An Integrated Ergonomics Framework for Evaluation and Design of Construction Operations

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Abstract

Labor is one of the most critical resources in the construction industry due to its impact on the productivity, safety, quality, and cost of a construction project. Ergonomic assessment, as a tool and method for analyzing human activities and their interactions with the surrounding environment, is thus crucial for designing operations and workplaces that achieve both high productivity and safety. In construction, however, the constantly changing work environments and laborious tasks cause traditional approaches to ergonomic analysis, such as manual observations and measurements, to require substantial time and effort to yield reliable results. Therefore, to simplify and automate the assessment processes, this study explores the adaptation and integration of various existing methods for data collection, analysis, and output representation potentially available for comprehensive ergonomic analysis. The proposed framework integrates sensing for data collection, action recognition and simulation modeling for productivity and ergonomic analysis, and point cloud model generation and human motion animation for output visualization. The proposed framework is demonstrated through a case study using data from an off-site construction job site. The results indicate that integrating the various techniques can facilitate the assessment of manual operations and thereby enhance the implementation of ergonomic practices

during a construction project by reducing the time, effort, and complexity required to apply the techniques.

Keywords

Ergonomics, sensing, simulation, visualization, action recognition, point cloud generation.

1 INTRODUCTION

Since the construction industry is labor-intensive, worker activities can significantly affect the success of construction operations. Labor is one of the most crucial resources (Jarkas and Bitar 2011; Muqeem et al. 2012) and has the highest direct impact on the outcomes of a project, including time, cost, and quality (Leung et al. 2012). Labor can account for nearly half the overall costs of a project (El-Gohary and Aziz 2013) and is highly associated with construction productivity, which is one of the most important and frequently used performance indicators in the industry (CII 2006). Furthermore, labor operations in construction involve physically demanding motions and tasks that frequently expose workers to risk in their working environments, leading to a rate of injuries and fatalities that are among the highest of any industry (Behm 2005; OHS 2017; Zhou et al. 2015).

As an approach to human-oriented work design, ergonomics is the study of human interactions with the surrounding environment with the intent to improve human safety and well-being, as well as productivity (IEA 2017; Dul and Neumann 2009; van Deursen et al. 2005; Hedge and Sakr 2005). An effective and comprehensive ergonomic analysis involves evaluating ongoing operations and proposing modifications and new designs that fit jobs and work environments to worker capabilities and limitations. Accordingly, the implementation of ergonomic principles can contribute to the success of a construction project by providing workers with comfortable working environments in which work procedures and tools are designed for safe and productive use. However, conducting an ergonomic analysis often requires extensive time and effort to yield reliable results as the data collection and evaluation involve human observations and measurements. This is particularly true in the dynamic environment of construction job sites, which involve many physically demanding manual tasks that create vast amounts of data to collect, analyse, and represent (Tak et al. 2011; Golabchi et al. 2016a). Furthermore, the variety of tasks and postures required of workers necessitates methods for collecting and analyzing data that can address human error; the resulting low reliability of the analysis inputs and outputs make completing a meaningful ergonomic evaluation difficult (Kadefors and Forsman 2000; David 2005; Golabchi et al. 2017c). Reliable and detailed visual representations of the analysis outputs can greatly improve the implementation of interventions or new workplace designs. Accordingly, the development and use of methods to automate, simplify, and increase the accuracy of data collection, analysis, and output representation could enable effective and comprehensive ergonomic evaluations. Furthermore, integrating such methods into an overall framework would potentially enhance the implementation of ergonomic practices at actual construction job sites by minimizing the need for experts, decreasing the time and effort required for analysis, and reducing the complexity of applying the various methods.

Therefore, this study proposes a framework to integrate different methods for evaluating and designing manual construction operations to achieve a more unified and reliable ergonomic analysis. The framework and its modules are presented with a focus on linking the different components together. A manual operation at an actual job site is then used to implement the proposed approach and evaluate its effectiveness.

2 BACKGROUND

2.1 Limitations of Manual Observation–based Ergonomic Analyses

A complete ergonomic analysis involves evaluating the motions and postures of workers and the physical attributes of a job site to assess current work conditions and propose new designs for manual operations (e.g., safe motions) and workplaces (e.g., workstation dimensions). To carry out such an assessment, an ergonomist generally needs to complete three stages: (i) data collection, (ii) data analysis, and (iii) interpretation and representation of results.

Prior to data collection, the ergonomist has to design the experiments and define the strategy based on the particular conditions of the work being analyzed. After planning the procedure, which enables identifying the methods to be implemented and the required inputs for each, relevant data is gathered, traditionally, through observing the subjects (e.g., anthropometry, posture), their motions while working (e.g., leaning, bending), and the attributes of the work environment (e.g., workbench, tools, equipment). The inputs of an ergonomic assessment thus include various types of data, such as the distance between a worker and a necessary tool or material, or the joint angles between different body parts, which are often challenging to observe simultaneously. Typically, an ergonomist either visits a job site to collect the required data in real-time or uses video recordings to extract the inputs later (David 2005). In both cases, such a procedure results in subjectivity in the collected inputs introduced by the ergonomist's personal judgement (Golabchi et al. 2017c). Although this traditional approach can work effectively in static workplaces, such as offices and manufacturing assembly lines, it can produce unreliable data at construction job sites because of the variety of manual tasks performed, complexity of exposures, and constantly changing work environment (Kadefors and Forsman 2000; Golabchi et al. 2016c).

After data collection is complete, the ergonomist uses the gathered data to conduct an ergonomic evaluation using tools such as ergonomic assessment checklists (e.g., RULA (McAtamney and Corlett 1993), ROSA (Sonne et al. 2012)) and time and motion studies (e.g., MTM (Maynard et al. 1948), MOST (Zandin 2002)). To complete this step, the ergonomist inputs the data into the tools, which use a set of predefined rules to produce the output of the analysis. For example, inputting a worker's posture (i.e., joint angles) along with the frequency and duration of exposure allows posture-based tools to report on the level of ergonomic risk associated with a task. Also, using inputs that describe working conditions (e.g., walking distance, motions involved), time and motion systems (e.g., predetermined motion time systems) provide the standard duration for a task (Golabchi et al. 2016b). However, similar to the challenges presented to data collection, manual analysis of construction tasks can be inefficient since job sites and the motions required change every day.

Following data analysis, the ergonomist interprets and represents the gathered data and analysis results to illustrate how any modifications should be implemented and address any discovered risks. Traditionally, this involves reports that reflect the ergonomist's conclusions from the analysis and state any modifications suggested by the outputs from the checklists and tools used. Typically, those reports include only whether the level of ergonomic risk associated with a task is acceptable, moderate, or unacceptable based on the inputs provided. Such reports are thus limited data representations that do not allow re-evaluation of the proposed changes and designs because of the difficulty of assessing a non-observable task on a job site that does not yet exist (Laring et al. 2002). Furthermore, the traditional report-based approach does not offer managers a tool for practical decision-making, nor does it provide an effective means to accurately implement the proposed modifications or train the personnel involved. This approach also makes it difficult to effectively assess other ergonomic variables (e.g., clearance, vision) when modifying the design of a workplace.

Thus, the three stages of a thorough ergonomic analysis could be improved by adapting and integrating existing methods through automation to both enhance different aspects of the analysis and connect them to provide a more reliable and simplified assessment. The different stages of an evaluation, including data acquisition through sensing, productivity and safety analysis of the obtained data, and representation of the results through visualization, are shown in Table 1. For each stage, the research areas that could be beneficial for evaluation of manual operations and workplace design are identified as components of the framework, and both the input used for each component and its output are shown. The inputs and outputs show the connections among the different elements and indicate how data can be transitioned through the different components for an accurate and automated analysis.

Table 1. Research areas, inputs, and outputs for different stages of evaluation and design of manual operations

Stage	Research area	Input	Output	Example references in research area
Data acquisition (sensing)	Action recognition	Video/sensor recordings	Type and sequence of actions	Akhavian and Behzadan (2016), Cheng et al. (2013), Joshua and Varghese (2011)
	Motion capture	Worker motion recordings	Worker motion-capture data	Han and Lee (2013), Starbuck et al.

