Real-Time Optimal Reach-Posture Prediction in a New Interactive Virtual Environment

Jingzhou Yang (杨景周), R. Timothy Marler, Steven Beck, Karim Abdel-Malek, and Joo Kim

US Army Virtual Soldier Research (VSR) Program, Center for Computer-Aided Design, The University of Iowa
111 Engineering Research Facility, Iowa City, IA 52242-1000, U.S.A.

E-mail: jyang@engineering.uiowa.edu

Received December 15, 2004; revised December 8, 2005.

Abstract Human posture prediction is a key factor for the design and evaluation of workspaces, in a virtual environment using virtual humans. This work presents a new interface and virtual environment for the *direct human optimized posture prediction* (D-HOPP) approach to predicting realistic *reach postures* of digital humans, where reach postures entail the use of the torso, arms, and neck. D-HOPP is based on the contention where depending on what type of task is being completed, and human posture is governed by different human performance measures. A human performance measure is a physics-based metric, such as energy or discomfort, and serves as an objective function in an optimization formulation. The problem is formulated as a single-objective optimization (SOO) problem with a single performance measure and as multi-objective-optimization (MOO) problem with multiple combined performance measures. We use joint displacement, change in potential energy, and musculoskeletal discomfort as performance measures. D-HOPP is equipped with an extensive yet intuitive user-interface, and the results are presented in an interactive virtual environment.

Keywords reach posture prediction, MOO, human modeling and simulation, virtual environment

1 Introduction

A virtual human model provides an efficient tool for upstream manufacturing and design. Use of such a tool can reduce the required number of design iterations, which can save time and money. Of the many techniques for ergonomic analysis, reach analysis has become one of the most important applications for virtual humans. In addition, posture analysis is of vital interest to biomechanical engineers, who strive to understand joints and extremities of the musculoskeletal system. However, even the most advanced computer-aided design tool is ineffective without an intuitive easy-to-use environment with which the user interacts. Thus, in this paper, we present a new interface and virtual environment for our *direct human optimized posture prediction* (D-HOPP) approach to human posture prediction. The D-HOPP approach provides a substantial amount of predictive autonomy, enabling one to simulate infinitely many scenarios, rather than depend on prerecorded data. It also provides a platform with which one can study which physics-based metrics govern posture for different tasks. The interface for D-HOPP has been developed such that it is intuitively easy to use. In addition, as much as possible, the user should be able to focus on the virtual human, its interaction with the environment, and the task at hand, rather than having to focus on the interface. We have taken this goal into consideration. The environment, where the virtual human essentially lives, should be realistic and convincing, with the ultimate goal of allowing the user to actually interact with the virtual human.

Although there has been a substantial amount of work completed with human posture and motion prediction, either the human models are too simple, or the predictive methods do not function in real time. Generally, there are two main approaches to predicting reach posture. The first approach is empirical-statistical modeling and is a more traditional approach. It uses anthropometrical data collected from experiments involving human subjects[1,2]. These data are then analyzed statistically to form a predictive model of posture, e.g., a regression model. Such models have been implemented in various simulation software systems[3−6].

The second approach to posture prediction is inverse kinematics. There are two methods for inverse kinematics. One is the Moore-Penrose pseudo-inverse method as predictive tools to yield a posture that has not been observed but that has been estimated to be a natural posture for a task[7−13]. However, this pseudo-inverse method is limited to relatively simple models with few degrees of freedom and computational intensity. The other is the optimization-based method which was originally used to predict robot's trajectory motion where given the end-effector position of the robot the goal is to determine the joint angles. For each point on the path on which the end-effector should follow is the target point, the user can determine robot's configuration. [14, 15] present a multi-objective optimization (MOO) solution to the problem of moving a robot manipulator with objectives of minimum traveling time and mechanical energy of the actuators, considering dynamics and collision avoidance of moving obstacles. Saramago and Ceccarelli[16] propose a similar MOO approach with

* Regular Paper
This research was partly funded by the US Army TACOM Project: Digital Humans and Virtual Reality for Future Combat Systems (FCS) (Contract No. DAAE07-03-D-L003) and by Caterpillar Inc. Project: Digital Human Modeling and Simulation for Safety and Serviceability.

payload constraints. [17] proposes a single-objective optimization (SOO) method with load or torque as independent objectives, and an MOO method that combines the objectives. However, the maximum number of degrees of freedom for robots is six.

Work with motion prediction is related to posture prediction. However, much of the focus for motion prediction has been applied to robotics, and little work has been conducted with the development of objective functions that are tailored to human posture. [19–21] study SOO-based human posture prediction using genetic algorithms, and [22] extends this work to real-time simulation. [23] develops a discomfort objective function. [24–27] extend the single objective problem to multi-objective optimization problem.

The second component of this work, in addition to real-time posture prediction, is the development of an interface and a virtual environment with all of the aspects that a user interacts with. The virtual environment includes the interface, the visual appearance of the surroundings for the virtual human, etc. Such virtual environments offer people the ability to carry out actions that may not be possible or safe in a real environment. [28] provides a complete survey of virtual environment research including displays for presenting information to the user's visual, auditory, and haptic senses; sensors and other technologies for transferring information from the user to the computer; software; human factors; and applications. However, in current virtual environments, there is no highly realistic human model that actual humans can interact with.

An intuitive interface is the bridge connecting the users and the software. A better interface design is benefit to the users to learn the software. [29] develops an interactive interface for directing virtual humans. All commercial software such as Jack®, Pro/Engineer®, Safework®, etc. has their user-friendly interfaces. Therefore, for virtual human Santos™ it is necessary for the users to use this virtual human intuitively and friendly. We use traditional tools such as sliders, on/off buttons, and clicks, etc. to build a user-friendly controller.

