Motion Data-Driven Biomechanical Analysis during Construction Tasks on Sites

JoonOh Seo[1]; Richmond Starbuck[2]; SangUk Han, A.M.ASCE[3]; SangHyun Lee, A.M.ASCE[4]; and Thomas J. Armstrong[5]

Abstract: Work-related musculoskeletal disorders (WMSDs) are one of the major health issues that workers frequently experience due to awkward postures or forceful exertions during construction tasks. Among available job analysis methods, biomechanical models have been widely applied to assess musculoskeletal risks that may contribute to the development of WMSDs based on motion data during occupational tasks. Recently, with the advent of vision-based motion capture approaches, it has become possible to collect the motion data required for biomechanical analysis under real conditions. However, vision-based motion capture approaches have not been applied to biomechanical analysis because of compatibility issues in body models of the motion data and computerized biomechanical analysis tools. To address this issue, automated data processing is focused on to convert motion data into available data in existing biomechanical analysis tools, given the BVH motion data from vision-based approaches. To examine the feasibility of the proposed motion data processing, an experiment for both static and dynamic biomechanical analyses was conducted on lifting tasks. The results indicate that vision-based motion capture data—converted as proposed in this paper—can provide a sufficient level of detail on human kinematics to conduct biomechanical analysis, thus allowing for the identification of particular body parts where excessive forces are placed during tasks. The issues and directions of future research are also discussed to perform on-site biomechanical analysis during construction tasks. **DOI:** **10.1061/(ASCE)CP.1943-5487.0000400.**

Author keywords: Work-related musculoskeletal disorders; Biomechanical analysis; Motion data.

Introduction

The construction industry is labor intensive and relies largely on manual handling tasks. Because of physically demanding construction tasks involving forceful exertions with awkward postures, 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 WMSDs accounted for 24% of nonfatal occupational injuries and illnesses in U.S. construction workers in 2011 (BLS 2012), which means that construction workers are at about a 50% higher risk of WMSDs than workers in other industries (Schneider 2001). These WMSDs are a leading cause of lost work days (Meerding et al. 2005), and temporary or permanent disability by WMSDs have an adverse effect on a worker's livelihood and self-esteem (Abásolo et al. 2012). In addition, great economic burden by WMSDs rests on construction firms due to lost productivity and increased workers' compensation costs (Albers and Estill 2007).

Biomechanical models—one of the ergonomic job analysis methods—have been widely applied to assess musculoskeletal risks that may contribute to the development of WMSDs during occupational tasks by estimating internal loads as a function of external exposure data (e.g., postures, movements, force exertions on hands and feet; Chaffin et al. 2006). Because an estimation of internal loads requires tedious computations with three-dimensional (3D) whole-body biomechanical models, several computerized software packages such as three-dimensional static strength prediction program (*3D SSPP*), *OpenSim*, *Visual 3-D*, and *AnyBody* have provided practical solutions to study musculoskeletal stresses.

Even though these computerized tools have provided comprehensive physical stress analysis for diverse occupational tasks, the use of these tools has been applied in only limited or controlled environments due to the difficulty of collecting and analyzing the motion data required for biomechanical models. However, compared with other industries such as manufacturing where work methods and processes are usually fixed when designing workplaces, construction takes place in unstructured and varying environments, and thus work methods and postures are changing over time. Further, task requirements in construction vary depending on project-specific context (Mitropoulos and Memarian 2013), which results in different levels of physical exertion by workers' musculoskeletal systems. As a result, an effective and easily accessible means for on-site biomechanical analysis is required to assess risk factors (e.g., awkward postures, forceful exertions) that may cause excessive musculoskeletal stresses beyond human capability during construction tasks under real conditions.

[1]Ph.D. Student, Tishman Construction Management Program, Dept. of Civil and Environmental Engineering, Univ. of Michigan, 2350 Hayward St., Ann Arbor, MI 48109. E-mail: junoseo@umich.edu

[2]Undergraduate Research Assistant, Tishman Construction Management Program, Dept. of Civil and Environmental Engineering, Univ. of Michigan, 2350 Hayward St., Ann Arbor, MI 48109. E-mail: rstarbuc@umich.edu

[3]Assistant Professor, Dept. of Civil and Environmental Engineering, Univ. of Alberta, 9105 116th St., Edmonton, AB, Canada T6G 2W2. E-mail: sanguk@ualberta.ca

[4]Assistant Professor, Tishman Construction Management Program, Dept. of Civil and Environmental Engineering, Univ. of Michigan, 2350 Hayward St., Ann Arbor, MI 48109 (corresponding author). E-mail: shdpm@umich.edu

[5]Professor, Dept. of Industrial and Operations Engineering, Univ. of Michigan, 2350 Hayward St., Ann Arbor, MI 48109. E-mail: tja@umich.edu

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The implementation of on-site biomechanical analysis may broadly involve two technical challenges. One is to collect accurate motion data without interfering with ongoing works in construction sites; the other is to process the motion data to make it compatible with existing computerized biomechanical analysis tools. With regard to the former, previous studies have proposed vision-based motion capture using ordinary video or network surveillance cameras (Han et al. 2012b, 2013a) and an RGB-D sensor (e.g., Kinect; Han et al. 2012a, 2013b), which allows to collect motion data without invasive measures under real conditions. However, the human skeleton-based motion data extracted from motion capture systems are not readily applicable to existing biomechanical analysis tools. For example, *3D SSPP* (Chaffin et al. 2006)—the only available computerized static biomechanical analysis tool designed to evaluate static postures or motions without acceleration—defines a human posture with horizontal and vertical angles in a global coordinate system (i.e., defined for a full body). *OpenSim* (Delp et al. 2007)—one of the popular dynamic analysis tools that considers inertial forces caused by acceleration—simulates motions using marker-based motion data that contains positions of markers rather than body joints (i.e., more than one marker generally is attached to one body joint). However, vision-based motion capture systems generally characterize motions using Euler rotation angles at a body joint in a local coordinate system (i.e., defined for each body joint), for example, as in the biovision hierarchical (BVH) format (Meredith and Maddock 2001). In this regard, a motion data reconfiguration that converts vision-based motion capture data into the proper form for ergonomic analysis tools is the key to the successful implementation of on-site biomechanical analysis.

This paper thus proposes on-site biomechanical analysis as a way to assess the risk of WMSDs during construction tasks using vision-based motion data. Specifically, automated data processing was conducted to convert motion data into available data in existing biomechanical analysis tools, given the BVH motion data from vision-based approaches. As biomechanical analysis tools to be studied, *3D SSPP* and *OpenSim* are selected because they are not only widely used static and dynamic biomechanical analysis tools, but they also enable us to customize existing functionality to run biomechanical analysis. Then, an experiment for both static and dynamic biomechanical analyses was conducted on lifting tasks with postural variations not only to examine the feasibility of the proposed motion data processing, but also to understand the need for on-site biomechanical analysis. Based on the results, the possibility of on-site biomechanical analysis as a field-based ergonomic evaluation method is discussed by addressing how motions during construction tasks can be understood from the biomechanical analysis results to identify the risk of WMSDs. The contributions and potential issues when applying motion data from vision-based approaches for on-site biomechanical analysis were also discussed. In conclusion, the findings of this paper are summarized.

Biomechanical Analysis for Risk Identification of WMSDS

Previous research efforts have identified mechanisms for WMSDs to describe various factors that may play into the development of musculoskeletal disorders, and to address biomechanical and physiological aspects and interactions between those factors (Kumar 1999). The factors are categorized into external factors (e.g., awkward postures and forceful exertions) and internal factors referring to musculoskeletal stresses (e.g., joint moments and muscle forces) and metabolic demands (e.g., muscle fatigue; Armstrong et al. 1996). The underlying hypothesis of mechanisms of WMSDs is that the risk of WMSDs increases when a worker is excessively exposed to risk factors beyond the worker's functional capacity (Kumar 1999). Radwin et al. (2001) recognized the interrelatedness of risk factors causing WMSDs, and identified that external loads produced in the physical work environment are transmitted to the body through a biomechanical pathway.

