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A New Discomfort Function for Optimization-Based Posture Prediction

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ABSTRACT

Using multi-objective optimization, we develop a new human performance measure for direct optimization-based posture prediction that incorporates three key factors associated with musculoskeletal discomfort: 1) the tendency to move different segments of the body sequentially, 2) the tendency to gravitate to a comfortable neutral position, and 3) the discomfort associated with moving while joints are near their respective limits. This performance measure operates in real-time and provides realistic postures. The results are viewed using Santos^{TM}, an advanced virtual human, and they are validated using motion-capture. This research lays groundwork for studying how and why humans move as they do.

INTRODUCTION

Virtual humans (avatars) that act and look like real humans offer a means to evaluate and test virtual prototypes without having to build an actual costly prototype. This also reduces the design-cycle time for any product that requires human interaction. In addition, accurate models that move as humans do enable one to study humans how and why humans move in a particular way, thus providing insight and data for ergonomic studies, injury prevention, and general human-centric design. A key requirement of these virtual humans is the ability to predict postures quickly and realistically. The most basic posture prediction problem entails having an avatar use a natural posture to contact a specified target point with an *end-effector*, which is a point of interest (typically the end-point in a series of links) on a kinematic system such as a human arm. This paper focuses on an optimization-based approach in exploring such functionality.

With an optimization-based approach, the joint angles for all of the degrees-of-freedom (DOFs) in the human model provide the design variables and are determined by optimizing an objective function that represents a human performance measure, such as discomfort. In general, performance measures are metrics that govern how a virtual human moves, given a particular scenario. Since different measures can result in slightly different postures, a primary question concerning the optimization-based approach is which performance measure or combination of measures should be used as objective functions. In general, this question can be addressed with the following three-stage process: 1) hypothesize that a physically significant (rather than purely mathematical) concept influences posture, 2) model that concept with a performance measure, 3) test the new performance measure in the context of the optimization problem, and 4) evaluate and/or validate the results. In this way, the optimization-based approach enables one to study which factors govern human posture. The appropriateness of a particular performance measure may depend on the task being completed. In addition, multiple performance measures may need to be combined using multi-objective optimization (MOO). However, this work addresses just one basis for posture prediction; it concerns initial steps towards modeling some components of discomfort. Essentially, the focus is on providing initial results for stage two of the above-mentioned process.

We contend that posture is governed, in part, by musculoskeletal discomfort. Although much research has been conducted that pertains to human discomfort, most of it involves evaluation experiments with human subjects. Relatively little research has focused on providing a general predictive model for discomfort. Of course, the concept of discomfort can be vague and subjective, varying from person to person, but it is possible to incorporate distinct factors that stem from the idea of discomfort, while the absolute value for discomfort is not necessarily consequential. Thus, we present initial results with a new human performance measure that is based on the following three factors associated with discomfort: 1) the tendency to move different segments of the body sequentially, 2) the tendency to gravitate to a reasonably comfortable neutral position, and 3) the discomfort associated with moving while joints are near their respective limits. The primary concern is with static discomfort, corresponding to an instantaneous posture. In addition, environmental or psychological factors, such as ambient temperature, humidity, perception, fear, are not considered. Rather, the emphasis is on factors related to the musculoskeletal system. The proposed performance measure was introduced by Yang *et al* (2004) in the broader context of using MOO for posture prediction. In this paper, we elaborate on the development, analysis, and testing of this measure. Note that the absolute value for discomfort is not necessarily significant; we do not intend to quantify precisely the fuzzy idea of discomfort. Rather, we design a discomfort function that governs human posture.

OVERVIEW OF THE PAPER

This paper presents work towards a predictive discomfort model. Although the consequent human performance measure does not require experimental data, it incorporates factors that have been shown to influence discomfort experimentally. Discomfort is not the same as simple joint displacement, despite the semantic discrepancy in the literature. Rather, the new performance measure is based on three different biomechanical concepts, and the effectiveness of incorporating these concepts is studied.

The current literature is reviewed with respect to optimization-based posture prediction and discomfort. Then, before presenting the details of the proposed discomfort function, we present an overview of direct optimization-based posture prediction, including a description of the human model and an outline of the optimization formulation. Then, MOO is leveraged in detailing the components of the performance measure. Finally, we discus the effectiveness of this performance measure and compare the results to those obtained with motion capture.

