Dynamic Biomechanical Analysis for Construction Tasks Using Motion Data from Vision-Based Motion Capture Approaches

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ABSTRACT

In the labor-intensive construction industry, workers are frequently exposed to manual handling tasks involving forceful exertions and awkward postures. As a result, construction workers are at about a 16 percent higher risk of work-related musculoskeletal disorders (WMSDs) than workers in other industries. A biomechanical model-based musculoskeletal stress analysis is one of the widely used methods to identify the risk of WMSDs during occupational tasks. However, the use of biomechanical analysis has been limited in only laboratory experiments due to the difficulty of collecting motion data required for biomechanical models under real conditions. To reflect postural variations when performing construction tasks, an effective and easily accessible mean that enables us to conduct biomechanical analysis under real conditions is required. To address this issue, we propose a motion-data–driven biomechanical analysis by enabling automatic processes to convert motion data from vision-based motion capture into available data for representing motions in biomechanical analysis tools. We conduct a case study on masonry work to determine the feasibility of the proposed method. The results show that the proposed approach has the potential to assess an individual's motions and to provide personalized feedback for the purpose of reducing biomechanical loads and WMSD risk in real workplaces.

INTRODUCTION

Construction work largely relies on labor-intensive manual tasks. Due to physically demanding manual construction tasks involving awkward postures or forceful exertions, workers frequently suffer from work-related musculoskeletal disorders (WMSDs) such as sprains, tendonitis, carpal tunnel syndrome, and back pain (Boschman et al. 2012; CPWR 2013). Statistics show that the rate of WMSDs in construction was 16% higher than the rate for all other industries combined (BLS 2012; CPWR 2013). Over 90% of risk factors for WMSDs in construction are associated with overexertion in lifting, pushing, pulling and carrying, and back bending (CPWR 2013). Therefore, it is important to measure physical stresses and to eliminate—or at least minimize—excessive stresses for preventing WMSDs during construction tasks.

For a comprehensive physical stress analysis during occupational tasks, biomechanical model-based musculoskeletal stress analysis has been widely applied. By quantifying internal loads (e.g., joint moments or muscle forces) on human bodies as a function of postures and external forces on hands and feet, biomechanical models assess musculoskeletal risks on human bodies that may contribute to the development of WMSDs during occupational tasks (Chaffin et al. 2006). Several computerized software packages (e.g., 3D SSPP^{TM} (Three-Dimensional Static Strength Prediction Program^{TM}), OpenSim, Visual 3-D^{TM}, and AnyBody^{TM}) have provided practical solutions to estimate musculoskeletal stresses. The use of biomechanical analysis for simulating tasks has been limited to controlled environments due to the difficulty of collecting motion data required for biomechanical models under real conditions. However, when performing tasks such as picking up a heavy load in a controlled environment, the load may result in no hazard in certain postures, while slightly different postures caused by different individual work styles and job conditions could generate excessive musculoskeletal stresses beyond limits. Therefore, to reflect postural variations due to individual preference and diverse work environments in construction, an effective and easily accessible mean that enables us to conduct biomechanical analysis under real conditions is required.

The implementation of such an on-site biomechanical analysis may broadly involve two technical challenges: one is to collect accurate motion data without interfering with on-going works in construction sites; the other is to process the motion data to make it compatible with existing computerized biomechanical analysis tools (Seo et al. 2013b). With regard to the first challenge, our research group has developed and applied vision-based motion capture using ordinary video or network surveillance cameras (Han et al., 2012b; Han et al., 2013) and an RGB-D sensor (e.g., Kinect^{TM}) (Han et al., 2012a; Han & Lee, 2012) to obtain accurate motion data without invasive measures in construction sites.

This paper focuses on the compatibility issue between vision-based motion capture data and existing biomechanical analysis tools. Specifically, we propose a motion-data–driven biomechanical analysis by enabling automatic processes to convert motion data from vision-based motion capture into available data for representing motions in biomechanical analysis tools. We conduct a case study on masonry work to determine the feasibility of on-site biomechanical analysis using the motion data. Based on the results, the possibility of on-site biomechanical analysis as a field-based ergonomic evaluation method is discussed. Before proceeding with the next sections, the authors would like to note that some of the results shown in this paper are also part of a paper submitted for the ASCE Journal of Computing in Civil Engineering (Seo et al. 2013c).

