Using a Marker-Less Method for Estimating L5/S1 Moments during Symmetrical Lifting

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.

Keywords: Marker-less Motion Capture, Lifting, Computer Vision;

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, 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, 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 et al. (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 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 et al., 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 et al., 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, 1998; Kingma et al., 1996; Larivière, 1998, 1999; Plamondon, 1996), balance recovery movement (Robert et al., 2007) and walking (e.g. Hendershot, 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, 2003; Coenen et al., 2013; Coenen et al., 2011; 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, 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, 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, 2005; Sandau et al., 2014), front crawl swimming (Ceseracciu et al., 2011), sit-to-stand tasks (Goffredo et al., 2009) and ladder climbing (Lee, 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

Participants and Procedure. The data set consists of 12 healthy male (age, Mean±SD = 47.5±11.3 years; height, Mean±SD = 1.74±0.07 m; weight, Mean±SD = 84.5±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 × 31 × 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).

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 720×480 pixel, synchronized with the motion tracking system resolution also recorded the lifting from 90 (side view) and 135 degrees positions. Figure 1 shows the Experimental setup and subject postures carrying the crate at three different levels (floor, knuckle and shoulder).

Insert Figure 1 about here

2.2.Data Processing and Analysis

The workflow of the proposed tool consists of three steps as summarized in Figure 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.

Insert Figure 2 about here

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 Sminchisescu, 2010; Kanaujia et al., 2007) is a discriminative method which maps directly from image features to human pose. The model used in TGP considers dependencies between the joint angles themselves in addition to the dependencies between image features and joint angles. Based on this intuition it is assumed that both inputs and outputs are normally distributed with mean zero and a covariance matrix. Since similar inputs are expected to produce similar outputs, TGP measures the offset between the input and output using Kullback-Leibler divergence and then estimates output targets (test data) by minimizing this offset. It can be used to reconstruct 3D poses of the subjects and estimate the joint kinematics. More details about the algorithm can be found elsewhere (Bo and Sminchisescu, 2010; Kanaujia et al., 2007). Since TGP is a discriminative algorithm, it needs to be trained first. In this study, models for each subject are trained separately. In other words, all motions (FK, KL and FS) of one subject are divided to four equal folds and three of them are used for training the model and the remaining fold is used as a test data. Predicted joints position are then smoothed by using Moving Average Method and span of 0.2 seconds.

Directly applying the TGP algorithm on our video data did not give acceptable results, especially for the upper body joints since this algorithm is developed for activity recognition. In order to improve the accuracy for biomechanical analysis, we have extended it and developed the Constrained TGP algorithm (Li et al., 2016). The Constrained TGP algorithm adds a new morphology constraint to the model which keeps the upper and lower arm segments length constant over all frames. These lengths are defined as the Euclidian distance between shoulder-elbow and elbow-wrist joints respectively and the difference between these distances and related constant length values are added as a penalty to the cost function which should be minimized. Search space decreases as a result of adding this new constraint and more accurate results are achieved. The average of reconstruction distance error between predicted joints position and the real joints position without the modification was 40 mm (about 50 mm for upper body joints and 30 mm for lower body joints) and after modification it decreased to 12.68 mm and 5.57 mm for upper and lower body joints, respectively (Li et al., 2016).

Body Segments Parameters Calculation. For the assessment of joint kinematics, a 3D manikin consisting of twenty one joints was used to define the pose. This manikin allows for following body segments: upper and lower arms, head, upper and middle trunk, pelvis, thighs, shanks and feet. Distal and proximal joints of each segment are defined based on the approaches proposed by de Leva (1996). Given 3D coordination of joints, total body mass and height, then segments mass, length, position of the center of mass (COM) and inertia tensor were estimated based on the parameters from de Leva (1996).

