Applied Ergonomics xxx (2017) 1–10

Contents lists available at ScienceDirect

Applied Ergonomics

journal homepage: www.elsevier.com/locate/apergo

Using a marker-less method for estimating L5/S1 moments during symmetrical lifting

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ARTICLE INFO

Article history:
Received 13 July 2016
Received in revised form
9 January 2017
Accepted 10 January 2017
Available online xxx

Keywords:
Marker-less motion capture
Lifting
Computer vision

ABSTRACT

The aim of this study is to analyze the validity of a computer vision-based method to estimate 3D L5/S1 joint moment during symmetrical lifting. An important criterion to identify the non-ergonomic lifting task is the value of net moment at L5/S1 joint. This is usually calculated in a laboratory environment which is not practical for on-site biomechanical analysis. The validity of the proposed method, was assessed externally by comparing the results with a lab-based reference method and internally by comparing the estimated L5/S1 joint moments from top-down model and bottom-up model. It was shown that no significant differences in peak and mean moments between the two methods and intra-class correlation coefficients revealed excellent reliability of the proposed method (>0.91). The proposed method provides a reliable tool for assessment of lower back loads during occupational lifting and can be an alternative when the use of marker-based motion tracking systems is not possible.

1. Introduction

Lower back disorders are very common in modern society. In the United States, back pain is the most common cause of impairment among young and middle-aged people and the second most frequent reason for visiting physicians (Andersson, 1999). The cost associated with occupational lower back pain is also high. The total direct medical and indirect costs of low-back pain in the United States exceed $100 billion per year (Frymoyer and Cats-Baril, 1991; Katz, 2006). The data from other western countries are similar. For example, it accounted for 76% of the total compensation cost in 1981 in Canada and was estimated 4.2 billion euros in Dutch society in 1991 (Andersson, 1999; Lambeek et al., 2011).

Lower back pain is often the consequence of lifting and manual material handling (MMH). This association is confirmed in a study by Bigos et al. (1986) showing among 900 back injury cases, about 63% of which was attributed to lifting and manual materials handling. The result of another study done by Chaffin (1973) recommended that load lifting should be considered as a potential risk factor for lower back stress. Kuiper et al. (1999) and da Costa and Vieira (2010) also showed with reasonable evidence that lifting is one of the main risk factors for lower back, hip and knee work related musculoskeletal disorders (WMSD).

In order to improve workplace safety and mitigate the risk of lower back pain, it is important to quantify the exposure to the risk of developing musculoskeletal disorders. Biomechanical analysis approaches have been proposed to link the musculoskeletal risks with joint loadings applied on worker's body in performing industrial tasks. They are useful tools for calculating the peak and cumulative loads on the body joints in order to compare the result with the limit of a person's capacity. Generally, there are two three-dimensional multi-segment models to estimate the joints reaction loads: top-down and bottom-up (Riemer et al., 2008). In the top-down model the starting point is at both hands and in the bottom-up model, it is at both feet. When there are no “gold standard” values from literature, the results of joints reaction forces

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http://dx.doi.org/10.1016/j.apergo.2017.01.007
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Please cite this article in press as: Mehrizi, R., et al., Using a marker-less method for estimating L5/S1 moments during symmetrical lifting, Applied Ergonomics (2017), http://dx.doi.org/10.1016/j.apergo.2017.01.007

and moments can be internally validated by comparing the calculated value at L5/S1, at which both models end up.

Biomechanical analysis approaches require assessment of human body postures and movements associated with lifting and manual material handling tasks. A variety of methods and tools have been developed for assessment postures and movement of manual tasks. These methods are mainly categorized as self-report questionnaires, direct measurement and observational methods (Van der Beek and Frings-Dresen, 1998; Spielholz et al., 2001; David, 2005). Results show that self-report questionnaires are the least accurate assessment method and most estimates of external exposure are imprecise and overestimated. (Van der Beek and Frings-Dresen, 1998; Spielholz et al., 2001). Most direct measurement methods require the attachment of reflective markers onto subjects' body to measure body segment movements or 3D positions of body joints, which can be used for relatively reliable and accurate estimation of the joints loads. In order to calculate external forces, force plates may be in need, especially in the case of bottom-up models. Numerous studies have investigated lower back joint load and moment by using direct measurement methods and have compared the results obtained from bottom-up and top-down approaches. There are reported values for a variety of tasks like lifting (De Looze et al., 1992; Desjardins et al., 1998; Kingma et al., 1996; Larivière and Gagnon, 1998, 1999; Plamondon et al., 1996), balance recovery movement (Robert et al., 2007) and walking (e.g. Hendershot and Wolf, 2014). Since direct measurement approaches require the use of complicated experimental setup in laboratory environments, which may affect the task behavior, they are not practical for onsite analysis and field studies.

