An Alternative Formulation for Determining Weights of Joint Displacement Objective Function in Seated Posture Prediction

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Abstract. The human posture prediction model is one of the most important and fundamental components in digital human models. The direct optimization-based method has recently gained more attention due to its ability to give greater insights, compared to other approaches, as how and why humans assume a certain pose. However, one longstanding problem of this method is how to determine the cost function weights in the optimization formulation. This paper presents an alternative formulation based on our previous inverse optimization approach. The cost function contains two components. The first is the weighted summation of the difference between experimental joint angles and neutral posture, and the second is the weighted summation of the difference between predicted joint angles and the neutral posture. The final objective function is then the difference of these two components. Constraints include (1) normalized weights within limits; (2) an inner optimization problem to solve for the joint angles, where joint displacement is the objective function; (3) the end-effector reaches the target point; and (4) the joint angles are within their limits. Furthermore, weight limits and linear weight constraints determined through observation are implemented. A 24 degree of freedom (DOF) human upper body model is used to study the formulation. An in-house motion capture system is used to obtain the realistic posture. Four different percentiles of subjects are selected and a total of 18 target points are designed for this experiment. The results show that using the new objective function in this alternative formulation can greatly improve the accuracy of the predicted posture.

Keywords: Posture prediction; direct optimization-based posture prediction; digital human.

1 Introduction

Posture prediction is the fundamental utility of digital human models and applied in vehicle interior design and other tasks in product design. Different approaches have

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been proposed in the past decades (Das and Sengupta, 1995; Das and Behara, 1998; Faraway et al., 1999; Kee et al., 1994; Jung and Choe, 1996; Wang and Verriest, 1998; Wang, 1999; Tolani et al., 2000; Byun, 1991; Bean et al., 1998; Park, 1973; Kerk, 1992; Dysart and Woldstad, 1996). Compared to other methods, the direct optimization-based approach attracts a lot of attention from the digital human community because this method has advantages over traditional methods (Yang et al., 2004; Yang et al., 2006; Yang et al., 2007; Mi et al., 2009; Yang et al., 2010; Howard et al., 2010). However, one longstanding issue for this method, that has not yet been completely addressed and studied, is how to determine the relative importance of the different components in the weighted-sum form of the objective function, e.g. joint displacement (Jung et al., 1994; Yang et al., 2004).

Among other methods, such as the consistency ratio method (Saaty, 1977; 1991), the most common way of determining these weights is the trial and error approach, (Yang et al., 2004; Messac and Mattson 2002). Kim and Weck (2004; 2005) and Khan and Ardil (2009) proposed an adaptive weighted-sum method for bi-objective optimization and multi-objective optimization. It focuses on unexplored regions by changing the weights adaptively, rather than by using a priori weight selection. Zhang and Gao (2006) integrated adaptive weightings in a min-max method for optimization. Dong (2008) adopted an orthogonal interactive genetic algorithm to calculate the weights of different factors, which affect posture selection.

In our previous study (Zou et al., 2010), a mathematical model was developed to systematically determine the weights of joint displacement function in posture prediction. This paper presents an alternative formulation to improve the accuracy of the predicted posture.

This paper is organized as follows: Section 2 briefly introduces a digital human model based on the Denavit-Hartenberg method (DH method) (Denavit and Hartenberg, 1955). Section 3 briefly gives the optimization-based posture prediction. Section 4 gives detailed formulation of a bi-level optimization problem. Section 5 discusses the realistic postures for various tasks obtained through experiments. Section 6 illustrates the procedure through examples to demonstrate the efficiency and effectiveness of the proposed method.

2 Upper Body Model

A human's upper body can be modeled as a kinematic system. This system 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, where the hip has 3 DOFs, the spine has 12 DOFs, and the right arm has 9 DOFs. In this study, the left arm is not included. Joint angles are defined as $\mathbf{q} = \begin{bmatrix} q_1 & \cdots & q_{24} \end{bmatrix}^T$. 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 transformation matrices defined by the DH method as

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

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. ${}^{j-1}\mathbf{T}_{j}$ is the transformation matrix.