LITERATURE REVIEW

The focus of this paper concerns the incorporation of discomfort-related factors into a human performance measure for an optimization-based approach to posture prediction. Consequently, a brief overview of approaches to posture prediction is provided, followed by a review of current literature pertaining to a direct optimization-based approach and to discomfort.

POSTURE PREDICTION

While a thorough review of methods for posture prediction is provided by Mi (2004), a brief overview is provided here. There are two fundamental approaches to posture prediction. First, one can predict posture based on prerecorded motion, anthropometric data, and functional regression models (Beck and Chaffin, 1992; Zhang and Chaffin, 1996; Farraway, 1997; Das and Behara, 1998; Faraway *et al*, 1999; Chaffin, 2002). This approach has been used extensively with automotive seating evaluation and design (Reed *et al*, 1999, 2000a).

Alternatively, one can use inverse kinematics to predict posture, without observed data. There is a variety of approaches to inverse kinematics, one of the most a common of which is the pseudo-inverse method (Liegeois, 1977; Klein and Huang, 1983; Jung *et al*, 1995). Essentially, the solution (set of joint angles representing a posture) is determined iteratively using the pseudo-inverse of the Jacobian matrix, which represents the derivatives of the end-effector position with respect to the joint angles. In addition, during each iteration, an optimization algorithm is run to minimize the deviation of the resolved posture from a predetermined reference posture. Eventually, the algorithm converges on a final posture (set of joint angles). Zhang et al (1998) incorporate optimization in a weighted pseudo-inverse approach whereby the weights ere estimated such that the predicted motion approximates prerecorded motion. Reed *et al* (2000b) also combine the use of optimization and experimental data by using an optimization prediction model with three DOFs to find a posture that approximates the data most accurately.

It is possible to use optimization to determine a posture directly, without experimental data, and with only one run of the optimization algorithm. Joint angles provide the design variables that are determined to minimize a human performance measure, subject to constraints concerning joint limits and the final position of the end-effector. We refer to this as a *direct optimization-based approach*. It affords the virtual human a substantial amount of autonomy in reacting to infinitely many scenarios rather than using a finite set of recorded motions or postures. In addition, it is applicable to human models with a relatively high number of DOFs, and it provides real-time predictions. Consequently, the work in this paper builds on the advantages of this approach.

Zhao and Badler (1994) provide one of the earliest works with the direct use of optimization for posture prediction. A gradient-based optimization routine is used to minimize an objective function formed by the weighted sum of components that model various factors, such as the position of the end-effector (a specified point, line, or plain) or the orientation of the hands. Limits on the joint angles are incorporated as constraints. The work is demonstrated using a 22-DOF full-body virtual human. Riffard and Chedmail (1996) use a similar approach and determine the optimum placement of the torso and the optimum posture of a seven-DOF arm, using simulated annealing, which is a global optimization method. Equations for target contact, collision avoidance, vision, body-orientation, and torque are combined in a weighted sum to form the objective function.

Yu (2001) uses *joint displacement* and potential energy as objective functions for a three-DOF arm, while the position of the end-effector is modeled as a constraint along with limits on eth joint angles. Joint displacement is defined as follows:

$$f_{Joint\ displacement}(\mathbf{q}) = \sum_{i=1}^{DOF} w_i f_i(q_i) \tag{1}$$

$$f_i(q_i) = \left(q_i - q_i^N\right)^2 \tag{2}$$

where **q** is a vector of joint angles. q_i^N is the *neutral position* of a single joint, and the neutral position of the complete system, $\mathbf{q}^N$, represents a relatively comfortable position. With this formulation, the avatar's position gravitates towards the neutral position. w_i are scalar weights and are used to stress the importance of particular joints. Mi *et al* (2002b) and Mi (2004) extend the work of Yu (2001) to a 15-DOF upper-body model with similar objective functions. In addition, a real-time optimization algorithm is developed that combines genetic-algorithm results from a library of off-line computations with results from a faster unconstrained gradient-based algorithm.

Although some work has been completed concerning the concept of optimization-based posture prediction, this approach depends heavily on the objective function, and relatively little work has been conducted that implements varied human performance measures. In addition, human models with the optimization approach have been relatively simple, with few DOFs. We respond to this deficiency by introducing a new performance measure with a high-DOF human model.