L5/S1 Joint Moment Estimation. To estimate the net moment of the L5/S1 joint, both top-down and bottom-up model were performed using a global equation of the motion (Hof, 1992). In addition to the segment kinematics and anthropometrics, external forces also need to be measured. In the top-down model, external forces and moments can be calculated based on the mass and acceleration of the box. In bottom-up model on the other hand, force plates data can be used to measure the external forces, external moments and their points of application.

Validation. In order to validate our proposed marker-less method, we compared the estimated peak and mean value of L5/S1 joint moments in coronal, sagittal and transverse planes, as well as its total moments, with those obtained from marker-based method as a reference. In other words, we calculated the 3d joints position with both marker-less and marker-based methods and used them to find the peak and mean of L5/S1 moment and then compared the results together. The results were also validated internally by comparing the estimated L5/S1 joint moment obtained from the top-down model with those from the bottom-up model. The validations were done by both performing repeated measures t-tests and calculating intra class correlation coefficients (ICC). For all statistical tests, p-value 0.05 was assumed to be significant. For all ICC calculations, ICCs less than 0.40 were assumed poor, ICCs between 0.40 to 0.75 were good and ICCs greater than 0.75 were considered as excellent (Fleiss, 2011).

3. RESULTS

3.1. Estimated L5/S1 Torque versus Reference

Repeated measures t-tests show that overall estimated peak and mean values of L5/S1 joint moment are not significantly different from the actual values obtained from the marker-based method as a reference, for both top-down or bottom-up models (Table 1).

The grand mean (±SD) of the peak moment absolute errors across all the subjects and trials is 11.14 (±13.45) Nm and 6.70 (±7.38) Nm for the top-down and bottom-up model respectively. The grand mean (±SD) of the moment absolute error across all the subjects and trials is 4.67 (±2.75) Nm and 5.14 (±2.37) Nm for the top-down and bottom-up models respectively. No systematic errors were observed for both models; the accuracy of bottom-up model for assessment of peak moment is higher than that of top-down models on average. (Table 2 & Figure 3).

Insert Table 1 & Table 2 & Figure 3 about here

There is a good agreement between the estimated L5/S1 joint moments in each of the three planes and the references when calculating with both of the top-down and bottom-up models as shown in Figure 4. The joint reaction moments at each plane can be decomposed into four components including external forces/torques, weight of segments, linear acceleration and angular acceleration (Hof, 1992). The mean percentage contributions of each components on the L5/S1 moments error for the three planes are shown in table 3. It can be observed that in the case of bottom-up models, approximately half of the moment error is generated by the external forces/torques. The contributions of weight of segments and linear acceleration in the net moment error are approximately 24% and 21%, respectively. The contribution of weight of the segments was larger for the top-down model than that for the bottom-up model, particularly on the transverse axis. The external forces and linear acceleration account for about 11% and 33% of the moment generated at L5/S1, respectively. Angular acceleration in both bottom-up and top-down models generates negligible moment error compared to the other terms. Among the three planes, sagittal plane has the highest and rotational plane has the lowest contribution in the moment error calculated at L5/S1 joint.

Insert Table 3 & Figure 4 about here

Since the absolute error does not necessarily indicate whether the moment is overestimated or underestimated, the relative estimation error which is defined by subtracting the reference moment from the estimated moment is also calculated. The histogram of the estimation error across all the dataset is shown in figure 5 for 3D L5/S1 moments. It can be seen that most of the error distributions for top-down and bottom-up models are approximately normal distributions. For those cases with non-zero centered distribution, it can be skewed to the right or left, but for the total moment in both models, it is skewed to the right which means that the video-based method overestimates the moment. The time of the peak moment is also very close between reference and video-based method. The peak moments for video-based method, occurs at 0.26 ±0.26 s and 0.27 ±0.36 s after the reference peak moments for the top-down and bottom-up model, respectively.