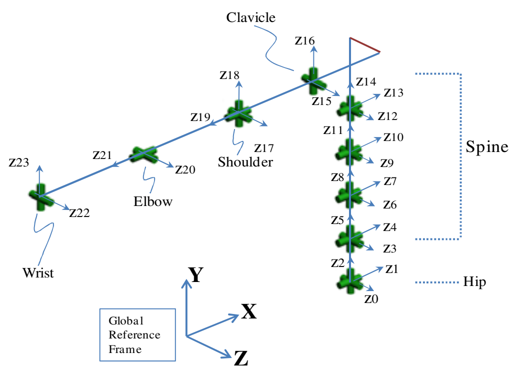


Fig. 1. A 24 DOF human upper body model

In Fig. 1, q_0 through q_2 represent middle of hip joints, q_3 through q_{14} represent the spine, q_{15} through q_{19} represent the shoulder and clavicle, q_{20} through q_{23} represent the right arm.

3 Optimization-Based Posture Prediction

The direct optimization-based posture prediction formulation (Yang et al., 2004) is listed as follows:

Find: Joint angles $\mathbf{q}$

$$\textit{Minimize}:\; f(\mathbf{q}) = \sum w_i \left(\frac{q_i - q_i^N}{q_i^U - q_i^L}\right)^2 \tag{3}$$

$$\textit{Subject to}:\; d^2 = (\mathbf{x} - \mathbf{x}^{\text{Target}})^2 = 0$$

$$q_i^L \le q_i \le q_i^U\,,\; i = 1, \cdots, n$$

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

4 Formulation

The alternative formulation to determine the weights in Eq. (3) is a bi-level optimization problem as follows:

$$Find\text{: } \mathbf{q}\text{, } \mathbf{w}$$

$$Minimize\text{: } \sum_{i=1}^{n} w_i \left(\frac{q_i^* - q_i^N}{q_i^U - q_i^L}\right)^2 - \sum_{i=1}^{n} w_i \left(\frac{q_i - q_i^N}{q_i^U - q_i^L}\right)^2 \tag{4}$$

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

The variable $\mathbf{q}$ is found using the following optimization problem:

$$Find\text{: Joint angles } \mathbf{q}$$

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

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

$$q_i^L \leq q_i \leq q_i^U\text{, } i = 1, \cdots, n\ .$$

To solve the bi-level optimization problem in Eq. (4), one can transfer it to a one level optimization problem by using the Lagrange and KKT theory as follows:

$$Find\text{: } \mathbf{q}\text{, } \mathbf{w}$$

$$Minimize\text{: } \sum_{i=1}^{n} w_i \left(\frac{q_i^* - q_i^N}{q_i^U - q_i^L}\right)^2 - \sum_{i=1}^{n} w_i \left(\frac{q_i - q_i^N}{q_i^U - q_i^L}\right)^2 \tag{5}$$

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

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

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

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

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

λ_i, μ_i, and ν_i are Lagrange multipliers and $f_i(q) = \left(\frac{q_i - q_i^N}{q_i^U - q_i^L}\right)^2$.

$$w_i^L \leq w_i \leq w_i^U\ ,\ w_1 = w_3 = 2w_4\ ,\ w_2 = 2w_5\ ,\ w_4 = w_7 = w_{10} = w_{13} = 80w_{21}$$

$$w_5 = w_8 = w_{11} = w_{14}\ ,\ w_6 = w_9 = w_{12} = w_{15} = w_4\ ,\ w_{22} = w_{23} = w_{24} = w_4$$

$$w_{18} = w_{19} = w_{20} = w_{21}\ .$$

Where q* is the realistic posture (given).

The original formulation (Zou et al., 2010) is defined as follows:

$$Find\text{: } \mathbf{q}\text{, } \mathbf{w}$$

$$Minimize: \sum_{i=1}^{n} w_i \left(\frac{q_i - q_i^*}{q_i^U - q_i^L}\right)^2 \tag{6}$$

Subject to: All constraints same as in Eq. (5)

5 Realistic Postures from Motion Capture

Realistic postures are obtained through motion capture experiments. In the experiments, the target points (tasks) are as in Fig. 2. There are 18 target points, which are set in three different heights (high, medium, and low) with six different target points at each height. The six different target points at each height level are set at three different orientations (right, center, and left) with three points closer to the subject (marked by odd numbers) and three points further away from the subject (marked by even numbers).

