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SAE TECHNICAL PAPER SERIES

2005-01-2686

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Digital Human Modeling for Design and Engineering Symposium
Iowa City, Iowa
June 14-16, 2005

SAE International™

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The Engineering Meetings Board has approved this paper for publication. It has successfully completed SAE's peer review process under the supervision of the session organizer. This process requires a minimum of three (3) reviews by qualified reviewers.

ISSN 0148-7191

Printed in USA

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ABSTRACT

In the field of human modeling, there is an increasing demand for predicting human postures in real time. However, there has been minimal progress with methods that can incorporate multiple limbs with shared degrees of freedom (DOFs). This paper presents an optimization-based approach for predicting postures that involve dual-arm coordination with shared DOFs, and applies this method to a 30-DOF human model. Comparisons to motion capture data provide experimental validation for these examples. We show that this optimization-based approach allows dual-arm coordination with minimal computational cost. This new approach also easily extends to models with a higher number of DOFs and additional end-effectors.

INTRODUCTION

Evaluation of human postures and reaches has become essential in workspace-design and simulation. However, current posture-prediction methods are often limited to single-arm reaches with one end-effector. A more accurate human upper body model should include dual-arm coordination, where each of two arms reaches a target point and both depend on the movement of the spine. Hence, a model should include at least two end-effectors and shared degrees-of-freedom (DOFs). In order to more accurately represent human postures and reaches, we have developed a method to handle dual-arm coordination with shared DOFs.

There are several current approaches to human posture prediction. Empirical approaches calculate realistic postures using anthropometrical data. Using statistical analyses of the data, predictive posture models are formed, and then used to select the most probable posture [2, 3, 5, 16]. Although this method can be accurate and useful when extensive motion capture data exists, it has limited application in the absence of an accessible database.

Inverse kinematics solutions, in particular pseudo-inverse methods, can also provide sufficient posture prediction. In this approach, the motion of each limb is mathematically modeled to formulate a set of governing joint equations [7, 8, 9, 10, 14, 15]. However, as the number of DOFs increases, solving the resulting system of equations becomes increasingly computationally challenging.

Optimization-based approaches to posture prediction have gained momentum as an alternative. These methods optimize to find a set of joint values that minimize a given human performance measure(s), such as joint displacement. The joint values become design variables in the optimization and are constrained by joint limits. Restricting the end-effector to reach the target point is treated as another constraint in the optimization problem [1, 13]. This approach requires no extensive data and is computationally efficient [6].

These approaches to posture prediction have been primarily concerned with only a single arm and end-effector. The empirical approach conceptually works for dual-arm coordination with no modification; however, the increased number of possible postures will necessarily require a much larger motion capture database to maintain accuracy. Hence, the method can become progressively more limited as more DOFs and multiple end-effectors are introduced. The optimization-based approach, however, lends itself to easy and effective modeling of multiple end-effectors, and its advantages in this capacity are addressed in this paper.

Kim and Martin (2004) present another approach for modeling multiple limbs with shared DOFs, which extends inverse kinematics solutions to solve the subsystem of each limb separately [11]. In this work, the subsystems consist of the manual subsystem, which includes the torso and right arm, and the visual subsystem, which includes the torso and neck. Given an inverse kinematics solution for each subsystem, a secondary objective is applied to reconfigure the shared joint angles, which occur in the torso. This could be extended to combine more subsystems, including the torso and left arm. However, extending inverse kinematics solutions can amplify related issues, such as computational complexity. In addition, several subsystems sharing the same joints could result in difficulties when reconfiguring the shared joint angles.

A new method for dual-arm coordination is developed in this paper based on the optimization-based approach to posture prediction. Rather than solving a separate problem for each subsystem, each end-effector is simply associated with one additional constraint in the optimization problem. Shared DOFs are optimized exactly as independent DOFs, and are governed by the same human performance measure(s).

The objectives of this paper are to 1) present a method for modeling multiple limbs; 2) introduce an optimization formulation incorporating multiple end-effectors; and 3) provide initial validation for the accuracy of this approach applied to dual-arm coordination.

