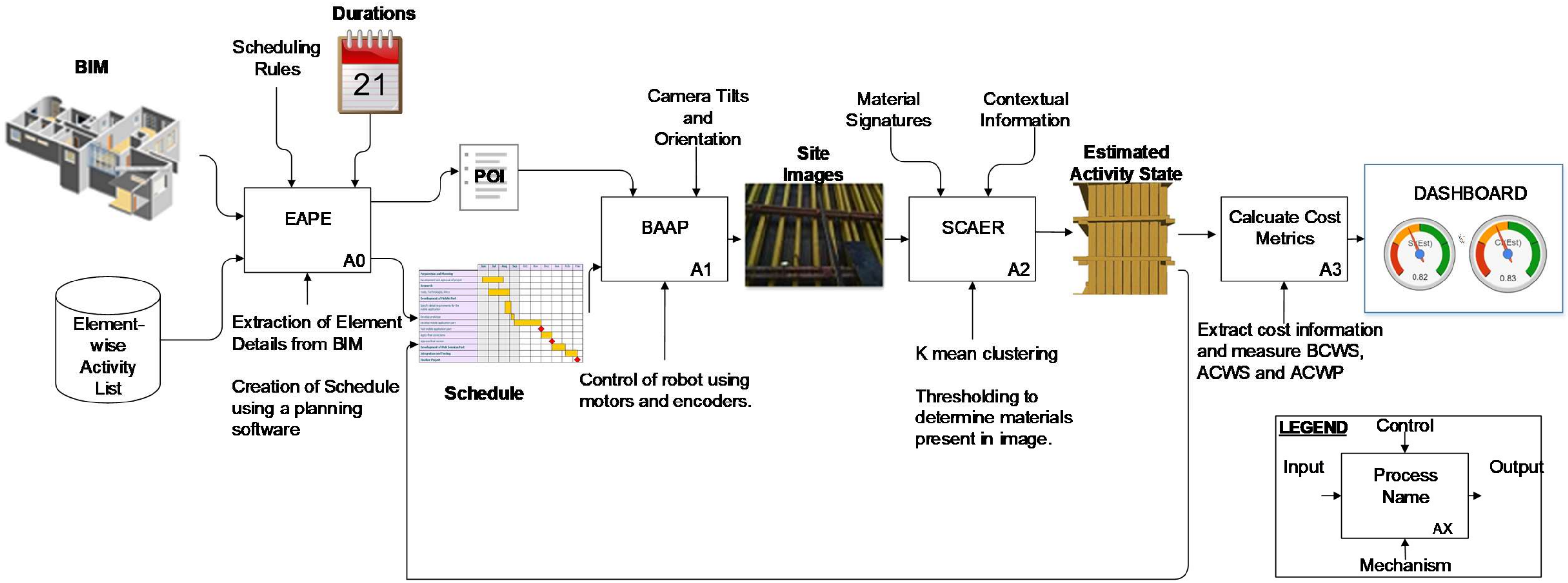


Figure 12 Vision for Context Aware Automated Progress Monitoring System (CAPMS).

A client-server architecture is proposed for CAPMS as shown in Figure 13, which is prevailing nowadays and is being used on various applications on daily basis [122]. Images are taken at the client end and transmitted to server for further processing and extraction of progress information. The client in the case of this research is an autonomous data navigation device that navigates construction sites and acquires images of building elements to detain their state at a particular time, the details of which are discussed in Chapter 5, BIM based Data Acquisition Platform.

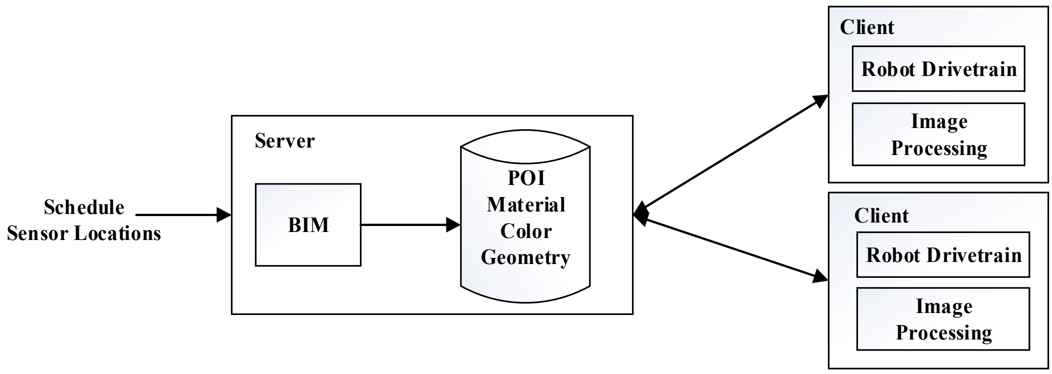


Figure 13 Server Client Architecture of CAPMS.

The server side may be remotely connected to the site over the internet or it can also be present on site connected via Local Area Network (LAN). The server will act as storage for all information including pictures and as a processing unit for CAPMS. Server, whether remote or local, will be at a fixed location connected to the router that provides access to the thin clients. The server will contain a comprehensive 4D Building Information Model (4D-BIM), comprising of a three-dimensional semantic model and an up-to-date as planned schedule along with computer vision and web server protocols.

SCAER uses material signatures and contextual information to process image obtained by the robot to determine whether the actual state of element matches the expected state of the element. Activity is completed if expected state matches the current state and not completed if expected and current states don't match which translates into progress achieved for the former case and lack of progress for the latter case. Once the status of activities is ascertained at all POIs, the schedule is updated with completed activities which can be reviewed by project management team.

Since imaging is being utilized to determine monitoring activity, only activities that are visible to a human eye can be monitored. Internal or hidden changes in the state of an element that can be characterized as an activity, can be monitored using Context-Aware Progress Monitoring System (CAPMS). The Custom Activity Code List (CACL) containing activities monitored as part of CAPMS are shown in Table 4.

Table 4 Custom Activity Code List (CACL).

Relevant Activity	**Code**	**Materials**
Masonry Work	MW	LWC Blocks, Masonry
Door Installation	DR	Doors
Plastering Work	PL	Gypsum, Cement
Installation of Formwork	FW	DOKA Formwork
Reinforced Concrete Work	CN	Cement Concrete
Laying of Rebar's	RF	Deformed Rebar's

Hardware, as well as algorithms, was developed during this study to achieve the objectives above. The main research outputs are 'Context-Aware Progress Monitoring and Visualization System (CAPMS)' whose ancillary components developed during this research are as follows:

a. Element-wise Automated Activity and POI Extraction algorithm (EAPE).
b. BIM-based Data Acquisition Platform (BAAP).
c. Schedule based Context-Aware Element-state Recognition algorithm (SCAER).
d. Construction Information Visualization (CInfo).

2.9. Conclusion

Project managers require a robust system that provides information in timely and comprehensive manner so that they can make decisions quickly and easily [18]. Progress monitoring system should be effective and efficient, accurately converting as-built progress data from construction works into information [123]. Real-time reporting may become very useful in ensuring adherence to project's scope, time and budget-related constraints. Adopting automated progress monitoring technologies will assist project stakeholders by facilitating more accurate schedule forensics, delay analysis, and corrective action planning [8]. Real-time data acquisition is wholly beneficial when collected without human interference.

Studies have contributed to the retrieval of as-built information from site photos and as-built BIM models. However, the content and context of individual photos were not covered in these studies. The image location was manually acquired using fixed cameras installed at pre-determined points throughout the site subject to occlusions and unable to cover all site elements. Photos must be aligned manually and compared to 3D/4D models, involving manual interventions to determine viewpoints, camera settings and selecting a set of overlapping features. Furthermore, no attempt was made to provide information to clients in near real-time, which represents a missed opportunity, and this research aims to cover these gaps. This study tends to overcome these limitations by employing a mobile robot-based camera which takes element-wise images and processes them to attain activity-wise progress information for each element in an automated manner.

CHAPTER 3

ELEMENT-WISE AUTOMATED ACTIVITY AND POINT OF INTEREST (POI) EXTRACTION (EAPE)

A context-aware algorithm requires tagging of the image with building element information for identification of progress. In this chapter, the formulation of a methodology to extract data points, from BIM, for robot navigation and image acquisition purposes is discussed followed by verification on As-planned BIM created for an actual construction site. A process is also suggested to create an activity list for BIM elements which will reduce the amount of time and effort required for the creation of 4D BIM. This chapter discusses the algorithm developed for extraction of the so-called Points of Interest (POI) and Activities from BIM elements using a python script followed by verification on multiple BIMs obtained from two different construction sites.

3.1. Introduction

A large amount of data is exchanged during the construction phase between project stakeholders [93]. However, this data is hard to retrieve and reuse. Thousands of photos are taken on site during the construction phase as evidence of work performed on a mid-size construction project with the number expanding vastly with the project scale. These images contain information that may be valuable to construction and contract managers during and after completion of the project for interim payments and dispute resolution. Utilization of data stored in images can lead to 5-6% saving in overall project costs through early detection of the problem followed by prompt corrective action [116]. However, we can only achieve these benefits, if images are acquired and stored systematically making their instant retrieval from databases a possibility. A framework is required to tag site pictures with corresponding BIM element IDs and activity IDs at the time of acquisition. Image tagging will assist in the instant retrieval of images when queried by the element ID or activity ID, bringing great value to project stakeholders for scheduling, tracking, and decision-making purposes.

Automated daily progress measurement is based on the schedule and the spatial information that we can extract from the BIM, for site activities. However, a considerable amount of detailed work is necessary for effective utilization of the 4D model. Activities are of significance in any monitoring process, and it is essential that the relationship between elements and their corresponding tasks is consistent. The schedule should be consistent in the level of detail hence either a single task should not encompass multiple 3D elements in one to one relation between activity and element or a one to many relationships between element and activities should be present across the 4D model. Too little detail may result in the critical component being overlooked thereby providing information that may not be enough to determine project performance. 4D schedule creation from BIM elements while maintaining consistency is a cumbersome process which is time-consuming and defeats the purpose of the automation by the inclusion of one monotonous step. It was, therefore, necessary to develop a schedule with the consistent element-activity relationship without making it a costly and arduous task, thereby, maintaining the cost efficiency of a fully automated progress monitoring system.

3.2. Methodology of EAPE

A 4D model provides additional consolidated information by combining both spatial and temporal aspects of a construction project and graphically representing the relationship between space and time [124]. It offers an opportunity to derive planned state of an element and compare it with the current state of that element to ascertain delays in progress. This comparison can be made at a macro (project) level or micro (element) level by the requirement of project management.

BIM is an as-planned 3D geometric model of a structure which combines with the as-planned schedule creating a 4D model [125]. 4D Building Information Model (4D BIM) forms the basis for extraction of data and its conversion into information using both spatial and temporal aspects of a project plan [121]. BIM being a database of object-oriented geometric and semantic information, can be queried using a Python script to extract desired data related to elements and their semantics. 4D BIM consists of parametric building elements which are classified into categories of families and types by Revit as shown in Figure 14.

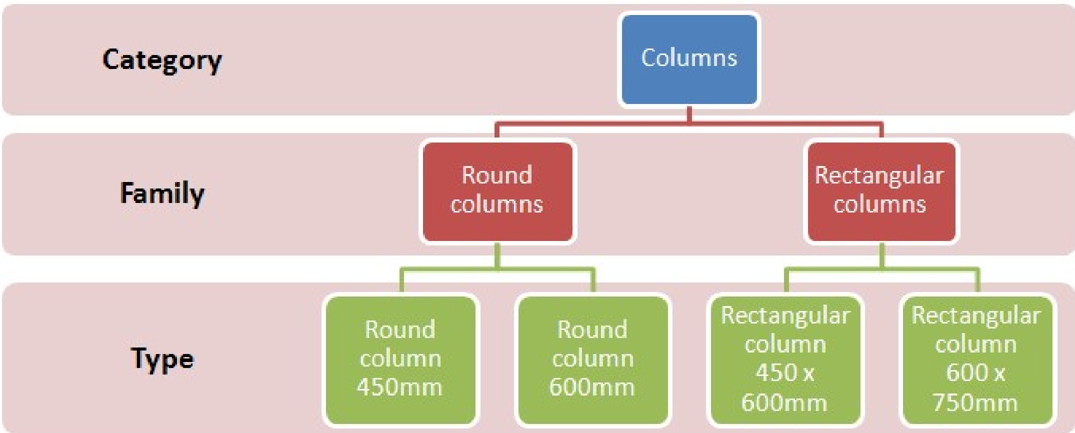


Figure 14 Revit Element Classification System [126].

In Figure 14; a Category is a group of elements in a model or a document which includes walls, beams, columns, doors, etc. Revit category IDs for example elements are shown in Table 5. *Element* or Instance is the building block of BIM which is the actual item placed in a project and has specific location along with a unique ID and we can identify them separately from every other element in BIM. The unique ID is an integer and Revit doesn't repeat ID throughout the model, but the software may be replicate IDs across different models. The unique ID is used to identify and differentiate an element from another.

Table 5 Example Categories with their Revit IDs.

Category	Category ID
Columns	-2000100
Walls	-2000011
Doors	-2000023
Floors	-2000032

A Building Information Model (BIM) being a rich source of information, provides a very suitable basis for automated progress monitoring [127]. BIM provides a digital representation of 3D elements of all structural components along with semantic descriptions [125]. BIM contains unique element IDs and category ID that can be used to identify elements to extract information about different components of BIM. Additional material specific details and material color signatures can be added as parameters to each element as has been done during this research. *EAPE* is an acronym for Element-wise Activity and Point of Interest Extraction which was developed to attain the activity list and navigation coordinates for image acquisition. Figure 15 depicts EAPE methodology that includes BIM as the source of element information to create a list of activities which is then fed to a planning software to attain a schedule. Once we create the schedule, the daily navigation list, referred here as daily monitoring list, is extracted by the remote client using a pull request.

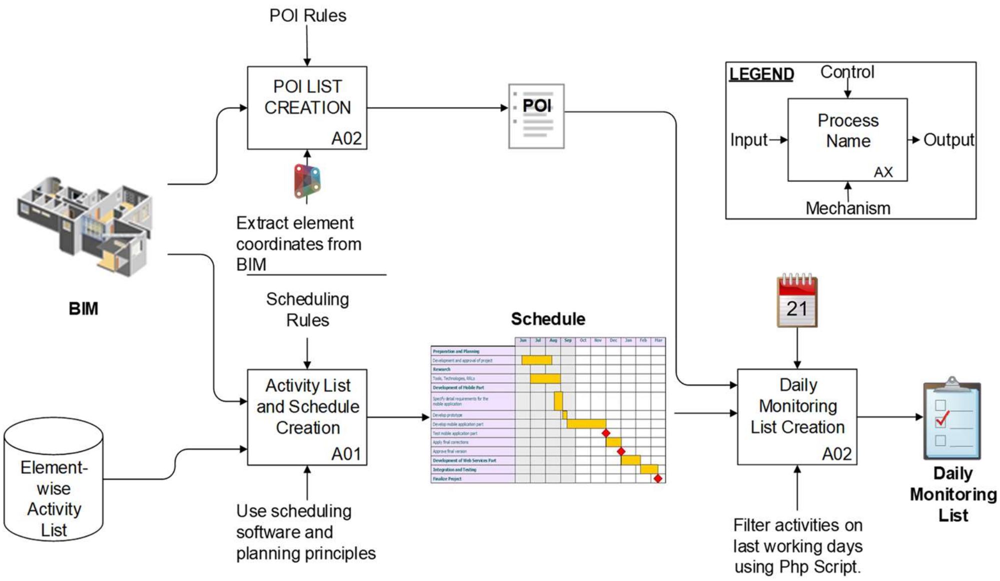


Figure 15 Process flow for EAPE.

The material related information embedded in elements along with geometric details can be extracted using a Python script, which includes elements ID, coordinates, level, and category (see Figure 16). The element coordinates fed into another python script to attain image navigation points which are at a distance of one to two meters from the element. The activity IDs and activity names are assigned to elements and fed into a planning software to create a schedule following principles of construction planning. The schedule and POI information is used for robot navigation which will be discussed in Chapter 5; BIM based Data Acquisition Platform.

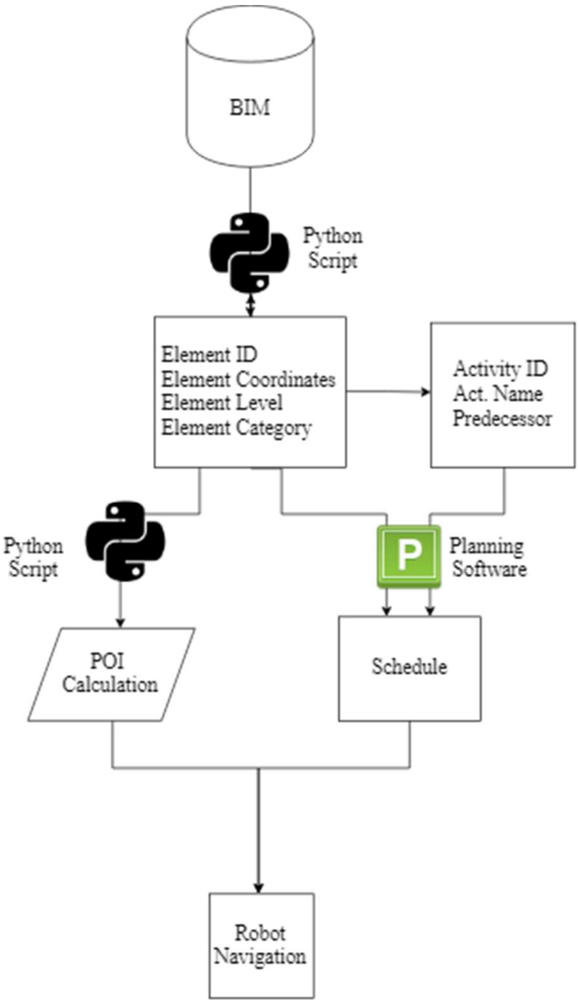


Figure 16 Process Flow for Activity List and POI Creation.

3.3. BIM-based POI List Creation

The Element ID will refer to the image acquisition point, where the imaging sensor will be placed to picture the element. It will be named as *Point of Interest (POI)* in the scope of this research, defining the point in the building coordinate system where imaging will take place. An imaging sensor will navigate to POIs and assess progress at the element adjacent to that POI. Figure 17 shows example POIs for the wall, door, and window elements where the robot will stop and take images which will be subsequently processed using computer vision algorithms to determine the progress. The high level process flow for extraction of POI is shown in Figure 18.

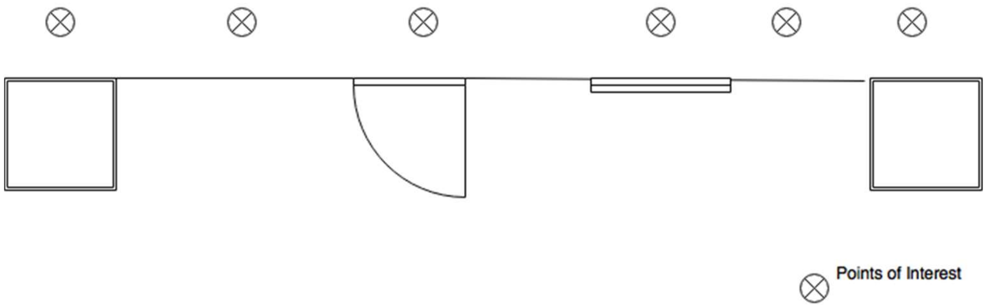


Figure 17 Sample POIs for varying categories.

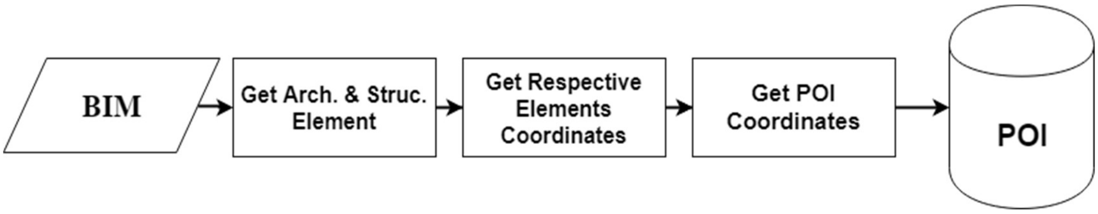


Figure 18 POI extraction process flow.

POIs are in front of every separate element (see Figure 17) to determine if the activity related to that element has been completed or not. To ensure comprehensive monitoring, POIs are extracted using a python script according to process flow adhering to the following rules:

a. Wall elements should be divided into portions based on work packages.
b. Discontinuity and openings should have a picture.
c. Every different task on the element should be photographed (e.g., Brickwork, Plaster, Paint for masonry walls).
d. Every element related to every task should be monitored.

Autodesk Dynamo tool was used to extract POI for each architectural and structural element using visual programming interface and Python scripts. Autodesk Dynamo is a visual programming tool that provides access to Revit API (Application Programming Interface) by manipulating graphic elements called nodes as shown in Figure 19. Each node performs a specific task and has input as well as output. The output from one node is connected to the next as an input using wires. Dynamo is a good tool for repetitive tasks and extraction of data from building elements. Once dynamo code is created it can be run on different models to extract the desired information.

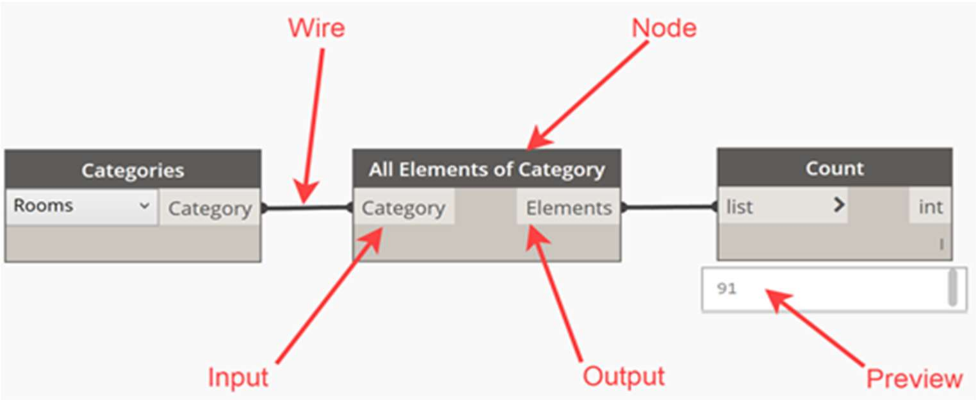


Figure 19 Dynamo visual programming interface [128].

Steps involved in the extraction of POI from BIM for each level separately, is shown in Figure 20. POIs are two-dimensional coordinates with the level number instead of the third dimension for ease of reference and extraction. Floor level which is a constant for all POI across the same level is later concatenated, using process shown in Figure 21, into an exhaustive list containing all POI in the structure sorted according to their respective levels. POI calculation starts with the extraction of all elements present within a structure, followed by extraction of their spatial coordinates within the building frame of reference. The image acquisition points or the POI is located two meters from the element, which is used as the maximum possible distance of image acquisition from building elements in this research. Any distance greater than two meters cannot be used for image acquisitions since alleyways in the structure don't have a width greater than three meters. The extracted POIs are stored in a database along with the relevant element description and tasks that involve the respective element. To validate correct placement of the POIs, wall elements in the model and respective POIs for those wall elements are extracted and plotted on MATLAB® as shown in Figure 22.

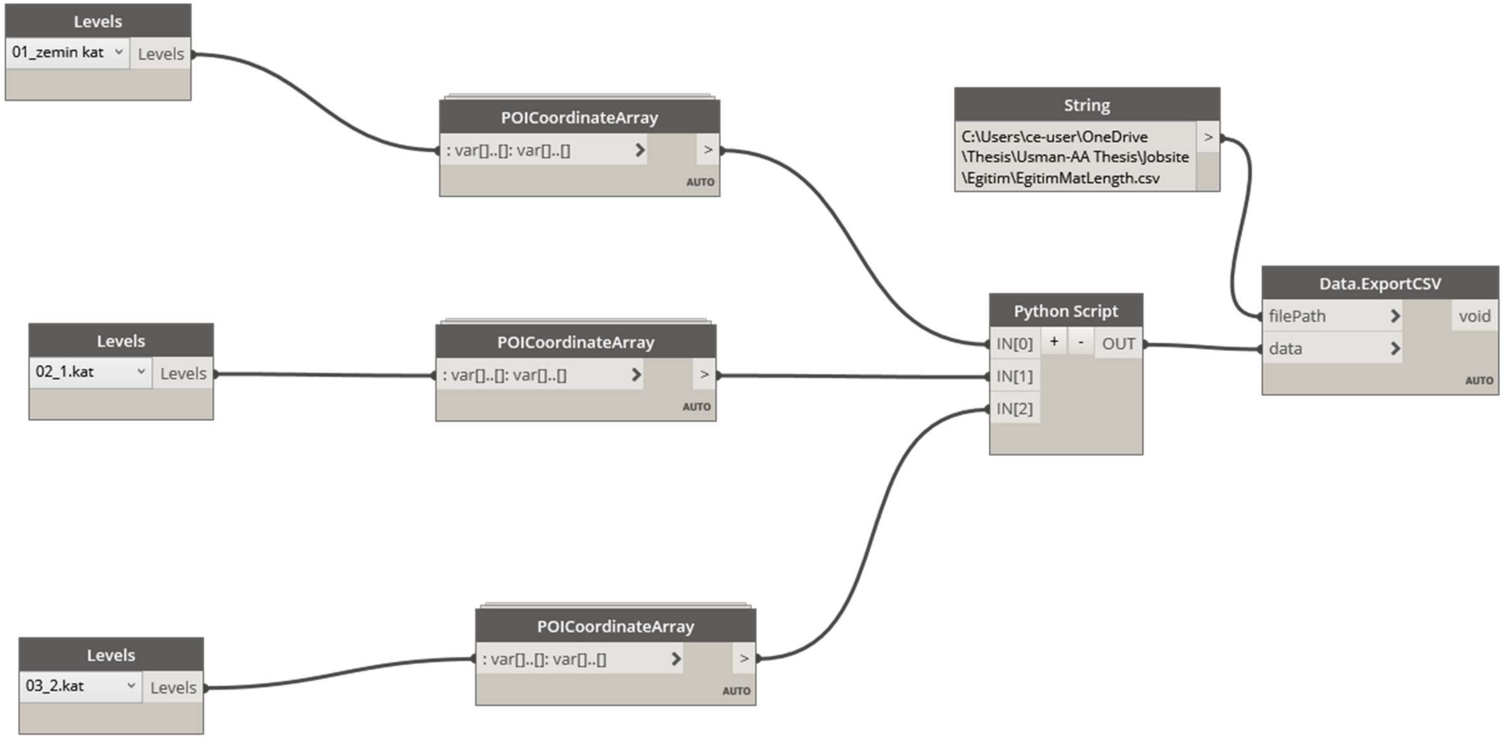


Figure 20 Dynamo code for level-wise POI extraction from BIM.

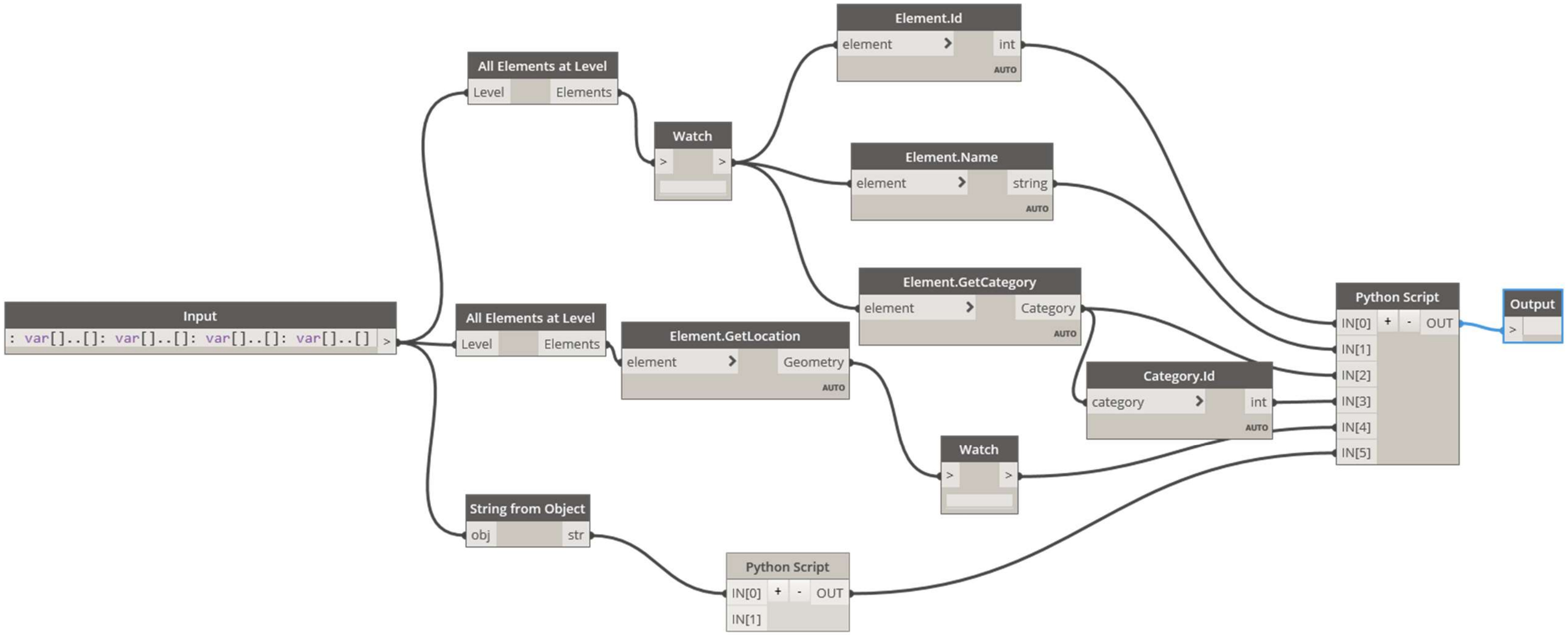


Figure 21 Function for POI extraction from each level.

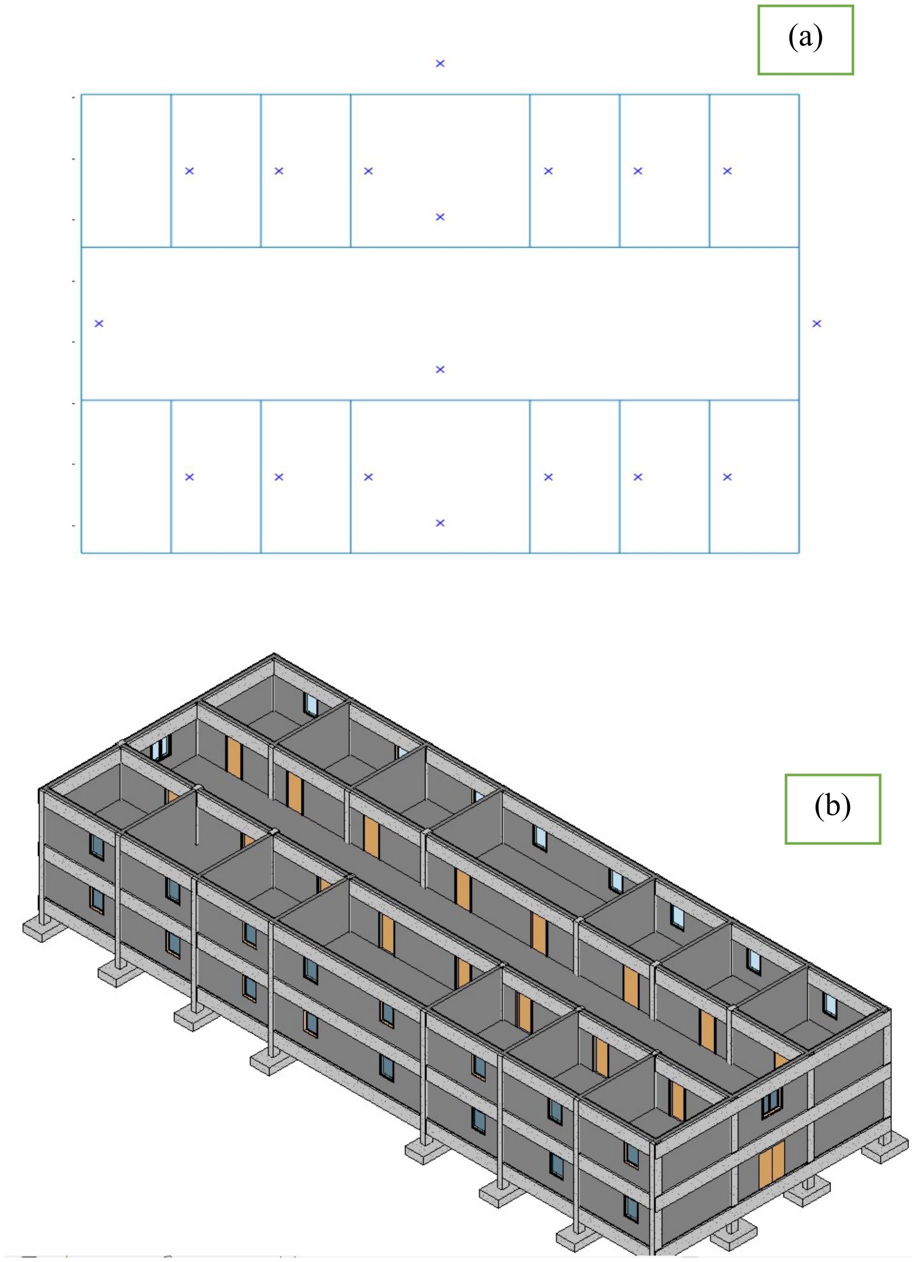


Figure 22 Validation of (a) extracted POIs for wall elements and (b) 3D model used for the test.

As seen in Figure 22, all POIs are correctly placed adjacent to the walls which are an expected result of the algorithm. Table 6 lists the number of POIs extracted for walls, doors, and windows from the BIM of the example building floor. Table 7 shows a partially extracted POI List containing category name, category ID, element name and two-dimensional spatial coordinates along the level. Algorithm did not miss any elements during POI extraction and neither did it extract false POI. However, currently the algorithm can only create one POI for one building element and does not create multiple POIs for a big component (e.g., a long wall) in case multiple monitoring locations are necessary. Similarly, the algorithm only finds the coordinates on the north face and east face of the elements, hence some POIs are found to be out of the building for indoor elements. These will be fixed in the POI generation algorithm in the future.

Table 6 POI Detected from BIM

Element	POI Detected
Walls	18
Doors	16
Windows	16

Table 7 Partial sample output for POI extraction.

Lvl	ID	Cat ID	Category	Name	X	Y
L1	328468	-2000100	Columns	130x30 Concrete Column	-5955.39	-417.497
L1	328561	-2000100	Columns	130x30 Concrete Column	-5455.39	-417.497
L1	328801	-2000100	Columns	130x30 Concrete Column	-4455.39	-417.497
L1	328864	-2000100	Columns	130x30 Concrete Column	-3955.39	-417.497
L3	438442	-2000023	Doors	Single Door 75x220	-5376.95	-883.278
L3	439283	-2000023	Doors	Single Door 75x220	-456.948	15.22195
L3	465165	-2000023	Doors	Single Door 300x110	-600.394	-413.029
L1	337278	-2000011	Walls	20 mm Masonry	-2205.39	1108.186
L1	337444	-2000011	Walls	20 mm Masonry	-2705.39	1108.186

3.4. BIM-based Activity List and Schedule Creation

An Activity ID format is established for the sake of uniformity and to determine the planned state (*p(X)*) of an element. The activity ID consists of 4 parts as shown in Table 8.

Table 8 Activity ID Breakdown

L1	330	FW	4322
Level	Category Identifier	Activity Code	Element Identifier

In Table 8 Category Identifier comes from last three digits of Revit Category ID (see Table 8) and Element Identifiers are the last four digits of unique element IDs extracted from Revit. The Custom Activity Codes List (CACL) (e.g., FW, CN, RF) are used to create activity IDs. We based the method on the principle that elements from the same category will go through the same activities during the execution of the project as shown in Figure 23. In the course of this research only reinforced concrete and masonry wall building elements within column and wall categories are considered.

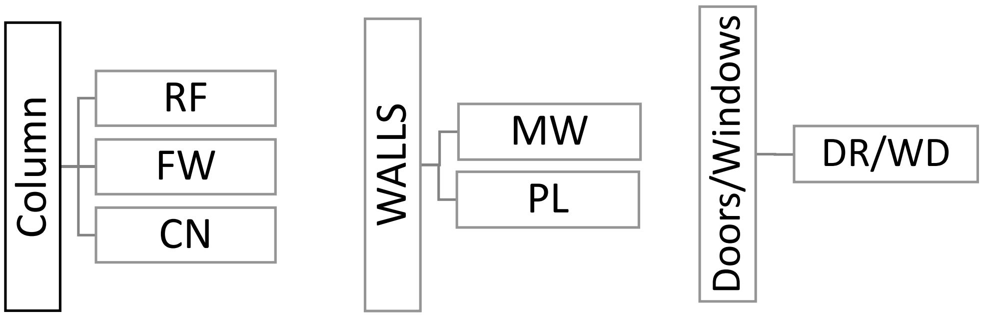


Figure 23 Category and Related Activity List

A Python script (see Figure 20) was written and executed on Autodesk Dynamo code to extract element-wise spatial and semantic information for each level (see Figure 21) separately. The information is consolidated in a CSV file, similar to the sample list shown in Table 9. The activity list is augmented with predecessor information and fed to Microsoft Project to create a work schedule. The code initially extracts elements' information, their coordinates, their category ID and unique BIM IDs for elements at each level separately and concatenates them together into one array. Extracting level-wise information helps in eliminating the need to extract z coordinate and perform processing in three-dimensional domains. Instead, all processing is done for each floor separately considering a two-dimensional plane.

Table 9 Sample extracted activity list for BIM elements.

Lvl	ID	Code	Act ID	Activity Description
L1	328468	FW	L1-100FW8468	Installation of Formwork for 130x30 Concrete Column
L1	328561	FW	L1-100FW8561	Installation of Formwork for 130x30 Concrete Column
L1	328801	FW	L1-100FW8801	Installation of Formwork for 130x30 Concrete Column
L1	349212	DR	L1-023DR9212	Installation of Single Door 300x110
L1	349247	DR	L1-023DR9247	Installation of Single Door 300x110
L1	387581	MW	L1-011MW7581	Masonry work for 20 mm Masonry
L1	389846	MW	L1-011MW9846	Masonry work for 20 mm Masonry
L1	389927	MW	L1-011MW9927	Masonry work for 20 mm Masonry

The activity list is fed into a planning software like Primavera or MS Project and inter element activity relationships are defined according to principles of construction planning to obtain a work schedule.

3.5. Daily POI Extraction

Daily POI extraction is the only recurring process in this methodology, where image acquisition platform will extract list of activities that were scheduled to be completed on the last working day. Figure 24 shows the process for extraction of the so-called Daily Monitoring List (see Table 10) containing the POI, Task ID, activity description, and Cartesian coordinates of the POI where image acquisition will take place.

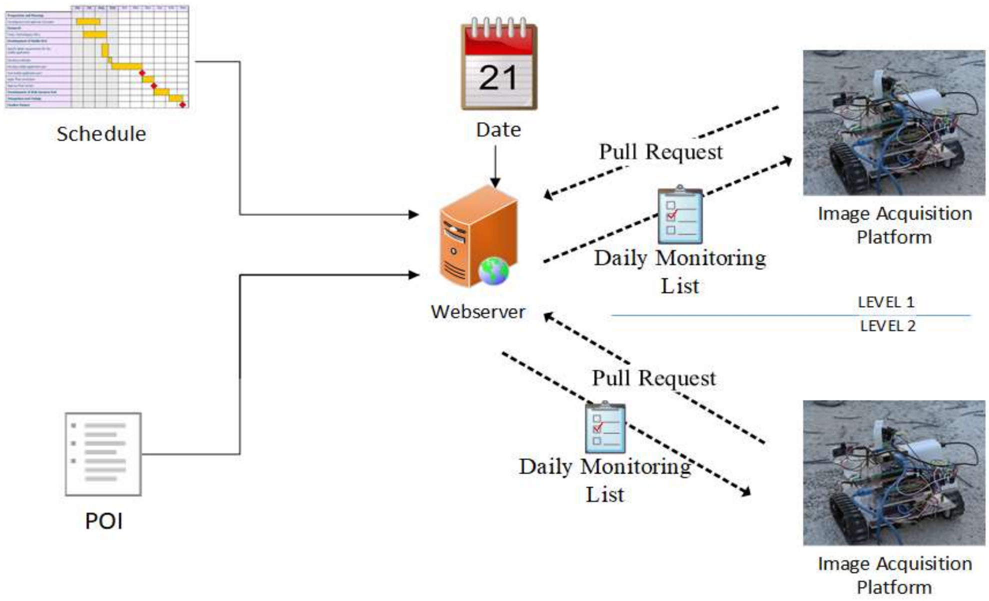


Figure 24 Daily POI extraction by image acquisition platform using Pull request.