[30, 31] develop a networked virtual environment in which users can interact. The COVEN project[32] studies collaborative virtual environments in depth, where multiple users handle multiple tasks simultaneously. [33] develops virtual presenters, virtual guides, and virtual actors in a networked virtual environment. [34] proposes a new collaborative environment, in which a human-shaped virtual agent communicates with real humans. However, there exists a problem the workload for the construction is too large for the practical use. Therefore, the system for simulating the collaborative environment is divided into several subsystems according to its function, and for each subsystem a new construction method to reduce the construction workload has been developed individually. In this paper we present an interactive virtual environment and the virtual human lines in this environment and the users use them as design tools.

2 Digital Human Modeling

Using the Denavit-Hartenberg (DH) method[35], an upper-body digital human model, including the spine, neck, shoulder, and arms, has been developed[18,19,36,37]. The DH-method characterizes the joints of a mechanism, such that a position vector describing the location of any given point, which is based on all of the joint displacements, can be determined. In this study, we use the DH-method to translate from a series of joint angles to the Cartesian coordinates of an end-effector, in a multi-segmental chain (see Fig.1) that leads from the waist to an upper extremity. Local coordinate systems are systematically embedded at each segment (i.e., link). In Fig.1, q_i are called generalized coordinates and represent the rotational displacements of the joints. Thus, $\boldsymbol{q} = [q_1 \ \dots \ q_n]^{\mathrm{T}} \in \boldsymbol{R}^n$ is the vector of n-generalized coordinates in an n-DOF model. $\boldsymbol{x}(\boldsymbol{q})$ is the position vector that describes the location of the end-effector (defined as any point on the human model for which a position in Cartesian space is determined) as a function of the generalized coordinates.

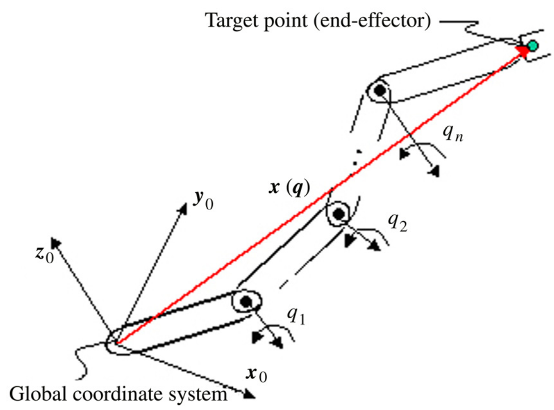

Fig.1. General kinematic model.

The complete human model is shown in Fig.2. q_1 through q_{12} represent the degrees of freedom for the spine. q_{13} through q_{21} refer to the left arm, q_{22} through q_{30} refer to the right arm. Although not shown in the figure, q_{31} through q_{35} represent the neck. Each joint is represented by one or more DOFs. For instance, the shoulder has five DOFs, i.e., five rotational joints. The position vector function $\boldsymbol{x}(\boldsymbol{q})$ (shown in Fig.1), generated by a point of interest and calculated as a multiplication of rotation matrices ${}^{j-1}\boldsymbol{R}_j$ and position vectors ${}^{i-1}\boldsymbol{p}_i$, is expressed by

$$\boldsymbol{x}(\boldsymbol{q}) = \begin{bmatrix} x(\boldsymbol{q}) \\ y(\boldsymbol{q}) \\ z(\boldsymbol{q}) \end{bmatrix} = \sum_{i=1}^{n} \Big[\prod_{j=1}^{i-1} {}^{j-1}\boldsymbol{R}_j \Big]^{i-1} \boldsymbol{p}_i \qquad (1)$$

where both ${}^{i-1}\boldsymbol{p}_i$ and ${}^{j-1}\boldsymbol{R}_j$ are defined using the DH method such that

$$\begin{cases} {}^{i-1}\boldsymbol{R}_i = \begin{bmatrix} \cos\theta_i & -\cos\alpha_i\sin\theta_i & \sin\alpha_i\sin\theta_i \\ \sin\theta_i & \cos\alpha_i\cos\theta_i & -\sin\alpha_i\cos\theta_i \\ 0 & \sin\alpha_i & \cos\alpha_i \end{bmatrix} \\ {}^{(i-1)}\boldsymbol{p}_i = [a_i\cos q_i \quad a_i\sin q_i \quad d_i]^{\mathrm{T}} \end{cases} \tag{2}$$

where θ_i is the joint angle from $\boldsymbol{x}_{i-1}$ axis to the $\boldsymbol{x}_i$ axis, d_i is the shortest distance between $\boldsymbol{x}_{i-1}$ and $\boldsymbol{x}_i$ axes, a_i is the offset distance between $\boldsymbol{z}_i$ and $\boldsymbol{z}_{i-1}$ axes, and α_i is the offset angle from $\boldsymbol{z}_{i-1}$ and $\boldsymbol{z}_i$ axes shown in Fig.3.

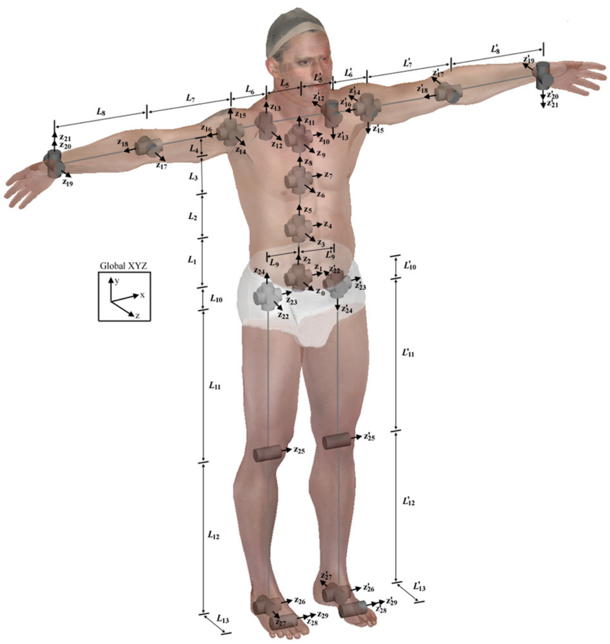

Fig.2. Kinematic modeling of digital humans.

