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AUTOMATED CONSTRUCTION MATERIALS DATA ACQUISITION USING DIGITAL IMAGING AND RFID

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Abstract: Recent researches in the construction materials management demonstrate an obvious negligence towards the interconnectivity of near real-time data acquisition technologies and measuring material consumption rate on daily basis. This research aims to calculate the near real-time consumption rate of materials using digital imaging and RFID technologies. Construction materials are classified in "Tagged materials and Bulk materials", and then based on materials nature, ease of use, related expenses, and applicability, digital imaging and RFID technologies are applied to measure the consumption rate of bulk and tagged materials respectively. Change detection methods in 2D images and also in 3D structure of an under-constructing element from multi-view images captured by a camera at consecutive days are applied to calculate the bulk material consumption. Calculation the amount of installed tagged materials is addressed using RFID as a novel activity-based progress tracking method. The results show that the proposed method can be applied practically in the construction projects and influence positively not only on the efficiency of construction materials management but also on the construction project cost and schedule, claim settlement and ease of project progress tracking.

1 INTRODUCTION

The significance of the materials and materials management role in the construction industry and also the negative impact of ineffective materials management on the cost and schedule of the construction projects have been explored in a large number of studies and reports. Material cost makes up around 50-60% of the industrial construction projects cost (Stukhart, 1995; Bernold & Treseler, 1991), and controls 80% of the project schedule (Stukhart, 1995; Kerridge, 1987). The current extensive literature with the purpose of improving materials management for the construction projects can be categorized in two domains, construction materials management, and automation of construction materials management. The second domain "Automated construction materials management" consists of the application of Automated Data Collection (ADC) technologies in the materials management and computer-based materials management systems. Studies in the first domain have focused on the concepts of materials management and try to improve it by the implementation of JIT strategies, materials storage optimization, performance measurement of the materials management process, materials management problems and their impacts on project productivity, cost and schedule. Then researchers tried to develop computerized systems to achieve uniformity of documents generation, efficiency, and automatic process implementation. They also came to the conclusion that applying Automated Data Collection (ADC) technologies to acquire construction materials data instead of manual data collection could reduce slow, inaccurate, and extensive amounts of paperwork collected data and improve materials management(Golkhoo & Moselhi, 2016).ADC technologies have been applied in the construction industry for various purposes such as labor productivity measurement; tracking, positioning and monitoring of resources including material, labor and equipment; progress tracking, measuring of earth moving materials consumption, improving safety, improving material receiving process, and quality control. Focusing on construction materials management indicates that Automated Data Collection (ADC) technologies have been too often applied for positioning and tracking critical resources including materials, equipment, and laborers in construction sites or for identifying unique materials received at the job site. But in order to achieve an effective materials management system especially in the construction phase not only the near real-time data related to the materials position, location and their arrival to the site should be acquired but also the near real-time data of their consumption rate or installation on the construction site should be obtained. So critical future decisions and corrective actions can be taken based on more accurate and near real-time collected data to avoid project delays and cost overruns. So there is a need to a higher level of automation and computerization of materials management. Since there is an obvious negligence towards the interconnectivities of near real-time data acquisition methods or technologies and measuring material consumption rate on a daily basis, this paper proposes proper data acquisition technologies and related algorithms for measuring the amount of installed materials on the construction site.