The method, shown in Figure 24, extracts Daily POI list from web server by using PHP Pull request before the beginning of daily image acquisition by the imaging device that we refer as the client. The client sends the pull request to server IP already stored in the client. The web server extracts daily activities list by filtering planned finish date corresponding to the last working day, which contains the BIM element ID that is used to look up element POI coordinates from POI list. The daily POI list containing the activity information and POI coordinates is acquired by the client for navigation to the respective element, image acquisition of the element, and archival of the stored image. Table 10 is a sample daily POI list extracted by robot based on activities planned to be completed on the last working day. Where POIs are unique element IDs from BIM, task ID contains the level and activity information that will be useful in activity extraction, and POI coordinates are used for robot navigation purpose.

Table 10 Sample extracted daily POI list.

POI	"Task ID"	Activity	X	Y
328468	L1-100FW8468	Installation of Formwork for 130x30 Concrete	-5955.39	-417.497
328561	L1-100FW8561	Installation of Formwork for 130x30 Concrete	-5455.39	-417.497
328801	L1-100FW8801	Installation of Formwork for 130x30 Concrete	-4455.39	-417.497
328864	L1-100FW8864	Installation of Formwork for 130x30 Concrete	-3955.39	-417.497
328939	L1-100FW8939	Installation of Formwork for 130x30 Concrete	-3455.39	-417.497
329014	L1-100FW9014	Installation of Formwork for 130x30 Concrete	-2955.39	-417.497
438442	L3-023DR8442	Installation of Single Door 75x220	-5376.95	-883.278
439283	L3-023DR9283	Installation of Single Door 75x220	-456.948	15.22195
465165	L3-023DR5165	Installation of Single Door 300x110	-600.394	-413.029
337278	L1-011MW7278	Masonry work for 20 mm Masonry	-2205.39	1108.186
337444	L1-011MW7444	Masonry work for 20 mm Masonry	-2705.39	1108.186

3.6. Validation on BIM of two different construction projects

EAPE was conducted on two under construction structures in Middle East Technical University (METU), Ankara, for whom 3D models were obtained or created. One of them was Educational Science Department Building (ESDB) which is a multi-story framed concrete structure in L-shaped layout consisting of two separate sections, a steel bridge and a top overhang floor as shown in Figure 25 (a). Revit Model was created by utilizing the information obtained through interviews with site management and from CAD drawings. The second structure for the case study was a central classroom hall building (CHB) which is a more complicated structure since it contains classrooms as well as large auditoriums with overhangs. The structure has 2 x 250 people and 2 x 150 people auditoriums along with 19 classrooms of different sizes. The structure has elements belonging to column, wall and door categories. The architect provides the BIM for CHB building.

Figure 25 (a) Rendering of Educational Science Department Building and (b) Revit 3D Model for Classroom Hall Building (Courtesy of METU).

Low level schedule was not provided by the contractor of either projects, and therefore, a schedule was created using EAPE with one to one relationship between BIM element and activity in an efficient manner without investing excessive man-hours in manually connecting each element with an activity. The prepared schedule was discussed with site management team and agreed with the timeline that the contractor was pursuing. Table 11 shows POIs extracted from ESDB and CHB BIM enlisting elements in CACL. CHB is an unsymmetrical structure with multiple auditoriums having walls modeled as columns in level 1, therefore the higher number of columns is observed in ground floor. CHB didn't have any windows modeled in BIM and storefronts are modeled as walls in Autodesk Revit, which is the reason behind zero windows. The algorithm has to be improved further to cater for multiple levels within one floor and also to ensure that no POI overlaps with a building element.

Table 11 POI Extracted from ESDB and CHB BIM.

	Category/Floor	L1	L2	L3	Total
ESDB	**Columns**	52	48	51	151
	Doors	32	32	36	100
	Walls	33	24	34	91
	Windows	29	43	27	99
CHB	**Columns**	273	82	120	475
	Doors	14	19	18	51
	Walls	59	64	104	227
	Windows	0	0	0	0

3.7. Conclusion

EAPE is a preparatory algorithm to attain readiness for automated progress monitoring through creation of calculation of navigation points and creation of activity list that add time dimension to BIM. 4D BIM creation is a manual and time consuming process that could render an automated progress monitoring less attractive due to the involvement of a laborious step. EAPE makes it easier to create a schedule by extraction of activity list which can be converted into a schedule by providing dependencies. The methodology is more applicable to models with similar repetitive elements belonging to similar families of a category. The activity list for concrete columns will remain the same irrespective of the size of the column but would change if the material of columns changes from concrete to steel. Schedule still has to be created by given dependencies, but scheduling is performed on all sites, whether BIM is present or not.

Image acquisition points provide coordinates for placement of camera to attain site images and are referred as Point of Interest (POI). The robot uses these locations as navigation points for calculation of navigation vectors for the robot to traverse and acquire images. The client extracts daily-POIs (d-POIs) which correspond to the activities performed on the last working day, for the robot to navigate. The robot transmits images to the server where progress is determined using computer vision algorithms. The imaging points can be either navigable or non-navigable, and further study should be done to improve data acquisition points to ensure all points remain navigable by autonomous devices.

This method is, therefore, a precursor to schedule based element recognition and progress measurement discussed in the following chapters. POI provides geographical context and element tag to the images which narrow down the list of expected materials in a particular image. This information can be used to improve the accuracy of element state detection algorithm as discussed in Chapter 5. The next chapter explains BIM-based data Acquisition Platform (BAAP) which a robot that uses POIs obtained through EAPE to navigate and acquire images.

CHAPTER 4

BIM BASED DATA ACQUISITION PLATFORM

A fully automated progress monitoring system requires a human-free image acquisition mechanism to ensure complete automation. A robotic platform that navigates around the structure and acquires images of elements for progress monitoring purposes is discussed in this chapter including a review of robots in the construction industry and details of the developed robot. The images taken by the robot on a construction site were reviewed and discussed in the final part of this chapter.

4.1. The need for Robots in Construction

It is estimated that more than fifty percent of a country's gross investment is in built-environment signifying the importance of construction to a country's economy. Therefore, the construction industry needs efficiency that only is achieved by using sophisticated technology. In highly developed nations there is shortage of human capital, and young generations have lost interest in construction [28], the lack of human capital can be supplemented by nonlinear advances in machine technology and productivity. In the manufacturing sector, the concepts of Industry 4.0 [129] and Cognitive factory 4.0 [130] have emerged. Advances autonomous, and distributed but networked robots can collaborate to produce products in a sustained manner promising higher productivity and increased safety.

Successfully integrating site machinery and processes using real-time site meteorology will enable data utilization for process automation and concurrent project planning [131]. Robots are very good at performing monotonous tasks, and their productivity does not suffer from tiredness and fatigue. Robots can traverse dangerous places, move under scaffoldings and form works without hindering progress. They can also go to confined spaces, underwater, and into sewage pits without any risk. Site inspection is a non-value adding task that requires the highly qualified worker to traverse site which is risky and costly. BIM provides semantic information combined with geometric data that can enable robot navigation and operation utilizing advancement in machine learning techniques. Automated real-time acquisition can be achieved using fixed sensors, cameras and scanners which need relocation and expensive infrastructure as well as human resources. The construction site is also scarce of resources and committing workers to non-value adding activities is unacceptable to site management especially when work is being accelerated. A mobile platform doesn't suffer from occlusions or require extensive infrastructure to operate, and with autonomous navigation cost, it is effective to operate. A robotic platform can autonomously provide human-error free real-time data freeing up important human resources for intellectual work.

Bock[132] has suggested that construction has reached its peak productivity with current technology and has mentioned that construction has to transform from conventional to automated methods to attain higher efficiency levels. Figure 26 shows Foster S-curve [133] applied to technology adoption in construction mentioning technologies leading the construction automation transformation. Overtime robotic technology is progressing, becoming ubiquitous, and becoming part of daily human life in service, manufacturing, and retail industry.

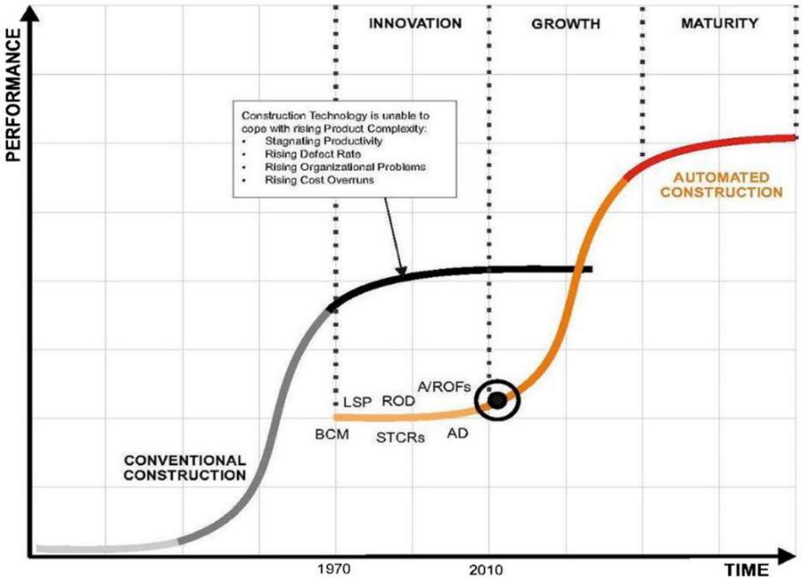


Figure 26 S-curve applied to construction transformation from conventional to automation [132] where building component manufacturing (BCM), large-scale refabrication (LRP), single task construction robots (STCR), robot-oriented design (ROD), automated robotic on-site factories (A/ROF), and automated deconstruction (AD).

4.2. Review of Robots in Construction

Robot-oriented design, robotic industrialization, construction robots, site automation, and ambient robots are five aspects of future construction automation solution involving robotics [132]. Robots and humans can work together in two types of interactions, one is teleoperation where robots are achieving a certain task for humans by obeying their commands. The second type of interaction has a robot working in an autonomous manner where human will only interfere if anything goes wrong [115]. An autonomous robot with very limited to no human interaction can attain maximum saving in term of cost and man-hours.

Today, large numbers of Architecture/Engineering/Construction and Facility Management (AEC/ FM) firms and relevant service companies use robotic platforms to visually monitor construction and operation of buildings, bridges and other types of civil infrastructure systems. Space agencies are seeking to build infrastructures without any human interference; and construction industry is looking toward robots [134] to provide improved efficiency, quality, and safety as well as the flexibility to implement improved architectural designs. Robots are more suited for construction operations because construction is inherently dangerous and repetitive work. Robotics offers to eliminate stagnancy in productivity levels of the construction industry due to their ability to reduce costs, shorten lead-times and improved worker safety [135].

Robot has started making inroads into construction sector with robot developed to perform masonry works (Figure 27(a)), rebar works (Figure 27 (b)), earth moving operations (Figure 28(b)), load carrying (Figure 28(a)), piling, frame erection, wall assembly, floor finishing works, painting, fire retardant spray, finishing works and supervision (see Figure 29). Spot is a robot created by Boston Dynamics® that is a quadruped and can roam around site efficiently while acquiring images. Robotic arms are the most prevalent among construction robots. Robotic arms (Figure 27 (a)-(b)) are used in the manufacturing industry for decades as stationary platforms, however, the mobile version of robotic arms are developed for better suitability in the construction industry. Little detail is available with regard to techniques used by the robot for progress monitoring, however, it has been deployed on a construction site in Japan [136]. Robotic arms perform various operations like rebar tying, masonry work and 3D printing of structures. These robots can contribute to safety thus improving the condition of construction site notorious for high accident and fatality rate. Robotic arms can be programmed to create a complex form that was not possible before the advent of this technology in the construction sector.

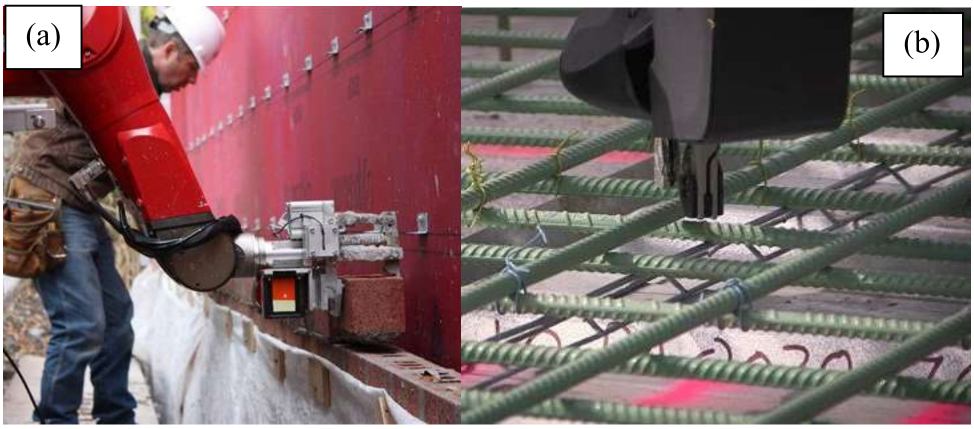


Figure 27 (a) SAM100 world's first commercially available robot [137], (b) Tybot robot for rebar tying [138].

Figure 28 (a) Effibot will follow workers carrying heavy items [139], (b) Built robotics dozer to carry out works automatically [140].

Figure 29 Boston dynamics robot for monitoring [136].

4.3. Method for BIM-based data acquisition

Construction image acquisition is an essential aspect for image processing-based progress monitoring techniques. Image processing results vary based on the quality of image attained from the construction site. Therefore, careful camera placement and image data management would determine the success of image processing algorithms. A fixed camera cannot be a viable solution for construction site data acquisition since site teams have to move the camera from time to time to counteract occlusions. The solution to this issue is a camera based on a mobile platform, which can also be referred as a client, traversing the site and acquiring images.

In this study, a thin client model is used, and the majority of processing is performed by the server to avoid extraordinary processing at the server, which would, in turn, preserve its battery and avoid latency issues. Thin clients are especially useful when user mobility is involved, and the total cost of ownership is kept to be minimum [141]. Multiple clients can be added to the system if their price remains low. Majority of processing at a central location provides greater flexibility of addition of new modules or integration with other imaging sources like security cameras, drones and handheld or helmet-based cameras which currently is not in the scope of this research but can be added later in future studies.

The BIM-based data Acquisition Platform (BAAP) is developed to attain images at specific predefined element at a particular time and transmit it to server for further processing (as seen in Figure 30). BAAP can be a robot, drone or human mounted camera (see Figure 31). A terrestrial robot mounted with the camera is the realization of BAAP which is utilized instead of a drone proposed by previous researchers for site image acquisition [142]. Terrestrial robots are preferred as they are not prone to crashing, hence safer and more efficient for indoor use.

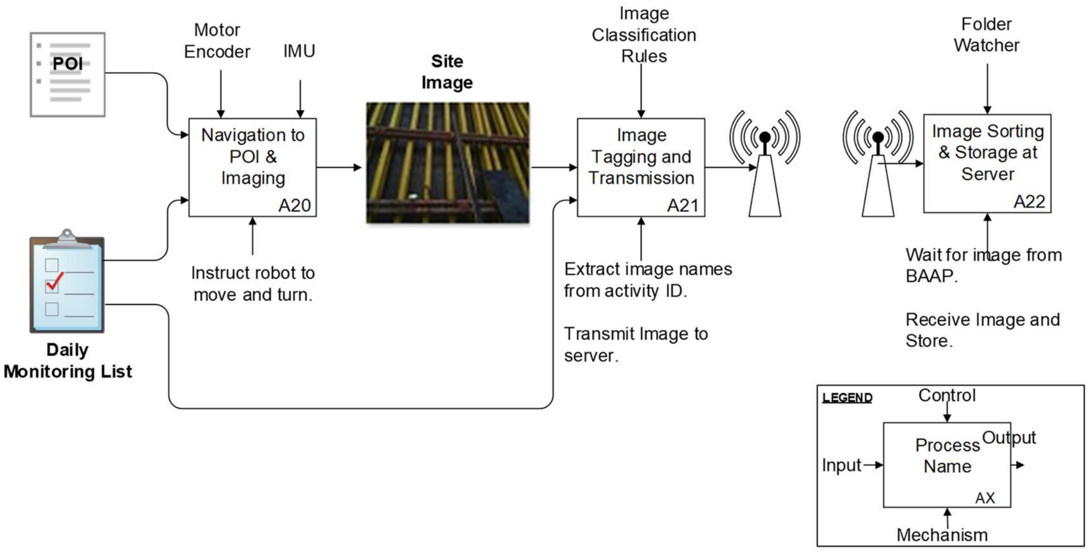


Figure 30 Process flow within BAAP framework.

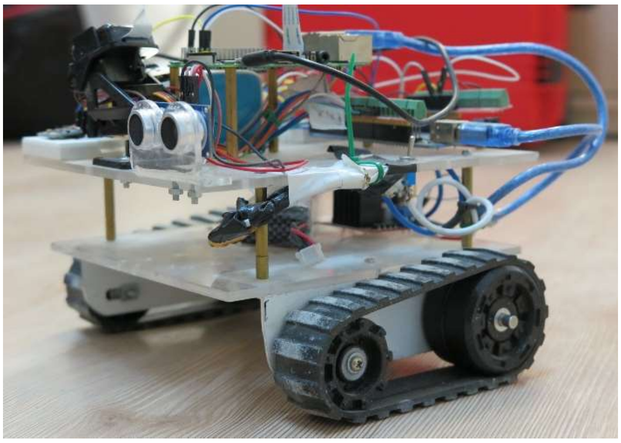
Figure 31 BAAP in different forms (a) Terrestrial robot (b) Drone (c) Helmet mounted camera.

4.4. Navigation to POI and Imaging

The robot is a prime component of the CAPMS. The main parts of the robot are shown in Table 12 and the robot fabricated for the scope of this research is shown in Figure 32. The robot has an onboard Raspberry Pi 3 with 1.2 GHz processor and 1 GB RAM, to perform client operations and process images. Client queries the database and gets d-POIs according to the process mentioned in the previous sections and navigates to them automatically.

Table 12 Robot components and characteristics.

Component	Description
Processor	Raspberry Pi 3B+ (1.4GHz 64-bit quad-core processor, dual-band wireless LAN)
Drive Train	120 RPM, 6 volt encoder motors
Camera	8 Megapixel with pan and tilt motor
Gyroscope	MPU6050 MEMS accelerometer, and MEMS gyro
Power Supply	12V Li-ion for the drivetrain, 5v Li-ion for processor



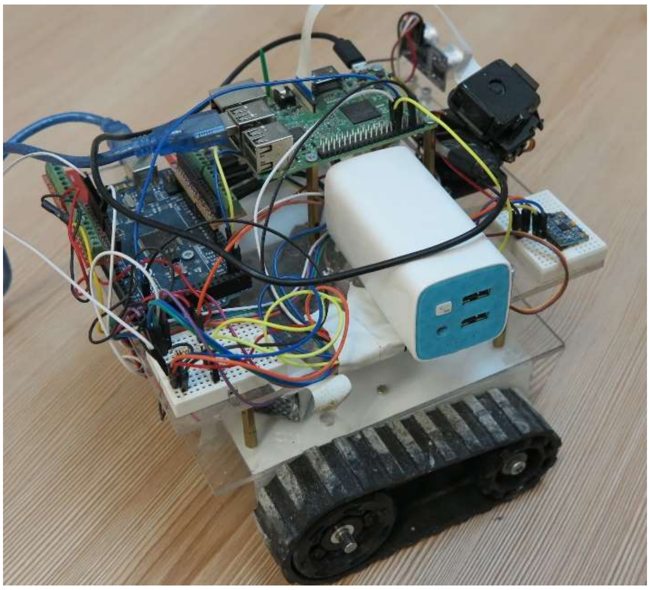


Figure 32 Robot Views from Different Angles.

4.4.1. Chassis and Drive Train

The robot consists of a tracked chassis for greater traction and correct wheel count measurement from optical motor encoders. 120 RPM low power consumption encoder motors are controlled by the microcontroller through H-bridge circuitry. The robot performs differential turns, measured by the onboard gyroscope. Gyroscope measures angular velocity which is integrated over time (d_t) to obtain angular displacement. The microcontroller continuously measures angular displacement using rotary encoders installed on motor shafts, and once the robot has turned to the desired angle, the microcontroller stops the turn and instructs the robot to move in the direction of the turn. Magnetometers are also used for turn measurement. However, the magnetic sensor may not work efficiently due to the presence of steel and other ferromagnetic materials on site.

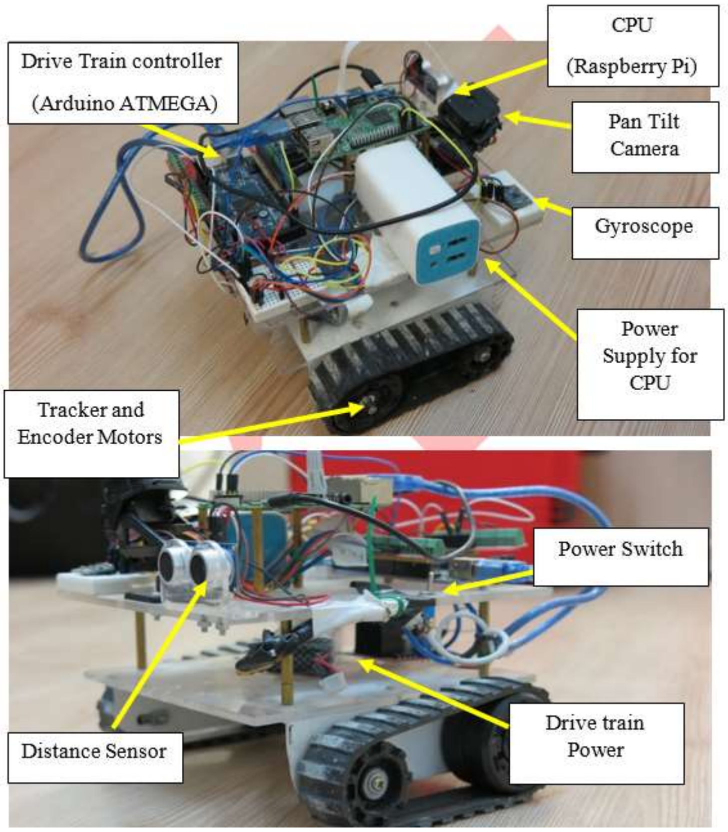


Figure 33 Robot Chassis and Components.

The client instructs the onboard microprocessor to move towards the POI which in turn moves the motors and counts revolutions using an interrupt-based mechanism until distance till POI is covered. The client also commands the microcontroller to perform turns, take images, and then process those images.

4.4.2. Imaging Sensor Distance and Tilt

Materials reflect specific wavelengths of light and absorb the rest. The camera sensors capture light wave in visible spectrum reflected from the object. A digital camera contains a charge coupled device (CCD) comprising of photosensitive diodes which produce an electric charge on pixels present on it whenever light is incident upon them. The CCD is divided into many light-sensitive areas known as pixels. The higher the luminosity of light, higher is the amount of charge accumulated on the pixel. The charge is transported to an array and digitized to build up an image. Visible spectrum lies between 400-700 nm. The wavelength of Red, Green and Blue colors is standardized at 700 nm, 546.1 nm, and 435.8 nm respectively. The wavelength intensities are distributed between the spectral band by Grassman's law based on a set of rules to define Red, Blue, and Green for a full visible spectrum [143]. The CCD sensor itself cannot differentiate between colors; therefore, color filters are utilized to determine the amount of incident color [144].

Robot reaches POI location marked in Revit model and an on board ultrasonic sensor ensures correct distance from Elements of Interest (EOI) using onboard ultrasonic sensor which has an accuracy of +/- 3mm and can measure up to 250cm. Image acquired on the sensor depends upon light reflected from EOI incident on the camera sensor, the energy carried by which is a function of illumination, distance of EOI from sensor and angle of tilt of sensor with respect to EOI. According to Kim et al. [54], a camera for image acquisition from the site should be equipped with pan, tilt, zoom (PTZ) movement function and should efficiently transfer data over wired and wireless internet connections. The Pan and Tilt function coupled together allows image acquisition at different tilts in a customized manner. The robot in this study is mounted with a servo motor couple controlling pan and tilt mechanism determining the tilt of camera with respect to ground surface and an ultrasonic measurement sensor to calculate the distance from EOI. Figure 34 shows schematic of camera orientation where angle *a* is tilt and its orientation along with the distance from EOI, which governs the percentage representative pixels of EOI and noise in the image, making SCAER algorithm unable to detect EOI. Distance affects the scene and reduces the percentage of pixels representing the EOI in the image and adds additional elements which act as noise. Camera tilt and distance values are shown in Table 13.

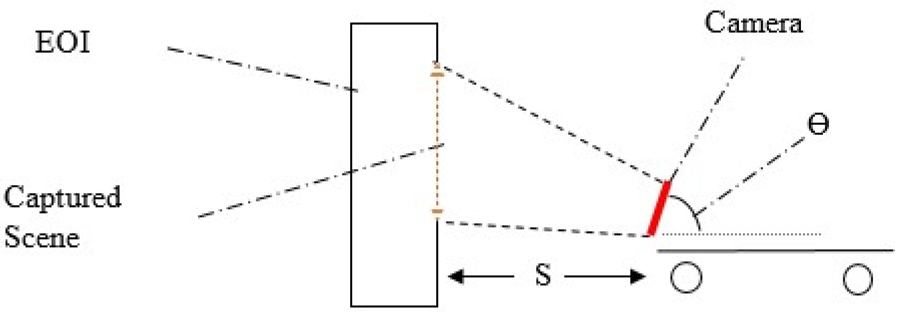


Figure 34 Robot camera orientation and scene representation.

Table 13 Camera tilt and EOI distance for imaging.

Parameter (Symbol)	Values
Distance from EOI (s)	50 cm, 100 cm, 200 cm
Camera tilt (ϴ)	30°, 45°, 60°, 90°

Any distance greater than 2m is not considered since corridors and alleys do not have width greater than 3m. Any distance less than 50cm is not considered since it would be too close to take a reasonable image and, if only one material is present in an image, white balancing algorithms do not work. Three distance parameters of distance d shown are evaluated for different values of tilt in Figure 35.

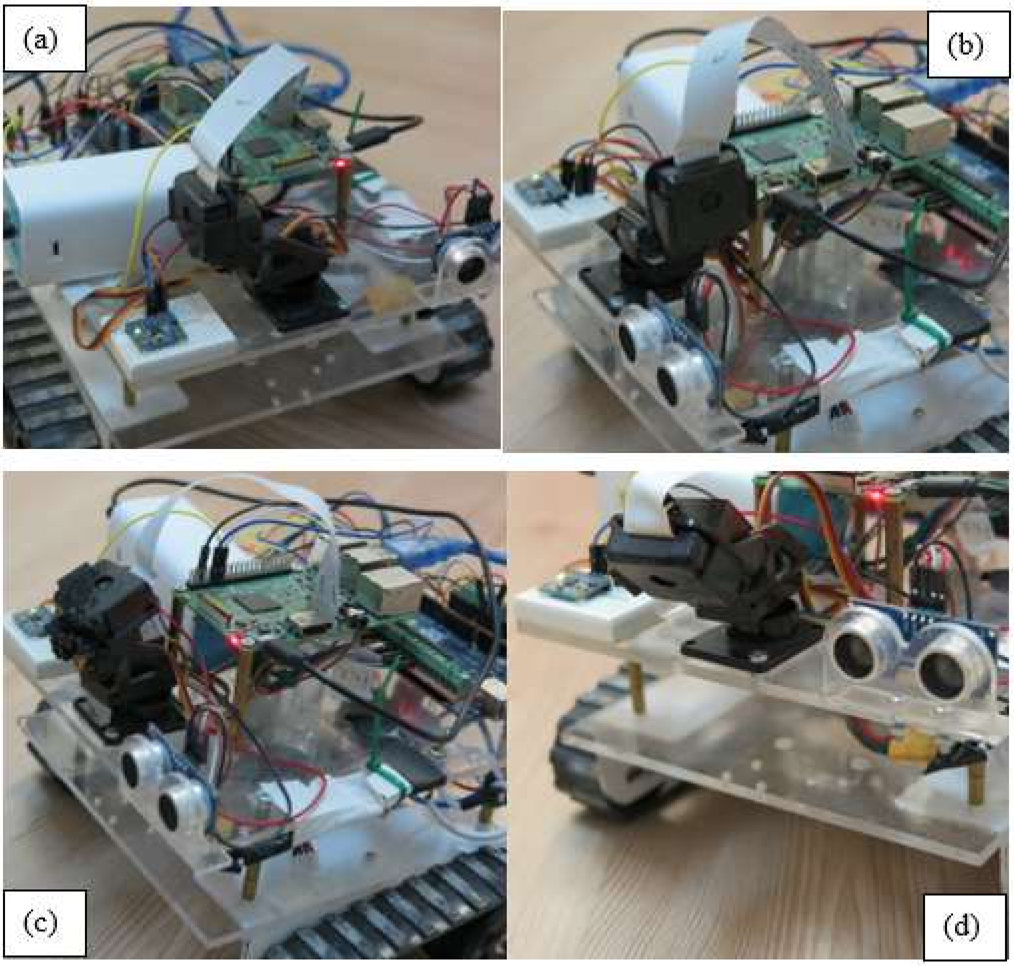


Figure 35 Camera-tilt at (a) 0°, (b) 180°, (c) 30°, and (d) 140° to capture the EOI.

The tilt mechanism allows the camera to take image of objects above, below and in front of the robot. Figure 36 shows image of roof slab formwork acquired from a lower level. Figure 37 shows imaging performed at 90 degrees when camera is looking directly in front and image of a vertical element like the one shown in figures is acquired. Figure 38 shows image from camera when it is tilted downward and image of floor slab is acquired. The figure shows rebar installation for a roof slab. The movement of robot camera allows imaging of wide array of elements that can be used in future development of this research.

Figure 36 Imaging of elements above the robot with very low ϴ < 20°.

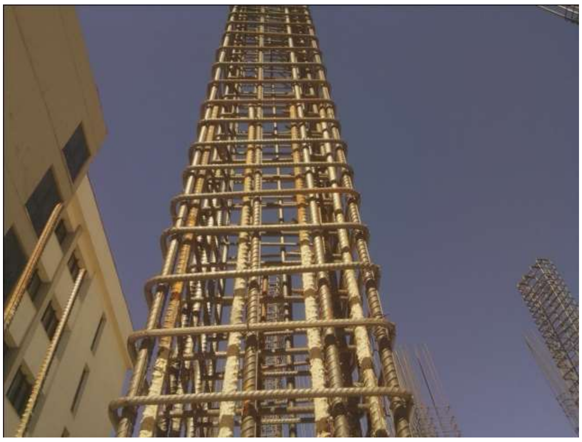


Figure 37 Imaging of element in front of robot. camera Point forward. 40° < ϴ < 90°.

Figure 38 Imaging of elements below the robot with ϴ > 90°.

4.5. Image Tagging and Transmission

Once Image is acquired, it is tagged for ease of retrieval for automated processing or manual review purposes. The image tag or name contains the level, activity ID, angle and distance of sensor from image when it was acquired. Figure 39 shows screenshot of images stored with POI, activity, and sensor related information in the image tags. The python script in BAAP extracts the activity and POI information from daily monitoring list while tilt angle comes from BAAP. Once the image is taken, it is then sent to the server using push request, where further image processing and storage takes place.

Figure 39 Images tagged with POI, Activity ID, angle and distance of acquisition.

4.6. Image Storage at Server

BAAP acquires images and pushes it to the server, where a file watcher is waiting for an image transmitted over a Wi-Fi. Once the image reaches the server, its filename is read using python script, which retrieves its POI, activity and sensor related information. The server acts as a repository containing images sorted according to their respective POIs as seen in Figure 40 (a). Each POI folder contains all images acquired at that particular POI for every planned activity present in the schedule.

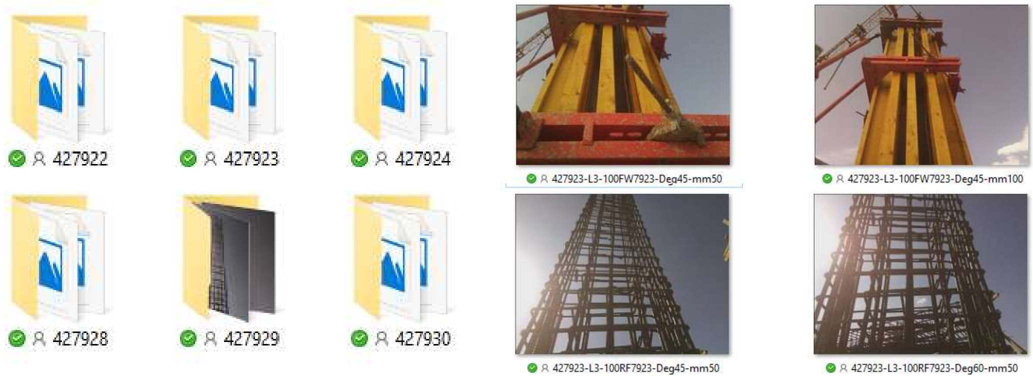


Figure 40 (a) Image storage according to POI at server end, (b) Image storage within according to activities.

POI-wise data storage makes its retrieval very easy, for instance when images of activities on a certain element are being sought for further processing and evaluation. POI folders containing site image with activity IDs in filename provides a pictorial view of various stages of progress at a particular element. This methodology provides an intuitive platform for visual and automated monitoring.

4.7. Experiment for Validation of Navigation Algorithm

4.7.1. Creation of BIM and Extraction of POI Information

Validation of robot navigation was performed in the corridor of METU civil engineering METU civil engineering department K1 Building corridor. Partial BIM of corridor was created on Autodesk Revit (see Figure 41) with actual dimension taken from the structure. The corridor has five separate spaces connected to one corridor through panel doors. Roof is not shown in the model for visualization purpose. It is assumed that the structure is being constructed and robot will navigate the site to acquire images of progress. POI and activity list is obtained using EAPE which was further processed to create a schedule.

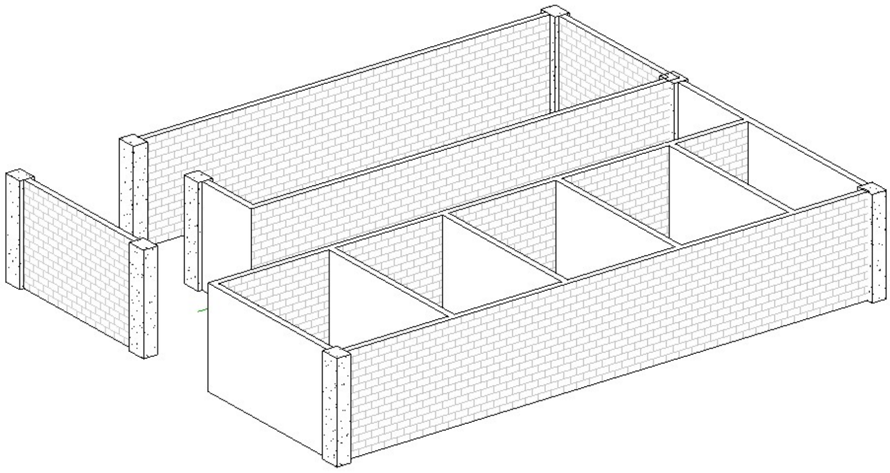


Figure 41 3D model of navigation test site created on Autodesk Revit.

Three elements are sampled for robot navigation that include two doors and two walls. Figure 42 shows sample points for robot navigation which involves three colinear points and one right turn. The robot starts from Initial Navigation Point (INP), whose coordinates are known to robot, and navigates to each POI by calculating position vector between its current location and target location. The schedule is made in a manner that ensures sample POI activities are completed on the same working day to ensure monitoring in one run of robot.

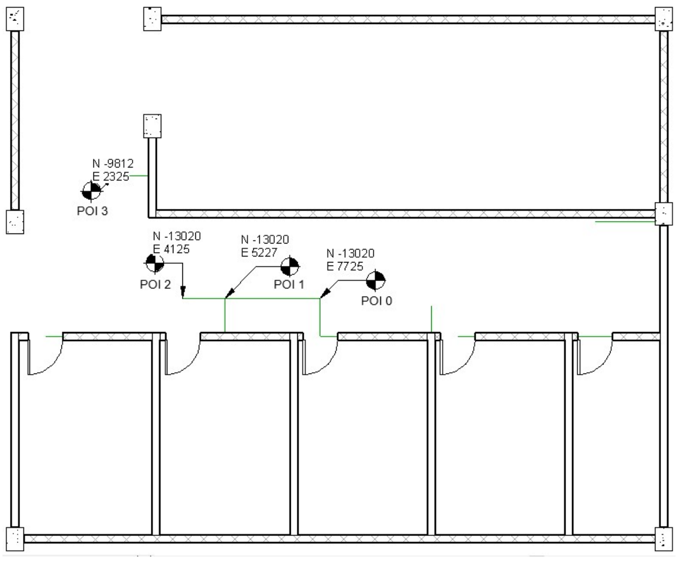


Figure 42 Extracted POI locations for robot navigation validation.

The robot extract coordinates from server using Php pull request and calculates position vector for POI 1 by subtracting coordinates of its current location which was POI 0. The robot navigates to POI 1, takes images and moves to POI 2 using vector calculated between consecutive POIs. EAPE provides two-dimensional coordinates for each level and the navigation vector calculated in the form of rectangular coordinates is shown in Eq. (1) and represented in vector form in Figure 43.

$$x_N\hat{\imath} + y_N\hat{\jmath} = (x_2\hat{\imath} + y_2\hat{\jmath}) - (x_1\hat{\imath} + y_1\hat{\jmath}) \tag{1}$$

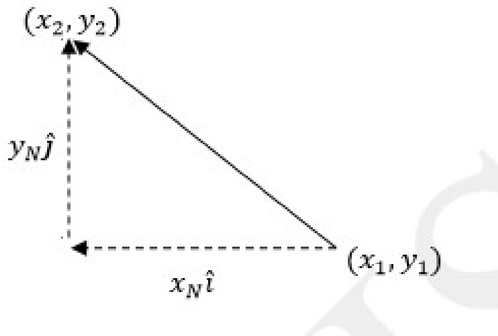


Figure 43 Navigation vector calculation from POI coordinates.

The robot also follows the path along the rectangular component of navigation vector between two POIs. The reason being most conventional structures shell and core structures are rectangular and symmetrical due to structural and construction related reasons. A robot moving along the rectangular components instead of the shortest distance between two points is less likely to encounter obstacles esspecially during construction phase. However, in real life scenario, a more robust algorithm that depends upon predetermination of expected obstacles needs to be developed for uninterrupted navigation. The site also has to be kept clear of clutter and walkways should be designated for safe movement of worker on site. The same walkways can be used by robot for navigation.

4.7.2. Experiment Results and Discussion

Robot performed ten navigation runs intiated from INP and terminated at POI 3, taking instruction from BIM through server via a pull request. Two types of navigation runs were performed: Continous run is uninterrputed through all POIs replicating proposed site setup. Controlled run is performed with correction of robot position at every POI to ensure that cummulative errors are not reflected at each POI rather individual error for each vector is attained seperately. Figure 44 to Figure 46 shows continous and corrected error at POI 1 to POI 3. As seen in this figure the error is greater in transvere direction and less along the direction of movement of robot for POI 1 and POI 2. The lateral errror is caused due to uneven speed of drive wheels and change in relative speed of rotation which causes the robot to move in direction of slower wheel. The error along the direction of movement is caused by incorrect counter of interrupt due to slippage of both wheels which has been made less likely due to the use of track instead of wheeled system. POI3 involves a right turn, which results in rotation of axis of movement by 90° and trasverse axis of movement becomes lateral axis of movement while the lateral axis become transverse axis. This causes error to appear in both axes unlike other POIs where error was more pronounced in transverse direction (as seen in Figure 47).