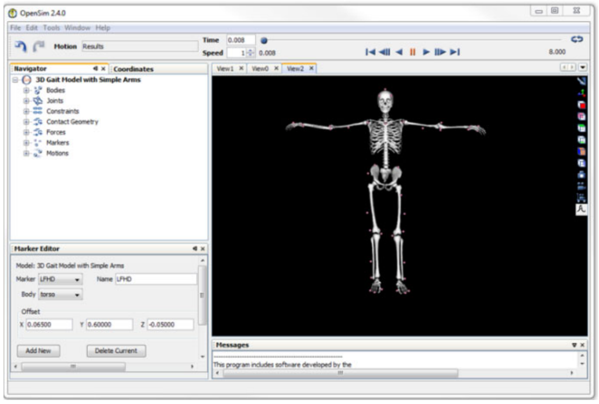
MOTION CAPTURE METHODS FOR BIOMECHANICAL STUDIES

There are two types of biomechanical models; 1) a static model to evaluate static postures or motions without acceleration: and 2) a dynamic model that considers inertial forces caused by acceleration. While a static model requires static postural information such as joint angles, it is necessary to measure kinematic motion data including direction, velocity and acceleration of motion for dynamic evaluations (Chaffin et al. 2006). For three-dimensional dynamic biomechanical analysis, optical motion capture systems using passive (e.g., retro-reflective) or active markers (e.g., light-emitting diode) attached to a subject's body parts have been generally applied (Davis et al. 1991; Aminian and Najafi 2004). Optical motion capture systems—such as VICON™, Qualysis™ ,Optotrak™ and others—track a subject's movements by triangulating the three-dimensional positions of markers on the skin from one or more cameras, and provide motion data in various file formats (e.g., TRC and C3D file formats). Existing dynamic biomechanical analysis tools are designed to obtain kinematic information required for biomechanical models from motion data in the specific file formats. Even though these systems provide accurate motion data for biomechanical studies, there are several limitations: 1) they require complex and expensive equipment, 2) a controlled environment for lighting conditions is necessary, and 3) markers attached to the subject interfere with the subject's movement (Corazza et al. 2006). Due to these limitations, previous research efforts to study dynamic musculoskeletal stresses during construction tasks such as panel (Jia et al. 2011) or drywall (Kim et al. 2011) installation have been conducted only in controlled environments by mimicking the tasks in laboratories and obtaining motion data from optical motion capture systems.

Recently, vision-based motion capture approaches are becoming popular as attractive solutions to address the limitations of optical motion capture systems for biomechanical studies (Corazza et al. 2006) because they are the only non-invasive methods for obtaining human motion information (Moeslund et al. 2006). Vast research efforts have developed emerging computer vision techniques or algorithms to extract motion data from video cameras (e.g., 2D images) (Moeslund and Granum 2001, Moeslund et al. 2006, Poppe 2007), and the use of RGB-D sensors (e.g., Kinect™) has simplified the process for vision-based motion capture algorithms (Shotton et al. 2013). The main advantage of the vision-based motion capture is that it does not require any markers or sensors attached to the subject during motion capture, and allows researchers to generate human skeleton–based motion data. We have applied vision-based motion capture data for static biomechanical analysis (Seo et al. 2013a); however, vision-based motion capture approaches have not been applied to dynamic biomechanical analysis because of the compatibility issue in motion data from vision-based motion capture and dynamic biomechanical analysis tools such as OpenSim (Seo et al. 2013b).