2 BACKGROUND

During recent decades, among existing automated data collection technologies, RFID systems and the Global Positioning System (GPS) are the foremost technologies applied for automated tracking and monitoring of construction resources and assets (Soleimanifar, 2011; Chin&Yoon, 2008; Khoury&Kamat, 2009). However there exist other technologies including barcodes, Ultra-Wide Band (UWB), Ekahau, ZigBee-based wireless sensor network, ultrasound positioning and RF (Radio Frequency) technologies which have been utilized for localization, tracking and monitoring of construction resources. RFID has been used to enhance construction operations specifically in materials receiving process by Jaselskis and El-Misalami (2003). Tracking process of pipe spools in the long supply chain process was automated through applying RFID by Song et al. (2006). Binti Kasim (2008 & 2015) integrated RFID-based materials tracking and resource modeling systems to develop a real- time prototype system for improving materials tracking and inventory management processes on construction projects. On top of the above mentioned technologies, there are other technologies such as digital cameras, 3D range cameras, and laser scanners have been applied for image-based modeling of as-built status of buildings. In fact these optical-based spatial data acquisition technologies have been used for defect and deviation detection, construction job site planning, on-site safety enhancement and as-built documentation (Bhatla et al., 2012). But the As-built documentation including a set of records, construction drawings, specifications and equipment location and as-built conditions of projects (Bhatla et al., 2012) is the main application of these technologies needed for construction progress monitoring purposes. In researches applying laser scanner, as-built data are captured by laser scanners in order to create 3D as-built models. Then 3D design model is comparing with 3D as-built models to achieve the goal. Kim et al. (2013) tried to obviate the shortcomings of other automated construction progress measurement methods which were the result of incomplete data sets. So they used a 4D BIM and 3D data obtained by a laser scanner to align the as-built data with the as-planned model, match the as-built data to information in the BIM, and finally revise the as-built status. As Golparvar-Fard et al. (2015) has stated, in spite of the extensive studies about the application of laser scanners in automated data collection, they have some shortcomings including limited spatial and temporal resolutions (Furukawa and Ponce 2006), need for frequent and manual registrations due to discontinuity of spatial information, the mixed-pixel phenomenon (Kiziltas et al. 2008), need for regular sensor calibrations, and slow warm-up time, creation of noise resulted from moving objects, reduction of captured detail due to increase of distance between laser scanner and the building components and finally since they are not easily portable, so they are not proper for indoor environments.
In contrast because of digital imaging advances, low prices of cameras, and their high resolution images, it has been perceived as a proper ADC technology especially for the progress monitoring of construction projects. As Rankohi (2013) stated, daily photographs on construction sites are captured for documentary purposes, however these taken images could also have other applications including monitoring progress, resolving disputes and training for similar projects. Kim and Kano (2008) proposed a method to determine the 3-dimensional viewpoint and the direction vector of a construction photograph through surveying of location of fixed-point camera for the comparison of the construction photograph and the corresponding Virtual Reality (VR) image. An analytical approach was developed by Dai et al. (2011) to map the computer-generated 3D graphics of invisible underground infrastructure on the site photos with the

purpose of generating a more integral view of the construction site situation. Golparvar-Fard et al. (2015) presented an automated approach to measure the physical progress of buildings under construction. All the required information was obtained from building information models (BIMs) and unordered daily construction photos. In this process, a dense as-built point cloud model in four dimensions was reconstructed through a set of unordered and un-calibrated site photographs and by using structure-from motion, multi-view stereo, voxel coloring and labeling algorithms. Then by registration of an Industry Foundation Class–based (IFC-based) BIM and reconstructed as-built scene and by applying machine-learning scheme based on a Bayesian probabilistic model, physical progress was detected automatically. Hamledari and McCabe (2016) proposed a method in which color and shape-based approaches were integrated for visual recognition of indoor project-related objects for automated progress monitoring and providing as-built 3D models.

In can be concluded that even though various studies have improved materials management process copiously in the construction industry using ADC technologies, most of them have applied above mentioned technologies for positioning and tracking critical resources including materials, equipment, and laborers in construction sites, identifying unique materials received at the job site, recognition of project-related objects or comparing as-planned and as-built status with the purpose of monitoring the project progress and discrepancies control. So the benefits of directly measuring of quantities of materials installation on site using ADC technologies has been left out. Calculation of materials consumption on daily basis in the construction projects along with a computerized construction materials management system (Refer to Golkhoo and Moselhi (2016) for more details) would result in taking more accurate and near real-time corrective actions and reduction of project time and cost overruns. In the present study construction materials have been categorized in two groups called “Tagged materials and Bulk materials”. Digital imaging technology is used to measure the near real-time consumption rate of bulk materials, and in order to find the most proper algorithm for measuring the amount of consumed bulk materials from the captured images, both 2D and 3D change detection algorithms have been investigated and compared. Calculation the amount of installed tagged materials on daily basis is addressed using RFID as a novel activity-based progress tracking method.