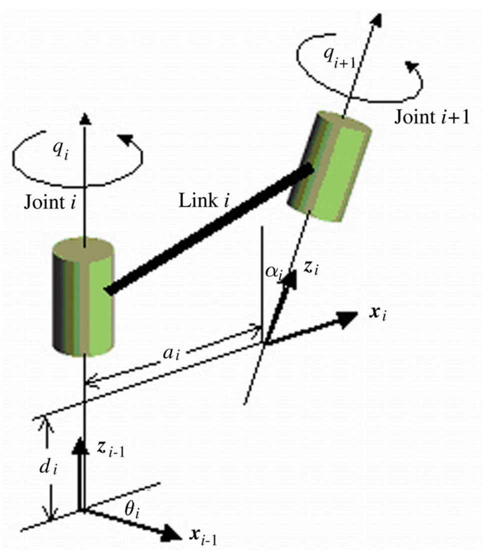

Fig.3. Joint coordinate system convention and its parameters.

3 Optimization-Based Approach

The posture for the above-described human model is simulated using D-HOPP, a new optimization-based approach discussed in [38, 39]. With this approach, the joint angles, which essentially define a posture, provide the design variables that are determined by solving a single optimization problem. We consider the upper body, so there are 35 design variables, representing the 35 degrees of freedom (DOFs) for the torso, neck, left arm, and right arm, but not including the hands and eyeballs.

There are two primary types of constraints. First, the end-effectors are constrained to contact a specified target point in Cartesian space, and the consequent constraints are called *distance constraints*. With the examples in this paper, the end-effectors are the tips of the index fingers. However, the user can specify an end-effector anywhere and can associate it with any local coordinate system. In addition, the end-effectors can be restrained to a line or a plane as well as a point. The second set of constraints represents joint-angle limits, which are dictated by anthropometric data.

The objective function(s) for the optimization problem are human performance measures, which represent physically significant quantities, such as joint displacement, potential energy, or discomfort. A fundamental premise behind D-HOPP is that different human performance measures govern posture depending on what type of task is being completed. Of course, in many instances, posture may not be governed by just one performance measure; multiple measures may need to be combined using multi-objective optimization. Various performance measures used with this work are described briefly as follows.

3.1 Performance Measures

The first performance measure (objective function) is called joint displacement and represents a baseline for developmental comparison[20,21,40]. This performance measure represents the joint displacement when a given joint is displaced from its *neutral position*, which is a generally comfortable position, and in this case it is defined as the posture with one's arms at one's sides. With q_i^N representing the neutral position, the displacement from the neutral position is then given by $|q_i - q_i^N|$, which is modeled as $(q_i - q_i^N)^2$ in order to avoid numerical difficulties. Scalar weights are used to model approximately joints that are articulated more readily than others. Thus, the total joint displacement of all joints is then characterized by the following function:

$$f_{\text{Joint-displacement}}(\boldsymbol{q}) = \sum_{i=1}^{n} w_i (q_i - q_i^N)^2 \tag{3}$$

where w_i is a weight assigned to each joint. The weights are defined in Table 1.

Table 1. Joint Weights for Joint-Displacement

Joint variable	Weight	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	When $q_i - q_i^N > 0$
	1000	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_{14}, q_{15}, q_{16} q_{23}, q_{24}, q_{25} $q_{18}, q_{19}, q_{20}, q_{21}$ $q_{27}, q_{28}, q_{29}, q_{30}$ q_{35}	1	Used with both positive and negative values of $q_i - q_i^N$
q_{17}, q_{26}	50	When $q_i - q_i^N > 0$
	1	When $q_i - q_i^N < 0$
q_{31}, q_{34}	100	Used with both positive and negative values of $q_i - q_i^N$
q_{32}	50	When $q_i - q_i^N < 0$

In an effort to use weights that have a more physically significant meaning, [24, 26] develop the second performance measure, f_{Energy}, which represents the change in potential-energy (called delta-potential-energy) and uses weights that are based on the mass of different segments of the body.

With this performance measure, the primary segments of the upper body are represented with six lumped masses: three for the lower, middle, and upper torso; one for the upper arm; one for the forearm; and one for the hand. Based on the definition of potential energy, the heights of the masses provide the components of the human performance measure. Then, mathematically, the weight (force of gravity) of a body segment provides a multiplier for movement of that segment in the vertical direction. The height of each segment is a function of the joint angles, so the weights (gravitational forces) of the lumped masses essentially replace the scalar multipliers w_i used in the joint displacement function. In order to avoid having the virtual human constantly bend over and thus minimize potential energy, we actually minimize the *change* in potential energy. This means that each body segment essentially has a different datum, where the potential is assumed to be zero.

The final objective function is given as follows, with reference to Fig.4:

$$f_{\text{Energy}}(\boldsymbol{q}) = \sum_{i=1}^{\kappa}(P_i - P_i')^2 = \sum_{i=1}^{\kappa}(m_i g)^2(\Delta h_i)^2 \quad (4)$$

$P_i' = m_i \boldsymbol{g}^T\ {}^0\boldsymbol{A}_1' \cdots {}^{i-1}\boldsymbol{A}_i' \boldsymbol{r}_i$ is the initial potential energy, defined at the neutral position, and $P_i = m_i \boldsymbol{g}^T\ {}^0\boldsymbol{A}_1 \cdots {}^{i-1}\boldsymbol{A}_i \boldsymbol{r}_i$ is the final potential energy. $\kappa = 9$ is the number of lumped masses for the 35 DOF model. In contrast to joint displacement, $(m_i g)^2$ serve as weighting factors for $(\Delta h_i)^2$.

The third performance measure is musculoskeletal discomfort $f_{\text{Discomfort}}$, and is developed by [23]. As with joint displacement and delta-potential-energy, the avatar again tends to gravitate towards the neutral position. However, this function incorporates three facets of musculoskeletal discomfort: 1) the tendency to move towards a generally comfortable position, 2) the tendency to avoid postures with which joint angles are pushed to their limits, and 3) the idea that people strive to reach or contact a point using one set of body parts at a time. With regards to component 2), the avoidance of joint limits does not apply to joints where ligaments and/or tendons are not stretched, as with the elbow and clavicle. With regards to component 3), in terms of upper body motion, one first tries to reach a point using one's arm. If that is unsuccessful, then one bends the torso. Finally, if necessary, the clavicle is extended. The intent in developing this performance measure is not to quantify discomfort but to model components that are proportional to discomfort. Consequently, only its relative values (from one posture to another), not its absolute values, are significant.

