

A Computer Vision Based Method for 3D Posture Estimation of Symmetrical Lifting

Rahil Mehrizi¹, Xi Peng², Xu Xu⁵, Shaoting Zhang⁶, Dimitris Metaxas², Kang Li^{1,2,3,4}

¹Department of Industrial & Systems Engineering, ²Department of Computer Science,

³Department of Biomedical Engineering, Rutgers University, Piscataway, New Jersey

⁴Department of Orthopaedics, Rutgers New Jersey Medical School, Newark, New Jersey

⁵ Edward P. Fitts Department of Industrial and Systems Engineering, North Carolina State

University, Raleigh, North Carolina

⁶Department of Computer Science, University of North Carolina, Charlotte, North

Carolina

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19 *Corresponding author. Tel.: +1-848-445-8787; fax: +1-732-445-5467

20 *E-mail address:* kl419@soe.rutgers.edu (K. Li)

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1 **Abstract**

2 Work-related musculoskeletal disorders (WMSD) are commonly observed among the workers
3 involved in material handling tasks such as lifting. To improve work place safety, it is necessary
4 to assess musculoskeletal and biomechanical risk exposures associated with these tasks. Such an
5 assessment has been mainly conducted using surface marker-based methods, which is time
6 consuming and tedious. During the past decade, computer vision based pose estimation techniques
7 have gained an increasing interest and may be a viable alternative for surface marker-based human
8 movement analysis. The aim of this study is to develop and validate a computer vision based
9 marker-less motion capture method to assess 3D joint kinematics of lifting tasks. Twelve subjects
10 performing three types of symmetrical lifting tasks were filmed from two views using optical
11 cameras. The joints kinematics were calculated by the proposed computer vision based motion
12 capture method as well as a surface marker-based motion capture method. The joint kinematics
13 estimated from the computer vision based method were practically comparable to the joint
14 kinematics obtained by the surface marker-based method. The mean and standard deviation of the
15 difference between the joint angles estimated by the computer vision based method and these
16 obtained by the surface marker-based method was 2.31 ± 4.00 degree. One potential application of
17 the proposed computer vision based marker-less method is to noninvasively assess 3D joint
18 kinematics of industrial tasks such as lifting.

19 **1. Introduction**

20 Lifting is one of the common manual material handling tasks performed in the workplaces.
21 It is considered as one of the main risk factors for low back disorders (Kuiper et al. 1999, da Costa
22 et al. 2010, Nimbarte et al. 2010). In order to improve work place safety, it is necessary to analyze
23 musculoskeletal and biomechanical risk exposures associated with lifting by measuring the joint
24 kinematics and assessing the critical joint stress through biomechanical analysis.

25 The most common method for measuring joint kinematics is the surface-marker based
26 motion capture method. This method uses reflective surface markers and optical motion capture
27 systems to track the body movements: the surface markers are attached near the joints of the subject
28 and the 3D positions of each joint are estimated using the 3D coordinates of these surface markers.
29 This method is limited since it requires expensive optical motion capture equipment; and attaching
30 surface markers to human body is time consuming and tedious.

1 Non-invasive computer vision-based marker-less motion capture systems have recently
2 gained an increasing interest for pose estimation. A variety of computer vision algorithms have
3 been proposed for 3D human pose estimation (Gavrila 1999, Mündermann et al. 2006, Poppe 2007,
4 Holte et al. 2012). These algorithms can be categorized into two types of approaches, generative
5 (model-based) and discriminative (model-free) approaches. Generative approaches use an a priori
6 model of the subject including body dimensions and kinematic trees; and perform a local search
7 around an initial pose estimate. Disadvantages of this type of approaches are the need of
8 initialization and high computational cost. Discriminative approaches use training data to predict
9 the pose directly and are computationally efficient compared to the generative approaches.