MOTION-DATA–DRIVEN BIOMECHANICAL ANALYSIS

The purpose of this paper is to test the usability of available motion capture data from vision-based motion capture for biomechanical analysis that helps assess the risk of WMSDs during construction tasks under real conditions. As a dynamic biomechanical analysis tool that performs biomechanical analysis on dynamic motions (motions with velocity and acceleration), OpenSim (Delp et al., 2007)—a popular musculoskeletal and engineering software package (Mansouri and Reinbolt 2012)—was selected. One of the advantages of this tool is that it can be partially or fully customized depending on the user's needs. For example, OpenSim is an open-source platform written in C++, and provides an Application Programming Interface (API) that allows researchers to access and customize OpenSim functionality (Anderson et al. 2012).



Motion: Results
Time: 0.008
Speed: 1 0.008
8.000

Model: 3D Gait Model with Simple Arms
Marker: LFHD Name: LFHD
Body: torso
Offset
X 0.06500 Y 0.60000 Z -0.05000

This program includes software developed by the

Figure 1. A screenshot of OpenSim window and a musculoskeletal model

Given motion and external force data (e.g., hand and foot forces) during certain tasks, OpenSim estimates joint moments at body joints (e.g., wrists, elbows, shoulders, hips, knees etc.) with a pre-defined musculoskeletal model (Figure 1) that has rigid skeletal bones (Symeonidis et al. 2010). To simulate the musculoskeletal model, OpenSim uses marker-based motion capture data in the TRC file format that contains geometric marker positions attached to the subject. The procedures required to run OpenSim are as follows (Anderson et al. 2012): 1) scaling that adjusts both the mass properties (mass and moment of inertia) and the dimensions of the musculoskeletal model for the subject using locations of markers, 2) inverse kinematics to create motions by matching experimental markers with virtual markers in the musculoskeletal model and to calculate joint angles, 3) inverse dynamics that determines the net joint moment at each body joint that produces movement by solving the equations of motion with joint angles from inverse kinematics and external force data. For scaling (adjusting anthropometric factors) and inverse kinematics (calculating body angles) processes, marker positions in the TRC marker data are the primary sources.

However, vision-based motion capture approaches generally generate skeleton-based motion data in the BVH file format that is not available in OpenSim. The main difference between TRC and BVH motion data is the definition of motions. While the motion data in the TRC file format defines human motion using three dimensional positions of markers that can be obtained from optical motion capture systems (Figure 2(a)), the BVH motion data format defines the hierarchical and spatial structure of a human body and stores a 3D position of a root body joint (e.g., a hip) (Figure 2(b)).

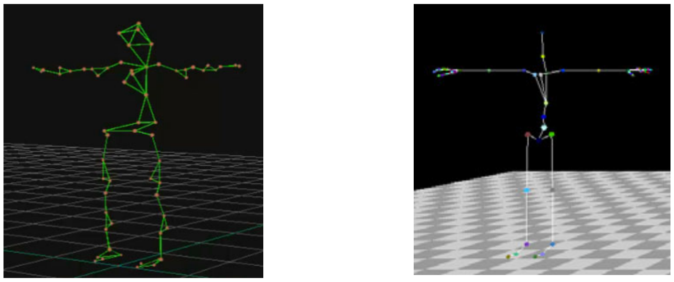
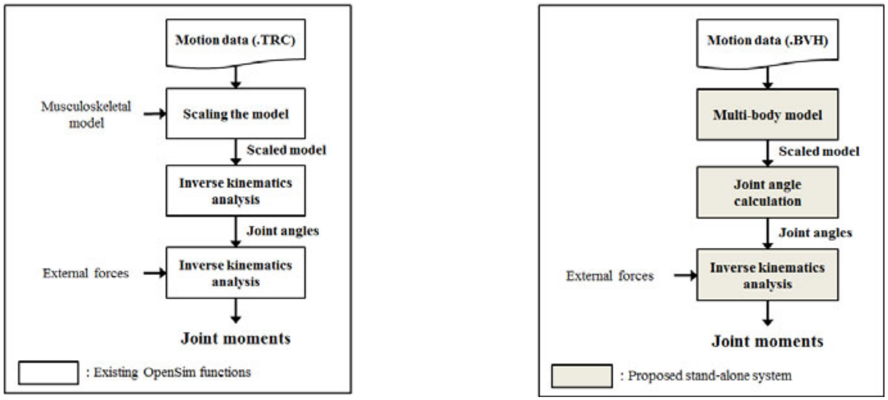