DISCOMFORT

There is an extensive amount of literature concerning discomfort, but most of it pertains to experimentation with subjective feedback provided by human subjects rather than predictive modeling (Redfern and Chaffin, 1995; Olendorf and Drury, 2001; Monnier *et al*, 2002; Fehren *et al*, 2003). In some cases, regression models are developed based on the experimental results (Chevalot and Wange, 2004; Moschandreas and Sofuoglu, 2004). However, little work involves predictive mathematical modeling that does not depend on experimentation. The experimental work has flushed out factors that contribute to discomfort, but these components have not yet been incorporated collectively in an effective optimization-based performance measure for use with virtual humans.

Much work has been conducted involving discomfort that stems from factors outside the human body or unrelated to motion (Toftum *et al*, 2000; Hoppe, 2001; Fehren *et al*, 2003; Fisekis *et al*, 2003; Kaynakli and Kilic, 2005; Nagano and Horikoshi, 2005). Da Silva (2002) provides a thorough review of environmental factors (thermal conditions, air quality, noise, etc.) that effect comfort in a vehicle. However, this paper focuses on discomfort issues related to the musculoskeletal system.

Shen and Galer (1993) determine that discomfort while sitting is multifaceted, depending on different components, including the relative position of the body joints with respect to the environment (i.e. a seat), the ability to alter the position of the joints over time, duration of a fixed posture, and applied pressure.

Allread *et al* (1998) perform experiments to evaluate discomfort in manufacturing environments and find that overall total-body discomfort depends on external loads and on the nature of tasks that are being completed (i.e., lifting and moving objects). Alternatively, discomfort in specific body parts depends on kinematics of the torso area. Discomfort is often highest in the lumbar region and in the shoulder, implying that different segments of the body should be considered separately.

Santos *et al* (2000) conduct experiments to correlate subjective indications of discomfort with biomedical indices that are evaluated using a 54-DOF motion-capture model. They find that discomfort increases as the distance between the human and the intended target point increases. Reaching out from the body, as opposed to reaching across the body, results in the highest discomfort. The authors find a linear relationship between discomfort and the following two biomedical indices: 1) the deviation from a neutral position, and 2) the moments in the muscles that are necessary to counter the effect of gravity. Other authors also suggest that joint stresses and loads provide an additional factor for modeling discomfort (Kayis and Hoang, 1999; Bubb and Estermann, 2000).

Zacher and Bubb (2004) draw similar conclusions with respect to a proposed force-based discomfort model. They find that discomfort depends on the magnitude and direction of forces at the joints. In addition, discomfort is proportional to how close a joint angle is to its limits, i.e., the degree of flexion. The authors suggest that overall discomfort is highly dependent on the maximum discomfort for a single body part. This suggests that different joints should be viewed independently to some extent. Chung *et al* (2002) also distinguish between the discomfort at each joint and the total-body discomfort, and they use a neural network to relate the two. Although limited to work with the wrists, Carey and Gallway (2002) also find a correlation between discomfort and extreme flexion.

Zhang (1996) suggests that comfort and discomfort should be treated as different but complementary quantities, finding that discomfort tends to be associated with biomechanical factors, whereas comfort is associated with "feelings of relaxation and well-being." With respect to sitting, Shen and Vertiz (1997) refine the general concept of comfort, also contrasting it with discomfort and suggested that comfort is a temporal quantity. In this paper, since we are concerned only with static posture prediction, we are concerned only with static, instantaneous discomfort.

In addition to the above-mentioned experimental work, some work has been completed with the development of discomfort-based human models, although the representation of discomfort in this capacity and the models themselves are limited. Jung *et al* (1994) provide one of the first mathematical metrics for discomfort. Drawing on the work of Liegeois (1977), who uses the pseudo-inverse method for motion prediction of a six-DOF robot, the authors essentially use a normalized form of (1) with each component of the neutral position determined as the center angle for each joint. They refer to this as discomfort (as opposed to joint displacement), and it is based on the idea that discomfort for the arm reaches a minimum approximately when each joint is at its center angle (Cruse *et al*, 1990). This form of discomfort is used with a two-dimensional, four-DOF human model that is based on inverse kinematics. Jung and Choe (1996) extend the work of Jung *et al* (1994) to a three-dimensional, seven-DOF human model, with externally applied forces. Again, a regression model is used to create a discomfort function. Yu (2001), Mi *et al* (2002), and Mi (2004) use a similar concept for discomfort, although the term *joint displacement* is used. In this case, the weights are based on trial-and-error.