10 Most of these computer vision algorithms for human pose estimation are designed for
11 activity recognition; and their accuracy and robustness are not sufficient for 3D joint kinematics
12 assessment and biomechanical analysis. There are only few studies proposing computer vision
13 based marker-less methods for joint kinematics assessment. Drory et al. (2017) presented a
14 discriminative computer vision based method for marker-less estimation of the full body
15 kinematics for a cyclist. Their method is capable of estimating the pose in 2D space accurately,
16 however; its performance is not tested for the 3D body pose estimation. Several studies
17 (Mündermann et al. 2005, Saboune 2005, Corazza et al. 2006, Ceseracciu et al. 2014, Sandau et
18 al. 2014) proposed generative computer vision based methods for joint kinematics assessment
19 during gait, which have been validated against the joint kinematics obtained by the surface marker-
20 based method. These studies used eight cameras to capture images from different views around
21 the subjects and converted the captured images data to 3D surface meshes by applying background
22 subtraction and constructing visual hulls. Pose estimation was then performed by fitting the
23 predefined 3D body models to the 3D surface meshes. In order to achieve the results comparable
24 to the surface marker-based system, these studies required a substantial number of cameras. The
25 data processing of points fitting was computationally expensive. Little research has been
26 conducted for assessing 3D joint kinematics for work-related activities including lifting using
27 computer vision-based marker-less methods although manual lifting is a common task in the
28 workplace and associated injuries are substantial.

29 This paper proposes a computer vision-based marker-less motion capture method for
30 estimating and assessing full-body kinematics and validates the method for symmetrical lifting. In
31 this method, we integrate a discriminative approach for pose estimation with morphological

1 constraints to achieve the accuracy and robustness sufficient for 3D joint kinematics assessment.
2 We tested our method on three types of manual lifting with different starting and ending heights.
3 The joint kinematics estimated from the computer vision based method were practically
4 comparable to the joint kinematics obtained by the surface marker-based method. Therefore, the
5 proposed computer vision method can be potentially considered as a simpler and faster substitute
6 for the surface marker-based systems.

7

8 **2. Methods**

9 **2.1. Data Acquisition**

10 The data set (Mehrizi et al. 2017) consists of 12 healthy males (age 47.50 ± 11.30 years;
11 height 1.74 ± 0.07 meters; weight 84.50 ± 12.70 kg) performing various symmetric lifting tasks in a
12 laboratory at self-selected speed while being filmed by both camcorder and a synchronized motion
13 tracking system that directly measured the body movement. They lifted a plastic crate ($39 \times 31 \times$
14 22 cm) weighing 10 kg and placed it on a shelf without moving their feet. They performed three
15 vertical lifting ranges from floor to knuckle height (FK), knuckle to shoulder height (KS) and floor
16 to shoulder height (FS).

17 45 Reflective markers (Cappozzo et al. 1995) were attached to the lifters' body segments
18 and 3D positions of markers during the lifting tasks were measured by a motion tracking system
19 (Motion Analysis, Santa Rosa, CA) with a sampling rate of 100 Hz. The raw 3D coordinate data
20 were filtered with a fourth-order Butterworth low-pass filter at 8 Hz. Two digital camcorder (GR-
21 850U, JVC, Japan) with 720×480 pixel, synchronized with the motion tracking system resolution
22 also recorded the lifting from two views, 90 degree (side view) and 135 degree positions.

23 **2.2. Computer Vision Method for Joint Kinematics Assessment**

24 In this study, we propose a computer vision based marker-less method using a discriminative
25 approach for joint kinematics assessment. The workflow of the proposed method consists of three
26 steps including feature extraction, 3D pose reconstruction, and angle calculation, which are
27 summarized in Figure 1. The input of this system is the video (image sequence) recorded by digital
28 camcorders.

29 -----

30 Insert Figure 1 about here

2.2.1. Feature Extraction

In the first step, the recorded images are converted to image features. The descriptor of the image feature used in this study is Histogram Orientation Gradient (HoG) (Dalal et al. 2005), which characterizes the distribution of gradient directions of images and has been widely used for object recognition and human detection (Suard et al. 2006, Zhu et al. 2006, Yang et al. 2011).

In order to extract the HoG features, the input image is divided into cells, i.e. small groups of connected pixels. A histogram of gradient orientation is calculated for pixels within the cell. The histograms are contrast-normalized by calculating a measure of intensity across a larger region of an image and then using this measure to normalize all the cells within this region. The descriptors of the HoG features are the concatenation of the histograms for the input image. Since we want to use captured images from both views in our data for pose estimation, the HoG features extracted for each view are concatenated to make a longer image descriptor. The HoG feature extraction is now implemented as a standard function in Matlab. It took around 0.05 second per image (480×720 pixels) to complete the HoG feature extraction for a PC with a 3.4 GHz i7 processor and 8 GB of RAM.