				(2014), Ray and Teizer (2012)
	3D reconstruction	Photo/video of job site	As-is point cloud model	Rashidi et al. (2015), Fathi and Brilakis (2011), Guo et al. (2016)
Analysis	Simulation modeling	Action recognition	Operation efficiency	Seo et al. (2016), Golabchi et al. (2016b)
			Motion generation	Golabchi et al. (2016a), Golabchi et al. (2015a)
	Biomechanical analysis	Motion capture	Level of safety	Seo et al. (2014), Mehta and Agnew (2010), Golabchi et al. (2015b)
Representation (visualization)	Motion generation	Simulation modeling	Worker motions	Wei et al. (2011), Taylor et al. (2007), Golabchi et al. (2017b)
	Path planning	Start and end location of motion	Animation of worker motions	Yao et al. (2010), Wu et al. (2007), Pettré et al. (2002)
	Visualization	3D reconstruction	Complete virtual model	Al-Hussein et al. (2006), Budziszewski et al. (2011), Golabchi et al. (2015b)
		Motion generation		

As shown in Table 1, many researchers have worked on different elements that can contribute to an ergonomic evaluation of labor operations and workplace design. However, many of the previous studies have focused on methods developed for a different purpose (e.g., 3D reconstruction for progress monitoring, action recognition for productivity measurements). As a result, different methods require different types of inputs which can hinder efficient data sharing between the methods. Thus, further investigation is required to understand the inputs and outputs of the existing methods and the potential transition of data among them to enable their integration and achieve a comprehensive ergonomic analysis framework.

2.2 Integrated Ergonomic Analysis

To carry out a thorough ergonomic analysis, information about the effects of physical activities on a worker's body needs to be available. Main contributors to those effects are the type, duration, and sequence of manual tasks. Although this information can be collected through time studies, they are time-consuming and challenging to conduct for many manual construction operations. Furthermore, those data are difficult to gather when designing new operations for new or prospective workplaces. As a result, ergonomists rely on human judgment and estimates in acquiring data, which can lead to unreliable information. This issue can be addressed through linking simulation modeling with action recognition. The use of video cameras for action recognition can automatically identify the type, duration, and sequence of activities. The results can then be used to create a simulation model for the operation that can be used to test any required modifications to the operation design. Furthermore, integrating Predetermined Motion Time Systems (PMTSs), which enable calculating the standard duration of a manual task based on the movements involved, into the simulation environment allows not-yet-existing scenarios to be conveniently modeled and explored. Previous research has used sensing devices to identify different types of activities and tasks for applications such as operation analysis, work rate measurement, and productivity monitoring (Gong et al. 2011; Kim and Caldas 2013; Escorcia et al. 2012). Furthermore, simulation modeling has been used extensively in different phases of construction for planning, budgeting, design, maintenance, etc. (Ozcan-Deniz and Zhu 2015; Corona-Suárez et al. 2014; Yang et al. 2012). Despite the effectiveness of these methods, linking video-based action recognition to PMTS-based simulation modeling to enable reliable and automated creation of simulation models for ergonomic analysis has not yet been fully explored.

Another main contributor to an operation's level of safety is the posture and motions of the workers. While ergonomic and biomechanical tools rely on such information for their evaluations, watching a worker carrying out the tasks to obtain the required inputs (e.g., body joint angles) is time-consuming and can produce low-reliability results. On the other hand, Digital Human Modeling (DHM) technologies are developed and used in manufacturing industries with the intention to generate virtual representations of human models to design and evaluate equipment and work environments without requiring physical mock-ups (Zhang and Chaffin 2005; Duffy 2008; Sundin and Örtengren 2006; Chaffin 2008). DHM tools are effectively used in these industries for modeling of stationary work stations and repetitive tasks as well as evaluation of visual ergonomic risk factors. However, the dynamic nature of construction job sites and the diversity of its laborious tasks still calls for the adoption of tools and methods tailored to the needs of the industry, that can address challenges such as the time and effort required for data acquisition and analysis, as well as the reliability of the results. Accordingly, the use of motion-capture data, recorded using sensing devices (e.g., depth sensors, stereo cameras), can greatly simplify data capture and improve data accuracy (Seo et al. 2014; Han and Lee 2013; Ray and Teizer 2012). Furthermore, motion data can be used in conjunction with 3D models of the work environment to visualize an operation and provide a virtual platform for managerial decision-making, implementation of designs, training, etc., as well as assessment of ergonomic variables such as clearance, visibility, fit, and reach. Connecting motion data with simulation models of operations can also be used to generate the motions of proposed operations for a more effective visualization.

Creating an effective and complete virtual model to represent the results of an analysis requires 3D models of the different components of the current conditions on a job site. However, given the dynamic nature of construction sites, creating and updating as-is models using only 3D modeling tools and software is unfeasible. Therefore, previous work has focused on generating point-cloud models of work environments (Golparvar-Fard et al. 2011; Fathi and Brilakis 2011; El-Omari and Moselhi 2008; Pučko and Rebolj 2017). Cameras can be simply and inexpensively used to create as-is point cloud models of the work environment, replacing the need to manually create complicated models. Integrating such a model into a visualization environment that includes other components, such as building information modeling (BIM) elements and worker motions, can provide a robust, reliable, and complete virtual model, which has not yet been examined to its full potential. Furthermore, worker models need to be connected to the other 3D elements in the virtual model to enable animating the worker motions along a path that does not collide with other objects and is also a realistic representation of worker motions and paths on an actual job site. Thus, there is a need to implement an automated path-planning algorithm inside the visualization to enable accurate animation of worker models and motions.

As there is a high correlation between safety and productivity (Hallowell 2011) and an ergonomic analysis works to improve both health and productivity, the effects of safety interventions on productivity and vice versa have to be considered for an analysis and design to be effective. Integrating methods that can measure productivity (e.g., PMTS-based simulation modeling) with methods that evaluate safety (e.g., motion capture-based ergonomic and biomechanical assessments) and representing them using inclusive virtual models (i.e. point cloud models in conjunction with worker motions) will thus enable the analysis of different scenarios in terms of both productivity and safety to select the best option.

3 METHODS

This study proposes and tests an integrated framework that couples data acquisition and visualization with analysis of manual operations to enable an effective evaluation of those manual operations for a comprehensive ergonomic analysis. Specifically, the objectives are: (1) exploring the data associated with the various sensing, analysis, and visualization methods, (2) examining the possibility and applicability of sharing data among those different methods, and (3) testing the feasibility and effectiveness of integrating the various methods.

The proposed framework and its components are shown in Figure 1. As shown in the figure, the framework is composed of three main modules: simulation, as-is modeling, and safety assessment. The analysis starts by gathering information about conditions in the work environment through sensing. Videos of worker activities are recorded, and then an action recognition process extracts the type, sequence, and duration of tasks used to build a simulation model of the operation. The simulation model serves to evaluate the productivity of the operation, as well as to generate worker motions for animation in the final virtual model. On the other hand, photos or videos of the job site are also used to create an as-is point cloud model of the work environment. Other 3D modeling elements (e.g., worker models, material, equipment, and tools not existing in the as-is representation)—created using other 3D modeling platforms or inherited from previous designs—can be added to the model and be used to run a path planning algorithm that enables a realistic representation of worker motions in the virtual environment. Worker motion data are also captured and used for a precise, automated, biomechanical assessment, and worker motions and workplace design are updated based on the results. The outputs of the modules are used to create a complete virtual model of the manual operations, which can be used for various visualization applications (e.g., communication and implementation of design, decision making, and training).