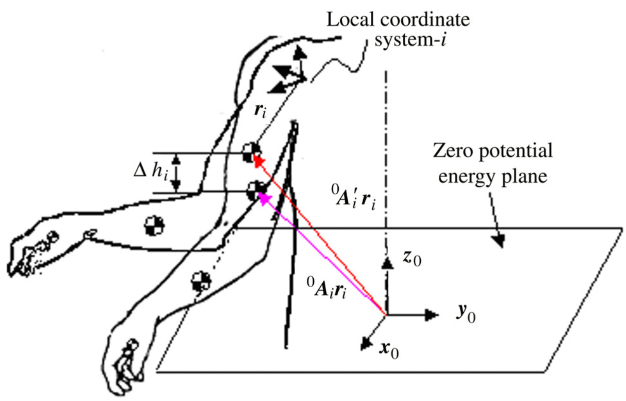

Fig.4. Illustration of the potential energy of the forearm.

The final function is given as follows:

$$f_{\text{Discomfort}}(\boldsymbol{q}) = \sum_{i=1}^{DOF}[\gamma_i(\Delta q_i^{norm}) + QU_i + QL_i] \quad (5)$$

where $\Delta q^{norm} = \dfrac{q_i - q_i^N}{q_i^U - q_i^L}$. QU and QL are specially designed penalty functions that incorporate the discomfort associated with joint angles that approach joint limits. They are defined as follows:

$$QU = \left(0.5\sin\left(\frac{5.0(q_i^U - q_i)}{q_i^U - q_i^L} + 1.571\right) + 1\right)^{100} \quad (6)$$

$$QL = \left(0.5\sin\left(\frac{5.0(q_i - q_i^L)}{q_i^U - q_i^L} + 1.571\right) + 1\right)^{100} \quad (7)$$

QU is zero until a joint angle is in the upper 5% of its range, and QL is zero until a joint angle is within the lower 5% of its range. γ_i represent weights, but these weights are not used in the same way where weights for joint displacement are. Instead, as [23] explains, these are used to model the tendency to move different sets of body parts sequentially. The specific values for these weights are irrelevant; the weights simply need to have significantly different orders of magnitude. The weights for the arms are equal to 1. The weights for the spine and neck DOFs are all of 1×10^4. The weights for the clavicle DOFs are of 1×10^8.

3.2 Optimization Formulation

Given the design variables, constraints, and objective functions discussed above, the final optimization problem is formulated as follows:

Find: $\boldsymbol{q} \in R^{DOF}$

To minimize: $F(\boldsymbol{q}) = f_{\text{Joint-displacement}}, f_{\text{Discomfort}},$ or f_{Energy}

$$\text{Subject to:} \quad \|\boldsymbol{x}(\boldsymbol{q})^{end\text{-}effector} - \boldsymbol{x}^{target\text{-}point}\| \leqslant \varepsilon \quad (8)$$
$$q_i^L \leqslant q_i \leqslant q_i^U, \quad i = 1, 2, \ldots, DOF$$

where $\boldsymbol{x}(\boldsymbol{q})^{end\text{-}effector}$ is the position of the end-effector in Cartesian space, $\boldsymbol{x}^{target\text{-}point}$ is the position of the target point, and ε is a small positive number approximating zero. q_i^L and q_i^U represent the lower and upper limits for a joint angle, respectively.

(8) can be treated as a single-objective problem with which each of the three objective functions are minimized independently. However, posture may be governed by more than one performance measure, in which case MOO is used. There are many methods for aggregating multiple objectives and articulating preferences as to which objectives are more important[41]. However, the objective of this work is to demonstrate our posture prediction approach and capabilities. Therefore, in terms of MOO methods, we use a global criterion, shown as follows:

$$F(\boldsymbol{q}) = \left[(f_{Joint\text{-}displacement})^2 + (f_{Discomfort})^2 + (f_{Energy})^2\right]^{1/2}. \quad (9)$$

Before using (9), the objective functions are normalized such that they all have similar ranges of values. [24] demonstrates additional MOO methods for posture prediction.

4 Posture Prediction Results

In this section, the formulation in (8) is solved using SNOPT software[42]. Results are shown for SOO, where each performance measure is minimized independently, and for MOO where (9) is used. For this study, Santos$^{\text{TM}}$ is required to contact the targets shown in Fig.5. Depending on which performance measure is used, the D-HOPP problem takes between approximately 0.1 and 0.5 seconds to run, thus yielding real-time results.

Results using joint displacement, discomfort, and energy are shown in Figs. 6, 7 and 8, respectively.

Fig.5. Target points.

Clearly, different human performance measures result in different postures. Generally, the discomfort function provides the most realistic results. It differs from joint displacement, primarily because it incorporates the tendency to move arms before moving the torso, as well as the tendency to avoid postures where joint angles are at limits inducing stretching in ligaments and/or tendons.

5 Interface and Virtual Reality Simulation

Research on virtual humans produces various capabilities for Santos$^{\text{TM}}$. It is necessary to integrate all capabilities in one package, for real humans to interact with the virtual human, and friendly use these capabilities of Santos$^{\text{TM}}$ in design. In this section we discuss Santos$^{\text{TM}}$ interface and the virtual environment that Santos$^{\text{TM}}$ lives.

5.1 Interface for Santos$^{\text{TM}}$

Despite our advancements with posture prediction, it is necessary to provide not just various capabilities but useable tools as well. Consequently, significant effort has gone into developing a system of interfaces for various capabilities. In developing the interface, we pursue two objectives. First, the interface must be intuitively easy to use, and it must be well organized. Secondly, the interface must allow for the separation of the technical executables that govern the various capabilities, from the virtual environment. In this context, the virtual environment is the software that is used to visualize Santos$^{\text{TM}}$.