2.2.2. 3D Pose Reconstruction

A modified algorithm based on Twin Gaussian Process (TGP) (Bo et al. 2010) is proposed to extract the 3D pose from each frame of the videos. TGP (Bo et al. 2010) is a discriminative approach, which maps directly from image features to a human pose as follows. Assume that we have a set of inputs e.g. image feature observations ($R = (r_1, r_2, \dots, r_N)$) and a set of the corresponding outputs e.g. 3D pose measures ($X = (x_1, x_2, \dots, x_N)$). Since the Gaussian distribution of the inputs (N_R) is known, we can calculate the offset between the estimated Gaussian distribution of outputs (N_X), including the unknown pose for a testing image, and the homologous input distribution using Kullback-Leibler divergence function (D_{KL}). Then, for a testing image, we can estimate the corresponding 3D pose measure (x^*) by minimizing Kullback-Leibler divergence:

$$x^* = \arg \min(D_{KL}(N_X || N_R))$$

The TGP method can be applied on either a monocular image or multi view images for predicting whole-body 3D poses. Note that the 3D pose measures can be a set of estimated virtual

1 markers defining the body joints. In this study, we used the 3D coordinates of 45 estimated
2 ‘virtual’ markers as the 3D pose measures, which matched with the definitions proposed by
3 (Cappozzo et al. 1995).

4 Since the errors of predicted 3D poses from the TGP method (Bo et al. 2010) could be
5 extremely high and may not be good for joint kinematics assessment, we propose a modified TGP
6 method by introducing the morphology constraints of the upper limb segment lengths to the
7 original TGP algorithm, since lifting tasks involve significant upper limb motion. These
8 morphology constraints enforce the consistency of upper limb segment lengths, i.e., the Euclidian
9 distances between shoulder-elbow and elbow-wrist should be constant over all frames. With these
10 constraints, the differences between predicted segment lengths and the constant length values are
11 added as penalties to the Kullback-Leibler divergence cost function, which should be minimized.
12 By adding these constraints to the algorithm, the search space is much smaller and thus more
13 accurate pose estimation can be achieved.

14 The TGP algorithm requires a training dataset to train the model parameters used for
15 calculating the Kullback-Leibler divergence. Bo et al. (2010) have examined the effect on pose
16 estimation results of two type of training, jointly training and separately training. Jointly training
17 trained the model parameter on the motions of all subjects (the whole data set) while separately
18 training trained the model on the motions of individual subject separately. They have reported no
19 significant difference between the two types of training on pose estimation. Since jointly training
20 uses a bigger training data set and is computationally more expensive, separately training was
21 employed to train the model for each subject in this study. Accordingly, the k-fold cross validation
22 technique was used to test our modified TGP method for each subject, i.e., we divided the videos
23 and corresponding marker based motion data into four partitions, and then used three of them to
24 train the model and the remaining partition for testing each time. By repeating the test four times,
25 we obtained the results for the whole dataset.

26 2.2.3. *Angle Calculation*

27 Once the 3D pose measures (3D coordinates of 45 estimated ‘virtual’ markers) were
28 estimated at each frame, we used OpenSim (Delp et al. 2007) to perform inverse kinematics to
29 calculate the joint kinematics. Both our proposed modified TGP algorithm and the surface marker
30 based method output a set of marker trajectories: 45 estimated ‘virtual’ marker trajectories for the

1 modified TGP algorithm (our proposed computer vision based marker-less method) and 45 surface
2 marker trajectories (the surface marker based method).

3 The use of OpenSim for computing joint kinematics from these estimated ‘virtual’ or surface
4 marker motions required the creation of a subject-specific musculoskeletal model via scaling of a
5 generic model. The musculoskeletal model developed by Hamner et al. (Hamner et al. 2010) was
6 chosen as the generic model. An internal Marker Set defined by (Cappozzo et al. 1995) was placed
7 on the model. The scaling procedure utilized the Scale Model tool in OpenSim, which adjusted the
8 body segment lengths of a generic model to best match the internal markers and the corresponding
9 experimental surface markers captured during a standing posture or the corresponding ‘virtual’
10 markers estimated from the computer vision based marker-less method. After scaling, the inverse
11 kinematics tool embedded in OpenSim (Delp et al. 2007) was used to solve for the joint angles
12 such that the discrepancy between experimentally measured surface markers and virtual markers
13 on the model was minimized.