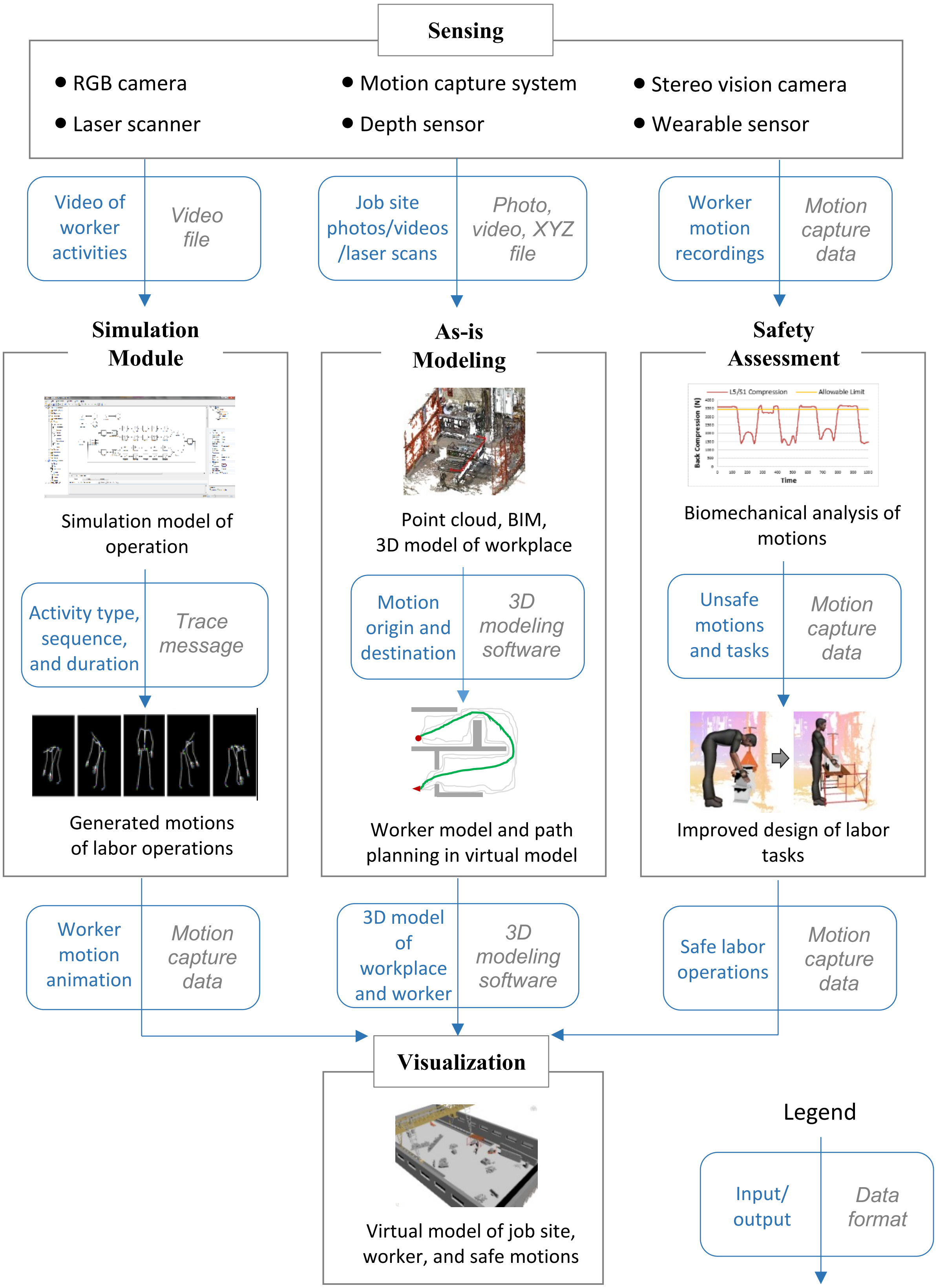


Figure 1. Framework for integrated analysis of manual operations

3.1 Simulation Module

To create a simulation model of a manual operation and analyze its operational efficiency, either human observation or sensing methods have to be used to gather the required inputs (e.g., types of tasks, activity durations). Human observation typically not only requires time, effort, and expertise but also can be subjective. To address this issue, among various sensing methods including high-end sensors, the action recognition approach in this study uses video recordings from ordinary cameras to identify the type, sequence, and duration of different manual tasks. The action recognition method, adapted with modifications from the authors' previous work (Liu et al. 2016), recognizes the activity type for each frame and estimates the activity duration (Figure 2). Every frame is described using a feature vector and classified to specific activity types based on its similarity to samples in a training dataset. Here, the feature vector including a histogram of the silhouette and of the optical flow, is primarily derived from the extracted human silhouette and the pixel-wise direction and magnitude of its movements (Tran and Sorokin 2008). The similarity between feature vectors is then obtained by calculating the Euclidean distance between feature vectors of two action samples. The frame-wise action is initially recognized by a classification method, namely the K-nearest neighbor (Peterson 2009). Given training frames as action templates, the unknown action in the testing frame is identified as the one with the greatest similarity to the template. With an initial estimate for every frame, the activity sequence is optimized by an enforced temporal constraint, based on the shortest duration possible for an activity. The temporal optimization module enables assessing the initial estimate from the result of frame-by-frame action classification (i.e. classifying the feature vector to a specific action) and correcting the detected noise frames to optimized ones. Consecutive frames are detected as noises if the duration (i.e. number of consecutive frames) exceeds the minimally feasible duration of a specific action (e.g., three seconds). With the optimized action recognition result, the duration of each task is calculated by counting the number of frames given the video frame rate (e.g., 30 fps).

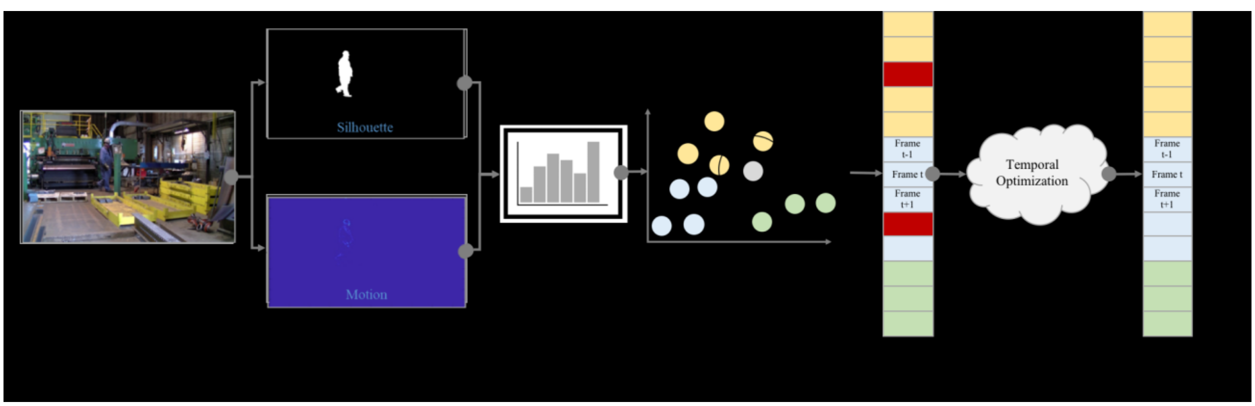


Figure 2. Action recognition from video recordings

The result of the action recognition process, aiming to estimate the duration of the different actions, is linked to a discrete-event simulation modeling environment called Symphony (Hajjar and

AbouRizk 1999). The integration between the results of action recognition and simulation modeling is achieved by first extracting the activity types (e.g., walking, moving hand, grasping, etc.), their sequence (e.g., worker walks, grasps object, carries object, places object), and their duration (action recognition in Figure 3), and then creating a simulation model based on those data, including different simulation modeling elements (e.g., walking task, carrying task, marking task) to represent different activities (model generation in Figure 3). The extracted data from the action recognition enables creating the simulation model since the pieces of data required for creating a discrete-event model are provided. This data includes: the events taking place (i.e., task types, derived from the videos), the time that events take place (determined by the duration of each task from the video), and the order of the events (obtained from the sequence of tasks from videos). For cyclic operations, the simulation model includes a full cycle of the operation and the duration of each task in the cycle is obtained by calculating the average duration of that particular task type from action recognition.

The developed simulation model represents the current status of an ongoing operation which can be used for two purposes. First, it serves as a base model to evaluate different scenarios for an operation (including the current practice) in terms of productivity and safety to find the most desirable. This process is greatly improved by integrating PMTSs into the simulation environment to accurately model potential scenarios (Golabchi et al. 2017a). PMTSs are work measurement systems that break up tasks into basic human movements (e.g., reach, move, get, put) and categorize them based on the working conditions which the movement is carried out in (e.g., walking distance, complexity of grasp, body motions). Each movement classification is associated with a duration based on research, data collection, analysis, and validation. Thus, these systems can be effectively used to obtain the standard duration of manual operations based on job site conditions.

As a secondary purpose, the simulation model is linked to the motion generation component, which creates the complete motion of a worker by pulling from a database of captured motions and combining them (Golabchi et al. 2017b). The linkage between the simulation model and the motion generation is achieved by first generating a trace message based on the simulation, which contains information regarding the different motions carried out. This information is then used as input for an algorithm that queries basic motions (e.g., get, put, walk) from a database of motion-capture data and creates the complete motion. A detailed description of the motion generation process can be found in Golabchi et al. (2017b); while previous work has looked into the details of developing PMTS-based simulation (Golabchi et al. 2016b) and motion generation from simulation (Golabchi 2017b), this study focuses on creating the simulation model from the output of action recognition and using it for evaluation and improvement of the operation.