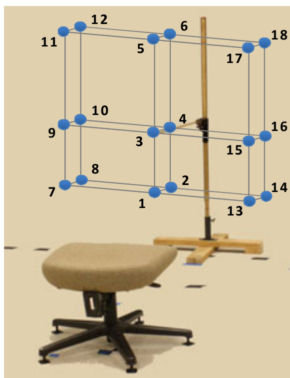


Fig. 2. Experimental setup

Four subjects were used. The average height was 170.1 (SD 11) cm and the average mass was 71.2 (SD 12) kg. They were between the ages of 21 and 34 years. All participants gave informed consent prior to the study. Subject 1 is the 50% male, Subject 2 is the 95% male, Subject 3 is the 5% female, and Subject 4 is the 50% female. These percentiles are by stature.

In the experiment, the optical motion capture system (Motion Analysis®) is used to collect objective data for 3D motion analysis. This system includes eight Eagle-4 cameras. The cameras have a 4 megapixel resolution, a shutter speed from 0-2000 μs, a focal length ranging from 18 mm to 52 mm, and a maximum of 500 frames per second in up to a 10ftx10ft envelope. In our experiments, the frame rate was set to 120 frames per second.

The marker protocol we used for the motion analysis system is the plug-in gait marker protocol. In all cases, the joint center location for each joint 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 location of each joint center with respect to the human global coordinate system.

The experimental data, recorded from the motion capture system, are the joint center locations (x, y, and z with respect to the global coordinate system). In order to obtain the joint angles from the joint center data, a posture reconstruction model has been used (Gragg, et al., 2011).

6 Illustrative Example

In this paper, we use the same subjects and target points (tasks) as those in Zou et al. (2010). By implementing the formulation in Eq. (5), one can determine all weights for each subject for each task.

The goal of the direct optimization-based method is to have one set of weights for all tasks and all populations. We call this set of weights the global weights. In this work, we propose that the global weights are defined as the average weights from all subjects and all tasks in Table 1.

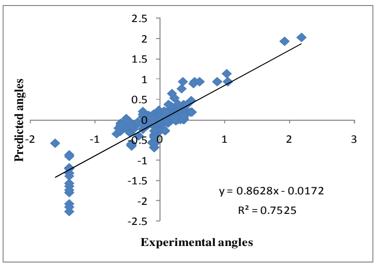
After the global weights are obtained, we use the direct optimization-based posture prediction in Eq. (3) to predict postures $\mathbf{q}$ for all subjects and all tasks. Note that the neutral posture (position) is from Yang et al. (2004): $q_i^N = 0; i = 1, 2, ..., 15, 22, 23$, $q_{16}^N = \text{-}0.261792$, $q_{17}^N = 0.349056$, $q_{18}^N = 1.74529$, $q_{19}^N = 0.17453$, $q_{20}^N = \text{-}1.39622$, $q_{21}^N = \text{-}0.61085$, $q_{24}^N = 0.2617917$. To validate whether the weights obtained by the proposed method are plausible, we need to compare the experimental postures $\mathbf{q}^*$ with those predicted postures $\mathbf{q}$ from the obtained weights.

Table 1. The global weights for all subjects and all tasks

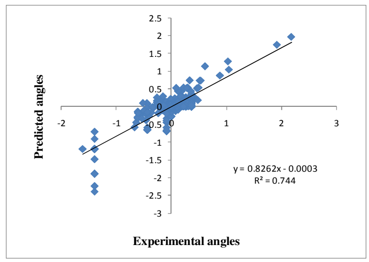
	Subject 1-Average	Subject 2-Average	Subject 3-Average	Subject 4 - Average	Global Weights	Standard Deviation
w1	0.102568167	0.098515111	0.096888333	0.098704889	0.099169125	0.002408232
w2	0.067227	0.072844722	0.075561611	0.074301333	0.072483667	0.003676074
w3	0.102645778	0.098598222	0.096949611	0.098748944	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

Two different criteria are used to compare these postures: linear regression and joint angle difference. The Fig. 3 is the linear regression for Subject 1. The horizontal axis denotes experimental postures (joint angles) and the vertical axis represents predicted postures (joint angles) from the direct optimization-based posture prediction with the global weights obtained by the proposed method in this work. All joint angles are in radians.