14 **2.3. Data Analysis and Validation**

15 The proposed computer vision based marker-less method was validated against the surface
16 marker-based method. For each frame of the video, the average Euclidean distance between the
17 estimated ‘virtual’ marker positions and the corresponding experimental surface marker positions
18 was calculated as the 3D pose measure error for the frame. The 3D pose reconstruction error was
19 calculated as the average of the 3D pose measure errors over all the frames. We also calculated
20 the joint angle difference between the marker-less and marker-based method. Paired t-tests were
21 performed to examine whether the joint angles estimated from the marker-less and marker-based
22 method were significantly different. All the preceding data analyses were performed using
23 MATLAB® programs (The MathWorks, Boston, MA).

24 **3. Results**

25 Our proposed computer vision based marker-less method successfully estimated the 3D
26 human pose as illustrated in Figure 2. The grand mean \pm SD of the 3D pose reconstruction error
27 with the modified TGP algorithm was 9.52 ± 7.95 mm (Table 1).

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30

Insert Table 1 and Figure 2 about here

1 For all of the lifting trials, there is a good agreement of joint angle trajectories estimated by the
2 computer vision based marker-less and surface marker-based methods as illustrated by Figure 3.
3 The joint angle differences between the two methods are presented in Table 2. The mean \pm standard
4 deviation of the joint angle differences over the whole data set was 2.31 ± 4.00 degree. The joint
5 angle differences for three lifting styles are similar (2.31 ± 2.01 degree for FK, 2.33 ± 1.87 degree
6 for KS, and 2.30 ± 1.68 degree for FS), but the joint angle differences vary across subjects, from
7 1.66 ± 1.03 degree to 3.58 ± 2.96 degree.

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9 Insert Table 2 & Figure 3 about here

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11 For the symmetrical lifting, the joint angle differences between the computer vision based
12 marker-less method and the surface marker-based method for the left- and right- side joints of the
13 body are comparable (Figure 4).

14 -----

15 Insert Figure 4 about here

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17 Joint angle differences between the computer vision based marker-less method and the
18 surface marker-based method vary across body joint angles as shown in Table 3. The maximum
19 difference was observed for the elbow flexion with the mean \pm standard deviation of 5.08 ± 6.38
20 degree (3.38% of the range motion). No significant difference was observed in joints angle
21 difference between the two methods for most joint angles except the arm adduction. However,
22 there is no systematic error of the joint angle estimation as illustrated by Figure 5 based on the
23 distribution of the joint angle differences.

24 -----

25 Insert Table 3 & Figure 5 about here

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28

1 **4. Discussion**

2 The present study proposed and validated a computer vision based marker-less method for
3 assessing 3D joint kinematics during symmetrical lifting. The whole body 3D pose during
4 symmetrical lifting was successfully reconstructed by the proposed computer vision based marker-
5 less method. The success of our proposed method in 3D pose reconstruction results from the
6 integration of morphological constraints and the discriminative computer vision approach. The
7 average 3D reconstruction error for the original TGP (Bo et al. 2010) without integrating with the
8 morphological constraint, was much higher (40 mm vs. 9.52 mm, unpublished result). The
9 integration of morphological constraints prevented the infeasible solutions with large
10 reconstruction errors. Thus, our proposed method was able to achieve a low reconstruction error,
11 which enabled us to estimate 3D joint angles with reasonable accuracies. The 3D joint kinematics
12 estimation from the proposed method were practically comparable to the 3D joint kinematics from
13 the surface marker-based method.

14 The performance of our proposed method may be activity-dependent and be affected by
15 self-occlusion and object-occlusion. We have shown that the joint angle estimation accuracy
16 varies across body joints for the proposed computer vision based marker-less method. Among all
17 of the joints, the elbow flexion angle exhibited the highest difference between the proposed
18 marker-less method and the surface marker-based method. This may be attributed to the self-
19 occlusion and object-occlusion during lifting. When the subject placed the box on the shelf, lower
20 arms could be blocked by the shelf (Figure 2) and the arms could be occluded by the torso.
21 However, the joint angle estimation accuracy for the left- and right- side of the body were very
22 similar, which may be caused by that all of the lifting motions were symmetrical in this study.