Because WMSDs develop over time due to repeated exposure to physical, biomechanical, and physiological risk factors, corrective actions by identifying and eliminating any risks of WMSDs should be taken before the symptoms get worse (Simoneau et al. 1996). Previously, a wide range of ergonomic methods such as self-reports (e.g., interviews and questionnaires), observational methods, and direct measurements (e.g., sensors) have been developed to assess risk factors of WMSDs during occupational tasks (Li and Buckle 1999; David 2005). Inyang et al. (2012) emphasized on an application of these ergonomic assessments during the planning and execution of construction tasks not only to improve safety issues, but also to reduce the costs associated with WMSDs. In construction, Han et al. (2013b) applied observational methods based on vision-based motion capture to detect unsafe actions during construction tasks. Ray and Teizer (2012) also suggested the automatic ergonomic monitoring system to identify nonergonomic postures using RGB-D sensors. Dai and Ning (2013) pointed out that remote sensing technologies using surveillance cameras have great potential as a video-based assessment method for identifying the risk of WMSDs. In addition, sensors such as physical status monitors (i.e., heart rate sensor; Gatti et al. 2010) or anisotropic magnetoresistive (AMR) sensors (i.e., body angle measurement system; Alwasel et al. 2012) attached to workers have been suggested as a way to directly measure the physical or postural risk factors of WMSDs during construction tasks.

Although these methods focused on the identification of external risk factors, biomechanical models have helped to understand how external factors create musculoskeletal stresses such as joint moments or muscle forces that can rarely be measured directly (Chaffin et al. 2006). Based on the assumption that the actions of the human body follow the laws of Newtonian mechanics, the biomechanical models provide a quantitative assessment of the musculoskeletal loads during occupational tasks, given kinematic information such as postures and motions during occupational tasks (Chaffin et al. 2006). As a result, biomechanical models help one to identify hazardous loading conditions that exceed human's physical capability (Marras and Radwin 2005). However, it is very difficult to measure postures and motions because of the numerous articulations of the human body and the multiple degrees of freedom at body joints (Monroe Keyserling and Budnick 1987). To collect motion data, previous biomechanical studies have relied on complex motion measurement systems such as video-based posture analysis, optical motion capture systems, or body-fixed sensors.

Video-based motion analysis systems rely on two-dimensional (2D) photographic images to measure postural angles of the human body through visual estimation, mathematical calculations (Paul and Douwes 1993), or a flexible 3D mannequin (Monroe Keyserling and Budnick 1987). However, even though these methods are cost-effective and noninvasive, they have limitations; they are time-consuming, and large errors still exist (Chaffin et al. 2006). Optical motion capture systems using passive (e.g., retroreflective) or active markers (e.g., light-emitting diode) attached to a subject's body parts are the most common techniques for collecting kinematic data for biomechanical studies (Davis et al. 1991; Aminian and Najafi 2004). Recently, various commercially available systems—such as VICON, Qualysis, Optotrak, and others—have provided whole-body motion data with a positional accuracy of less than 1 mm (Wiles et al. 2004). Because optical motion

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capture systems require a large, dedicated, controlled environment, previous biomechanical studies on construction tasks generally collected motion data by mimicking the tasks through laboratory experiments (Jia et al. 2011; Kim et al. 2011). In contrast with optical motion capture systems, body-fixed sensors—such as a goniometer, an accelerometer, and a gyroscope—have flexibility in use, which enables us to collect kinematic information anywhere (Morris 1973; Aminian and Najafi 2004). Recently, inertial measurement units (IMUs)-based motion capture systems (e.g., Xsens) using a combination of accelerometers and gyroscopes—and sometimes also magnetometers—provide a more plausible solution for body motion capture by complementing the drawbacks of different sensors. However, for whole-body motion capture, the body-fixed sensors should be attached to all body segments, and thus they may interfere with ongoing works when collecting motion data under real conditions.

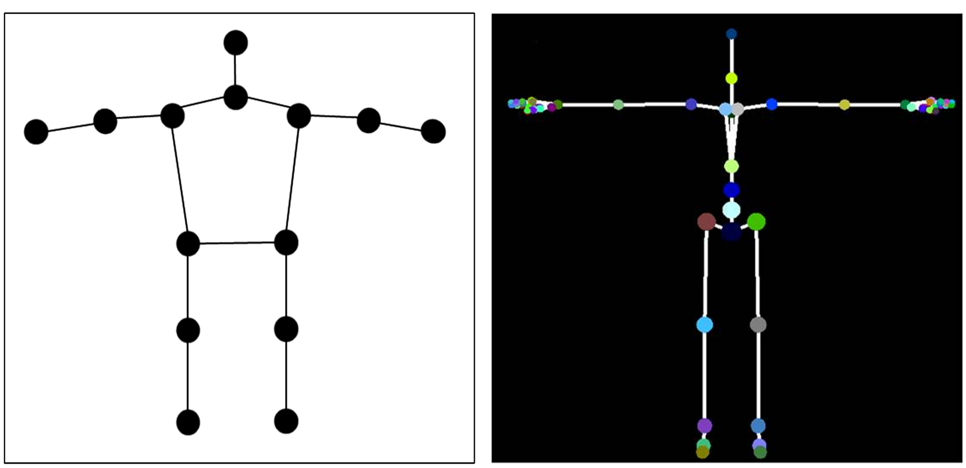
Recently, vision-based motion capture approaches have been considered attractive solutions to the limitations (e.g., need for controlled environments and a possibility of interfering with ongoing work) on existing motion capture systems for biomechanics and clinical problems (Corazza et al. 2006; Moeslund 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). In construction, Han et al. (2012b, 2013a) applied a multiple camera–based approach to extract motion data during ladder climbing from different viewpoints of images using 2D pose estimation and 3D reconstruction algorithms. In addition, the use of RGB-D images (i.e., 2D images plus depth information) collected from RGB-D sensors (e.g., Kinect) has simplified the process for vision-based motion capture algorithms (Shotton et al. 2013). Several computer vision algorithms have been developed to estimate human poses by detecting the 3D positions of body joints directly from RGB-D images (Lee and Cohen 2006; Plagemann et al. 2010; Siddiqui and Medioni 2010; Shotton et al. 2013). Recently, motion capture solutions such as iPi Desktop Motion Capture (www.ipisoft.com) and OpenNI (http://www.openni.org) have provided effective solutions for extracting skeleton-based motion data from RGB-D images obtained by RGB-D sensors. 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 (Fig. 1 shows examples of human skeleton-based motion data). For example, Han et al. (2012b, 2013a) extracted 3D skeleton models consisting of 14 key body joints (e.g., head, neck, shoulders, elbows, wrists, knees, and ankles) using ordinary video or network surveillance cameras. These skeleton models can be converted into the BVH motion data format (Chun et al. 2003) that is a standard representation of movements based on skeleton models. In addition, an RGB-D sensor-based motion capture approach (e.g., Kinect) provides motion data in the BVH format. However, despite their potential as effective noninvasive measures of motions under real conditions, vision-based motion capture approaches have not been applied to biomechanical analysis because of compatibility issues in body models of the motion data and computerized biomechanical analysis tools.

Motion Data-Driven Biomechanical Analysis

This research is undertaken to explore the usability of vision-based motion capture data for on-site biomechanical analysis that helps assess workers' postures or movements during construction tasks. As biomechanical analysis tools to be studied, *3D SSPP* and *OpenSim* are selected because they can be partially or fully customized depending on the user's needs. For example, *3D SSPP* enables the automatic analysis of tasks using a batch file that follows a specific format with all of the information including postural angles required for biomechanical analysis (Center for Ergonomics, University of Michigan 2011). *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). This chapter provides the details on the suggested processes that automatically convert the BVH motion data from vision-based motion capture approaches into available file formats in existing biomechanical analysis tools, *3D SSPP* and *OpenSim*, thus allowing us to perform biomechanical analysis using the motion data without any time-consuming data processing.