From Fig. 3, R^2 value for Subject 1 is greater than 0.7. R^2 values for all other subjects are also greater than 0.7. This shows the direct optimization-based posture algorithm can predict reasonably accurate postures by using the global weights obtained through the proposed formulation. By comparing (a) and (b) in Fig. 3, it is seen that the alternative formulation is shown to have a consistently higher R^2 than the original formulation. The similar results are also for subject 2 – 4. Therefore, the alternative formulation can generate more accurate postures than the original formulation. In Fig. 4 all joint angles are plotted for all of the subjects on the same graph. The R^2 value in Fig. 4 is greater than 0.7, which shows the alternative formulation is accurate.



(a) Alternative formulation



(b) Original formulation in Zou et al. (2010)

Fig. 3. Experimental and predicted postures for Subject 1

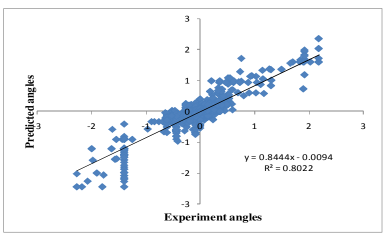


Fig. 4. Regression of the alternative formulation

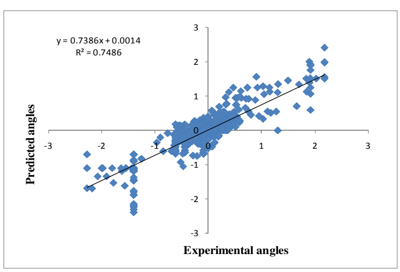
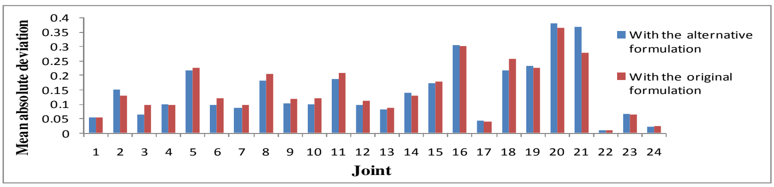


Fig. 5. Regression of the original formulation

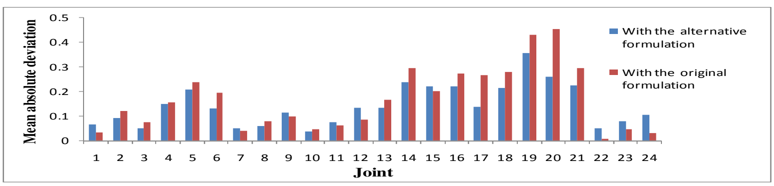
Fig. 5 shows the regression results for all the subjects with the original formulation used in Zou et al. (2010).

By comparing Figs. 4 and 5, the R^2 value is larger for the alternative formulation, which shows that the alternative formulation is better.

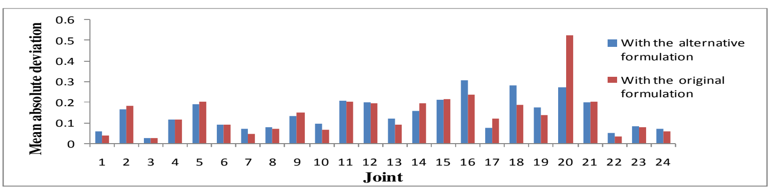
Fig. 6 show the mean value of the absolute joint angle errors for all tasks of each subject with two different formulations. Note that the mean values are in radians. The largest errors occur at the elbow and shoulder joints. For more joints, the joint angle deviations from the alternative formulation are smaller than those from the original formulation. The wrist joints have larger deviation from the alternative formulation.