ICCs of peak and mean moments over all pooled video dataset (12 subjects and 3 lifting for each one) were about 0.98 between the reference and the proposed marker-less methods for both the top-down and the bottom-up models (Figure 6). The ICCs were between 0.95 to 0.98 when data were averaged over different lifting motion and were 0.91 to 0.99 when data were averaged over subjects which are considered as excellent. Table 4 shows the mean, standard deviation (SD) and root mean squared deviation (RMSD) of error for each motion and subject separately. For both top-down and bottom-up models, error is smaller in KS lifting compared to FK and FS. Error for each subject averaged across motions, ranges from 11.2 Nm to 23.51 Nm and 9.65 Nm to 16.65 Nm for top-down and bottom-up models respectively, with minimum belongs to subject 11 and maximum is for subject 3.

Insert Table 4 & Figure 5 & 6 about here

3.2. Top-Down versus Bottom-Up Estimated L5/S1 Moment

The results of the video-based method are also validated internally. Since both top-down and bottom-up models chain end up at L5/S1 joint, so calculated torque at this joint can be compared. Of course, any other joints could have been chosen for this purpose, but if a joint in an extremity had been chosen, the separation between top-down and bottom-up analysis would have been less clear (Kingma et al., 1996).

The internal validation is done again by both performing repeated measures t-tests and calculating ICC between the L5/S1 joint moments obtained from top-down model with those for bottom-up model. The correlations between models for all subjects are generally above 0.85. Mean and RMS differences are generally below 28 Nm but could reach 34 Nm. Repeated measures t-tests with p-value 0.05 also confirms that net L5/S1 joint moments are not significantly different between the top-down and bottom-up models, except for subject 11 whose p-value is equal to 0.014 (Table 5). The comparison between models are presented for a typical subject (subject 6) doing floor to knuckle (FK) lifting (figure 7).

In order to get an overall picture of each model's performance, independent of the subjects, we can normalize the moments with respect to the subjects' weight and height and then calculate the average across the subjects. The normalization is done by dividing the moment value by subject's weight× subject's stature (Hendershot and Wolf, 2014; Shojaei et al., 2016). Since the lifting speed is chosen by the lifters, the total time that the lifter finishes the lifting is different for each subject. To be able to take the average of the normalized moments across the subjects and plot the result over the time, we need to normalize the lifting time as well. This normalization is done by mapping the lifting cycle time for each subject between 0 to 100%. Lifting cycle time is defined as the time that a lifter starts moving toward the box to the time he puts it on the shelf and comes back to his starting position (figure 8).

Insert Table 5 & Figure 7 & Figure 8 about here

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4. DISCUSSION

In this study, we aimed to develop and validate a video-based method for analyzing of L5/S1 joint moment during symmetrical lifting by comparing the results with the references obtained from a marker based motion capture system. No significant difference was observed in the peak and mean moments between the proposed video-based and marker-based systems. Note that the peak and mean moments were calculated using both top-down and bottom-up models. The ICCs showed a strong correspondence between the proposed video-based and reference marker-based method for the assessment of peak and mean moments. This correspondence was also strong (above 0.91) for averaged data over lifting motions and subjects.

Lifting motion may affect the accuracy of joint moment estimation. The average error for the knuckle to shoulder (KS) was lower than the other two motions. It may be caused by that the insignificant movement of lower body for grabbing the box from knuckle height level in comparison with floor level leads to higher accuracy of the joints kinematic estimation.

The models used for joint moment calculation overall have a limited effect on joint moment estimation. Top-down versus bottom-up calculated moments revealed excellent coefficients of correlation (above 0.85) and only non-systematic differences. The RMS difference between the bottom-up model and the top-down model was generally below 28 Nm which is higher in comparison with what is reported when marker based methods are used (Kingma et al., 1996; Plamondon, 1996), but for all of the subjects except one, t-test shows no significantly difference between results.