Although substantial research concerning the nature of discomfort exists, little work has been completed towards developing a general discomfort model that can be incorporated in an optimization-based posture prediction algorithm. We argue that although (1) is a common and necessary ingredient for modeling discomfort, conceptually, it is incomplete and yields an overly simple model. Additional factors should be considered.

OVERVIEW OF OPTIMIZATION-BASE POSTURE PREDICTION

Simulating human posture depends largely on how the human skeleton is modeled, so we briefly describe the model that provides the foundation for this study. A skeleton can be viewed as a kinematic system, a series of links with each pair of links connected by one or more revolute joints. Therefore, a complete human body can be modeled as several kinematic chains, formed by series of links and revolute joints, as shown in Figure 1.

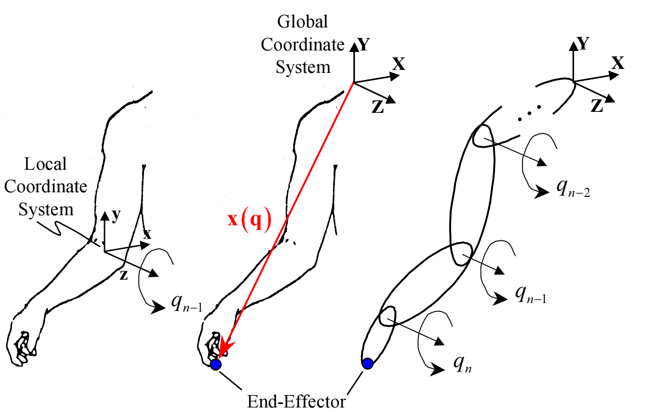


Figure 1: A Kinematic Chain of Joints

q_i is a *joint angle* and represents the rotation of a single revolute joint. There is one joint angle for each DOF. $\mathbf{q} = [q_1, \ldots, q_n]^T \in R^n$ is the vector of joint angles in an *n*-DOF model and represents a specific posture. Each skeletal joint is modeled using one, two, or three kinematic revolute joints. $\mathbf{x}(\mathbf{q}) \in R^3$ is the position vector in Cartesian space that describes the location of the *end-effector* as a function of the joint angles, with respect to the global coordinate system. An end-effector is a point of interest on a kinematic chain, and in this case, the end-effector is the tip of the index finger. For a given set of joint angles **q**, the position of the end-effector in Cartesian space $\mathbf{x}(\mathbf{q}) \in R^3$, is determined using the Denavit-Hartenberg method (Denavit and Hartenberg, 1955).

With this study, a 21-DOF model for the human torso and right arm is used and is shown in Figure 2, where each cylinder represents a rotational DOF. q_1 through q_{12} represent the spine. q_{13} through q_{17} represent the shoulder and clavicle. q_{18} through q_{21} represent the right arm. The link lengths between each of the joints are variable and can be set based on anthropometric data, thus representing various population variations. The same is true of the masses for various body segments.

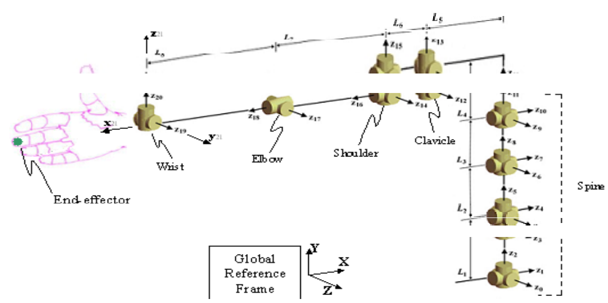


Figure 2: 21-DOF Kinematic Model

OPTIMIZATION PROBLEM FORMULATION

The posture of the above-described model can be determined by solving the optimization problem presented in this section. The design variables for the final optimization problem are q_i, measured in units of degrees. The vector **q** represents the consequent posture. Because listing values for all of the joint angles with each predicted posture can be cumbersome and unrevealing, results are depicted with actual pictures of the avatar.

