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Nonlinear inverse optimization approach for determining the weights of objective function in standing reach tasks

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ABSTRACT

This paper presents a nonlinear inverse optimization approach to determine the weights for the joint displacement function in standing reach tasks. This inverse optimization problem can be formulated as a bi-level highly nonlinear optimization problem. The design variables are the weights of a cost function. The cost function is the weighted summation of the differences between two sets of joint angles (predicted posture and the actual standing reach posture). Constraints include the normalized weights within limits and an inner optimization problem to solve for joint angles (predicted standing reach posture). The weight linear equality constraints, obtained through observations, are also implemented in the formulation to test the method. A 52 degree-of-freedom (DOF) human whole body model is used to study the formulation and visualize the prediction. An in-house motion capture system is used to obtain the actual standing reach posture. A total of 12 subjects (three subjects for each percentile in stature of 5th percentile female, 50th percentile female, 50th percentile male and 95th percentile male) are selected to run the experiment for 30 tasks. Among these subjects one is Turkish, two are Chinese, and the rest subjects are Americans. Three sets of weights for the general standing reach tasks are obtained for the three zones by averaging all weights in each zone for all subjects and all tasks. Based on the obtained sets of weights, the predicted standing reach postures found using the direct optimization-based approach have good correlation with the experimental results. Sensitivity of the formulation has also been investigated in this study. The presented formulation can be used to determine the weights of cost function within any multi-objective optimization (MOO) problems such as any types of posture prediction and motion prediction.

1. Introduction

Digital human modeling and simulation play an important role in modern product design. Human modeling and simulation can reduce the development time and the cost. Posture prediction is a key component in digital human modeling and simulation. Three methods are found in the literature to predict postures: the empirical–statistical approach, the direct inverse kinematics approach, and the direct optimization-based approach.

For the empirical–statistical method, thousands of experimental data are collected and processed by computer-aided software, and then the data are analyzed statistically (Beck & Chaffin, 1992; Das & Sengupta, 1995; Faraway, Zhang, & Chaffin, 1999). This approach is direct but not flexible. If the posture prediction scenario changes, a new experiment has to be carried out. In the inverse kinematics approach, a set of equations is used to find a solution (Griffin, 2001; Kim, Gillespie, & Martin, 2004; Tang, Cavazza, Mountain, & Earnshaw, 1999; Tolani, Goswami, & Badler, 2000; Wang, 1999; Wang & Verriest, 1998). For the optimization-based method, the key point is to find the minimum value of a cost function by meeting all the constraint requirements. There are some performance measurements which act as cost functions; for example, discomfort (Jung & Choe, 1996) and joint displacement (Jung & Park, 1994; Zou, Zhang, Yang, Boothby et al., 2011; Zou, Zhang, Yang, Cloutier et al., 2011) can be used as cost function when formulating multi-objective optimization (Howard, Cloutier, Yang, accepted; Yang, Marler, Kim, Arora, & Abdel-Malek, 2004). Determining the relative importance for different human performance measures is a key issue in multi-objective optimization. Among the methods (weighted sum method, min–max method and global criterion method) used to obtain Pareto solutions of a MOO problem, the weighted sum method is commonly used.

To determine weights, a trial and error method is usually used (Athan & Papalambros, 1996; Messac & Mattson, 2002; Yang et al., 2004). Another approach is the self-adaptive weighted sum

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technique (Khan, 2009; Kim, 2004; Kim & Weck, 2005; Ryu, Kim, & Wan, 2009; Zhang, Li, & Song, 2008). The basic idea is to change weights adaptively within a searching region, rather than to adopt a priori weights or to define inequality constraints. The third method is the consistency ratio method (Saaty & Vargas, 1991). In this method, a hierarchy matrix is used to perform pair-wise comparisons, and the weights for all factors could be obtained. Then a consistency ratio, representing the relationship between the judgments and large samples of purely random judgments, could be determined. The fourth method is to use the genetic algorithm in weight calculations (Dong, Xu, Zou, & Chai, 2008; Rachmawati & Srinivasan, 2006). In addition, Zhang, Domaszewski, and Fleury (2001) presented a weighting method with a multi-bounds formulation and convex programming for multi-criteria structural optimization.