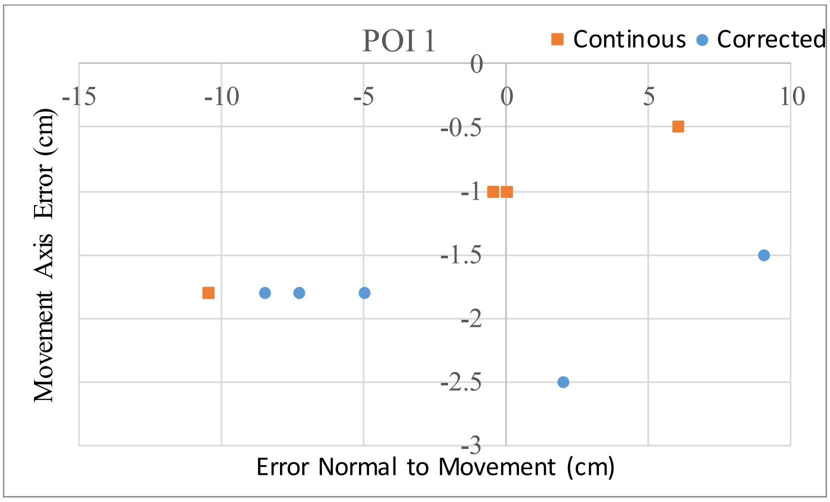


Figure 44 Error at POI 1.

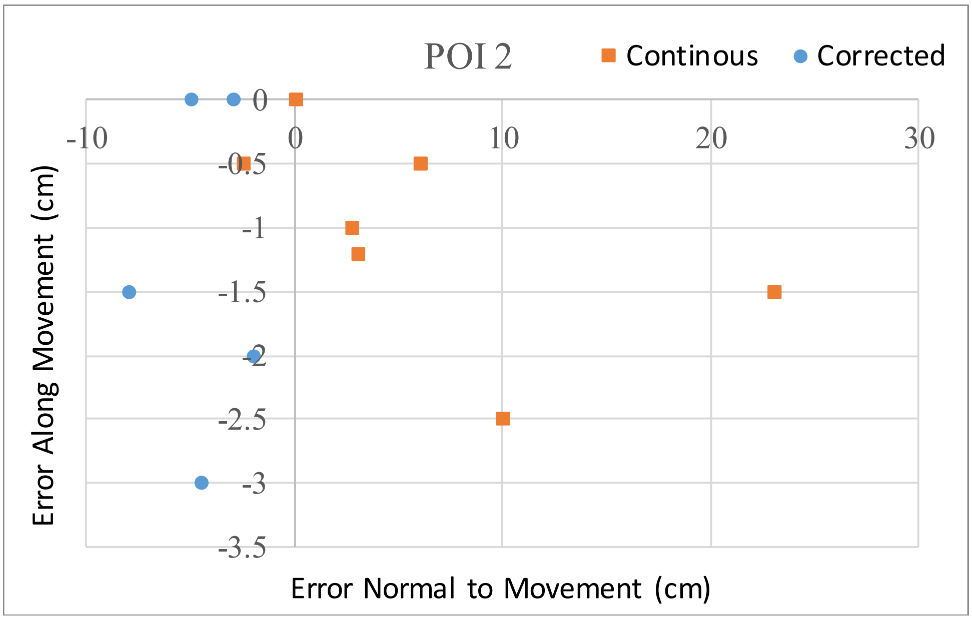


Figure 45 Error at POI 2.

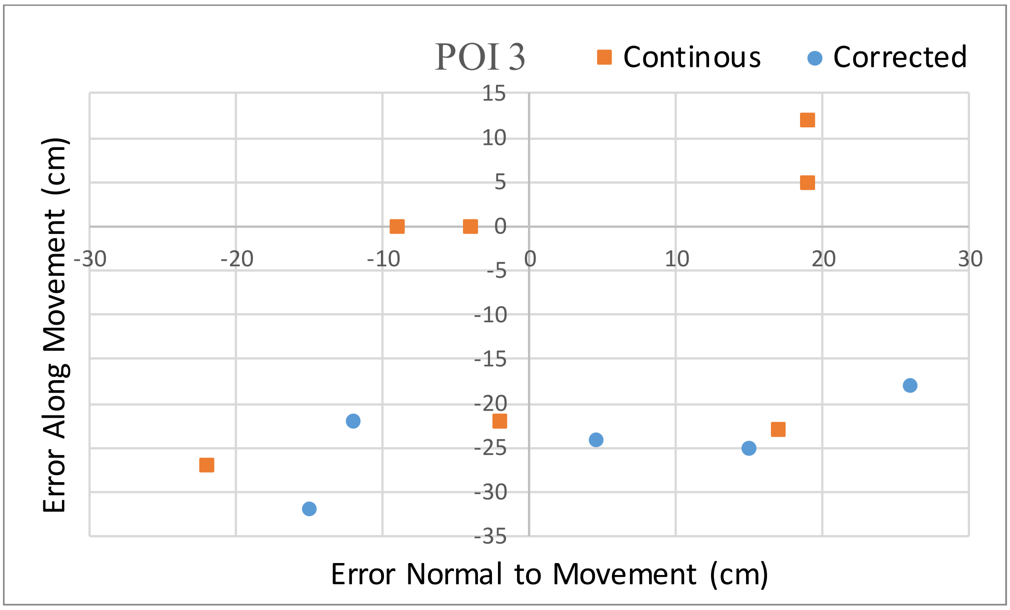


Figure 46 Error at POI 3.

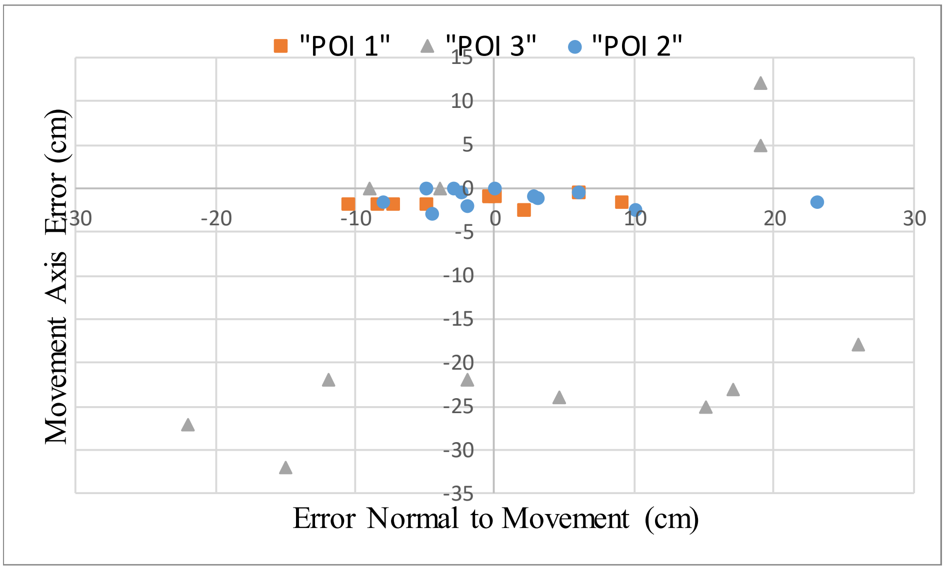


Figure 47 Combined plot of error at POI 1, POI2, and POI3.

Figure 48 shows box and whisker plot for error with respect to magnitude of navigation vector. It can be seen from the figure that error stays below 0.04% for POIs where no turning is involved and below 0.1% for cases where the turn was involved. It can be inferred that error would be increased as distance increases and after distance exceeds a certain threshold, the Elements of Interest might go out of frame, esspecially when they are narrow like door and columns. Walls are of greater length than doors and columns and the drift or error in robot beyond several meters is not possible unless the robot has to move through long corridors. There is certainly a requirement for intermediate calibration points that will determine robot position and remove error that may have occured during movement or turning. Calibration can be done by placing markers like QR codes that can be read by robot camera and decoded to determine the exact positon of the robot. The robot can then recalculate the navigation vectors and continue with accurate movement. The biggest problem would occur if the robot misses one turn or movement due to any hardware error, in that case the error will be excessive, which should be kept in mind during further development of this system.

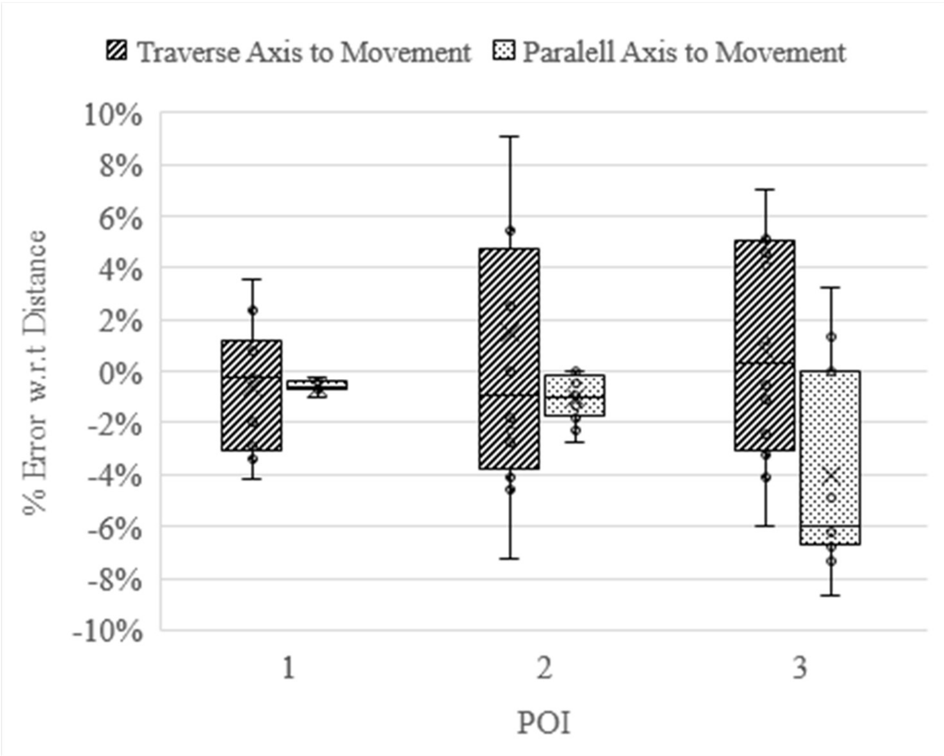


Figure 48 Box and whisker plot for percentage error w.r.t length.

4.8. Validation of Imaging on Site using BAAP

In order to test SCAER, a process was developed for the robot at selected POIs with pre-determined angles, distances, POI and activity ID in the image name for future reference (see Figure 49). The image was sent by robot (client) to the server using PHP post-request, where image was stored in a folder with POI name.

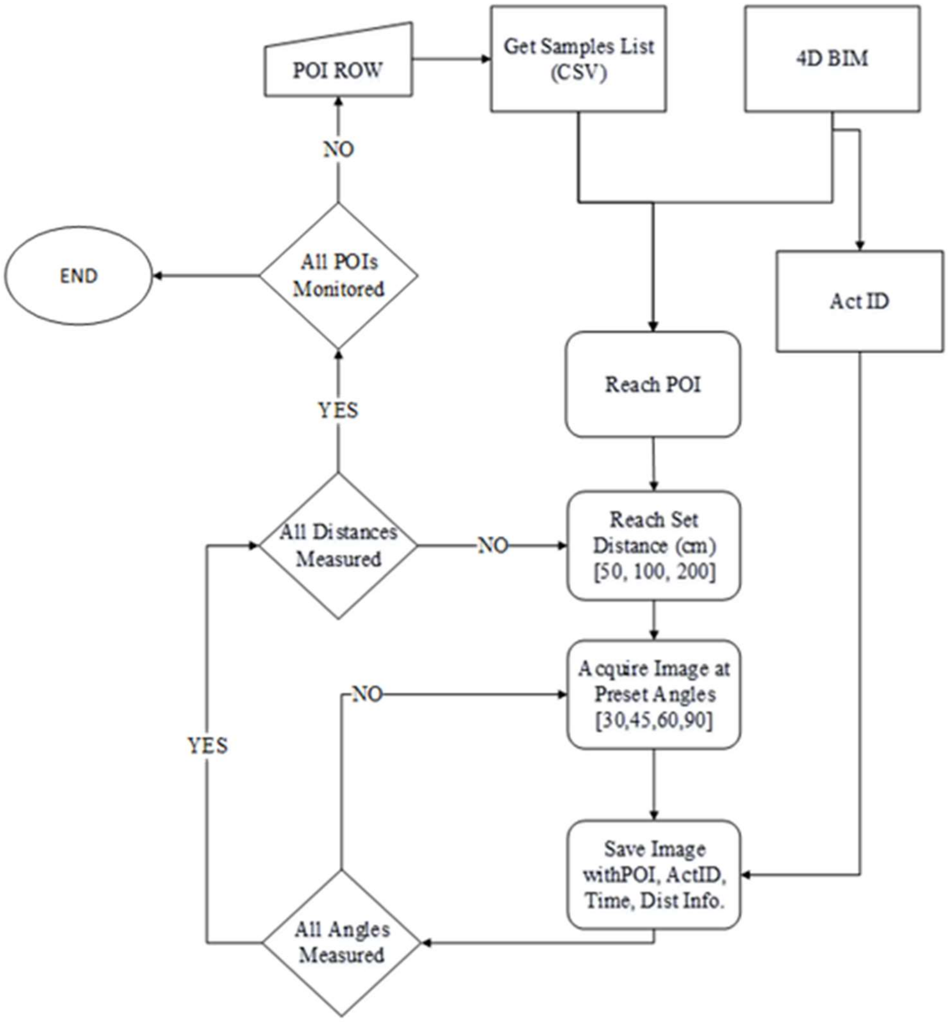


Figure 49 Process flow for conduct of field test.

A frame is characterized by the POI which provides it a unique identity. SCAER is then applied on image for clustering and subsequent detection based on Euclidean distance from samples in the database. A list of materials D detected for all images is created containing POI (Pi), Angle (Θ), Distance (S) and material d is obtained. An actual material list R (see Eq. (2) and Eq.. (3)) is created for materials which are *'actually'* present in each frame characterized by Angle, Distance and POI information.

$$D = \{d_{P1,\Theta1,S1}, d_{P1,\Theta2,S1}, \dots \dots \dots, d_{PN,\Theta4,S3}\} \tag{2}$$

$$R = \{r_{P1,\Theta1,S1}, r_{P1,\Theta2,S1}, \dots \dots \dots, r_{PN,\Theta4,S3}\} \tag{3}$$

Images were taken on four different camera tilts capturing both top and bottom edges of EOI, which are assumed to be vertical in all cases. Any tilt angle outside this range would not capture EOI except in the cases of slabs and roof slabs which are not considered in the scope of this research. Overall 9 pictures of each element are supposed to be acquired but total number of pictures of each category (see Figure 50) may vary from element to element based on lack of space or presence of clutter between the camera and the element.

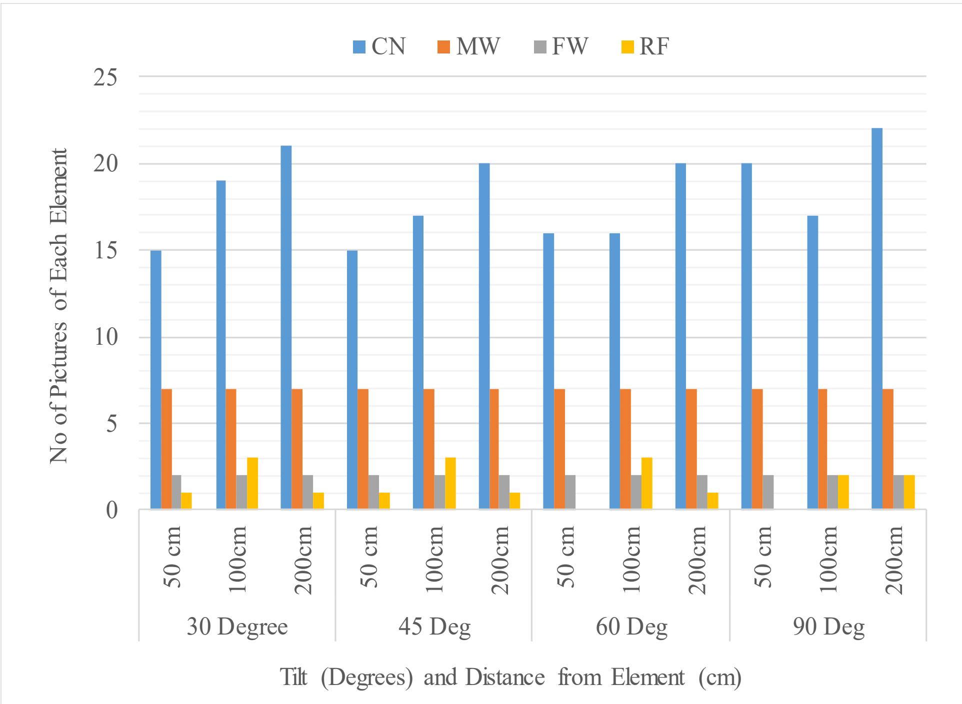


Figure 50 Number of pictures taken of subject materials taken at given tilt and distance values.

Before application of SCAER, pictures were manually observed to determine the ratio of pixels that represent Element of Interest (EOI) versus those that do not represent EOI. Figure 51 shows various defects in image obtained from site that included occlusion from clutter and temporary works like scaffolding, ladder, tools, and glare that may affect white balancing and darken the picture. Quality of image is therefore based on a percentage of EOI pixels in the complete image, the presence of foreign elements causing occlusion by blocking the view of the EOI, and incident light on a camera sensor that affects illumination and darkens the EOI.

Figure 51 Poor Image Examples (a)-(b) Acquired at 30% misses EOI and captures roof slab, (c)-(d) Images acquired at 90% captures clutter on the floor next to wall.

Images are hence classified on the criteria of quality as mentioned above. The result of classification shown in Figure 52 (a) depicts the correction between tilt and distance with image classification based on its visual quality. It is observed that almost 80% of poor quality pictures are with the imaging sensor tilted at 30° and 90°. The minimum Recall for tilt angles imaging at 30° is less than those observed in all other angles. It has also been observed that recall for imaging at 200 cm distance shows lower recall as compared to other distances. However, the presence of poor quality pictures is quite significant and can affect recall and false positives as the number of images increases when every element of a project being is imaged.

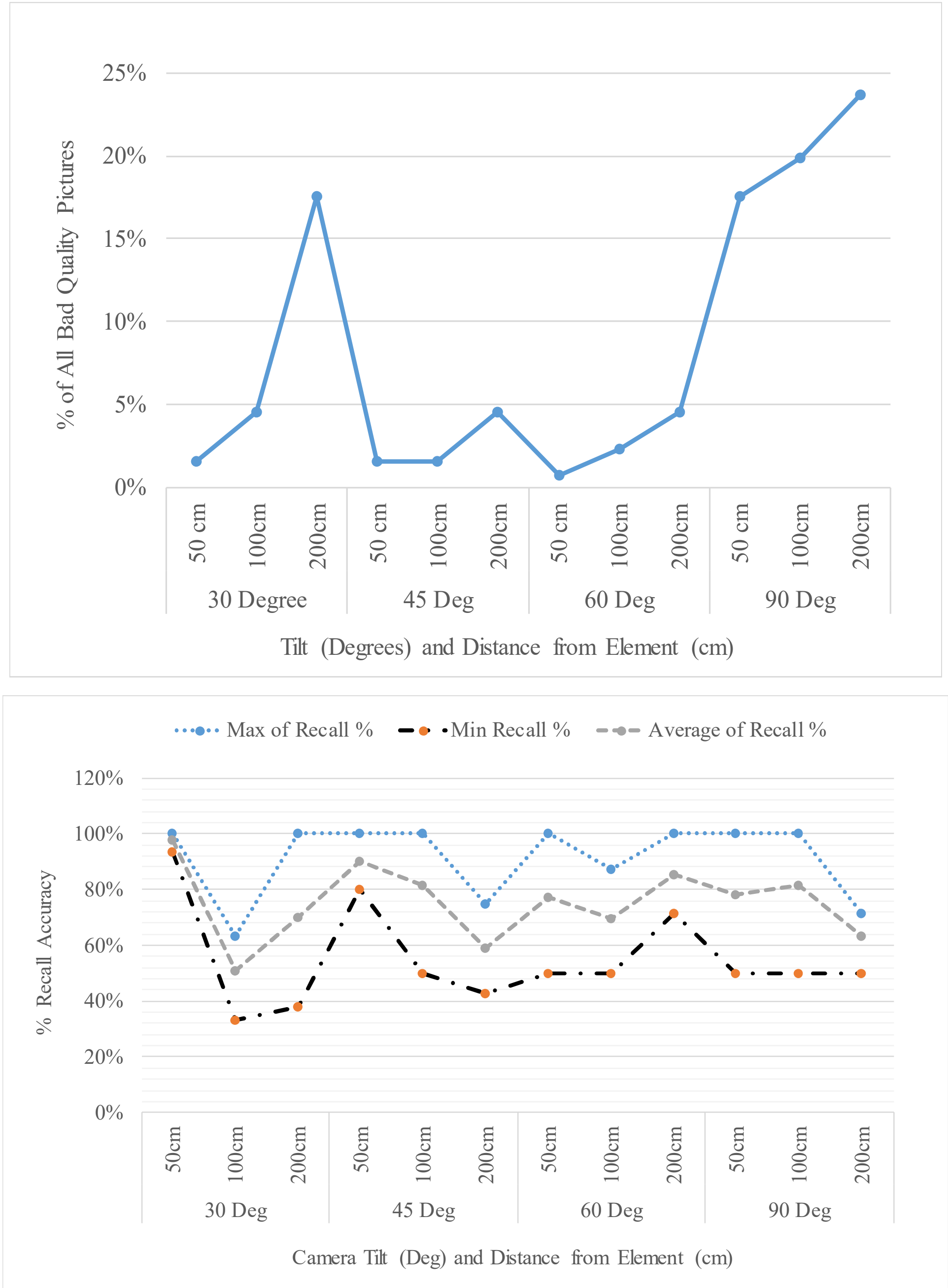


Figure 52 (a) Poor quality pictures w.r.t angles and distances, (b) recall for images at angle-distance combination.

The reason for a poor quality picture at very high tilts (low angle of tilt) makes the camera point towards the top of the EOI capturing a large portion of the roof slab while reducing the percent pixels comprising the EOI. Imaging sensor positioned vertically with 90° tilt, captures a major part of floor slab while reducing the ratio of EOI to irrelevant elements. The reduced number of EOI pixels, when the camera is too flat or too obtuse, reduces the probability of image identification. The % recall (shown in Figure 53) is for an image acquired at the extreme angles which have lower minimum values as compared to mid tilt. There is considerable improvement in the recall if images captured at 30° and 90° tilts are not considered in material detection.

Images taken with 60° tilt (see Figure 54) have better recall than those acquired with 45° tilt since image plane is flatter with former compared to latter. 90° would have been the best choice of tilt if the focal axis of the camera wasn't very close to the ground and robot, like in the case of a robot developed for this research. Mounting camera at a greater height causes stability problems in the robot and was not attempted during this research.

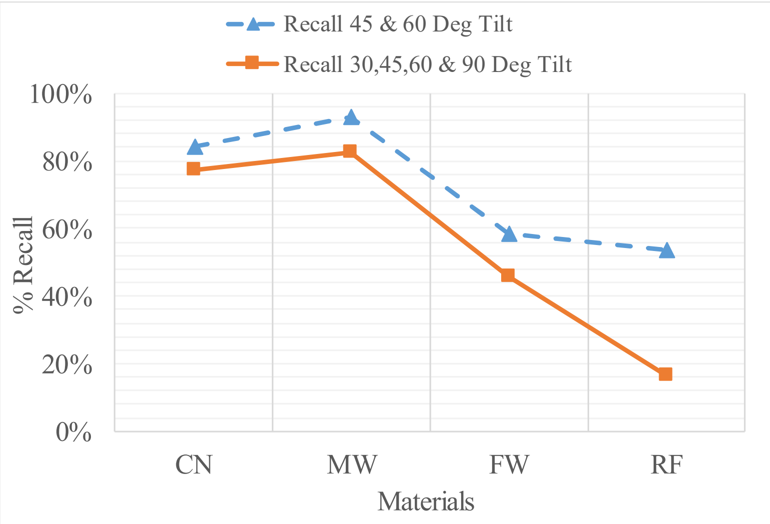


Figure 53 Images acquired with all tilt angles.

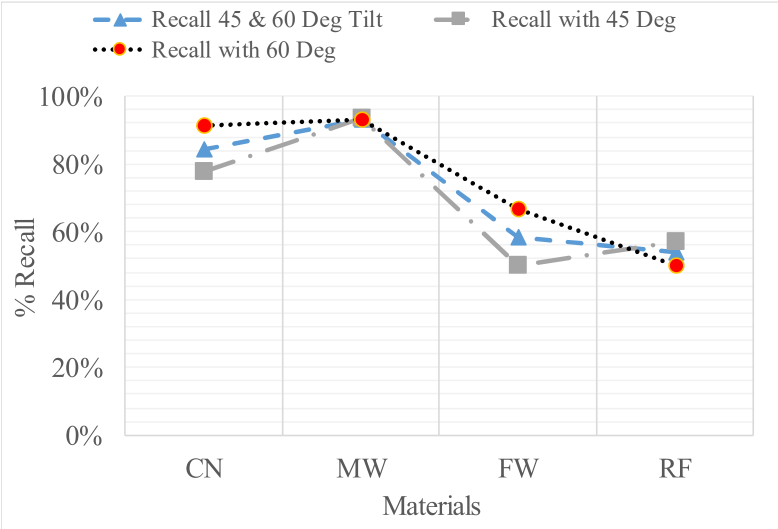


Figure 54 Material wise recall for image with good tilt angles.

Although the recall percentage may appear less in comparison with algorithms which have given results greater than 90% in some cases, detection of the image is just part of the solution which is augmented by contextual information attained from the schedule and POI resulting in almost perfect results which will be discussed in later section.

4.9. Conclusion

BAAP is the embodiment of robotic construction monitoring, which can take the form of a drone or terrestrial robot as well as a worker. The image acquisition, storage, and retrieval system provides a much-required archival system for the construction site that is very useful for future referencing. BAAP provides an efficient, low cost and accurate platform for BIM-based imaging. The images obtained are tagged at the source and transmitted to the server and processed for SCAER for progress determination. The robot developed as a realization of BAAP was able to attain POIs from BIM and navigate to site with an error less than 4% in the direction of motion of the robot and less than 10% in the direction perpendicular to the direction of its motion. The robot with the current setup needs intermediate calibration points to remove error that may accumulate during motion. The error in the perpendicular direction is greater than the direction of motion due to the variation of wheel speed and slippage. The setup involved the use of prototyping electronics and very low cost circuitry which may not be able to give a very high quality output. Development of the robot by using professional grade electronics may further improve robot accuracy. A verification of image acquisition and tagging was done on actual construction site as presented in the next chapter, and the algorithm was able to attain images, tag them and transmit to a server in a seamless manner which in itself is a useful function for site operatives.

CHAPTER 5

SCHEDULE BASED CONTEXT AWARE ELEMENT RECOGNITION (SCAER)

Automatic analysis of digital images is an active research field where computer vision, automated progress monitoring, and material identification converge. Computer vision has been part of various civil engineering studies like pothole detection [68], worker detection [145], equipment action recognition [63] and performance monitoring [146], [147], etc. The basic problem in computer vision techniques is occlusion due to which progress can only be measured on an element in the closest structural frame of the camera [8]. This issue has been resolved with the use of the robot-mounted camera, which can move around occlusion and take a close image of building components.

5.1. Introduction and Background Information

Context-aware Automated Construction Progress Monitoring System (CAPMS) provides a framework to acquire data, convert that into progress information and deliver it to project leadership team promptly which is the goal for an automated progress monitoring system [106]. Imaging is a contactless way of acquiring data on site and requires no investment in infrastructure or worker training. It is, therefore, a preferred means of data acquisition for the automated progress monitoring system. CAPMS uses imaging to attain real-time site progress data accurately, that is not affected by human factors and does not cause disruption on site.

Automated progress monitoring system relies on material recognition to ascertain the status of various elements on site. The material recognition can be done using computer vision techniques which apply mathematical principles on images to extract information contained in them. Imaging is a semantically rich data source that can be acquired using equipment whose cost has decreased considerably in recent decades. The computer vision algorithms requires contextual information in the form of R, G, B values (color) of architectural and structural elements which are stored in BIM along with other element properties. Information extracted from images can be further processed to ascertain element status information.

5.1.1. Contextual Information

Material identification from images of construction site elements is related to but differs from material classification in computer vision problems. In computer vision, most methods assume the absence of a strong prior for material recognition thus computer vision algorithm should be able to handle a certain degree of randomness in expected results [55]. In contrast, material identification on model-based construction automation methods can take advantage of contextual information [58] in the form of expected elements and materials. Restated, contextual information can either come from within an image, or it can be derived from non-image sources such as geographical information or time of capture. Geographical information comes from Cartesian coordinates in building the frame of reference for indoor pictures and GPS coordinates for outdoor pictures, while the time of capture comes from the image EXIF data.

Mathematically contextual data can be linked to current data using Markov process, which is a random process where the future state depends upon the present state only and has no knowledge of any of the previous states. It consists of a set of transitions, adhering to probability distributions that satisfy Markov property. Markov chains are quite useful in real-world applications [113]. They are relatively simple and are meant to statistically model random processes applied in different domains from speech recognition to text generation to financial modeling. Markov property is very valid for construction-related applications since any activity performed on site is dependent upon the previous activity only and is not dependent on the activity performed before the previous activity, specifically in shell and core construction on building sites.

A state is a set of values that the chain is allowed to take which, in our case, can be characterized by a possible set of materials that can be present at a particular point. Since the presence of a state is dependent upon the previous state and independent of all other previous states, the *memoryless* property, also known as Markov property, can be applied. Markov chain (Figure 55) is probabilistic automation [100] and depends upon the probability distributions of transition from one state to another which can be represented by a *Transition Matrix* as shown in Eq. (8).

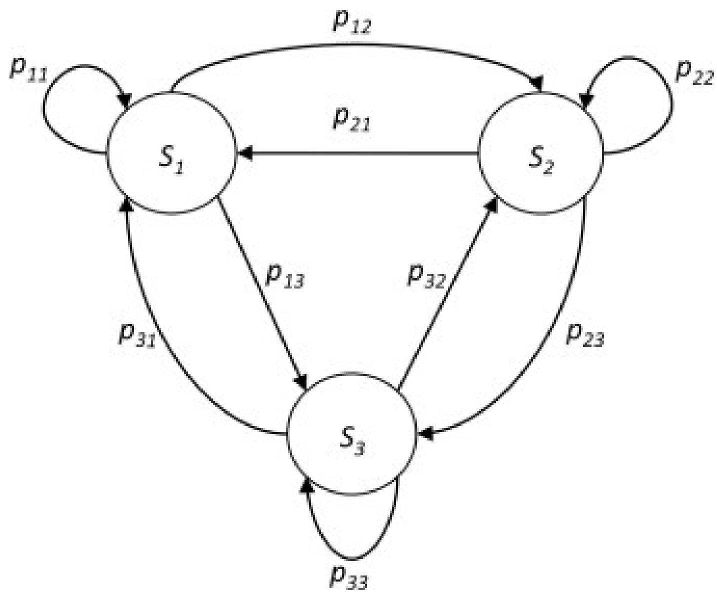


Figure 55 Markov chain transition probabilities and transition matrix [148].

$$P = \begin{bmatrix} p_{11} & p_{21} & p_{31} \\ p_{12} & p_{22} & p_{32} \\ p_{13} & p_{23} & p_{33} \end{bmatrix} \tag{4}$$

State Space is a set of possible set of events that can occur. The state space for current research takes a finite number of distinct values and is time-homogeneous. The transition operator is defined by matrix P, and each entry is given by Eq. (5).

$$p_{i,j} = p(X^{(t+1)} = j | X^{(t)} = i) \tag{5}$$

Where in Eq. (5), the chain is currently in i-th state and transition operator assigns a probability to move to the j-th sate by entries of i-th row of P. The scope of this research is limited to structural and architectural elements of the reinforced concrete shell and core structures. In CAPMS, the state of an element will define the completion of an activity. The list of activities completed and elements whose presence in the image frames proves the completion of that particular activity in CACL, the states for each element will be based on the last activity completed at that element and state space can be given by Eq. (6).

The transition for the Element States in CAPMS: We will consider the state of an element (X) to be defined by a stochastic process [141] where n in Eq. (6) is the inspection number on a particular element.

$$\{X^{(n)}, n = 0,1,2,3, \dots\} \tag{6}$$

Where the state of the element can be defined by a finite set of element states given by Eq. (6). Each state representing the last completed activity on that particular element, considering there is one to one relationship between activities and elements in 4D BIM. Eq. (7) shows the finite set of states at a particular element which can be represented as Eq. (8).

$$S = \{RF, FW, CN, MW, PL, DR\} \tag{7}$$

$$X^{(0)} = RF,\ X^{(1)} = FW, X^{(2)} = CN, \dots \tag{8}$$

A state transition diagram for states represented in state space M is shown in Figure 56 and matrix representation is in Eq. (9). Whenever an activity is being monitored, there are two distinct possibilities whether an activity has been completed or whether the element is still in the previous state. All states cannot transition between each other due to logical constraints; e.g., CN cannot be followed by RF without formwork. The memoryless property is also retained since CN will follow formwork whether reinforcement was installed or not. The transition probabilities will be discussed in a later section and would be dependent upon the results of the image processing.

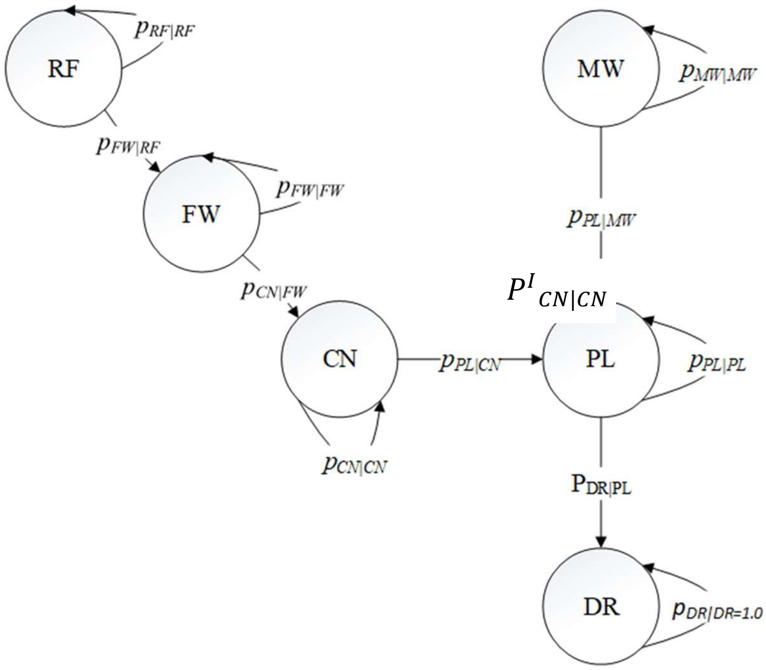


Figure 56 Transition state diagram for various element states

$$P = \begin{bmatrix} p_{RF|RF} & 0 & 0 & 0 & 0 & 0 \\ p_{FW|RF} & p_{FW|FW} & p_{CN|FW} & 0 & 0 & 0 \\ 0 & p_{CN|FW} & p_{CN|CN} & 0 & 0 & 0 \\ 0 & 0 & p_{PL|CN} & p_{PL|PL} & p_{PL|MW} & 0 \\ 0 & 0 & 0 & 0 & p_{MW|MW} & 0 \\ 0 & 0 & 0 & p_{DR|PL} & 0 & p_{DR|DR} = 1.0 \end{bmatrix} \tag{9}$$

5.1.2. Color Space

Color is defined as the reaction of the brain to a specific stimulus. Therefore color is not an intrinsic property of an object, rather the perception of energy emitted by or reflected from the object [149]. Spectral power distribution is the physical property of light that is relevant to color vision, which specifies the amount of power it contains at each wavelength in visible spectrum [150]. Color is an essential feature used for distinguishing different materials. Although all computer vision-based algorithms do not rely solely on color information, other features such as edges, shapes, and textures are also useful. Color processing is, however, advantageous because of its simplicity, robustness, power and efficiency related benefits [151]. The color of a particular pixel can be observed as a stochastic event within the *n*-dimensional space defined by the color space used.

A color space or color model is a method used to visualize and specify color. Color for humans is defined by its attributes of hue, brightness, and saturation but for a monitor, it is the right combination of red, green, and blue lights needed to match a color [152]. In color printers, colors are produced based on reflectance and absorbance of cyan, magenta, yellow and black inks on paper. Color gamut is the area enclosed by a color space in three dimensions where three coordinates will specify the location of color in that particular color space. Color gamut also defines the range of colors in a color space. Each color will have different coordinates for each color space. There are various color models proposed in literature including RGB, XYZ, $L^*a^*b^*$, $L^*u^*v^*$, HSV, HLS, YCrCb, YUV, I1I2I3, and TSL [153]. A color space may be device dependent and device independent, e.g., specifying the same RGB coordinates on two different computer monitors may produce contrasting results. RGB, HSV, and LAB color spaces will be used for the scope of this research which is explained in the subsequent text with the reason for their selection.

Red Blue Green (RGB) is an additive color system based on trichromatic theory. The Red, Green, and Blue features denote the energy carried by light waves incident on the image sensor of wavelengths corresponding to red, green, and blue colors according to spectral bands based on Grassman's Law. The RGB color model has been illustrated by a Cartesian model with each color represented on each orthogonal axis (as seen in Figure 57). Every single point in the RGB subspace can define a particular color (see Figure 57. RGB is easy to implement and is very common, as it is being used in every display system, e.g., computer screens, television, videos, etc. Color filters present in a digital camera allow a very narrow spectral bandwidth corresponding to red, blue and green wavelengths of the visible spectrum to pass through. Once red, blue, and green wavelength intensities are obtained, they can be combined using RGB color model to represent true color visible to the human eye; therefore, the RGB bands can be directly separated from any image without any pixel-wise post-processing operation.

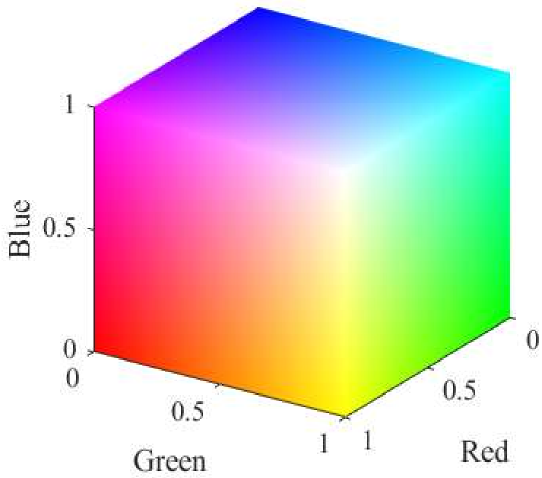


Figure 57 RGB color space.

Hue Saturation Value (HSV) color space is obtained as a linear transformation of RGB and, therefore, is device dependent. This color space (see. Figure 58) is extremely intuitive, and color can be specified by desired hue and adjustment of saturation and intensity values, where Hue is the color motion of the color model and is expressed in a number from 0 to 360, each defining a separate color. The hue of different shades of red will remain the same, and the only difference will be the amount of saturation. Saturation is the amount of grey, the color with 0 saturation means it is completely grey while a color with one saturation means it is a primary color. The Intensity component describes brightness that varies from black at 0 to brightest revealing complete color at 100.

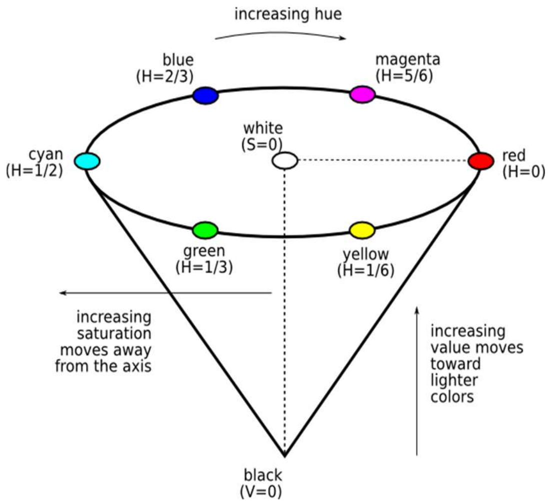


Figure 58 Hue Saturation Value (HSV) color space [154].

*CIE L*a*b* has been defined by Commission Internationale de l'Eclairage (French: International Commission on Illumination - standardization body) system of classification of colors and is based on Human Visual System (HVS) [152]. LAB is a CIE based color space (see. Figure 59) that is nearly linear with color perception [152] and is as close to color perception as is possible. Being based on human vision, it is device independent, however, quite unintuitive. CIE L*a*b color space is used due to its device independency and closeness to human perception.