The first constraint, called the *distance* constraint, requires the end-effector to contact the target point. In addition, each joint angle is constrained to lie within predetermined limits. q_i^U represents the upper limit for q_i, and q_i^L represents the lower limit. These limits ensure that the virtual human adheres to natural restrictions on joints and does not assume an unrealistic posture.

The optimum posture for the 21-DOF system shown in Figure 2 is determined by solving the following problem:

Find: $\mathbf{q} \in R^{DOF}$ (3)

to minimize: $f_{Discomfort}(\mathbf{q})$

subject to: $distance = \left\| \mathbf{x}(\mathbf{q})^{end\text{-}effector} - \mathbf{x}^{target\ point} \right\| \le \varepsilon$

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

where ε is a small positive number that approximates zero. (3) is solved using the software SNOPT (Gill *et al*, 2002), which uses a sequential quadratic programming algorithm. Analytical gradients are determined for the objective function and for all constraints.

DEVELOPMENT OF A DISCOMFORT PERFORMANCE MEASURE

We view the development of the discomfort performance measure in terms of MOO. Therefore, before discussing the details of the measure, we provide a brief overview of MOO. Each component of the final discomfort function (involving a single joint angle) is referred to as a *joint term*, an example of which is given in (2). Each joint term constitutes a separate, individual objective function. The general MOO problem is posed as follows:

Find: $\mathbf{q} \in R^{DOF}$ (4)

to minimize: $\mathbf{f}(\mathbf{q}) = \left[f_1(q_1) \quad f_2(q_2) \quad \cdots \quad f_k(q_k) \right]^T$

subject to: $g_i(\mathbf{q}) \le 0 \quad i = 1, 2, \cdots, m$

where k is the number of objective functions and m is the number of inequality constraints. $\mathbf{f}(\mathbf{q}) \in E^k$ is a vector of joint terms $f_i(q_i)$. Given a set of concepts that relate to the idea of discomfort and that must be incorporated in a model, one must determine the most effective form of $f_i(q_i)$ and how to incorporate these functions in (4).

The idea of a solution for (4), where multiple objectives may conflict with one another (e.g., what minimizes one function may increase another), can be unclear. Consequently, the idea of *Pareto optimality* is used to describe solutions for MOO problems. A solution point is Pareto optimal if it is not possible to move from that point and improve at least one objective function without detriment to any other objective function. Typically, there are infinitely many Pareto optimal solutions for a MOO problem. Thus, it is often necessary to incorporate user preferences in order to determine or select a single suitable solution. With methods that incorporate *a priori articulation of preferences*, the user indicates the relative importance of the objective functions or desired goals before running the optimization algorithm. Different methods allow one to articulate preferences in different ways, but the most common approach is to have the user set parameters such as the weights in (1).

DISCOMFORT FACTORS

Using the idea of MOO, three key factors are incorporated in the proposed performance measure. In order to incorporate the first factor, the tendency to move different segments of the body sequentially, we base the discomfort function on the *lexicographic method* for MOO, which is discussed in detail by Marler and Arora (2004). With the lexicographic method, one simply prioritizes the objectives rather than articulating preferences with weights that indicate the relative importance of individual objective functions as shown in (1). Then, one objective at a time is minimized in a sequence of separate optimization problems. After an objective has been minimized, it is incorporated as a constraint in the subsequent problems. By using the concept behind the lexicographic method, one is able to model the idea that groups of joints are utilized sequentially. That is, in an effort to reach a particular target point, one first uses one's arm. Then, only if necessary, does one bend the torso. Finally, if the target is still out of reach, one may exercise the clavicle joint. Essentially, different groups of joints are included in one of three objective functions (one for the arm, torso, and clavicle), which are then optimized lexicographically. However, solving a sequence of optimization problems can be time consuming and impractical for real-time applications. Miettinen (1999) and Romero (2000) suggest that the weighted sum method can be used to approximate results of the lexicographic method if the weights have infinitely different orders of magnitude. This is the approach taken with the proposed discomfort function.

The weights γ_i, that are used to approximate the lexicographic approach, are shown in Table 1.

Joint Variables	γ_i
$q_1, \cdots, q_{12}$	1×10^4
q_{13}, q_{14}	1×10^8
$q_{15}, \ldots, q_{21}$	1

Table 1: Joint Weights for Discomfort

There is one γ_i associated with each joint variable, but only three different values. Although weights are used, they do not need to be determined as indicators of the relative significance of their respective joints; they are simply fixed mathematical parameters. The exact values of the weights are irrelevant; they simply have to have significantly different orders of magnitude. An additional benefit is that this approach avoids computational difficulties associated with discontinuous values for the weights in (1), which are common in the literature.

