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An inverse optimization approach for determining weights of joint displacement objective function for upper body kinematic posture prediction

Qiuling Zou†, Qinghong Zhang‡, Jingzhou (James) Yang†,* and Jared Gragg†

†*Human-Centric Design Research Lab, Department of Mechanical Engineering, Texas Tech University, Lubbock, TX 79409, USA*
‡*Department of Mathematics and Computer Science, Northern Michigan University, Marquette, MI 49855, USA*

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SUMMARY
Human posture prediction can often be formulated as a nonlinear multiobjective optimization (MOO) problem. The joint displacement function is considered as a benchmark of human performance measures. When the joint displacement function is used as the objective function, posture prediction is a MOO problem. The weighted-sum method is commonly used to find a Pareto solution of this MOO problem. Within the joint displacement function, the relative value of the weights associated with each joint represents the relative importance of that joint. Usually, weights are determined by trial and error approaches. This paper presents a systematic approach via an inverse optimization approach to determine the weights for the joint displacement function in posture prediction. This inverse optimization problem can be formulated as a bi-level optimization problem. The design variables are joint angles and weights. The cost function is the summation of the differences between two set of joint angles (the design variables and the realistic posture). Constraints include (1) normalized weights within limits and (2) an inner optimization problem to solve for joint angles (predicted posture). Additional constraints such as weight limits and weight linear equality constraints, obtained through observations, are also implemented in the formulation to test the method. A 24 degree of freedom human upper body model is used to study the formulation and visualize the prediction. An in-house motion capture system is used to obtain the realistic posture. Four different percentiles of subjects are selected to run the experiment. The set of weights for the general seated posture prediction is obtained by averaging all weights for all subjects and all tasks. On the basis of obtained set of weights, the predicted postures match the experimental results well.

KEYWORDS: Inverse optimization; Posture prediction; Weighted sum; Multiobjective optimization; Novel applications of Robotics; Design.

* Corresponding author. E-mail: james.yang@ttu.edu

1. Introduction

Digital human modeling and simulation have proven to revolutionize the way new vehicles are designed for manufacturing, operation, and maintenance. The expected benefits entail the reduction of development time, the reduction of development costs, and increasing quality. Posture prediction is a main component in digital human modeling. Posture prediction aims to predict a single static posture for a specific scenario, which includes user characteristics, tasks to be performed, and constraints that are active. Significant research has focused on posture prediction models. Three types of approaches are generally utilized: the empirical-statistical approach, the direct inverse kinematics approach, and the direct optimization-based approach.

Literature review

In the empirical-statistical approach, the data are collected either from thousands of experiments with human subjects or from simulations with three-dimensional computer-aided human-modeling software.[7,33] The data are then analyzed statistically in order to form predictive posture models. These simulation models are implemented in the simulation software along with various methods for selecting the most probable posture, given a specific scenario instead of predicting a posture for all scenarios due to the experiment constraints of this approach.[2,8,11]

In the direct inverse kinematics approach, the position of a limb is modeled mathematically with the goal of formulating a set of equations that are used to solve for the joint variables.[18–21,38,40,42] Griffin[15] reviewed the validation of these biodynamic models. Wang *et al.*[41] demonstrated the validation of the model-based motion in the REALMAN project.

In the direct optimization-based approach, posture prediction is considered to be an optimization problem, in which humans choose a posture to minimize certain objective functions. In the biomechanics literature, significant efforts have focused on static lifting posture prediction using three different behavioral criteria or objective functions. The first criterion assumes that subjects choose a posture, which requires the minimum overall effort,[4] which is defined

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as the total external torque (summation of all the joints) created by the posture. This criterion assumes that when a large amount of torque is exerted, a human perceives that a large amount of effort is required. The second criterion assumes that subjects minimize local effort or fatigue.[1,32] The third criterion assumes that subjects choose the posture with the greatest stability.[22] Woldstad and Stewart[45] developed a computer-based method to predict three-dimensional body postures. Dysart and Woldstad[10] compared these three models. Recently, Ma *et al.*[26] incorporated the musculoskeletal discomfort function[46] into a multiobjective optimization (MOO) posture prediction problem considering fatigue effect. In the previous research, a MOO-based kinematic posture prediction model was proposed.[29,30,46–48,50] Recently, a new pregnant woman model was developed and the MOO posture prediction was implemented.[17] Gragg *et al.*[14] determined the driver seat adjustment range by employing this optimization-based posture prediction formulation.

Different human performance measures have been proposed for direct optimization-based posture prediction (DOPP). Jung and Choe[20] proposed a joint displacement function, which is the weighted sum of the differences between the current joint angles and the angles that constitute a predetermined neutral position. A perceived discomfort about the joint movement from a regression model was developed by Kee *et al.*[21] Visual displacement, delta potential energy, and musculoskeletal discomfort were proposed as well.[46,50] Within direct optimization-based methods, different human performance measures were considered as the cost functions in a MOO problem. How to combine different human performance measures is a key issue for the direct optimization-based approach. Several methods were used to find Pareto solutions of the MOO problem, such as the weighted-sum method, the global criterion method, and the min–max method.[28] Among them, the weighted-sum method is most commonly used. Weights are used to indicate the relative importance of the cost functions. The value of each weight is only significant relative to the other weights and the value of its corresponding objective function.

Several approaches have been used to determine the weights in the weighted-sum method. Consistency, Ratio method was proposed by Saaty[36,37] to determine the values in Analytic Hierarchy Process. It is necessary to construct a hierarchy matrix in order to express the relative values of a set of attributes, to perform pair-wise comparisons, to obtain the weights of importance for all the factors, and finally, to calculate a Consistency Ratio that measures how consistent the judgments have been relative to large samples of purely random judgments. A trial and error method is a common method that has been used in human modeling and simulation and other areas.[27,46] Kim and Weck[24,25] and Khan and Ardil[23] proposed an adaptive weighted-sum method for bi-objective optimization and MOO. It focuses on unexplored regions by changing the weights adaptively, rather than by using *a priori* weight selection. Zhang and Gao[51] integrated adaptive weightings in a min–max method for optimization. Dong *et al.*[9] adopted an orthogonal interactive genetic algorithm to calculate the weights of different factors, which affect posture choosing.

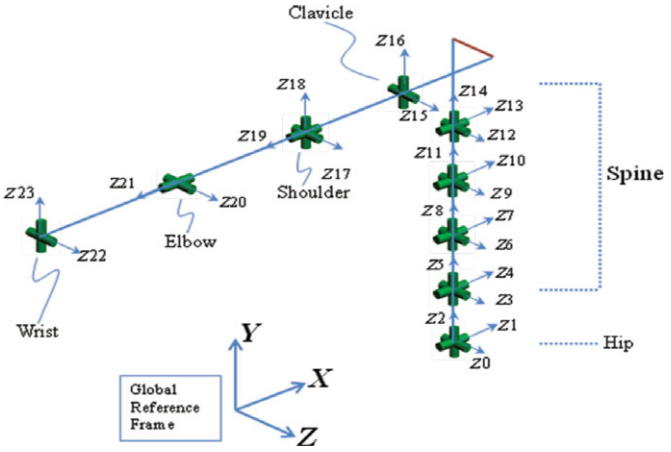


Fig. 1. (Colour online) A 24-DOF human upper body model.

Objectives

There is lack of research effort to systematically determine the weights for the weighted-sum method in literature. This paper is to investigate a systematic mathematical model to determine the weights for the joint displacement function in DOPP based on the pilot study.[52]

Overview of the paper

This paper is organized as follows: Section 2 briefly introduces a digital human model based on the Denavit–Hartenberg method (DH method).[6] Section 3 describes the problem definition. Section 4 gives detailed formulation of a bi-level optimization problem. Section 5 discusses the experiment to obtain the realistic postures for different tasks. Section 6 gives a brief summary of posture reconstruction. Section 7 illustrates the procedure through examples to demonstrate the efficiency and effectiveness of the proposed method.

2. Human Model

The human body can be modeled as a kinematic system, which is a series of links connected by revolute joints that represent musculoskeletal joints, such as spine, shoulder, arm, and wrist. The rotation of each joint in the human body is described as a generalized coordinate, q_i. Although the posture reconstruction algorithm can be used for the whole body model, this study only focuses on the human upper body. A 24 degree of freedom (DOF) model is used and shown in Fig. 1, where the hip has 3-DOFs, the spine has 12-DOFs, and the right arm has 9-DOFs. Joint angles are defined as $\mathbf{q} = [q_1 \cdots q_{24}]^{\mathrm{T}}$. According to the DH method, the position vector of a point of interest (the end-effector) of a human articulated model (e.g., a point on the thumb with respect to the torso coordinate system) can be written in terms of joint variables as

$$\mathbf{x} = \mathbf{x}(\mathbf{q}), \tag{1}$$

where $\mathbf{q} \in \mathbf{R}^{24}$ is a joint angle vector, and $\mathbf{x}(\mathbf{q})$ can be obtained from the multiplication of the homogeneous

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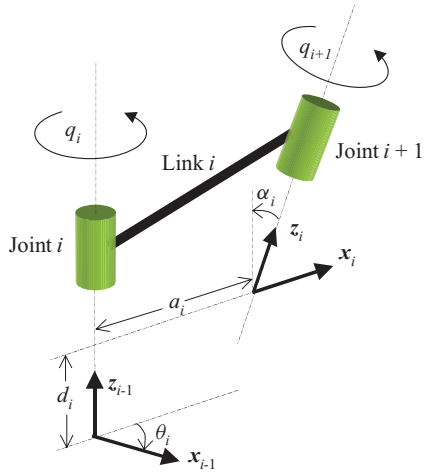


Fig. 2. (Colour online) DH parameters.

transformation matrices defined by the DH method as

$$ {}^{0}\mathbf{T}_n = {}^{0}\mathbf{T}_1 {}^{1}\mathbf{T}_2 \ldots {}^{n-1}\mathbf{T}_n = \begin{bmatrix} {}^{0}\mathbf{R}_n(\mathbf{q}) & \mathbf{x}(\mathbf{q}) \\ \mathbf{0} & 1 \end{bmatrix}, \quad (2) $$

where ${}^{i}\mathbf{R}_j$ is the rotation matrix relating coordinate frames i and j. The vector function $\mathbf{x}(\mathbf{q})$ characterizes the set of all points touched by the end-effector. The transformation matrix can be defined as

$$ {}^{i-1}\mathbf{T}_i = \begin{bmatrix} \cos\theta_i & -\cos\alpha_i \sin\theta_i & \sin\alpha_i \sin\theta_i & a_i \cos\theta_i \\ \sin\theta_i & \cos\alpha_i \cos\theta_i & -\sin\alpha_i \cos\theta_i & a_i \sin\theta_i \\ 0 & \sin\alpha_i & \cos\alpha_i & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad (3) $$

where $q_i = \theta_i$. There are four DH parameters shown in Fig. 2: θ_i is the joint angle from the x_{i-1} to the x_i-axis, d_i is the distance from the origin of the $(i-1)$th coordinate frame to the intersection of the z_{i-1}-axis with the x_i-axis, a_i is the offset distance from the intersection of the z_{i-1}-axis with the x_i-axis, and α_i is the offset angle from the z_{i-1}-axis to the z_i-axis.