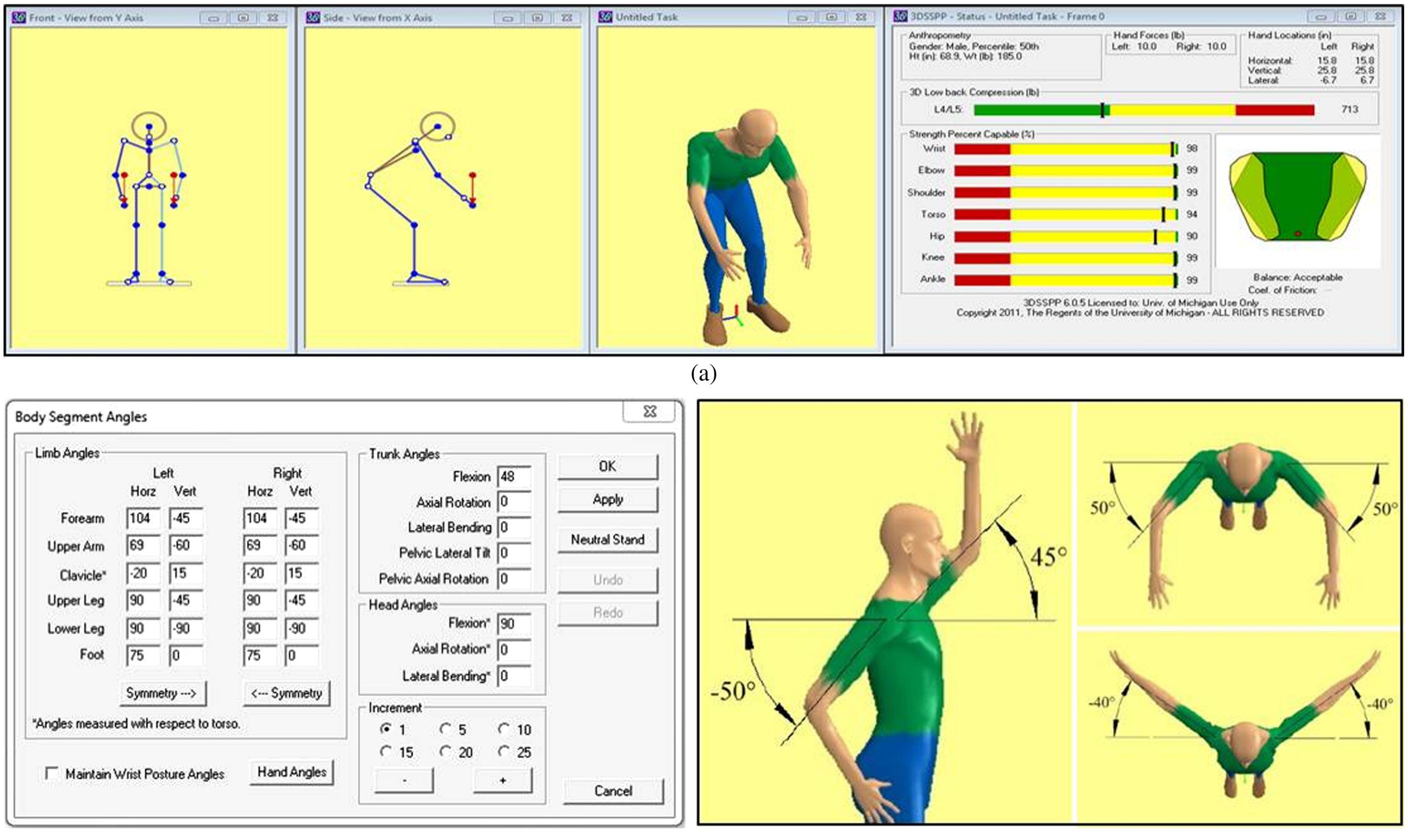
Automated Motion Data Processing for Static Biomechanical Analysis in 3D SSPP

3D SSPP is static biomechanical analysis software developed by the Center of Ergonomics at the University of Michigan (Chaffin et al. 2006). With posture data, anthropometry data, and force parameters, workers' motions can be simulated in a virtual 3D environment. Based on the biomechanical simulation, static strength



(a) (b)

Fig. 1. Skeleton-based motion data: (a) 3D skeleton; (b) an example of skeleton model in BVH motion data



(b)

Fig. 2. *3D SSPP*: (a) user interface; (b) angular configurations of a human model

requirements (e.g., joint moments) for certain tasks are predicted, including the spinal compression force using the static biomechanical model (Center for Ergonomics, University of Michigan 2011) that assumes the effects of acceleration and momentum are negligible. More important, based on the analysis results of postures, the body parts that endure forceful exertion can be found as compared with the relevant human capacity such as the National Institute for Occupational Safety and Health (NIOSH)-recommended limits for percent capables (i.e., percent of the population with sufficient strength; Center for Ergonomics, University of Michigan 2011). For example, Fig. 2(a) shows an example of the biomechanical analysis result in *3D SSPP*. The left three images in Fig. 2(a) are the same pose from different viewpoints, and the right image in Fig. 2(a) shows the analysis result. The limits in the bar graphs correspond to the NIOSH action limit (AL) and maximum permissible limit (MPL; NIOSH 1981) that were substantiated epidemiologically and biomechanically (Jäger and Luttmann 1999). The joint moments below the AL can be achieved by 99% of men and 75% of women, which means almost every type of worker can perform the task. On the other hand, the joint moments beyond the MPL can be exerted only by 25% of men and 1% of women, and thus should not be permitted to prevent musculoskeletal injuries. For back compression forces, the AL is set to 3,400 N, and the MPL is set to 6,400 N. As a result, if the bar that represents joint moments and back compression forces in certain postures is in the red zone, the body segments have a high risk of getting injured.

Generally, a static biomechanical model requires three types of input data: (1) anthropometric factors (body lengths, masses, and centers of mass of body segments), (2) force parameters (external forces exerted on hands and feet), and (3) body angles at each body joint. In *3D SSPP*, anthropometric factors are set as default values

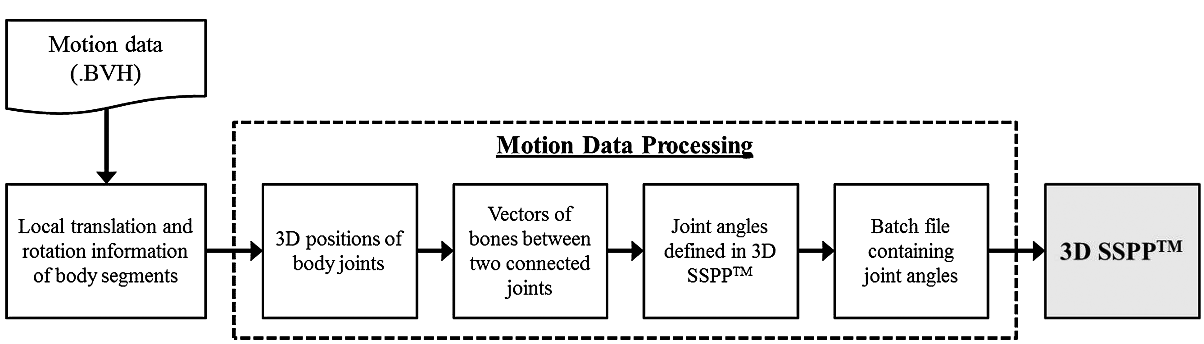


Fig. 3. Work flow for automated motion data processing in *3D SSPP*

for a U.S. industrial population and can be adjusted based on the subject's height and weight. Force parameters referring to hand forces during lifting, pushing, and pulling—foot forces are determined by summing body weight and hand force vectors—specify external forces during tasks. While anthropometric factors and force parameters can be included by simply inputting the subject's height and weight, and hand forces in *3D SSPP*, postural angles should be determined from motion data. The body model in *3D SSPP* defines a posture as body segment angles with three degrees of freedom, and thus can be manipulated by inputting the angles for each frame, as shown in Fig. 2(b).