Recent studies have used observational methods such as video-based coding systems instead of direct measurement to estimate the joints force and moment (Chang et al., 2003; Coenen et al., 2011, 2013; Hsiang et al., 1998; Xu et al., 2012). These video-based coding systems extract a few key frames from captured task videos and then raters make an optimal fit of digital manikins to the selected video frames. Then the lifter's angular trajectory for the whole frames are identified and serve as the input of inverse biomechanical models to calculate the L5/S1 joint loadings. It was shown that the video-based coding system was not as accurate as a marker-based motion tracking system in estimating joint loads (Andrews et al., 1997; Chang et al., 2003; Xu et al., 2012). Another drawback of the video coding systems is that the result accuracy also rely on the experience of the observer, especially when joint angles become close to the posture boundaries and when they have to analyze more variables at once (Coenen et al., 2013). These video-based systems provide an alternative solution for in-field ergonomic evaluation where the use of a marker-based motion tracking system may be impossible. They are not intended to replace traditional direct measurement methods that usually provide more accurate results (Chang et al., 2003).

Advances in computer vision, offer novel potential solutions using optical camera and marker-less motion capture systems to overcome the limitations of the direct measurement and observational methods for biomechanical analysis. Studies have been conducted to evaluate the accuracy of the predicted joint positions and the resulting joint angles from marker-less motion capture systems compared to direct measurement methods. The comparison has been performed for activities such as gait cycle (Ceseracciu et al., 2014; Corazza et al., 2006; Mündermann et al., 2005; Saboune and Charpillet, 2005; Sandau et al., 2014), front crawl swimming (Ceseracciu et al., 2011), sit-to-stand tasks (Goffredo et al., 2009) and ladder climbing (Lee and Armstrong, 2014). These studies demonstrate the feasibility of the marker-less method; however, only a few motions were examined in the previous works (mostly in gait analysis) and lifting as one of the most common motions in the workplace and an important risk factor for WMSD is missed.

In this paper, we propose a marker-less and optical camera based tool to estimate the 3D L5/S1 joint moments during symmetrical lifting. Optical camera/digital camcorders are used for capturing the task movements. The angular trajectory is estimated by the novel computer vision techniques proposed in this study. It does not need to attach markers onto subjects' body segments or hire raters to estimate the pose of the subjects. The main goal was to evaluate the validity of this tool for onsite biomechanical analysis against a reference marker-based method. With this method, we aim to overcome the abovementioned drawbacks associated with direct measurement and observational methods.

2. Method and materials

2.1. Data acquisition

2.1.1. Participants and procedure

The data set consists of 12 healthy male (age, Mean $\pm$ SD $=$ 47.5 $\pm$ 11.3 years; height, Mean $\pm$ SD $=$ 1.74 $\pm$ 0.07 m; weight, Mean $\pm$ SD $=$ 84.5 $\pm$ 12.7 kg) performing various symmetric lifting tasks in a laboratory at self-selected speed while being filmed by both camcorder and a synchronized motion tracking system that directly measured the body movement. They lifted a plastic crate (39 $\times$ 31 $\times$ 22 cm) weighing 10 kg and placed it on a shelf without moving the feet. They performed three vertical lifting ranges from floor to knuckle height (FK), knuckle height to shoulder height (KS) and floor to shoulder height (FS).

2.1.2. Direct measurement

45 Reflective markers were attached to the lifters' body segments based on the method proposed by Cappozzo et al. (1995). 3D positions of markers during the lifting tasks were measured by a motion tracking system (Motion Analysis, Santa Rosa, CA) with a sampling rate of 100 Hz. The raw 3D coordinate data were filtered with a fourth-order Butterworth low-pass filter at 8 Hz. The ground reaction force was measured with two force plates (Model 9286AA, Kistler, Switzerland) and was synchronized with the motion tracking system. Two digital camcorder (GR-850U, JVC, Japan) with 720 $\times$ 480 pixel, synchronized with the motion tracking system resolution also recorded the lifting from 90 (side view) and 135° positions. Fig. 1 shows the Experimental setup and subject postures carrying the crate at three different levels (floor, knuckle and shoulder).

2.2. Data processing and analysis

The workflow of the proposed tool consists of three steps as summarized in Fig. 2. The first step is *3D Pose Reconstruction* by which the body pose and joints position are estimated at each frame of the video. The second step is *Body Segments Parameters Calculation,* which determines body segment parameters including mass, length, center of mass (COM) and inertia tensor for each subject. Finally, the third step is *L5/S1 Joint Moment Estimation,* calculating the L5/S1 joint moment by using the last two steps' outputs and the external forces information. Each of the three steps are explained in more details below. The results of the calculated joint moments are then validated internally by comparing the results of the top-down and bottom-up models together and externally against marker-based method as a reference.

2.2.1. 3D pose reconstruction

In this step, Constrained Twin Gaussian Process algorithm (Li et al., 2016) is used to extract the 3D skeleton from each frame of videos. Twin Gaussian Process (TGP) algorithm (Bo and