Using delta-potential-energy appears to yield particularly unrealistic results. This suggests that energy does not dictate posture independently, which is a counterintuitive result. However, as determined by [23, 26], energy can play a significant role in posture prediction when combined with other performance measures using MOO. The MOO results when (9) is used are shown in Fig.9.

Fig.6. Joint displacement results.

Fig.7. Discomfort results.

Fig.8. Energy results.

Fig.9. Posture prediction using MOO.

The interface we have developed currently houses six areas of functionality: posture prediction, inverse kinematics, joint modifications, link-length (skeletal dimensions) modifications, workspace evaluation, and dynamic motion prediction. Here we discuss the interface for posture prediction as well as other related interfaces.

Fig.10 shows the posture prediction interface. This interface includes several parts: which hand for the posture prediction; cost functions; resetting to the neutral posture; the command to run posture prediction; and final predicted cost function values. In the hand selection part, the user can choose left hand, or right hand, or both hands. In the cost function selection part, the user can use the sliders to adjust the weights for the cost functions and the weights are shown bellow the slider bars. The user can also directly input the weights in the weight spaces. The weights satisfy $\omega_i \leqslant 1$ and $\sum_i \omega_i = 1$. If the weight value is "0", that means this cost function does not contribute to the final object function for the optimization problem. The user can also choose "Hold" to keep that weight value of cost function unchanged. In the command to run posture prediction, the user can simply click "Apply Settings" and a horizontal slider will show the status of running. There are three buttons "Back", "Play/Pause" and "End" to animate the posture result. The user can use "Show Posture Data" button to view the output data of the posture prediction. The absolute values of cost functions are not significant, however, the relative values are important to evaluate the human performance measures. Therefore we show the cost function percent in this interface, which means the percent of current cost function value over the maximum value for that cost function.

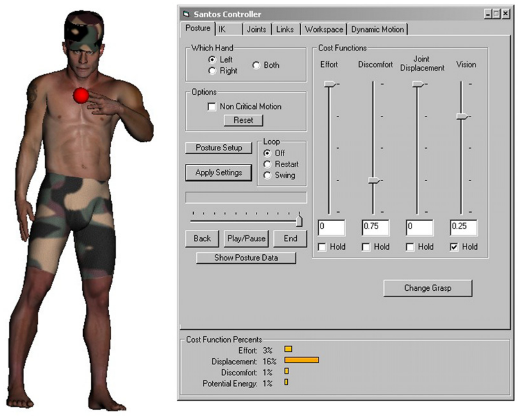

Fig.10. Posture prediction interface.

Fig.11 shows the inverse kinematics interface. This interface includes types of IK that the user can choose standard IK and advanced IK, manipulation of standard IK, advanced IK segment selection which the user can choose left arm, right arm, both arms, left leg, right leg, both legs, or all of them, and cost function percent. We have developed two versions of IK: *standard IK* and *advanced IK*[39]. With standard IK, the user is able to select *hot points* on Santos$^{\mathrm{TM}}$ and then place them wherever necessary. The complete avatar then moves accordingly, in real time. With advanced IK, we capitalize on posture prediction capabilities to yield an exciting new tool. As the user moves the hot points, the consequent posture is automatically predicted/optimized. That is, a version of the posture prediction algorithm is run every frame using the hot points as target points. This version of posture prediction currently has been optimized for speed, and non-critical features have been omitted. The algorithm is able to run approximately 20 times per second. This alleviates the need for a user to predict realistic postures as he/she positions the avatar; realistic postures are actually predicted automatically. Both standard IK and advanced IK include the legs.

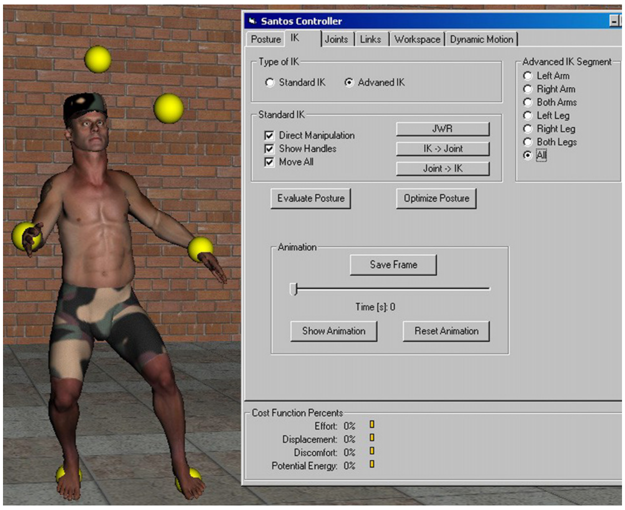

Fig.11. Inverse kinematics interface.

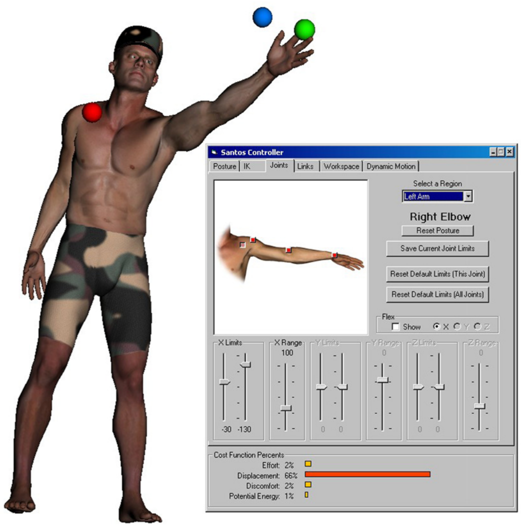

Fig.12. Joint limits interface.