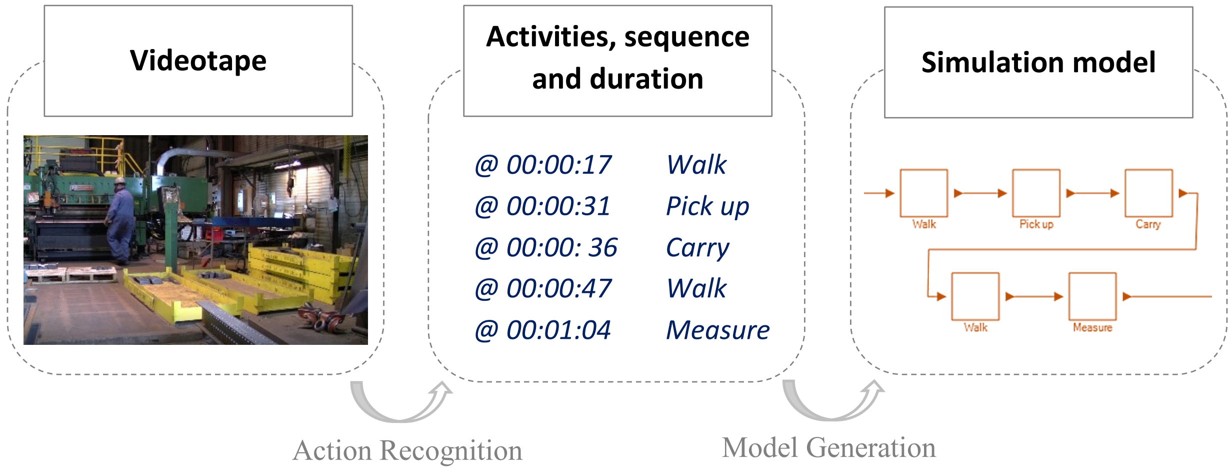


Figure 3. Simulation model generation from action recognition results

3.2 As-is Modeling Module

The as-is modeling module includes two main components. First, the current conditions of the existing workplace (structure and objects) have to be modeled. Second, the path that each worker's 3D animation will use in the virtual representation is identified through path planning. The two components are further described below.

3.2.1 Point cloud generation

The virtual representation of a job site needs to reflect current conditions, including the shape, size, and location of building components, equipment, and materials. Since as-designed CAD and BIM models might not accurately reflect the current, ongoing status of the surrounding work environment or temporary structures and objects, point cloud data models have emerged as a solution. These models can later be converted into 3D models, similar to the ones in a BIM (Hichri et al. 2013). Specifically, different tools and approaches can be used for point cloud model creation, including image-based approaches, video-based approaches, and laser scanners. The use of laser scanners has been thoroughly studied in construction (Akinci et al. 2006; Tang et al. 2010; El-Omari and Moselhi 2008). Despite the high accuracy of models created using laser scanners and their scaling capabilities, the cost of the scanners and the need for experts to implement them can limit their use in practice. Image-based approaches, in which a structure from motion algorithm is used to generate a point cloud from ordinary photographs (Golparvar-Fard et al. 2011; Fathi and Brilakis 2011), can be used as an alternative approach since compared to using laser scanners, an acceptable model can typically be created without substantial need for special equipment or high levels of expertise (Guo et al. 2016). However, such approaches involve high processing times and require images with high overlap to ensure the reliability of the output. Therefore, this study uses a video-based approach, which can potentially address the issues with both prior methods.

To create a point cloud model using the video-based approach, a stereo vision camera is used to generate depth data for objects. This approach simplifies the data recording process since there is little concern regarding the overlap of the images, as experienced with single image-based approaches. Using the stereo vision approach, every point of an object is recorded through the left and right lenses at the same time, and then the videos are rectified (Fusiello et al. 2000). Rectification is a transformation process in which two or more images are projected onto the same image plane to find the matching points between them. After this process, the images from every frame of the recorded videos will be appropriately aligned.

To implement the point cloud generation process, a video of the job site is required as input, and the point cloud model is generated as output. Through this simple process, the generated point cloud model reflects the existing conditions at a job site. When evaluating different scenarios and representing new designs, 3D models of other elements, including building components, equipment, material, tools, etc., are added by importing the point cloud model, 3D model or BIM elements, and other 3D objects into the final visualization platform and positioning them in the correct locations. Human models and motions are added to the virtual model at a later stage.

3.2.2 Worker path planning for virtual modeling

To realistically represent a human model in a virtual environment, the anthropometric properties of the model, an animation of the motions the human carries out, and the path that they take inside the 3D model all need to be reflected reliably. The anthropometric attributes are considered while creating the skeleton of the 3D model of the human by choosing appropriate values for the joint lengths and body-part ratios (Meredith and Maddock 2001; Golabchi et al. 2015b). The motion is created from the sequence of activities and durations in the simulation model and by querying a database of motions, as explained above. The path that each worker will take to complete a motion also needs to be acquired to provide a reliable representation of activities. Thus, path planning needs to be used to predict the paths that workers will take on an actual job site and animate them in the virtual model.

For this purpose, the A* path planning algorithm (Yao et al. 2010; Hart et al. 1968) is adapted for its speed and reliability, where the start and end nodes of the path and the locations of obstacles are the inputs and the shortest path is the output. After the 3D model is created, it is analyzed to extract the coordinates of all objects in the model by recording their X and Y coordinates for all points on the Z axis, as shown in Figure 4. The size of the matrices with the X and Y coordinates is determined by finding the largest distance in each of the X and Y directions among all the Z planes and using those values for the corresponding axis.

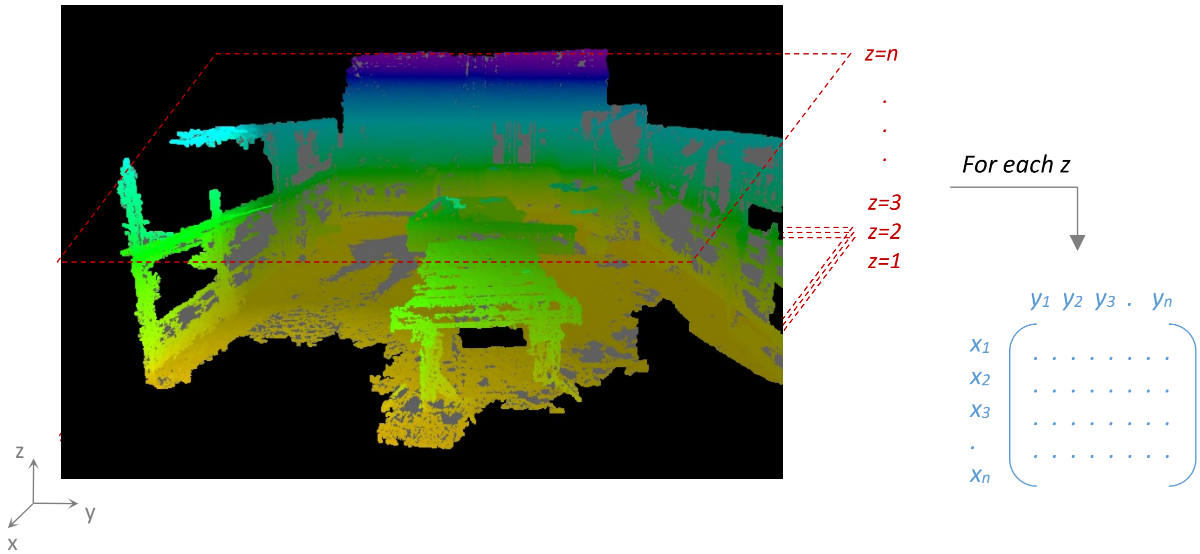


Figure 4. Registering the coordinates of all objects of the 3D model in different planes

Next, the start and end locations in the virtual model are selected to extract the coordinates. Also, based on the Z coordinate of the start and end nodes, the object coordinates need to be filtered to find any obstacles in the worker's path. Thus, the coordinates of obstacles that could block the worker's path, defined by having a Z value between the worker's foot and head, are extracted. Then, the X and Y values of all nodes that represent an obstacle that the worker cannot pass (i.e., for the same X and Y, a Z range larger than the height of a step) are registered as obstacles. The start, end, and obstacle nodes are then fed into the A* algorithm, and the coordinates of the path are extracted. This path is then used to animate a human animation in the virtual model by feeding the coordinates into the visualization environment, along with the basic motions already attached to the animation.