This paper proposed an automated process to convert the BVH motion data into postural angles defined in *3D SSPP*, and then to run biomechanical analysis, given the BVH motion data as shown in Fig. 3. BVH motion data defines hierarchical body segments as local translation and rotation information from a root body joint (e.g., a hip). However, the definitions of rotation angles and the coordinate system in BVH motion data are different from the definitions and coordinate system in *3D SSPP*. To address the difference, the body angles required for *3D SSPP* were computed based on spatial information (local translations and rotations) in BVH motion data. First, 3D positions (x-y-z coordinates) of all of the body joints in the BVH motion data are iteratively computed from the root joint using local translations and rotations (i.e., a transformation matrix) based on the predefined hierarchical structure of a human skeleton in the BVH motion data. Then, the joint angles are computed based on the vectors of bones between two connected body joints in a local coordinate system of the body, following the definitions of horizontal, vertical, and rotational angles for each body joint in *3D SSPP* (Center for Ergonomics, University of Michigan 2011).

The postural angles calculated from the BVH motion data for each frame are integrated in a batch file that allow automatic analysis of tasks just by importing the batch file into *3D SSPP* (Center for Ergonomics, University of Michigan 2011). Fig. 4(a) shows an example of a batch file automatically generated, containing information to run a biomechanical analysis in *3D SSPP*. All lines in the batch file have one command describing relevant data. Types and functions of commands used in a batch file are illustrated in Fig. 4(b). For example, ANTHROPOMETRY, HANDLOADS, and SEGMENTANGLES commands are for inputting anthropometry data (gender, height, and weight), hand forces required to perform the tasks, and body angles. Specifically, the values for body angles are computed directly from the BVH motion data. The other commands—such as COMMENT, DESCRIPTION, AUTOEXPORT, FRAME, and EXPORT—are used to set configurations of output data (.exp). By running this batch file in *3D SSPP*, an external text file (.exp) containing the results (e.g., summary results, joint moments, back compression forces, and strength capabilities) from a biomechanical analysis can be generated.

Automated Motion Data Processing for Dynamic Biomechanical Analysis in OpenSim

OpenSim (Delp et al. 2007) is a freely available software package that estimates biomechanical stresses including inertial forces exerted on human body joints due to changes in the velocity and direction of the motion (Anderson et al. 2012). Given the motion and external force data, *OpenSim* performs inverse dynamics analysis with a multibody musculoskeletal system that has rigid skeletal bones with virtual markers, as shown in Fig. 5, to calculate joint moments (Symeonidis et al. 2010). *OpenSim* is designed to conduct

Example of batch file

```
General command lines
3DSSPPBATCHFILE #
COM     #
DES     0 "Example of Batch File" #
AUT     1 #
ANT     0 3 68.9 185 #

Command lines for frame #1
FRM     1 #
JOA     16.9698    -7.5702    16.9698    -7.5702    12.2084
        -10.7369   -20        0          -0.64244   -64.0564
        -88.9659   -85.4295   85.1361    -5.7582    2.2298
        -4.3079    0          2.2298     -4.3079    0.85105
        -4.8446    -20        0          -23.9018   -80.3754
        -28.722    -81.1688   93.9952    -7.998     88.3453
        0          -4.0454    0          0          0
        78.44      -2.2991    1.3629     0          0 #
HAN     20 -90 0 20 -90 0 #
EXP     #
AUT     1 #

Command lines for frame #2
FRM     1 #
JOA     18.0219    -7.9502    18.0219    -7.9502    12.6864
        -11.2829   -20        0          0.90062    -63.8582
        -86.4393   -84.6193   87.5135    -5.9056    2.0483
        -4.0814    0          2.0483     -4.0814    -0.30886
        -4.8004    -20        0          -23.6184   -80.5151
        -28.331    -81.3217   94.208     -8.3682    87.8099
        0          -3.7762    0          0          0
        78.6671    -2.18      1.2585     0          0 #
HAN     20 -90 0 20 -90 0 #
EXP     #
AUT     1 #
```

(a)

Commands in batch file

- First line
  - must be 3DSSPPBATCHFILE #
- COMMENT command
  - COM Anything you want to type to document your file. #
- DESCRIPTION command
  - DES 0 (English unit) or 1 (Metric unit) "Task Name" #
- AUTOEXPORT command
  - AUT 0 (Do not export the results) or 1 (Export the results) #
- ANTHROPOMETRY Command
  - ANT 0 (Male) or 1 (Female) 3 (set according to the next two data) Height Weight #
- FRAME Command
  - FRM Frame numbers. #
- SEGMENTANGLES Command
  - JOA 41 body segment angles (e.g., Hand left horizontal, hand left vertical, hand left rotation, forearm left horizontal….) #
- HANDLOADS Command
  - HAN Left magnitude, left vertical angle, left horizontal angle, right magnitude, right vertical angle, right horizontal angle #
- EXPORT Command
  - EXP (no data item, just for initiating data exports) #

(b)

Fig. 4. Batch file to run *3D SSPP*: (a) an example of a batch file; (b) commands in a batch file

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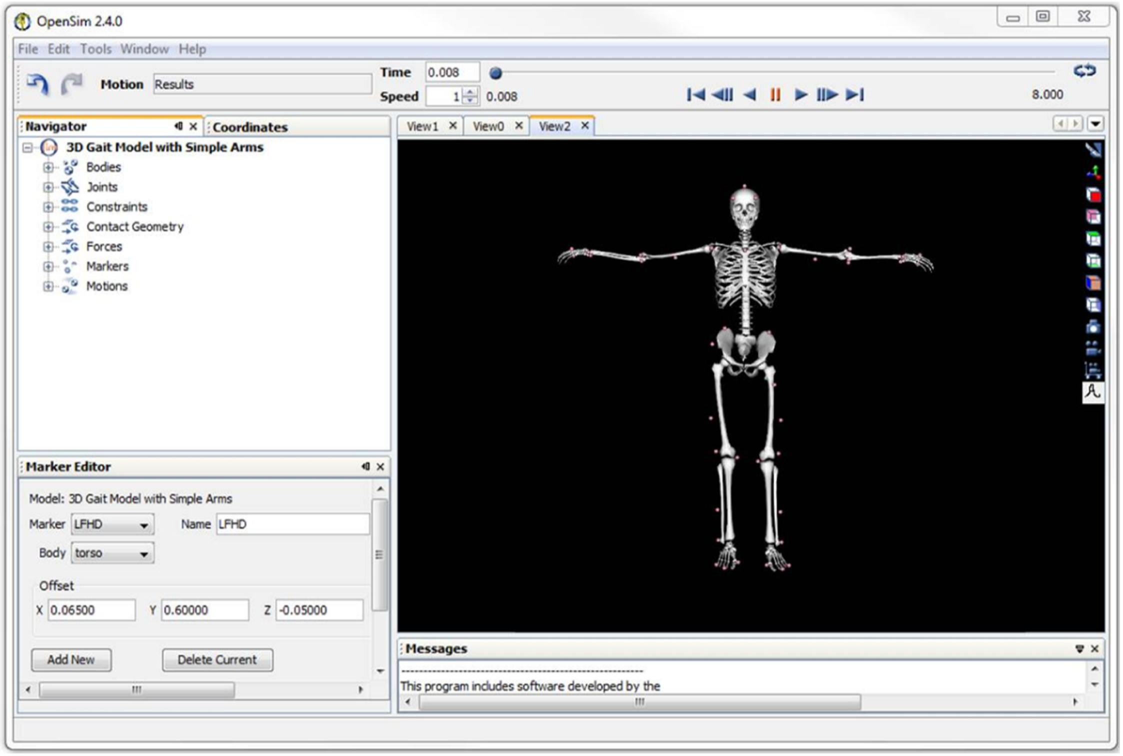


Fig. 5. A screenshot of *OpenSim* window and a multibody model with virtual markers

biomechanical simulation with experimental data, such as marker positions and kinematics obtained from marker-based motion capture systems. For this reason, the TRC file format that contains markers' geometric information from optical motion capture systems such as VICON is the only motion data format available in the current version of *OpenSim*.

The procedures required to run *OpenSim* with marker data (i.e., TRC file) 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 body segment for the subject using locations of markers, (2) inverse kinematics to create motions in the body model by matching experimental markers with virtual markers and to calculate joint angles, (3) inverse dynamics that determines the net forces and torques at each joint that produces movement by solving the equations of motion with the given motion data (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, such marker information is not available in the BVH motion data. To enable these two processes to be done with the BVH motion data, a user-friendly stand-alone system that automatically generates joint moments from motion capture data was developed. This system is based on the *OpenSim* API to generate a human multibody model (.osim) with anthropometric and physical properties (e.g., body mass, center of mass, and moment of inertia) fitted to the subject, and a motion file (.mot) containing information on joint angles at each body joint from the BVH motion data; Fig. 6 illustrates the overall workflow.