In Fig. 1, q_1 through q_3 represent middle of hip joints, q_4 through q_{15} represent the spine, q_{16} through q_{20} represent the shoulder and clavicle, and q_{21} through q_{24} represent the right arm.

3. Problem Definition

The problem is defined as: Given a set of joint angles $\mathbf{q}^*$ (posture), the objective is to determine the weights in the joint displacement cost function such that $\mathbf{q}^*$ is close to an optimal solution of the following DOPP formulation:[20,46]

$$ \begin{aligned} &\text{Find: Joint angles } \mathbf{q}, \\ &\text{Minimize: } f(\mathbf{q}) = \sum_{i=1}^{n} w_i \left(\frac{q_i - q_i^N}{q_i^U - q_i^L} \right)^2, \\ &\text{Subject to: } d^2 = (\mathbf{x} - \mathbf{x}^{\text{Target}})^2 = 0, \quad (4) \\ &\qquad q_i^L \le q_i \le q_i^U, \quad i = 1, \ldots, n, \end{aligned} $$

where $\mathbf{q}^N$ denotes a relatively comfortable position (neutral posture). n is the number of DOFs q_i^L and q_i^U are the lower and upper boundaries of q_i, $\mathbf{w} = [\, w_1 \cdots w_n \,]^{\mathrm{T}}$.

4. Formulation

On the basis of the above problem definition, one can formulate it as a bi-level optimization problem as follows:

$$ \begin{aligned} &\text{Find: } \mathbf{q}, \mathbf{w}, \\ &\text{Minimize: } \sum_{i=1}^{n} w_i \left(\frac{q_i - q_i^*}{q_i^U - q_i^L} \right)^2, \quad (5) \\ &\text{Subject to: } \sum_{i=1}^{n} w_i = 1, \quad w_i \ge 0, \end{aligned} $$

$\mathbf{q}$ is a solution of the following optimization problem:

$$ \begin{aligned} &\text{Find: Joint angles } \mathbf{q}, \\ &\text{Minimize: } f(\mathbf{q}) = \sum_{i=1}^{n} w_i \left(\frac{q_i - q_i^N}{q_i^U - q_i^L} \right)^2, \\ &\text{Subject to: } g(\mathbf{q}) = (\mathbf{x} - \mathbf{x}^{\text{Target}})^2 = 0, \\ &\qquad q_i^L \le q_i \le q_i^U, \quad i = 1, \ldots, n. \end{aligned} $$

It is difficult to directly solve the bi-level optimization problem in Eq. (5). In the literature, the inner optimization problem is usually replaced by its Karush–Kuhn–Tucker (KKT) conditions.[3,5] The KKT conditions are necessary and sufficient optimality conditions[35] for certain classes of objective and constraint functions. While one may verify whether the KKT conditions are necessary and sufficient for the inner optimization problem presented in this paper, the inner optimization problem is replaced by its KKT conditions in order to perform a numerical implementation. Therefore, the original bi-level optimization problem becomes a regular

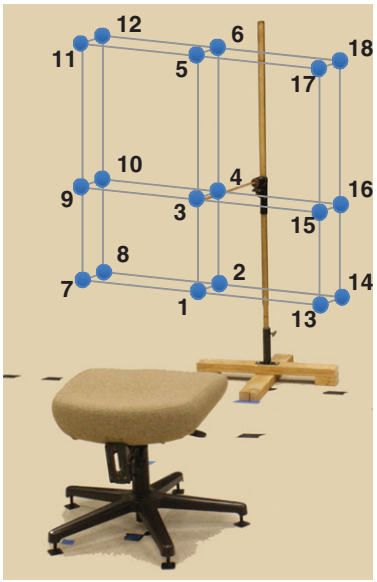
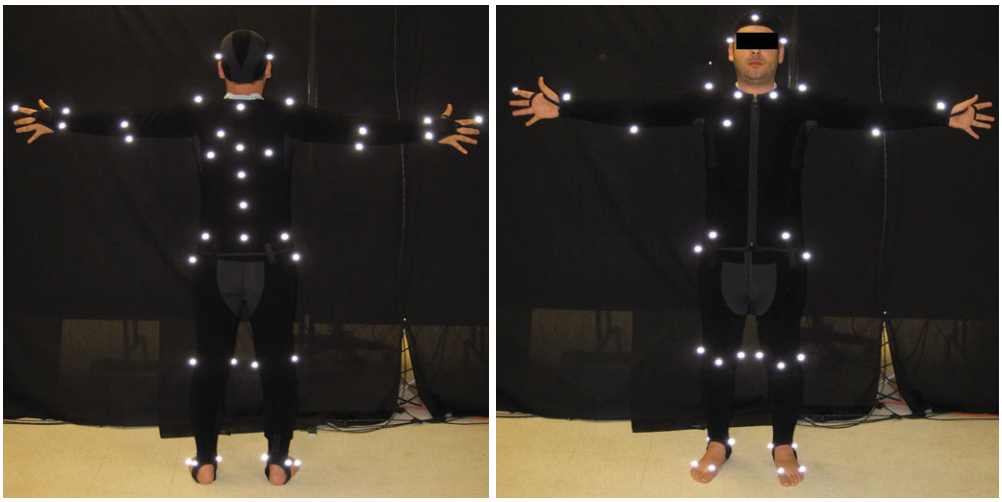


Fig. 3. (Colour online) Tasks.

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(a) (b)

Fig. 4. (Colour online) Marker protocol (a) T pose back (b) T pose front.

optimization problem as follows:

$$\text{Minimize: } \sum_{i=1}^{n} w_i \left(\frac{q_i - q_i^*}{q_i^U - q_i^L} \right)^2,$$

$$\text{Subject to: } \sum_{i=1}^{n} w_i = 1, \quad w_i \geq 0,$$

$$\sum_{i=1}^{n} w_i \nabla f_i(\mathbf{q}) + \lambda \nabla g(\mathbf{q}) + (\mu_1, \mu_2, \ldots, \mu_n)^{\mathrm{T}} + (\nu_1, \nu_2, \ldots, \nu_n)^{\mathrm{T}} = 0, \tag{6}$$

$$g(\mathbf{q}) = (\mathbf{x} - \mathbf{x}^{\text{Target}})^2 = 0,$$

$$\mu_i (q_i - q_i^L) = 0, \quad \nu_i (q_i^U - q_i) = 0, \quad u_i \geq 0, v_i \geq 0,$$

$$q_i^L \leq q_i \leq q_i^U, \quad i = 1, 2, \ldots, n,$$

λ_i, μ_i, and ν_i are Lagrange multipliers and

$$f_i(q) = \left(\frac{q_i - q_i^N}{q_i^U - q_i^L} \right)^2.$$

In the pilot study,[52] results showed that the above formulation can be improved. To obtain more realistic postures, the following constraints have to be added in the above formulation. These constraints are from observation (knowledge)

$$w_i^L \leq w_i \leq w_i^U,$$
$$w_1 = w_3 = 2w_4,$$
$$w_2 = 2w_5,$$
$$w_4 = w_7 = w_{10} = w_{13} = 80w_{21},$$
$$w_5 = w_8 = w_{11} = w_{14},$$
$$w_6 = w_9 = w_{12} = w_{15} = w_4,$$
$$w_{22} = w_{23} = w_{24} = w_4,$$
$$w_{18} = w_{19} = w_{20} = w_{21},$$

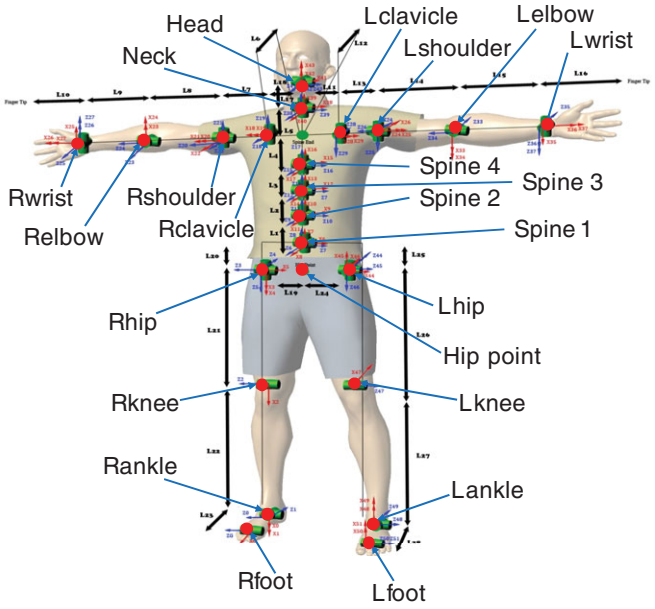


Fig. 5. (Colour online) Important joint centers for the posture reconstruction.

where L denotes the lower limit and U represents the upper limit. The total number of linear equality constraints should be less than the total number of DOF. This optimization problem is solved by using SNOPT.[12]

5. Motion Capture Experiments

To obtain correct postures, an experimental method is used to obtain these postures. This section describes task selection, subject selection, data collection using a motion capture system, and experimental protocols.