The second discomfort factor, the tendency to gravitate to a reasonably comfortable neutral position, is incorporated by using the weights in Table 1 with a function that is based loosely on (1) with the neutral position representing a posture with the arms straight down, parallel to the torso. Note that for this model, the neutral position is chosen based on observations of the skinned model in Figure 3 rather than on a skeletal model like the one shown in Figure 2. As argued by Marler and Arora (2005, in press), objective functions should be normalized when weights are incorporated a priori. Consequently, prior to applying the weights, each joint term is normalized as follows:

$$\Delta q^{norm} = \frac{q_i - q_i^N}{q_i^U - q_i^L} \tag{5}$$

With this normalization scheme, each term $\left(\Delta q_i^{norm}\right)^2$ acts as an individual objective function and has values between zero and one. The final aggregated discomfort function is given as follows:

$$f_{Discomfort}\left(\mathbf{q}\right) = \sum_{i=1}^{DOF} \gamma_i \left(\Delta q_i^{norm}\right)^2 \tag{6}$$

where γ_i are the weights defined in Table 1.

Generally, (6) is effective in modeling the tendency to move body segments sequentially and the tendency to gravitate towards a neutral position. However, it often results in postures with joints extended to their limits, and such postures can be uncomfortable and unrealistic. Consequently, to rectify this problem and to incorporate the final factor, the discomfort associated with moving while joints are near their respective limits, specially designed *penalty terms* are added to the discomfort function. Consequently, the modeled discomfort increases significantly as joint values approach their limits. The final discomfort function is given as follows:

$$f_{Discomfort}\left(\mathbf{q}\right) = \frac{1}{G}\sum_{i=1}^{DOF}\left[\gamma_i\left(\Delta q_i^{norm}\right) + G\times QU_i + G\times QL_i\right] \tag{7}$$

$$QU_i = \left(0.5 sin\left(\frac{5.0\left(q_i^U - q_i\right)}{q_i^U - q_i^L} + 1.571\right) + 1\right)^{100} \tag{8}$$

$$QL_i = \left(0.5 sin\left(\frac{5.0\left(q_i - q_i^L\right)}{q_i^U - q_i^L} + 1.571\right) + 1\right)^{100} \tag{9}$$

where $G \times QU$ is a penalty term associated with joint values that approach their upper limits, and $G \times QL$ is a penalty term associated with joint values that approach their lower limits. Each penalty term varies between zero and G, as the following two terms vary between zero and one:

$$\left(q_i^U - q_i\right) \Big/ \left(q_i^U - q_i^L\right) \tag{10}$$

$$\left(q_i - q_i^L\right) \Big/ \left(q_i^U - q_i^L\right) \tag{11}$$

Figure 3 illustrates the curve for the following function, which represents the basic structure of the penalty terms:

$$Q = \left(0.5 sin\left(5.0r + 1.571\right) + 1\right)^{100} \tag{12}$$

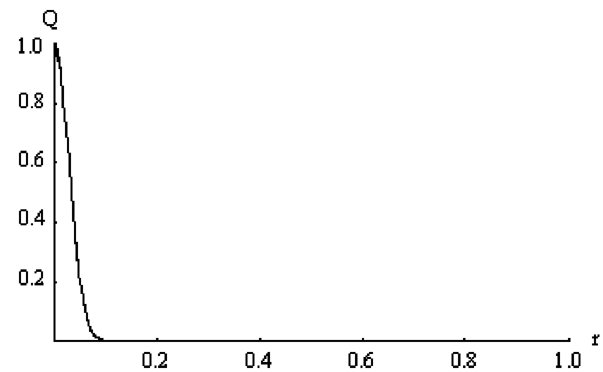


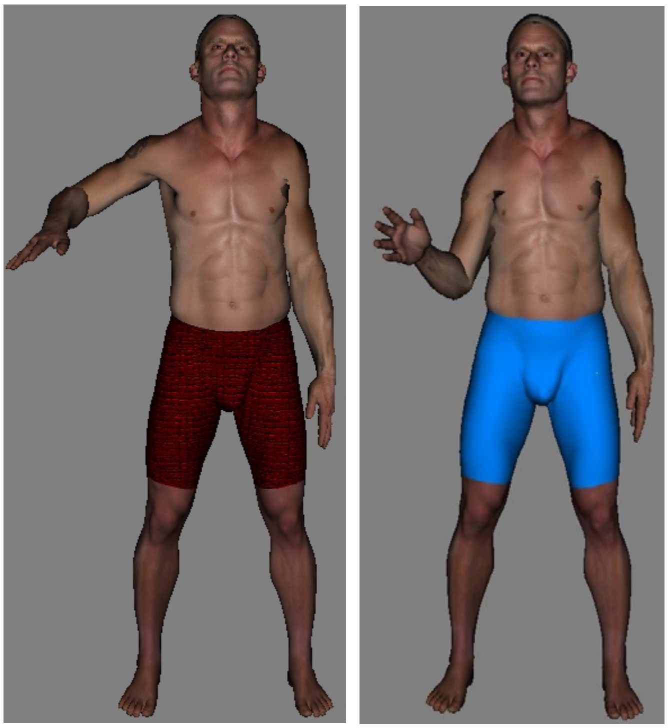
Figure 3: Graph of Discomfort Joint-Limit Penalty Term

r represents either the expression in (10) or (11). Thus, as Figure 4 illustrates, the penalty term has a value of zero until the joint value reaches the upper or lower 10% of its range. The curve for the penalty term is differentiable, and it reaches its maximum penalty value of $G = 10^6$ when $r = 0$.

RESULTS

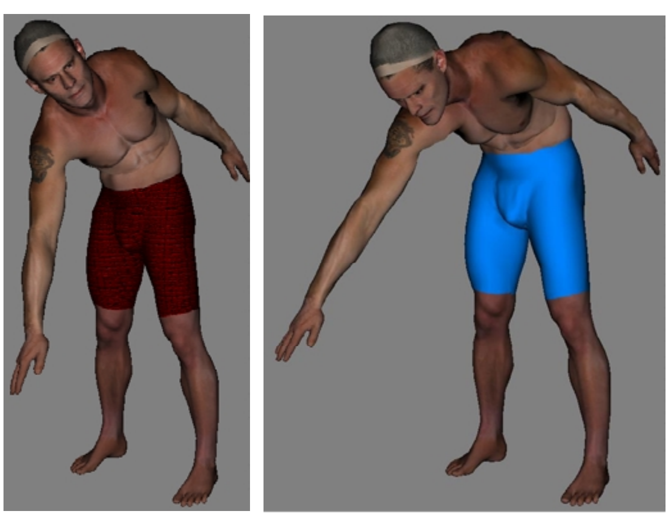
In general, when various target points are considered, the proposed discomfort function provides realistic results, where basic validation is performed using visual comparison between predicted postures and postures determined using an eight-camera Vicon motion-capture system. The specific results shown in this section, which illustrate some differences between predicted postures and captured postures, provide particularly interesting insight into human posture.

Figures 4 through 6 show results when the discomfort function is used to predict posture, given a target point to be touched with the right index finger. The results are illustrated using Santos™, an advanced virtual human based on the kind of skeleton discussed with respect to Figure 2. The virtual human (Santos™) in the dark shorts represents the predicted posture, and the virtual human in the light shorts represents the posture obtained with the motion capture system. Note that the nuances of skin deflection are not addressed. In fact, deformation in the stomach (Figure 6) is not necessarily an indication of discomfort.



Predicted Posture   Motion Capture

Figure 4: Results with Front Right Target Point



Predicted Posture   Motion Capture

Figure 5: Results with Front Lower Target Point

Predicted Posture   Motion Capture

Figure 6: Results with Back Target Point

With these preliminary results, one motion-capture subject is used for basic validation of the predicted posture. Markers are placed on the subject, and joint angles are determined based on the final position of the markers. These joint angles are then input into the virtual human model to yield a representation of the captured posture. Minor differences between the position of the end-effector for the predicted posture and the captured posture, stem from differences in the proportions of the motion-capture subject and Santos™. Nonetheless, the overall forms of the two postures (one with the motion-capture subject and one with Santos™) are comparable and revealing.