While the average of errors was not comparably different between top-down and bottom-up models, which one of the top-down or bottom-up models should be used for joint moment calculation in the video-based biomechanical analysis may be still under debating. On the one hand, although there is no exact answer to this question that which one of the top-down or bottom-up models should be used for biomechanical analysis, bottom-up models are usually recommended as more accurate models, because the trunk is included in the top-down calculations which is the least rigid body segment and also it is difficult to obtain a reliable estimate of the trunk center of mass (Kingma, 1996; Plamondon, 1996). Indeed, our results (Figure 3 and Table 2) suggested that the accuracy using bottom-up models might be higher than that using top-down model, especially for peak moment estimation. Normalizing joint moments (w.r.t. subject's weight and stature) shows that changes in the calculated joint moment in the bottom-up model is smoother than the top-down model. It may be caused by that a higher level of noise is expected when the calculation method involves more and heavier segments which is the case in the top-down model(De Looze et al., 1992). On the other hand, one of the sources of error for the bottom-up calculation is the measurement of the point of application of the ground reaction force. For example, if the ground reaction force is 1000 N, each mm error in the calculation of the point of application, can lead to an error of 1 Nm in L5/S1 joint moment (Kingma, 1996). Furthermore, it may be more practical to calculate joint moments using top-down models for on-site biomechanical analyses since it does not need to use force plates.

Among the four components contributing to the net moment calculation, segment weight for the top-down model and external forces for the bottom-up model had the highest contribution percentage to the estimation error because the net moment generated by these two components is higher than the other components. This result is in the agreement with the findings from Plamondon et al. (1996) who observed a similar trend. Additionally, among the estimated peak and mean moments of the lateral, sagittal and rotational planes, the moments of the lateral plane correlated best with the reference values and their histograms of the estimation errors indicated that the overall numbers of overestimation and underestimation were about the same. On the other hand, the estimation error distribution for total moment is skewed to the right, which means that it has more overestimation than underestimation. Since the method for calculating segment parameters and L5/S1 joint moment were the same for both the video-based and reference method, the only source of the error is the estimated segment angles. The average estimated error for different body segments angle ranged from 0.53° to 5.08° (Li et al., 2016) for this data set and it leaded to average peak and mean L5/S1 joint moment error of 11.14 Nm and 4.67 in top-down and 6.70 Nm and 5.14 Nm in bottom-up, respectively.

External validation of the results confirms the performance of the proposed video-based method for predicting L5/S1 joint moment. The results from this study were comparable to the literature with generally similar experiments (Coenen et al., 2011; Xu et al., 2012), which reported the peak moment of L5/S1 joint between 200 Nm to 250 Nm for lifting from the ground postion. The estimated peak moments in our study is over the range of the reported values in some existing studies (Faber et al., 2009; Kingma et al., 2016) with lighter subjects (84.5 kg compared to 68.7 kg and 70.9 kg)

One of the limitations of this study is that the validity of the proposed video-based method was tested with only a limited lifting tasks. To generalize the current results, more lifting configurations like asymmetrical lifting, lifting with moving feet and fast speed lifting should be examined. Another limitation is about the configuration of the cameras, generalization of these results should be done with testing position of cameras other than 90 and 135 degrees. Finally, in real world work place, the clothes a lifter wears or the environment lighting can affect the accuracy of the 3D pose reconstruction. These limitations are not considered in this study and should be further investigated in future research.

5. CONCLUSION

The current study shows that the proposed video-based analysis method is a viable tool for noninvasive assessment of lower back loads during occupational lifting. The accuracy of the method is comparable with motion tracking system for L5/S1 joint moment calculation and is a solution to the drawbacks associated with that method. This simple and relatively cheap method can be used for on-site ergonomic practice in order to decrease the risk of lower back pain in the workplaces.

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Table 1- P-values obtained from t-test between the peak and mean of the L5/S1 joint moment calculated from the proposed video-based method and the reference for both top-down and bottom-up models. Since all the p-values are greater than 0.05, we conclude that results are not significantly different.