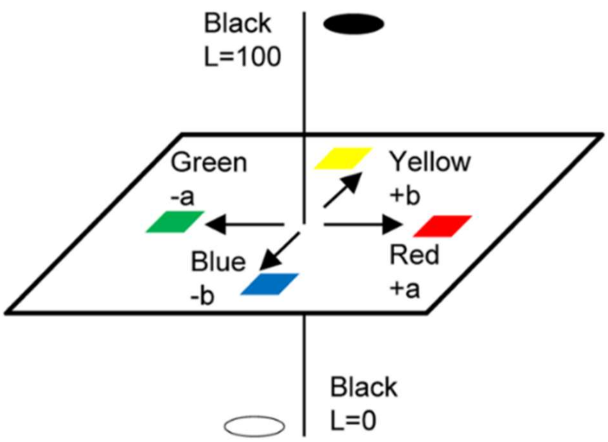


Figure 59 CIE L*a*b color space model [155].

L* depicts lightness which can vary from dark to white, a* denotes the point between red and green axis where that color lies, and b* depicts the point between yellow and blue color that a certain pixel lies, effectively denoting whether the color is near to red or green on a* axis and yellow or blue on b* axis. The L*a*b color scale gamut encompasses entire visible spectrum, unlike RGB and HSV color models which encompass a subset for visible spectrum [153].

5.2. Proposed Methodology

SCAER (see. Figure 60) is the backbone of CAPMS by converting data acquired by BAAP into information. It is a server end process that acquires images from BAAP, which is acts as a thin client. BAAP navigates to BIM elements and captures their images. 4D BIM is stored in the server, containing '*Element'* coordinates and their respective tasks in an updated schedule. BAAP traverses to the POI and takes images at different camera orientations controlled by the onboard camera and servo motor. The images sent to the server, are processed using SCAER to determine *e(X).*

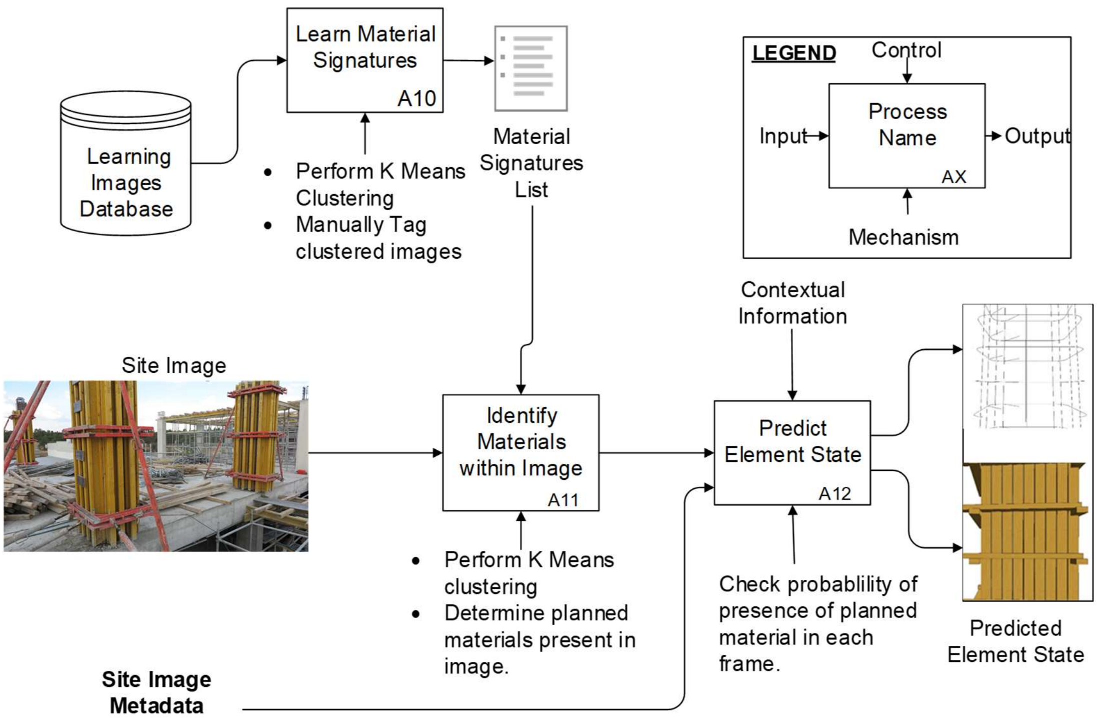


Figure 60 Process flow for Schedule-based Context-aware Element Recognition (SCAER)

Activity completion is confirmed if estimated state *e(X)* matches the planned state *p(X)* and unconfirmed if *e(X)* and *p(X)* don't match, which translates into progress achieved for the former case and delay for the latter case. Once the statuses of activities at all POIs are ascertained, an updated schedule with confirmed activity completions is generated for review by the project management team. Since imaging is being utilized for monitoring activity, only activities that are visible to the human eye are validated. Internal or hidden changes in the state of an element are characterized as activities that cannot be detected as progress using CAPMS. Generic tasks included in the scope of this research are present in CACL.

5.3. Learning Material Signatures

In order to train the algorithm to identify materials, a two-step approach is undertaken. The first step involves division of the image into its constituent materials based on their color differences using K-means clustering followed by tagging of cluster centers visually as shown in flow chart in Figure 61.

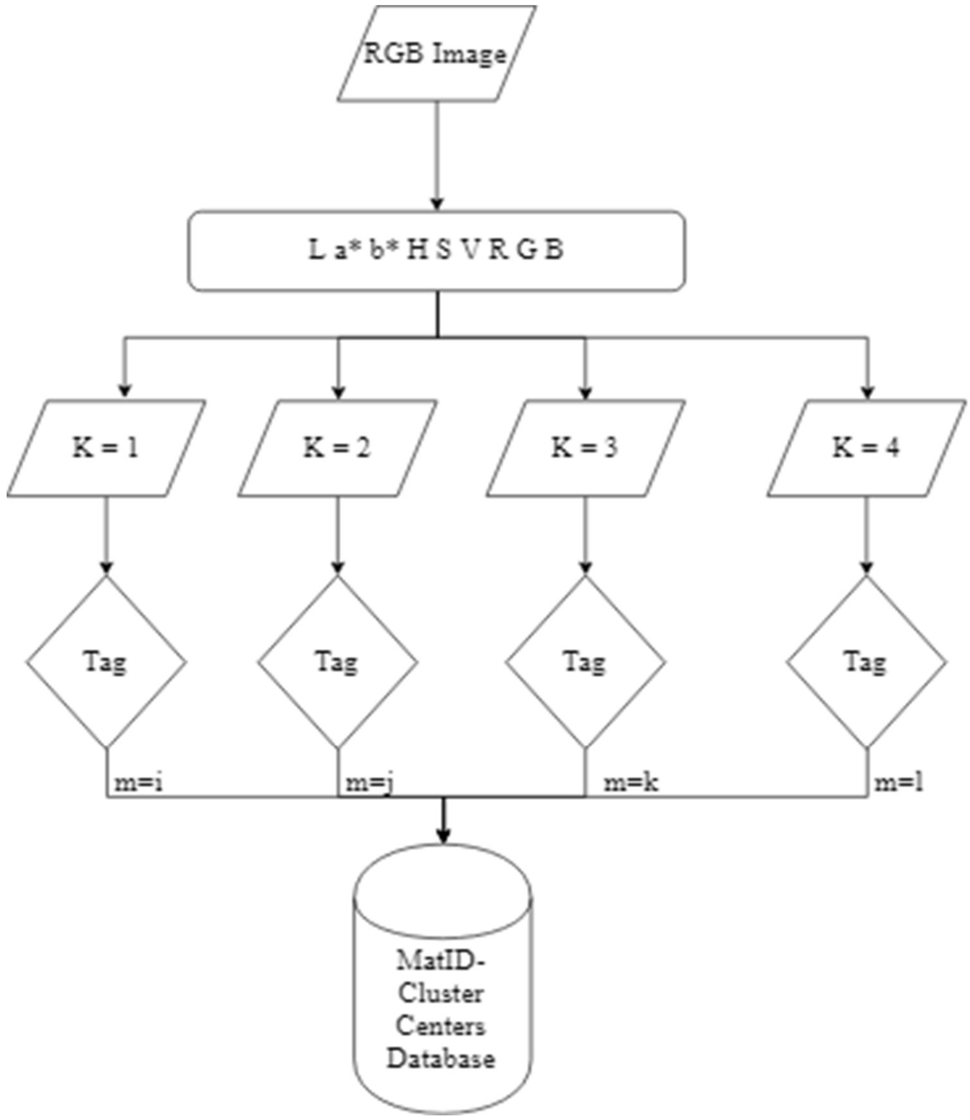


Figure 61 Flowchart of the learning algorithm

A training set of data is acquired from a materials database. Figure 62 is an image from the learning database to demonstrate the learning algorithm. The obtained image can be from an actual installation that will be replicated in a newer structure or an image taken at the factory or provided by the manufacturer.

Figure 62 Training image for a demonstration of the learning algorithm.

5.3.1. K-Means Clustering

K-means clustering [156] is an unsupervised learning algorithm which is used when unlabeled data is present, such as the 2-dimensional image color of whose pixels are not known. The algorithm works in an iterative manner where each data (pixel in the case of this research) is assigned to a cluster K based on the similarity of features. This divides the data pixels into a data set organically [157]. K-means clustering algorithm for material segmentation has a feature vector given as:

$$x^{(j)} = [L, a^{*}, b^{*}, H, S, V, B, G, R\ ] \tag{10}$$

Where $x^{(j)}$ denotes the feature vector for the pixel at position j in the 2D image, $\boldsymbol{L}$ for lightness, and $\boldsymbol{a}$ and $\boldsymbol{b}$ for the color-opponent dimensions. H is hue, S is saturation and V is brightness from HSV color model. R is red, G is green and B is blue reflectance intensity levels in the RGB color model.

K-means clustering has two steps, the first being data assignment, where each pixel is assigned to nearest cluster centroid based on squared Euclidean distance. Using K-means clustering algorithm, a matrix containing cluster centers given in Eq. (11) is obtained.

$$Cl_k = \begin{bmatrix} cl_{11-k} & cl_{ij`-k} & cl_{19-k} \\ cl_{21-k} & & cl_{19-k} \\ \vdots & \ddots & \vdots \\ cl_{K1-k} & \cdots & cl_{K9-k} \end{bmatrix} \quad (11)$$

In the above Equation $cl_{ij`-k}$ donates feature *j*, and cluster center *i* for image k from learning dataset. Eq. (11) shows clustering centers of K=4 clustering performed on training dataset image in Figure 62 using 9 dimension feature vector mentioned in Eq. (10). The image corresponding to the clusters in Eq. (12) are shown in

Figure 63.

$Cl_T =$ (12)

L	A	B	H	S	V	B	G	R
39.52	127.27	129.26	43.97	21.59	39.87	37.21	39.17	38.68
137.52	126.12	129.30	67.84	15.12	131.39	126.72	130.05	126.74
207.93	126.56	131.00	38.75	9.07	203.64	196.92	203.17	202.12
41.31	132.85	137.75	14.02	128.55	51.80	26.12	37.44	51.75

5.3.2. Material Tagging

The result of K-means clustering performed on test image *T in* Figure 62 is shown in

Figure 63. Once images are clustered, they are displayed on the screen for the user to identify material corresponding to each cluster.

Figure 63 Result of K-means clustering on test image: (a) Cluster 0, (b) Cluster 1, (c) Cluster 2, (d) Cluster 3.

A list is prepared for materials which are part of the scope of this study and each material is given a numeric identifier as shown in Table 14. Numeric identifiers make it easy to tag materials and help in sorting and further prediction study. Common architectural and structural materials visible on shell and core structures are used. It is intended to select materials of varying colors to see robustness of the algorithm. Since the algorithm works using color information, different materials with similar colors will be considered as same by the algorithm. In order to offset this weakness, context information is used which will be discussed in following sections.

Table 14 Material and numeric material identifier list.

Numeric Mat ID	Material Description
1	Door Painted Green
2	Door Painted Grey
3	Door with Wood Finish
4	Blue Painted Wall
5	White Painted Wall
6	Red Brick
7	Terrazzo Tile
8	Concrete
9	LWC Block Masonry
11	Unidentified
12	Formwork
13	Reinforcement
14	Safety Barricades
15	Construction Eqpt

The code developed for the creation of the database of cluster centers gets the material ID from the user for each clustered image and creates a database entry containing the material ID and its respective cluster center. The generic form of material cluster centers matrix with tagged material IDs from learning dataset is shown in Eq. (13).

$$Cl_k MatID = \begin{array}{cc} c_1 & m_1 \\ c_i & m_i \\ \vdots & \vdots \\ c_K & m_K \end{array} \begin{bmatrix} cl_{11-k} & \cdots & cl_{19-k} \\ cl_{21-k} & & cl_{19-k} \\ \vdots & \ddots & \vdots \\ cl_{K1-k} & \cdots & cl_{K9-k} \end{bmatrix} \qquad (13)$$

where in Eq. (13), c_i is the cluster number i which has been manually identified to belong to the material m_i with each cluster center represented by a nine dimensional feature vector such as $cl_{11-k} \ldots cl_{19-k}$. Material tagging performed on test image shown in Figure 62 is represented in matrix form as shown in Eq. (14).

$Cl_T MatID =$

Cluster	Mat	L	A	B	H	S	V	B	G	R
0	2	39.52	127.27	129.26	43.97	21.59	39.87	37.21	39.17	38.68
1	4	137.52	126.12	129.30	67.84	15.12	131.39	126.72	130.05	126.74
2	5	207.93	126.56	131.00	38.75	9.07	203.64	196.92	203.17	202.12
3	7	41.31	132.85	137.75	14.02	128.55	51.80	26.12	37.44	51.75

(14)

The learning process shown in Figure 61 is repeated for all images in learning data set, and a database of cluster centers is created. This database contains cluster centers of all materials that are present in test images to encompass the materials in the scope of this research. Eq. (15) shows material centers obtained from a learning dataset of 10 images. Multiple centers are obtained for each image and are stored separately in the database during learning.

$Cl_{1 \ldots N} MatID =$ (15)

Mat	L	A	B	H	S	V	B	G	R
1	8.61	127.83	129.01	39.52	62.97	10.87	8.33	9.86	9.85
1	39.02	128.12	128.69	5.69	9.61	39.14	37.53	38.39	39.07
1	14.56	125.91	128.95	73.41	79.98	19.03	16.42	18.87	14.03
1	5.47	126.09	129.01	72.99	166.71	9.28	6.09	9.02	3.48
1	10.90	127.17	129.46	55.98	96.57	14.02	10.57	13.28	11.71
1	7.72	126.70	129.47	64.57	132.97	11.52	7.64	10.96	7.63
1	6.48	126.48	129.56	57.79	136.73	10.20	6.31	9.77	6.54
2	47.24	129.00	125.96	119.93	22.24	49.02	48.67	45.54	45.63
2	19.38	127.66	129.08	32.27	28.10	23.21	20.90	22.49	22.34
2	39.52	127.27	129.26	43.97	21.59	39.87	37.21	39.17	38.68
2	40.48	127.86	128.85	18.72	12.43	40.35	38.44	39.60	39.91
2	65.39	128.81	126.44	124.44	15.58	64.03	63.72	60.89	61.12
2	37.82	127.45	127.64	96.47	19.95	38.97	38.34	37.84	36.36
3	123.98	134.17	143.83	14.14	87.26	135.37	89.17	111.16	135.37
3	123.95	133.41	141.60	13.87	76.92	132.96	92.95	111.73	132.96
4	151.43	127.39	129.75	40.69	7.91	143.88	139.66	143.15	142.76
4	117.86	126.62	128.87	60.74	9.24	110.74	107.91	110.21	107.75
4	119.03	125.95	113.45	106.38	81.22	134.88	134.84	112.92	91.78
4	118.67	126.19	113.91	106.33	78.17	133.73	133.70	112.36	92.60
4	137.52	126.12	129.30	67.84	15.12	131.39	126.72	130.05	126.74
5	129.14	128.63	128.45	66.39	6.97	122.54	119.93	120.24	122.13
5	194.24	127.49	128.65	48.57	3.92	188.63	186.31	188.07	187.25
5	152.14	127.84	129.15	27.13	8.37	145.52	141.48	143.58	144.15
5	207.93	126.56	131.00	38.75	9.07	203.64	196.92	203.17	202.12
5	82.64	125.18	131.21	53.40	28.10	78.91	71.61	77.86	74.06
5	186.44	127.93	132.35	21.58	15.57	182.66	171.57	179.11	182.60
5	110.63	126.02	130.36	52.09	20.00	105.66	98.97	103.68	101.04
5	173.23	127.75	129.57	31.16	10.34	168.21	162.54	165.46	166.21
5	111.75	128.38	129.81	42.44	15.83	106.35	101.12	103.71	105.92
5	92.60	127.79	129.73	47.84	17.17	87.69	82.91	85.64	86.55
5	191.72	128.43	132.83	20.71	17.90	189.56	176.34	184.40	189.53
5	184.24	125.34	129.95	95.77	11.13	179.98	173.78	178.64	173.43
5	153.78	127.88	128.30	55.35	6.54	147.07	144.70	145.38	145.35
5	206.43	127.85	130.83	22.79	8.84	202.81	195.85	200.75	202.69
5	180.76	126.74	129.37	47.08	6.61	174.33	170.46	174.00	172.24

5.4. Identification of Materials within Image

The robot upon reaching the POI rotates the camera towards the element of interest and takes an image. The image is then processed according to the process flow shown in Figure 64 based on the type of the activity that has taken place at that specific POI to determine the progress.

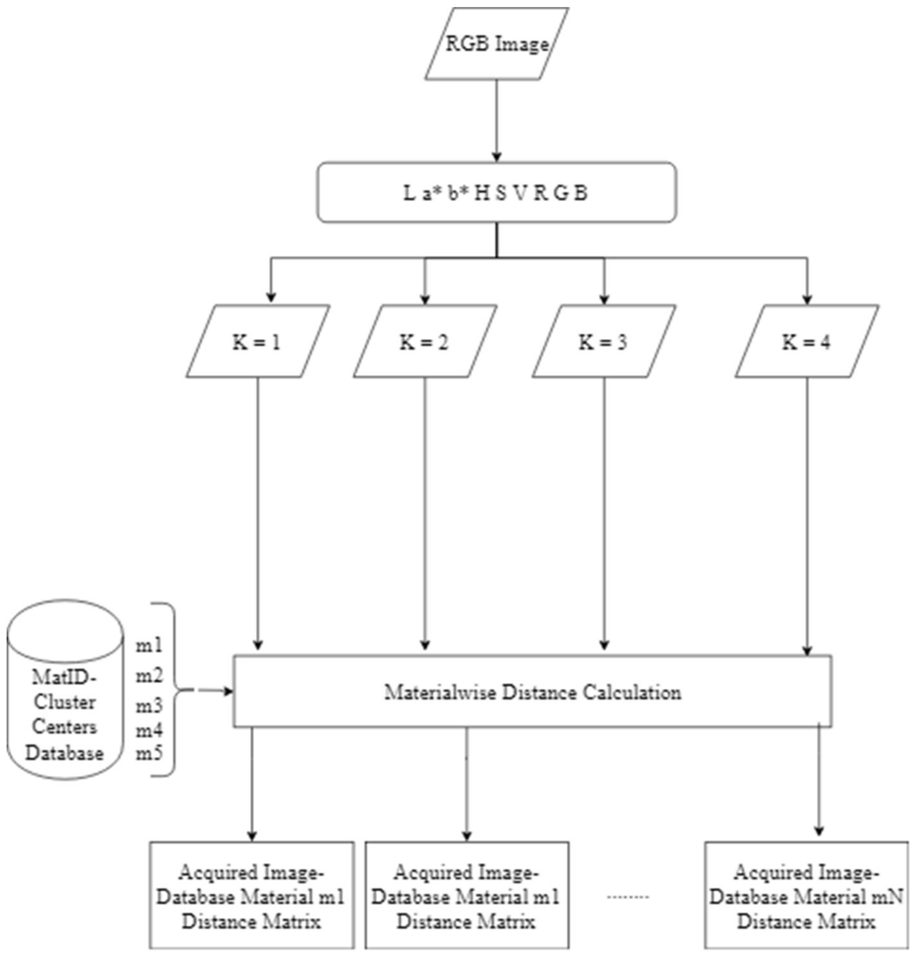


Figure 64 Process flow for material prediction in acquired image

In order to determine progress at a particular POI, the presence of material is determined using computer vision. Presence of a particular material corresponding to the activity that was planned to be performed on the last working day determines whether that activity has been completed or not. An acquired image to test the prediction algorithm is shown in Figure 65.

Figure 65: Image acquired for prediction of material using prediction algorithm.

The image is clustered, and cluster centers are obtained using K-means clustering algorithm explained in Figure 64 in details. Once clustering is completed, a matrix similar to that shown in Eq. (11) containing cluster centers is obtained. Euclidean distances ($D_{C_{A1}CM_{i1}}$) (see Eq. (16)) of cluster centers k (C_{Ak}) of acquired image from database material centers ($CM_{i1..iN}$) of material i having *N* samples obtained and tagged during learning process is acquired and stored in matrix form. A series of matrices, giving distances of *m* number of database material centers from acquired image cluster centers are denoted by $C_AD_{i..m}$. Each C_AD_x matrix will have distance centers with one material only and therefore for *m* number of materials there will be *m* matrices.

$$C_AD_i = \begin{bmatrix} D_{C_{A1}CM_{i1}} & \cdots & D_{C_{AK}CM_{i1}} \\ D_{C_{A1}CM_{i2}} & & D_{C_{AK}CM_{i2}} \\ \vdots & \ddots & \vdots \\ D_{C_{A1}CM_{iN}} & \cdots & D_{C_{AK}CM_{iN}} \end{bmatrix} \tag{16}$$

The cluster center distance matrix from material 1 for the test image (Figure 65) is shown in Eq. (17).

$$C_A D_1 = \begin{array}{c} \begin{array}{cccc} C_{A1} & C_{A2} & C_{A3} & C_{A4} \end{array} \\ \left| \begin{array}{rrrr} 260.07 & 88 & 78 & 405 \\ 197.02 & 40.96 & 155.49 & 338.55 \\ 247.94 & 92.49 & 63.81 & 393.38 \\ 304.31 & 163.94 & 31.98 & 439.31 \\ 262.73 & 101.92 & 43.25 & 405.93 \\ 283.08 & 132.87 & 9.16 & 422.38 \\ 287.36 & 135.69 & 1.93 & 425.96 \end{array} \right| \end{array} \quad (17)$$

Once $C_A D_i$ matrices are obtained, the column wise statistical measures, namely min, mean, median, and max of each column of the subject matrix is obtained in a tabular form as given in Table 15.

Table 15 Column-wise statistical metric of $C_A D_i$ Matrix.

$\min\{D_{C_{A1}CM_{i1}}, \dots, D_{C_{A1}CM_{iN}}\}$	$\text{mean}\{D_{C_{A1}CM_{i1}}, \dots, D_{C_{A1}CM_{iN}}$	$\max\{D_{C_{A1}CM_{i1}}, \dots, D_{C_{A1}CM_{iN}}\}$
$\vdots$	$\ddots$	$\vdots$
$\min\{D_{C_{A1}CM_{i1}}, \dots, D_{C_{A1}CM_{iN}}\}$	$\cdots$	$\max\{D_{C_{A1}CM_{i1}}, \dots, D_{C_{A1}CM_{iN}}\}$

The column-wise statistical material measure of $C_A D_1$ for the image in Figure 65 is given in Table 17 where thresholding is applied to determine whether any of clusters in C_A belongs to material 1. The thresholds for classification of materials are given in Eq. (18).

$$\min\{D_{C_{Ak}CM_{i1}}, \dots, D_{C_{A1}CM_{iN}}\} < 16 \wedge \text{mean}\{D_{C_{Ak}CM_{i1}}, \dots, D_{C_{A1}CM_{iN}}\} < 120 \implies C_{Ak} \in M_i \quad (18)$$

Table 16 Column-wise statistical measures for $C_A D_1$ Matrix.

Cluster	Min	Mean	Max
C_{A1}	197.02	263.22	304.31
C_{A2}	40.96	107.98	163.94
C_{A3}	1.93	54.80	155.49
C_{A4}	338.55	404.36	439.31

The thresholds for min and mean distance determined presence of material in a particular frame. It is observed in Table 16 that material three has the least values for minimum distance and mean distance, therefore it can be inferred that material three among all materials to those present in the acquired image. Using the criteria of minimum distance, it can be inferred that $C_{A3} \in M_3$. The thresholds and their tuning to obtain optimum values are discussed in later section.

5.5. Prediction of Element State

5.5.1. Context Awareness based on the Logic of Scheduling

In material classification related studies based on content-based image retrieval [26] or material recognition algorithms [158], false positives are an indication of performance gap in the algorithm which is not the case for SCAER. False positives do not have an impact on the overall performance of the algorithm until or unless material of preceding or the following activity is falsely detected instead of relevant material depicting a particular state at a specific POI. Figure 66 shows false positives that affect the performance of the algorithm by falsely depicting progress at POIs when there is no progress. As seen in Figure 67, if formwork is falsely detected in images that were containing reinforcement, progress will be falsely predicted while there will be none. This is the case of false detection of material denoting the previous state, and this will result in the false conclusion that POI is behind schedule. Progress is falsely detected when expected state from current POI activity is detected instead of relevant material that is associated with preceding state.

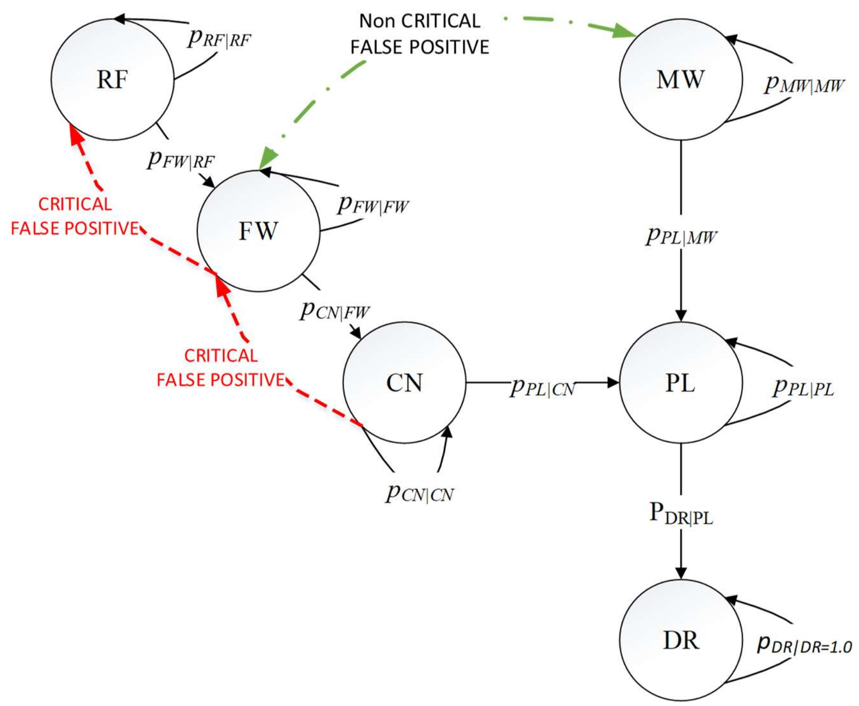


Figure 66 False positives affecting results vs false positives not affecting results.

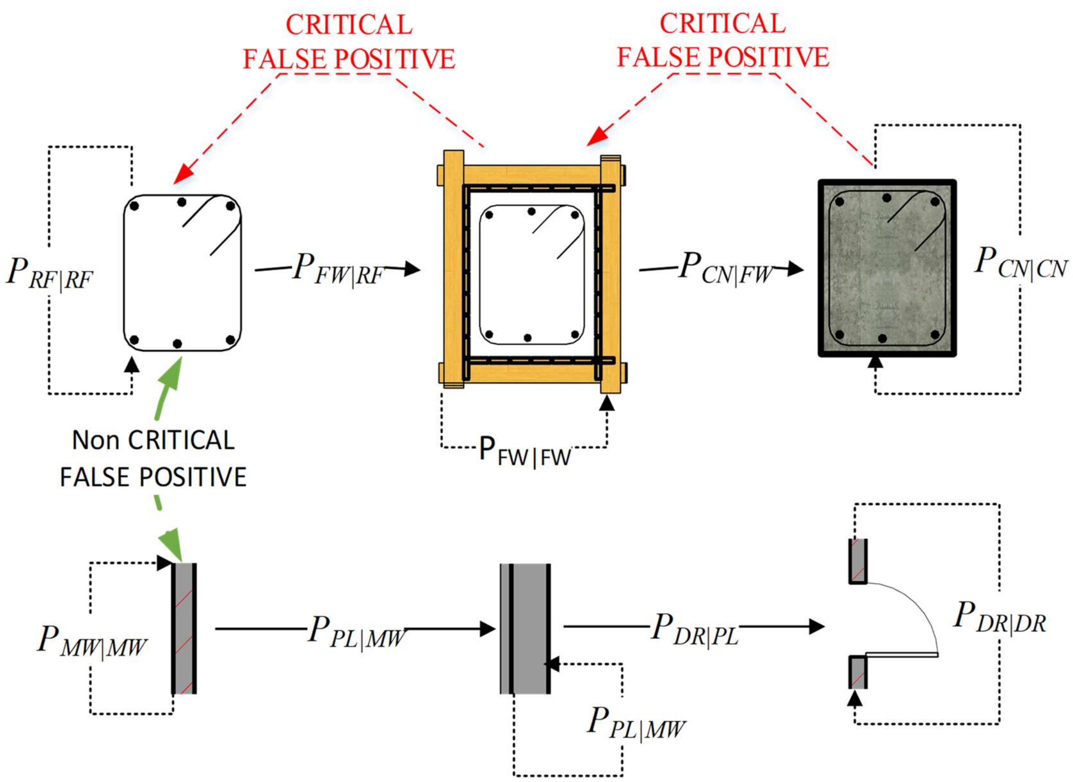


Figure 67 Critical vs noncritical false positives represented on BIM elements.

5.5.2. Prediction based on Probability of Presence

The process flow for prediction server level operations is shown in Figure 68, where a file watcher is waiting for an image to arrive from an acquisition device over Wi-Fi via PHP post request. PHP is a script language and interpreter which is freely available and used primarily on Linux Web servers, used for all communications between client and server. As soon as the image reaches the server, it contains the activity ID and POI information. The server code saves the images in the relevant POI folder with the activity ID, POI name, and other important image information such as the file name. The computer vision algorithm then gets into action, to determine the most probable current state of the element being evaluated. If the expected state matches the planned state of the element, the activity is deemed to be completed, and the same is marked in the schedule CSV.

The image-based probability of a particular state to occur at a particular instant is the ratio of a number of frames where planned material is detected to the total number of framed acquired as seen in Eq. (19). If the probability of a planned state is high, i.e, greater than 0.5, activity is deemed to be completed and activity is deemed to be delayed if the image based probability is less than 0.5 as shown in Eq. (20).

$P_{P\|C} = \frac{No. of\ frames\ where\ planned\ state\ is\ detected}{Total\ No.\ of\ frames}$	(19)
$P_{P\|C} > 0.5 \Longrightarrow X^t \epsilon\, p\ \wedge\ P_{P\|C} > 0.5 \Longrightarrow X^t\ \notin p$	(20)

Where $P_{P|C}$ is the probability of Planned State (P) given Confirmed State (C) while $P_{C|C}$ is the probability of C which remains the same and doesn't change. X represents the state of the element at time t.

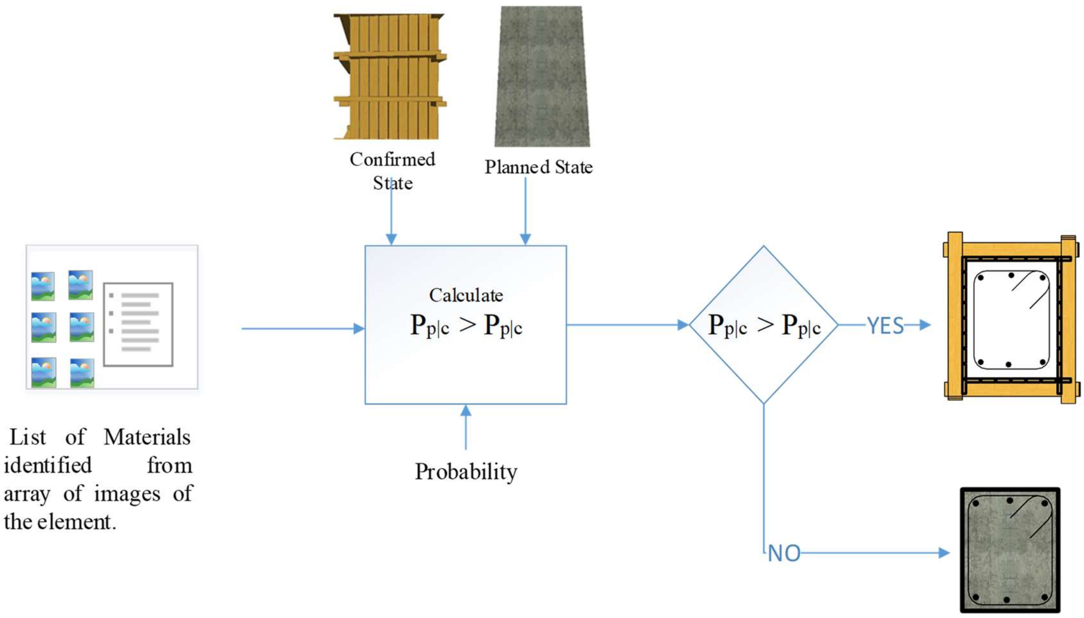


Figure 68 Element state prediction process.

The change in state is marked on schedule CSV file as a completed activity which is then fed into a planning software to visualize planned vs actual progress or recompute schedule using critical path method. As discussed in the previous section, the number of false positives will not affect the performance of the algorithm until or unless it confuses with the state of the preceding activity. This can help in keeping more liberal thresholds thus increasing overall recall. It has been observed that in all cases except the reinforcement, relevant materials were detected in more than fifty percent of the frames.

5.6. Parameter Tuning

5.6.1. K Clusters

A number of clusters have been decided earlier and are based on efficiency and optimum output. Increasing number of clusters beyond the elbow point (optimum) doesn't yield sufficiently better results. There is no method of determining the exact value of K, however, in the case of this research, it has been observed that all images contain 4 or less than four colors. The distance between cluster centers is decreased if K=4 is used for an image containing three colors and the same color is observed in multiple clusters. As observed in Figure 69, using 4 clusters for K-means clustering yields the best results with minimum number of clusters.

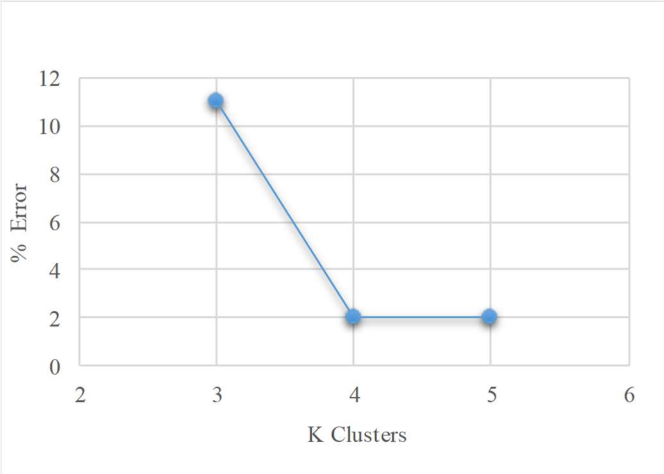


Figure 69 K value vs. % recall error chart.

5.6.2. Threshold

Thresholds are critical in determining the success of an algorithm. When they are too conservative false negatives will be in excess due to the inability of the algorithm to detect materials that are existing in the image. Contrary to this, making threshold too liberal would result in excessive false positives where materials absent in image will be falsely inferred by the algorithm as present.

Min Distance Threshold; variation in error with different min thresholds is shown in Figure 70. It can be inferred from the chart that minimum error value between 15 and 18 will yield optimum results. The input vector is nine-dimensional which would result in high Euclidean distances even for centers that are relatively close to each other, thus reducing threshold beyond optimum increases false positives. Variation from cluster centers is expected in cases when one clustered image may have traces of multiple materials.

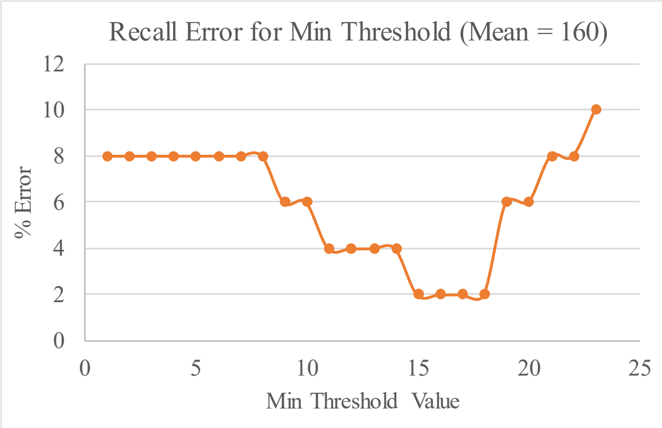


Figure 70 % Recall error variation with change in min distance threshold.

Mean Value Threshold; is the secondary threshold to ensure that an outlier with low minimum value but high remaining cluster center distances aren't inferred as a positive material presence in a picture. The effect of multiple threshold values on error is shown in Figure 71.

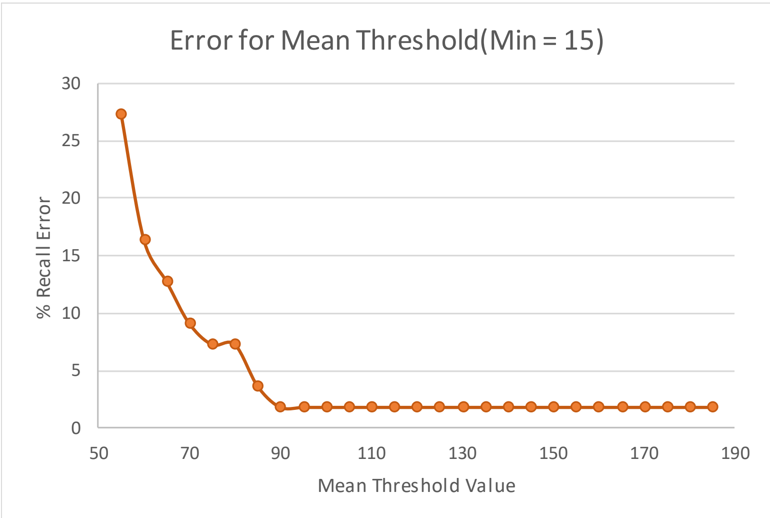


Figure 71 % Prediction error for different values of mean.

5.6.3. Color Space

As discussed in the previous section, L, a*, b*, H, S, V and R, G, B color models are used within the scope of this research. Different combinations of color models were tried to see their effect on error. A total of 4 possible combinations of color spaces are possible which are shown in Figure 72. Four complete learning and prediction algorithms were performed using the color model feature vectors with combinations and the resulting errors are reported in Figure 73. Similar errors with LABHSV and HSVRGB feature vector combination were observed while maximum error was observed in LABRGB combination. 9 feature vector space with LABHSVRGB space showed minimum error during development of algorithm.

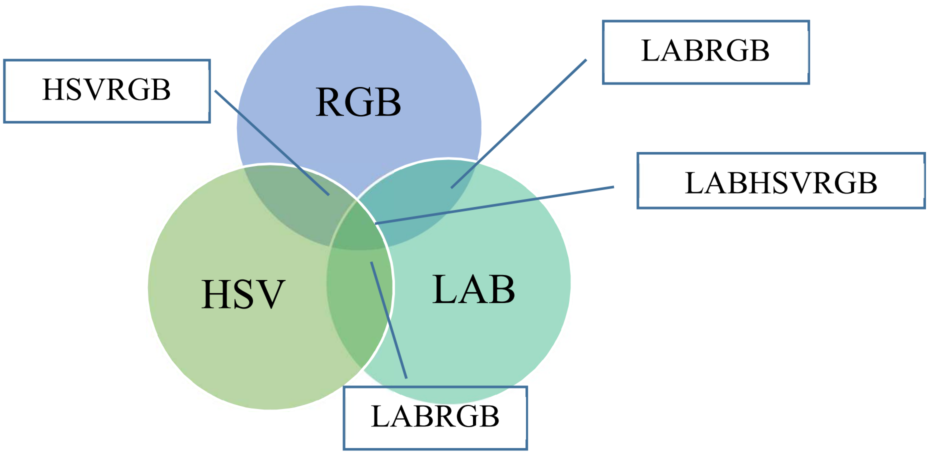


Figure 72 Color model combination for feature vector.