Figs. 12 and 13 show the joint limits and link lengths interface. Limits on the rotation of the joints can be modified either to represent actual human data or to model restrictions such as biomechanic deficiencies, injuries, or disabilities. The link lengths, which represent the various skeletal components, can be altered just as joint limits can. In this way, the size and shape of an avatar can be tuned as necessary. The joint limit interface includes selection a region of the body, selection joint by click the red square on the body, sliders to adjust the joint limits in local x, y, and z directions although each joint has a default limit, and cost function percent. After the user adjust the joint limits and save them, they can go back to posture prediction to predict posture under the new joint limits. Therefore the cost function percent will show the bar graph. The link length interface is similar to the joint limit one shown in Fig.13.

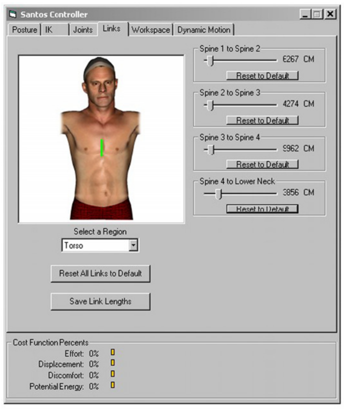

Fig.13. Link lengths interface.

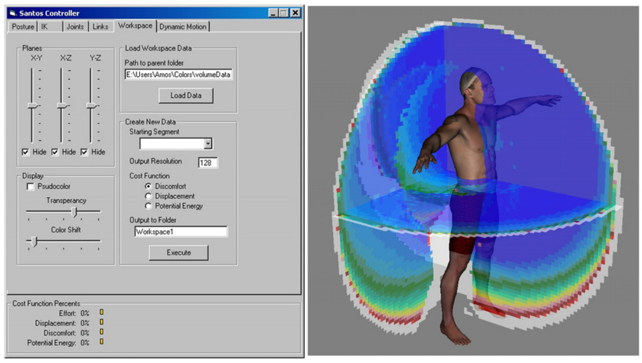

Fig.14. Workspace zone differentiation interface.

As a final example of functionality that has grown out of our approach to posture prediction, we have extended the optimization-based posture prediction to *zone differentiation*, where one can distinguish zones within the envelope where the various performance measures take on different ranges. In this way, one can determine not only which items Santos$^{\mathrm{TM}}$ can touch but also which items can be handled most comfortably, with the least amount of energy expenditure, with the least amount of effort, etc. Fig.14 shows the workspace zone differentiation interface. This interface includes workspace data input and output, cross section planes to cut the workspace, and display color selection. Currently, the zone differentiation code runs off-line and we load the results and show the zone differentiation results. The ultimate goal will be the real-time capability with which the user can choose the body segment for the workspace, cost function, output resolution.

5.2 Interactive Virtual Environment

Given the advanced capabilities discussed above as well as interfaces for using these capabilities, the ultimate goal is to have users actually interact directly with Santos™ in an immersive virtual environment. Such an environment for hosting Santos™ provides an extra advantage in the design and evaluation process. For this purpose, a 6-wall virtual reality environment, called the Portal, has been built at The University of Iowa. The Portal is a room with a rear-projection (using CRT projectors) screen for each wall shown in Figs. 15 and 16. Six individual computers are connected using a local area network (LAN), and each computer's graphics card is gen-locked and frame-locked to the other computer such that the projections from all of the computers are synchronized. One computer is designated as the Lead and is used to issue a synchronization signal to the other five computers.

Users have full flexibility in interacting with the Portal, whether by using virtual gloves and sensors, a hand-held controller, or a simple mouse. Figs. 17 and 18 illustrate potential interactivity between the user and Santos™ in a virtual environment.

Fig.15. Portal.

Fig.16. Santos™ Living in the Portal.

Fig.17. User and digital human in VR environment.

Users can test maintainability and serviceability of vehicles using this virtual environment and interact with Santos™ to evaluate the design. One example is that users can directly test the reachability and space of service areas by a hand-held controller to manipulate the vehicles in this virtual environment.

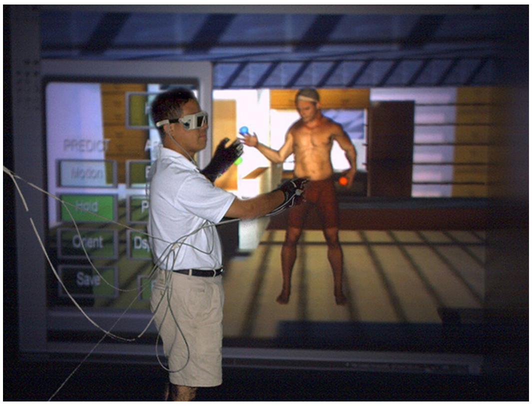

Fig.18. User interaction within the digital human environment.

6 Conclusions

In this paper, a general and robust mathematical formulation for predicting human posture has been proposed and demonstrated using a variety of human performance measures. The modeling method is not restricted to any specific number of DOFs. We have developed six different interfaces for Santos™, and with these interfaces, users can easily interact with Santos™ while focusing on analysis and design issues. Finally, an interactive digital-human virtual environment system has been presented, with which one can visualize simulation results and interact with Santos™.

The results obtained with D-HOPP are intended to demonstrate basic real-time capabilities. However, with D-HOPP, incorporating additional capabilities is simply a matter of introducing new constraints and/or objective functions. For instance, we are able to dictate the orientation of different parts of the avatar, incorporate self-avoidance allowing the avatar to acknowledge his/her body, and have the user specify any end-effector whether it is actually located on the body or not. In addition, the user can restrict various end-effectors to a specified point, bounded line, or bounded plane. Finally, D-HOPP has been developed such that anthropometric data concerning skeletal structure and joint limits are easily altered.

In coupling interactive capabilities with advanced posture prediction capabilities, the ultimate goal is to have Santos™ act as a design companion. The work discussed in this paper is geared towards having an actual design engineer or analyst not only use the proposed capabilities as a tool but also actually work with Santos™.

References

[1] Porter J M, Case K, Bonney M C. Computer Workspace Modelling. Evaluation of Human Work, Wilson J R, Corlett E N (eds.), London, UK: Taylor & Francis, 1990, pp.472–499.