In Figure 4, the primary difference between the two postures is the height of the elbow. The elbow for the captured posture is lower than the elbow for the predicted posture. However, we found that this can depend in part, on the starting point (posture) for the motion-capture subject. With these tests, the subject started from the neutral position, where discomfort is essentially zero. However, when the subject began with both arms extended vertically, the final posture mimicked the predicted posture in Figure 4. This supports the idea behind another human performance measure called effort, which is modeled as follows (Yu, 2001; Mi *et al*, 2002):

$$f_{Effort}(\mathbf{q}) = \sum_{i=1}^{DOF} w_i \left(q_i - q_i^{initial} \right)^2 \qquad (13)$$

(13) is similar to (1) except that an initial position q_i^I is used in place of the neutral position q_i^N. Whereas $\mathbf{q}^N$ represents a generally comfortable position, $\mathbf{q}^I$ represents the initial posture of the avatar before a new posture is predicted. Consequently, postures resulting from (13) depend on the virtual human's starting posture and tend to gravitate towards that posture. In addition, initial studies have shown that when the discomfort function is coupled with a form of potential energy using MOO, the resulting predicted posture tends to have a slightly lower and more realistic elbow position (Marler, 2005).

In Figure 5, the predicted results involve a twist in the waist. This is because the legs in the model are fixed, so a twist in the waist is necessary to reach the target point. The motion-capture subject, however, was able to adjust the waist and ankles for balance and extended reach. This discrepancy between the two postures indicates the significance of modeling balance even for static posture prediction.

Figure 6 illustrates two distinctly different postures, but this does not necessarily reflect a deficiency in the discomfort function. In terms of skeletal mechanics, the predicted posture is relatively comfortable, because joints in the torso and shoulder are not forced to approach their limits. The captured posture appears to be slightly more reasonable only because one typically strives to see the target. Note that the eyes and neck are not incorporated in this posture prediction model. In this sense, no form of musculoskeletal discomfort is ideal for predicting postures that involve target points behind the avatar.

CONCLUSION

In this paper, we have introduced a new human performance measure for optimization-based posture prediction. The optimization-based approach facilitates the study of how and why people move the way they do, and by modeling specific factors hypothesized to govern posture, we are able to study the significance of such components. By leveraging the idea of multi-objective optimization, we have incorporated in the new performance measure three key factors that are associated with musculoskeletal discomfort: 1) the tendency to gravitate to a comfortable neutral position, 2) the tendency to move different segments of the body sequentially, and 3) the tendency to avoid postures where joints approach their limits. The consequent discomfort function generally yields realistic and acceptable postures, resulting in a successful feasibility study. We have highlighted examples that shed light on the nature of human posture.

The proposed performance measure depends on the selected neutral position and yields postures that tend to gravitate towards this datum. Alternate neutral positions can be used for different scenarios that dictate different sets or classes of postures. In fact, this datum provides a means for tailoring the discomfort function to a particular type of task. For instance, sitting would require a neutral position different from standing.

An added feature of the proposed performance measure is inherent self-avoidance, which entails the ability of the virtual human to avoid unrealistic intersections between different body segments. Addressing this issue can be extremely complex, but the penalty associated with joint limits provides a natural approximate guard against such inaccuracies.

The emphasis of this work has been on predicting static posture rather than precisely modeling discomfort. We have incorporated key components that effect posture and that are typically tied to discomfort. In doing so, we have discovered opportunities for additional work, much of which is ongoing. Vision can play a significant role in dictating posture, especially with target points behind the avatar. Thus, although it is not directly associated with musculoskeletal discomfort, it should be considered when predicting posture. In addition, incorporating joint torques could provide a physically significant substitute for the penalty that is associated with joint-angle limits. Modeling joint torques would also respond to experimental work that suggests that joint stresses and loads provide an additional factor for modeling discomfort.

The idea of modeling balance is typically associated with dynamic gait analysis. However, we have shown that balance can play a role in posture prediction as well, and work with a dynamic balance and gait model is ongoing. The work presented in this paper suggests that coupling the proposed discomfort function with other performance measures such as joint displacement, effort, or potential energy could be advantageous. In fact, Yang *et al* (2004) provide an initial study of incorporating MOO in this way. More extensive motion-capture studies and statistical analysis will provide additional validation studies for the predicted postures. In addition, the relative values for discomfort, given a variety of target points and consequent postures, will be validated with subjective evaluation of motion-capture subjects.

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