3D Modeling of Workplaces for Time and Motion Study of Construction Labor

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Abstract:

Human movement adapts dynamically to the surrounding circumstances. Geometry information of workplaces thus offers the key to better planning of manual activities in a built environment. Measurement and modeling of the physical surroundings, however, requires significant time and effort for on-site investigation. This challenge makes it difficult to gain sufficient understanding of working environments in terms of operational planning and analysis. Accordingly, this paper introduces a 3D reconstruction approach that enables manual tasks to be quickly and accurately designed by utilizing geometry information directly extracted from point cloud data. First, still images representing the workplace are collected by a handheld camera and used to reconstruct the point cloud of the working environment by employing a structure-from-motion algorithm. Then, the point cloud is analyzed and geometry information is extracted from the point cloud data. This geometry data is then used for (1) calculating movement distances of labor personnel when completing tasks, which are then used to calculate time durations of tasks based on available motion-time standards, and (2) analyzing human motion trajectories affected by jobsite conditions to evaluate worker health and safety. As a case study, the proposed approach is applied to a steel welding task in a steel fabrication shop, where workers carry out manual tasks such as measuring, fitting, and welding of steel components into steel beams. The experimental results show that the proposed approach can perform well in conducting time and motion study and potentially saving substantial time and effort.

Keywords: 3D modeling, point cloud data, geometry information, manual task.

1. INTRODUCTION

Time study of manual tasks can be beneficial for productivity improvement, which is of great importance for enhancing construction practice. Productivity can be improved once the resources are optimized by project planners. In order to optimize resource allocation, the most essential piece of information to be obtained is the time duration of manual tasks. However, it is difficult to calculate time duration of manual tasks based only on historical time records because these records are unreliable in most cases (e.g., changes are made to the working environments or to what products are being produced, such that the relevance of historical records is attenuated). A more efficient approach to accurately calculating time data is needed; if such an approach is achieved, then the accurate time data can be inputted to simulation tools in order to analyze and modify the flow of work processes, thus improving productivity (Golabchi et al., 2015a).

In another aspect, time and motion study of construction labor can also contribute to ergonomic analysis, which is an important consideration in workplace design (Golabchi et al., 2015b). According to the United States Occupational Safety and Health Administration (OSHA, 2007), 35% of construction workers report they are working in an environment with health risks (Aires et al., 2010). The construction industry continues to have such a high injury rate and negative reputation over recent decades because construction workplaces have more potential hazards than other industries (Golabchi et al., 2016). To address this problem, workplace design is an approach to improving workplace layout in order to provide construction labor personnel with safer working environments. However, despite the fact that numerous hazards exist in construction workplaces, in current practice workplace design focuses more on improving the productivity of projects rather than on preventing workers from being injured (Freivalds & Niebel, 2014). Improper workplace design entails a high possibility of injury because the construction movements of labor personnel are affected by surrounding circumstances. Motion study, a method taken up in this research, analyzes the influence of jobsite conditions on human motion. It can be utilized as input for ergonomic analysis aiming to assess the health and safety of labor personnel, by means of which a better workplace design can be achieved.

Human actions and postures involved in performing manual tasks are determined by working environments (Golabchi et al., 2015c). Geometry information extracted from 3D models of workplaces thus offers the key to conducting time and motion study of manual tasks. However, rapid changes in working environments necessitate a significant amount of time and effort to model and measure the physical surroundings because traditional approaches to obtaining geometry information entail time-consuming on-site investigation (Golabchi et al., 2015d). A quicker and more accurate approach to obtaining geometry information as input for time and motion study is thus required which can be used to establish a platform for analysis and improvement of productivity and ergonomic safety. Considering the increasing prevalence of information technology in the Architecture, Engineering, Construction and Facility Management (AEC/FM) industry, the research presented in this paper employs a 3D reconstruction approach with the potential to streamline the process of obtaining geometry information. By building a 3D model, this approach offers a quicker and more accurate way to represent frequently changing workplaces, and then enables manual tasks to be designed by analyzing the geometry information calculated from point cloud data. The research method involves collecting still images, processing images to reconstruct point cloud data, carrying out format conversion of point cloud data, and extracting input for time and motion study. The extracted input is then used for (1) calculating movement distances of labor personnel performing tasks, which are used to calculate movement durations based on available motion-time standards, and (2) evaluating worker health and safety by analyzing human motion trajectories as they are influenced by jobsite conditions.