[2] Das B, Sengupta A K. Computer-aided human modeling programs for workstation design. *Ergonomics*, 1995, 38: 1958–1972.

[3] Beck D J, Chaffin D B. An Evaluation of Inverse Kinematics Models for Posture Prediction. Computer Applications in Ergonomics, Occupational Safety and Health, Amsterdam, The Netherlands: Elsevier, 1992, pp.329–336.

[4] Zhang X, Chaffin D B. Task effects on three-dimensional dynamic postures during seated reaching movements: An analysis method and illustration. In *Proc. the 40th Annual Meeting of the Human Factors and Ergonomics Society*, Philadelphia, PA, Part 1, 1996, pp.594–598.

[5] Das B, Behara D N. Three-dimensional workspace for industrial workstations. *Human Factors*, 1998, 40(4): 633-646.

[6] Faraway J J, Zhang X D, Chaffin D B. Rectifying postures reconstructed from joint angles to meet constraints. *Journal of Biomechanics,* 1999, 32: 733–736.

[7] Tracy M F. Biomechanical methods in posture analysis. In Evaluation of Human Work, Wilson J R, Corlett E N (eds.), London, UK: Taylor & Francis, 1990, pp.571–604.

[8] Jung E S, Kee D, Chung M K. Reach posture prediction of upper limb for ergonomic workspace evaluation. In *Proc. the 36th Annual Meeting of the Human Factors Society*, Atlanta, GA, Part 1, 1992, 1: 702–706.

[9] Jung E S, Kee D, Chung M K. Upper body reach posture prediction for ergonomic evaluation models. *International Journal of Industrial Ergonomics,* 1995, 16: 95–107.

[10] Kee D, Jung E S, Chang S. A man-machine interface model for ergonomic design. *Computers & Industrial Engineering,* 1994, 27: 365–368.

[11] Jung E S, Choe J. Human reach posture prediction based on psychophysical discomfort. *International Journal of Industrial Ergonomics,* 1996, 18: 173–179.

[12] Wang X G. A behavior-based inverse kinematics algorithm to predict arm prehension postures for computer-aided ergonomic evaluation. *Journal of Biomechanics,* 1999, 32: 453–460.

[13] Tolani D, Goswami A, Badler N. Real-time inverse kinematics techniques for anthropomorphic limbs. *Graphical Models*, 2000, 62(5): 353–388.

[14] Saramago S F P, Steffen Jr V. Optimization of the trajectory planning of robot manipulators taking into account the dynamics of the system. *Mechanism and Machine Theory*, 1998, 33(7): 883–894.

[15] Saramago S F P, Steffen Jr V. Optimal trajectory planning of robot manipulators in the presence of moving obstacles. *Mechanism and Machine Theory,* 2000, 35(8): 1079–1094.

[16] Saramago S F P, Ceccarelli M. An optimum robot path planning with payload constraints. *Robotica,* 2002, 20(4): 395–404.

[17] Zhao J, Bai S X. Load distribution and joint trajectory planning of coordinated manipulation for two redundant robots. *Mechanism and Machine Theory,* 1999, 34(8): 1155–1170.

[18] Abdel-Malek K, Yu W, Jaber M. Realistic posture prediction. *SAE Digital Human Modeling and Simulation*, 2001.

[19] Abdel-Malek K, Yu W, Mi Z, Tanbour E, Jaber M. Posture prediction versus inverse kinematics. In *Proc. the ASME Design Engineering Technical Conference,* Pittsburgh, PA, USA, 2001.

[20] Yu W. Optimal placement of serial manipulators [Dissertation]. University of Iowa, Iowa City, IA, 2001.

[21] Mi Z. Task-based prediction of upper body motion [Dissertation]. University of Iowa, Iowa City, IA, 2004.

[22] Mi Z, Yang J, Abdel-Malek K. Real-time inverse kinematics for humans. In *Proc. ASME Design Engineering Technical Conferences*, Sept. 29–Oct. 2, 2002, Montreal, Canada.

[23] Marler R T, Rahmatalla S, Shanahan M, Abdel-Malek K. A new discomfort function for optimization-based posture prediction. *SAE Human Modeling for Design and Engineering Conference*, Iowa City, IA, Society of Automotive Engineers, Warrendale, PA, June 2005.

[24] Yang J, Marler R T, Kim H, Arora J S, Abdel-Malek K. Multi-objective optimization for upper body posture prediction. In *10th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference*, August, Albany, NY, American Institute of Aeronautics and Astronautics, Washington DC, 2004.

[25] Farrell K, Yang J, Abdel-Malek K. Santos$^{\mathrm{TM}}$: A new interactive virtual human. In *SIGGRAPH 2004 Real-Time 3DX: Demo or Die*, Los Angeles, California, Aug. 8–12, 2004.

[26] Marler R T. A study of multi-objective optimization methods for engineering applications [Dissertation]. University of Iowa, IA, 2005.

[27] Marler R T, Yang J, Arora J S, Abdel-Malek K. Study of bi-criterion upper body posture prediction using pareto optimal sets. *IASTED International Conference on Modeling, Simulation, and Optimization*, August, Oranjestad, Aruba, International Association of Science and Technology for Development, Canada, 2005.

[28] Boman D K. International survey: Virtual-environment research. *Computer*, 1995, 8(6): 57–65.

[29] Balsicoy S, Sannier G, Magnenat-Thalmann N, Thalmann D. An interactive interface for directing virtual humans. In *Proc. ISCIS,* IOS Press, Antalya, Turkey, 1998.

[30] Pandzic I, Thalmann N M, Capin T, Thalmann D. VirtualLifeNetwork: A body-centered networked virtual environment. *Presence, MIT*, 1997, 6(6): 676–686.

[31] Çapin T K, Pandzic I S, Noser H, Thalmann N M, Thalmann D. VirtualHuman representation and communication in VLNET. *IEEE Computer Graphics and Applications,* 1997, 17(2): 42–53.