METHOD FOR MODELING MULTIPLE LIMBS

For the purpose of representing postures, a human body can be represented by a series of links. In this respect, modeling a human closely parallels modeling a high-DOF robotic manipulator. Accordingly, a model incorporating the torso, spine, shoulders, and arms can characterize human motion by using generalized coordinates q_i to represent joint displacement. For a series of n degrees of freedom, a vector $\mathbf{q} \in \mathbf{R}^n$ of n generalized coordinates represents a posture. Figure 1 shows a general, n-DOF chain of links with the end-effector defined at the end of the chain. The global position vector, $\mathbf{x}(\mathbf{q})$, represents the Cartesian position of the end-effector with respect to the global coordinate system.

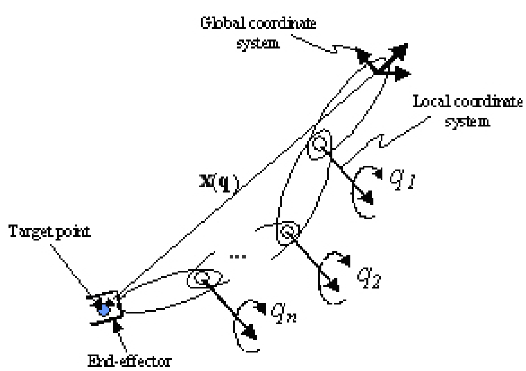

Figure 1. A general n-DOF kinematic chain.

Creating a single-arm human model requires only one such chain and yields realistic results using the 21-DOF model shown in Figure 2 [6].

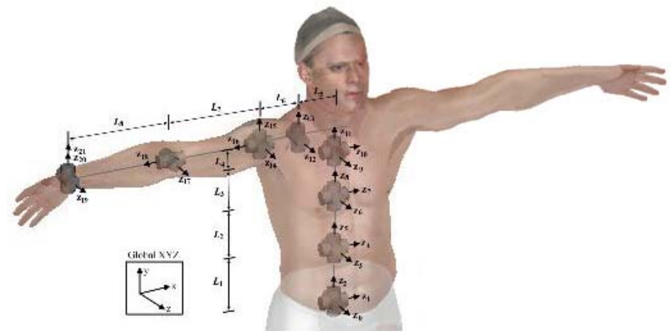

Figure 2. SANTOS™: A 21-DOF single-arm human model.

However, for human models with multiple limbs, additional chains are necessary, and these chains often share links. For example, modeling two arms requires a chain that starts at the waist and ends at the right hand as well as a chain that starts at the waist and ends at the left hand. Both cases include links in the torso. For our dual-arm model, the single-arm model in Figure 2 is reflected to the left arm for an additional 9 degrees of freedom. The result is the 30-DOF model shown in Figure 3. Although the development of the left arm is conceptually the same as that of the right, it is important to note that this addition leads to a *double dependence* on the torso. Hence, there are 12 DOFs in torso that will contribute to the positions of both the right and left end-effectors.

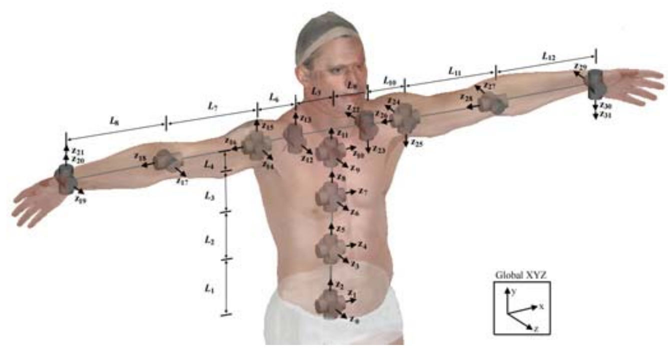

Figure 3. SANTOS™: A 30-DOF dual-arm human model.