Model	Response	P-Value
Top-Down	Peak	0.753
	Mean	0.501
Bottom-Up	Peak	0.724
	Mean	0.490

Table 2- Peak and mean moment at L5/S1 joint calculated from marker based and marker-less methods and top-down and bottom-up models. The results are given for each motion separately and are averaged over the subjects.

Model	Response (Nm)	Lifting					
		FK		KS		FS	
		Estimated	Reference	Estimated	Reference	Estimated	Reference
Top-Down	Peak	270.10	267.78	172.91	165.97	279.87	273.83
	Mean	132.64	126.47	101.19	99.06	128.38	122.67
Bottom-Up	Peak	218.16	213.41	136.00	128.49	217.73	216.03
	Mean	128.06	122.10	98.24	95.03	120.67	114.82

Table 3- Mean percentage contribution of each of the four terms in the L5/S1 joint moment error for both top-down and bottom-up models.

Term 1= external forces, Term 2= weight of segments, Term 3= linear acceleration, Term 4= angular acceleration.

	Top-Down				Bottom-Up			
	Lat. Plane (Nm)	Sag. Plane (Nm)	Rot. Plane (Nm)	Total (Nm)	Lat. Plane (Nm)	Sag. Plane (Nm)	Rot. Plane (Nm)	Total (Nm)
Term 1	1.43	8.84	1.23	11.50	15.74	30.46	0.09	46.29
Term 2	10.23	43.11	0.00	53.34	8.44	15.78	0.00	24.22
Term 3	4.40	23.37	6.05	33.82	5.22	10.41	5.67	21.30
Term 4	0.48	0.37	0.49	1.34	1.47	4.46	2.26	8.20
Total	16.54	75.69	7.77	100.00	30.87	61.11	8.02	100.00

Table 4- mean, standard deviation (SD) and root mean squared deviation (RMSD) of error between proposed method and reference for each motion and subject separately

Lifting	Subject	Top-Down			Average (Nm)	Bottom-Up			Average (Nm)
		Mean (Nm)	SD (Nm)	RMSD (Nm)		Mean (Nm)	SD (Nm)	RMSD (Nm)	
FK	1	21.39	24.95	32.63	19.91	15.68	16.00	22.25	16.01
	2	16.16	19.65	25.25		16.19	15.39	22.20	
	3	29.08	29.32	41.04		22.54	20.28	30.15	
	4	27.22	22.94	35.41		17.43	13.62	22.02	
	5	22.66	24.76	33.34		18.33	18.06	25.57	
	6	12.84	15.02	19.61		10.79	11.25	15.48	
	7	20.45	18.89	27.68		17.91	19.50	26.30	
	8	24.52	25.91	35.44		21.06	19.75	28.71	
	9	13.63	21.50	25.23		14.95	17.05	22.51	
	10	18.93	20.20	27.50		10.59	9.85	14.38	
	11	14.12	15.35	20.71		10.25	9.20	13.70	
	12	17.93	21.38	27.70		16.45	12.26	20.42	
KS	1	11.40	14.36	18.20	9.95	7.73	6.89	10.29	7.52
	2	5.40	5.56	7.70		5.35	5.69	7.76	
	3	14.12	14.33	19.99		7.94	9.30	12.14	
	4	14.61	10.99	18.20		8.50	6.89	10.89	
	5	7.70	8.25	11.21		6.84	5.85	8.95	
	6	6.75	5.99	8.97		9.11	7.82	11.94	
	7	13.62	12.24	18.21		5.96	5.73	8.22	
	8	10.91	11.92	16.05		7.66	5.97	9.67	
	9	7.92	12.25	14.46		7.61	8.47	11.31	
	10	12.00	13.27	17.77		8.01	6.65	10.36	
	11	5.14	5.08	7.18		5.97	6.02	8.43	
	12	9.85	11.18	14.79		9.50	10.00	13.71	
FS	1	25.75	32.34	41.02	20.18	17.85	21.85	28.00	15.58
	2	16.27	18.99	24.82		16.49	17.69	24.02	
	3	27.31	26.74	37.99		19.45	24.10	30.74	
	4	23.24	22.21	31.96		17.37	18.12	24.94	
	5	22.36	25.22	33.47		15.57	16.48	22.52	
	6	13.94	15.20	20.48		13.69	12.81	18.64	
	7	19.77	22.77	29.94		17.39	20.66	26.81	
	8	23.59	25.41	34.43		17.49	21.78	27.72	
	9	17.00	25.36	30.26		11.64	16.93	20.37	
	10	19.42	22.57	29.56		11.73	13.85	18.02	
	11	14.36	15.75	21.16		12.73	9.17	15.62	
	12	19.11	17.54	25.79		15.59	18.73	24.19	