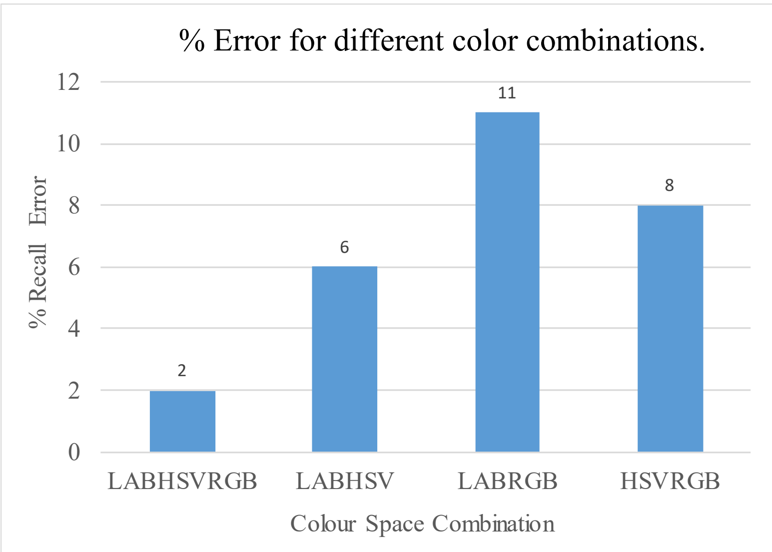


Figure 73 Percent error for different color space combinations.

This chapter summarized the computer vision algorithm that forms the core of SCAES. The image has been segmented using K-means clustering followed by presence of material determination based on Euclidean distance from samples in the database using a minimum threshold criterion. Different color spaces were tested, and the results were compared. It has been observed that using the LAB, HSV, RGB combined space gives the optimum results.

5.7. SCAER Validation Using Site Images

A pilot implementation of SCAER was conducted on two under construction structures in Middle East Technical University (METU), Ankara, which were in different stages of construction. The Educational Science Department Building (ESDB) already mentioned in EAPE chapter is a multi-story concrete structure shown in

Figure 74. The structure is in initial stages of construction, and only mat foundation along with underground tanks have been poured till the time that the access to the site was granted. Formwork (FW), Concrete Work (CW), and Reinforcement (RF) state detection cases have been evaluated in this structure.

Figure 74 Images of under construction (a) Educational Science Department Building, (b) Classroom Hall Building.

The second structure for the case study was central classroom hall building (CHB) which contains class rooms as well as large auditoriums with overhangs. The structure has a wider variety of walls such as light weight cement, red brick, and panel walls. The structure has concrete pouring activities as well as masonry work activities being performed at the time of grant of access. The site is a three-story structure with an area of approximately 5000 m^2. The structure was already in its advanced stages of completion when access was granted and most of the concrete work had already been completed. MW, CW, and DR installation states at different points have been evaluated at CHB site.

5.7.1. Evaluation Metrics

The accuracy of material identification using SCAER was measured by evaluating detected and actual materials in each frame to determine which category of decision table does the resulting detection belongs. Frame is appearing in the list of 'Detected Materials' but absent from the list of 'Relevant Materials', is classified as False Positive, while frames where material m is not detected but is present in 'Relevant Materials' list for that frame is determined as False Negative. Decision table, given in Table 17 determines the performance of an algorithm based on Precision and Recall, as seen in Eq. (21). Suppose we have an F number of frames, T_m be the number of relevant frames where material m is presented; d_m is number of relevant frames where material m has been detected by SCAER; N_m is the total number of frames where material m is detected.

Table 17 Decision Table.

	Detected	**Not Detected**	**Total**
Relevant	d_m (True Positive)	$T_m - d_m$ (False Negative)	T_m
Irrelevant	$N_m - d_m$ (False Positive)	$(F - N_m) - (T_m - d_m)$ (True Negative)	$F - T_m$
Total	N_m	$(F - N_m)$	

Performance characterization of SCAER uses performance characteristics (Eq. (21)) developed in last three decades for probabilistic text retrieval [159] which has also been used in content-based image retrieval [26].

$$Recall = \frac{d_m}{T_m}, \qquad Precision = \frac{d_m}{N_m}$$	(21)

5.7.2. Sampling

The POI is containing materials in CACL that were selected for verification of SCAER. Sample locations were marked on BIM that was created in Revit using Keynotes, which is a parameter to tag the elements with standard CSI keynotes or custom keynotes. Custom keynotes were used to create a POI-wise list of activity IDs. Each sample POI was then tagged with activity ID (see Figure 75) to annotate the expected state at the POI which will be determined. A complete list of activities that were monitored at ESDB for verification of CAPMS and a summary of the type of activities that were monitored on each floor is shown in Table 18.

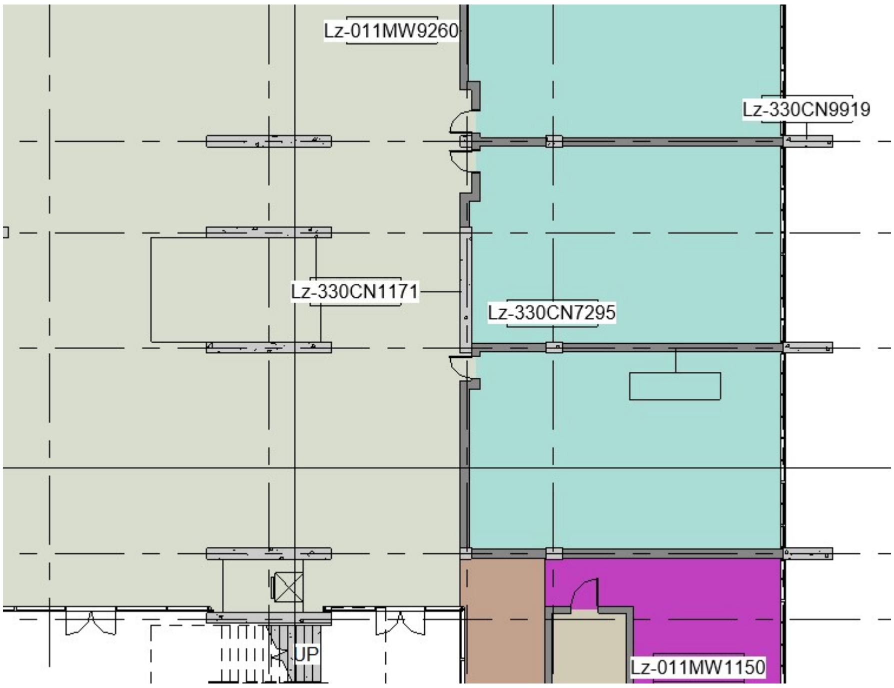


Figure 75 Test locations marked according to activity on floor.

Elements were selected to ensure validation of SCAER on elements of varying sizes that are located across the site at different levels. An attempt was made to bring diversity to sampling and while avoiding repetition of similar types of elements which may share spatial location, dimensions or materials from the same stockpile. CHB was at its finishing stage with the majority of concrete work completed and brick masonry work in progress. Concrete columns, being omnipresent, had a maximum number of samples (see Figure 76(a)), followed by non-structural elements that included masonry walls and doors. The purpose of the case study was to determine the performance of the code in ascertaining expected state of the EOI. Figure 76 (b) contains concrete columns forming the framing of the structure along with walls that were monitored for testing.

Table 18 Activity monitoring list for ESDB.

Lvl	Activity ID	POI	Description	Category	Family	Act Type	Ser
L1	L1-100CN9239	329239	Concrete Work and Removal of Formwork 130x30 Concrete Column	Columns	130x30 Concrete Column	CN	1
L1	L3-100CN7918	427918	Concrete Work and Removal of Formwork 130x30 Concrete Column	Columns	130x30 Concrete Column	CN	2
L1	L3-100FW7922	427922	Installation of Formwork for 70x40 Concrete Column	Columns	70x40 Concrete Column	FW	3
L1	L3-100FW7923	427923	Installation of Formwork for 70x40 Concrete Column	Columns	70x40 Concrete Column	FW	4
L3	L1-100FW9196	329196	Installation of Formwork for 130x30 Concrete Column	Columns	130x30 Concrete Column	FW	5
L3	L3-100FW7924	427924	Installation of Formwork for 70x40 Concrete Column	Columns	70x40 Concrete Column	FW	6
L3	L3-100FW7925	427925	Installation of Formwork for 70x40 Concrete Column	Columns	70x40 Concrete Column	FW	7
L3	L3-100FW7926	427926	Installation of Formwork for 70x40 Concrete Column	Columns	70x40 Concrete Column	FW	8
L3	L3-100FW7927	427927	Installation of Formwork for 70x40 Concrete Column	Columns	70x40 Concrete Column	FW	9
L3	L3-100RF1124	411124	Rebar Placement for 70x40 Concrete Column	Columns	70x40 Concrete Column	RF	10
L3	L3-100RF7910	427910	Rebar Placement for 130x30 Concrete Column	Columns	130x30 Concrete Column	RF	11
L3	L3-100RF7911	427911	Rebar Placement for 130x30 Concrete Column	Columns	130x30 Concrete Column	RF	12
L3	L3-100RF7912	427912	Rebar Placement for 130x30 Concrete Column	Columns	130x30 Concrete Column	RF	13
L3	L3-100RF7913	427913	Rebar Placement for 130x30 Concrete Column	Columns	130x30 Concrete Column	RF	14
L3	L3-100RF7914	427914	Rebar Placement for 130x30 Concrete Column	Columns	130x30 Concrete Column	RF	15
L3	L3-100RF7922	427922	Rebar Placement for 70x40 Concrete Column	Columns	70x40 Concrete Column	RF	16
L3	L3-100RF7923	427923	Rebar Placement for 70x40 Concrete Column	Columns	70x40 Concrete Column	RF	17
L3	L3-100RF7924	427924	Rebar Placement for 70x40 Concrete Column	Columns	70x40 Concrete Column	RF	18
L3	L3-100RF7925	427925	Rebar Placement for 70x40 Concrete Column	Columns	70x40 Concrete Column	RF	19
L3	L3-100RF7926	427926	Rebar Placement for 70x40 Concrete Column	Columns	70x40 Concrete Column	RF	20
L3	L3-100RF7928	427928	Rebar Placement for 70x40 Concrete Column	Columns	70x40 Concrete Column	RF	21
L3	L3-100RF7929	427929	Rebar Placement for 70x40 Concrete Column	Columns	70x40 Concrete Column	RF	22
L3	L3-100RF7930	427930	Rebar Placement for 70x40 Concrete Column	Columns	70x40 Concrete Column	RF	23
L3	L3-100RF7931	427931	Rebar Placement for 70x40 Concrete Column	Columns	70x40 Concrete Column	RF	24

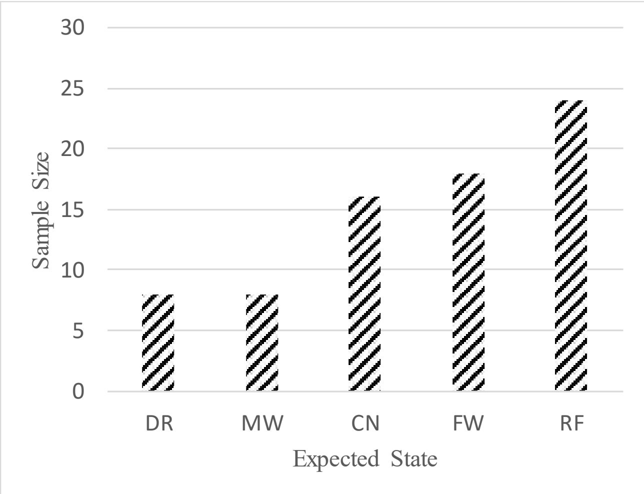


Figure 76 Sample size for (a) Category (b) Expected State; where, DR: Door, MW: Masonry Work, CN: Concrete, FW: Formwork, RF: Reinforcement.

The frequency of visits to the site is based on the expected change in the state of activity and frequency of visit is not fixed which can be either on consecutive days or weeks depending upon the duration between activities and expected change in state. Image acquisition device or the so-called BAAP can move on site only on timings of break between construction operations to have a pervasive and non-invasive monitoring mechanism. Also, during working hours, movement of robot and materials will affect BAAP navigation and compromise its safety. The timings of the day for data collection should also be considered as it can affect lighting, humidity, temperature, and exterior elements facing the sun, i.e., North, South, and West.

5.7.3. Material Recognition from Site Images

In this section, recall for the Expected States of samples are discussed separately along with the reason behind recall values. The threshold for minimum distance value of materials in database cluster to the cluster center from acquired images at POI is kept at 26 for all expected state detections in this section.

Concrete Work (CN), which most of the structure comprises of, can be safely classified as the primary material both structurally and visually. Regular pre-mix concrete is used without any color additives. Columns and shear walls are photographed to determine their performance using vision based algorithm. Figure 77 shows cluster containing concrete column element extracted from an image obtained from the site. The algorithm has been very successful with concrete and has been able to detect concrete in more than 80% of the cases. Concrete was detected in at least 50% of the images obtained at each POI as seen in Figure 78. Glare had a negative effect on detection, and all POIs with 50% true negatives had sun rays directly incident on the imaging sensor. In the majority of cases, there were no glare issues, and 100% of such pictures had the concrete element correctly detected.

Figure 77 (a) Concrete column images using robot at 45 degrees (b) Extracted column from the image.

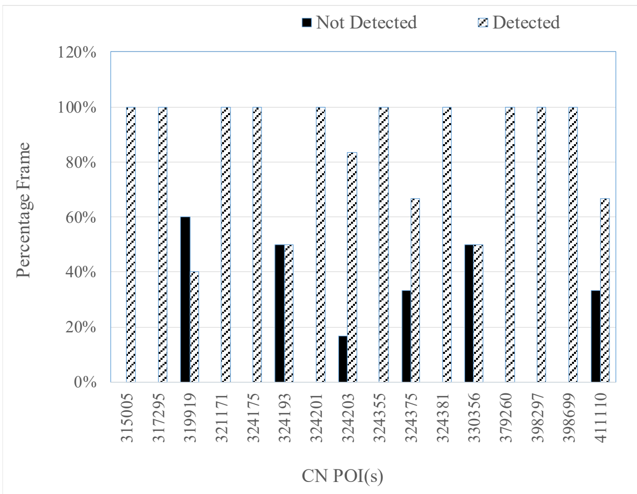


Figure 78 Correctly detected concrete from column POIs.

Concrete elements are solid, usually rectangular with dimensions greater than 50 cm, because of slenderness related constraints. Due to the size of the concrete elements, they usually encompass a large number of pixels and are not affected by minor occlusions.

Formwork (FW) being the prior requirement to concrete work is an important task that will be used to validate the vision algorithm. Images are taken after installation of formwork (see Figure 79) to see if the algorithm detects the presence of formwork or not. Doka formwork is installed on the test structure which consists of vertical wooden beams which are yellow in color and horizontal steel beams which are red. The plywood component that forms the concrete surface is dark brown and will not be considered in learning and validation of the algorithm.

Figure 79 (a) Image with formwork (FW) with (b) extracted formwork from the image.

Figure 80 shows POI-wise recall on the image of formwork. It is observed that formwork showed recall greater than 90% in all instances. The reason being that formworks are bright in color contrasting with their background or any element on site. Formworks are reusable and weathered unless formwork is being used for the first time, the faded color may fail SCAER to detect formwork. Nevertheless, in all the cases, the algorithm was able to detect FW in 50% or more of the acquired frames.

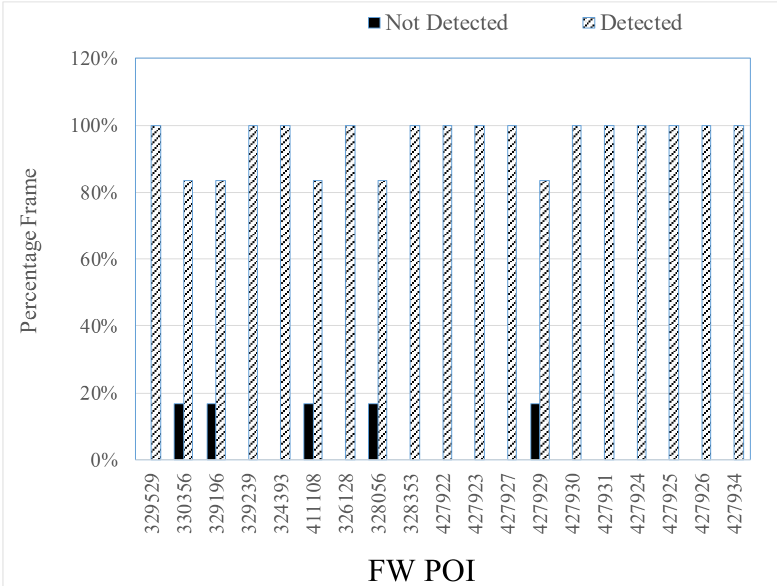


Figure 80 Correctly detected formwork POI.

Masonry Walls (MW) in ESDB and CHB sites were of lightweight concrete, red brick, and modular pre-fabricated panels. Walls are constructed after column and slab work has finished and all formwork has been removed from the interior. Walls are also a very visible component and, therefore, selected for the validation study. Figure 81 shows masonry extracted from the image acquired from the site. Although the Lightweight concrete is similar to column concrete, however, contrast in color and presence of only two materials in the frame allowed clear extraction of masonry work. Figure 82 shows recall from masonry work images where it is observed that wall element had recall greater than 90%. All frames on all elements are detected except one POI, where only in 60% of frames the algorithm was able to detect masonry using SCAER.

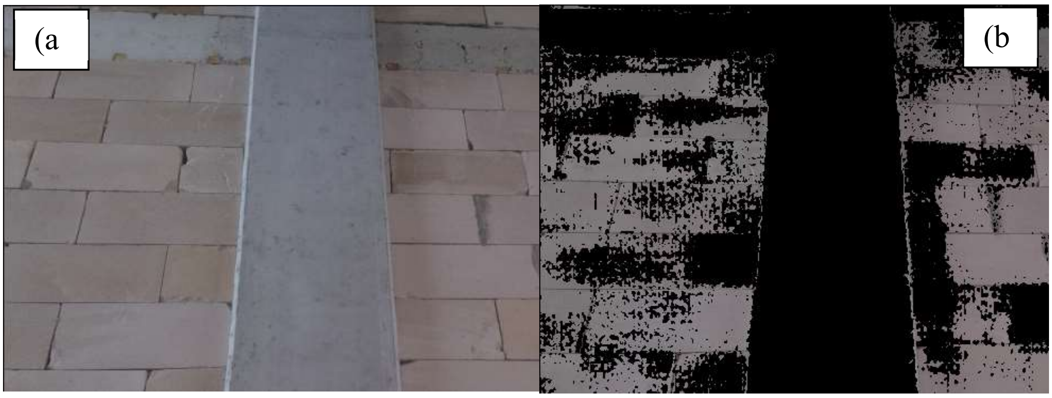


Figure 81 (a) Image with masonry and concrete (b) Extracted masonry from the image.

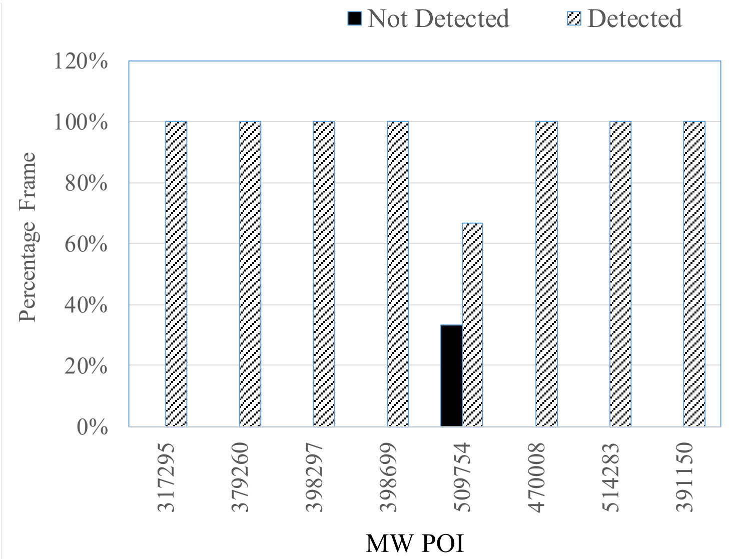


Figure 82 Correctly detected concrete from masonry POIs.

Walls like concrete are large elements occupying the complete frame captured by the imaging sensor. They are monochromatic and homogeneous except mortar joint, which was of the same color as the wall block in the case of a project under consideration because of LWC blocks that were used. Wall elements lacking any discontinuities were not affected by background elements.

Reinforcement image obtained from the site is shown in Figure 83(a) and extracted reinforcement cluster is shown in Figure 83 (b). They are very thin elements, don't occupy a large number of pixels and, if the distance from Element increases, the width of reinforcement may encompass less than one pixel making them hard to detect.

Figure 84 shows POI-wise recall of reinforcement from images taken at respective POIs. It is observed that reinforcements have a low recall as compared to all other materials. Reinforcement members are thin and affected by background elements that are completely visible causing a reduction in recall.

Figure 83 (a) Image with reinforcement (b) Extracted reinforcement from image.

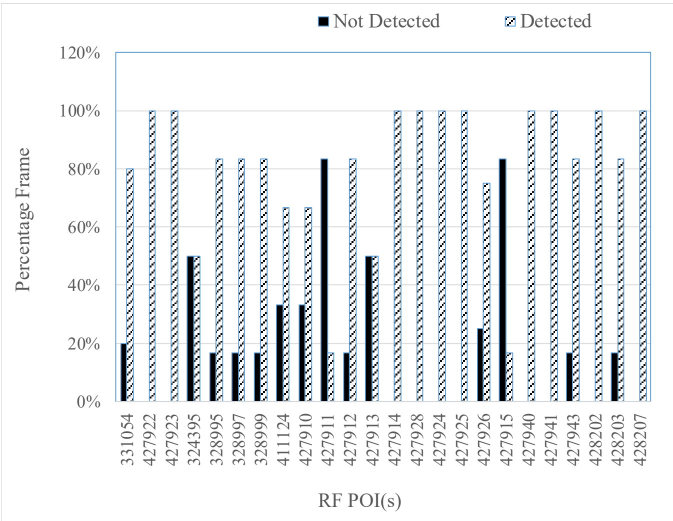


Figure 84 Correctly detected POI for reinforcement.

In two instances, SCAER was not able to detect reinforcement in even 50% of frames obtained at those particular POIs. The reason being their thin structure and rust that forms quickly especially in the open environment, as they are kept open on most sites. They are cut, bent and later fixed keeping them in contact with dust and dirt creating a coating that may change the appearance of reinforcement further reducing the probability of detection. Reinforcements are always installed in the open and outdoor imaging is affected by glare problem especially when imaging in done on a very sunny day or if the focal axis of the camera points toward the sun.

Doors (DR) installation is performed in later stages of construction and is determined using color information. Doors can be made up of glass, wood or steel, with paint applied either on-site or at factory. The structures had a long time before door installation could start and therefore validation of SCAER on doors was performed in another structure that was already constructed and in-use. The doors are similar to those expected on site, mostly consisting of single or double leaf painted doors giving classrooms access to corridors. Figure 85 shows the door image attained from site and door cluster extracted from it. As seen in Figure 86, Doors have a recall greater than 90% due to their homogeneity and monochromatic nature.

Figure 85 (a) Image with formwork (b) Extracted formwork from the image.

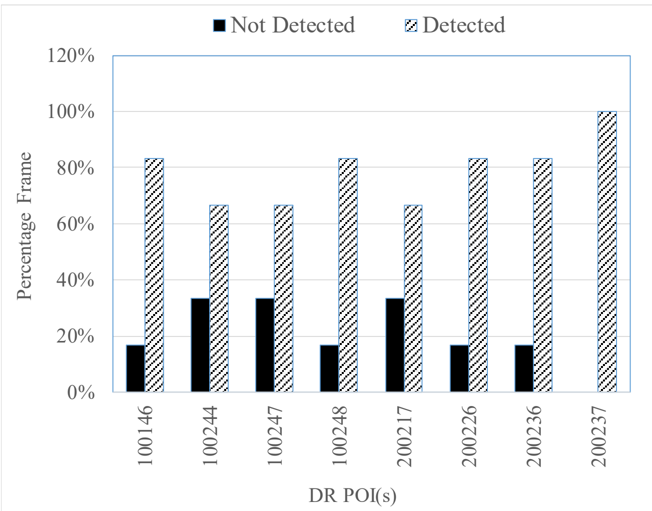


Figure 86 Correctly detected door in frames acquired for each POI.

Doors are again large elements that occupy 50% of the pixels on the frame, and the clusters are well packed due to the homogenous nature. No discontinuities are present, and therefore no background noise is observed. Since all doors imaged during the scope of this research are installed indoors, glare is not an issue. Doors provide better result as compared to other homogeneous elements like concrete columns since the color of doors contrasts with its surroundings.

5.7.4. False Positive and Confusion

False detection of materials in images that are not present, is also called confusion of one material with the other. Figure 87 shows the confusion of concrete work, which is preceded by formwork and followed by plastering and painting. The architecture of structure in consideration followed a brutalist approach. Therefore, there was no activity following concrete work.

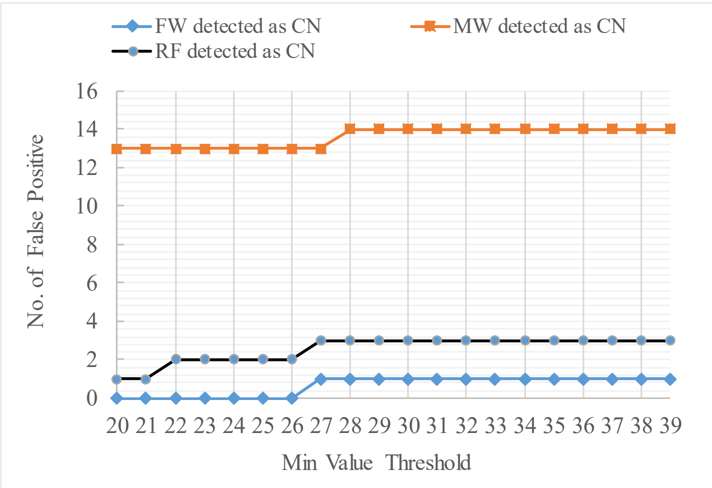


Figure 87. False positive of CN with all other materials for different minimum threshold values.

Figure 88 shows the confusion of formwork with other materials, being the only directly connected activity on the same POI, is the point of concern and it was observed that formwork was not confused with concrete for minimum value threshold of 24 or less. The color difference and the decision to use the stiffeners for developing material signatures for FW completely removed confusion for concrete.

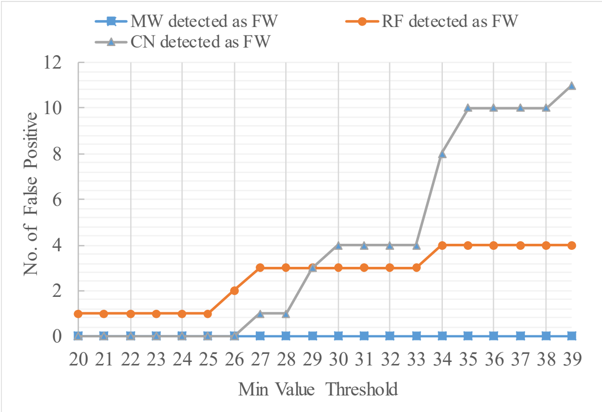


Figure 88 False positives of FW with all other materials for different minimum threshold values.

Figure 89 shows the confusion of Masonry with other materials. There is no preceding activity for masonry wall locations. Although it has a high degree of confusion with concrete due to its cement-based constituents, it does not affect the performance of SCAER. Masonry work will be followed by painting and plaster work, but these activities could not be monitored since they did not occur during the window of site access granted by the project management.

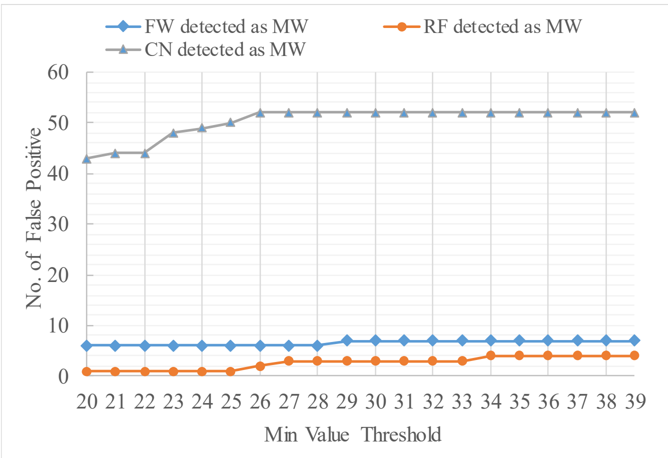
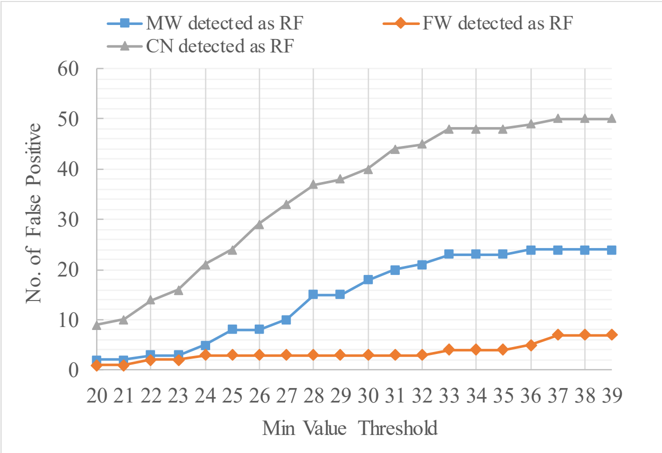


Figure 89 False positive MW with all other materials for different minimum threshold values.

Figure 90 shows confusion for Reinforcement (RF). RF precedes FW and followed by CN, and it can be observed for threshold values of less than 26. FW has no confusion with concrete but a limited confusion with RF. RF consists of thin members; the presence of background noise affects reinforcement and tends to confuse it with formwork especially when threshold value increases.



(d)

Figure 90 False positives of RF with other materials for different minimum threshold values.

5.7.5. Element State Prediction Recall

As discussed in the previous section, the number of false positives will not affect the performance of the algorithm until or unless it confuses with state of preceding activity. This can help in keeping more liberal thresholds thus increasing overall recall. It has also been observed that in all cases except reinforcement, 50% or more frames were detecting the relevant material. Hence it can be considered as a threshold for determination of Element state at POI. Following this rule CN, MW, and FW were correctly detected as current state for all relevant POIs (See Figure 91). RF is the only expected state that has a recall of less than 100% which is caused by its form, presence of dust/rust, background noise and presence in the open environment being subject to glare.

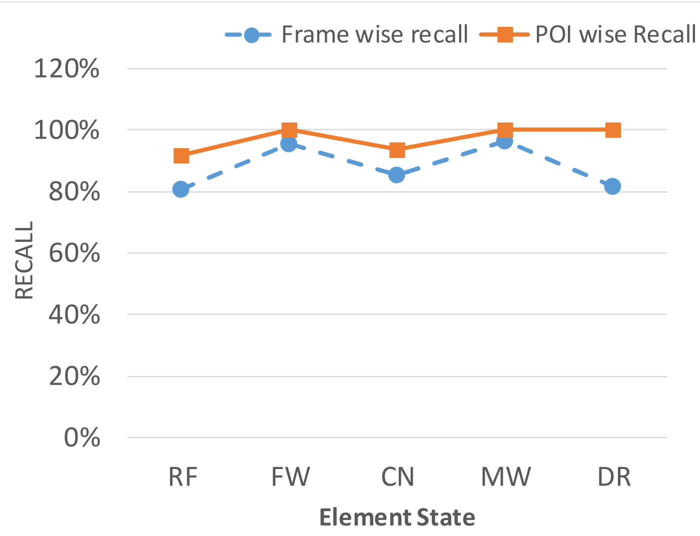


Figure 91 Percent recall for materials in the project.

This result is a considerable improvement over CBIR [26], [55], and 4D photo-log [160] based images detection since none of those cases will be able to give 100% recall for any element. It has only been possible due to the use of context-aware schedule based algorithm that reduces search space to only a couple of materials that may represent the preceding state or the expected state. Acquisition of multiple images at every POI also reduces the probability of a false detection since one or more images are affected by environment or hardware related issues.

5.8. Conclusion

SCAER uses contextual information to attain accurate element state information that is used for progress measurement. The contextual information is attained from the schedule and provides robust results as compared to other image-based progress monitoring techniques that rely solely on computer vision algorithms. The algorithm was able to detect concrete, formwork, masonry, and door with accuracy greater than 95%. However accuracy for detection of rebar was less than 90% because of background noise and thin structure of elements. Although individual frame wise accuracy goes down to 80% due to the presence of images with lighting and glare, use of multiple images and contextual information improves the accuracy of the proposed methodology to 100% for some cases like masonry, doors, and formwork. Pattern information can also be used to further improve the accuracy of SCAER.

Construction imaging can be done in varying site conditions in the presence of clutter with an element in different conditions due to dust. Therefore computer vision algorithms does not always give desired results. SCAER covers this gap and provides robust information for fully automated progress determination. Image acquisition is an important aspect of SCAER which is done using BAAP, which has been discussed in the previous chapter.

CHAPTER 6

PROGRESS SIMULATION AND VISUALIZATION

An End to End implementation of CAPMS is performed on a simulated structure to validate its performance using actual site image and estimated cost performance. This chapter verifies all processes in CAPMS by implementing them on an imaginary structure.

6.1. Framework for Progress Visualization using Dashboard in CAPMS

A well-devised dashboard is an effective tool for project control. A real-time control allows the management team to make small changes that may add-up to make a tangible effect on a project's performance. The approach to building the dashboard is to use common questions that the project management team needs to answer. A construction manager would require to answer the following questions:

1. Is my project on schedule? What is the budget cost of work scheduled?
2. Is my project on-budget? What are the budgeted cost and actual cost of work performed?
3. How far behind or ahead is the project from schedule and budget?
4. What percentage of the project is complete? What is the rate of progress throughout the project?

The answers to questions one and two is Budgeted Cost of Work Scheduled (BCWS), Budgeted Cost of Work Performed (BCWP) and Actual Cost of Work Performed (ACWP) measures (see Figure 92 (a)) while CI and SI measures (see Figure 92(c)) will answer question three. The S-curve and progress measures (see Figure 92(b)) will provide the rate of progress and percent progress respectively. The SI and CI are attained using the relation given in Eq. (22)).

$SI_T = \dfrac{BWCP_T}{BCWS_T}; \quad CI_T = \dfrac{BWCP_T}{ACWP_T}$	(22)

Where, $BWCP_T$ is Budgeted Cost of Work Performed at time T, $BCWS_T$ is Budgeted Cost of Work Scheduled at time T, $ACWP_T$ is Actual Cost of Work Performed at time T.

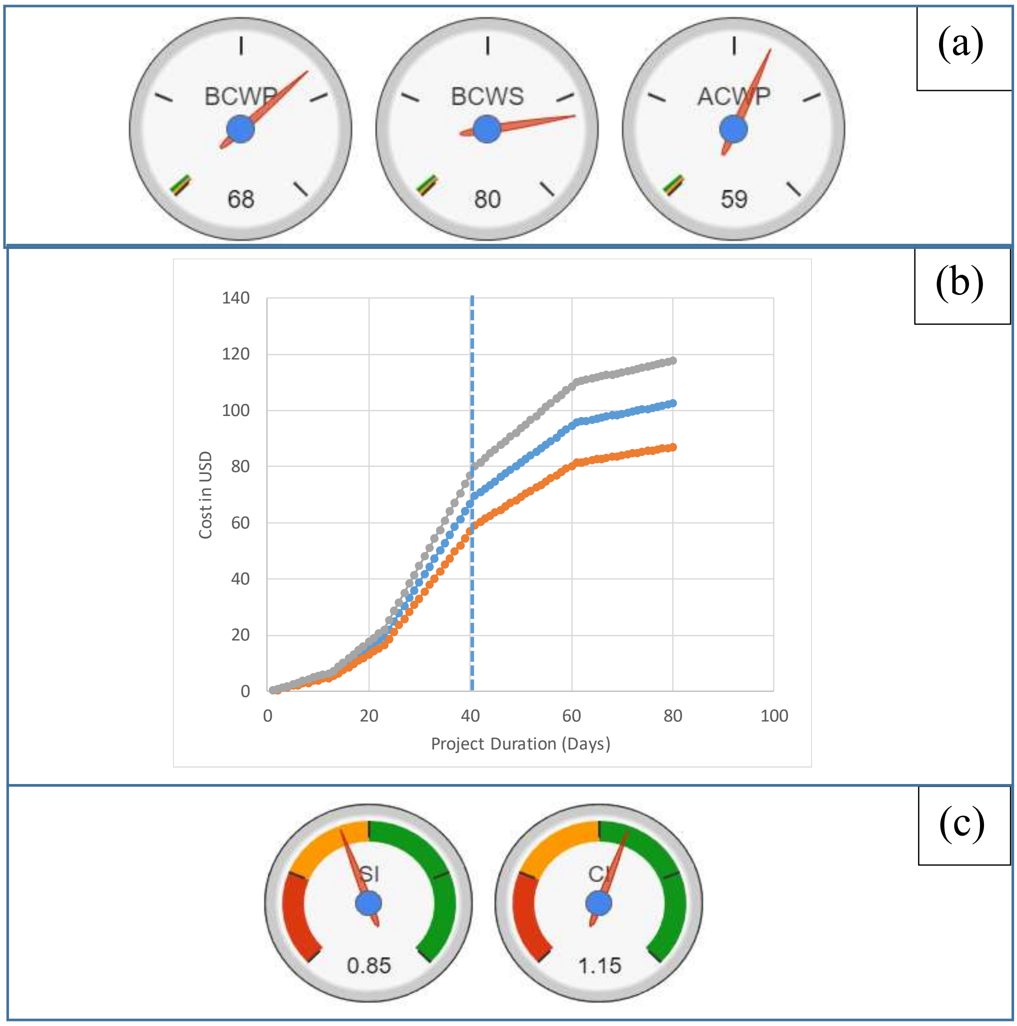


Figure 92 Project management dashboard.

Dashboards provide great advantage over traditional paper-based monitoring techniques, however, to get full benefit the data should be attained systematically and should be reliable. Figure 93 shows data acquisition and processing methodology for dashboard update using 4D BIM. BAAP attains daily monitoring list from 4D BIM based on activities completed on the last working day, navigates to the site and attains images of BIM elements which are processed using SCAER where the previously confirmed state is compared with the scheduled state to determine its actual state. The cost which is stored in BIM as a parameter for each element is queried to determine BCWP. The BCWS is attained from the baseline schedule and is updated whether any progress has or has not been achieved while ACWP is attained from the company cash flow and accounts. If the progress is confirmed, ACWP, BCWP and BCWS is updated using cost information queried from BIM. These metrics are then used to calculate CI, SI and Percentage Progress using Eq. (22) for visualization of the measures and charts in the dashboard (see Eq. (23)).