3.3 Safety Assessment Module

The biomechanical analysis component of the framework enables the evaluation of an operation by examining the loads exerted on the human joints and comparing them to safe limits. The results can be used along with the productivity analysis output to improve the operation and select an optimal design (Golabchi et al. 2017a). To carry out an automated ergonomic analysis, worker motions need to be extracted from either video recordings (Han and Lee 2013), vision-based sensing devices (e.g., Microsoft Kinect) (Han et al. 2013), or wearable sensors (Yan et al. 2017), and then the motion data can be used to automatically identify unsafe actions through ergonomic and biomechanical assessments (Golabchi et al. 2015b). Those results are used to modify the design elements that cause the unsafe conditions and ensure representations of safe motions. The captured motions are also used to animate the worker model in the final virtual environment to accurately represent current conditions. When improving prospective operational scenarios, the motion generation element uses pre-recorded motions of ergonomically safe actions to visualize worker activities, enabling the use of the virtual representation for safety training applications. The safety analysis component and detailed descriptions pertaining to it can be found in Golabchi et al. (2015b), Golabchi et al. (2015a), and Golabchi et al. (2016a). This study adapts biomechanical analysis in conjunction with the virtual visualization of the workstation as part of the analysis.

4 CASE STUDY: ILLUSTRATION OF FRAMEWORK IMPLEMENTATION

The application of the proposed framework and its components is demonstrated by implementing it using data from an off-site construction job site. A steel fabrication shop is selected as the work environment due to the existence of many manual operations and their importance in ensuring safe and productive processes. In particular, the task of handling steel plates is observed, recorded, modeled, and analyzed using the proposed integrated approach since its productivity is critical in the whole operation and it also involves physically demanding activities (e.g., carrying steel plates). The main activities carried out to complete the task include picking up steel plates from a cutting machine, carrying them to a worktable, measuring and sorting them, and carrying them to storage bins. As the first step, the workstation is recorded using a video camera to extract time stamps and activity types using the action recognition component. This data is used to create a simulation model representing the existing, ongoing operation. Figure 5 shows the work setup and samples of the identified worker tasks.

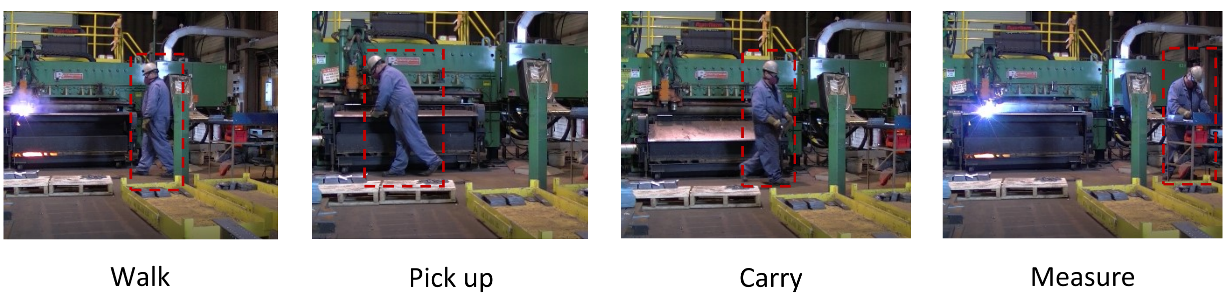


Figure 5. Sample actions identified through action recognition

By using the proposed action recognition algorithm on the video recording of the operation, 32 actions are identified in the four categories of walking, picking up, carrying, and measuring. Since the operation is cyclic, after running the action recognition, the most repeated cycle is found and used as the correct sequence of activities for the simulation modeling. Activities not following the correct identified sequence are distinguished as outliers and removed. The simulation model of the cycle is then built using the average durations for each task, as derived from the action recognition results. Based on the 32 actions identified from the video recording, which includes 4010 data points (i.e., video frames of the recording), the error in finding the correct sequence is 7.14%, and the error in calculating the correct durations is 8.48%. Figure 6 shows the ground truth and predicted activities of the steel plate handling task. The horizontal axis represents the video frame data points. The video is recorded with 30 frames per second.

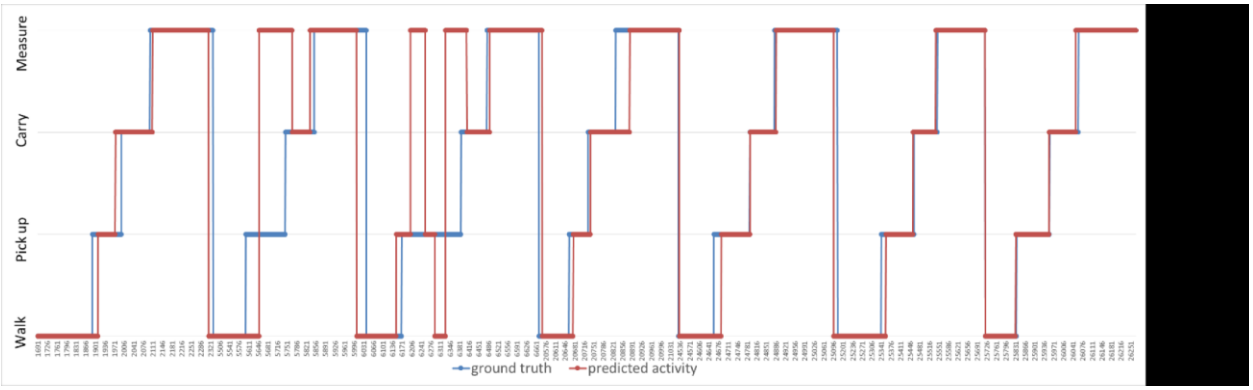


Figure 6. Comparison of the ground truth and predicted activity for steel plate handling

The results of the action recognition are used to create the simulation model that represents the current status of the operation. This is achieved with a script that uses the type and sequence of activities with timestamps from the action recognition. This simulation model serves as the basis to evaluate different scenarios of the operation (e.g., using a worktable with a different height, relocation of the worktable and storage bins, reducing the number of plates carried at each cycle) for potential improvement. As explained above, integrating PMTSs into the simulation environment enables representation of manual activities that do not currently exist. This modeling process can be used to analyze the productivity of the current activities and improve it by assessing different methods for carrying out the process (e.g., different task sequence, more labor resources). Furthermore, the sequence of activities and task durations from the simulation model are used to generate motions from a pre-recorded motion-capture database. As shown in Figure 7, models using PMTSs such as Modular Arrangements of Predetermined Time Standards (MODAPTS), Methods-Time Measurement (MTM-2), and Maynard Operation Sequence Technique (MOST) can be developed and tested from the base simulation model. These three systems are widely used and differ in their level of focus (cycle duration, repetitiveness of motions, complexity of movements, etc.). As these systems originated in industries other than construction, all three are used here to further validate the proposed simulation approach. Table 2 shows the result of running the simulation model for one cycle of the task, comparing the average duration for one full cycle from the video recordings, with the PMTS-based simulation durations. The durations are derived from running the simulation models shown in Figure 7, using inputs collected from the actual job site. As shown in the figure, the modeling elements developed and used for the different PMTSs depend on the system design. For example, MODAPTS has a GET element to represent grasping an object, for which the input is the complexity of the grasp, and MTM2 has a step element representing a walking activity, for which the input is the number of steps taken. After this step, the Biovision Hierarchy (BVH) motion file of the operation is attached to a human model based on the sequence of the tasks from the simulation, making it ready for the path planning and visualization phase.