In terms of optimization-based posture prediction, it is necessary to compute the Cartesian position $\mathbf{x}(\mathbf{q}) \in \mathbf{R}^3$ of an end-effector in order to constrain it to the specified target point. Consequently, the Denavit-Hartenberg (DH) method is used to calculate $\mathbf{x}(\mathbf{q})$ for each end-effector, given a set of joint angles $\mathbf{q}$ [4]. Developing a model for the DH method involves embedding local frames at each DOF, where the i^{th} z-axis represents axis of motion for the $(i+1)^{th}$ DOF and the i^{th} x-axis is perpendicular to the $(i-1)^{th}$ z-axis as well as the i^{th}. The transformation matrix ${}^{i-1}\mathbf{T}_i$ relates position and orientation in the i^{th} frame to the $(i\text{-}1)^{th}$ frame. It is expressed in terms of the angle θ_i from x_i to x_{i-1} about z_{i-1}, the distance d_i from x_i to x_{i-1} along z_{i-1}, the angle α_i from z_i to z_{i-1} about x_i, and the distance a_i from z_i to z_{i-1} along x_i. These values are shown in Figure 4, where q_{i+1} is the joint displacement corresponding to frame *i*.

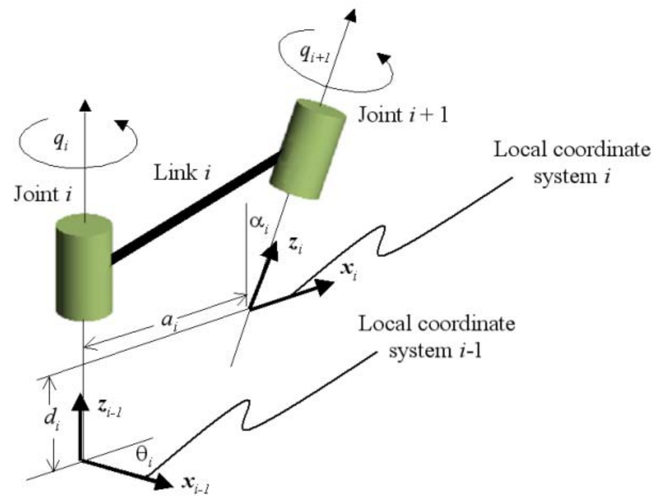

Figure 4. Parameters for the DH method.

The global position vector $\mathbf{x}(\mathbf{q})$ of the end-effector is expressed in terms of the transformations ${}^{i-1}\mathbf{T}_i$ and is given by:

$$\mathbf{x}(\mathbf{q}) = \left(\prod_{i=1}^{n} {}^{i-1}\mathbf{T}_i \right) \mathbf{x}_n \tag{1}$$

$${}^{i-1}\mathbf{T}_i = \begin{pmatrix} \cos\theta_i & -\cos\alpha_i \sin\theta_i & \sin\alpha_i \sin\theta_i & a_i \cos\theta_i \\ \sin\theta_i & \cos\alpha_i \cos\theta_i & -\sin\alpha_i \cos\theta_i & a_i \sin\theta_i \\ 0 & \sin\alpha_i & \cos\alpha_i & d_i \\ 0 & 0 & 0 & 1 \end{pmatrix} \tag{2}$$

where $\mathbf{x}_n$ is the position of the end-effector with respect to the n^{th} frame and *n* is the number of DOFs. Note that rotational displacement q_{i+1} changes the value of θ_i.

For modeling multiple limbs, it is possible to compute the position of the end-effector of each chain separately using (1) and (2). However, the transformations for the shared DOFs need only be calculated once. In general, the position $\mathbf{x}_{\mathbf{limb}}(\mathbf{q})$ of a given limb's end-effector can be calculated by:

$$\mathbf{x}_{limb}(\mathbf{q}) = (\mathbf{T}_{shared})(\mathbf{T}_{transform})(\mathbf{T}_{limb})\mathbf{x}_n \tag{3}$$

where $\mathbf{T}_{shared}$ is the transformation matrix describing the position and orientation of the last shared coordinate frame with respect to the global coordinate system. $\mathbf{T}_{transform}$ describes the position and orientation of the first coordinate frame of the limb with respect to the last shared coordinate frame. $\mathbf{T}_{limb}$ describes the position and orientation of the last coordinate frame of the limb with respect to the first coordinate frame of the limb. These transformations are depicted in Figure 5.