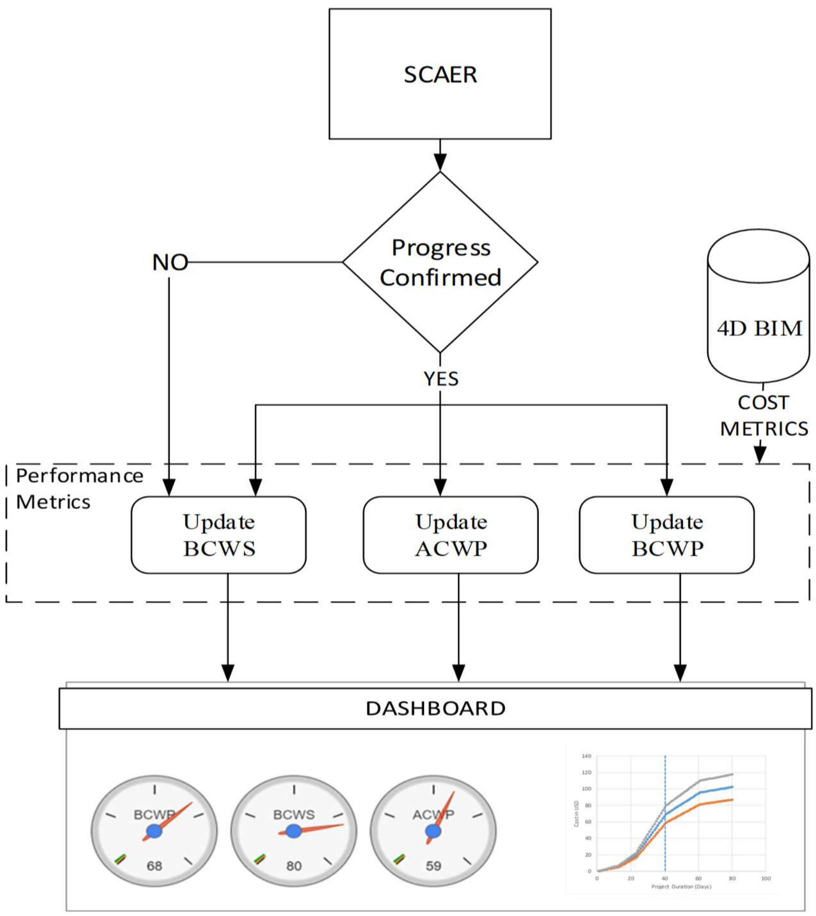


Figure 93 Schedule update from POI and dashboard update.

$$Percentage\ Progress_T = \frac{BCWP_T}{Total\ Cost}$$	(23)

The cost metrics are visualized on a dashboard (see Figure 94) for birds eye view of progress and instant update to the management team without any extensive calculation. The proposed dashboard has a summary schedule which is a direct output from the planning software, providing the percentage completion of summary activities and milestones (see Figure 94 (a)). The S-Curve provides the rate of progress throughout the project (see Figure 94 (b)) showing how progress varied through different stages of construction and whether the rate is slowing down for the management team to take corrective action. Dial gauges for cost-based metrics that include BCWP, BCWS, ACWP (see Figure 94 (d)) and the performance parameters as CI and SI (see Figure 94 (c)). The percentage progress bar shows the progress completion as a ratio of BCWS and Total Cost of Work Calculated during the creation of baseline schedule SI (see Figure 94 (e)). The ID of last activities performed and checked by BAAP are also enlisted for information of project stakeholders (see Figure 94 (f)). The dashboard is not only useful for the management team and assists them in making a timely decision, but it is also useful to stakeholders in a remote location and interested in determining the state of the project through an independent source.

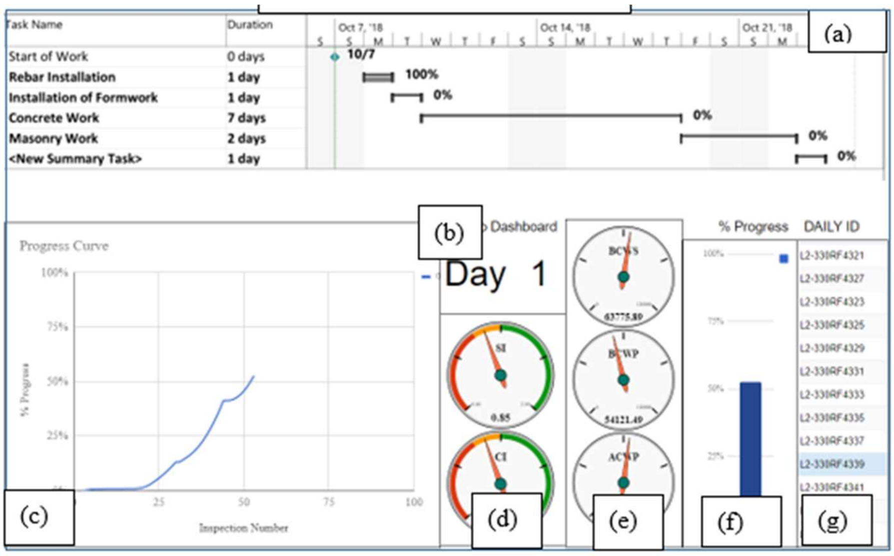


Figure 94 Cinfo dashboard with (a) updated Gantt chart tracking, (b) Day of last activity, (c) S-curve (d) KPI (e) Cost Metrics (f) Progress bar (g) Daily monitoring list.

6.2. Simulated structure and activities tracking

End to End (E2E) validation of the proposed automated progress monitoring system, CAPMS, was performed on a virtual structure through various stages of its simulated progress. Simulation is kept as realistic as possible by using images of actual elements taken from the construction site at various stages of progress. Figure 95 shows the floor plan for the under-construction virtual structure whose progress is being updated using images attained from the site. The structure consists of columns, masonry walls, and doors. The number of activities performed on the structure is shown in Figure 96.

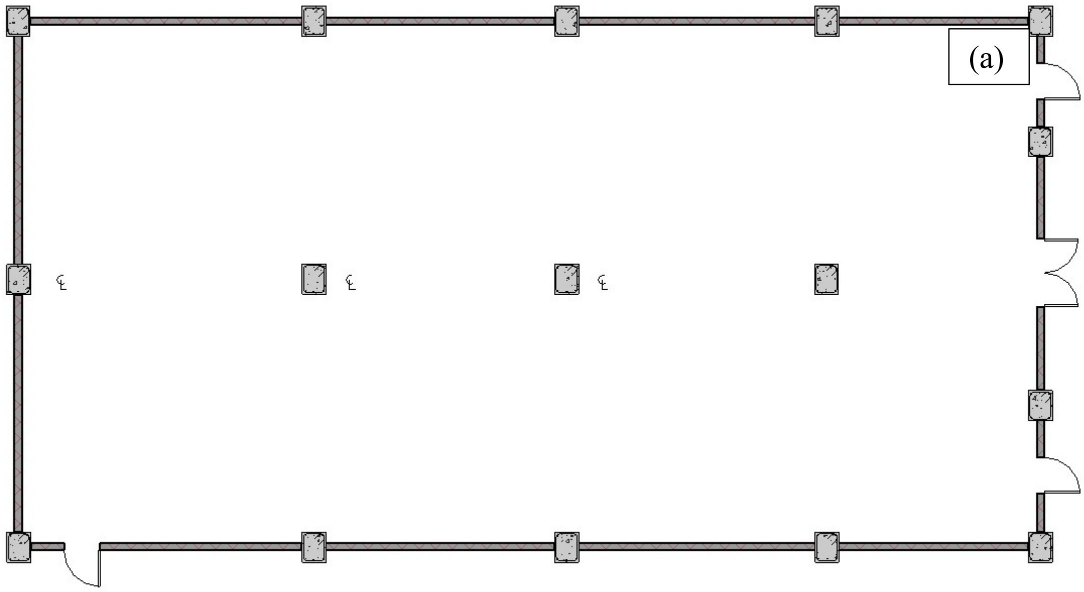


Figure 95 Floor plan for the virtual structure.

BIM was created on Autodesk Revit, and activity list along with POI list (see Table 19) was extracted using EAPE methodology. Number of POIs extracted for elements belonging to each category is shown in Figure 96. Activity list was used to create a construction schedule on a planning software with the activity relationships defined according to principles of construction planning. Figure 97 shows a summary of the schedule while the detailed schedule is shown in Appendix A.

Table 19 POI list extracted from virtual structure BIM.

Lvl	POI	Cat ID	Category	Family	X	Y
L0	277717	-2001330	Structural Columns	24 x 30	-8424.83	11388.55
L0	277727	-2001330	Structural Columns	24 x 30	-8424.83	-1958.12
L0	277741	-2001330	Structural Columns	24 x 30	-940.711	-1958.12
L0	277750	-2001330	Structural Columns	24 x 30	-940.711	11388.55
L0	277759	-2001330	Structural Columns	24 x 30	5483.158	11388.55
L0	277768	-2001330	Structural Columns	24 x 30	5483.158	-1958.12
L0	277777	-2001330	Structural Columns	24 x 30	12094.13	-1958.12
L0	277786	-2001330	Structural Columns	24 x 30	12094.13	11388.55
L0	277795	-2001330	Structural Columns	24 x 30	12094.13	4839.95
L0	277804	-2001330	Structural Columns	24 x 30	5483.158	4839.95
L0	277813	-2001330	Structural Columns	24 x 30	-940.711	4839.95
L0	277822	-2001330	Structural Columns	24 x 30	-8424.83	4839.95
L0	277831	-2001330	Structural Columns	24 x 30	17520.11	11388.55
L0	277849	-2001330	Structural Columns	24 x 30	17520.11	-1958.12
L0	277872	-2001330	Structural Columns	24 x 30	17520.11	8332.538
L0	277881	-2001330	Structural Columns	24 x 30	17520.11	1659.2
L1	277919	-2000011	Walls	Generic - 8"	2271.224	11388.55
L1	277993	-2000011	Walls	Generic - 8"	8788.643	11388.55
L1	278078	-2000011	Walls	Generic - 8"	14807.12	11388.55
L1	278186	-2000011	Walls	Generic - 8"	14807.12	-1958.12
L1	278258	-2000011	Walls	Generic - 8"	8788.643	-1958.12
L1	278318	-2000011	Walls	Generic - 8"	2271.224	-1958.12
L1	278605	-2000011	Walls	Generic - 8"	18520.11	-1149.46
L1	278762	-2000011	Walls	Generic - 8"	18520.11	3995.869
L1	278808	-2000011	Walls	Generic - 8"	18520.11	8860.546
L1	279399	-2000011	Walls	Generic - 8"	-4674.51	-1958.12
L1	279464	-2000011	Walls	Generic - 8"	-7424.83	440.9127
L1	279518	-2000011	Walls	Generic - 8"	-7424.83	7114.252
L1	279574	-2000011	Walls	Generic - 8"	-4682.77	11388.55
L1	278884	-2000023	Doors	36" x 84"	17520.11	-149.462
L1	278943	-2000023	Doors	36" x 84"	17520.11	9860.546
L1	281018	-2000023	Doors	68" x 80"	-8424.83	9093.153
L1	281164	-2000023	Doors	68" x 80"	-8424.83	-1815.12

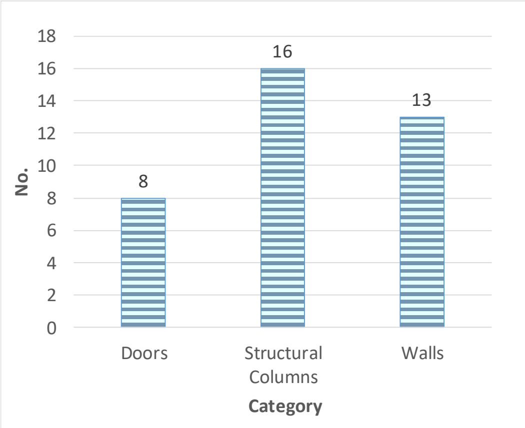


Figure 96 No of elements from each category in the simulated structure.

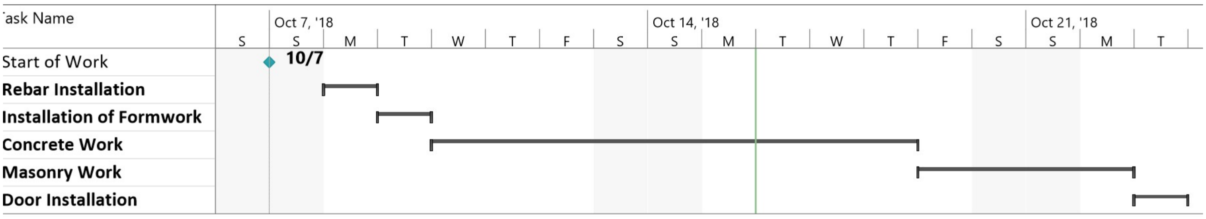


Figure 97 Schedule summary of the virtual structure.

All images that were acquired on ESDB construction site are of elements similar in size to those assumed during creation of simulated structure BIM. The realization of BAAP which is the robot discussed in BAAP chapter was taken to the site to take images of the actual elements in a state that matches the simulated states, according to a daily monitoring list.

6.2.1. Day 1: Rebar Installation, Imaging and Analysis

At the end of Day 1, all rebar fixing is planned to be completed on a total of sixteen columns as shown in Revit representation in Figure 98. The images attained from the site using BAAP are transmitted to the server using PHP and processed using SCAER with results shown in Figure 99. SCAER detected rebar in more than fifty percent of frames for all POIs except one, predicting the presence of rebars on those POIs. All activities planned to be completed at the end of the first day of construction are complete, therefore, the BCWP is equal to BCWS. The actual cost of work scheduled is estimated to be 10% greater than budgeted cost because of unforeseen expenditures.

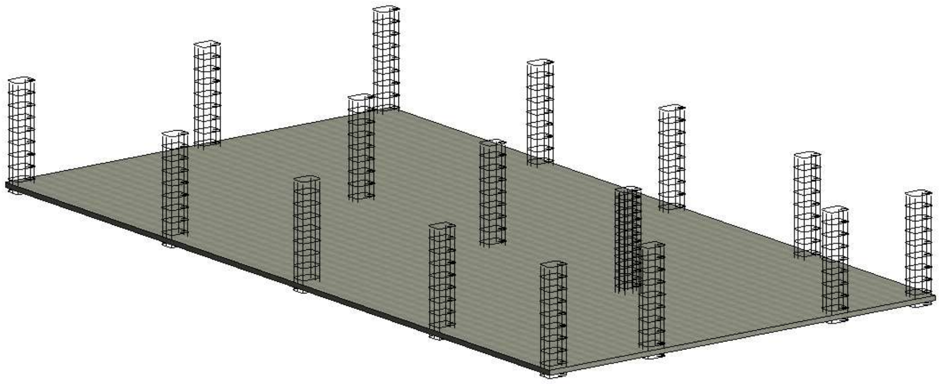


Figure 98 Activities completed at the end the first day of construction.

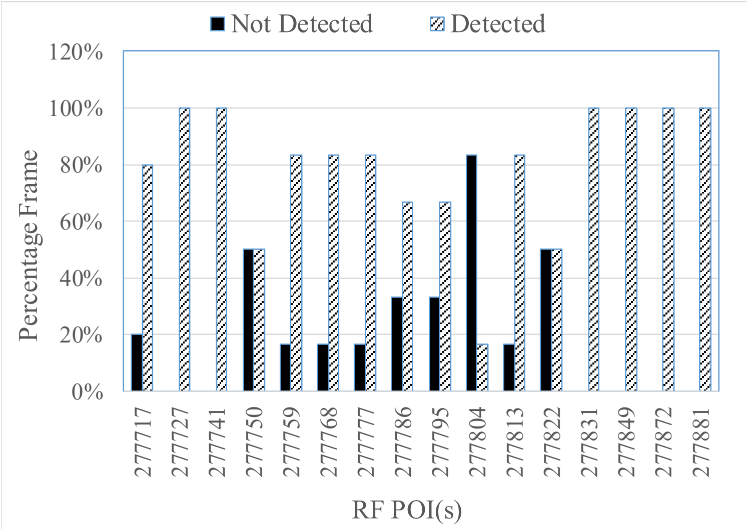


Figure 99 SCAER output for Day 1 of inspection.

Figure 100 shows dashboard at the end of Day 1, when the placement of reinforcement at all columns has been completed. Rebar is made up of thin members and therefore difficult to detect and has a higher error rate.

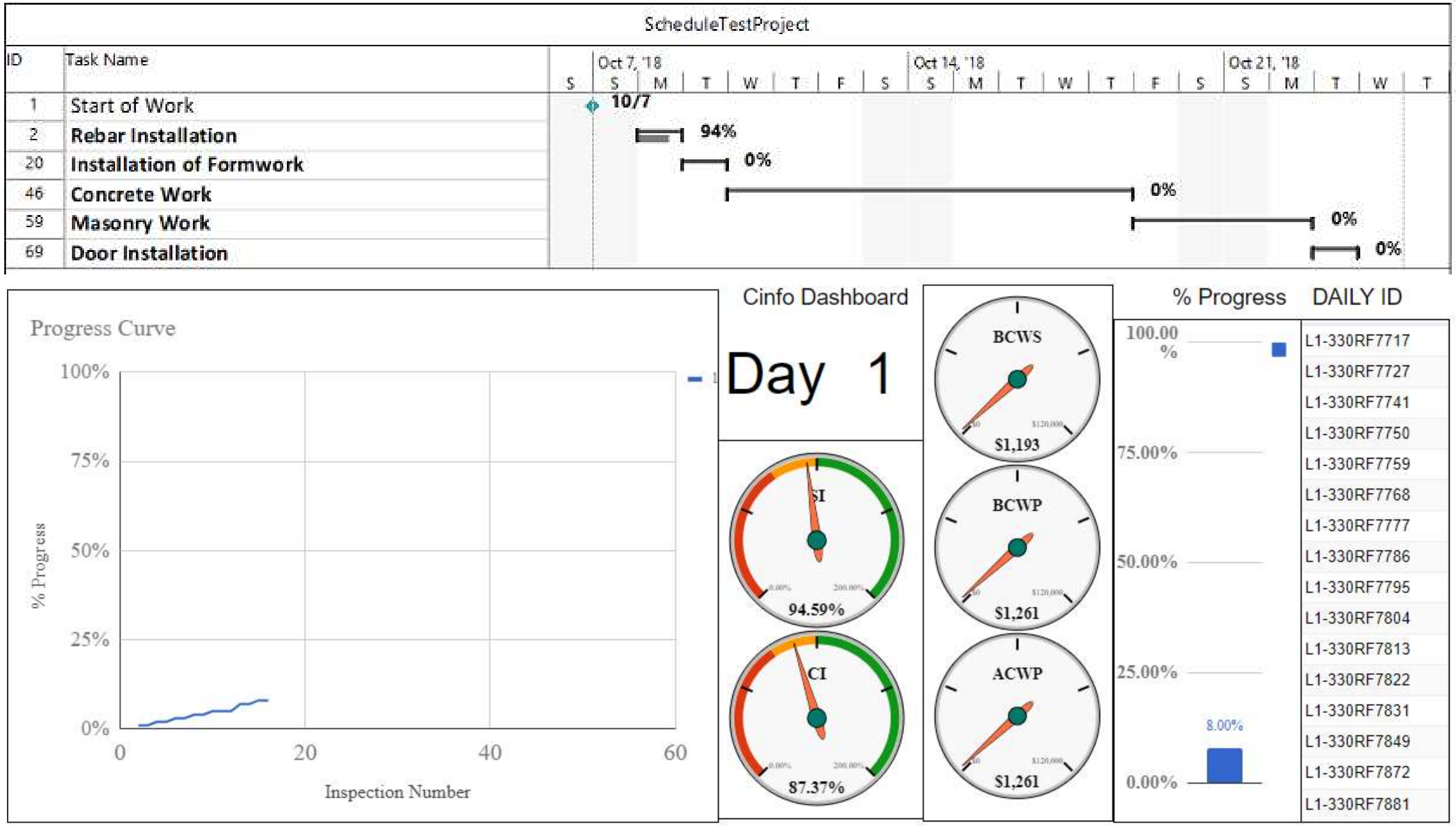


Figure 100 Dashboard view after completion of rebar installation work.

6.2.2. Day 2: Formwork Installation, Imaging, and Analysis

The activities completed at the end of Day 2 are the installation of formwork as shown in Revit representation in Figure 101. The images of formwork attained from construction site are transmitted to the server and processed using SCAER whose result is shown in Figure 102. SCAER was able to detect all formwork in all images correctly. Figure 103 shows the dashboard for a project manager, displaying cost and schedule metrics. At the completion of formwork, the project manager can see 29% completion of work and BCWS, BCWP, and ACWP values. The SI is not equal to one due to the failure of SCAER to detect rebar's installation on Day 1, the effect of which will be seen throughout the project.

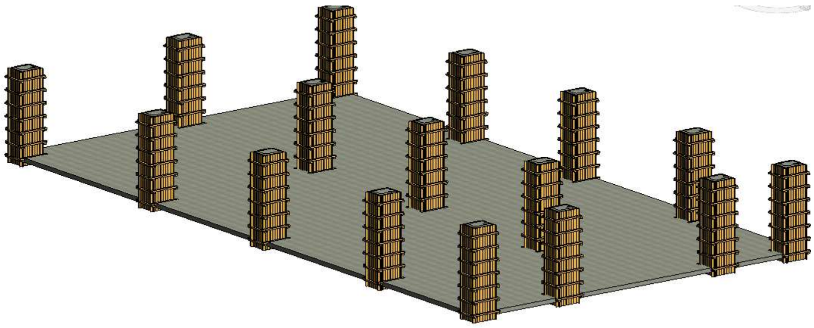


Figure 101 Site status at the end of Day 2 of construction.

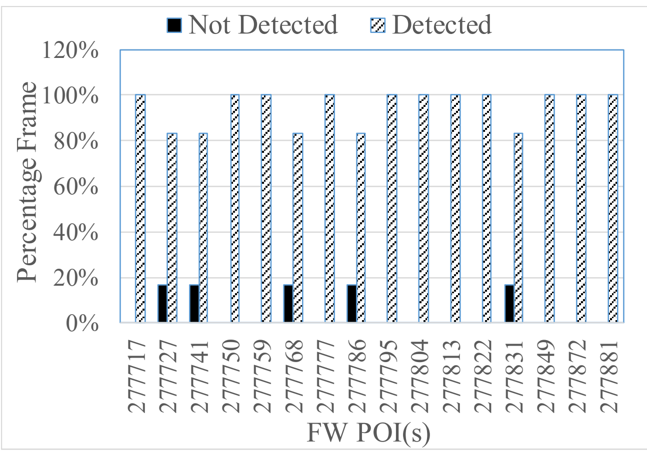


Figure 102 SCAER Output for Day 2 of inspection.

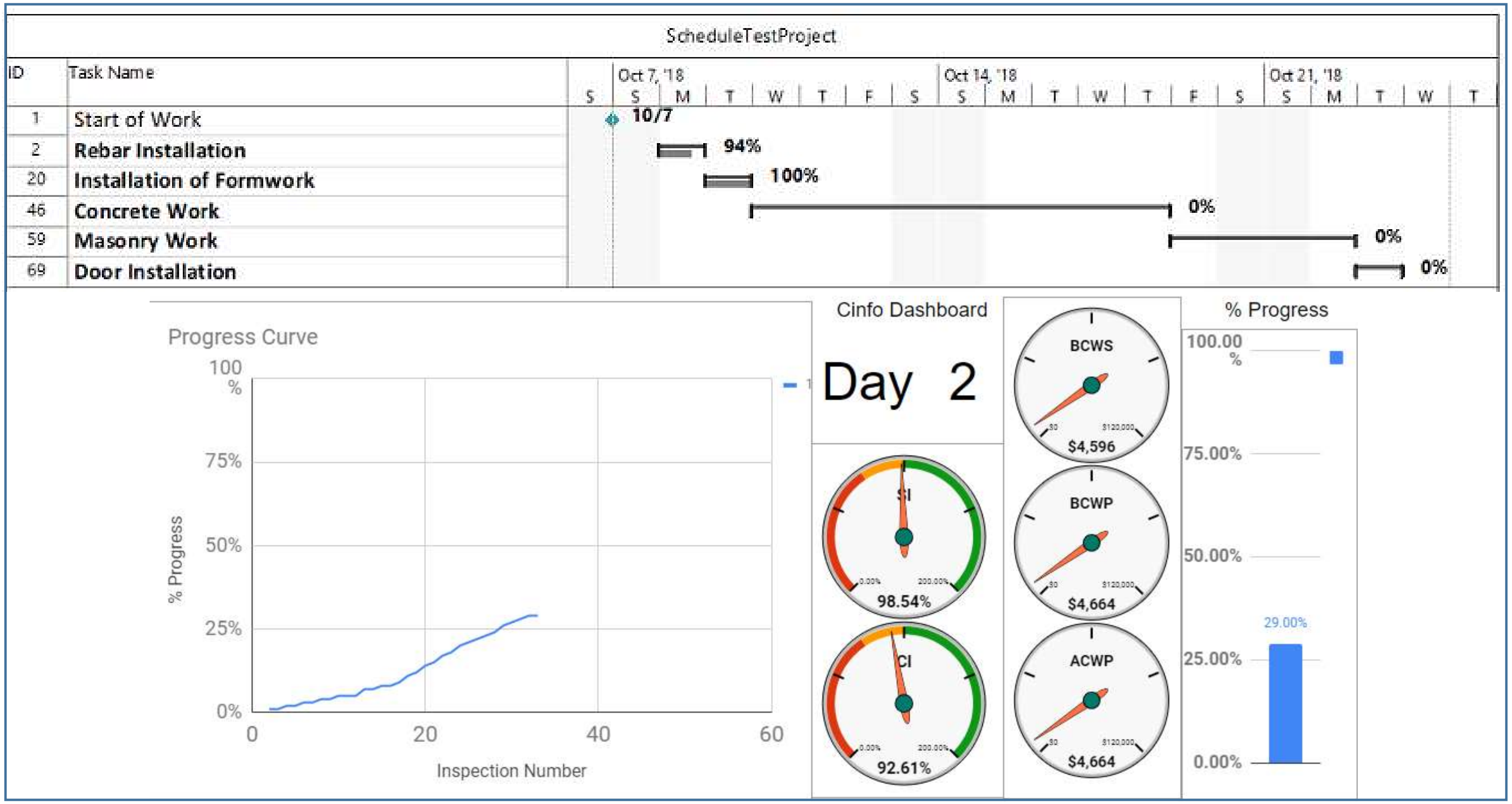


Figure 103 Dashboard view after completion of formwork installation work.

6.2.3. Day 7: Removal of Formwork, Imaging, and Analysis

The activities completed at the end of Day 7 are the removal of formwork after concrete work has been completed, as shown in Revit representation in Figure 104. The images of concrete columns are again attained using the robot and transmitted to the server for processing with SCAER as the results are shown in Figure 105. SCAER was able to detect correct element state at all POIs except one. Figure 106 shows the dashboard for a project manager on the completion of concrete work. The project manager can see 66% completion of work and progress metrics calculated from cost values. Although all columns were supposed to be completed, SCAER was unable to detect one concrete column.

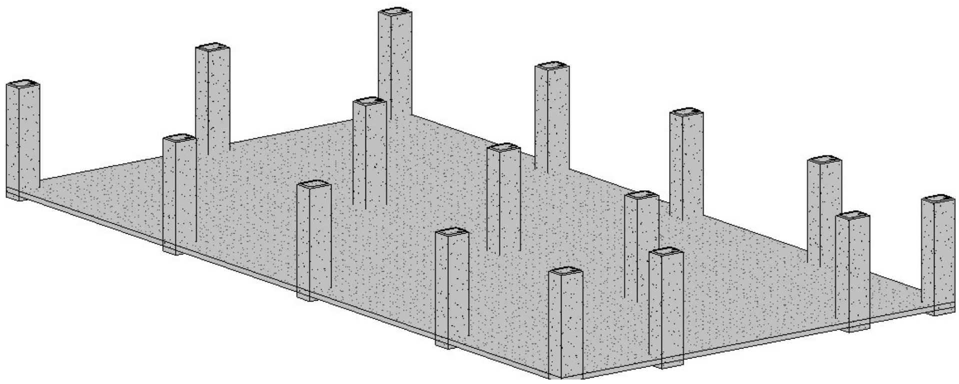


Figure 104 Virtual site view at the end of Day 7 of construction.

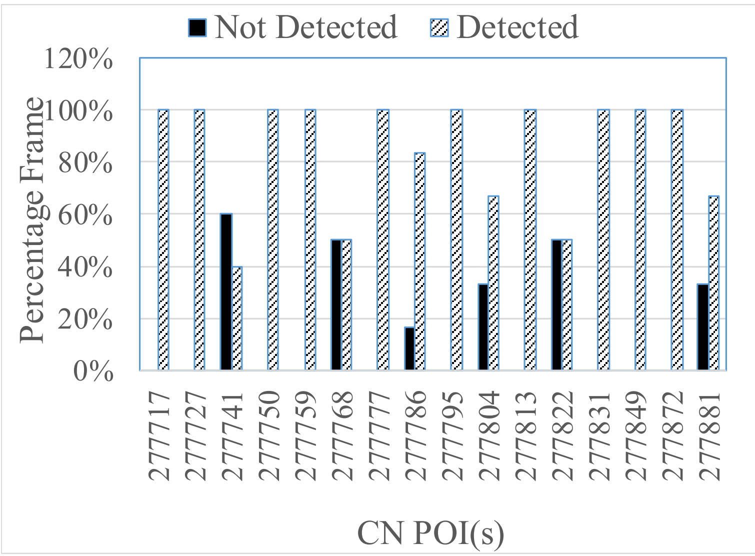


Figure 105 SCAER output at the end of Day 7 of inspection.

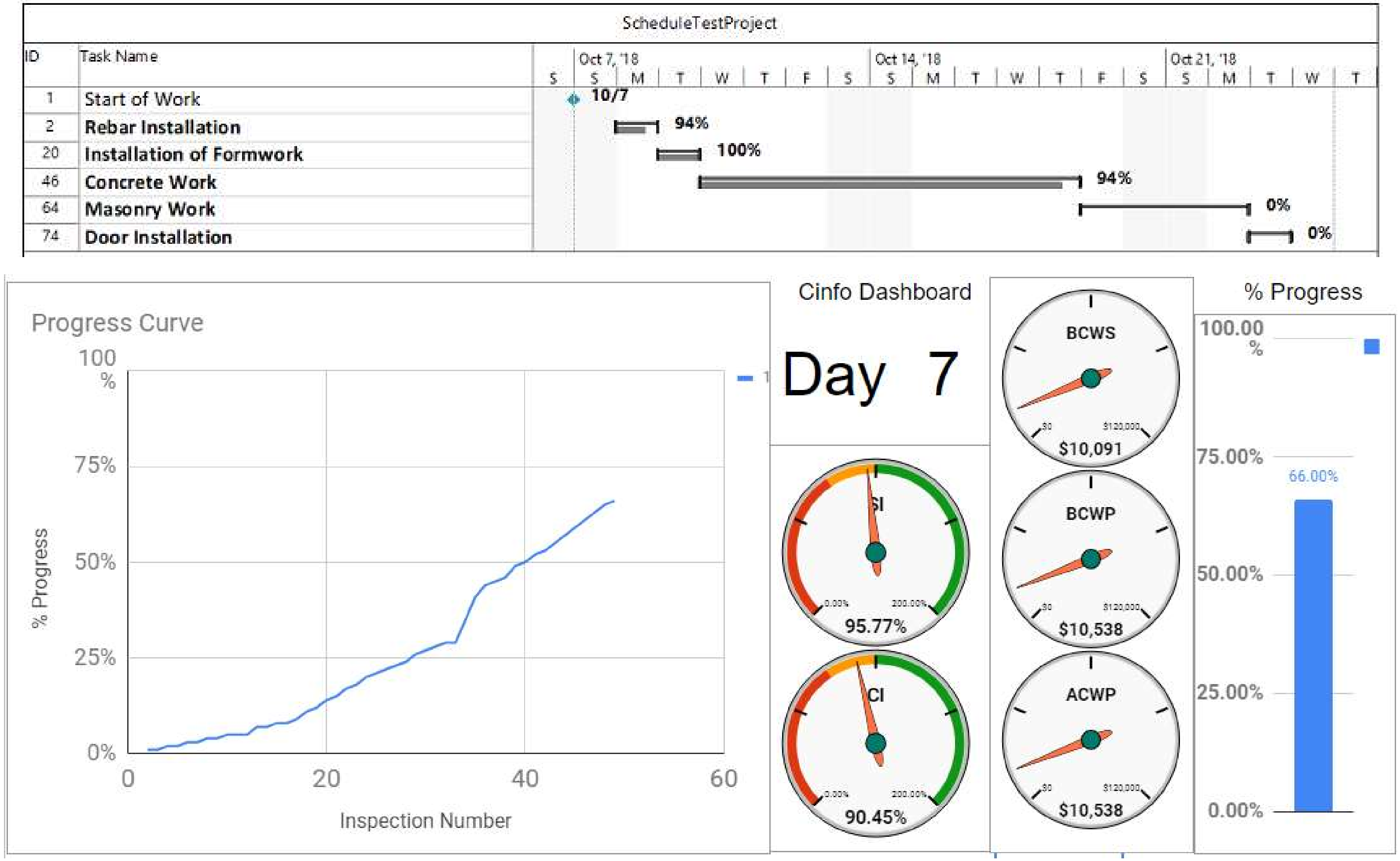


Figure 106 Dashboard view after completion of concrete work.

6.2.4. Day 9: Masonry Work Completion, Imaging, and Analysis

The activities completed at the end of Day 9 are masonry work as shown in Figure 107. The robot is taken to site and images of lightweight concrete block walls are acquired, transmitted to the server and processed using SCAER with results shown in Figure 108. As seen, SCAER can detect all walls in the images and update dashboard shown in Figure 109. As seen in dashboard 98% of progress is complete, and CI, SI, BCWS, BCWP, and ACWP are updated. Masonry work has a higher recall as compared to other elements, but since this activity is during later stages of construction, the error from previous SCAER implementation is carried forward.

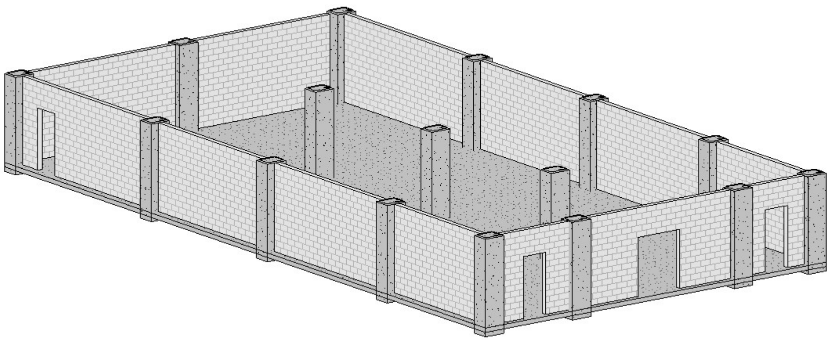


Figure 107 Rendered Site status at the end of Day 9 of construction.

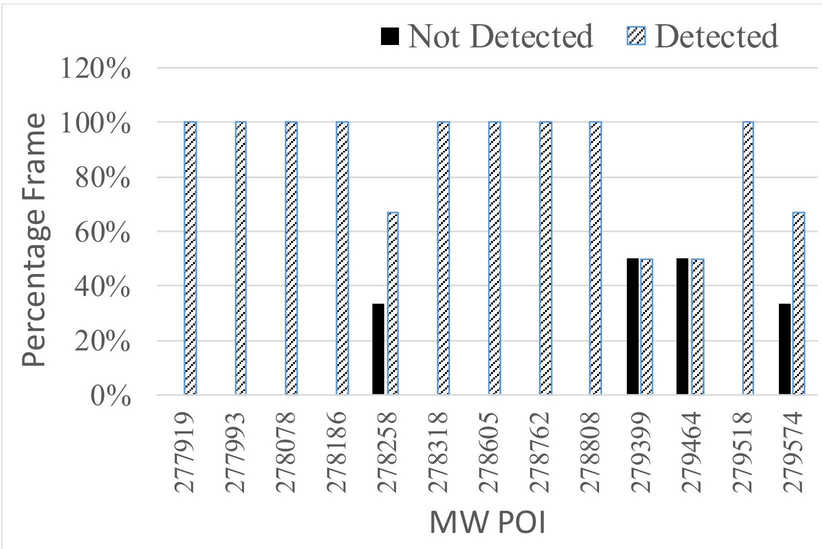


Figure 108 SCAER output at the end of Day 9 of inspection.

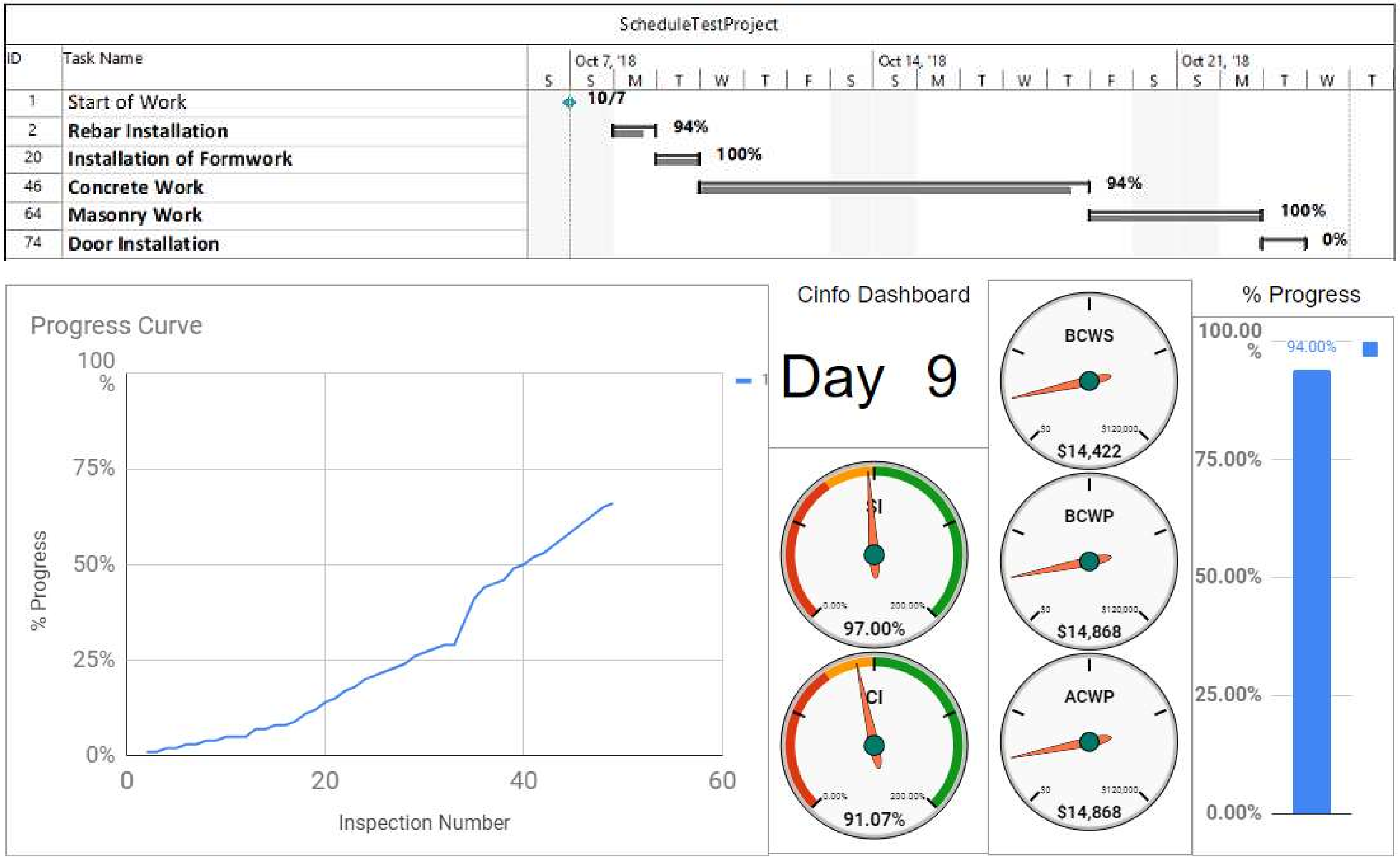


Figure 109 Dashboard view after completion of masonry work.

6.2.5. Day 11: Final Site Status and Dashboard

The activities completed at the end of Day 11 are the final activities and include installation of doors as shown in Figure 110. Images of doors are acquired from a finished structure since doors were not present on the construction site during acquisition. The images acquired using the robot, transmitted to the server and processed using SCAER with results shown in Figure 111. As seen, SCAER can detect all doors in the images and updates dashboard shown in Figure 112. As seen in the dashboard, 100% of progress is showing completion of all work. Although all activities were completed, SI is still not 100% because of the failure of SCAER to preform recall. Doors being distinct in color have high recall, and therefore all were detected.

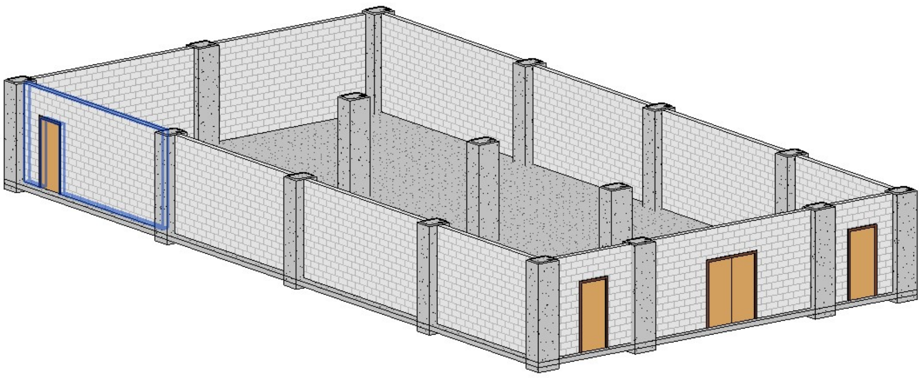


Figure 110 Activities completed at the end of Day 11 of construction.