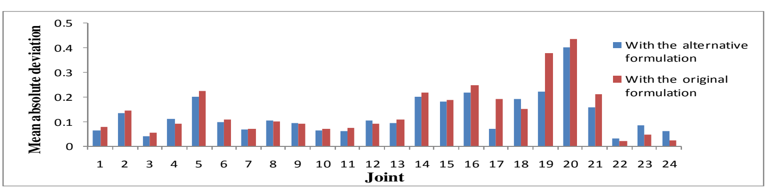
(a) Subject 1: 50% Male



(b) Subject 2: 95% Male



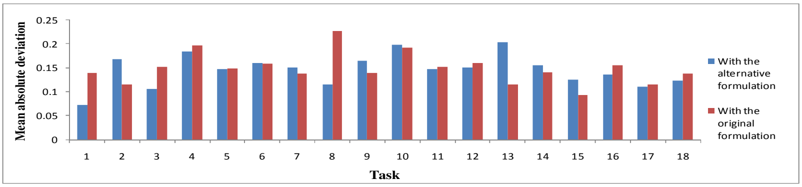
(c) Subject 3: 5% Female



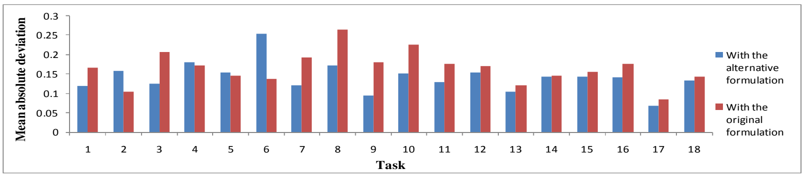
(d) Subject 4: 50% Female

Fig. 6. Mean values of absolute joint angle errors for all joints

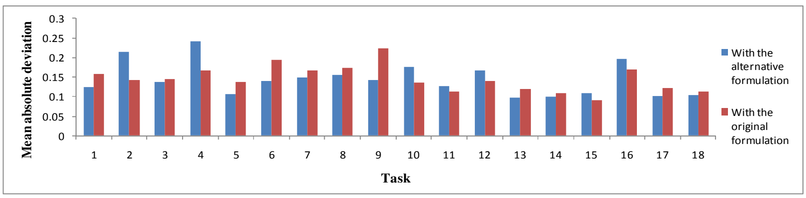
Fig. 7 shows that mean values of the absolute joint angle errors for all joints of each subject. For more tasks, the mean absolute deviations from the alternative formulation are smaller than those from the original formulation.



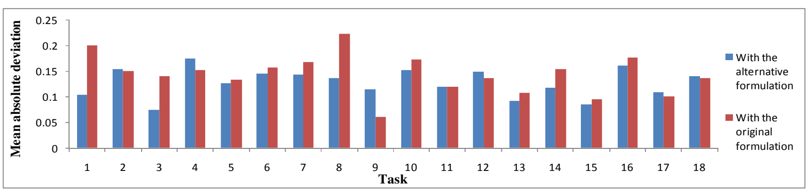
(a) Subject 1



(b) Subject 2



(c) Subject 3



(d) Subject 4

Fig. 7. Mean values of absolute joint angle errors for all joints

7 Conclusion

An alternative inverse optimization method was proposed in this paper to determine the weights of the joint displacement cost function for seated posture prediction. A bi-level optimization problem was formulated and then this formulation was transferred to a regular optimization problem by using Lagrange theory and KKT theory. Four subjects from four different percentiles participated in the experiments, where eighteen tasks for each subject were studied. Experimental and predicted postures were used to demonstrate the accuracy of the proposed formulation, and the results were compared in terms of two criteria- joint angle errors (deviations) and linear regression.

Two important factors (weight limits and weight linear constraints) play an important role in this formulation. The weights obtained through this formulation are different for different subjects and tasks. The global weights are obtained by averaging the weights for all subjects and all tasks. This set of global weights can be used for direct optimization-based posture prediction.

The R^2 value for the alternative formulation is higher than that of the original formulation in Zou et al. (2010). In addition, the joint angle deviations are smaller for the alternative formulation.

Future work includes 1) testing other ways to obtain the global weights such as by using the summation of mean and standard deviation; 2) investigating whether the standing and seated posture share the same set of global weights; 3) having larger number of subjects; 4) extending this formulation for other human performance measures in posture and motion prediction.

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