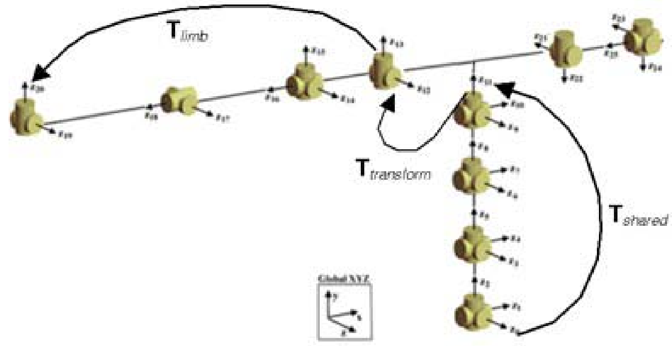

Figure 5. The transformations $\mathbf{T}_{shared}$, $\mathbf{T}_{transform}$, and $\mathbf{T}_{limb}$.

In reference to Figure 3, there are two end-effectors and 12 shared DOFs, which are in the spine. From equations (1), (2), and (3), a new formulation is given as follows to calculate the global Cartesian positions $\mathbf{x}_R$ and $\mathbf{x}_L$ of the right and left end-effectors respectively:

$$\mathbf{x}_R(\mathbf{q}) = (\mathbf{T}_{spine})({}^{12}\mathbf{T}_{13}) \left(\prod_{i=14}^{21} {}^{i-1}\mathbf{T}_i \right) \mathbf{x}_{Rn} \tag{4}$$

$$\mathbf{x}_L(\mathbf{q}) = (\mathbf{T}_{spine})({}^{12}\mathbf{T}_{22}) \left(\prod_{i=23}^{31} {}^{i-1}\mathbf{T}_i \right) \mathbf{x}_{Ln} \tag{5}$$

$$\mathbf{T}_{spine} = \prod_{i=1}^{12} {}^{i-1}\mathbf{T}_i \tag{6}$$

where $\mathbf{x}_{Rn}$ and $\mathbf{x}_{Ln}$ are the local position vectors for the right and left end-effectors, respectively.

OPTIMIZATION FORMULATION

The optimization-based approach to posture prediction involves determining a set of joint values $\mathbf{q}$ that minimizes a given human performance measure(s). For a human model with multiple end-effectors, the optimal posture is found by solving the following optimization problem:

Find: $\mathbf{q} \in R^n$ (7)

to minimize: *Human performance measure(s)*

$$\text{subject to:} \quad \left[\mathbf{x}(\mathbf{q}) - \mathbf{x}^{\text{target}}\right]^2 \le \varepsilon \text{ for each } \mathbf{x}(\mathbf{q})$$

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

In this case, the design variables are the n joint angles q_i. The first constraint in (7) requires that each end-effector meet its corresponding Cartesian target point, where ε is a small positive number sufficiently close to zero. The second constraint in (7) ensures that the joint angles stay within the lower joint limits, q_i^L, and upper joint limits, q_i^U. Note that in this general formulation, the proposed optimization-based approach allows us to restrict multiple end-effectors simply by using additional constraints.

To predict posture for the 30-DOF dual-arm model in Figure 3, the constraints must restrict both the right and left end-effectors to reach their target points. Using (4) and (5), the optimization formulation becomes:

Find: $\mathbf{q} \in R^n$ (8)

to minimize: *Human performance measure(s)*

$$\text{subject to:} \quad \left[\mathbf{x}_R(\mathbf{q}) - \mathbf{x}_R^{\text{target}}\right]^2 \le \varepsilon$$

$$\left[\mathbf{x}_L(\mathbf{q}) - \mathbf{x}_L^{\text{target}}\right]^2 \le \varepsilon$$

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

where $\mathbf{x}_R^{\text{target}}$ and $\mathbf{x}_L^{\text{target}}$ are the given Cartesian target points for the right and left end-effectors, respectively. Note that the quality of the result in this formulation will depend on the same human performance measure(s) that dictates the single-arm result. Using this new optimization-based approach for dual-arm coordination, the shared joints are treated equally with the independent joints with respect to the objective function.