(a) TRC motion data (b) BVH motion data

Figure 2. Comparison of motion data in the TRC and BVH file formats

To enable the two processes (scaling and inverse kinematics) to be done with the BVH motion data, we developed a user-friendly stand-alone system that automatically generates joint angles for inverse dynamics from the BVH motion data. Figure 3 shows comparison between workflows in OpenSim and the proposed system. First, the proposed system creates the multi-body model that is similar to the musculoskeletal model in OpenSim. The mass properties and dimensions of the model are adjusted based on the subject's weight and height. Next, instead of inverse kinematics in OpenSim, the system calculates joint angles directly from the BVH motion data. Once the multi-body model and the joint angles are generated, the system performs inverse dynamics analysis to estimate joint moments. For inverse dynamics analysis, the system uses the source code provided by OpenSim. These workflows are automatically processed only by inputting a subject's anthropometric information (height and weight) and the BVH motion data in the stand-alone system.

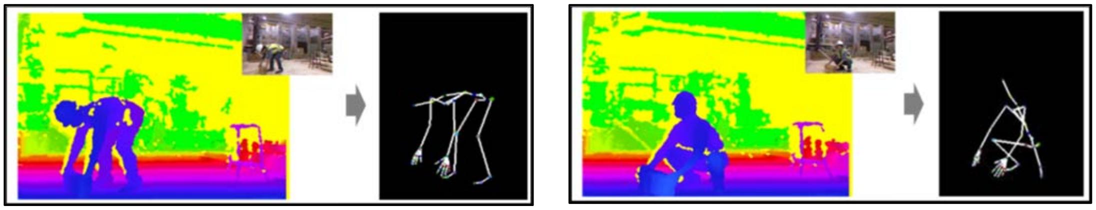


(a) Workflow in OpenSim (b) Workflow in the proposed system

Figure 3. Workflow comparison between OpenSim and the proposed system

CASE STUDY ON MASONRY WORK

To evaluate the proposed system for performing dynamic biomechanical analysis, this research conducted a case study on masonry work, specifically lifting a concrete block. Motion data during the concrete block lifting was collected using an RGB-D sensor–based motion capture approach by mimicking the tasks in a laboratory. A male subject (175 cm, 70kg) was asked to repeatedly lift a concrete block of 20 kg (196 N) from one side and move it to the opposite side using stoop and squat techniques. As shown in Figure 4, during the trials, Kinect^{TM} took RGB-D images at a frame rate of 30 Hz, and the images were processed in iPi Mocap Studio (www.ipisoft.com) to extract BVH motion data. For external forces, hand forces were assumed as same as the weight of the block, and foot forces were the sum of the body weight and the weight of the block.



(a) Stoop lifting technique (b) Squat lifting technique

Figure 4. Motion data collection

Given anthropometric information (the subject's height and weight), motion data in the BVH format, and external forces, we conducted dynamic biomechanical analysis to estimate joint moments during squat and stoop lifting using the proposed system. Figure 5 shows joint moments at L5/S1 (i.e., an intervertebral disc between the fifth lumbar and first sacral vertebra), left knee, and left elbow joints during one cycle of squat and stoop lifting. The results show that the L5/S1 and knee joint moments were larger in the stoop lifting than in the squat lifting while there is no significant difference in the elbow joint moments during both techniques. This result corresponds to the previous study that the squat lifting produced about 10% and 50% fewer maximum joint moments at the lumbar and knee joints respectively than the stoop lifting when a subject lifted a heavy object (15kg) (Hwang et al. 2009).