5.1. Tasks

In daily life, seated postures are common and target points could be anywhere around the human. To cover most targets (tasks), a seated apparatus was designed for the experiment. A regular office chair is used without the back

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Table I. Tasks for Subject 1.

Target	x (cm)	y (cm)	z (cm)
1	0.7	−9.47	76.58
2	−0.11	−11.5	69.14
3	1.06	34.84	77.46
4	0.35	32	68.76
5	6.78	84.98	69.77
6	7.52	83.96	63.08
7	50.49	−15.77	68.16
8	48.18	−16.63	62.57
9	49.68	29.17	69.51
10	47.09	27.43	60.33
11	50.25	77.19	60.65
12	50.27	78.71	58.03
13	−51.2	−10.79	70.49
14	−51.43	−12.59	66.44
15	−53.76	26.6	74.39
16	−52.26	24.86	66.63
17	−34.46	85.44	69.41
18	−34.35	84.83	65.37

Table II. Tasks for Subject 2.

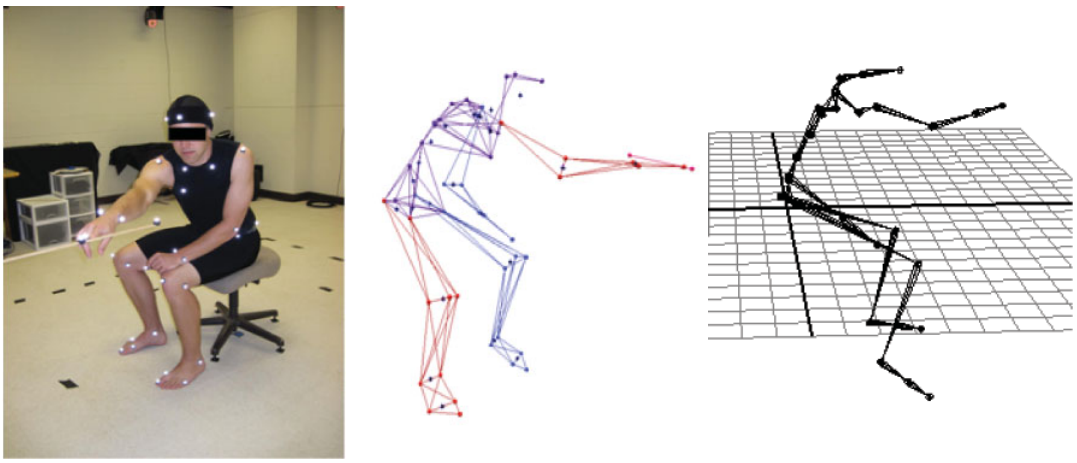
Target	x (cm)	y (cm)	z (cm)
1	10.26	−13.71	77.61
2	9.5	−14.89	74.72
3	7.61	29	77.63
4	7.61	27.85	74.82
5	7.29	88.09	75.85
6	6.9	86.07	71.33
7	61.52	−15.58	72.97
8	60.8	−16.07	71.17
9	56.17	27.06	73.65
10	55.23	25.7	70.92
11	54.84	87.12	72.27
12	53.54	84.88	66.61
13	−45.8	−13.1	77.5
14	−45.32	−14.54	73.83
15	−46.12	28.63	76.77
16	−45.69	26.98	73.32
17	−45.86	87.77	76.38
18	−46.07	84.5	68.99

Table III. Tasks for Subject 3.

Target	x (cm)	y (cm)	z (cm)
1	3.22	−10.35	72.93
2	3	−10.68	69.85
3	3.12	33.25	75.18
4	2.94	32.61	72.01
5	4.83	89.4	65.76
6	4.61	88.47	63.89
7	56.89	−11.31	66.9
8	56.59	−11.14	65.41
9	56.85	32.34	69.56
10	56.46	31.57	65.85
11	39.74	76.83	59.65
12	39.86	76.59	59.58
13	−50.78	−10.8	70.37
14	−50.73	−10.77	67.11
15	−51.13	32.72	70.93
16	−50.18	32.14	67.03
17	−40	81.88	61.46
18	−40.92	81.83	60.11

Table IV. Tasks for Subject 4.

Target	x (cm)	y (cm)	z (cm)
1	3.29	−12.72	74.4
2	2.65	−13.64	68.13
3	3.87	31.63	78.59
4	4.17	29.9	70.45
5	5.01	90.09	69.15
6	6.06	89.9	67.29
7	52	−14.01	77.35
8	50.35	−14.56	71.94
9	15.72	50.18	60.56
10	15.59	50.05	59.56
11	−49.12	−12.58	77.33
12	−47.85	−13.48	69.41
13	−45.48	31.72	78.34
14	−43.58	29.93	68.9
15	−45.48	31.72	78.34
16	−43.58	29.93	68.9
17	−40.89	86.15	64.95
18	−42.74	86.54	63.43



(a) (b) (c)

Fig. 6. (Colour online) Posture for Subject 2—Task 8: (a) subject picture, (b) motion capture posture, and (c) posture reconstruction.

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Table V. Obtained weights for Subject 1.

	Target 1	Target 2	Target 3	Target 4	Target 5	Target 6	Target 7	Target 8	Target 9	Target 10	Target 11	Target 12	Target 13	Target 14	Target 15	Target 16	Target 17	Target 18
$w1$	0.095138	0.095138	0.10621	0.094938	0.094938	0.095138	0.107311	0.095138	0.099487	0.105737	0.095138	0.099364	0.113326	0.113326	0.113993	0.113486	0.113283	0.095138
$w2$	0.080178	0.093493	0.047619	0.093226	0.093873	0.093426	0.047619	0.093615	0.047619	0.047619	0.093026	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619	0.093059
$w3$	0.095238	0.095238	0.10631	0.094838	0.094838	0.095238	0.107411	0.095238	0.099587	0.105837	0.095238	0.099464	0.113426	0.113426	0.11409	0.113586	0.113383	0.095238
$w4$	0.047519	0.047519	0.053055	0.047519	0.047519	0.047519	0.053606	0.047519	0.049693	0.052819	0.047519	0.049632	0.056613	0.056613	0.056946	0.056693	0.056591	0.047519
$w5$	0.040139	0.046796	0.02376	0.046663	0.046949	0.046763	0.02376	0.046858	0.02376	0.02376	0.046563	0.02376	0.023759	0.023759	0.023759	0.023759	0.02386	0.04658
$w6$	0.047419	0.047419	0.052955	0.047619	0.047419	0.047419	0.053506	0.047419	0.049793	0.052919	0.047619	0.049732	0.056713	0.056713	0.05685	0.056793	0.056691	0.047619
$w7$	0.047619	0.047619	0.053155	0.047619	0.047619	0.047619	0.053706	0.047619	0.049793	0.052919	0.047619	0.049732	0.056713	0.056713	0.056972	0.056793	0.056691	0.047619
$w8$	0.040206	0.046896	0.02386	0.046763	0.047031	0.046863	0.02386	0.046758	0.02366	0.02366	0.046663	0.02366	0.02366	0.02366	0.023682	0.02366	0.02396	0.04668
$w9$	0.047319	0.047319	0.053055	0.047719	0.047319	0.047319	0.053406	0.047319	0.049893	0.053019	0.047719	0.049832	0.056813	0.056813	0.05675	0.056893	0.056791	0.047719
$w10$	0.047619	0.047619	0.053155	0.047619	0.047619	0.047619	0.053706	0.047619	0.049793	0.052919	0.047619	0.049732	0.056713	0.056713	0.056936	0.056793	0.056691	0.047619
$w11$	0.040239	0.046896	0.02386	0.046763	0.046975	0.046863	0.02366	0.046958	0.02366	0.02366	0.046663	0.02386	0.02386	0.023859	0.023821	0.023659	0.02396	0.04668
$w12$	0.047519	0.047519	0.052855	0.047719	0.047319	0.047519	0.053406	0.047519	0.049893	0.053019	0.047719	0.049832	0.056813	0.056813	0.056774	0.056893	0.056791	0.047719
$w13$	0.047619	0.047619	0.053155	0.047619	0.047619	0.047619	0.053706	0.047619	0.049793	0.052919	0.047619	0.049732	0.056713	0.056713	0.056872	0.056793	0.056691	0.047619
$w14$	0.040237	0.046896	0.02366	0.046763	0.047049	0.046863	0.02366	0.046891	0.02366	0.023859	0.046663	0.02386	0.02386	0.023859	0.023836	0.02386	0.02396	0.04668
$w15$	0.047419	0.047219	0.053155	0.047819	0.047219	0.047419	0.053306	0.047219	0.049993	0.053119	0.047819	0.049932	0.056913	0.056913	0.05665	0.056993	0.056884	0.047819
$w16$	0.00184	0.00184	0.008744	0.00184	0.00184	0.00184	0.00184	0.00184	0.059874	0.06	0.00184	0.06	0.00184	0.00184	0.00184	0.00184	0.00184	0.00184
$w17$	0.040451	0.000576	0.047619	0.000576	0.000576	0.000576	0.047619	0.000576	0.047619	0.000576	0.000576	0.047619	0.000576	0.000576	0.000576	0.000576	0.000576	0.000576
$w18$	0.000576	0.000576	0.000764	0.000576	0.000576	0.000576	0.000576	0.000576	0.000676	0.000576	0.000576	0.000676	0.000676	0.000676	0.000611	0.000676	0.000606	0.000576
$w19$	0.000576	0.000576	0.000864	0.000576	0.000576	0.000576	0.000676	0.000576	0.000776	0.000576	0.000576	0.000576	0.000576	0.000576	0.000576	0.000576	0.000576	0.000576
$w20$	0.000576	0.000576	0.000864	0.000576	0.000576	0.000576	0.000676	0.000576	0.000576	0.000676	0.000576	0.000576	0.000776	0.000776	0.00058	0.000576	0.000576	0.000576
$w21$	0.000593	0.000593	0.000664	0.000593	0.000593	0.000593	0.000671	0.000593	0.000622	0.000659	0.000593	0.000619	0.000706	0.000706	0.000711	0.000707	0.000706	0.000593
$w22$	0.047619	0.047619	0.053155	0.047619	0.047619	0.047619	0.053706	0.047619	0.049593	0.052719	0.047619	0.049732	0.056713	0.056713	0.056846	0.056593	0.056691	0.047619
$w23$	0.047719	0.047719	0.053255	0.047719	0.047719	0.047719	0.053806	0.047619	0.049693	0.052819	0.047719	0.049632	0.056813	0.056813	0.05675	0.056693	0.056791	0.047619
$w24$	0.047623	0.047719	0.053255	0.047719	0.047619	0.047719	0.053806	0.047719	0.049493	0.052619	0.047719	0.049832	0.056813	0.056813	0.056746	0.056493	0.056791	0.047719

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Table VI. Obtained weights for Subject 2.