3 DIGITAL IMAGING AND IMAGE PROCESSING TECHNIQUES

An image is considered as highly accurate information in the construction projects (Kim and Kano, 2008). Cameras have been applied widely to monitor and record various activities on a construction site specially for the purpose of construction control and inspection. Image processing alludes to the quantitative evaluation techniques which can be used to images for the quality improvement for analysis purposes. These techniques have been introduced to and used in the civil engineering discipline not long ago and enable civil engineers to carry out many labor intensive tasks automatically (Shehab-Eldeen, 2001).It is expressed that there are no clear cut boundaries between image processing and computer vision. The fields of computer vision uses computers in order to emulate human vision which includes learning and ability to deduce and take actions based on visual inputs. So there are some definitions to illustrate these field boundries, for instance a distinction is made by determining that the input and output of a process are images in the image processing discipline or the area of image analysis/ image understanding is in between image processing and computer vision. But the best paradigm considers three types of computerized processes in this continuum: low-level (both inputs and outputs are images), mid-level (inputs are generally images, but its outputs are attributes extracted from those images), and high-level (making sense of recognized objects, and performing the cognitive functions normally associated with human vision) processes (Gonzalez et al., 2009).Image-based methods for progress monitoring can be categorized into two types, one using 2D spatial data from digital image, and the other using 3D spatial data obtained from two or more digital images. In the method employing 2D information, digital images are often taken and updated at regular intervals to be compared for detecting status changes. The condition of a construction site can be obtained and assessed easily and rapidly using these approaches but when the location information about objects of interest is required, they have limited accuracy. In contrast the 3D spatial data using two or more images can be acquired through 3D methods such as photogrammetry, laser scanning system and stereo vision system. Photogrammetry provides 3D spatial data at a low cost; however, it needs a complicated process and a considerable amount of time for multiple digital images analysis. On the other hand not only obtaining 3D spatial data in real-time through laser scanning technology takes considerable time to process the data but also the equipment costs are still high. But a recently developed stereo vision system can provide 3D spatial data based on acquired images more efficiently, rapidly, and cheaply without high computational processing, cost, and time requirements (Choi et al., 2008).There exists various vision-techniques which have been applied on 2Dimages for various purposes and if they are selected and applied properly, they can be cost-effective, accurate, and easy to implement. Object recognition technique based on a stereo vision system, Structure from Motion (SfM) technique applied to estimate camera motions and reconstruct 3-D shape of objects simultaneously based on epipolar geometry, image registration techniques and etc. are some examples of image processing techniques. In this research image change detection algorithms have been applied on the images captured from each element under construction on consecutive days. The algorithms and the process will be elaborated in the proposed method section. Investigating and defining the set of pixels which are different among captured images from a scene is the core operation in the change detection techniques. Remote sensing, surveillance, medical diagnosis and treatment, civil infrastructure, and underwater sensing are disciplines in which detecting changes plays a significant role and has been used widely. It should be stated that changed pixels can be investigated and defined in terms of appearance or disappearance of objects, motion of objects, and shape change of objects. Change detections algorithms have been classified in various categories by different researchers. A major portion of the research efforts has been focused on the study and use of automatic image change detection methods for various applications specially in the field of computer vision. Extensive studies use stationary cameras to take input images for performing change detection methods, and using non-stationary camera positions to take input images has not been well developed (Beulah David, 2011). Among the studies focusing on detecting temporal changes of a scene, some of them consider detecting 2D changes which can be seen in image appearance and some others detect changes in 3D structure of the scene. In the most studies of 2D and 3D change detection, in the first step a steady state model of the scene is created and then the model generated from newly-captured image(s) is compared against it for detecting changes (Sakurada, K., 2015). In this research, both 2D and 3D automatic change detection methods have been proposed for applying on images taken by non- stationary cameras.