First, the proposed system creates a multibody model consisting of body segments and joints based on the hierarchical structures of bones and joints in the BVH motion data [Fig. 7(a)]. In addition, anthropometric parameters of the multibody model—such as mass, length, mass-center location, and moment-of-inertia of each body segment—are determined using a subject's height and weight based on previous studies on these anthropometric parameters (Zatsiorsky et al. 1990; DeLeva 1996).

The next step is to generate a motion file (.mot) containing joint angles from the BVH motion data. Because both the BVH motion data and the motion file (.mot) in *OpenSim* define motions as joint rotations in degrees relative to the initial position of the joint, geometric information on skeleton structures from the BVH motion data are immediately written to the motion file in *OpenSim* (.mot). The multibody model that has motion information is shown in Fig. 7(b).

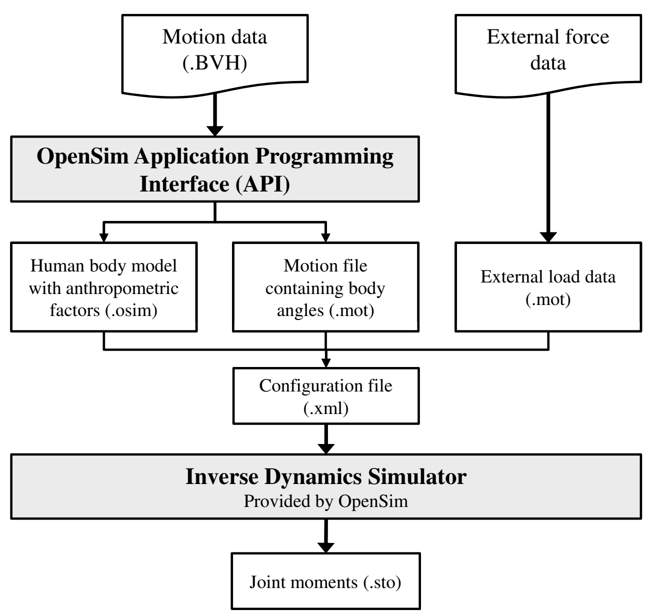
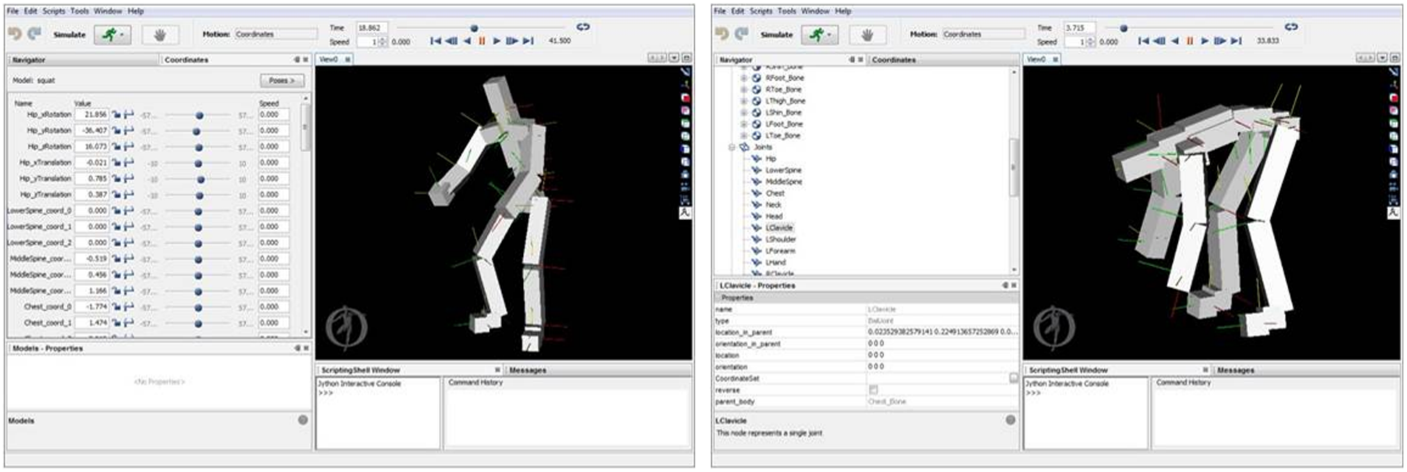


Fig. 6. Work flow for automated motion data processing in *OpenSim*



(a) (b)

Fig. 7. Multibody model from the BVH motion data: (a) a multibody model with anthropometric parameters fitted to the subject; (b) represented motions in the multibody model based on the BVH motion data

Once the *OpenSim* body model (.osim) and the motion file (.mot) are generated, the system also creates a configuration file (.xml) that will be used by the *OpenSim* inverse dynamics simulator to integrate the model (.osim), motion (.mot), and external force (.mot) files. The inverse dynamics simulator is an executable module built from the source codes for inverse dynamics from *OpenSim*, and thus enables us to perform inverse dynamics using the configuration file. The simulator saves the joint moments from dynamic biomechanical analysis to a storage file (.sto). 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.

To verify the proposed approach, motion data was collected during ladder climbing from one male subject using an optical motion capture system, VICON, because climbing activities involve dynamic movements of the whole body. The raw data captured from VICON was converted into the motion data in different file formats: TRC and BVH. Then, anthropometric parameters and joint angles were compared from the approach that uses BVH motion data with the parameters and angles from the existing approach of *OpenSim* that uses TRC motion data. To measure the differences in anthropometric parameters, the percentage error between the values was used. For joint angles, the normalized root-mean-square errors (NRMSE) were calculated between the values from this approach and the ones from the existing approach during one cycle of climbing (240 frames, 2 s). As shown in Table 1, the differences in anthropometric parameters except for the radius of gyration of a lower leg were less than 5%. The radius of gyration is determined by the square root of the moment of inertia divided by the mass. Considering that only the dynamic rotational moment is affected by the value of the moment of inertia, the error in the inertial parameters of a lower leg would not significantly affect the joint moments at a knee joint. In addition, NRMSE values for body angles at elbows and knees were 0.079 and 0.081, respectively (Fig. 8). These results indicate that the proposed approach accurately estimates anthropometric parameters and joint angles based on BVH motion data, compared with the values from the existing approach.

An Experiment on Lifting Tasks

The proposed automated motion data processing was experimentally tested by conducting an experiment on lifting tasks with postural variations. An RGB-D sensor-based motion capture approach was used to collect BVH motion data, and both static and dynamic biomechanical analyses in *3D SSPP* and *OpenSim* were performed. The results of joint moment estimation by applying the proposed approaches are presented and then compared with previous studies that estimated joint moments during lifting tasks using optical motion capture data in this section. In addition, the results from static and dynamic biomechanical analyses are compared to understand how variations in postures and movements affect musculoskeletal stresses. From the results, considerations when applying the proposed approaches for on-site biomechanical analysis and when

Table 1. Comparison of Anthropometric Parameters from *OpenSim* and the Proposed Approach

Anthropometric parameters		Existing approach	Our approach	% of error
Upper arm	Mass (kg)	1.96	1.97	−0.22
	Length (m)	0.29	0.30	−5.43
	Distance from center of mass to proximal joint as % of length	57.37%	57.72%	−0.62
	Radius of gyration as % of length, transverse	26.73%	26.89%	0.61
	Radius of gyration as % of length, longitudinal	15.70%	15.80%	0.60
	Radius of gyration as % of length, frontal	0.28	0.29	0.60
Lower leg	Mass (kg)	3.50	3.30	5.71
	Length (m)	0.43	0.42	2.30
	Distance from center of mass to proximal joint as % of length	43.42%	44.58%	−2.69
	Radius of gyration as % of length, transverse	27.11%	25.10%	−7.43
	Radius of gyration as % of length, longitudinal	8.63%	10.20%	18.26
	Radius of gyration as % of length, frontal	0.27	0.25	−9.89