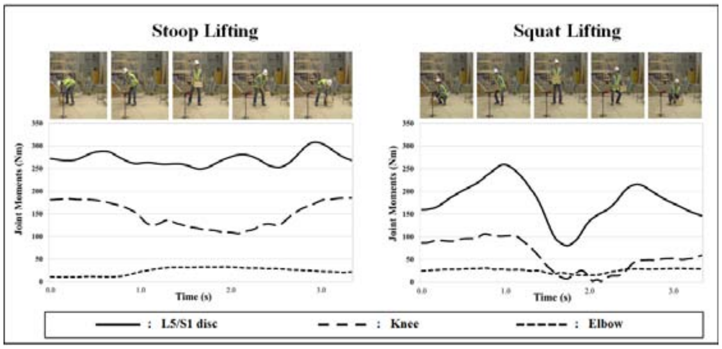


Figure 5. Joint moments at L5/S1 disc, knee and elbow

DISCUSSION AND CONCLUSIONS

In this paper, we proposed automatic processes to convert motion data from vision-based motion capture into available data for representing motions in OpenSim. The results from a case study on lifting tasks show that the proposed method for motion data processing was successfully used to perform dynamic biomechanical analysis using the BVH motion data. However, the reliability of the proposed method needs to be more closely examined. While we used inverse kinematics equations provided by OpenSim, we applied our own approach to generate anthropometric parameters in a multi-body model (e.g., mass, length, mass-center location, and moment-of-inertia of each body segment) and body angles that are input data for inverse kinematics. As future research, we will compare anthropometric parameters and body angles from our approach with those from OpenSim to test the robustness of the proposed method.

When analyzing the results from dynamic biomechanical analysis, it should be noted that joint moments during diverse tasks can only be relatively compared. Tissue injuries occur when the applied musculoskeletal stresses exceed the failure tolerance that refers to the strength of the tissue (McGill 1997). While static strengths have been well-reported from previous studies, dynamic joint strengths have not yet been fully studied because of their complexity (Chaffin et al. 2006).

Despite this limitation, the results from dynamic biomechanical analysis can be meaningful to reduce the risk of WMSDs. As shown in our case study, different postures may create considerably different levels of musculoskeletal stress on human bodies. By conducting dynamic biomechanical analysis on workers' motion during construction tasks, we can provide feedback to workers on their working styles to minimize the possibility of being exposed to relatively greater musculoskeletal stresses that may contribute to the development of WMSDs.

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REFERENCES

Aminian, K., and Najafi, B. (2004). “Capturing human motion using body-fixed sensors: outdoor measurement and clinical applications.” Computer Animation and Virtual Worlds, 15(2), 79–94.

Anderson, F. C., Delp, S., DeMers, M., Guendelman, E., Habib, A., Hamner, S., Hicks, J., Higginson, J., John, C., van der Krogt, M., Ku, J., Liu, M., Lund, K., Loan, P., Reinbolt, J. Seth, A., and Sherman, M. (2012). OpenSim user's guide. https://opensim.stanford.edu

Boschman, J., van der Molen, H., Sluiter, J., and Frings-Dresen, M. (2012). “Musculoskeletal disorders among construction workers: a one-year follow-up study.” BMC musculoskeletal disorders, 13(1), 196.

Bureau of Labor Statistics (BLS). (2012). National Census of Fatal Occupational Injuries in 2011. http://www.bls.gov/news.release/cfoi.nr0.htm

Center for Construction Research and Training (CPWR) (2013). The Construction Chart Book: The U.S. Construction Industry and Its Workers (Fifth Edition). <http://www.cpwr.com/publications/construction-chart-book> (April, 2013)

Chaffin, D.B., Andersson, G.B., and Martin, B.J. (2006). Occupational Biomechanics (fourth edition). John Wiley & Sons, Inc., Hoboken, New Jersey

Corazza, S., Mündermann, L., Chaudhari, A. M., Demattio, T., Cobelli, C., & Andriacchi, T. P. (2006). A markerless motion capture system to study musculoskeletal biomechanics: Visual hull and simulated annealing approach. Annals of biomedical engineering, 34(6), 1019-1029.

Davis, R. B., Ounpuu, S., Tyburski, D., and Gage, J. R. (1991). “A gait analysis data collection and reduction technique.” Human Movement Science, 10(5), 575–587.