	Target 1	Target 2	Target 3	Target 4	Target 5	Target 6	Target 7	Target 8	Target 9	Target 10	Target 11	Target 12	Target 13	Target 14	Target 15	Target 16	Target 17	Target 18
$w1$	0.110341	0.095138	0.106411	0.095138	0.095138	0.095138	0.099011	0.095138	0.101565	0.094938	0.099416	0.103272	0.107138	0.095138	0.095138	0.095138	0.095138	0.094938
$w2$	0.055921	0.073873	0.065118	0.093283	0.093029	0.073873	0.083975	0.093517	0.047619	0.08024	0.047619	0.047619	0.047619	0.073839	0.093039	0.073806	0.093393	0.073823
$w3$	0.110255	0.095238	0.106511	0.095238	0.095238	0.095238	0.099111	0.095133	0.101652	0.095038	0.099516	0.103372	0.107238	0.095238	0.095238	0.095238	0.095238	0.095038
$w4$	0.05516	0.047519	0.053227	0.047519	0.047519	0.047519	0.049455	0.047519	0.050805	0.047519	0.049658	0.051686	0.053519	0.047519	0.047519	0.047519	0.047519	0.047519
$w5$	0.02791	0.036886	0.032558	0.046691	0.046565	0.036886	0.042019	0.046808	0.02386	0.04017	0.02376	0.02376	0.02386	0.03687	0.04657	0.036853	0.046746	0.036861
$w6$	0.05526	0.047619	0.053233	0.047478	0.047619	0.047619	0.049355	0.047419	0.050747	0.047619	0.049558	0.051586	0.053419	0.047619	0.047619	0.047619	0.047419	0.047619
$w7$	0.05526	0.047619	0.053327	0.047619	0.047619	0.047619	0.049555	0.047619	0.050747	0.047619	0.049758	0.051786	0.053619	0.047619	0.047619	0.047619	0.047619	0.047619
$w8$	0.027814	0.036786	0.032464	0.046791	0.046665	0.036986	0.041973	0.04682	0.02396	0.04007	0.023726	0.02386	0.023959	0.03677	0.04663	0.036953	0.046846	0.036961
$w9$	0.05536	0.047719	0.053142	0.047534	0.047719	0.047719	0.049255	0.04743	0.050833	0.047719	0.049658	0.051486	0.053519	0.047719	0.047719	0.047719	0.047319	0.047719
$w10$	0.055113	0.047619	0.053327	0.047619	0.047619	0.047619	0.049555	0.047619	0.05076	0.047619	0.049758	0.051786	0.053619	0.047619	0.047619	0.047619	0.047619	0.047619
$w11$	0.02783	0.036986	0.032625	0.046791	0.046665	0.036786	0.042119	0.046908	0.02396	0.04007	0.02366	0.02366	0.023959	0.03697	0.04667	0.036953	0.046846	0.036961
$w12$	0.055332	0.047719	0.05314	0.047509	0.047719	0.047719	0.049279	0.047319	0.0507	0.047719	0.049458	0.051686	0.053319	0.047719	0.047719	0.047719	0.047519	0.047719
$w13$	0.055199	0.047619	0.053327	0.047619	0.047619	0.047619	0.049555	0.047619	0.050905	0.047619	0.049758	0.051786	0.053619	0.047619	0.047619	0.047619	0.047619	0.047619
$w14$	0.027877	0.036986	0.032602	0.046791	0.046655	0.036986	0.041999	0.046908	0.02396	0.04027	0.02386	0.023859	0.023959	0.03697	0.04667	0.036953	0.046846	0.036761
$w15$	0.05546	0.047819	0.053087	0.047634	0.047819	0.047819	0.049155	0.04753	0.050933	0.047819	0.049758	0.051386	0.053619	0.047819	0.047819	0.047819	0.047419	0.047819
$w16$	0.00184	0.06	0.00184	0.00184	0.00184	0.06	0.00184	0.00184	0.06	0.029293	0.06	0.06	0.00184	0.06	0.00184	0.06	0.00184	0.06
$w17$	0.000576	0.000576	0.000576	0.000576	0.000576	0.000576	0.000576	0.000576	0.030852	0.011822	0.047619	0.017761	0.047619	0.000576	0.000576	0.000576	0.000576	0.000576
$w18$	0.000588	0.000576	0.000576	0.000576	0.000576	0.000576	0.000576	0.000576	0.000736	0.000695	0.000722	0.000747	0.000576	0.000576	0.000576	0.000576	0.000576	0.000693
$w19$	0.000576	0.000576	0.000576	0.000576	0.000576	0.000576	0.000576	0.000576	0.000836	0.000795	0.000822	0.000847	0.000576	0.000576	0.000576	0.000576	0.000576	0.000793
$w20$	0.000576	0.000576	0.000576	0.000576	0.000576	0.000576	0.000576	0.000576	0.000836	0.000795	0.000822	0.000847	0.000676	0.000576	0.000576	0.000576	0.000676	0.000793
$w21$	0.000688	0.000593	0.000664	0.000593	0.000593	0.000593	0.000617	0.000593	0.000636	0.000595	0.000622	0.000647	0.000668	0.000593	0.000593	0.000593	0.000593	0.000593
$w22$	0.05526	0.047619	0.053327	0.047619	0.047619	0.047619	0.049555	0.047619	0.050705	0.047619	0.049758	0.051786	0.053619	0.047619	0.047619	0.047619	0.047619	0.047619
$w23$	0.05536	0.047719	0.053427	0.04767	0.047719	0.047719	0.049655	0.047619	0.050645	0.047719	0.049858	0.051886	0.053719	0.047719	0.047719	0.047719	0.047719	0.047719
$w24$	0.05516	0.047619	0.053339	0.047719	0.047719	0.047619	0.049655	0.047719	0.05075	0.047619	0.049858	0.051886	0.053719	0.047719	0.047719	0.047619	0.047719	0.047619

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Table VII. Obtained weights for Subject 3.