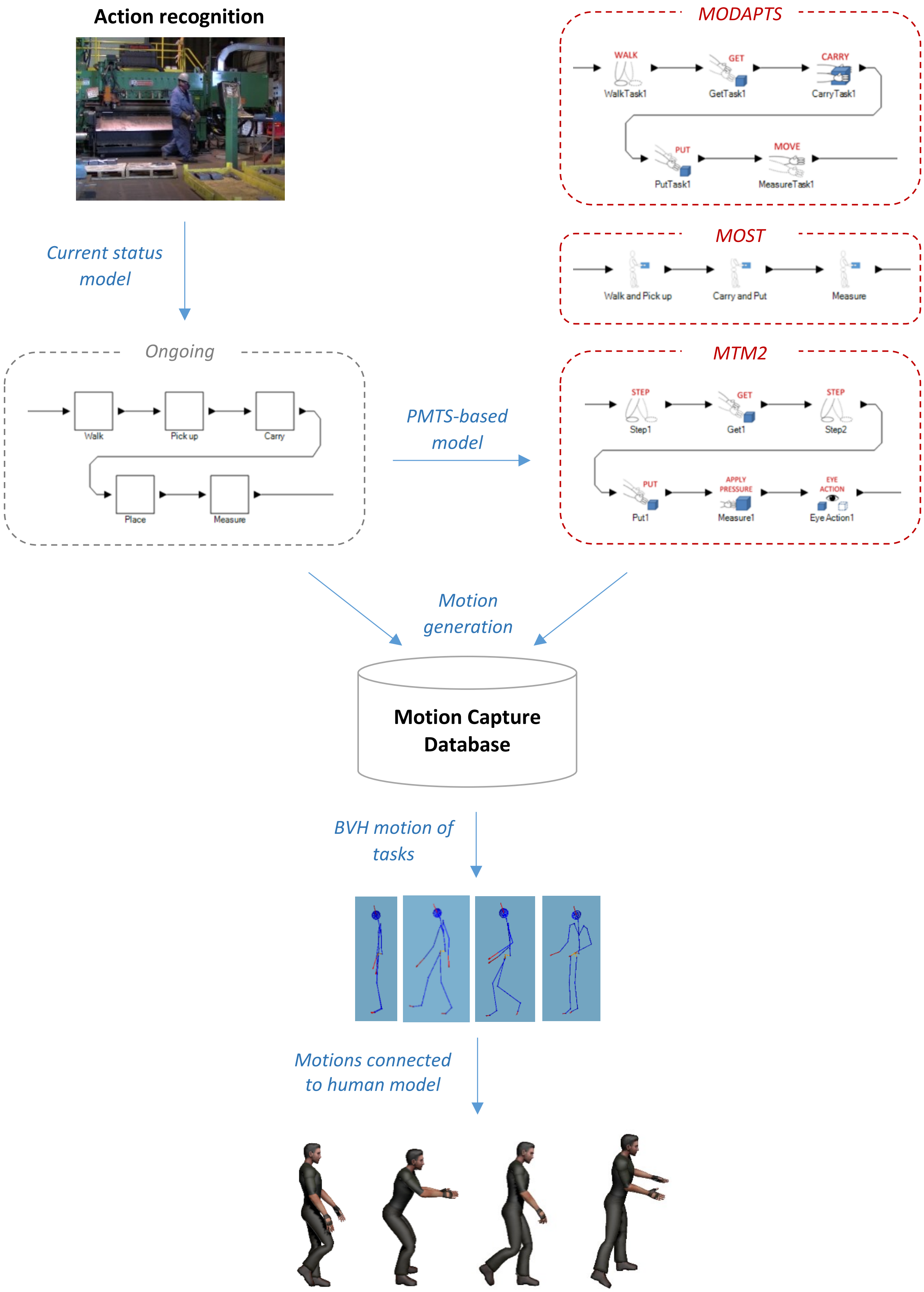

Action recognition
Current status model
Ongoing
Walk
Pick up
Carry
Place
Measure
PMTS-based model
MODAPTS
WALK
WalkTask1
GET
GetTask1
CARRY
CarryTask1
PUT
PutTask1
MOVE
MeasureTask1
MOST
Walk and Pick up
Carry and Put
Measure
MTM2
STEP
Step1
GET
Get1
STEP
Step2
PUT
Put1
APPLY PRESSURE
Measure1
EYE ACTION
Eye Action1
Motion generation
Motion Capture Database
BVH motion of tasks
Motions connected to human model

Figure 7. Simulation model and motion generation using action recognition

Table 2. Actual vs simulation durations for one cycle of the steel plate handling task

Average duration from job site (seconds)	PMTS-based simulation			Average difference between actual and PMTS-based
	MODAPS duration (seconds)	MTM2 duration (seconds)	MOST duration (seconds)	
8.66	8.06	8.42	8.28	4.70%

To create the 3D representation of the workstation, a 34-second video (1020 frames) of the job site is recorded. A stereo vision camera is used with a stereo baseline of 120 millimeters, a depth range of 0.5 to 20 meters, 8.5 millimeters backside illumination sensors with high low-light sensitivity and resolution of 4M pixels per sensor, and the capability of recording videos with 15 to 100 frames per second. Using the process described before, the point cloud model representing the as-is conditions is generated. Running the data to generate the point cloud model for the steel plate handling workstation takes approximately 10 minutes. A snapshot of the point cloud model of the steel plate handling workstation is shown in Figure 8.

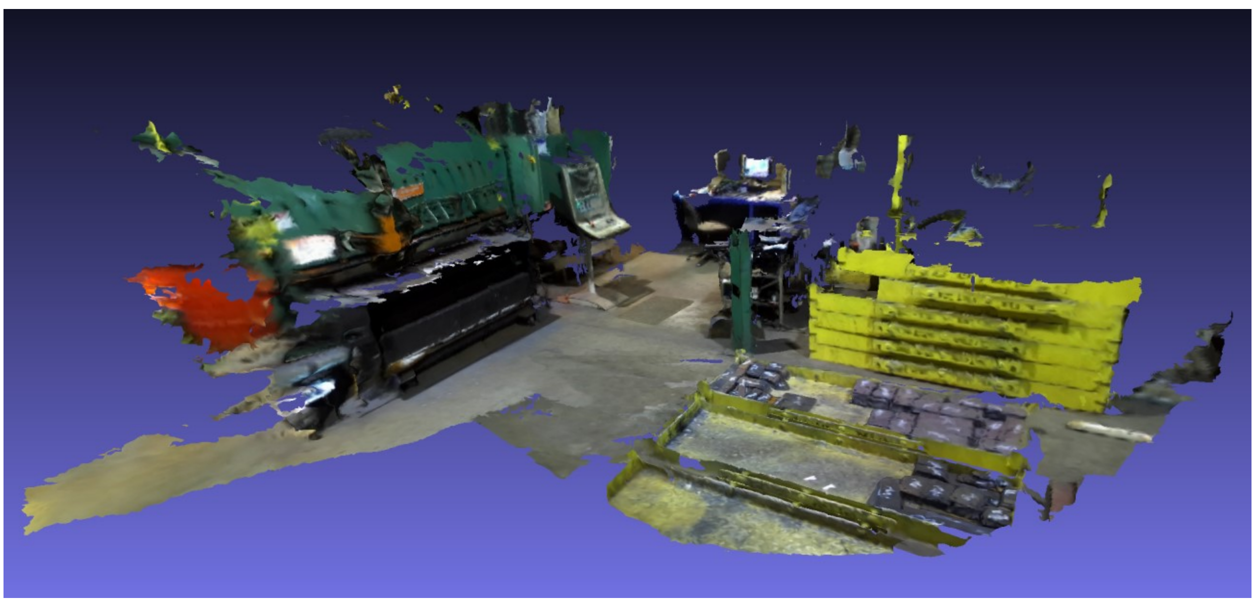


Figure 8. Point cloud model of the steel plate handling workstation

As an example of the ergonomic and biomechanical analysis for safety evaluation, the process of picking up the plates from the machine is demonstrated. As shown in Figure 9, this analysis begins by modeling the worker's posture at any given point during the operation and using biomechanical models (Chaffin et al. 2006) to calculate the forces on different body joints and compare them to allowable limits (Golabchi et al. 2015b). Any ergonomic concerns can be addressed during this modeling, and the worker's posture and workplace design can be changed, if required, to ensure the tasks are acceptably safe. This process can be carried out using any of several available biomechanical analysis tools and software, such as 3DSSPP, openSim, SIMM, or Visual 3D. The 3DSSPP software (2018) is used in this study as it can examine variables such as back compression (i.e., load on lower back shown in Figure 9) and the strength-percent capability of different body joints (i.e., load on body joint percentages shown in Figure 9) that are useful for assessing the steel plate handling task. Furthermore, it can effectively visualize and export posture modifications and their effects on biomechanical loads.