Delp, S. L., Anderson, F. C., Arnold, A. S., Loan, P., Habib, A., John, C. T., and Thelen, D. G. (2007). “OpenSim: open-source software to create and analyze dynamic simulations of movement. Biomedical Engineering.” Biomedical Engineering, IEEE Transactions on, 54(11), 1940-1950.

Han, S., Achar, M., Lee S., and Peña-Mora, F. (2012a). “Automated 3D Human Skeleton Extraction Using Range Cameras for Safety Action Sampling.” 12th International Conference on Construction Applications of Virtual Reality (ConVR 2012), Taipei, Taiwan.

Han, S., and Lee, S. (2012). “Vision-based Detection of Unsafe Actions of a Construction Worker: A Case Study on Ladder Climbing.” Journal of Computing in Civil Engineering. (Accepted)

Han, S., Lee, S., and Armstrong, T. (2013). “Automated 3D Skeleton Extraction from Multiple Videos for Biomechanical Analysis on Sites.” 8th International Conference on Prevention of Work-related Musculoskeletal Disorders, Busan, Korea.

Han, S., Lee, S., and Peña-Mora, F. (2012b). “Vision-based motion detection for safety behavior analysis in construction.” Proceeding of 2012 Construction Research Congress (CRC), 21–23.

Hwang, S., Kim, Y., and Kim, Y. (2009). “Lower extremity joint kinetics and lumbar curvature during squat and stoop lifting.” BMC musculoskeletal disorders, 10(1), 15.

Jia, B., Kim, S., and Nussbaum, M. A. (2011). “An EMG-based model to estimate lumbar muscle forces and spinal loads during complex, high-effort tasks: Development and application to residential construction using prefabricated walls.” International Journal of Industrial Ergonomics, 41(5), 437–446.

Kim, S., Nussbaum, M. A., and Jia, B. (2011). “Low back injury risks during construction with prefabricated (panelised) walls: effects of task and design factors.” Ergonomics, 54(1), 60–71.

Mansouri, M., and Reinbolt, J. A. (2012). “A platform for dynamic simulation and control of movement based on OpenSim and MATLAB.” Journal of biomechanics, 45(8), 1517–1521.

Moeslund, T. B., and Granum, E. (2001). “A survey of computer vision-based human motion capture.” Computer Vision and Image Understanding, 81(3), 231-268.

Moeslund, T. B., Hilton, A., and Krüger, V. (2006). “A survey of advances in vision-based human motion capture and analysis.” Computer Vision and Image Understanding, 104(2), 90-126.

Poppe, R. (2007). “Vision-based human motion analysis: An overview.” Computer Vision and Image Understanding, 108(1), 4-18.

Seo, J., Han, S., Lee, S., and Armstrong, T. J. (2013a). “Motion-Data–driven Unsafe Pose Identification Through Biomechanical Analysis.” ASCE International Workshop on Computing in Civil Engineering, Los Angeles, CA, USA

Seo, J., Lee, S., Armstrong, T. J., and Han, S. (2013b). “Dynamic Biomechanical Simulation For Identifying Risk Factors For Work-Related Musculoskeletal Disorders During Construction Tasks.” Proceedings of 30th International Symposium on Automation and Robotics in Construction and Mining (ISARC), Monteal, Canada

Seo, J., Starbuck, R., Han, S., Lee, S., and Armstrong, T. J. (2013c). “Motion-Data–driven Biomechanical Analysis During Construction Tasks on Sites”. Journal of Computing in Civil Engineering, ASCE (Submitted).

Shotton, J., Sharp, T., Kipman, A., Fitzgibbon, A., Finocchio, M., Blake, A., and Moore, R. (2013). “Real-time human pose recognition in parts from single depth images.” Communications of the ACM, 56(1), 116–124.

Symeonidis, I., Kavadarli, G., Schuller, E., and Peldschus, S. (2010). “Simulation of Biomechanical Experiments in OpenSim.” In XII Mediterranean Conference on Medical and Biological Engineering and Computing 2010, Springer Berlin Heidelberg, 107-110.