	Target 1	Target 2	Target 3	Target 4	Target 5	Target 6	Target 7	Target 8	Target 9	Target 10	Target 11	Target 12	Target 13	Target 14	Target 15	Target 16	Target 17	Target 18
$w1$	0.094996	0.095138	0.094938	0.095738	0.094938	0.105651	0.094938	0.099398	0.099425	0.099425	0.099478	0.099292	0.095138	0.095138	0.095138	0.095138	0.094945	0.095138
$w2$	0.084693	0.073606	0.0939	0.091825	0.094626	0.047619	0.093993	0.047619	0.047619	0.047619	0.047619	0.047619	0.093491	0.093026	0.093494	0.074106	0.094391	0.093244
$w3$	0.094973	0.095238	0.094948	0.095838	0.095038	0.105751	0.094838	0.099498	0.099525	0.099525	0.099578	0.099392	0.095238	0.095238	0.095154	0.095238	0.094845	0.095238
$w4$	0.047519	0.047519	0.047519	0.047819	0.047519	0.052776	0.047519	0.049649	0.049662	0.049662	0.049689	0.049596	0.047519	0.047519	0.047519	0.047519	0.047519	0.047519
$w5$	0.042308	0.036853	0.046936	0.045962	0.047263	0.023759	0.046946	0.023759	0.02376	0.02376	0.02376	0.02376	0.046796	0.046563	0.046697	0.037103	0.047154	0.046672
$w6$	0.047419	0.047619	0.047419	0.047919	0.047419	0.052876	0.047419	0.049549	0.049562	0.049562	0.049589	0.049696	0.047419	0.047619	0.047604	0.047419	0.04758	0.047619
$w7$	0.047619	0.047619	0.047619	0.047919	0.047619	0.052876	0.047619	0.049749	0.049762	0.049762	0.049789	0.049696	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619
$w8$	0.042219	0.036953	0.046924	0.046062	0.047163	0.02386	0.047046	0.02386	0.02386	0.02366	0.02386	0.023659	0.046896	0.046663	0.04666	0.037203	0.047102	0.046772
$w9$	0.047519	0.047719	0.047319	0.048019	0.047319	0.052976	0.047319	0.049649	0.049662	0.049662	0.049489	0.049796	0.047319	0.047719	0.047507	0.047319	0.047574	0.047519
$w10$	0.047619	0.047619	0.047619	0.047919	0.047619	0.052876	0.047619	0.049749	0.049762	0.049762	0.049789	0.049696	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619
$w11$	0.042218	0.036953	0.046988	0.046062	0.047163	0.02366	0.046846	0.02386	0.02386	0.023859	0.02366	0.023859	0.046896	0.046663	0.046797	0.037203	0.047254	0.046772
$w12$	0.047319	0.047719	0.047319	0.047819	0.047519	0.052776	0.047319	0.049449	0.049462	0.049462	0.049489	0.049596	0.047519	0.047719	0.047704	0.047319	0.047555	0.047719
$w13$	0.047619	0.047619	0.047619	0.047919	0.047619	0.052876	0.047619	0.049749	0.049762	0.049762	0.049789	0.049696	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619
$w14$	0.042408	0.036953	0.047036	0.046062	0.047163	0.02386	0.046846	0.02366	0.02366	0.02366	0.02366	0.02386	0.046817	0.046663	0.046797	0.037203	0.047054	0.046762
$w15$	0.047619	0.047819	0.047243	0.048119	0.047419	0.053076	0.047219	0.049749	0.049762	0.049762	0.049589	0.049896	0.047302	0.047819	0.047407	0.047419	0.047474	0.047419
$w16$	0.029011	0.06	0.00184	0.00184	0.00184	0.06	0.00184	0.06	0.06	0.06	0.06	0.06	0.00184	0.00184	0.001842	0.06	0.00184	0.00184
$w17$	0.000576	0.000576	0.000576	0.000576	0.000576	0.000576	0.000576	0.047619	0.047619	0.047619	0.047619	0.047619	0.000576	0.000576	0.000576	0.000576	0.000576	0.000576
$w18$	0.000576	0.000676	0.000576	0.000676	0.000576	0.000758	0.000576	0.000722	0.000722	0.000722	0.000722	0.000721	0.000576	0.000576	0.000576	0.000576	0.000576	0.000576
$w19$	0.000576	0.000576	0.000576	0.000776	0.000576	0.000858	0.000676	0.000822	0.000622	0.000822	0.000822	0.000821	0.000576	0.000576	0.000576	0.000576	0.000576	0.000576
$w20$	0.000576	0.000576	0.000576	0.000576	0.000576	0.000858	0.000576	0.000822	0.000822	0.000822	0.000822	0.000821	0.000576	0.000576	0.000576	0.000576	0.000576	0.000576
$w21$	0.000593	0.000593	0.000593	0.000596	0.000593	0.000658	0.000593	0.000622	0.000622	0.000622	0.000622	0.000621	0.000593	0.000593	0.000593	0.000593	0.000593	0.000593
$w22$	0.047619	0.047619	0.047619	0.047719	0.047619	0.052676	0.047619	0.049749	0.049762	0.049762	0.049789	0.049696	0.047619	0.047619	0.047619	0.047619	0.047619	0.047619
$w23$	0.047719	0.047719	0.047619	0.047619	0.047619	0.052776	0.047719	0.049849	0.049862	0.049862	0.049889	0.049796	0.047719	0.047719	0.047651	0.047719	0.047619	0.047719
$w24$	0.047687	0.047719	0.04768	0.047619	0.047619	0.052576	0.047719	0.049849	0.049862	0.049862	0.049889	0.049796	0.047719	0.047719	0.047656	0.047719	0.047719	0.047674

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Table VIII. Obtained weights for Subject 4.

	Target 1	Target 2	Target 3	Target 4	Target 5	Target 6	Target 7	Target 8	Target 9	Target 10	Target 11	Target 12	Target 13	Target 14	Target 15	Target 16	Target 17	Target 18
$w1$	0.095138	0.095138	0.099257	0.095138	0.099451	0.095138	0.094938	0.099577	0.09947	0.113635	0.09494	0.0951	0.113371	0.095138	0.106146	0.095138	0.09503	0.09495
$w2$	0.07795	0.093426	0.047619	0.093293	0.047619	0.093814	0.093728	0.047619	0.047619	0.047619	0.09463	0.09364	0.047619	0.073839	0.065628	0.093093	0.08409	0.09459
$w3$	0.095238	0.095238	0.099157	0.095238	0.099551	0.095238	0.094838	0.099677	0.09957	0.11354	0.09484	0.095	0.113471	0.095238	0.106246	0.095238	0.09512	0.09505
$w4$	0.047519	0.047519	0.049678	0.047519	0.049676	0.047519	0.047519	0.049738	0.049685	0.056868	0.04752	0.04752	0.056635	0.047519	0.05306	0.047519	0.04752	0.04752
$w5$	0.038925	0.046763	0.023759	0.046596	0.02376	0.046857	0.046914	0.02376	0.02376	0.02386	0.04736	0.04687	0.023759	0.03687	0.032859	0.046596	0.04206	0.04724
$w6$	0.047419	0.047419	0.049778	0.047619	0.049576	0.047419	0.047419	0.049638	0.049785	0.056967	0.04742	0.04742	0.056735	0.047619	0.053123	0.047619	0.04742	0.04742
$w7$	0.047619	0.047619	0.049778	0.047619	0.049776	0.047619	0.047619	0.049838	0.049785	0.056967	0.04762	0.04762	0.056735	0.047619	0.05316	0.047619	0.04762	0.04762
$w8$	0.038825	0.046663	0.023859	0.046496	0.02386	0.046757	0.047014	0.02386	0.02366	0.02376	0.04746	0.04691	0.02366	0.03697	0.0328	0.046696	0.04215	0.04714
$w9$	0.047519	0.047519	0.049878	0.047719	0.049676	0.047319	0.047319	0.049738	0.049885	0.056868	0.04732	0.04732	0.056835	0.047719	0.053212	0.047719	0.04747	0.04732
$w10$	0.047619	0.047619	0.049778	0.047619	0.049776	0.047619	0.047619	0.049838	0.049785	0.056967	0.04762	0.04762	0.056735	0.047619	0.05316	0.047619	0.04762	0.04762
$w11$	0.038894	0.046863	0.023659	0.046696	0.02366	0.046757	0.047014	0.02386	0.023659	0.023759	0.04726	0.04697	0.02366	0.03697	0.032792	0.046696	0.04215	0.04734
$w12$	0.047319	0.047319	0.049878	0.047719	0.049476	0.047519	0.047319	0.049538	0.049885	0.057067	0.04732	0.04732	0.056835	0.047719	0.053092	0.047719	0.04747	0.04732
$w13$	0.047619	0.047619	0.049778	0.047619	0.049776	0.047619	0.047619	0.049838	0.049785	0.056967	0.04762	0.04762	0.056735	0.047619	0.053157	0.047619	0.04762	0.04762
$w14$	0.039025	0.046863	0.023662	0.046696	0.02386	0.046957	0.047011	0.02366	0.02366	0.02376	0.04726	0.04697	0.02386	0.03677	0.032959	0.046696	0.04214	0.04714
$w15$	0.047619	0.047619	0.049978	0.047819	0.049776	0.047219	0.047219	0.049838	0.049985	0.056768	0.04722	0.04742	0.056935	0.047819	0.053265	0.047819	0.04753	0.04742
$w16$	0.00184	0.00184	0.06	0.00184	0.06	0.001877	0.00184	0.06	0.06	0.00184	0.00184	0.00184	0.00184	0.06	0.00184	0.00184	0.0307	0.00184
$w17$	0.047619	0.000576	0.047619	0.000576	0.047619	0.000576	0.000576	0.047619	0.047619	0.000576	0.00058	0.00058	0.000576	0.000576	0.000576	0.000576	0.00058	0.00058
$w18$	0.000576	0.000576	0.000585	0.000576	0.000722	0.000576	0.000673	0.000676	0.000676	0.000692	0.00058	0.00058	0.000607	0.000576	0.000576	0.000576	0.00058	0.00058
$w19$	0.000576	0.000576	0.000685	0.000576	0.000822	0.000576	0.000576	0.000576	0.000776	0.000792	0.00058	0.00058	0.000576	0.000576	0.000576	0.000576	0.00058	0.00058
$w20$	0.000576	0.000576	0.000685	0.000576	0.000622	0.000576	0.000576	0.000576	0.000576	0.000594	0.00058	0.00058	0.000707	0.000576	0.000576	0.000576	0.00058	0.00058
$w21$	0.000593	0.000593	0.000622	0.000593	0.000622	0.000593	0.000593	0.00062	0.000622	0.00071	0.00059	0.00059	0.000707	0.000593	0.000662	0.000593	0.00059	0.00059
$w22$	0.047619	0.047619	0.049768	0.047619	0.049776	0.047619	0.047619	0.049638	0.049585	0.056808	0.04762	0.04762	0.056735	0.047619	0.05316	0.047619	0.04762	0.04762
$w23$	0.047634	0.047719	0.049868	0.047619	0.049876	0.047619	0.047719	0.049738	0.049685	0.056908	0.04762	0.04772	0.056835	0.047719	0.053192	0.047619	0.04766	0.04772
$w24$	0.047719	0.047719	0.049668	0.047619	0.049676	0.047619	0.047719	0.049538	0.049485	0.056708	0.04762	0.04762	0.056835	0.047719	0.053183	0.047619	0.04765	0.04762

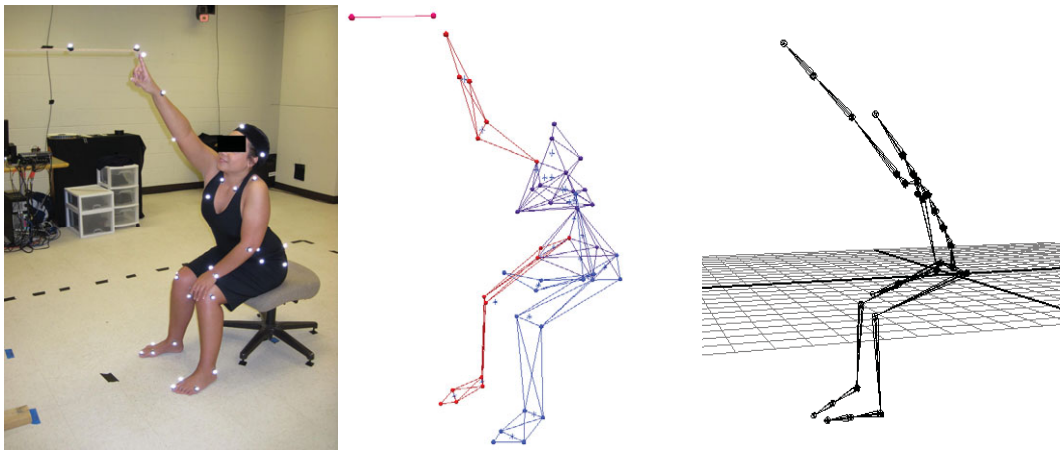
Table IX. The global weights for all subjects and all tasks.