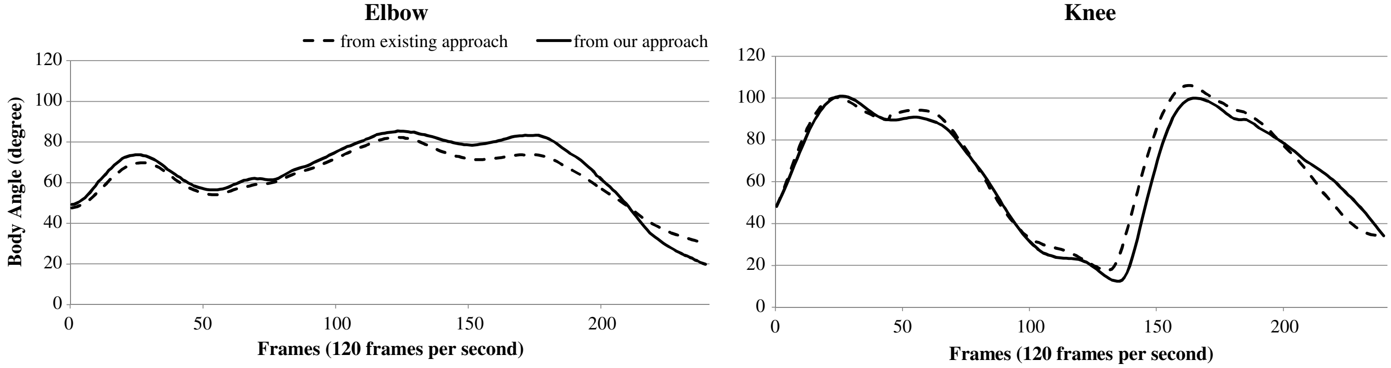


Fig. 8. Comparison of body angles between existing and proposed approaches

analyzing the results in the context of tasks are discussed in the next section.

Motion Data Collection

Motion data during the concrete block lifting was collected by mimicking the tasks in a laboratory. A single RGB-D sensor was positioned at the front of a subject to minimize self-occlusion, and likewise was positioned 3 m away from the subject who wore slim clothes to minimize noise; Fig. 9 illustrates the experimental scenes. A male subject (175 cm, 70 kg) was asked to stand in a T-pose, facing the RGB-D sensor, and then repeatedly lift a 20-kg (196-N) concrete block from one side on a floor and move it to the opposite side 10 times. This protocol reflects practices during masonry work in which a worker lifts a block in stock, and puts it on a wall. The RGB-D images associated with the T-pose were used just for reference frames. To study an impact of postural variations on musculoskeletal stresses, two different lifting techniques were employed. First, he was asked to lift a block using the squat technique in which the back remains straight and the knees are bent (Garg and Moore 1992) [Fig. 9(a)]. After taking a break to minimize fatigue, he was asked to apply the stoop technique in which the back is bent to lift a block [Fig. 9(b)]. During the trials, Kinect took RGB-D images at a frame rate of 30 Hz, as shown at the top of Fig. 9, and the images were processed in iPi Desktop Motion Capture to extract BVH motion data, as shown at the bottom of Fig. 9. The tracking of motions was made through shape-fitting algorithms after matching body silhouettes in T-pose images with 3D prior body models. However, hands are sometimes occluded by a concrete block during lifting, resulting in tracking errors. To clean up a sequence of incorrect frames, inverse kinematics tools provided by iPi Desktop Motion Capture were applied to estimate plausible arm postures based on manipulated hand positions for occluded hands. In addition, noise in motion data was reduced using post-processing filters.

Results from Static and Dynamic Biomechanical Analyses

The BVH motion data was post-processed by applying the proposed motion data conversion methods to obtain postural angles

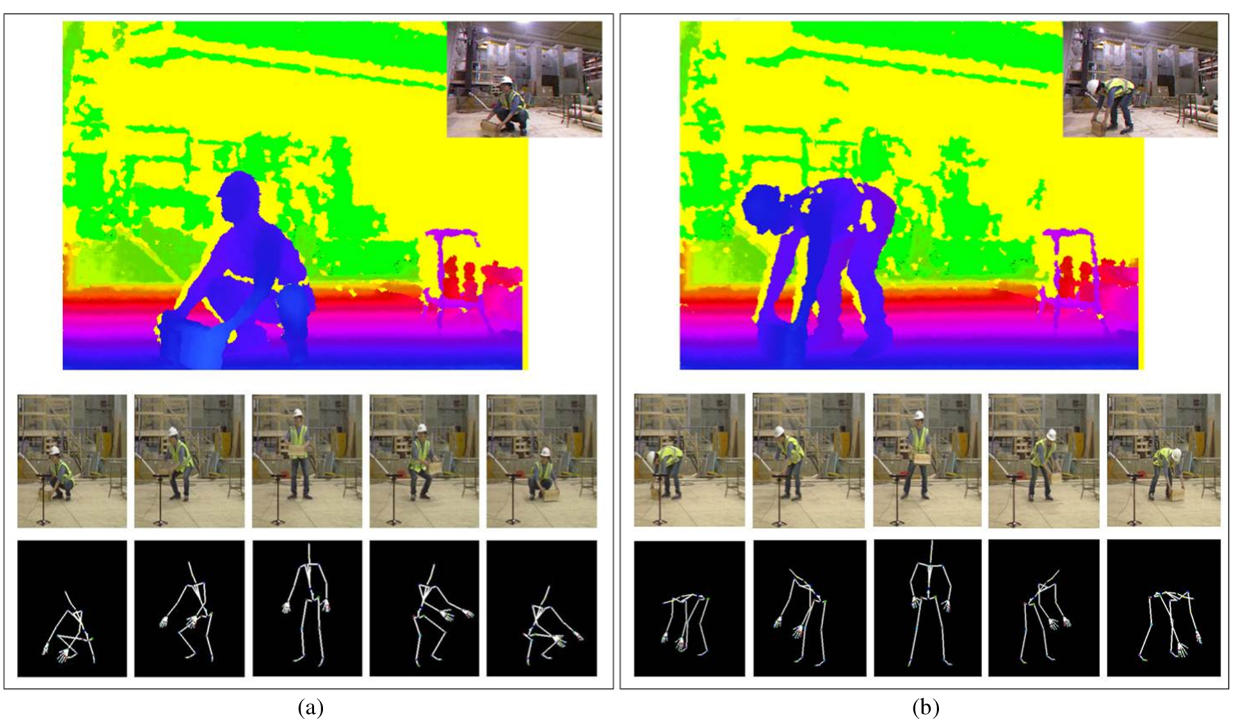


Fig. 9. Motion data collection during concrete block lifting: (a) squat lifting; (b) stoop lifting

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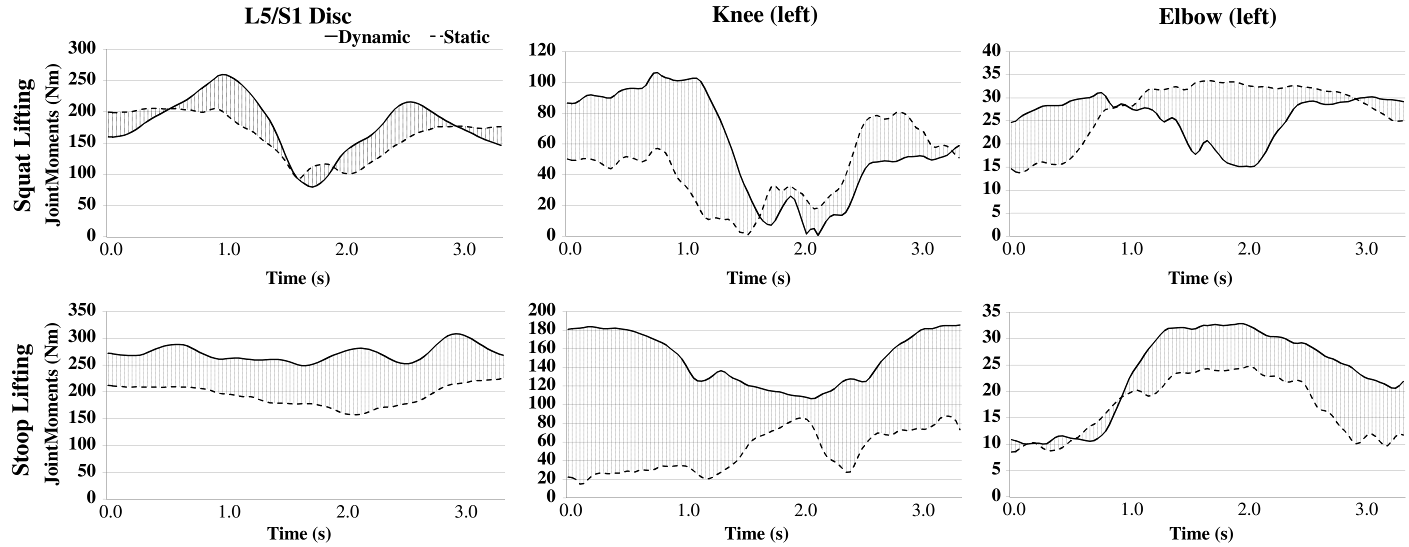