With 4 subjects and 18 targets for each subject, Zou, Zhang, Yang, and Gragg (2012) proposed a systematic approach to obtain a set of weights in upper body posture prediction and also developed an alternative method (Zou, Zhang, Yang, Boothby, et al., 2011). Based on the seated posture case, Zou, Zhang, Yang, Cloutier, et al. (2011) extended this method to standing reach tasks. In previous work (Zou, Zhang, Yang, Boothby, et al., 2011; Zou, Zhang, Yang, Cloutier, et al., 2011; Zou et al., 2012), the global weights were obtained by averaging all weights for all subjects and tasks. This paper presents new results based on the inverse optimization method by dividing the workspace into three zones (i.e. left, middle, and right zone) and investigating the sensitivity of this method. By observation, humans employ different strategies for standing reach tasks than for seated reach tasks in terms of motion. In seated reach tasks, the arms move significantly and spine joints move little. However, in standing reach tasks, the hip joints move significantly. Therefore, by intuitive observation, the weights should be different for standing and seated reach tasks. This paper will examine whether this hypothesis is correct.

The rest of this paper is organized as follows: Section 2 introduces the 52 DOFs digital human model. Sections 3 and 4 give the problem definition and nonlinear inverse optimization formulation, respectively. Section 5 presents experimental data collection. Section 6 shows results. Finally, the conclusion and discussion are given in Section 7.

2. Human body model

From a kinematic standpoint, the human body can be modeled as a series of links connected by resolute joints, as Fig. 1 shows. This model has 52 DOFs including the pelvis, spine, left arm, right arm, left leg, right leg, and neck. The rotation of each joint in this model is described as a generalized coordinate q_i. The set of joint angles is defined as $\mathbf{q} = [q_1 \ldots q_{52}]^T$. In this model, the first three rotational joints are defined as the global rotation angles for the whole body. For all standing reach tasks, both feet are fixed on the ground.

With the Denavit Hartenberg (DH) method, the position for an end-effector is written as:

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

$\mathbf{x}(\mathbf{q})$ is obtained from the multiplication of the 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 ${}^{i}\mathbf{R}_j$ represents the rotation matrix from the coordinate frame i to j. ${}^{i-1}\mathbf{T}_i$ is the transformation matrix relating any two adjacent coordinate systems, which is defined as:

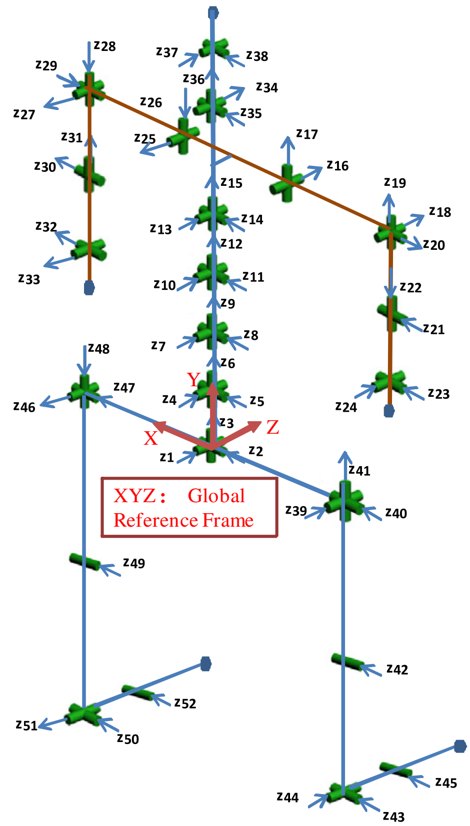

Fig. 1. Digital human model.

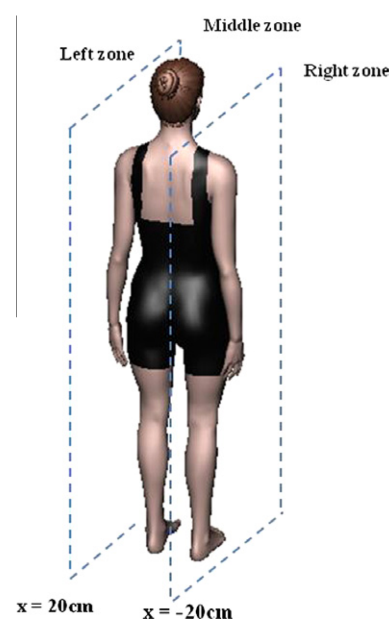

Fig. 2. Three zones in standing reach tasks.

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

In this study, there are four natural end-effectors—the right hand, left hand, right foot and left foot. In addition, three zones are defined in Fig. 2 for different sets of weights in the cost function.