	Subject1-Average	Subject2-Average	Subject3-Average	Subject4-Average	Global Weights	Standard Deviation
$w1$	0.102568167	0.098515111	0.096888333	0.098704889	0.099169125	0.002408232
$w2$	0.067227	0.072844722	0.075561611	0.074301333	0.072483667	0.003676074
$w3$	0.102645778	0.098598222	0.096949611	0.098748944	0.099235639	0.002415101
$w4$	0.051245167	0.049234389	0.048420111	0.049336056	0.049558931	0.001196565
$w5$	0.0336115	0.036424056	0.037767278	0.037143167	0.0362365	0.001834042
$w6$	0.0512565	0.049245889	0.048406	0.049322833	0.049557806	0.001206196
$w7$	0.051341056	0.049325611	0.048520111	0.049436	0.049655695	0.001195438
$w8$	0.033621222	0.036446333	0.037801222	0.037141167	0.036252486	0.001839335
$w9$	0.051278722	0.049293778	0.048411389	0.049353111	0.04958425	0.001208944
$w10$	0.051339056	0.049318167	0.048520111	0.049436	0.049653334	0.001195188
$w11$	0.033660889	0.036467722	0.037809611	0.037147944	0.036271542	0.001824622
$w12$	0.051313389	0.0492785	0.048376833	0.049324056	0.049573195	0.001239418
$w13$	0.0513355	0.049331	0.048520111	0.049435833	0.049655611	0.001192345
$w14$	0.033673111	0.036495111	0.037784667	0.037164167	0.036279264	0.001815481
$w15$	0.051322778	0.049362944	0.048450667	0.0494035	0.049634972	0.001208145
$w16$	0.011909889	0.029214056	0.0291985	0.019600722	0.022480792	0.008376619
$w17$	0.013245278	0.0090645	0.0136435	0.0136435	0.012399195	0.002231041
$w18$	0.000617833	0.000616278	0.000637722	0.000609278	0.000620278	1.22103E-05
$w19$	0.000608667	0.000643389	0.0006655	0.000618833	0.000634097	2.55092E-05
$w20$	0.000625556	0.0006545	0.000659944	0.000592889	0.000633222	3.08347E-05
$w21$	0.000639722	0.000614833	0.000604778	0.000616	0.000618833	1.4809E-05
$w22$	0.051300722	0.049323278	0.048497889	0.049404389	0.04963157	0.001185743
$w23$	0.051367611	0.049406111	0.048566333	0.049470389	0.049702611	0.001183947
$w24$	0.051345389	0.049376444	0.048560167	0.049407111	0.049672278	0.00118236

to prevent blocking the markers. A simple target apparatus was developed, where the height of the target points is adjustable (Fig. 3). There are a total of 18 target points (tasks) and three different height levels (high, medium, low). On each level, there are also three different target points: left, middle, and right. In addition, there are two set of target points: closer and further ones to the subject. The tasks are marked as 1 through 18. Note that for each subject, due to the anthropometric variation, each subject can adjust chair position to reach these target points comfortably. The global coordinate defined in Fig. 1 is located in the middle point of the hip joints of the subject. Therefore, the target points for each subject are different although they have the same tasks.

5.2. *Subject selection*

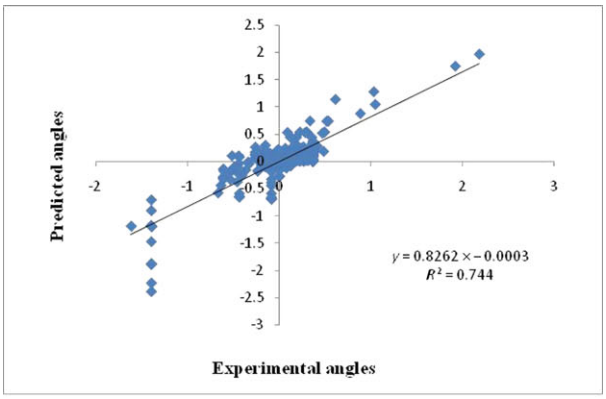
To consider different populations for posture prediction, one subject is selected from each of the populations (in stature):[44] 5th percentile female, 50th percentile female, 50th percentile male, and 95th percentile male. Within each population, one subject is selected to reduce the data processing time and cost. Therefore, the total number of subjects is 4. The average height was 170.1 (SD 11) cm and the average mass was 71.2 (SD 12) kg. They were well distributed between the ages of 21 and 34 years. All participants gave informed consent prior to the study. Subject 1 is the 50th percentile male, Subject 2 is the 95th percentile male, Subject 3 is the 5th percentile female, and Subject 4 is the 50th percentile female.



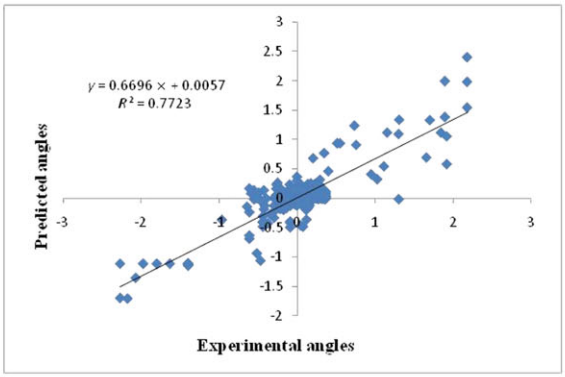
(a) (b) (c)

Fig. 7. (Colour online) Posture for Subject 3—Task 5: (a) subject picture, (b) motion capture posture, and (c) posture reconstruction.

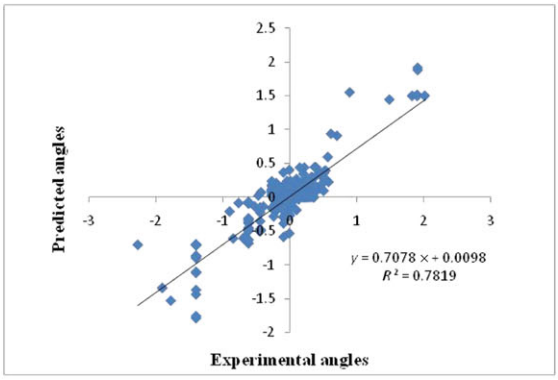
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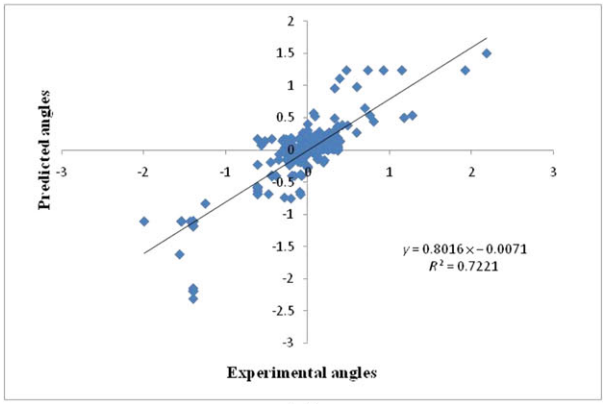
(a)



(b)



(c)



(d)

Fig. 8. (Colour online) Regression plot for each subject with the global weights: (a) experimental and predicted postures for Subject 1, (b) experimental and predicted postures for Subject 2, (c) Experimental and predicted postures for Subject 3, and (d) experimental and predicted postures for Subject 4.

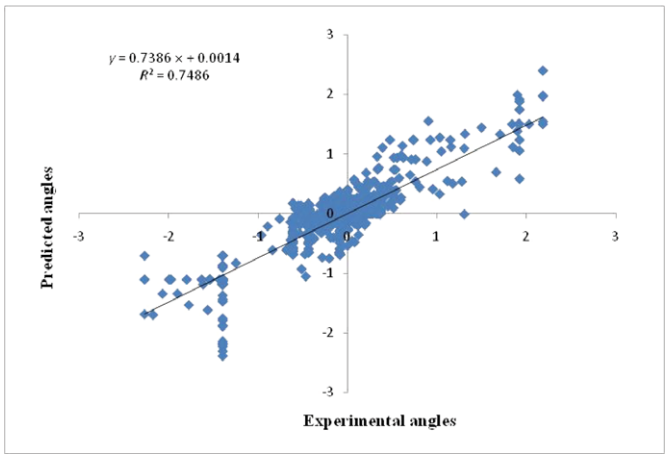


Fig. 9. (Colour online) Regression plot for all subject together with the global weights.

5.3. Data collection and experimental protocols

There are many techniques and devices on the market for measuring three-dimensional motion data. Examples include electromagnetic sensors, optical sensors, fiber-optic-based sensors, and inertia sensors. One system, which is both effective and efficient at collecting objective data for 3D motion analysis, is to use optical motion capture systems. Currently, the optical systems have many applications in biomechanical studies.[16,34] These systems have been shown to be accurate, repeatable, and consistent,[31] and, as an additional benefit, there is no pain or risk involved in using such systems. In the motion capturing process, a number of reflective markers are attached over bony landmarks on the participant's body, such as the elbow, the clavicle, or the vertebral spinous processes. As the participant walks or carries out a given physical task or function, a history of each marker's position is recorded using an array of infrared cameras.

An eight Eagle-4 camera systems (Motion Analysis®) was used to collect data. The cameras used in this system have a 4 megapixel resolution, a shutter speed from 0-2000 μs, a focal length ranging from 18 to 52 mm, and a maximum of 500 frames per second in up to a 4.5 m × 4.5 m envelope.