2. LITERATURE REVIEW

Many applications of point cloud data for the construction industry have been studied and developed. For instance, point cloud data enables project managers to identify and correct discrepancies for the purpose of progress monitoring (Golparvar-Fard et al., 2009), enables 3D status of buildings to be tracked for quality control (Akinci et al., 2006; Bosché, 2010), assists in measuring the 3D shape of the environment for the purpose of creating as-built BIM models (Tang et al., 2010), provides a way to recognize highway assets (Golparvar-Fard et al., 2012), and enables project engineers to separate target objects from surrounding environment in order to improve safety in heavy equipment operation (Wang & Cho, 2014).

Currently, the main methods of producing point cloud data are the digital image-based approach, the video streaming-based approach, and the laser scanning-based approach. The digital image-based approach to producing point cloud data does not require any extra light energy generated from the digital camera, which means it can work in existing light (Fathi & Brilakis, 2011). Also, the device required for this approach, the digital camera, is relatively inexpensive and readily available, making this method easy-to-use (Golparvar-Fard et al., 2011). The procedure of this approach mainly includes two steps. In the first step, project engineers need to take still images of the 3D space. Following image collection, the images need to be processed by means of a structure-from-motion algorithm (Fathi & Brilakis, 2011). This algorithm can recover the 3D structure of an object and the camera motion based on multiple images taken from different viewpoints (Dellaert et al., 2000; Tomasi & Kanade, 1992; Zhu & Brilakis, 2009). The video streaming approach can also work in existing light environments, but requires two or more video frames as input because the later video frame needs to be built on and to match with the previous video frame in order to reconstruct the spatial location of each point of an object (Zhu & Brilakis, 2009). The basic principle of the laser scanning approach is that, when the laser emitted from a scanner meets an object, the object can reflect the laser back to the laser scanner. The information gained in emitting and returning is used to build spatial relationships of elements in a space (Teizer, 2008).

Many applications of point cloud data have already been studied in previous research. However, the applications of 3D reconstruction can further be extended to time and motion studies in order to better understand human movements from the ergonomic perspective. Given that point cloud data can be analyzed for extracting geometry information of objects (Fathi & Brilakis, 2011), this research investigates the potential of point cloud data for time and motion analysis.

3. THE FRAMEWORK OF 3D MODELING FOR TIME AND MOTION STUDY

This study selects the image-based 3D reconstruction method for modeling workplaces because it shows the basic algorithm of generating point cloud data, is simple to apply, and does not require any advanced, costly data collection instrumentation such as laser scanners; instead, consumer-grade cameras are sufficient for data collection in this approach. The framework of this research is shown in Figure 1.