4 RADIO FREQUENCY IDENTIFICATION (RFID)

Another automated data collection technology which is used in this paper is Radio Frequency Identification (RFID). RFID system consists of three principal components: tag, which is attached to the item expected to be tracked; the reader, which identifies tags, reads tags’ data and transfers data to the host computer, and host computer as a data collector which receives data from the reader (Nasir, 2008). RFID tags can be classified as active tags, passive tags or semi-passive tags. In RFID system, a serial number or other required information are stored on RFID tags which have been attached to the items, then RFID tag transmits the identification information in forms of emitted radio waves to RFID reader. Finally the reader converts them into digital information to send to the computers for processing the data (Montaser, 2013).Tracking RFID tags is an inherent function of the RFID system. But in contrast with localization in 2-dimensional space applying RFID, a large number of reference tags and readers have to be deployed for being able to provide precise location information of the attached tags in 3-dimensional space. In order to locate an object in a 3-dimensional space through using RFID, there are two different 3-D localization schemes, namely, active scheme and passive scheme (Wang et al., 2007). It is obvious that for measuring the installed tagged materials, identifying the location of tagged material in 2-dimensional space cannot determine whether it is installed or it is just in the final zone but has not been installed yet. So using 3-D localization schemes is required and considering the system set up for RFID 3-D localization (Refer to Wang et al. (2007) for more details), it is concluded that providing a large number of tags and readers increase the cost of the system and moreover it is not applicable in the construction site. In order to obviate this issue and use RFID to measure tagged materials which are installed, RFID has been used as a novel activity-based progress tracking method which will be elaborated in the following section.

5 PROPOSED METHOD

Definition of material in this study is the same as material definition by Bailey and Farmer (1982). So construction materials are goods purchased from sources out of the owner/ contractor’s company and used to produce the construction project's output. Materials have been categorized in different types, for instance based on CII research (2011), there are three types of materials: engineered (tagged) materials, bulk materials and prefabricated materials, based on the study done by Stukhart (1995), materials can be classified as bulk materials, engineered materials, and fabricated materials. In the current study all types of construction materials are classified in two groups "Tagged and Bulk" based on the way of measuring their consumption. In the near real-time materials data acquisition process indicated in Figure 2, project schedule (Activity level) in which all the construction objects and required materials are assigned to the activities is used as an input. The next step is identifying the location of elements which are under construction on the current date (during the construction phase). Then by knowing the location of elements based on the 3D model and drawings, installed materials are tracked using digital imaging for bulk materials and RFID for tagged materials. The acquired real time data in terms of images and tags read by RFID reader on daily basis will be sent and analyzed in the next step. Finally by measuring the actual consumption rate of materials using related algorithms in data analysis and reporting stage, the schedule has to be updated considering the actual data for current and upcoming activities.

5.1 2D Change detection

The process of taking images which are used as inputs to the change detection algorithms is illustrated in Figure 3. Applying 2D change detection algorithm is elaborated in this section to visualize the changes of the elements under construction on daily basis. It is assumed that while taking images from the elements under construction there is not any occluded areas or unreachable areas.

This approach is mostly similar to the automatic change detection method applied by David (2011). In this approach the following steps have been implemented in order to identify the set of pixels that are significantly different between the last image of the sequence and the previous images.

1. Image acquisition: capturing sequential images from elements under construction at consecutive days by a specified mobile camera.