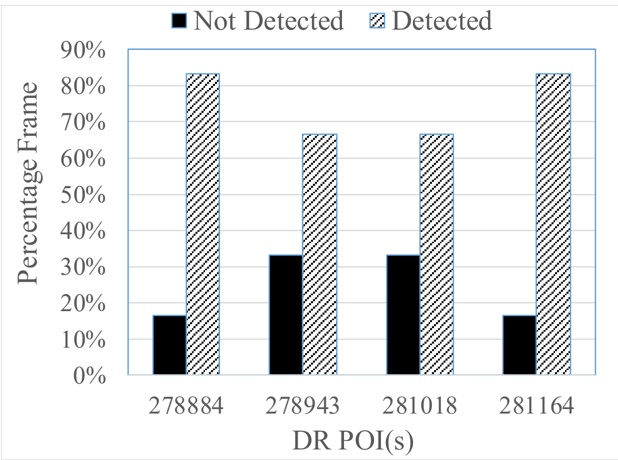


Figure 111. SCAER output at the end of Day 11 of inspection.

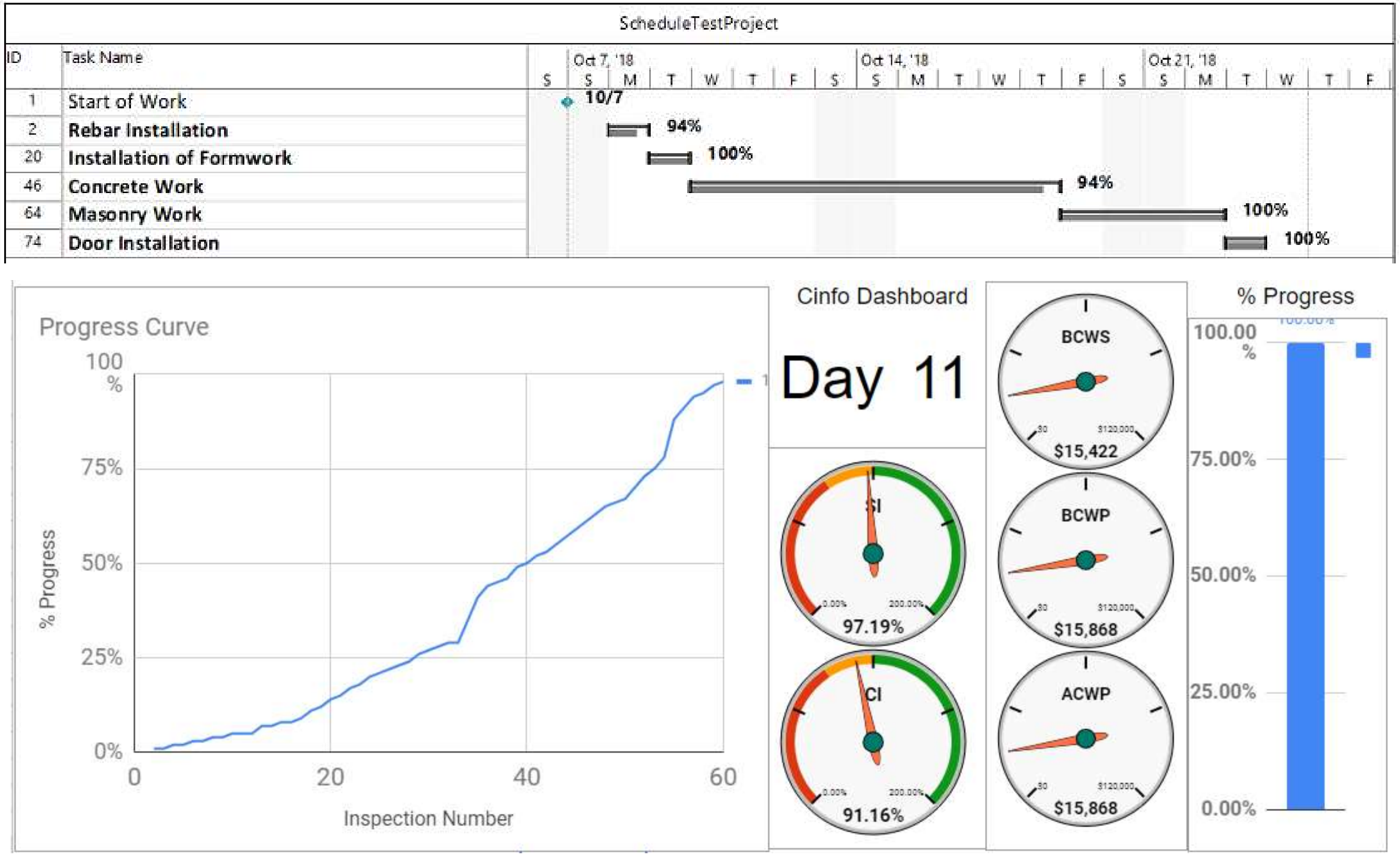


Figure 112 Dashboard at project completion.

6.3. Discussion on Cost Metrics

The error in schedule metrics is dependent upon the cost of elements; the higher the cost, the greater is the error. Figure 113 shows the comparison of estimated and actual cost metrics. The higher rate of error is observed in RF as compared to other element states when metrics are calculated for individual states.

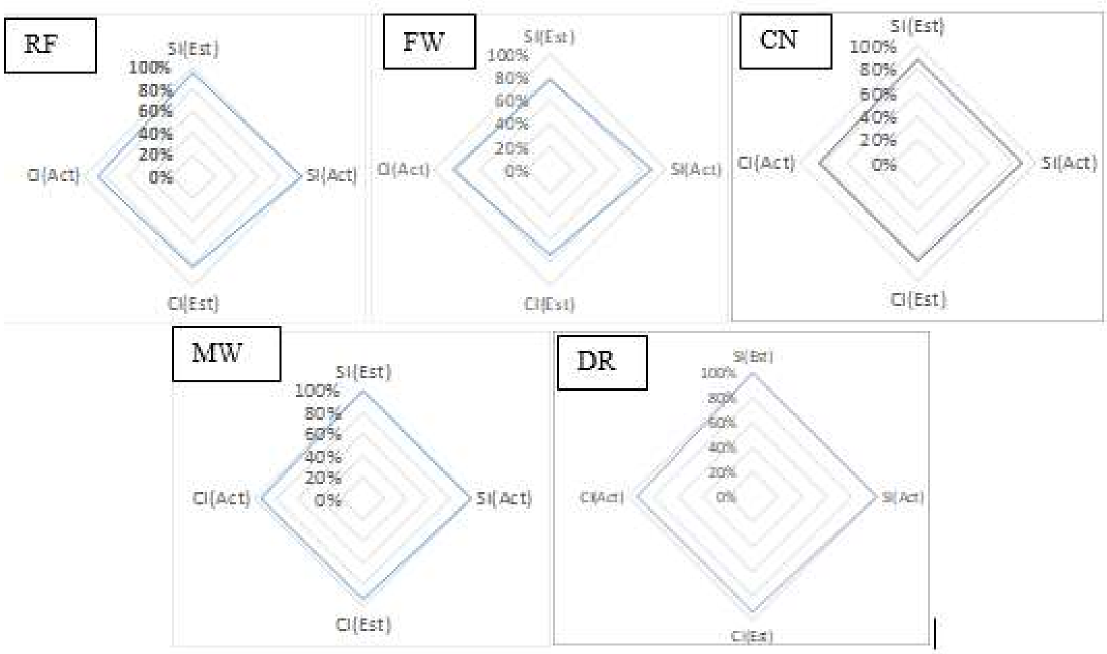


Figure 113 Estimated vs. Actual progress metrics comparison.

Error at the initial stage will be carried through the project while the error in later activities will only give erroneous results at the later stage of the project. Therefore, when cumulative progress metrics are calculated, error in earlier detection continues throughout the project even though following activities like doors have 100% recall (see Figure 114) if seen in isolation.

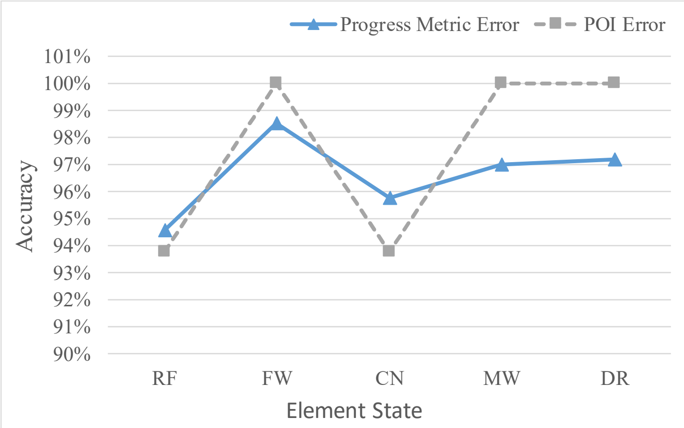


Figure 114 POI error and KPI error comparison.

6.4. Conclusion

All steps involved in CAPMS were performed on a simulated structure and progress information is visualized on a dashboard. Once the activity is confirmed by image processing operations, the client updates the schedule file by updating activity status and sends the file to the server using PHP push request. The server will store the record of the updated schedule which will be used along with cost information to provide progress KPIs in the form of Schedule Performance Index (SPI), Cost Performance Index (CPI), Schedule Index (SI), and Cost Index (CI). These parameters can be used to update the dashboard of real-time progress information to be used for project management.

The dashboard for a project manager that includes operational and analytical data; i.e., CI, SI and cost metrics at the end of the first day is generated according to the inspections performed in the morning of the second day before workers start their work. The rebar fixing according to cost information stored in the schedule is the actual cost of work performed while the company account provides ACWP. The metrics provide necessary information to project managers and help them asses the state of the project at a glance. The management is better equipped to take timely and pre-emptive decisions that will help to attain project objectives.

CHAPTER 7

CONCLUSION

Integration of site data with building information databases will assist in the automation of machines and processes [131]. A fully automated system providing real-time data to project management will assist in timely corrective action before delays start affecting project objectives. If data is not provided on time and corrective actions are not taken promptly, delay mitigation costs would exceed exponentially resulting in cost overruns and subsequent failure of the project. The objective of the automated monitoring system was to attain data from the site and convert it into information that could be used by project management. The data in the case of this research was images and information is the progress state that is updated into the schedule. The developed system was able to attain images from the site at tilts that were able to acquire images with minimum probability of the presence of occlusions and foreign elements. The acquired frame is then clustered, and presence of expected material is determined based on cluster center distances from material signatures stored in the database. The presence of expected material determines completion of activity at a particular POI which is then updated as per schedule as a completed activity.

In interviews and discussions with project management teams, it was ascertained that the frequency of updating the schedule is three months. Hence for a project like Classroom Hall Building (CHB), only 3-4 updates were conducted throughout the project, which is not sufficient for early detection of the delays. Any delay occurring on site will take up to three months to reach the knowledge of management and any counter measures taken by them will also be delayed by the same amount of time. If critical activities were delayed and the client was informed after that much of delay, the project objectives will be permanently compromised with no chance of redressal except that the remaining schedule will crash with the expenditure of massive amounts of money. In current age when money is in short supply and companies want to save as much as possible on projects without compromising on quality, delays of this nature cannot be allowed in the construction industry. The contractor will be getting activity-wise reports for work in progress which, along with cost, gives the total cash flow on daily or activity wise basis, giving the contractor ample time to arrange funds. The schedule metrics in the form of ACWP, BCWP, SI, or CI will give a bird's eye view of project performance; their regular update will be helpful for portfolio management with the top management not required to indulge in unnecessary minor details to get the true view of the site.

While developing an automated monitoring system, a site photo acquisition and the archival system have been developed. Sites usually have large servers where photos are archived, and retrieval of relevant images is not always an easy task. An element-wise image archive with date and activity information will have great value in claim and contract management, as well as manual progress monitoring. It is useful for technology repulsive managers, who do not want to implement automated progress monitoring system end to end (E2E). They can still make use of modules that create an automated progress monitoring system.

7.1. Review of Developed Methodologies

The suggested CAPMS is an amalgamation of three distinct processes namely EAPE, BAAP, and SCAER each of which is explained and validated using site experiments.

EAPE is a precursor to CAPMS which attains navigation points for image acquisition. It enables the acquisition of site images along with BIM element tags. It also helps to determine site activities that result in the creation of 4D BIM, which is used to be a manual and time-consuming process that could make implementation of an automated progress monitoring unviable. The creation of schedule becomes easier when the activity list containing element information is attained from BIM, and only dependencies have to be provided. The methodology is relevant to structures with repeating elements of the same materials having the same type of activities that would be performed on them. A more conclusive element-wise activity is required if the structure contains elements of varying materials and types.

Point of Interest (POI) are coordinates on the BIM frame of reference where images are acquired for progress monitoring purposes, enabling acquisition of images that contain element ID in its name. Robots navigate to POIs on a daily basis by extracting POI list from the database to acquire an image of an element that will be processed using computer vision algorithms to determine the progress. The imaging Points extracted by EAPE may be non-navigable due to the presence of adjoining elements or absence of approach path. The algorithm should be improved to ensure that all POIs are navigable. The element-wise activity list should also be expanded to increase the coverage to multiple family types within major categories.

SCAER processes images obtained at Points determined by *EAPE*, using contextual information embedded within image metadata to attain accurate element state information. The algorithm provides robust results as compared to other image-based progress monitoring techniques that rely solely on computer vision techniques without utilizing the spatial and temporal context of the image. The algorithm was able to detect concrete, formwork, masonry, and door with accuracy greater than 95%. However accuracy for detection of rebar was less than 90% because of background noise and thin structure of the elements. Although individual frame wise accuracy goes down to 80% due to the presence of images with lighting and glare, use of multiple images and contextual information improves the accuracy of the proposed methodology to 100% for some cases like masonry, doors, and formwork. Pattern information can also be used to further improve the accuracy of SCAER.

BAAP is a novel data acquisition technology that uses BIM for navigation to a data point and attains site data using sensors mounted on it. A robot is developed based on the BAAP framework to determine its viability in the construction industry. A methodology is proposed for acquisition, storage and retrieval of images providing a much needed site image archiving system using an autonomous platform. Robot attains navigation points from BIM, reaches them, acquires images and transmits them to the server. The navigation algorithm was validated in a corridor where the robot was able to navigate to predetermined points with less than 4% error in direction of motion. A verification of image acquisition and transmission algorithm was also validated on an actual construction site and it was observed that extreme tilt angles result in low quality images. A higher quality robot with commercial grade electronics will have higher accuracy.

A simulated structure was created to test end to end implementation of CAPMS including visualization on the dashboard. The images were obtained on building components from an actual construction site, processed using SCAER to update schedule. The building elements cost information is processed using SCAER output to determine progress metrics like SI, CI, which are visualized on a dashboard. It is observed that accurate cost based metric is attained using CAPMS which can be visualized on the dashboard to provide quick progress summary.

7.2. Case for Robot as Employees

Use of robots in the construction industry for progress monitoring can be a huge cost saver. Cost of a worker is going up with new human resource regulations that tend to raise the cost of man hour and add legal complications for the employers. Worker need holidays, sick leaves, rest during work and psychological motivation. The productivity of a worker will also vary from time to time based on his mood, the weather and his overall wellbeing, the quality of food he is being served and the amount of sleep he is getting as well as his family and personal life. Worker meeting an accident puts severe legal burden on the employer, tarnishes his reputation and subjects him to severe penalties along with compensations that he has to dish out. This will have a domino effect resulting in rise in insurance costs and decrease in motivation and productivity. The robot does not suffer from any of these disadvantages since it does not need rest and holidays, and if it meets an accident, the only cost will be the cost of replacement until or unless the robot causes damage to a human being during its crash. The robot can negotiate risky terrains and go on unstable pathways (see Figure 115). The robots are very good at communication with each other and are immensely easy to train. Once the training algorithm has to be developed, all the remaining robots can be trained and rolled out in a matter of minutes if not in seconds. The robot does not suffer from intellectual differences as in the case of humans whose training may take months or even more. Information provided by the robot is also free from adulteration and personal biases since robots do not have ethical problems and have nothing to gain or lose from reporting problems in schedule adherence. The project management suffers repercussions if it is not able to deliver on time and its project is suffering delays, so it may take actions to project a rosy picture of progress to its higher management or stakeholders which may not match with the actual site conditions. This may have strategic implications while working in security sensitive and environmentally harsh conditions.

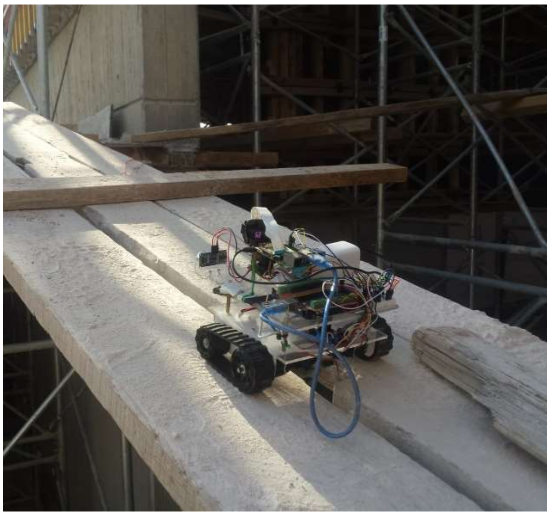


Figure 115 Robot can negotiate unsafe routes.

The total amount of money spent on development of the robot for this research is US $500 which is around a minimum monthly wage of a worker in Turkey during this research. Supervisors are usually paid much more than the minimum wage of a worker and their additional cost includes insurances and taxes. The cost of managing a robot for supervision instead of a human supervisor is many folds, but it should be accepted that research has not reached a point where this can be applied on sites as further work has to be done in developing protocols and making the sites robot-friendly.

7.3. Contribution to Field of Knowledge

Adopting automated progress monitoring technologies will assist project stakeholders by facilitating more accurate schedule forensics, delay analysis, and corrective action planning [8]. The purpose of this research is to develop a cost-effective and accurate mechanism for identification of building elements using computer vision algorithms assisted by robots. The system should require minimal or no human input and should not have any effect on-site activities which include no extra work for project management or workers.

Some research has been undertaken on image-based progress monitoring using images [16], [55], [161], [56] and other technologies [8], however, a fully comprehensive automated progress monitoring mechanism that can be implemented to the site has been lacking in such research studies as seen in Table 20. Robots are suggested but mostly for repetitive and mechanical tasks but not in context-aware intelligent role for data acquisition. This system can be further developed in controlling robots performing construction activities paving the way towards a construction site with no human presence bringing immense safety, productivity, and quality-related benefits.

Table 20 Comparison with other research on progress monitoring.

Research	Major Elements in Scope	5D BIM	Automated Data Acquisition	Automated Schedule Update	Image Content Determination	Progress Metrics Visualization
This Research	✓	✓	✓	✓	✓	✓
Brilakis et al. 2015 [26]	✓	✓	✗	✗	✓	✗
Han et al. 2015 [60]	✓	✗	✗	✗	✓	✗
Park et al. 2018 [162]	✓	✓	✗	✓	✗	✗
Hamledari et al. 2017 [61]	✗	✓	✗	✓	✓	✗
Han et al. 2015 [19]	✗	✓	✗	✓	✓	✗

7.4. Drawbacks of Context-Aware Progress Monitoring System

As mentioned earlier, construction sites are not yet suitable for automation and technology implementation. Clutter (as seen in Figure 116) should not be present on site because of OHS-related concerns. However, construction sites are full of clutter which makes robot navigation difficult. Elements on site that cannot be classified as clutter but can be placed by the contractor for various project management related reasons like a pathway for movement of hand trolley over stairs, an electrical socket for grinders and drill, etc. will also hamper the movement of the robot. The robot will keep on running into clutter and encounter objects which it is not programmed to avoid thus being unable to reach POI. The robot, being small in size, can be crushed underneath worker's foot or be kicked around by mischievous workers. Unguarded edges, pot holes, and floor openings are present in structure but not on BIM which will compromise the safety of the robot. Workers can also be present in images while robots are attaining site data continuously and the contractor may or may not want to share such images raising privacy concerns or legal issues. If the robot is stolen, the data inside can be retrieved and may also end up falling in wrong hands which can cause complicated legal and criminal issues for a contractor.

SCAER is affected mostly by glare since light incident on the imaging sensor affects white balancing making the image very dark and difficult to detect. The algorithm shows that recall is greater than 90% for solid homogenous elements like concrete and walls but decreases for non-homogeneous members like formwork to less than 50%. It is less than 50% for reinforcements which comprises of thin member and with many discontinuities within the frame causing background noise and false detections.

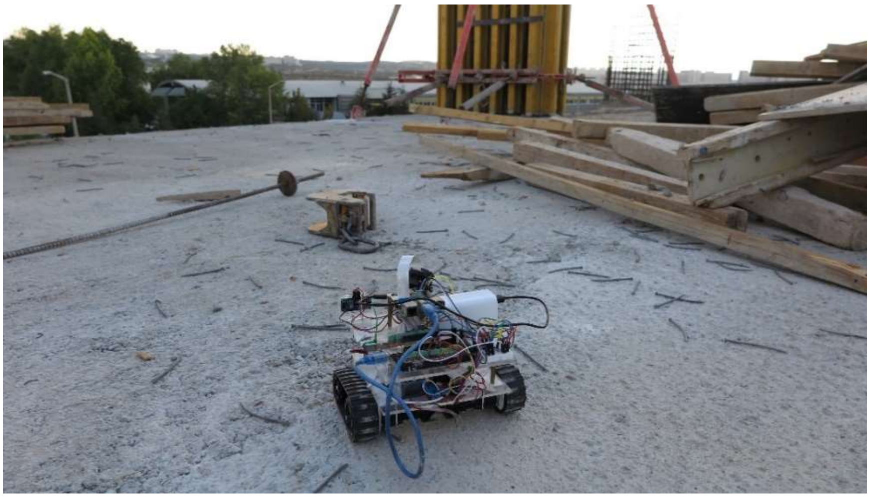


Figure 116 Cluttered site creates robot navigation difficulties.

The biggest issue with the system is exceptional handling due to errors caused by false positives and false negatives. If they are reported by a robot, they can cause unnecessary alarm and result in wastage of management's time defeating the whole purpose of the system. Special consideration should be given to handling these false alarms, and additional checks should be employed to ensure that reporting to management remains error free.

7.5. Site Requirements

In order to ensure free movement of robot following rules should be followed:

a. Pathways should always be kept clear which is also important from the OHS perspective since clutter creates fall hazard and material loss which any management would like to prevent.
b. Installation of temporary structures, e.g., supports, struts, and braces for formwork should not be placed at points that are within imaging range from elements.
c. BIM should block the location of openings to prevent the robot from falling through.
d. Sites should be vacated during lunch breaks for image capturing, but this may be a constraint where work is being carried out round the clock.

7.6. Future Work

The system has the potential for further development and expansion into quality assurance, health and safety, productivity measurement and all other domains where images can be used to ascertain information. The author conducted research [163] on use of images to determine rebar diameter and spacing (see. Figure 117) by performing processing in both 2D and 3D domains. The same research can be performed on multiple images acquired by SCAER to further enhance attained information. The research also has the potential to expand into MEP domain (see Figure 118), as was observed during clustering operations in SCAER. Hence the scope of application can be further expanded into building categories that were not validated in the scope of this thesis. During image acquisition for validation, images of the tower crane were also acquired, and it was observed that clustering approach worked on tower cranes very efficiently (see Figure 119), confirming the possibility of application beyond structural domain. SCAER can be used for inventory management to determine which material has arrived on trucks (see Figure 120) as well as different materials in stockpiles based on the package colors (see Figure 121). Safety barricades in images can be identified to see if edges are guarded against falls. Barricades have fixed location on edges, once marked on BIM model can be detected using SCAER. Confirmation of safety compliance by a worker can be based on detection of safety vests, climbing belts, and other safety Equipment on images during site work. Noncompliance of safety protocols can be used to measure safety score and enable project managers to enforce safety regulations before an incident occurs. Images on elements can be checked for cracks and textures which can be used for quality assurance and confirmation of compliance to specifications. Plenty of work has been done on quality assurance on the basis of images. The number of workers at the location during the conduct of an activity can provide number of man-hours spent per activity which will provide productivity measure of the project. Presence of worker can be detected on the basis of life vests. If High Visibility (HV) jackets have a unique symbol identifying the worker, then productivity can be measured for different types of teams and compared with each other. If the HV vest has a QR code or a symbol that can differentiate one worker from the other, then the images taken by the robot can be used as a substitute for marking attendance.

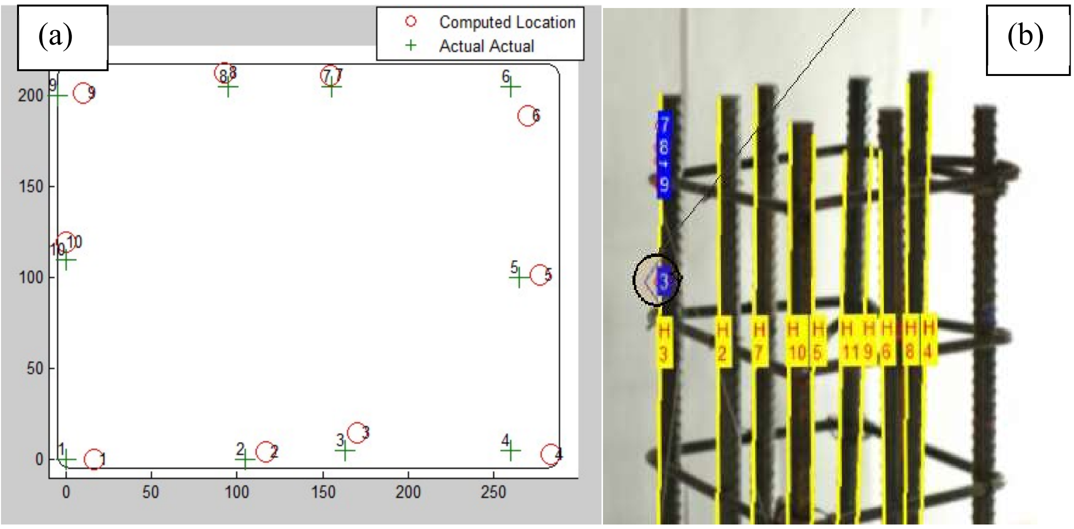


Figure 117 Reinforcement image processed to attain rebar diameter [108].

Figure 118 (a)-(b) SCAER for detection of MEP in masonry images.

As mentioned earlier, while creating the automated progress monitoring system, an automated imaging system has been formulated, which will have great value in claim management. Any claim can easily and quickly be verified by extracting images and reviewing the information. This process can be manual like most of the companies do and, with some computer vision algorithms, it can also be automated.

Figure 119 (a)-(b) Boom loader detected (c)-(d) crane detected by K-means clustering in SCAER.

Figure 120 Loaded truck image with extracted (b) Truck (c) Loaded Formwork.

Figure 121 (a) Insulation stockpile image with extracted (b) XPS stockpile (b) Glass wool stockpile.

A camera mounted on a drone or helmet can attain images and subsequently apply SCAER on them to determine completion of an activity. The location of the element has to be determined which can be done by using shoe mounted accelerometers or displacement sensors in case of drones. Drones may create safety issues inside the site which may need some special countermeasures. An additional laser scanner, thermal camera or stereo camera can be mounted on the robot to obtain 3D images, reflection values, and infrared maps to measure dimensions with pinpoint accuracy. Thermal cameras can measure temperature in a contactless manner that can give an idea about the maturity of concrete or provide information about hotspots. Additional sensors can also be used for Augmented Reality (AR) based creation of walk through by super positioning of planned and attained progress using computer vision techniques. Plenty of research exists on AR and its use in construction. RFID sensors mounted on the robot can help in determining movement of materials for inventory management purposes or embedded within materials which can help to attain data regarding hidden elements which were not photographed earlier. Robot-mounted with screen and speaker can relay information to workers and pass on instructions from the management team. A touch screen or voice recognition module can make communication two ways and enable workers to make queries regarding their work or see additional information, recent changes and provide feedback, most of which can be processed by onboard computer without taking time of site management team, freeing them for more intellectual work. A drill, probe or a sampler installed on the robot can take onsite samples which can be tested by the robot by simple optical means or carried to the laboratory for further testing. The robot will have access to laboratory records and can provide it to site workers when required, in case some anomaly is detected by workers in material and where more clarity is required. Hence a mini Mars rover type concept is applied here; the domain would change from a planet to site.

A robot undertaking human jobs has great social and political implications. While companies save millions of dollars through automation, humans may become jobless and unable to feed their families. The robot will not be buying from the market thus reducing the number of consumers and disturbing the very foundation of a capitalist economy. Despite all these repercussions for the human society brought about by automation, this is what is in store for humanity which has to fight its way out for survival and to safeguard its interests in the future.

REFERENCES

[1] T. Hegazy and M. Abdel-Monem, “Email-based system for documenting construction as-built details,” *Autom. Constr.*, vol. 24, pp. 130–137, Jul. 2012.

[2] R. Navon and R. Sacks, “Assessing research issues in Automated Project Performance Control (APPC),” *Autom. Constr.*, vol. 16, no. 4, pp. 474–484, 2007.

[3] H. Bae, M. Golparvar-Fard, and J. White, “Image-Based Localization and Content Authoring in Structure-from-Motion Point Cloud Models for Real-Time Field Reporting Applications,” *J. Comput. Civ. Eng.*, vol. 29, no. 4, p. B4014008, 2015.

[4] J. K. Yates and A. Epstein, “Avoiding and Minimizing Construction Delay Claim Disputes in Relational Contracting,” *J. Prof. Issues Eng. Educ. Pract.*, vol. 132, no. 2, pp. 168–179, Apr. 2006.

[5] E. J. Jaselskis *et al.*, “Using Tele-Engineering As a Tool to Reverse Engineer the Inka Road,” in *Construction Research Congress 2012*, 2012, pp. 2139–2148.

[6] M. Kopsida, I. Brilakis, and P. Vela, “A Review of Automated Construction Progress and Inspection Methods,” *Proc. 32nd CIB W78 Conf. Constr. IT*, no. OCTOBER, pp. 421–431, 2015.

[7] K. C. Iyer and K. N. Jha, “Factors affecting cost performance: evidence from Indian construction projects,” *Int. J. Proj. Manag.*, vol. 23, no. 4, pp. 283–295, May 2005.

[8] T. Omar and M. L. Nehdi, “Data acquisition technologies for construction progress tracking,” *Autom. Constr.*, vol. 70, pp. 143–155, Oct. 2016.

[9] R. Navon, “Automated project performance control of construction projects,”

Autom. Constr., vol. 14, pp. 467–476, 2005.

[10] S. Alizadehsalehi and I. Yitmen, “The Impact of Field Data Capturing Technologies on Automated Construction Project Progress Monitoring,” *Procedia Eng.*, vol. 161, pp. 97–103, Jan. 2016.

[11] I. N. Davidson and M. J. Skibniewski, “Simulation of Automated Data Collection in Buildings,” *J. Comput. Civ. Eng.*, vol. 9, no. 1, pp. 9–20, 1995.

[12] S. Scott and S. Assadi, “A survey of the site records kept by construction supervisors,” *Constr. Manag. Econ.*, vol. 17, no. 3, pp. 375–382, May 1999.

[13] M. Golparvar-Fard, “D4AR- 4 dimensional augmented reality- models for automation and interactive visualization of construction progress monitoring,” University of Illinois at Urbana-Champaign, 2010.

[14] M. Kopsida, I. Brilakis, and P. A. Vela, “A Review of Automated Construction Progress Monitoring and Inspection Methods,” in *32nd CIB W78 Conference 2015*, 2015.

[15] K. S. Saidi, A. M. Lytle, and W. C. Stone, “Report of the NIST Workshop on Data Exchange Standards at the Construction Job Site,” *Proc. 20th Int. Symp. Autom. Robot. Constr.*, pp. 617–622, 2003.

[16] D. Rebolj, N. Č. Babič, A. Magdič, P. Podbreznik, and M. Pšunder, “Automated construction activity monitoring system,” *Adv. Eng. Informatics*, vol. 22, pp. 493–503, 2008.

[17] A. Howell, “Reforming project management: the role of lean construction Title Reforming project management: the role of lean construction,” in *Eighth Annual Conference of the International Group for Lean Construction, IGLC-8*, 2000.

[18] M. Golparvar-Fard, F. Peña-Mora, C. A. Arboleda, and S. Lee, “Visualization of Construction Progress Monitoring with 4D Simulation Model Overlaid on Time-Lapsed Photographs,” *J. Comput. Civ. Eng.*, vol. 23, no. 6, pp. 391–404,

Nov. 2009.

[19] K. K. Han, J. Lin, and M. Golparvar-Fard, "A Formalism for Utilization of Autonomous Vision-Based Systems and Integrated Project Models for Construction Progress Monitoring," *Proc. 2015 Conf. Auton. Robot. Constr. Infrastruct.*, 2015.

[20] M. G. Fard and F. Peña-Mora, "Application of Visualization Techniques for Construction Progress Monitoring," in *Computing in Civil Engineering (2007)*, 2007, pp. 216–223.

[21] Y. Turkan, F. Bosché, C. T. Haas, and R. Haas, "Tracking Secondary and Temporary Concrete Construction Objects Using 3D Imaging Technologies," *Comput. Civ. Eng.*, 2013.

[22] R. Navon and R. Sacks, "Assessing research issues in Automated Project Performance Control (APPC)," *Autom. Constr.*, vol. 16, no. 4, pp. 474–484, Jul. 2007.

[23] I. K. Brilakis, L. Soibelman, and Y. Shinagawa, "Construction site image retrieval based on material cluster recognition," *Adv. Eng. Informatics*, vol. 20, pp. 443–452, 2006.

[24] M. Golparvar Fard, "Assessment of collaborative decision-making in design development and coordination meetings," University of British Columbia, 2006.

[25] T. Froese, "Interwoven Threads: Trends in the Use of Information Technologies for the Construction Industry.," in *Berkeley-Stanford CE&M workshop on defining a research agenda for AEC process/product development in 2000 and beyond,* 1999.

[26] I. Brilakis, L. Soibelman, and Y. Shinagawa, "Material-Based Construction Site Image Retrieval," *J. Comput. Civ. Eng.*, vol. 19, no. 4, pp. 341–355, Oct. 2005.

[27] E. Allmon, "U.S. Construction Labor Productivity Trends, 1970– 1998," *J.*

Constr. Eng. Manag. ASCE, vol. 126, no. 2, pp. 97–104, 2000.

[28] T. Bock, "The future of construction automation: Technological disruption and the upcoming ubiquity of robotics," *Autom. Constr.*, vol. 59, pp. 113–121, Nov. 2015.

[29] K. M. Kensek, "Integration of Environmental Sensors with BIM: case studies using Arduino, Dynamo, and the Revit API," *Inf. la Construcción*, vol. 66, no. 536, p. e044, 2014.

[30] T. Sawyer, *Modeling supply chains.*, vol. 260, no. 14. [McGraw-Hill], 2008.

[31] S. Moon and B. Yang, "Effective Monitoring of the Concrete Pouring Operation in an RFID-Based Environment," *J. Comput. Civ. Eng.*, vol. 24, no. 1, pp. 108–116, Jan. 2010.

[32] S. Chin, S. Yoon, Y.-S. Kim, J. Ryu, C. Choi, and C.-Y. Cho, "Realtime 4D CAD + RFID For Project Progress Management," *Constr. Res. Congr.*, pp. 1–10, 2005.

[33] M.-Y. Cheng and J.-C. Chen, "Integrating barcode and GIS for monitoring construction progress," *Autom. Constr.*, vol. 11, no. 1, pp. 23–33, Jan. 2002.

[34] D. Van Opdenbosch, G. Schroth, R. Huitl, S. Hilsenbeck, A. Garcea, and E. Steinbach, "Camera-based indoor positioning using scalable streaming of compressed binary image signatures," in *2014 IEEE International Conference on Image Processing (ICIP)*, 2014, pp. 2804–2808.

[35] M. Holopainen *et al.*, "Mobile terrestrial laser scanning in urban tree inventory," in *SilviLaser 2011 proceedings*, 2011.

[36] S. Higgins, "ROBIN: All-in-One Vehicle, Backpack, and UAV LiDAR System - SPAR 3D," *SPAR 3D*, 2016. [Online]. Available: https://www.spar3d.com/news/lidar/robin-backpack-uav-vehicle-lidar-system/. [Accessed: 24-Oct-2018].

[37] Luka Babić, Boško Pribičević, and Almin Đapo, "Mobile Laser Scanning

(MLS) in transport infrastructure documentation and research," *ekscentar*, no. 15, pp. 96–99, 2012.

[38] I. Puente, B. Akinci, H. González-Jorge, L. Díaz-Vilariño, and P. Arias, "A semi-automated method for extracting vertical clearance and cross sections in tunnels using mobile LiDAR data," *Tunn. Undergr. Sp. Technol.*, vol. 59, pp. 48–54, Oct. 2016.

[39] Harriet Brewitt, "MLS vs. TLS," *3D Laser Mapping*, 2019. [Online]. Available: https://www.3dlasermapping.com/blog-post/mls-vs-tls/. [Accessed: 06-Nov-2018].

[40] M. Ibrahim, C. Germain, M. Guevremont, M. Forcier, and O. Moselhi, "Automated development of construction schedules using onsite data acquisition," in *The 1st International Construction Specialty Conference, CSCE*, 2008.

[41] S. Rankohi and L. Waugh, "Image-Based Modeling Approaches for Projects Status Comparison," in *CSCE 2014 General Conference*, 2014.

[42] S. Shi, *Emgu CV Essentials*. Packt Publishing, 2013.

[43] M. R. Jahanshahi and S. F. Masri, "Multi-Image Stitching and Scene Reconstruction for Evaluating Change Evolution in Structures," in *Computing in Civil Engineering (2011)*, 2011, pp. 372–379.

[44] R. S. Adhikari, O. Moselhi, and A. Bagchi, "Image-based retrieval of concrete crack properties for bridge inspection," *Autom. Constr.*, vol. 39, pp. 180–194, Apr. 2014.

[45] S. Bang, H. Kim, and H. Kim, "UAV-based automatic generation of high-resolution panorama at a construction site with a focus on preprocessing for image stitching," *Autom. Constr.*, vol. 84, pp. 70–80, Dec. 2017.

[46] I. Brilakis and L. Soibelman, "Content-Based Search Engines for construction image databases," *Autom. Constr.*, vol. 14, no. 4, pp. 537–550, Aug. 2005.

[47] S. El-Omari and O. Moselhi, "Integrating 3D laser scanning and photogrammetry for progress measurement of construction work," *Autom. Constr.*, vol. 18, pp. 1–9, 2008.

[48] G. S. Cheok, W. C. Stone, R. R. Lipman, and C. Witzgall, "Ladars for construction assessment and update," *Autom. Constr.*, vol. 9, no. 5–6, pp. 463–477, Sep. 2000.

[49] R. Hartley and A. Zisserman, *Multiple View Geometry in Computer Vision [Paperback]*, Second. Cambridge University Press; 2 edition, 2004.

[50] J. Park *et al.*, "Bringing Information to the Field: Automated Photo Registration and 4D BIM," *J. Comput. Civ. Eng.*, vol. 32, no. 2, p. 04017084, 2018.

[51] I. Brilakis, H. Fathi, and A. Rashidi, "Progressive 3D reconstruction of infrastructure with videogrammetry," *Autom. Constr.*, vol. 20, no. 7, pp. 884–895, Nov. 2011.

[52] J. Yang, Z.-K. Shi, and Z.-Y. Wu, "Towards automatic generation of as-built BIM: 3D building facade modeling and material recognition from images," *Int. J. Autom. Comput.*, vol. 13, no. 4, pp. 338–349, Aug. 2016.

[53] H. Fathi and I. Brilakis, "Automated sparse 3D point cloud generation of infrastructure using its distinctive visual features," *Adv. Eng. Informatics*, vol. 25, no. 4, pp. 760–770, Oct. 2011.

[54] C. Kim, B. Kim, and H. Kim, "4D CAD model updating using image processing-based construction progress monitoring," *Autom. Constr.*, vol. 35, pp. 44–52, Nov. 2013.

[55] A. Dimitrov and M. Golparvar-Fard, "Vision-based material recognition for automated monitoring of construction progress and generating building information modeling from unordered site image collections," *Adv. Eng. Informatics*, vol. 28, no. 1, pp. 37–49, 2014.