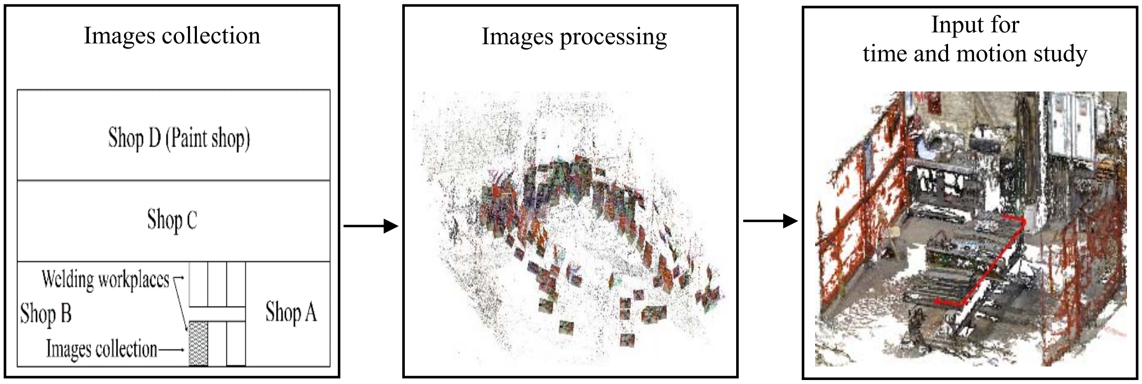

Figure 1. Framework of 3D modeling of workplaces for time and motion study

3.1 Image Collection

A handheld camera is used to capture still images of workplaces. The user's position when capturing images is of importance for producing accurate and intact point cloud data. Based on preliminary experiments, the images generate better point cloud data when captured in the following sequence: (1) capturing images from one side of walls, (2) at each position, capturing as many images as possible from the top of wall to the bottom of wall, (3) then, clockwise or counter-clockwise, changing the position of the photographer until one entire circle is finished, i.e., arriving back at the start-point, and (4) at the start-point, capturing images for the objects located at the center area of the workplace and also clockwise or counter-clockwise, changing the position again. The resolution of the camera also plays an important role in producing accurate and intact point cloud data since key points contained in the images need to be clear in order to be recognized and compared.

3.2 Image Processing

The main principle underlying the image-based 3D reconstruction approach is the structure-from-motion algorithm. A simple interpretation of structure-from-motion algorithm is shown in Figure 2. A key point (A) of an object is presented in two different images (A1 and A2), which are taken from two different viewpoints. The relationship between the locations of this point in two images can be utilized for recovery of the 3D shape of the object. Also, it should be noted that, the greater the number of key points are captured, the more accurate the 3D shape is.

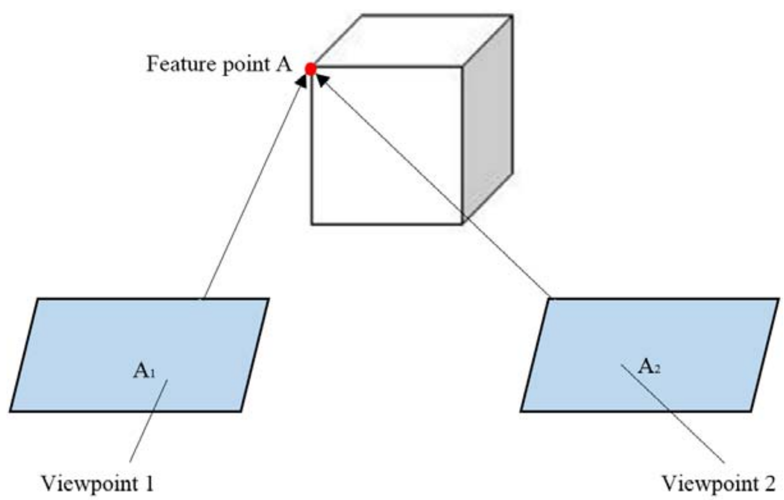

Figure 2. Interpretation of structure-from-motion algorithm (Modified from Zhu & Brilakis, 2009)

3.3 Input for Time and Motion Studies

Several predetermined motion time systems (PMTSs) are available for time and motion study. Modular arrangement of predetermined time standards (MODAPTS) (Heyde, 1966) is one of the most widely applied PMTSs due to the easy-to-understand human terms used in this system (Aft, 2000; Golabchi et al., 2015a). The basic principle of MODAPTS is that any human motion, i.e., manual tasks performed by workers, can be represented by multiples of a movement unit which is a single finger movement equaling 0.129 seconds (Golabchi et al., 2015a). MODAPTS requires two kinds of input in order to calculate the time duration of manual tasks. Point cloud data offers a platform where these two kinds of input can be measurably or visually obtained from point cloud data. To obtain the inputs, the originally generated point cloud data first needs to be converted to a measurable format of point cloud data. After that, for the measurable type of input, geometry data such as the dimension of an object or workers' moving distance can be extracted by first setting the scale of point cloud data and then measuring the distance between points. For instance, a worker's walking distance is the value of the distance between the walking start-point and walking end-point in point cloud data. Regarding the visual type of input, this input can be obtained by simply checking the location of objects. For example, the complexity of grasping an object can be determined by visually checking the picking up and placing location of the object. Obtaining these types of information will thus no longer require on-site investigation or checking numerous pages of notes. Table 1 provides details about the approach to obtaining the information. When each input is assigned a value, the time duration of performing a task can be obtained. Potentially, the time duration of manual tasks can then be used for productivity study, and time and motion data can be used for ergonomic analysis as well.