Several marker placement protocols have been introduced in the literature for studying various types of motion.[39] Among these protocols, plug-in gait is a typical protocol that has been adopted by systems, such as Motion Analysis, VICON, and LifeMOD. In the plug-in gait protocol, markers are attached to bony landmarks on the subject's body to establish local coordinate systems on various segments of the body. Joint centers can then be defined as virtual markers. In this research work, the marker placement protocol was designed to facilitate the process of obtaining the location of the joint centers of the whole body. In the marker placement protocol, one marker was attached to the end-effector, such as the end of the index finger. The detailed protocol is shown in Fig. 4. In all cases, the joint center location was estimated by the intersection of the lines connecting the markers on each joint. After obtaining the various joint centers, a transformation analysis was used to calculate the

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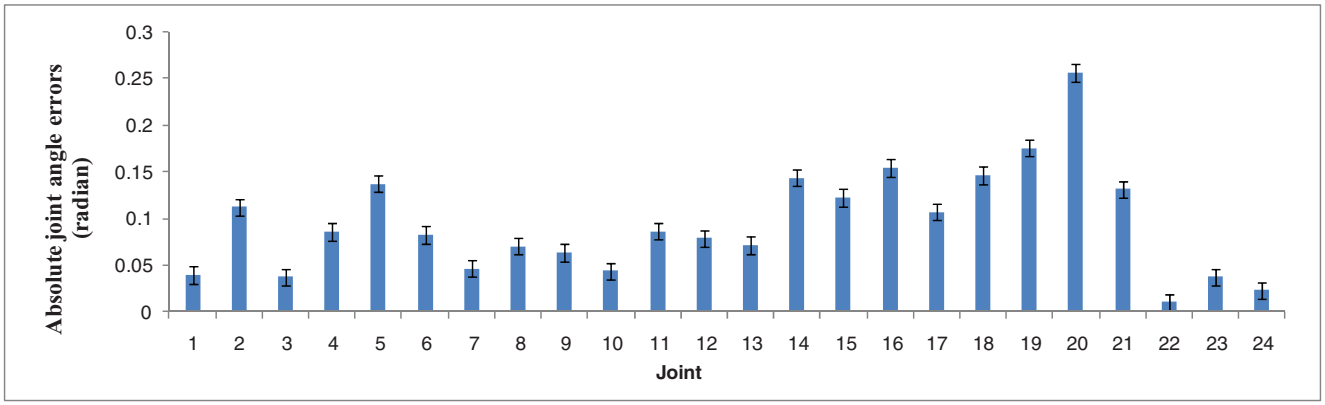


Fig. 10. (Colour online) Mean values and SD of the absolute joint angle errors for all tasks and all subjects.

location of each joint center with respect to the human global coordinate system. Total number of markers on subject body is 48, including two additional markers for the Target points.

6. Posture Reconstruction

Experimental data obtained through motion capture are the joint center locations (x, y, and z with respect to the global coordinate system). However, in simulation, posture is represented by the joint angles. This is called the mapping from Cartesian space to joint space or posture reconstruction.[13] The motion capture software has the capability to transfer Cartesian space to joint space; however, the error is large, so an alternative method is used and presented in this section.

The idea behind posture reconstruction is the same as posture prediction, but more end-effectors are used. In the previous posture prediction simulations, only the human's natural end-effectors (hands, feet, and head) are prescribed to a certain point in Cartesian space. All the joint centers, except for the end-effector joint centers, are free. In the posture reconstruction simulation, every joint center that represents the position of a physical joint in the human body is prescribed to some point in Cartesian space. Joints like the shoulders, clavicles, and elbows are now considered "end-effectors" and thus have an associated distance constraint. Figure 5 shows each of the joints whose position is prescribed.

Overall, there are 23 joint centers that are considered end-effectors. There are 55-DOF for the digital human model, 49 human DOF and 6 global DOF. The objective function in the optimization problem is given as a constant, and the objective gradient for all angles is zero. This means that the optimization problem is only trying to find a feasible solution. If a human performance measure is used, it would be more difficult to find an answer, thus greatly increasing the computational cost of the simulation. The posture reconstruction formulation is defined as follows:

- Find: $\mathbf{x} = [q_1\, q_2\, \cdots\, q_m]$, (7)
- Minimize: $\mathrm{f} = 1$,
- Subject to: $\mathrm{g}_j = (\mathbf{x}_j - \mathbf{TP}_x)^2 + (\mathbf{y}_j - \mathbf{TP}_y)^2 + (\mathbf{z}_j - \mathbf{TP}_z)^2$, $j = 1, \ldots, M$,
  $-\infty \le \mathrm{g}_j \le \varepsilon$,
  $q_i^L \le q_i \le q_i^U$,

where $m = 24$, $M = 9$, and $\varepsilon = .001$ for the 24-DOF upper body model used in this paper. Since the units associated with the simulation are meters, each of the joint centers is required to be within 1 mm of the experimental position of the joint center. Since all of the physical human joint centers' positions are prescribed, the result is a posture that fully recreates the experimental posture. The output of the

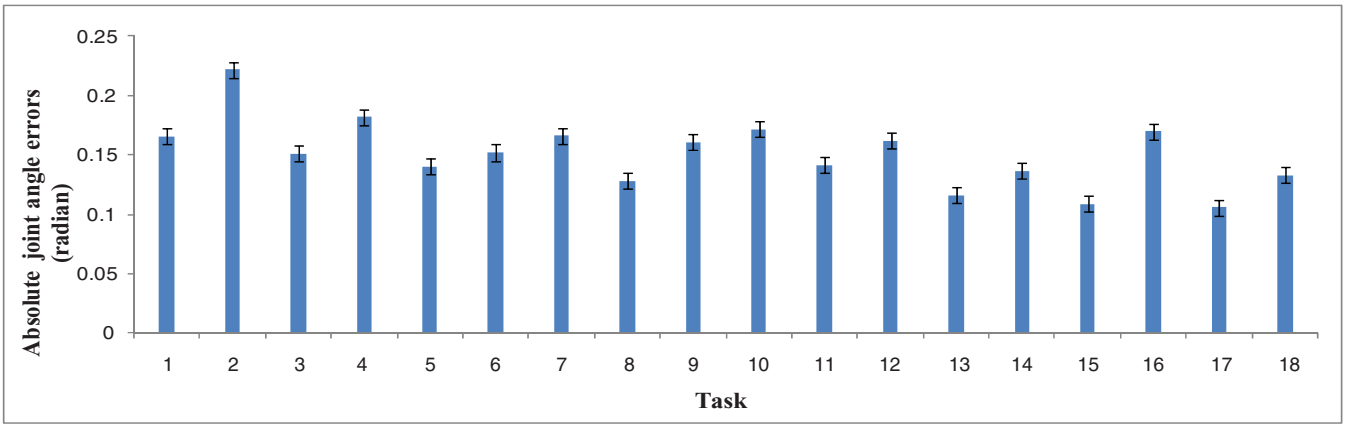
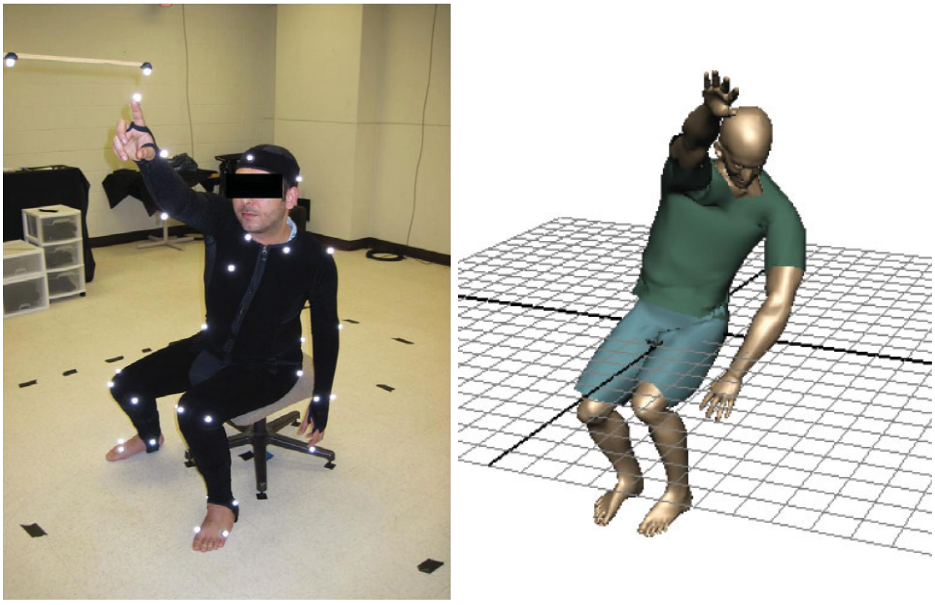
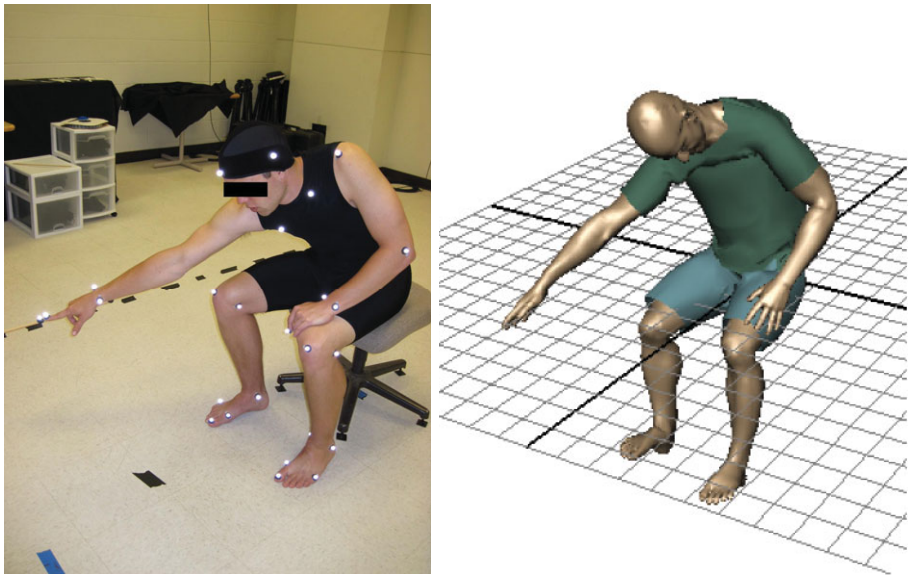


Fig. 11. (Colour online) Mean values and SD the absolute joint angle errors for each task and all subjects.