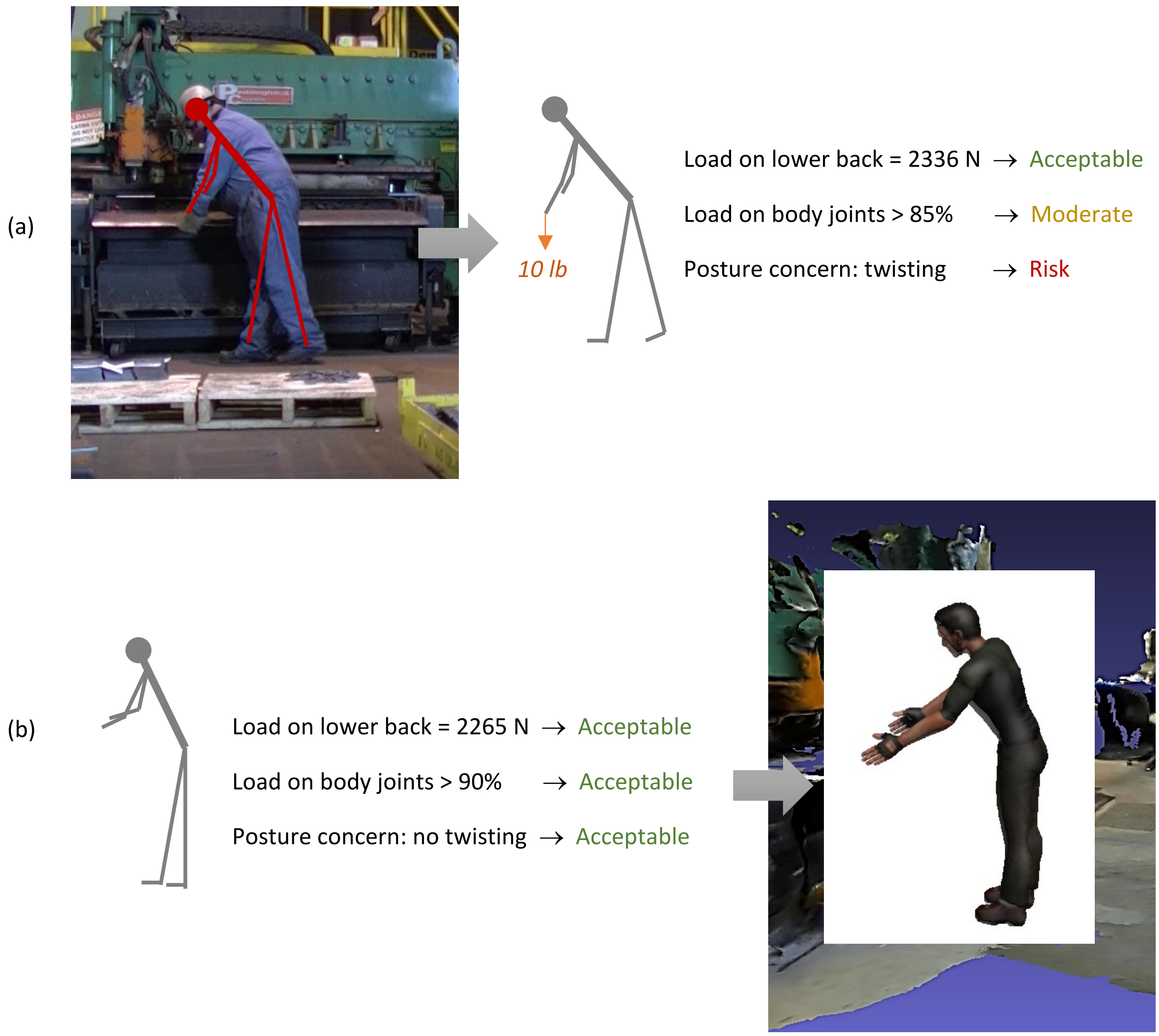
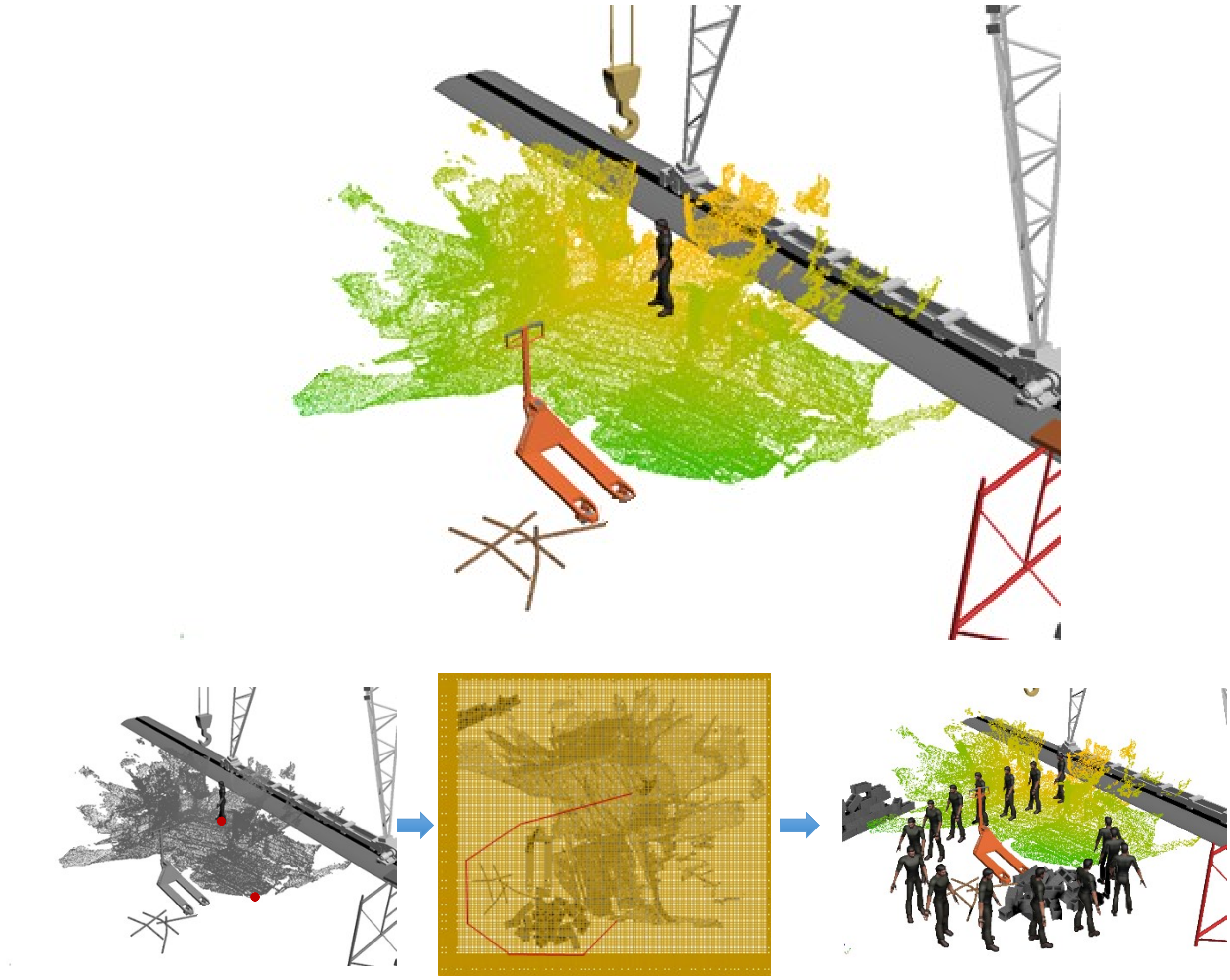


Figure 9. Biomechanical analysis of plate grasping task, (a) current conditions, (b) modified posture, added to the point cloud model after improvements

After creating the point cloud model of the steel plate handling workstation (Figure 9.b), the model is inserted into the platform for the final virtual representation. Autodesk 3ds Max is used as the final platform in this study. The point cloud can be used in conjunction with any 3D model (such as BIM) to evaluate ongoing operations and alternative scenarios. The human model and the motions attached to it from previous steps are also inserted into the visualization and manually aligned at the correct locations, along with other 3D models. The path planning algorithm is then used to find the best walking path for the worker model. Figure 10 shows a snapshot of part of the virtual model with the point cloud, the human model, and other 3D models of equipment and materials. The figure also shows the sequence for the path planning: by selecting the start and end locations, the obstacles are detected as described previously, and the shortest path is chosen and used to animate the human model. Examples of different scenarios for the steel plate handling operation can include using a different cutting machine, adjusting the height of the worktable, relocating the worktable or the storage bins closer to the cutting machine, and changing the number of plates carried to the bins at a time. The final output of the visualization is a complete virtual model representing the physical layout of the job site, building elements (e.g., walls, doors), 3D models of equipment, material, tools, and human models animating the motions of workers. This virtual model can be used in practice to further evaluate the design (e.g., assessing clearance and reach), improve the communication and implementation of new designs, train personnel, and more effectively manage decision-making.