23 Our proposed method can estimate 3D joint kinematics accurately with a low cost setup.
24 Many computer vision based approaches (Bodor et al. 2003, Mikić et al. 2003, Oreifej et al. 2013)
25 have been developed and successfully applied for human tracking and activity recognition based
26 on a small number of optical cameras, however, their accuracy for the 3D joint kinematics
27 estimation may not be sufficient for biomechanics research. On the other hand, the studies
28 (Mündermann et al. 2005, Saboune 2005, Corazza et al. 2006, Ceseracciu et al. 2014, Sandau et
29 al. 2014) capable of achieving suitable accuracy for the 3D joint kinematics estimation, usually
30 use a large number of cameras, which is not always practical in the workplace. Our proposed
31 method seem to work well with a low cost setup, which includes two low-resolution optical

1 cameras. This may result from the image features used in the methods. The HoG features were
2 required to be normalized to the contrast, which can minimize the effect of image quality and
3 account for changes in illumination. Recently depth sensors such as Kinect have been also used
4 for joint kinematics assessment (Dutta 2012, Diego-Mas et al. 2014, Plantard et al. 2016).
5 However, there are two major disadvantages of using Kinect for workplace activity assessment.
6 First, depth sensors can be only used in a short range of distance from the depth sensors, which
7 may not allow them to be used in large space workplaces and fields (Weerasinghe et al. 2012).
8 Second, depth sensors are sensitive to the environment illumination and would be difficult to use
9 in outdoor environments (Andersen et al. 2012). Since the proposed method uses a simple
10 experimental setup with only two regular optical cameras, it has the potential to be a viable
11 noninvasive alternative of the surface marker based method, especially for outdoor environments.

12 The ultimate goal of our research is to provide a field noninvasive biomechanical analysis
13 and joint kinematics assessment tool by taking the advantages of advanced computer vision
14 techniques. The present study is a starting point of the research along this direction. There are
15 three limitations about this study that should be further investigated in the future research. First,
16 the proposed method was mainly developed for symmetrical lifting tasks. Whether and how well
17 this method can be extended for measuring the 3D joint kinematics of other common workplace
18 activities, such as asymmetrical lifting, pushing, and pulling would be worth to investigate.
19 Second, the effects of clothing and image quality on the accuracy of the 3D pose estimation have
20 not been investigated. Finally, the proposed method requires training for individual subjects in
21 order to personalize subject-specific models. A more generalized method with a less restricted
22 training requirement will be more favorable.

23 **Conflict of interest statement**

24 The authors have no any financial or proprietary interests in the materials described in the article.

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1 **List of Tables**

2

3 Table 1- Mean \pm SD (mm) of Euclidean distance between the estimated ‘virtual’ marker positions
4 obtained from our proposed method and the corresponding experimental surface marker positions

5

Subject	FK	KS	FS	Average
1	14.57 \pm 8.71	10.42 \pm 9.67	8.72 \pm 7.51	11.24 \pm 9.47
2	9.63 \pm 7.29	7.90 \pm 6.79	11.83 \pm 6.75	9.79 \pm 7.63
3	7.79 \pm 7.06	9.30 \pm 7.00	7.89 \pm 6.99	8.32 \pm 7.58
4	7.64 \pm 6.23	10.31 \pm 7.96	6.96 \pm 5.61	8.30 \pm 7.19
5	7.45 \pm 5.32	6.82 \pm 5.91	6.41 \pm 3.89	6.89 \pm 5.73
6	6.77 \pm 4.39	10.02 \pm 4.56	6.84 \pm 4.21	7.88 \pm 4.94
7	7.09 \pm 4.76	10.95 \pm 6.77	8.30 \pm 5.46	8.78 \pm 6.27
8	8.34 \pm 5.73	7.99 \pm 6.36	9.22 \pm 6.71	8.52 \pm 7.02
9	12.66 \pm 10.41	15.96 \pm 15.81	12.32 \pm 11.14	13.65 \pm 14.74
10	7.08 \pm 3.10	8.35 \pm 6.69	6.86 \pm 3.51	7.43 \pm 5.56
11	5.10 \pm 3.07	5.54 \pm 3.73	5.29 \pm 2.74	5.31 \pm 3.52
12	6.81 \pm 3.67	9.55 \pm 5.69	6.83 \pm 3.76	7.73 \pm 4.88
Average	8.41 \pm 7.35	9.42 \pm 9.11	8.12 \pm 7.16	9.52 \pm 7.95

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1 Table 2- Mean \pm SD of the joint angle differences between the proposed marker-less method and
2 the surface marker-based methods.