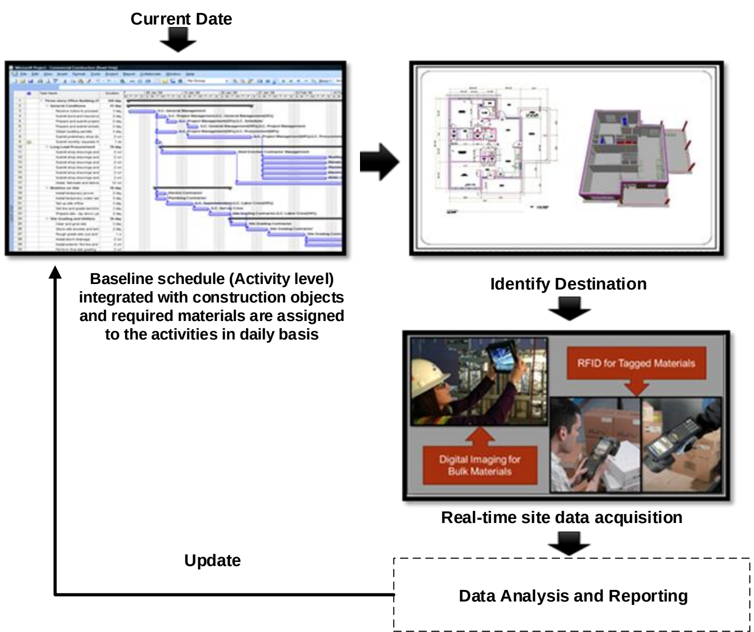

Figure 1: Near real-time data acquisition process in the construction phase (Golkhoo and Moselhi, 2016)

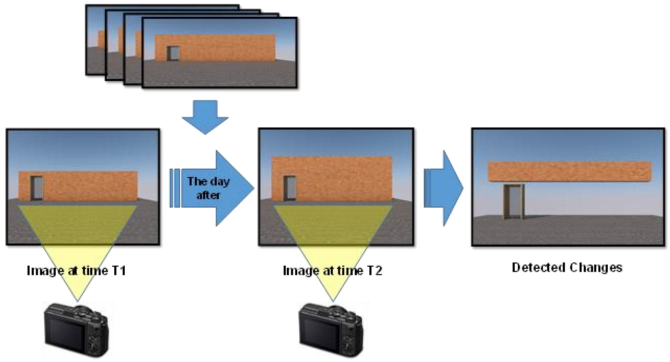

Figure 2: Change detection of an element under construction using a non-stationary camera

2. Automatic image registration: first and second step to register and align two images taken at consecutive days are feature extraction and feature matching. It is worth noting that checkerboard patterns are often used in the contexts of camera calibration and feature extraction and this is due to the fact that checkerboard patterns have alternating bright and dark grids and grid corners features which can be very strong features to be detected and recognized distinctly. So in this step checkerboards have been used for feature extraction and matching. Therefore after converting images to gray scale (with the purpose of decreasing the complexity of the model), the coordinates of the corner pixels of the squares in the checkerboards attached to both images (reference image and input image) are detected. Then based on the extracted corners, the transform parameters are calculated in such a way that it takes the points from the reference image as input and transforms them into the points in the input image. Therefore parameters of scaling, rotational, and translational differences between the reference and input images are estimated based on the corresponding points. In the third step which is determination of a transformation function, projective transform is selected as the transform type. Projective transforms map lines into lines but does not preserve parallelism, length, and angle. Projective transformation can be represented with the following matrix:

[1]Projective Transformation Matrix = $\begin{bmatrix} a_1 & a_2 & b_1 \\ a_3 & a_4 & b_2 \\ c_1 & c_2 & 1 \end{bmatrix}$