Fig. 10. Biomechanical analysis results during squat and stoop lifting

for *3D SSPP* and *OpenSim*. Anthropometric factors were adjusted based on the subject's height and weight. To determine external forces (e.g., hand and foot forces), it was assumed that the magnitude of external force exerted on each hand was 98 N, and that the direction of the forces was downward. In addition, the foot forces were assumed as a sum of the weight of the subject and a concrete block. Based on these data, static and dynamic biomechanical analyses were conducted to estimate joint moments during squat and stoop lifting.

Fig. 10 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 (i.e., lift, carry, and put down a concrete block) from the static and dynamic biomechanical analyses. In the graphs, the solid lines indicate joint moments from dynamic biomechanical analysis while the dotted lines indicate joint moments from static biomechanical analysis. Overall, the results show that joint moments from dynamic biomechanical analysis are higher than those from static analysis. In a dynamic biomechanical model, the moment at a certain body joint is defined as the sum of the static moment and the dynamic inertial forces (i.e., the instantaneous acceleration effect due to the tangential rotation force and the rotational acceleration effect; Chaffin et al. 2006). According to the study by McGill and Norman (1985), the peak lumbar moment in a static condition was 84% of the peak lumbar moment in a dynamic condition during lifting loads. The results are similar to the results from this study, by showing that the peak static joint moments at the L5/S1 disc are 79 and 73% of the peak dynamic joint moments at the L5/S1 disc during squat and stoop lifting, respectively. One of the reasons why the results showed higher dynamic joint moments compared with static joint moments than the previous study is that the subject lifted a load from waist height in the previous study, whereas the subject in the experiment lifted a concrete block from the floor. The lifting speed when lifting a load (200 N) from the floor level could be about 25% higher than the speed during lifting from waist height (Lavender et al. 2003). Thus, differences in lifting heights may contribute to differences in lifting speeds, resulting in higher dynamic joint moments in the experiment than the ones from the previous study. Overall results from the experiment indicate that rapid movements during lifting tasks could increase joint moments at the disc by 25–30%. In addition, the acceleration effects also considerably increase joint moments at other joints, such as a knee and an elbow. However, in some cases, dynamic joint moments can be less than static joint moments when deceleration exists. For example, at an elbow during squat lifting, dynamic joint moments were smaller than static joint moments in the middle of lifting (when the subject lifted a block at the highest height) because the lifting speed in a vertical direction decreased at this point, resulting in a deceleration that created joint moments in the opposite direction.

With regard to lifting techniques, the squat lifting is less stressful to the back from both static and dynamic analyses in this case. As shown in Table 2, the peak and average joint moments at the L5/S1 disc during squat lifting are 91 and 84% of those during stoop lifting in a static condition, and 84 and 66% in a dynamic condition. This result corresponds to the previous study that the squat lifting produced fewer maximum lumbar joint moments than the stoop lifting when a subject lifted the heavy object (15 kg; Hwang et al. 2009). However, this result is not always the case because the stoop lifting can maintain the object closer to the torso than squat lifting, resulting in the reduced moment arm of the load (Chaffin et al. 2006). For this reason, previous studies recommended squat lifting only when the subject can put an object between the feet to minimize the moment arm of the load (van Dieën et al. 1999). In addition, the joint moments at a knee during stoop lifting are higher than those during squat lifting, which is similar to the results from the previous study (Hwang et al. 2009). No significant difference in elbow joint moments was observed in the results because the joint angles between squat and stoop lifting were similar, as shown in Fig. 10.

Discussion

The results from the experiment imply that the motion data-driven biomechanical analysis provides a robust measure of

Table 2. Comparison of Peak and Average Joint Moments during Squat and Stoop Lifting

Joint moment (Nm)		L5/S1 disc		Knee (left)		Elbow (left)	
		Peak	Average	Peak	Average	Peak	Average
Squat lifting	Dynamic	259.5	179.0	119.2	64.9	31.2	25.7
	Static	205.3	163.0	80.8	42.5	33.7	27.7
Stoop lifting	Dynamic	308.4	271.8	207.6	166.1	32.9	23.4
	Static	225.6	193.2	87.9	49.5	24.8	17.1

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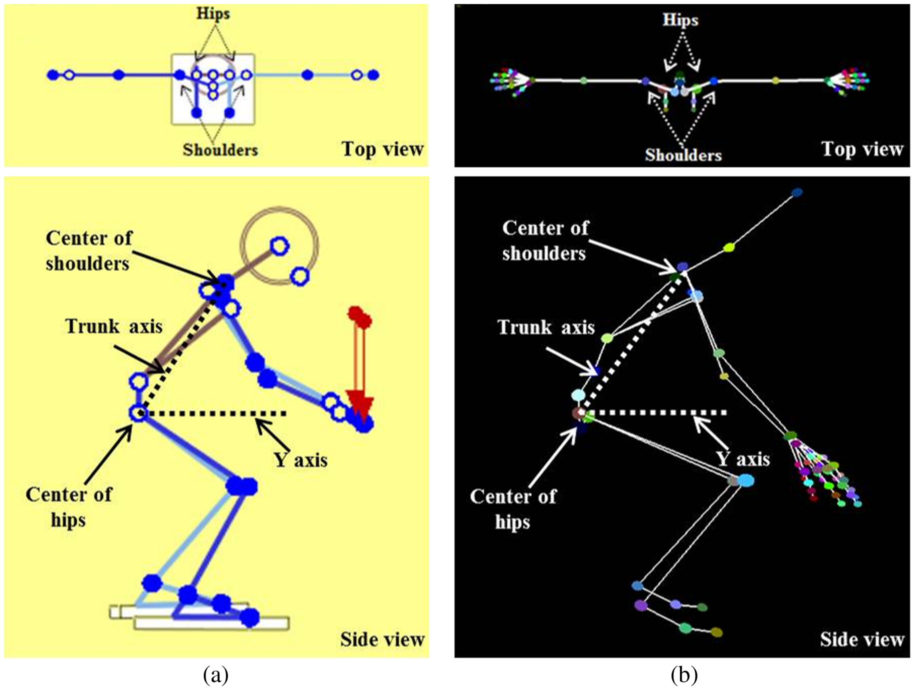

Fig. 11. Comparison of a trunk flexion angle in (a) *3D SSPP*; (b) BVH motion data

musculoskeletal stress from both static and dynamic points of view, given motion capture data (e.g., BVH files). From these results, it was also found that musculoskeletal stresses vary depending on the acceleration of motions and postures during certain tasks. In construction, working speeds and postures are affected by diverse factors, for example, individual factors (e.g., personal preference), environmental factors (e.g., working spaces), or managerial factors (e.g., work schedule). Thus, it is concluded that on-site biomechanical analysis is required to consider these factors that may expose workers to different levels of WMSD risks even when performing the same types of tasks in construction. In addition, the usability issue of the proposed method is also important from the practical perspective in making the biomechanical models useful when performing ergonomic evaluations during tasks (Chaffin 1997). In this context, it should be clear that the automatic processes of motion data obtained directly from work places enable ergonomists and practitioners to identify a potential risk of WMSDs that exists in certain tasks and work environments by evaluating hazardous internal loading conditions in a timely manner without technical sophistication or skill.