(a) (b) (c)

Figure 10. Top: virtual model of job site, bottom: path planning (a) start and end locations selected, (b) A* algorithm detects shortest path, (c) worker motions are animated along the selected path

5 DISCUSSION

The implementation of the framework enables an examination of the effectiveness of the different components and their strengths and weaknesses, and serves as a basis for further improvements to the framework. Based on the results, the following implications can be drawn.

(1) The results of implementing the action recognition process indicate that the process can potentially save time and effort in evaluating ongoing manual operations and improve the accuracy of the evaluation. Furthermore, the approach possibly eliminates the need for an expert in creating and analyzing simulation models of manual tasks because the only input is a video recording of the manual activity. The error values for the steel plate handling operation are 7.14% and 8.48%

for finding the correct sequence and calculating the correct durations, respectively. The accuracy of the action recognition component could potentially be improved by extracting refined motion features (e.g., human silhouette with a more accurate contour) and training a more robust action classifier (e.g., fed data with a wider distribution over motions). The action recognition process is probably most practical when modeling cyclic operations, first because a short video of the process can be used to identify the correct sequence of activities and average durations (minimizing processing time). Second, as noncyclic operations do not contain a fixed sequence, outliers cannot be identified, which reduces the reliability of the system. This is particularly important when modeling motions in on-site construction, as opposed to off-site and modular construction and fabrication, since motions, tasks, and job site conditions change more frequently.

In the proposed framework, the action recognition component serves as the basis for the simulation model used for productivity analysis and motion generation. However, the information derived from action recognition could also be used to integrate many other applications into the framework, such as safety evaluations and worker training. For example, time-related information obtained from action recognition, such as working vs idle durations and frequency of motions, can be used to evaluate level of safety of the operation (Nath and Behzadan 2017). Also, the methods of carrying out an operation by workers can be compared to that of a skilled worker (or any preset benchmark) for worker training.

Kinematic data can be collected using different types of sensors, such as wearable IMU-based motion capture systems (Yan et al. 2017). Different sensing methods encompass various advantages and disadvantages. A vision-based approach using video cameras is examined in this study due to advantages such as convenient access to ordinary cameras in job sites and the simplicity of implementation of the approach. However, it should be noted that this approach has limitations such as requiring the worker to stay in the camera's field of view, prevention of occlusions from machinery or other workers, existence of sufficient lighting without high reflections, selection of appropriate location for the camera, etc.

(2) The case study shows that the simulation model of the existing operation, created from video recordings using action recognition and used alongside a PMTS-based modeling platform, enables simple, accurate, and quick evaluation of ongoing activities. The action recognition–based simulation model represents the current operations, and the PMTS-based model represents the standard time for the operation. As shown in Table 2, the actual average duration for a cycle of the steel plate handling task is 8.66 seconds, and the simulation duration using MODAPTS, MTM2, and MOST is 8.06, 8.42, and 8.28 seconds respectively. The difference between the two durations can be used to represent the efficiency of the ongoing operation. Furthermore, the PMTS-based simulation enables convenient and accurate modeling of alternative scenarios for the operation to find the optimal process. Experiments with PMTSs in representing manual tasks, the simplicity of adopting them, and the amount of error associated with them (Golabchi et al. 2016b) indicate the importance of such systems in modeling construction operations. However, as these tools are

mainly originated in manufacturing industries, more studies focused on customizing them for non-cyclic on-site construction tasks are required.

(3) The generation of point cloud models from a video recording of a job site is a quick and simple method for obtaining a reliable 3D representation of current conditions. Since construction sites are dynamic and the status of the work environment changes frequently, this method ensures that the 3D virtual model accurately represents the as-is state of the job site. Obtaining the 3D as-is representation is critical in case of evaluating and redesigning ongoing operations or designing new operations in existing workplaces, as it provides a manageable but detailed view of the current status of the workplace and its different components and enables modification of the different design elements to evaluate its impact on performance and safety. In case of non-existing job sites, the effectiveness of the virtual visualization depends on existence of reliable and inclusive 3D representations (e.g., as-designed BIM). It should be noted that the stereo vison approach adapted in this study is limited to only a certain size of workstation since the distance between the two lenses is fixed and relatively short. With a longer distance between the lenses, the perception level increases, and thus the depth perception ability will be higher. One potential solution to the boundedness limitation would be building a stereo vision camera with adjustable lenses.

Considering the conversion and import/export capabilities of existing software, the point cloud model connects smoothly to the final visualization model. However, manual manipulation is still required, along with scaling in some cases, to align the model in its correct position. The accuracy and labor-intensity of this process could be improved in further studies by using universal coordinate and unit systems and creating a method to automatically register different models in the final platform. Using predefined targets can also facilitate the registration and scaling of the point cloud data. Furthermore, due to the dynamic nature of construction job sites, the process of updating the as-is representation is of great importance and requires development of approaches that enable smooth, efficient, and reliable update of the models. Overall, the integration of point cloud data, human model and motions, and 3D models of equipment, tools, material, etc., results in a data-rich virtual model that can be effectively used for various potential visualization applications in construction job sites.

(4) The path planning component, in conjunction with motion generation, enables an automated animation of worker motions, which are an important element in the visualization of manual operations. The path planning algorithm eliminated the time and effort required to manually set the animation of the human models and represented the motions in an acceptable and realistic scenario of worker activities in prospective work environments. This can be particularly useful when considering the existence of more than one worker in a single workstation, for which collision avoidance algorithms should also be incorporated. It should be noted that this process uses the shortest path between two points, and although it is generally safe to assume that workers will usually take the shortest path, this approach can be most useful for modeling prospective operations. If an exact representation of worker paths is required for an existing operation, it must

be observed and recorded at the actual job site. Although this information might not be required for most applications, it is possible to automate this process using location-aware sensors and devices. This study used the A* path planning algorithm due to its popularity and accuracy. However, implementing other algorithms and evaluating their effectiveness could be carried out in future studies.

Overall, the results indicate that integrating visual sensing methods, along with analysis of operations and workplace visualization, can facilitate the data linking required for an inclusive ergonomic analysis, streamlining the evaluation and design of safe and productive workplaces. The first benefit is the automation and simplicity of the analysis process, which can result in higher adoption of ergonomic methods in practice. Second, as the same data are used by several components and the initial inputs are gathered using sensing approaches, the results provide high reliability and minimal subjectivity. Integrating sensing with action recognition and simulation modeling requires less time and effort for evaluation of labor operations compared to traditional ergonomic analysis methods. Furthermore, incorporating productivity analysis through PMTSs into ergonomic analysis enables evaluating and improving both performance and safety simultaneously.

6 CONCLUSION

This study explores the adaptation and integration of methods to improve different stages of ergonomic analyses, including data collection, analysis, and representation of results. Improvements were achieved by proposing an overall framework to provide an automated, simple, and reliable analysis of manual operations. Specifically, the following framework components were investigated: (1) sensing to collect information about job site conditions, worker tasks and activities, and human motions; (2) action recognition from video recordings for simulation model creation; (3) predetermined motion time systems for efficiency evaluation; (4) biomechanical analysis for safety analysis; (4) motion generation and worker path planning for realistic animation of worker actions; (5) comprehensive virtual visualization for effective representation and implementation of the analysis and results. Overall, the results of implementing the framework indicate that integrating available methods of data collection, analysis, and visualization for labor operations can facilitate an inclusive ergonomic analysis. Such integration addresses challenges in traditional approaches to ergonomic evaluation, including labor-intensity, unreliable results, and time-intensity. Considering the physically demanding nature of manual tasks in the construction industry, this integration could result in a higher adoption of ergonomic methods in practice, as well as better reliability and reduced subjectivity in analysis results, which can lead to safer and more productive construction job sites.

The main limitations of the integration and potential directions for future research include: (1) recording worker motions using vision-based approaches requires proper lighting, inclusion of worker’s body in camera’s line of sight, avoiding occlusions, and setup of camera at proper locations; (2) vision-based action recognition works reliably for cyclic tasks but more testing and development is required for non-cyclic construction tasks; (3) currently available PMTSs need to be effectively customized for construction labor tasks for a more reliable evaluation; (4) use of point cloud as-is model, human model, and other 3D objects in the virtual visualization requires some manual registration and scaling; (5) considering the diversity of tasks in construction, robust methods for automated visualization of different type of worker motions in a virtual model can be highly effective; (6) with the use of the virtual representation of the workplace and worker motions, some level of expertise is still required for redesigning the workplace in case of unsafe tasks as well as evaluating risk factors such as clearance, vision, reach, and fit; automation of the redesign process can further improve the adaptation and reliability of the analysis.

7 ACKNOWLEDGEMENTS

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