This optimization formulation was implemented using a human performance measure based on joint displacement. Objective functions derived from joint displacement have been used in single-arm, optimization-based posture prediction with some success [13]. Conceptually, joint displacement refers to the difference between the final posture and a *neutral posture*. This neutral posture is selected to be a relatively comfortable posture, typically a standing position with the arms at the sides. Joint displacement is mathematically defined as:

$$f_{Displacement}(\mathbf{q}) = \sum_{i=1}^{n} w_i \left(q_i - q_i^N\right)^2 \quad (9)$$

where q_i is the i^{th} joint value in the final posture, and q_i^N is the i^{th} joint value for the neutral posture. One can view (9) as a weighted sum of objectives in a multi-objective optimization problem, where each joint term in the summation constitutes an individual objective. The weights w_i account for the fact that certain segments of the body articulate more readily than others. Assigning a higher value to w_i results in a particular objective contributing more significantly to the sum and thus having a stronger effect on the final solution. Essentially, it becomes more important for a heavily weighted joint to be near its neutral position. For this study, the weights are determined by trial and error, and are given in Table 1.

Table 1. Weights for displacement objective.

q_i	w_i	Comments
q_1, q_4, q_7, q_{10}	100	Used with both positive and negative values of $q_i - q_i^N$
q_2, q_5, q_8, q_{11}	100 1000	When $q_i - q_i^N > 0$ When $q_i - q_i^N < 0$
q_3, q_6, q_9, q_{12}	5	Used with both positive and negative values of $q_i - q_i^N$
q_{13}, q_{22}	75	Used with both positive and negative values of $q_i - q_i^N$
q_{17}, q_{26}	50	When $q_i - q_i^N > 0$

RESULTS

The repercussions of incorporating multiple limbs that share common DOFs can be demonstrated by viewing results with single-arm posture prediction. Figure 6 (a) shows a single-arm posture on SANTOS™, whereas Figure 6 (b) shows a dual-arm posture using the same target point for the right end-effector. Note how the shared DOFs in the spine shift to facilitate reaching both targets.

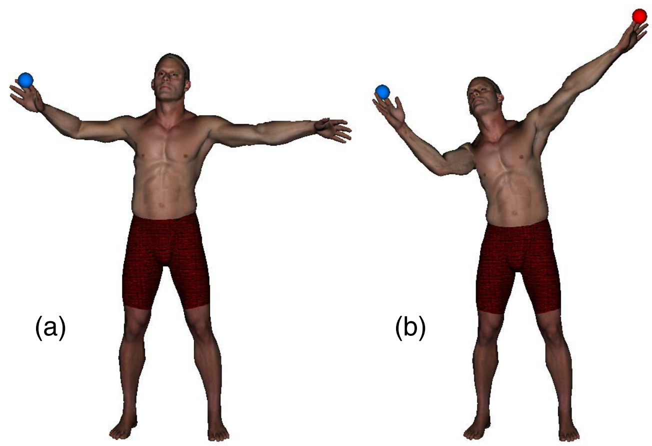

Figure 6. Posture prediction using (a) single-arm and (b) dual-arm.

The predicted postures for three sets of target points were compared to motion capture results from a male subject. Target positions are given with respect to a global coordinate frame located in the torso, coincident with the zeroth frame in Figure 3, and are measured in centimeters. For target set #1, the right end-effector target, $\mathbf{x}_R^{target}$, is (-41.7, -4.3, 38.7) and the left end-effector's target, $\mathbf{x}_L^{target}$, is (39.1, -4.4, 40.1). The predicted posture is visualized on SANTOS™ in Figure 7, while the motion capture result for the same target set are shown in Figure 8. Both postures are similar; however, the motion capture shows a slight bending at the elbow that is not predicted by this model. Slightly different anthropometries between SANTOS™ and the motion capture subject are a possible contributing factor. However, minimizing joint displacement conceptually means that the model will tend toward the neutral posture. Since the neutral posture is defined with a straight arm, the result of the optimization will tend toward a straight arm. Hence, more realistic results should be possible with a more inclusive human performance measure(s).