[32] Normand V, Babski C, Benford S *et al.* The COVEN Project: Exploring Applicative, Technical and Usage Dimensions of Collaborative Virtual Environments. Presence: Teleoperators and Virtual Environments, MIT Press, 1999, 8(2): 218–236.

[33] Thalman D. Virtual human as a multimodal interface. In *Proc. the Workshop on Advanced Visual Interfaces*, 2000, Palermo, Italy, pp.14–20.

[34] Ishii H, Endou K, Sharyo K, Komaki D, Ichiguchi N, Yoshikawa H. A new integration method of constructing an interactive virtual environment for the collaboration between virtual agent and real human. In *Proc. the IEEE International Workshop on Robot and Human Communication*, Bordeaux, Paris, 2001, pp.50–55.

[35] Denavit J, Hartenberg R S. A kinematic notation for lower-pair mechanisms based on matrices. *Journal of Applied Mechanics,* 1955, 77: 215–221.

[36] Abdel-Malek K, Yang J, Brand R, Tanbour E. Towards understanding the workspace of the upper extremities. *SAE Transactions—Journal of Passenger Cars: Mechanical Systems,* 2001, 110(6): 2198–2206.

[37] Yang J, Abdel-Malek K, Nebel K. Reach envelope analysis and visualization of a 9 degree of freedom model of the upper extremity. *International Journal of Robotics and Automation,* 2005, 20(4): 240–259.

[38] Farrell K, Marler R T, Abdel-Malek K. Modeling dual-arm coordination for posture: An optimization-based approach. *SAE Human Modeling for Design and Engineering Conference*, Juna, Iowa City, IA, Society of Automotive Engineers, Warrendale, PA, 2005.

[39] Yang J, Marler T, Beck S *et al.* New capabilities for the virtual-human Santos$^{\mathrm{TM}}$. *SAE 2006 World Congress*, April 3–6, 2006. Cobo Center, Detroit, Michigan.

[40] Jung E S, Choe J, Kim S H. Psychophysical cost function of joint movement for arm reach posture prediction. In *Proc. the Human Factors and Ergonomics Society 38th Annual Meeting*, Nashville, TN, Human Factors and Ergonomics Society, Santa Monica, CA, Oct. 1994, pp.636–640.

[41] Marler R T, Arora J S. Survey of multi-objective optimization methods for engineering. *Structural and Multidisciplinary Optimization*, 2005, 26(6): 369-395.

[42] Gill P, Murray W, Saunders A. SNOPT: An SQP algorithm for large-scale constrained optimization. *SIAM Journal of Optimization*, 2002, 12(4): 979–1006.

Jingzhou Yang is an adjunct assistant professor at Department of Mechanical & Industrial Engineering, research engineer with the Virtual Soldier Research (VSR) Program at the Center for Computer Aided Design (CCAD), the University of Iowa, Iowa City, USA. He received his B.S. and M.S. degrees in automotive engineering from Jilin University, China, the Master in computer science and the Ph.D. degree in mechanical engineering from the University of Iowa, Iowa City, USA. He was a faculty member at the Department of Automobile Engineering and a researcher at the State Key Laboratory of Automobile Safety and Energy Conservation, Tsinghua University, Beijing, China. He is a recipient of the 2001 Arch T. Colwell best paper award from the Society of Automotive Engineers (SAE), and 2004 outstanding paper award from the American Society of Mechanical Engineers (ASME). His research interests include geometric modeling, CAD/CAM/CAE, kinematic and dynamic analysis, digital human modeling and simulation, robotics, biomechanics, optimization methods and applications in human modeling, and ergonomics.

R. Timothy Marler is the senior research scientist with University of Iowa's Virtual Soldier Research (VSR) program. He is a licensed mechanical engineer with extensive experience in the fields of automotive design, lean manufacturing, teaching, and research. His general research interests include optimization, game theory, fuzzy function theory, and human modeling. Specifically, he works with applying optimization to predictive human models, developing advanced optimization-based posture prediction capabilities, and developing new methods and techniques for multi-objective optimization.

Steven Beck is a senior project manager for the Virtual Soldier Research (VSR) Program, Center for Computer Aided Design, The University of Iowa. He received his B.A. from The University of Iowa in 1994 and has used his background in CAD and design visualization, 3D computer graphics, and multidimensional data visualization to aid researchers at the University of Iowa through technical consulting, University course instruction, and project management.

Karim Abdel-Malek is a professor of biomedical engineering, director of Center for Computer Aided Design at the University of Iowa, Iowa City, IA. Prof. Abdel-Malek's research is in real-time kinematics and dynamics of robotics. He is internationally recognized for his work on swept volumes and robot manipulator kinematics. Prof. Abdel-Malek is the founder of VizTek, Inc., a leader in virtual reality and military simulation. He received his M.S. and Ph.D. degrees in robotics from the University of Pennsylvania and a B.S. in mechanical engineering from the University of Jordan. He has authored or co-authored over 100 technical papers in the field and 2 US Patens. He is the recipient of the Fulbright Scholarship, the IASTE Scholarship, the John T. Parsons Outstanding Manufacturing Engineer award from the Society of Manufacturing Engineers (SME), 2001 Arch T. Colwell best paper award from the Society of Automotive Engineers for his pioneering work on "Understanding the workspace of the upper extremities", 2004 outstanding paper award from the American Society of Mechanical Engineers (ASME), was nominated to the Academy of Sciences Frontiers of Engineers, and he serves on several national and international committees of conferences and review panels. Dr. Abdel-Malek is the Editor-in-Chief of the *International Journal of Human Modeling and Simulation*.

Joo Kim is currently a Ph.D. candidate of mechanical engineering and research assistant of the Virtual Soldiers Research Program in the Center for Computer-Aided Design at The University of Iowa. Mr. Kim received the M.S. degree in biomedical engineering in 2000 from The University of Iowa. His research interests include dynamics and control of manipulators, general robotics, optimization, and biomechanics. He is currently working on the digital human modeling and simulation project, which evaluates proper human dynamic motion, energy and required torques.