Table 1. Methods to obtaining inputs for MODAPTS (Modified from Golabchi et al., 2015a)

Class	Description	Required input	Options	Method
Movement (M)	Worker moves hand.	The distance that the worker's hand moves.	-	Measure distance between start and end points.
Get (G)	Worker grasps an object.	The complexity of grasping the object.	Simple grasp Difficult grasp	Visually check the workplace conditions.
Put (P)	Worker places and object.	The complexity of the placing motion.	General location Scheduled location Precise location	Visually check the workplace conditions.
Walk (W)	Worker walks.	The distance that the worker walks.	-	Measure the distance between origin and destination.
Load (L)	Incorporates weight of object.	The weight of the object that the worker handles.	-	From records and notes/ visually check the workplace conditions

4. IMPLEMENTATION

As a case study, the proposed approach is tested and validated in a steel welding workplace of a steel fabrication shop located in Edmonton, Canada. In this workplace, workers carry out manual tasks such as measuring, fitting, and welding of steel components into steel beams.

In order to generate accurate point cloud data of the workplace, a camera with the ability to capturing high resolution images is used to collect still images, with 351 images being collected according to the sequence described above. Figure 3 shows the path followed for image capture. In this figure, the black arrows denote the first path for image capture (for the walls of the workplace), and red arrows show the second path for image capture (for the objects located at the center area of the workplace). The time spent on image collection is 16 minutes.

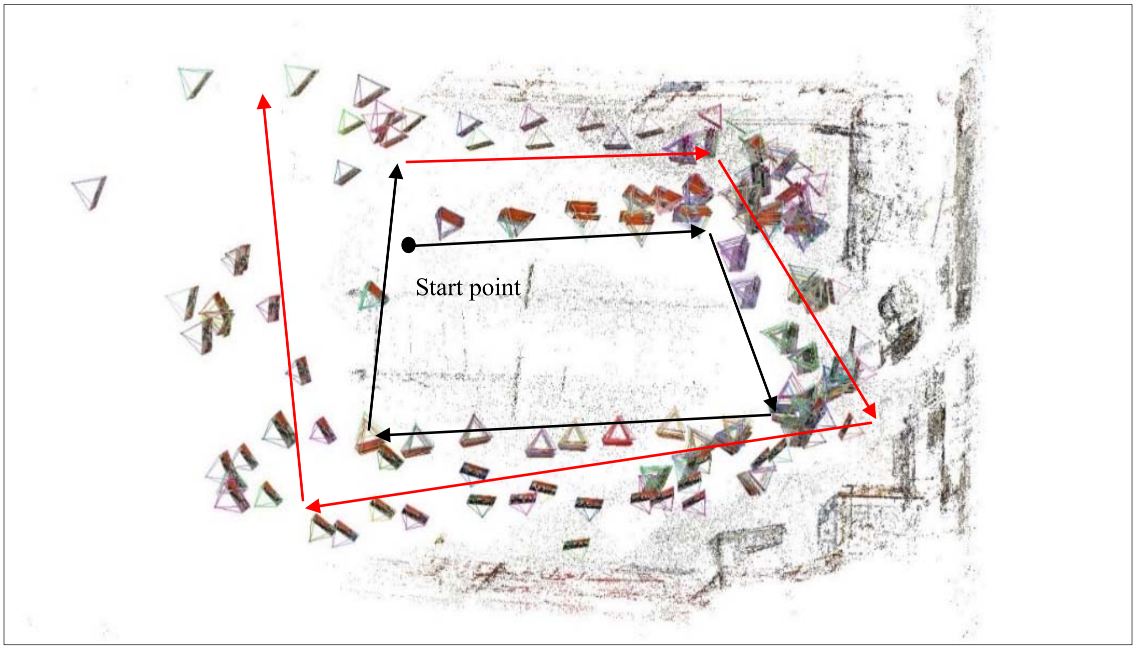

Figure 3. Paths for image capture

Structure-from-motion algorithm has been proposed and studied significantly in the field of computer vision. In the present research, VisualSFM (Wu et al., 2011) is selected to generate point cloud data. Four steps are included in generating the point cloud data: importing images, matching images, computing 3D reconstruction, and computing dense reconstruction (Falkingham, 2013).

The durations of image collection and of each processing step are listed in Table 2. The computation time may vary depending on the configuration of the computer. The computer used in this research has a 3.40 GHz processor and 16.0 GB of installed memory (i.e., RAM). The total computation time for 3D modeling of this steel welding workplace is found to be 192 minutes, which is much less than the time that would be spent for on-site investigation. Considering that work environments in construction frequently change, the actual time and effort required for on-site investigation can be significantly longer, entailing potential misunderstanding of working environments in operational planning and analysis.