3

Subject	FK	KS	FS	Average
	Mean\pmSD (Degree)	Mean\pmSD (Degree)	Mean\pmSD (Degree)	
1	2.90 \pm 2.21	2.83 \pm 2.08	2.76 \pm 2.18	2.83 \pm 2.16
2	2.26 \pm 1.52	2.38 \pm 2.19	2.78 \pm 1.72	2.48 \pm 1.85
3	2.01 \pm 1.62	2.53 \pm 2.03	2.49 \pm 1.90	2.35 \pm 1.87
4	2.18 \pm 1.65	2.32 \pm 1.50	2.73 \pm 2.35	2.41 \pm 1.89
5	1.53 \pm 0.96	1.71 \pm 1.30	1.86 \pm 1.48	1.70 \pm 1.27
6	1.49 \pm 0.81	2.07 \pm 1.47	2.07 \pm 1.39	1.88 \pm 1.29
7	2.00 \pm 1.12	2.53 \pm 1.96	2.34 \pm 1.43	2.29 \pm 1.56
8	5.92 \pm 3.41	2.26 \pm 1.66	2.55 \pm 1.90	3.58 \pm 2.96
9	2.32 \pm 1.56	2.99 \pm 2.50	2.24 \pm 1.36	2.52 \pm 1.90
10	2.09 \pm 1.22	2.45 \pm 1.97	1.86 \pm 1.15	2.13 \pm 1.51
11	1.40 \pm 0.72	1.80 \pm 1.20	1.77 \pm 1.08	1.66 \pm 1.03
12	1.62 \pm 0.84	2.09 \pm 1.67	2.17 \pm 1.21	1.96 \pm 1.31
Average	2.31 \pm 2.01	2.33 \pm 1.87	2.30 \pm 1.68	2.31 \pm 4.00

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1 Table 3- Mean \pm SD of the joint angle differences, and p-values of paired t-tests between the
2 computer vision based marker-less method and the surface marker-based method. Hip, knee, ankle,
3 arm, and elbow angles differences are calculated based on the average of the differences on the
4 left- and right- side of the body.

5

Joint	Angle	Mean \pm SD (Degree)	p-value
Hip	Flexion	2.01 \pm 2.86	0.643
	Adduction	0.53 \pm 0.67	0.060
	Rotation	0.75 \pm 1.07	0.899
Knee	Flexion	2.55 \pm 4.07	0.498
Ankle	Flexion	1.17 \pm 1.57	0.260
Lumbar	Extension	1.87 \pm 2.77	0.253
	Bending	0.57 \pm 0.69	0.150
	Rotation	0.74 \pm 1.02	0.051
Arm	Flexion	3.47 \pm 5.39	0.723
	Adduction	1.91 \pm 2.32	0.029
	Rotation	4.66 \pm 6.32	0.084
Elbow	Flexion	5.08 \pm 6.38	0.071
	Rotation	2.90 \pm 3.20	0.140

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1 **List of Figures**

2

3 Figure 1. Workflow of the proposed computer vision based marker-less method

4

5 Figure 2. Estimated full-body 3D posture from the proposed computer vision base marker-less
6 method for selected frames of a representative subject performing a FK lifting for both views (90
7 and 135 degree). Activities from top to down: grabbing the box from the floor, putting the box on
8 the shelf, in the standing position.

9

10 Figure 3. Joint angles calculated from the marker-based (red line) and the proposed computer
11 vision base marker-less method (blue line) for a representative subject performing a FK lifting.
12 The lifting task begins in a straight upright position and ends in the same position. Vertical axis
13 shows the joint angles in degree and horizontal axis shows the time in second.

14

15 Figure 4. Comparison of the mean joint angle differences of the left- and right- side of the body.
16 Boxes represent the mean values and bars show the standard deviation.

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18 Figure 5. Distribution of the joint angles difference. Middle line is the median and boxes represents
19 25 and 75 percentile and bars show the minimum and maximum values. Whisker size is set to two
20 percent.

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