Notably, in-depth understanding of the differences in body configurations between the BVH motion data and the *3D SSPP* body model may lead to the further improvement on the accuracy of biomechanical analysis. Skeleton structures of the multibody model in *OpenSim* follow those in the BVH motion data excluding joints in hands, and thus the motions can be exactly simulated according to the motions in the BVH motion data. On the other hand, *3D SSPP* has its own skeleton structures that are different from those in the BVH motion data, which makes errors when calculating joint angles. For example, in *3D SSPP*, the trunk flexion angle is defined as an angle between the projection of the trunk-axis (the center of the hips to the center of the shoulders) and the positive Y-axis as shown at the bottom of Fig. 11(a). In the top view of the skeleton model in *3D SSPP* [the top of Fig. 11(a)], it is found that hips and shoulders are aligned. On the other hand, the hips are located slightly forward in the Y-axis, compared with the shoulders [the top of Fig. 11(b)]. The differences in skeleton structures and joint positions cause errors in the trunk flexion angle that is calculated from the BVH motion data [the bottom of Fig. 11(b)], resulting in slightly different postures in *3D SSPP*. Generally, the hierarchical structures of bones and joints in the BVH motion data vary depending on the type of motion capture system and algorithm. For this reason, when applying the BVH motion data to *3D SSPP*, one should consider the differences in skeleton structures between skeleton models in *3D SSPP* and motion data, and adjust them if the differences are significant.

The reliability and practicability of the proposed on-site biomechanical analysis during construction tasks relies on not only automated motion data processing, but also on motion data collection. Previous studies found that vision-based motion data has some errors in body angles (about 10°; Han et al. 2012a) and bone lengths (about 6.3 cm; Han et al. 2013b). Especially, occlusions (e.g., self-occlusion or occlusion by an object) significantly increased errors in motion data, resulting in a failure to track the human body (Han et al. 2012a). To address the occlusion issue, Han et al. (2012a) suggested the need for positioning sensing devices at optimal viewpoints and using multiple sensors to minimize the impact of occlusions. In addition, when certain body joints are lost or incorrectly detected in a relatively short period of time due to occlusions, errors in vision-based motion data can be reduced through post processing on motion data (such as trajectory recovery) that optical motion capture systems apply to estimate missing markers (Sturman 1994). However, vision-based motion capture approaches rely only on pixel information on 2D or 3D images that make it fundamentally difficult to provide motion data that is as accurate as the data from optical motion capture systems. To provide the reliability of on-site biomechanical analysis, the acceptable errors in motion data for biomechanical analysis need to be further studied through sensitivity analysis by varying body angles. In addition, the use of infrared RGB-D sensors such as a Kinect for collecting 3D images is limited to only indoor environments with relatively small workspaces in construction sites. A multiple camera-based motion capture approach is expected (Han et al. 2012b, 2013a) to overcome the limitation of RGB-D sensors.

However, the feasibility of on-site biomechanical analysis using vision-based motion data needs to be further studied by conducting case studies in the diverse conditions of construction sites.

When applying biomechanical analysis on construction tasks, however, the selection of adequate analysis should be made considering the purpose of the analysis due to differences in tolerance limits under static and dynamic conditions. The results from the experiments indicated that acceleration effect could increase joint moments up to 30% in lifting tasks. Therefore, static analysis using *3D SSPP* is appropriate for tasks involving slow motions where accelerations can be ignored, whereas tasks involving jerking motions require dynamic biomechanical analysis in *OpenSim*. However, it should be noted that there is no available threshold to determine whether the dynamic joint moments are hazardous or not. Tissue injuries occur when the applied musculoskeletal stresses exceed the failure tolerance referring to the strength of the tissue (McGill 1997). Because it is difficult to specify individual differences in joint strength, population-based data is generally used to determine hazardous internal loads. For example, *3D SSPP* compares the joint moments produced at various body joints during tasks with the static strength moments reported from studies of various populations performing different types of exertions by setting the maximum permissible limit as the joint strength that only 25% of men and 1% of women can exert (Center for Ergonomics, University of Michigan 2011). However, because dynamic strengths are more complex than static strengths, studies on dynamic joint strengths have not yet been fully conducted (Chaffin et al. 2006). This means that joint moments from dynamic biomechanical analysis cannot be evaluated to determine the degree of risk in a given population of workers, but can only be relatively compared.

When assessing WMSD risks through biomechanical analysis, ergonomic evaluations and interventions should not be made fragmentarily only focusing on postural risks that create excessive internal forces on certain body parts. For example, the stoop lifting technique is generally recommended because frequent back bending can cause back pain and even back injuries. However, because squat lifting requires higher joint moments in lower extremities and higher energetic demand (e.g., oxygen consumption; Duplessis et al. 1998), it was reported that subjects tended to change their lifting technique from squat to stoop lifting during repetitive lifting to avoid or diminish fatigue development (Resnick 1996; Fogleman and Smith 1995). In this case, ergonomic interventions should be made considering not only postural risks due to individual preference, but also other factors such as the horizontal and vertical position of the load and the load mass (van Dieën et al. 1999).

Conclusions

Motion data-driven biomechanical analysis was proposed during construction tasks using motion data obtained from vision-based motion capture approaches. Specifically, the differences of configurations in BVH motion data from vision-based motion capture and data types required for existing biomechanical analysis tools, *3D SSPP* and *OpenSim*, was studied and compared. It was found that: (1) definitions of body angles in BVH motion data are different from the definitions of body angles in *3D SSPP*, and (2) experimental marker positions that are not available in BVH motion data are essential for generating anthropometric parameters and joint angles required to compute musculoskeletal stresses in *OpenSim*. To address these issues, body angles required for *3D SSPP* are computed directly from positions of body joints generated from BVH motion data. In addition, for *OpenSim*, a multibody model was created with anthropometric parameters adjusted for a subject based on the hierarchical structures of bones and joints in the BVH motion data, and computed joint angles based on joint rotations in degrees that are available in the BVH motion data. The proposed motion data processing for *OpenSim* was verified by comparing anthropometric parameters and joint angles from this approach with those from the existing approach in *OpenSim*.

In addition, an experiment on lifting tasks was conducted not only to test the feasibility of the proposed motion data processing, but also to understand the differences between static and dynamic biomechanical analyses on construction tasks with diverse postural variations. The results from the experiment showed that the proposed approaches for motion data processing were successfully used to perform static and dynamic biomechanical analyses by showing similar results from previous studies. From the experiment, it was also found that the speed of motions and postures could significantly affect the magnitude of musculoskeletal stresses even though workers perform the same tasks, which implies that on-site biomechanical analysis is necessary to reflect postural variations during the performance of construction tasks.

To enhance the reliability and practicability of on-site biomechanical analysis using motion data from vision-based approaches, understanding body configurations in the BVH motion data is required to reduce errors in biomechanical analysis, and the accuracy of motion data from vision-based motion capture approaches needs to be improved. In addition, when practitioners apply on-site biomechanical analysis during construction tasks, the selection of static or dynamic biomechanical analysis should be carefully made depending on the types of the tasks due to the effect of the acceleration of motions. The identification of excessive musculoskeletal stresses through biomechanical analysis will help to determine an ergonomic intervention for eliminating the risk of WMSDs. However, practitioners need to consider not only postural risks identified from biomechanical analysis, but also the design of tasks when developing effective interventions.

It is expected that the proposed approach will help practitioners perform on-site biomechanical analysis in a practical manner without technical sophistication or skill, given motion data from vision-based approaches. On-site biomechanical analysis has great potential as a field-based ergonomic risk assessment method that determines the degree of risk on each body part that other ergonomic evaluation methods (e.g., self-reports, observational methods, and direct measurements) cannot provide. Thus, it can identify potentially hazardous construction tasks, contributing to minimizing the risks of WMSDs by providing behavioral feedback to workers or redesigning work processes and environments that may cause excessive musculoskeletal stresses. Ultimately, the continuous monitoring of biomechanical stresses during construction tasks will enhance the understanding of the gap between physical work demands and workers' capability, and offer a firm foundation for the improvement of workers' productivity, as well as health in construction.

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