Where: $\begin{bmatrix} a_1 & a_2 \\ a_3 & a_4 \end{bmatrix}$ is a rotation matrix. This matrix defines the kind of the transformation that will be performed: scaling, rotation, and so on. $\begin{bmatrix} b_1 & b_2 \end{bmatrix}$ is the translation vector. It simply moves the points and $\begin{bmatrix} C_1 & C_2 \end{bmatrix}$ is the projection vector. The fourth and the final step for image registration is image transformation. So if *x* and *y* are the coordinates of a point, the transformation can be done by the following simple multiplication:

[2]Transformed Point Coordinates = $\begin{bmatrix} a_1 & a_2 & b_1 \\ a_3 & a_4 & b_2 \\ c_1 & c_2 & 1 \end{bmatrix} \times \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix}$

Here, *x'* and *y'* are the coordinates of the transformed point. At this point the first image is transformed and two images are aligned together.

3. Temporal differencing: in order to recognize the changed pixels, the temporal difference algorithm is used to subtract the reference image and the registered input image. So based on the position of checker board, a mask is firstly constructed in order to take into account only the changes in the

intended parts of the image; i.e. where there is a structure. In fact in order to focus on the structural changes of the object a region of interest (ROI) mask is created to determine which pixels are included in the region, because some pixels can be partially covered by the border of ROI. So the reference and registered input images are masked and subtracted. If the reference image is assumed as R(x, y) and the registered input image is I(x, y), then the subtracted image is:

[3] D(x, y) = R(x, y) − I(x, y)

Image thresholding is finally performed to the region of interest. For each pixel, if the result (D(x, y)) is larger than a threshold (τ), that pixel is considered changed. The threshold is calculated by taking the mean of the subtracted images. The result is a binary image where the changed pixels are marked as 1 and unchanged pixels as zeroes according to the following decision rule:

[4] B(x, y) = $\begin{Bmatrix} 1 & D(x,y) > \tau \\ 0 & D(x,y) \le \tau \end{Bmatrix}$

4. Removal of unimportant changes: in order to refine the results, a median filter is applied on the resulted mask. This will remove any isolated pixels in the mask which are not valid changed pixels; because the changed pixels are grouped together since the change is due to the change of structure.

5. Calculation of changed surface: having the size of the checker board in the real word, we proceed to calculate the scale of the image. Using the scale, we convert the number of changed pixels to changed surface.

5.2 3D Change detection

As Sakurada (2015) stated a naive approach for detecting temporal 3D scene changes from images, can be Multi-View Stereo (MVS). So in order to detect temporal changes of the 3D structure of the elements under construction, Multi-View Stereo (MVS) has been applied similar to the one implemented in the research done by Sakurada (2015). This method reconstructs the three dimensional scene structures at two time points from their images and then 3D reconstructions are differentiated for detecting changes. So this method is called MVS-based method.

In order to compare three dimensional structures of elements under construction at different times, the following steps have been performed:

1. Capturing sequential sets of images from elements under construction from different angels at consecutive days,

1. Performing Structure from Motion (SfM) independently for each sequence including extraction of feature points, calculation of essential matrices, calculation of camera poses and positions of feature points and optimization of camera poses and positions of feature points.

2. Aligning the two reconstructions with a similarity transform using RANSAC,

3. Minimizing the sum of the re-projection errors for all the correspondences by performing bundle adjustment,

4. Differentiating the two reconstructions in order to detect temporal changes. It is worth noting that while using point clouds for change detection, since point density which is reconstructed by SfM is in inverse proportional to distances from cameras so the difference of point densities must be considered. In this method the average distance (d_{same}) between the point of the first point cloud and the nearest N points of the same point cloud, along with the average distance (d_{diff}) between the point of the second point cloud and the nearest N points of the other time data are calculated. If $d_{diff} > 2d_{same}$, the “Changed Point” label is attached to this point, otherwise "Not Changed Point" label is attached.

5. Based on the location of the changed points, we then proceed to calculate the area of the changed structure. This is done by projecting the changed points on a plane parallel to the surface of the object and calculating the area of the projected points. We use the checker board to calculate the scale of the point cloud in relation to the real world and use this scale to convert the calculated area to real world unit.