Table 5- mean, standard deviation (SD) and root mean squared deviation (RMSD) of error between top-down and bottom-up model for each subject separately and averaged over all three motions. The results of performing t-test and calculated ICCs between two types of models are also given in the last two rows.

Subject	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Mean (Nm)	19.01	16.61	20.45	21.14	17.56	13.27	20.01	21.96	12.42	21.21	16.51	25.57
SD (Nm)	26.15	21.35	27.12	27.07	25.67	18.01	23.63	26.15	20.87	29.31	19.43	31.38
RMSD (Nm)	27.03	21.76	27.28	26.96	27.99	18.35	25.48	29.44	20.91	30.16	22.58	34.21
ICC	0.89	0.93	0.92	0.86	0.88	0.91	0.88	0.87	0.91	0.78	0.81	0.83
P-value	0.335	0.538	0.664	0.945	0.131	0.494	0.145	0.066	0.720	0.196	0.014	0.064

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Figure 1- Experimental setup for the simulated lifting tasks (upper row) (Xu, X., et al; 2012). Black dots on the subject's body represents markers which were used for capturing ground truth motion data. Three of ten used digital cameras of motion tracking system can be seen in this picture. One of two used digital camcorders which was installed on the side view is also shown. The lifting was performed at three vertical lifting ranges from floor to knuckle height, knuckle height to shoulder height and floor to shoulder height. The body postures when carrying the crate at floor level (left), knuckle level (middle) and shoulder level (right) are shown in the low row.

Figure 2- workflow of the proposed marker-less tool

Figure 3- Error of the Peak (upper column) and mean (lower column) of the total L5/S1 joint moment for 12 subjects. Moments averaged over motions and standard deviations are shown by error bars. Moments estimated by the top-down model (white bars) and bottom-up model (black bars) are shown.

Figure 4- Estimated L5/S1 joint moment versus reference L5/S1 joint moment for subject six with floor-to-knuckle-height lifting range (left). The total moment is the vector summation of the L5/S1 moments at each three planes (right). Upper and lower rows show the results for top-down and bottom-up models respectively.

Figure 5- Histograms of the estimation error for top-down (left column) and bottom-up (right column) models. A p value less than .05 shows the skew from zero mean. Error is defined by subtracting the reference moment from the estimated moment, so a skew to the right means overestimation and skew to the left means underestimation.

Figure 6-Scatter plot shows the relation between peak moment (left column) and mean moment (right column) estimated by the proposed video-based method and the reference using top-down (upper row) and bottom-up (lower row) models. Data are averaged over the whole data set. The solid line is the linear regression line fits trough the data points and the dashed diagonal line is the identity line. ICC indicates the intra-class correlation between the reference and estimated moments.

Figure 7- Comparison of the L5/S1 joint Moments calculated from top-down and bottom-up models. Results of subject six with floor-to-knuckle-height lifting range (up). The total moment is the vector summation of the L5/S1 moments at each three planes (down).

Figure 8- Comparison of the L5/S1 joint Moments calculated from top-down and bottom-up models for FK (top), KS (middle) and FS (bottom). Estimated moments are normalized to body mass× body stature and then are averaged over the subjects. All experiments are also time-normalized to their lifting cycle times.