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(a)



(b)

Fig. 12. (Colour online) Selected postures from experiments and prediction: (a) posture for Subject 1 with Task 11, (b) posture for Subject 2 with Task 14, (c) posture for Subject 3 with Task 3, and (d) posture for Subject 4 with Task 5.

posture reconstruction simulation is the joint angles for the experimental posture.

7. Illustrative Example of the Inverse Optimization Approach

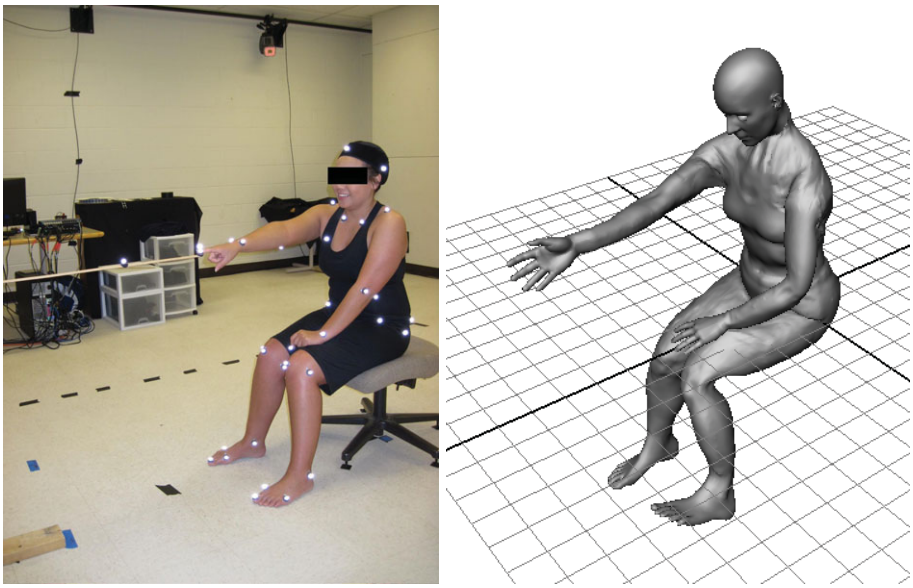
In this paper, subjects were selected and described in Section 5. The Target points for subjects were measured with respect to the global coordinate system in Fig. 1 and shown in Tables I–IV.

By implementing the formulation in Eq. (6), one can determine all weights for each subject per task shown in Table V–VIII.

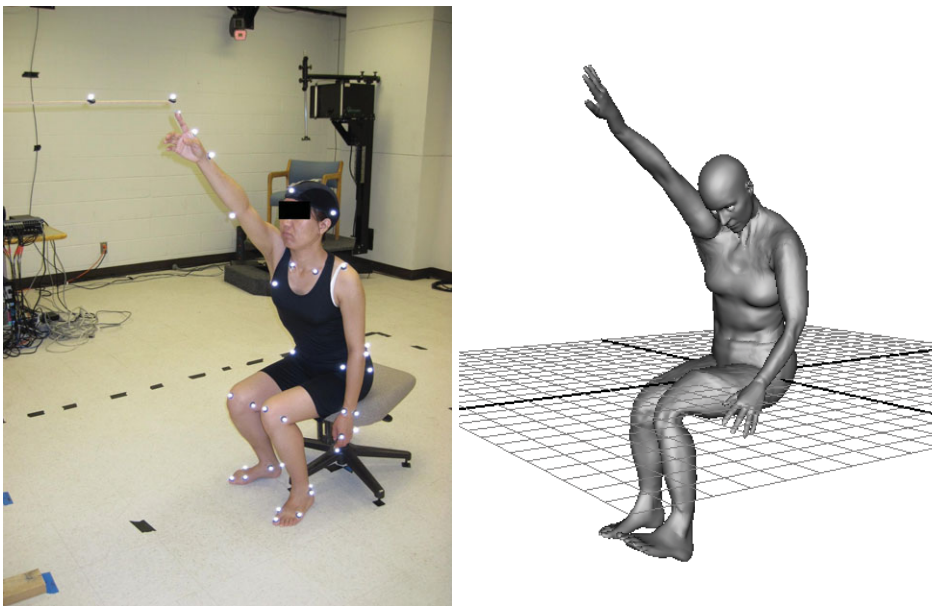
Figures 6 and 7 show two postures for Subject 2 and 3, respectively, from motion capture. Table V shows the obtained weights for Subject 1 for all tasks. It is obvious that the set of weights is different for different tasks for each subject. Table VI shows the results for Subject 2. Note that the weights of the same task are also different for different subjects. The goal of the direct optimization-based method is to have one set of weights for all tasks and all populations. This set of weights is called the global weights. In this work, we propose that the global weights are defined as the average weights (in Table IX) from all subjects and all tasks.

After the global weights are obtained, one can use the DOPP in Eq. (4) to predict postures $\mathbf{q}$ for all subjects

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(c)



(d)

Fig. 12. Continued.

and all tasks. Neutral posture (position) is from Yang *et al.*[46] $q_i^N = 0; i = 1, 2, \ldots, 15, 22, 23$, $q_{16}^N = -0.261792$, $q_{17}^N = 0.349056$, $q_{18}^N = 1.74529$, $q_{19}^N = 0.17453$, $q_{20}^N = -1.39622$, $q_{21}^N = -0.61085$, $q_{24}^N = 0.2617917$. To validate whether the weights obtained by the proposed method are a reasonable choice, it is necessary to compare the experimental postures $\mathbf{q}^*$ with those predicted postures $\mathbf{q}$ from the obtained weights.

Two different approaches are used to compare these postures: linear regression and joint angle difference. Figures 8(a)–8(d) are the linear regressions for Subject 1, Subject 2, Subject 3, and Subject 4, respectively. The horizontal axis denotes experimental postures (joint angles) and the vertical axis represents predicted postures (joint angles) from the DOPP with the global weights obtained by the proposed method in this work (all joint angles are in radians).

From Fig. 8, it is obvious that all R^2 values are greater than 0.7. That means, by using the global weights obtained through the proposed method in this paper, the direct optimization-based posture algorithm can predict reasonably accurate postures. If we plot all joint angles for all subjects together, the result is shown in Fig. 9. The R^2 value is also greater than 0.7.

Figure 10 shows that mean values and standard deviation (SD) of the absolute joint angle errors for all subject and all tasks (all joint angles in radians). The results show that the largest errors occur at the elbow and shoulder joints.

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Figure 11 shows the mean values and SD of the absolute joint angle errors for each task and all subjects. From this figure, the errors for the Target points closer to the subjects are smaller than those of the Target points on the same level but further from the subjects, except Target points 7 and 8.

Figure 12 shows the experimental and predicted postures for selected tasks and selected subject. It is obvious that the predicted postures are similar to the experimental postures. Note that in this formulation, vision function is not considered because only one human performance measure (joint displacement) is used to test the proposed method. However, vision plays an important role.[50] Vision and other human performance measures will be included in the proposed formulation in the future work.

8. Conclusion and Discussion

This paper proposed a systematic methodology to determine the weights of the joint displacement function in the DOPP approach. The problem was formulated as a bi-level optimization problem and then transferred to a regular optimization problem by using Lagrange theory and KKT theory. Additional constraints obtained from observations (knowledge) were added. Four subjects participated in the experiments and 18 tasks for each subject were studied in this work. Experimental and predicted postures were used to demonstrate the accuracy of the proposed formulation and results were compared in terms of joint angle errors (deviations) and linear regression.

Weight limits and weight linear constraints are important information to be considered as extra constraints in the final optimization problem. By deploying this formulation, each task generated different sets of weights. The global weights for the DOPP were obtained by averaging all weights for all tasks and all subjects. In addition, for the final posture prediction, only one neutral posture was selected for all tasks and one set of weights was implemented.

The validation analysis showed that there were some joint angle deviations for the shoulder joints. It is true that current shoulder model is an approximated one and did not consider the contribution of the scapula motion. Developing a new shoulder model is still ongoing.[49]

In this study, four subjects were selected (one from each percentile: 5th percentile female, 50th percentile female, 50th percentile male, and 95th percentile male) to reduce the total experiment cost. One can expect the joint angle deviations should be smaller if this work is extended to include more subjects.

The proposed methodology is useful in the DOPP package).[20,46,48,50] The relative value of the weights associated with each joint that represents the relative importance of that joint can be determined by this systematic method. This will definitely improve the accuracy of the DOPP.

This paper is just a preliminary investigation of the method and results. The method can be improved by modifying the cost function in the original formulation. In addition, when applying KKT theory to transfer bi-level problem to one-level optimization problem, the new formulation may be different from the original bi-level problem. The ad-hoc selection of additional constraints brought more uncertainty to the solution. In this paper, a global set of weights was obtained by averaging weights for all subjects and all tasks. Other method to obtain the global set of weights may be better, such as the summation of the mean and standard deviation. Furthermore, one may suggest to have four sets of weights instead of only one global set of weights: one for left upper zone, one for right upper zone, one for left lower zone, and one for right lower zone.

Future work includes the following: (1) development of a new shoulder model considering joint angle coupling and joint limit coupling, (2) extending this methodology to a general MOO posture prediction problem including other human performance measures, (3) collecting larger number of subjects, (4) other formulation investigation, (5) the bi-level optimization formulation transformation, (6) method of weights from different subjects and tasks, and (7) extending this methodology to motion prediction for digital human models.

Acknowledgments

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