Table 2. Time spent for each step

Step	Time (minutes)
Images collection	16
Import images	1
Match images	75
Compute 3D reconstruction	4
Compute dense reconstruction	96
Total	192

When image processing is complete, point cloud data of the steel welding workplace is generated, as shown in Figure 4. In this figure, the layout of different elements in the steel welding workplace can be clearly seen. For example, the preparation table is located at the upper-left corner, the working station is placed at the center area of the workplace, and a chair is placed on the workers' working path.

Figure 4. Point cloud data of the steel welding workplace

The original format of point cloud data produced by VisualSFM (Wu et al., 2011) is PLY format, which stores specifications of an object such as color and coordinates. However, this format cannot be used for extracting geometry information directly. Therefore, the conversion of formats of point cloud data is processed by the editing tool. PLY format is first converted to XYZ format using MeshLab (http://meshlab.sourceforge.net/). XYZ format only contains 3D coordinates of each point in point cloud data. Accordingly, the XYZ format of point cloud data is then edited and converted by Autodesk Recap (http://www.autodesk.ca/en) to the acceptable RCP format of point cloud data which can be used for analysis of geometry information. The RCP format of point cloud data is the final converted format. This format is compatible with both Autodesk Recap and Revit (http://www.autodesk.ca/en), thus offering a platform where engineers are able to set the scale for the 3D model and then extract geometry data for the purpose of time and motion study. One example illustrates how point cloud data works for MODAPTS. This example task includes a welder moving their hand a distance of 50 cm to pick up with a simple grasp a steel plate that weighs 5 kg, carrying the plate 4 m, and moving their hand 40 cm to place it at an exact location. Table 3 lists the value assigned to each class.

Table 3. The value for each class

Class	Property	Value assigned
Start movement (M)	50 cm	5
End movement (M)	40 cm	4
Get (G)	Simple	1
Put (P)	Precise	5
Walk (W)	4 m	31
Load (L)	5 kg	1

This task can then be expressed as a MODAPTS code: in this example, M5G1L1W31M4P5. Total MOD represents the sum of the values of each class, which is 47 in this example task. The time duration of manual task is then 47 × 0.129 = 6.063 seconds. Once the time durations of manual tasks are obtained, this time data can be applied to simulation tools to estimate the time duration of each work process, by means of which production planners are able to optimize resources. This can lead to significant productivity improvement.

In addition, the visual and measurable attributes of the point cloud data also enable ergonomic analysts to check for improper layout of workplaces based on the rich geometry information available through this method. For example, when a welder needs to use a heavy welding torch to weld two steel components into a steel beam, there may be cases in which the distance between welding point and a worker's hand exceeds the normal reachability of the welder's arm; in such a case the welder is required to maintain an uncomfortable posture for several seconds or even several minutes. If this uncomfortable posture has to be repeated several times a day, it is likely to contribute to musculoskeletal fatigue or injury. By analyzing point cloud data, the visual feedback and geometry information quickly extracted can assist ergonomic analysts in detecting over-reachability problems and preventing injuries to workers by giving recommendations for workplace redesign to improve worker health and safety.

The results of the case study indicate that the proposed approach enables the building of 3D models within a short time period (i.e., 192 minutes). Once 3D models are available, project engineers, production planners and ergonomic analysts are able to gather geometry information to be used in time and motion study of construction labor in order to evaluate worker health and safety, redesign improper workplaces, and improve construction productivity. The motion and time study analyzed through this proposed approach are found to perform well.

5. CONCLUSION

There are many applications of point cloud data in construction, but the application of point cloud data in time and motion analysis has not yet been thoroughly studied. Time and motion data is useful in ergonomic study, safety evaluation, and productivity improvement; it is therefore necessary to explore the potential application of point cloud data in time and motion study. The research has explored an approach integrating image-based 3D reconstruction and MODAPTS, demonstrating that this approach (1) provides a more time-efficient way to build 3D models of workplaces, compared with the traditional approach whereby engineers must measure geometry information for each element in the workplace; (2) is able to build 3D models of a frequently changing work environment; (3) offers reliable inputs for time and motion study; and (4) most notably, through the obtained time and motion data, facilitates improved productivity and ergonomic safety.

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