5.3 RFID as a novel activity-based progress tracking method

As before mentioned, in order to identify and track the installed tagged materials, RFID tags and readers are utilized in a new way called activity-based progress tracking in which a person who is responsible to install tagged materials is required to place a preconfigured tag on that special materials as soon as their installation is completed. So the identification of these pre-configured tags by monitoring system (RFID reader) is used to calculate the consumption rate of tagged materials. ALIEN ALR-H450 handheld RFID reader whose read range receives up to 32 feet and standard RFID passive tags are proposed to be used for this purpose.

6 CASE STUDY

All the above mentioned 2D and 3D change detection procedures are verified and validated through conducting a couple of laboratory experiments. In these lab experiments, playing construction LEGOS have been used in order to simulate a brick wall and its construction progress. So the construction progress has been simulated by recreating various patterns of a brick wall. There have been some assumptions during mentioned experiments. For instance the there is not any occluded/unreachable areas, significant illumination changes while tacking images. Utilization and installations of checker boards on the elements under construction is possible on jobsite. After image acquisition and performing mentioned change detection algorithms, output of both change detection methods in terms of changed surface has been compared with the ground truth of scene changes, and then the accuracy of the algorithms can be compared with each other. All the steps of 2D change detection approach in the section 5.1 have been performed and shown in Figure 3. The changed surface is calculated 82.0228 Cm^2 using 2D change detection approach.

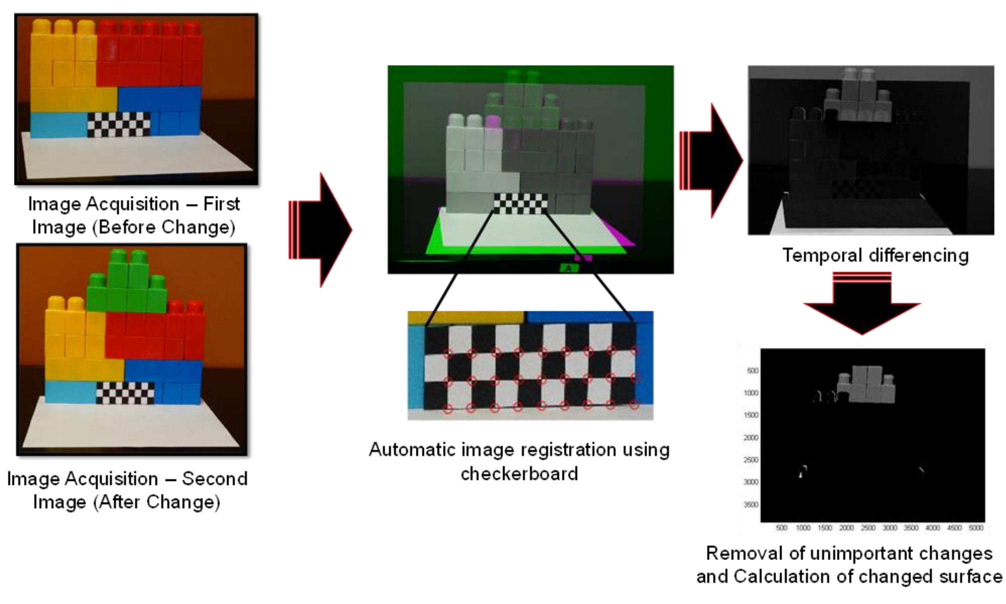

Figure 3: Laboratory experiment procedure for 2D Change detection method

The required steps for 3D change detection method elaborated in section 5.2 have been implemented and illustrated in Figure 4. Applying this approach resulted in 88.3012 Cm^2 as the changed surface.

Considering that the ground truth of scene changes which is around $80\,Cm^2$, it can be concluded that the accuracy of the 2D change detection method is 97.5% against the 3D change detection method with 90% accuracy. By having the changed surface and materials specification of the element under construction, the amount of consumed materials such as brick, cement and etc. can be measured.