For target set #2, $\mathbf{x}_R^{target}$ is (-65.3, 44.7, -41.0) and $\mathbf{x}_L^{target}$ is (39.4, -5.2, 40.6). Figure 9 and Figure 10 depict the predicted result and motion capture result, respectively. Again, the predicted result shows less bending in the elbow, and also less twisting in the arm. For target set #3, $\mathbf{x}_R^{target}$ is (-41.3, 44.5, 60.9) and $\mathbf{x}_L^{target}$ is (-36.4, 44.4, 63.8). The predicted result is shown on SANTOS™ in Figure 11 and the motion capture result shown in Figure 12. The predicted result more closely resembles the motion capture result in this case.

Figure 7. Predicted posture on 30-DOF SANTOS™ for target set #1.

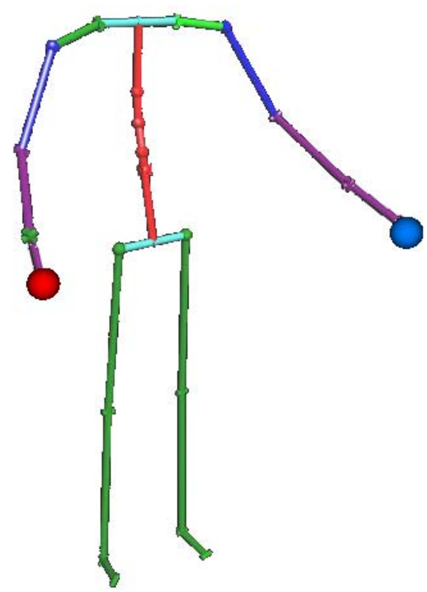

Figure 8. Motion capture result on 30-DOF model for target set #1.

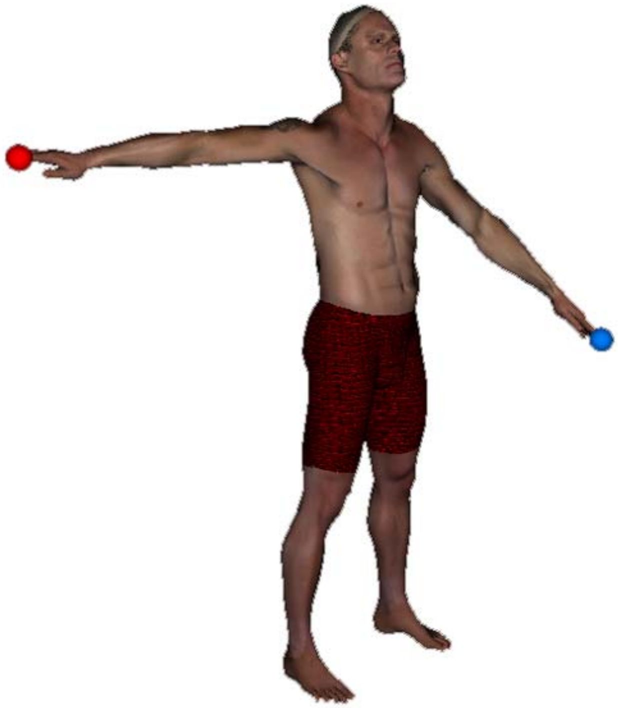

Figure 9. Predicted posture on 30-DOF SANTOS™ for target set #2.

Figure 11. Predicted posture on 30-DOF SANTOS™ for target set #3.