[56] J. Yang, M. W. Park, P. A. Vela, and M. Golparvar-Fard, "Construction

performance monitoring via still images, time-lapse photos, and video streams: Now, tomorrow, and the future," *Adv. Eng. Informatics*, vol. 29, no. 2, pp. 211–224, 2015.

[57] M. Golparvar-fard, F. Peña-mora, and S. Savarese, "Monitoring of Construction Performance Using Daily Progress Photograph Logs and 4D As-planned Models.," *Comput. Civ. Eng.*, no. 2009, pp. 55–63, 2009.

[58] Y. Turkan, F. Bosche, C. T. Haas, and R. Haas, "Automated progress tracking using 4D schedule and 3D sensing technologies," *Autom. Constr.*, vol. 22, pp. 414–421, Mar. 2012.

[59] A. Dimitrov and M. Golparvar-Fard, "Vision-based material recognition for automated monitoring of construction progress and generating building information modeling from unordered site image collections," *Adv. Eng. Informatics*, vol. 28, no. 1, pp. 37–49, Jan. 2014.

[60] K. K. Han and M. Golparvar-Fard, "Appearance-based material classification for monitoring of operation-level construction progress using 4D BIM and site photologs," *Autom. Constr.*, vol. 53, pp. 44–57, 2015.

[61] H. Hamledari, B. McCabe, and S. Davari, "Automated computer vision-based detection of components of under-construction indoor partitions," *Autom. Constr.*, vol. 74, pp. 78–94, Feb. 2017.

[62] Z. Zhu and I. Brilakis, "Parameter optimization for automated concrete detection in image data," *Autom. Constr.*, vol. 19, no. 7, pp. 944–953, 2010.

[63] M. Golparvar-Fard, A. Heydarian, and J. C. Niebles, "Vision-based action recognition of earthmoving equipment using spatio-temporal features and support vector machine classifiers," *Adv. Eng. Informatics*, vol. 27, no. 4, pp. 652–663, Oct. 2013.

[64] M.-W. Park and I. Brilakis, "Construction worker detection in video frames for initializing vision trackers," *Autom. Constr.*, vol. 28, pp. 15–25, Dec. 2012.

[65] B. Eddine Mneymneh, M. Abbas, and H. Khoury, “Automated Hardhat Detection for Construction Safety Applications,” 2017.

[66] M. Golparvar-Fard, ; Feniosky Peña-Mora, C. A. Arboleda, and S. Lee, “Visualization of Construction Progress Monitoring with 4D Simulation Model Overlaid on Time-Lapsed Photographs,” *J. Comput. Civ. Eng.*, vol. 23, no. 6, pp. 391–404, 2009.

[67] I. Abdel-Qader, O. Abudayyeh, and M. E. Kelly, “Analysis of Edge-Detection Techniques for Crack Identification in Bridges,” *J. Comput. Civ. Eng.*, vol. 17, no. 4, pp. 255–263, Oct. 2003.

[68] Y. O. Ouma and M. Hahn, “Pothole detection on asphalt pavements from 2D-colour pothole images using fuzzy c-means clustering and morphological reconstruction,” *Autom. Constr.*, vol. 83, pp. 196–211, Nov. 2017.

[69] A. Dimitrov and M. Golparvar-Fard, “Vision-based material recognition for automated monitoring of construction progress and generating building information modeling from unordered site image collections,” *Adv. Eng. Informatics*, vol. 28, no. 1, pp. 37–49, 2014.

[70] C. Liu, L. Sharan, E. H. Adelson, and R. Rosenholtz, “Exploring features in a Bayesian framework for material recognition,” in *2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2010, pp. 239–246.

[71] N. Dalal and B. Triggs, “Histograms of Oriented Gradients for Human Detection,” in *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR’05)*, vol. 1, pp. 886–893.

[72] C. Liu, J. Yuen, and A. Torralba, “Nonparametric scene parsing: Label transfer via dense scene alignment,” in *2009 IEEE Conference on Computer Vision and Pattern Recognition*, 2009, pp. 1972–1979.

[73] M. U. Hassan, A. Akcamete-Gungor, and C. Meral, “Investigation of Terrestrial Laser Scanning Reflectance Intensity and RGB Distributions to Assist Construction Material Identification,” *Lean Comput. Constr. Congr. - Vol. 1*

Proc. Jt. Conf. Comput. Constr., vol. I, no. July, pp. 507–515, 2017.

[74] H. Son, C. Kim, and C. Kim, "Automated Color Model-Based Concrete Detection in Construction-Site Images by Using Machine Learning Algorithms," 2012.

[75] C. Kim, B. Kim, and H. Kim, "4D CAD model updating using image processing-based construction progress monitoring," *Autom. Constr.*, vol. 35, pp. 44–52, 2013.

[76] J. Zou and H. Kim, "Using Hue, Saturation, and Value Color Space for Hydraulic Excavator Idle Time Analysis," *J. Comput. Civ. Eng.*, vol. 21, no. 4, pp. 238–246, Jul. 2007.

[77] H. Son and C. Kim, "3D structural component recognition and modeling method using color and 3D data for construction progress monitoring," *Autom. Constr.*, vol. 19, no. 7, pp. 844–854, 2010.

[78] P. Podbreznik and D. Rebolj, "Automatic comparison of site images and the 4D model of the building," in *CIB W78 22nd Conference on Information Technology in Construction*, 2005, pp. 235–239.

[79] F. Bosche, C. T. Haas, and B. Akinci, "Automated Recognition of 3D CAD Objects in Site Laser Scans for Project 3D Status Visualization and Performance Control," *J. Comput. Civ. Eng.*, vol. 23, no. 6, pp. 311–318, Nov. 2009.

[80] Helmut Cantzler, "Improving architectural 3D reconstruction by constrained modelling," University of Edinburgh, 2003.

[81] K. Yue, D. Huber, B. Akinci, and R. Krishnamurti, "The ASDMCon Project: The Challenge of Detecting Defects on Construction Sites," in *Third International Symposium on 3D Data Processing, Visualization, and Transmission (3DPVT'06)*, 2006, pp. 1048–1055.

[82] S. Pu and G. Vosselman, "Knowledge based reconstruction of building models

from terrestrial laser scanning data," *ISPRS J. Photogramm. Remote Sens.*, 2009.

[83] P. Tang, D. Huber, B. Akinci, R. Lipman, and A. Lytle, "Automatic reconstruction of as-built building information models from laser-scanned point clouds: A review of related techniques," *Autom. Constr.*, vol. 19, no. 7, pp. 829–843, Nov. 2010.

[84] A. Rashidi, M. H. Sigari, M. Maghiar, and D. Citrin, "An analogy between various machine-learning techniques for detecting construction materials in digital images," *KSCE J. Civ. Eng.*, vol. 20, no. 4, pp. 1178–1188, May 2016.

[85] Z. Man, K. Lee, Z. Cao, and S. Khoo, "An optimal weight learning machine for handwritten digit image recognition," *Signal Processing*, vol. 93, no. 6, pp. 1624–1638, Jun. 2013.

[86] P. Xanthopoulos and T. Razzaghi, "A weighted support vector machine method for control chart pattern recognition," *Comput. Ind. Eng.*, vol. 70, pp. 134–149, Apr. 2014.

[87] A. M. Pinto, L. F. Rocha, and A. Paulo Moreira, "Object recognition using laser range finder and machine learning techniques," *Robot. Comput. Integr. Manuf.*, vol. 29, no. 1, pp. 12–22, Feb. 2013.

[88] J. Abeid Neto, D. Arditi, and M. W. Evens, "Using colors to detect structural components in digital pictures," *Comput. Civ. Infrastruct. Eng.*, vol. 17, no. 1, pp. 61–67, 2002.

[89] I. Abdel-Qader, S. Pashaie-Rad, O. Abudayyeh, and S. Yehia, "PCA-Based algorithm for unsupervised bridge crack detection," *Adv. Eng. Softw.*, vol. 37, no. 12, pp. 771–778, Dec. 2006.

[90] S. Lee, L.-M. Chang, and M. Skibniewski, "Automated recognition of surface defects using digital color image processing," *Autom. Constr.*, vol. 15, no. 4, pp. 540–549, Jul. 2006.

[91] V. Benjaoran, "A cost control system development: A collaborative approach for small and medium-sized contractors," *Int. J. Proj. Manag.*, vol. 27, no. 3, pp. 270–277, Apr. 2009.

[92] R. Vanlande, C. Nicolle, and C. Cruz, "IFC and building lifecycle management," *Autom. Constr.*, vol. 18, no. 1, pp. 70–78, Dec. 2008.

[93] M. Martínez-Rojas, N. Marín, and M. A. Vila, "The Role of Information Technologies to Address Data Handling in Construction Project Management," *J. Comput. Civ. Eng.*, vol. 30, no. 4, p. 04015064, Jul. 2016.

[94] R. Eadie, M. Browne, H. Odeyinka, C. Mckeown, and S. Mcniff, "BIM implementation throughout the UK construction project lifecycle: An analysis," *Autom. Constr.*, vol. 36, pp. 145–151, 2013.

[95] D. Cao, G. Wang, H. Li, M. Skitmore, T. Huang, and W. Zhang, "Practices and effectiveness of building information modelling in construction projects in China," *Autom. Constr.*, vol. 49, pp. 113–122, 2015.

[96] S. Staub-French, A. Khanzode, and P. Candidate, "3D AND 4D MODELING FOR DESIGN AND CONSTRUCTION COORDINATION: ISSUES AND LESSONS LEARNED," 2007.

[97] C. Zhang and D. Arditi, "Automated progress control using laser scanning technology," *Autom. Constr.*, vol. 36, pp. 108–116, Dec. 2013.

[98] F. Bosché, "Automated recognition of 3D CAD model objects in laser scans and calculation of as-built dimensions for dimensional compliance control in construction," *Adv. Eng. Informatics*, vol. 24, no. 1, pp. 107–118, Jan. 2010.

[99] E. J. Jaselskis, Z. Gao, and R. C. Walters, "Improving Transportation Projects Using Laser Scanning," *J. Constr. Eng. Manag.*, 2005.

[100] Y. Turkan, F. Bosché, C. T. Haas, and R. Haas, "Toward Automated Earned Value Tracking Using 3D Imaging Tools," *J. Constr. Eng. Manag.*, vol. 139, no. 4, pp. 423–433, Apr. 2013.

[101] F. Bosche and C. T. Haas, “Automated retrieval of 3D CAD model objects in construction range images,” *Autom. Constr.*, vol. 17, no. 4, pp. 499–512, May 2008.

[102] S. El-Omari and O. Moselhi, “Data acquisition from construction sites for tracking purposes,” *Eng. Constr. Archit. Manag.*, vol. 16, no. 5, pp. 490–503, 1995.

[103] C. H. Oglesby, H. W. Parker, and G. a Howell, “Productivity improvement in construction,” *Journal of Construction Engineering and Management*. 1989.

[104] J. Abeid, E. Allouche, D. Arditi, and M. Hayman, “PHOTO-NET II: a computer-based monitoring system applied to project management,” *Autom. Constr.*, vol. 12, no. 5, pp. 603–616, Sep. 2003.

[105] S. Leung, S. Mak, and B. L. P. Lee, “Using a real-time integrated communication system to monitor the progress and quality of construction works,” *Autom. Constr.*, vol. 17, no. 6, pp. 749–757, Aug. 2008.

[106] D. Rebolj, N. Č. Babič, A. Magdič, P. Podbreznik, and M. Pšunder, “Automated construction activity monitoring system,” *Adv. Eng. Informatics*, vol. 22, no. 4, pp. 493–503, Oct. 2008.

[107] Y. Wu, H. Kim, ; Changyoon Kim, and S. H. Han, “Object Recognition in Construction-Site Images Using 3D CAD-Based Filtering,” *J. Comput. Civ. Eng.*, vol. 24, no. 1, pp. 56–64, 2010.

[108] O. Y. Abudayyeh, “A Multimedia Construction Delay Management System,” *Microcomput. Civ. Eng.*, vol. 12, pp. 183–192, 1997.

[109] E. Jaselskis, A. Sankar, A. Yousif, B. Clark, and V. Chinta, “Using Telepresence for Real-Time Monitoring of Construction Operations,” *J. Manag. Eng.*, vol. 31, no. 1, p. A4014011, 2015.

[110] S. Roh, Z. Aziz, and F. Peña-Mora, “An object-based 3D walk-through model for interior construction progress monitoring,” *Autom. Constr.*, vol. 20, no. 1,

pp. 66–75, Jan. 2011.

[111] E. Jaselskis, J. Ruwanpura, T. Becker, L. Silva, P. Jewell, and E. Floyd, "Innovation in Construction Engineering Education Using Two Applications of Internet-Based Information Technology to Provide Real-Time Project Observations," *J. Constr. Eng. Manag.*, vol. 137, no. 10, pp. 829–835, Oct. 2011.

[112] S. Leung, S. Mak, and B. L. P. Lee, "Using a real-time integrated communication system to monitor the progress and quality of construction works," *Autom. Constr.*, vol. 17, no. 6, pp. 749–757, Aug. 2008.

[113] T. Marrinan, "MARKOV CHAINS: ROOTS, THEORY, AND APPLICATIONS," Walla Walla, WA.

[114] C.-H. Kuo, M.-H. Tsai, and S.-C. Kang, "A framework of information visualization for multi-system construction," *Autom. Constr.*, vol. 20, no. 3, pp. 247–262, May 2011.

[115] Mary Ellen Foster, Tomas By, Markus Rickert, and Alois Kn, "Human-Robot Dialogue for Joint Construction Tasks," in *international conference on Multimodal interfaces, ICMI'06*, 2006.

[116] M. Alshawi and B. Ingirige, "Web-enabled project management: an emerging paradigm in construction," *Autom. Constr.*, vol. 12, no. 4, pp. 349–364, Jul. 2003.

[117] S. Y. L. Yin, H. P. Tserng, J. C. Wang, and S. C. Tsai, "Developing a precast production management system using RFID technology," *Autom. Constr.*, vol. 18, no. 5, pp. 677–691, Aug. 2009.

[118] R. Maalek and F. Sadeghpour, "Accuracy assessment of Ultra-Wide Band technology in tracking static resources in indoor construction scenarios," *Autom. Constr.*, vol. 30, pp. 170–183, Mar. 2013.

[119] R. Navon and Y. Shpatnitsky, "A model for automated monitoring of road

construction," *Constr. Manag. Econ.*, vol. 23, no. 9, pp. 941–951, Nov. 2005.

[120] M. Sousa, A. Techmer, A. Steinhage, C. Lauterbach, and P. Lukowicz, "Human tracking and identification using a sensitive floor and wearable accelerometers," *2013 IEEE Int. Conf. Pervasive Comput. Commun. PerCom 2013*, no. March, pp. 166–171, 2013.

[121] Jason Underwood and Umit Isikdag, "Handbook of Research on Building Information Modeling and Construction Informatics," *Information Science Reference - Imprint of: IGI Publishing*, 2009. [Online]. Available: https://dl.acm.org/citation.cfm?id=1823086#citedby. [Accessed: 04-Sep-2018].

[122] H. S. Oluwatosin, "Client-Server Model," *IOSR J. Comput. Eng.*, vol. 16, no. 1, pp. 57–71, 2014.

[123] B. Donald and B. Paulson, *Professional Construction Management*, 3rd ed. McGraw Hill, 1992.

[124] R. M. Webb, J. Smallwood, and T. Haupt, "The potential of 4D CAD as a tool for construction management," *J. Constr. Res.*, vol. 5, no. 1, pp. 43–60, 2004.

[125] C. M. Eastman, *BIM handbook : a guide to building information modeling for owners, managers, designers, engineers and contractors*. Wiley, 2011.

[126] Autodesk, "Understanding Revit Terms | Revit Products |," *Autodesk Knowledge Network*, 2014. [Online]. Available: https://knowledge.autodesk.com/support/revit-products/learn-explore/caas/CloudHelp/cloudhelp/2014/ENU/Revit/files/GUID-2480CA33-C0B9-46FD-9BDD-FDE75B513727-htm.html. [Accessed: 10-Sep-2018].

[127] A. Braun, S. Tuttas, and A. Borrmann, "A concept for automated construction progress monitoring using bim-based geometric constraints and photogrammetric point clouds," 2015.

[128] M. Kilkelly, "What Is Dynamo and 5 Reasons You Should be Using It -

ArchSmarter -," *ARCHSMARTER*, 2018. [Online]. Available: https://archsmarter.com/what-is-dynamo-revit/. [Accessed: 26-Nov-2018].

[129] J. Beyerer, J. Jasperneite, and O. Sauer, "Industrie 4.0," *At-Automatisierungstechnik*, 2015.

[130] H. A. ElMaraghy *et al.*, "The Cognitive Factory," *Chang. Reconfigurable Manuf. Syst. - Springer Ser. Adv. Manuf.*, 2009.

[131] W. C. Stone and L. E. Pfeffer, "Automation Infrastructure for a Robotic 30-ton Bridge Crane," in *Robotics 98 Conference, ASCE*, 1998, pp. 195–201.

[132] T. Bock and T. Linner, *Robot-oriented design : design and management tools for the deployment of automation and robotics in construction*. .

[133] R. N. Foster, *Innovation : the attacker's advantage*. Summit Books, 1986.

[134] T. Bock, "The future of construction automation: Technological disruption and the upcoming ubiquity of robotics," *Autom. Constr.*, vol. 59, pp. 113–121, 2015.

[135] R. Allan, "Busy robots spur productivity," *IEEE Spectr.*, vol. 16, no. 9, pp. 31–36, 1979.

[136] Steven Crowe, "Watch Boston Dynamics Spot robot inspect construction sites in Japan," *THE ROBOT REPORT*, 2018. [Online]. Available: https://www.therobotreport.com/spot-robot-inspects-construction-sites/. [Accessed: 11-Dec-2018].

[137] Construction Robotics, "SAM100." Victor, NY, USA, 2017.

[138] Ty Bot LLC, "Ty Bot." Pittsburgh, PA, USA, 2018.

[139] Effidence, "Effibot." Romagnat, France, 2017.

[140] B. R. Inc., "Built Robotics." San Francisco, LA, USA, 2018.

[141] Wai-Ki Ching, Ximin Huang, Michael K.Ng, and Tak-Kuen Siu, *Markov Chains. International Series in Operations Research & Management Science.*, 2nd ed. Springer US, 2013.

[142] Y. Ham, K. K. Han, J. J. Lin, and M. Golparvar-Fard, "Visual monitoring of civil infrastructure systems via camera-equipped Unmanned Aerial Vehicles (UAVs): a review of related works," 2011.

[143] D. Mihai and E. Străjescu, "From wavelength to R.G.B filter," *U.P.B. Sci. Bull. Ser. D*, vol. 69, no. 2, 2007.

[144] K. Nice and G. J. Gurevich, "How Digital Cameras Work Understanding the Basics A Filmless Camera," 2012.

[145] M.-W. Park and I. Brilakis, "Construction worker detection in video frames for initializing vision trackers," *Autom. Constr.*, vol. 28, pp. 15–25, Dec. 2012.

[146] M. G. Fard, A. Sridharan, S. Lee, and F. Peña-Mora, "Visual representation of construction progress monitoring metrics on time-lapse photographs," in *CME 2007 Conference - Construction Management and Economics: "Past, Present and Future,"* 2007.

[147] J. Yang, M.-W. Park, P. A. Vela, and M. Golparvar-Fard, "Construction performance monitoring via still images, time-lapse photos, and video streams: Now, tomorrow, and the future," *Adv. Eng. Informatics*, vol. 29, no. 2, pp. 211–224, Apr. 2015.

[148] F. Tagliaferri, B. P. Hayes, I. M. Viola, and S. Z. Djokić, "Wind modelling with nested Markov chains," *J. Wind Eng. Ind. Aerodyn.*, vol. 157, pp. 118–124, Oct. 2016.

[149] D. Pascale, "A Review of RGB Color Spaces." The BabelColor Company, Montreal (Quebec), 2003.

[150] D. H. Brainard, "Color Vision Theory," *Int. Encycl. Soc. Behav. Sci.*, pp. 2256–2263, Jan. 2001.

[151] G. García-Mateos, J. L. Hernández-Hernández, D. Escarabajal-Henarejos, S. Jaén-Terrones, and J. M. Molina-Martínez, "Study and comparison of color models for automatic image analysis in irrigation management applications,"

Agric. Water Manag., vol. 151, pp. 158–166, Mar. 2015.

[152] A. Ford and A. Roberts, "Colour space conversions," *Westminster Univ. London*, vol. 1998, pp. 1–31, 1998.

[153] R. . Gonzales and R. . Woods, *Digital Image Processing*, 3rd ed. Prentice Hall, 2008.

[154] J. W. Shipman, "Introduction to color theory," 2012. [Online]. Available: http://www.nmt.edu/tcc/help/pubs/colortheory/web/hsv.html.

[155] W. Liu, J. Ji, H. Chen, and C. Ye, *Optimal Color Design of Psychological Counseling Room by Design of Experiments and Response Surface Methodology*, vol. 9. 2014.

[156] J. MacQueen, "Some methods for classification and analysis of multivariate observations," in *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, Volume 1: Statistics*, 1967, pp. 281–297.

[157] Andrea Trevino, "Introduction to K-means Clustering," *Oracle+datascience.com*, 2018. [Online]. Available: https://www.datascience.com/blog/k-means-clustering. [Accessed: 16-Jul-2018].

[158] K. K. Han and M. Golparvar-Fard, "Appearance-based material classification for monitoring of operation-level construction progress using 4D BIM and site photologs," *Autom. Constr.*, vol. 53, pp. 44–57, 2015.

[159] D. P. Huijsmans and N. Sebe, "Extended performance graphs for cluster retrieval," in *Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. CVPR 2001*, vol. 1, p. I-26-I-31.

[160] K. K. Han and M. Golparvar-Fard, "Appearance-based material classification for monitoring of operation-level construction progress using 4D BIM and site photologs," *Autom. Constr.*, vol. 53, pp. 44–57, 2015.

[161] S. Roh, Z. Aziz, and F. Peña-Mora, "An object-based 3D walk-through model for interior construction progress monitoring," *Autom. Constr.*, vol. 20, no. 1, pp. 66–75, 2011.

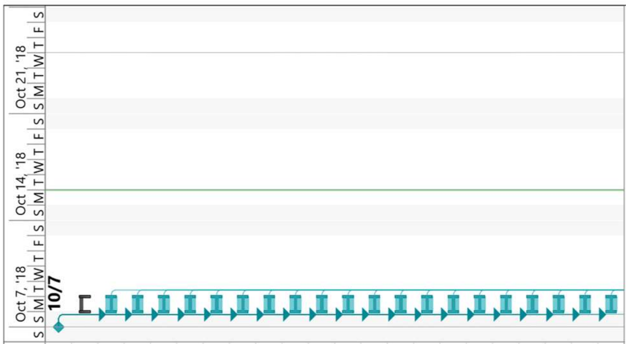
[162] J. Park *et al.*, "Bringing Information to the Field: Automated Photo Registration and 4D BIM," *J. Comput. Civ. Eng.*, vol. 32, no. 2, p. 04017084, 2018.

[163] M. U. Hassan, "A computer vision based method for semi-automated rebar detection and measurement of reinforced concrete columns," Middle East Technical Unversity (METU), 2014.

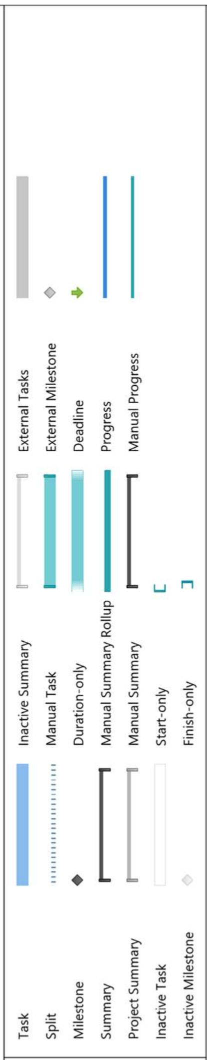
APPENDIX A

A. SIMULATED STRUCTURE SCHEDULE

ID		Task Mode	Task Name	Duration	Start	Finish
1			Start of Work	0 days	Sun 10/7/18	Sun 10/7/18
2			**Rebar Installation**	**1 day**	**Mon 10/8/18**	**Tue 10/9/18**
3			Rebar Placement for 70x40 Concrete Column	1 day	Mon 10/8/18	Mon 10/8/18
4			Rebar Placement for 130x30 Concrete Column	1 day	Mon 10/8/18	Mon 10/8/18
5			Rebar Placement for 130x30 Concrete Column	1 day	Mon 10/8/18	Mon 10/8/18
6			Rebar Placement for 130x30 Concrete Column	1 day	Mon 10/8/18	Mon 10/8/18
7			Rebar Placement for 130x30 Concrete Column	1 day	Mon 10/8/18	Mon 10/8/18
8			Rebar Placement for 130x30 Concrete Column	1 day	Mon 10/8/18	Mon 10/8/18
9			Rebar Placement for 70x40 Concrete Column	1 day	Mon 10/8/18	Mon 10/8/18
10			Rebar Placement for 70x40 Concrete Column	1 day	Mon 10/8/18	Mon 10/8/18
11			Rebar Placement for 70x40 Concrete Column	1 day	Mon 10/8/18	Mon 10/8/18
12			Rebar Placement for 70x40 Concrete Column	1 day	Mon 10/8/18	Mon 10/8/18
13			Rebar Placement for 70x40 Concrete Column	1 day	Mon 10/8/18	Mon 10/8/18
14			Rebar Placement for 70x40 Concrete Column	1 day	Mon 10/8/18	Mon 10/8/18
15			Rebar Placement for 70x40 Concrete Column	1 day	Mon 10/8/18	Mon 10/8/18
16			Rebar Placement for 70x40 Concrete Column	1 day	Mon 10/8/18	Mon 10/8/18
17			Rebar Placement for 70x40 Concrete Column	1 day	Mon 10/8/18	Mon 10/8/18
18			Rebar Placement for 70x40 Concrete Column	1 day	Mon 10/8/18	Mon 10/8/18
19			Rebar Placement for 70x40 Concrete Column	1 day	Mon 10/8/18	Mon 10/8/18
20			Rebar Placement for 70x40 Concrete Column	1 day	Mon 10/8/18	Mon 10/8/18
21			Rebar Placement for 70x40 Concrete Column	1 day	Mon 10/8/18	Mon 10/8/18
22			Rebar Placement for 70x40 Concrete Column	1 day	Mon 10/8/18	Mon 10/8/18

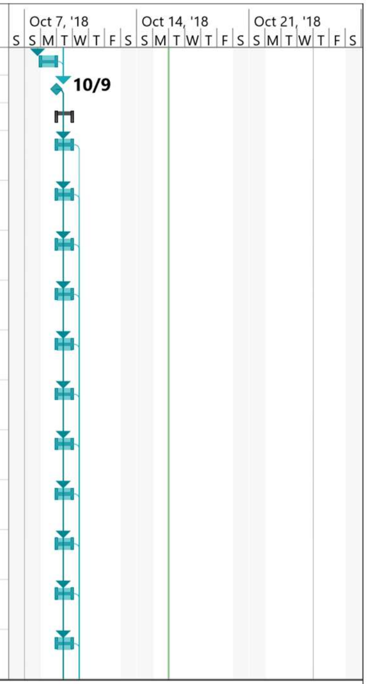


Project: ScheduleTestProject
Date: Tue 10/16/18



Page 1

ID		Task Mode	Task Name	Duration	Start	Finish
23			Rebar Placement for 70 x 30 Concrete Column	1 day	Mon 10/8/18	Mon 10/8/18
24			Rebar Placement Completed	0 days	Tue 10/9/18	Tue 10/9/18
25			**Installation of Formwork**	**1 day**	**Tue 10/9/18**	**Wed 10/10/18**
26			Installation of Formwork for 130x30 Concrete Column	1 day	Tue 10/9/18	Tue 10/9/18
27			Installation of Formwork for 130x30 Concrete Column	1 day	Tue 10/9/18	Tue 10/9/18
28			Installation of Formwork for 130x30 Concrete Column	1 day	Tue 10/9/18	Tue 10/9/18
29			Installation of Formwork for 130x30 Concrete Column	1 day	Tue 10/9/18	Tue 10/9/18
30			Installation of Formwork for 70x40 Concrete Column	1 day	Tue 10/9/18	Tue 10/9/18
31			Installation of Formwork for 70x40 Concrete Column	1 day	Tue 10/9/18	Tue 10/9/18
32			Installation of Formwork for 70x40 Concrete Column	1 day	Tue 10/9/18	Tue 10/9/18
33			Installation of Formwork for 70x40 Concrete Column	1 day	Tue 10/9/18	Tue 10/9/18
34			Installation of Formwork for 70x40 Concrete Column	1 day	Tue 10/9/18	Tue 10/9/18
35			Installation of Formwork for 70x40 Concrete Column	1 day	Tue 10/9/18	Tue 10/9/18
36			Installation of Formwork for 70x40 Concrete Column	1 day	Tue 10/9/18	Tue 10/9/18

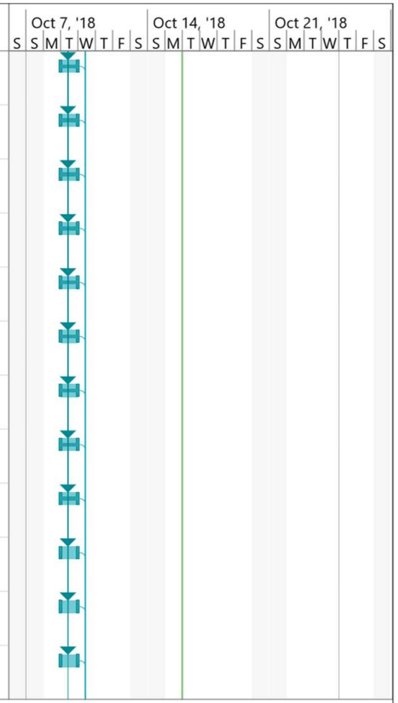


Project: ScheduleTestProject
Date: Tue 10/16/18

Task
Split
Milestone
Summary
Project Summary
Inactive Task
Inactive Milestone
Inactive Summary
Manual Task
Duration-only
Manual Summary Rollup
Manual Summary
Start-only
Finish-only
External Tasks
External Milestone
Deadline
Progress
Manual Progress

Page 2

ID	Indicators	Task Mode	Task Name	Duration	Start	Finish
37	✓		Installation of Formwork for 70x40 Concrete Column	1 day	Tue 10/9/18	Tue 10/9/18
38	✓		Installation of Formwork for 70x40 Concrete Column	1 day	Tue 10/9/18	Tue 10/9/18
39	✓		Installation of Formwork for 70x40 Concrete Column	1 day	Tue 10/9/18	Tue 10/9/18
40	✓		Installation of Formwork for 1270*40 Structural Columns 330356	1 day	Tue 10/9/18	Tue 10/9/18
41	✓		Installation of Formwork for 180*40 Structural Columns 324193	1 day	Tue 10/9/18	Tue 10/9/18
42	✓		Installation of Formwork for 250*30 Structural Columns 324393	1 day	Tue 10/9/18	Tue 10/9/18
43	✓		Installation of Formwork for 250*30 Structural Columns 324395	1 day	Tue 10/9/18	Tue 10/9/18
44	✓		Installation of Formwork for 1270*40 Structural Columns 330356	1 day	Tue 10/9/18	Tue 10/9/18
45	✓		Installation of Formwork for 940*50 Structural Columns 331054	1 day	Tue 10/9/18	Tue 10/9/18
46			Installation of Formwork for 1270*40 Structural Columns 329529	1 day	Tue 10/9/18	Tue 10/9/18
47			Installation of Formwork for 790*40 Structural Columns 326128	1 day	Tue 10/9/18	Tue 10/9/18
48			Installation of Formwork for 220*40 Structural Columns 328056	1 day	Tue 10/9/18	Tue 10/9/18

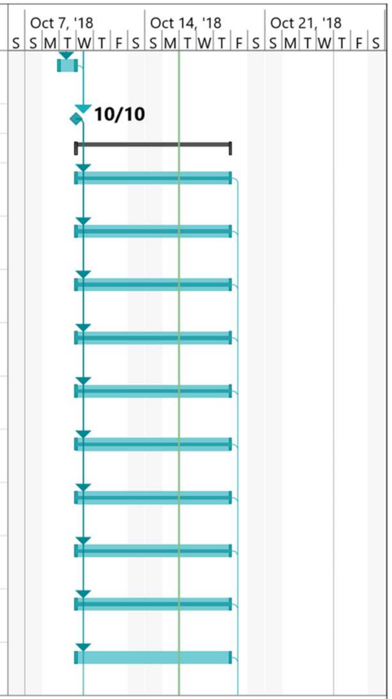


Project: ScheduleTestProject
Date: Tue 10/16/18

Task	Inactive Summary	External Tasks
Split	Manual Task	External Milestone
Milestone	Duration-only	Deadline
Summary	Manual Summary Rollup	Progress
Project Summary	Manual Summary	Manual Progress
Inactive Task	Start-only	
Inactive Milestone	Finish-only	

Page 3

ID		Task Mode	Task Name	Duration	Start	Finish
49			Installation of Formwork for 220*40 Structural Columns 328353	1 day	Tue 10/9/18	Tue 10/9/18
50	✓		Completed Formwork Installation	0 days	Wed 10/10/18	Wed 10/10/18
51			**Concrete Work**	**7 days**	**Wed 10/10/18**	**Fri 10/19/18**
52	✓		Concrete Work and Removal of Formwork 130x30 Concrete Column	7 days	Wed 10/10/18	Thu 10/18/18
53	✓		Concrete Work and Formwork Removal for 1270*40 Structural Columns 330356	7 days	Wed 10/10/18	Thu 10/18/18
54	✓		Concrete Work and Formwork Removal for 460*40 Structural Columns 321171	7 days	Wed 10/10/18	Thu 10/18/18
55	✓		Concrete Work and Formwork Removal for 450*40 Structural Columns 315005	7 days	Wed 10/10/18	Thu 10/18/18
56	✓		Concrete Work and Formwork Removal for 180*40 Structural Columns 319919	7 days	Wed 10/10/18	Thu 10/18/18
57	✓		Concrete work Finish at Removal of Formwork for 40*60 Structural Columns 324175	7 days	Wed 10/10/18	Thu 10/18/18
58	✓		Concrete work Finish at Removal of Formwork for 1350*40 Structural Columns 324201	7 days	Wed 10/10/18	Thu 10/18/18
59	✓		Concrete work Finish at Removal of Formwork for 460*40 Structural Columns 324203	7 days	Wed 10/10/18	Thu 10/18/18
60	✓		Concrete work Finish at Removal of Formwork for 40*60 Structural Columns 324355	7 days	Wed 10/10/18	Thu 10/18/18
61			Concrete work Finish at Removal of Formwork for 180*40 Structural Columns 324375	7 days	Wed 10/10/18	Thu 10/18/18

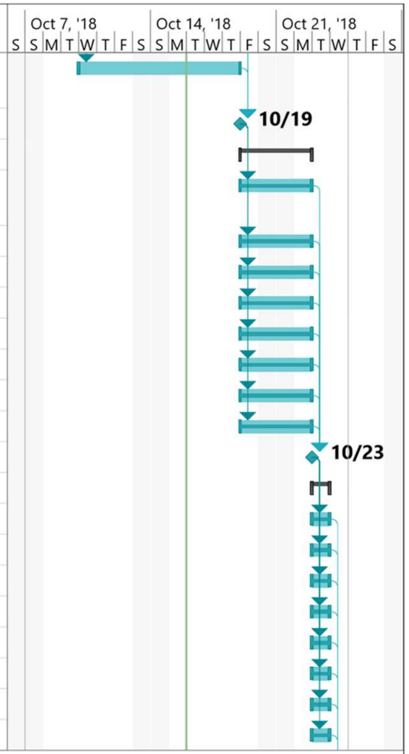


Project: ScheduleTestProject
Date: Tue 10/16/18

Task	Inactive Summary	External Tasks
Split	Manual Task	External Milestone
Milestone	Duration-only	Deadline
Summary	Manual Summary Rollup	Progress
Project Summary	Manual Summary	Manual Progress
Inactive Task	Start-only	
Inactive Milestone	Finish-only	

Page 4

ID		Task Mode	Task Name	Duration	Start	Finish
62			Concrete work Finish at Removal of Formwork for 460*40 Structural Columns 324381	7 days	Wed 10/10/18	Thu 10/18/18
63			Completed Concrete Work	0 days	Fri 10/19/18	Fri 10/19/18
64	✓		**Masonry Work**	**2 days**	**Fri 10/19/18**	**Tue 10/23/18**
65	✓		Masonry work for gazbeton-sÄ±va Walls 391150	2 days	Fri 10/19/18	Mon 10/22/18
66	✓		Masonry work for gazbeton 20 Walls 398699	2 days	Fri 10/19/18	Mon 10/22/18
67	✓		Masonry work for gazbeton Walls 379260	2 days	Fri 10/19/18	Mon 10/22/18
68	✓		Masonry work for gazbeton Walls 398297	2 days	Fri 10/19/18	Mon 10/22/18
69	✓		Masonry work for gazbeton Walls 517928	2 days	Fri 10/19/18	Mon 10/22/18
70	✓		Masonry work for gazbeton Walls 518071	2 days	Fri 10/19/18	Mon 10/22/18
71	✓		Masonry work for gazbeton Walls 518356	2 days	Fri 10/19/18	Mon 10/22/18
72	✓		Masonry work for gazbeton Walls 518541	2 days	Fri 10/19/18	Mon 10/22/18
73	✓		Completed Masonry work	0 days	Tue 10/23/18	Tue 10/23/18
74	✓		**Door Installation**	**1 day**	**Tue 10/23/18**	**Wed 10/24/18**
75	✓		Installation of Door	1 day	Tue 10/23/18	Tue 10/23/18
76	✓		Installation of Door	1 day	Tue 10/23/18	Tue 10/23/18
77	✓		Installation of Door	1 day	Tue 10/23/18	Tue 10/23/18
78	✓		Installation of Door	1 day	Tue 10/23/18	Tue 10/23/18
79	✓		Installation of Door	1 day	Tue 10/23/18	Tue 10/23/18
80	✓		Installation of Door	1 day	Tue 10/23/18	Tue 10/23/18
81	✓		Installation of Door	1 day	Tue 10/23/18	Tue 10/23/18
82	✓		Installation of Door	1 day	Tue 10/23/18	Tue 10/23/18



Project: ScheduleTestProject
Date: Tue 10/16/18

Task
Split
Milestone
Summary
Project Summary
Inactive Task
Inactive Milestone
Inactive Summary
Manual Task
Duration-only
Manual Summary Rollup
Manual Summary
Start-only
Finish-only
External Tasks
External Milestone
Deadline
Progress
Manual Progress

Page 5

ID		Task Mode	Task Name	Duration	Start	Finish	Oct 7, '18 — Oct 14, '18 — Oct 21, '18
83	✓		Completed door installation	0 days	Wed 10/24/18	Wed 10/24/18	10/24

Project: ScheduleTestProject
Date: Tue 10/16/18

Task	Inactive Summary	External Tasks
Split	Manual Task	External Milestone
Milestone	Duration-only	Deadline
Summary	Manual Summary Rollup	Progress
Project Summary	Manual Summary	Manual Progress
Inactive Task	Start-only	
Inactive Milestone	Finish-only	

CURRICULUM VITAE

PERSONAL INFORMATION

Surname, Name: Hassan, Muhammad Usman
Nationality: Pakistani
Date and Place of Birth: 15 April 1984, Pakistan
Marital Status: Married
Phone: +92 333 5247116
Fax: +90 312 210 22 91
email: wwwfbe@metu.edu.tr

EDUCATION

Degree	Institution	Year of Graduation
Ph.D.	**CONSTRUCTION MGMT**	**2018**
MS	MS STRUCTURAL ENGINEERING	2014
BS	NUST CIVIL ENGINEERING	2006

WORK EXPERIENCE

Year	Place	Enrollment
2015-Present	Yapıdestek Muhendıslık	Head of Solutions
2012-2014	Dorce Muh	BID Manager
2011-2012	Ericsson Pak	OHS Manager KSA/PAK
2008 July	Telenor Pakistan	Team Lead QA/QC
2006 July	Telenor Pakistan	Civil Works & Power Engr

FOREIGN LANGUAGES

Advanced English, Fluent Turkish

PUBLICATIONS

1. Hassan M.U., Akcamete-Gungor A., and Meral C. (2017). "Investigation of Terrestrial Laser Scanning Reflectance Intensity and RGB Distributions to Assist Construction Material Identification." In: LC3 2017: Volume I – Proceedings of the Joint Conference on Computing in Construction (JC3), July 4-7, 2017, Heraklion, Greece, pp. 507-515. DOI: https://doi.org/10.24928/JC3-2017/0312.