7 DISCUSSION AND FUTURE WORK

Positioning and tracking critical materials in the construction sites, identifying unique materials received at the job site, recognition of project-related objects or comparing as-planned and as-built status with the purpose of monitoring the project progress and discrepancies control are the frequent applications of ADC technologies improving construction materials management. But there is another perspective of view in which measuring installed materials directly on daily basis and based on the activity level can provide good indicators of progress for physical completion of project activities and can be used for both schedule and materials effective management. But tracking and measuring the actual installed quantities of materials is a more challenging task to carry out. So this paper proposed a method to calculate the near real-time consumption rate of materials using digital imaging and RFID technologies for tagged and bulk materials respectively. Both 2D and 3D change detection algorithms were investigated and compared for measuring the occurred scene changes. In the 3D change detection approach, it was assumed that the changed structure is convex. The non-convex changes can be considered in future work. This is not the case for the 2D change detection and therefore, it can lead to more accurate results using simpler methods. Considering the results of laboratory experiments, it can be concluded that among the above approaches, 2D change detection method can quickly detects scene changes from an image pair with an acceptable accuracy.

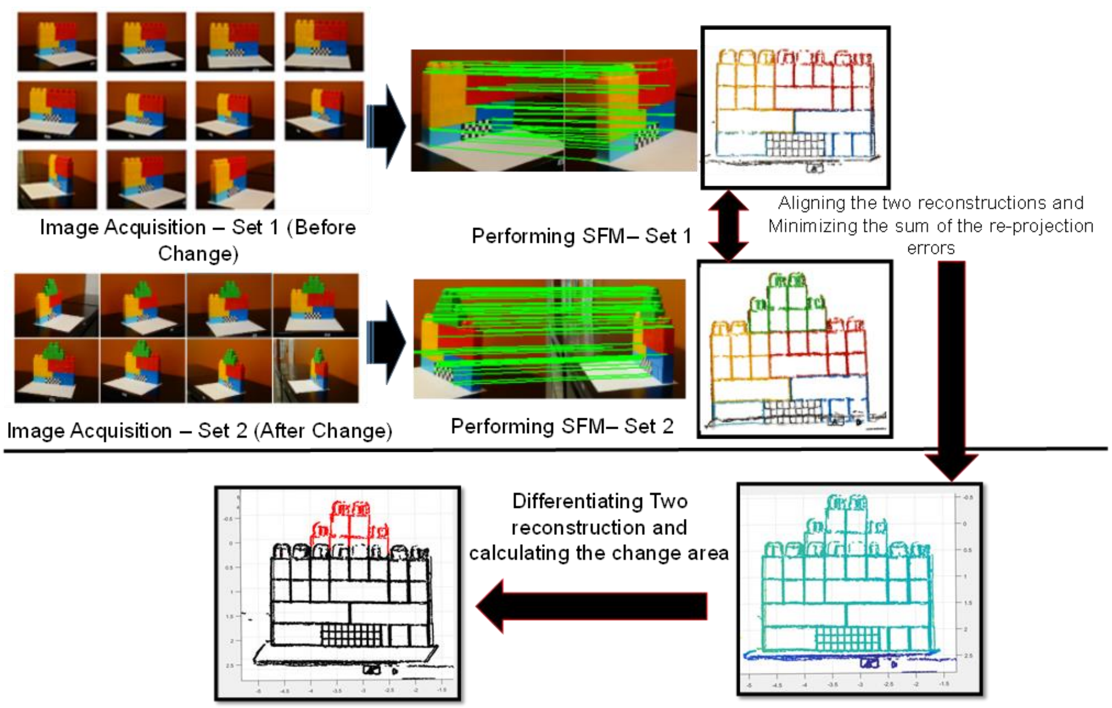

Figure 4: Laboratory experiment procedure for 3D Change detection method

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