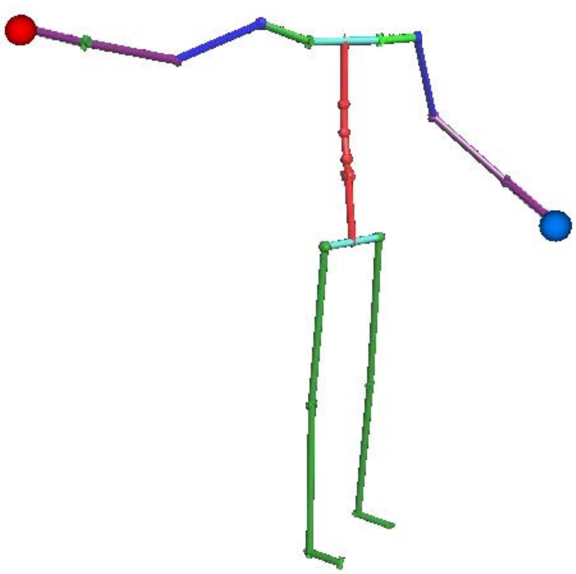

Figure 10. Motion capture result on 30-DOF model for target set #2.

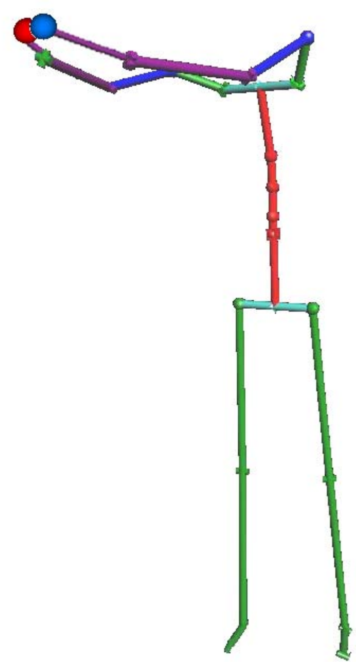

Figure 12. Motion capture result on 30-DOF model for target set #3.

One benefit of the optimization-based approach to posture prediction is computational efficiency. Hence, posture prediction feedback can be obtained in real-time or near real-time speeds. This might be especially useful to quickly evaluate workspace or compare a variety of postures over different anthropometries. In fact, the new approach, incorporating multiple limbs and shared DOFs, maintains computational speed. The dual-arm posture prediction on the 30-DOF SANTOS™ took only approximately 0.15 sec for each set of targets on a 2.6GHz Pentium4 CPU with 512MB RAM. Single-arm posture prediction on the 21-DOF SANTOS™ takes approximately 0.10 sec on a similar machine.

CONCLUSION

In this paper, we have presented a new optimization-based approach to modeling dual-arm coordination. This approach generalizes to the modeling of multiple limbs that share DOFs. The optimization formulation is conceptually straightforward, and allows us to incorporate additional end-effectors simply by adding additional constraints. In addition, the new approach is computationally efficient and has provided realistic predicted postures in near real-time. The results have been validated successfully using motion capture.

Validation of the results indicates that the proposed method can produce realistic postures. Although nuances of the final postures can depend of the particular performance measure (objective function) used in the optimization formulation, we have nonetheless demonstrated that using the optimization-based approach for posture prediction is easily and effectively adopted to models with multiple end-effectors. However, these validation studies are preliminary, and there are opportunities for additional research in terms of motion capture studies. First, the anthropometry of the human subject and the SANTOS™ model will be varied in order to study the generality of the new approach. Such variations are easily implemented in the proposed model in terms of kinematic link lengths. Second, a motion capture study involving many multiple subjects of various anthropometries will provide additional insight concerning posture prediction.

As the need for simulating human posture in digital environments grows, there is a demand to move beyond single-arm reaches into dual-arm coordination. The method presented addresses not only dual-arm coordination, but can also be easily extended to more complex human models with multiple end-effectors and shared DOFs. The optimization-based approach discussed in his paper offers a straightforward way to incorporate these additional end-effectors in with minimal computational cost.

ACKNOWLEDGMENTS

The authors would like to thank Dr. Salam Rahmatalla and Xiaolin Man for their work with the motion capture validation study. This research was funded by the US Army TACOM project: Digital Humans and Virtual Reality for Future Combat Systems (FCS).

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