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# Posture Prediction with External Loads – A Pilot Study

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## ABSTRACT

As the need for more advanced human modeling tools has grown, so has the focus on research and development with posture-prediction capabilities for the design and analysis of products, and for the study of human behavior. Virtual humans have grown from digital mannequins with limited fidelity, to realistic avatars with predictive capabilities. Now, one of the frontiers with posture prediction is the incorporation of external loads and joint torques. Although advancements have been made with dynamic motion prediction, relatively little work has been conducted with external load-based posture prediction. Drawing on past success with optimization-based kinematic posture prediction implemented with the virtual human Santos™, we present a new method for considering external loads. A pilot study is conducted whereby equations for static equilibrium are incorporated in the optimization formulation. Consequently, torque (as well as joint angles) is determined for each degree of freedom, and is incorporated in human performance measures that serve as objective functions in the optimization formulation. The intent is to test the feasibility of extending the formulation for kinematic posture prediction. Different external loads are applied to the right and left hands respectively, while the same target points are provided for these different lead cases on both hands. The results for the previous work (kinematic formulation) and the new formulation are compared. The predicted postures are evaluated quantitatively in terms of numerical output, and subjectively in terms of visible postures. In general, the pilot study was successful; the predicted postures were reasonable. Including torque provided more realistic predicted postures and sets the stage for new discomfort models as well as consideration of reaction forces.

## INTRODUCTION

Digital human models (DHMs) provide efficient tools for product and process design, and human analysis. Such tools allow one to assess human-product interaction in a virtual environment in order to reduce design-cycle time and cost while increasing safety. As DHM technologies advance, potential applications expand to areas such as military, medicine, sports, etc. With many applications, one of the most essential capabilities is fast and accurate posture prediction and analysis. And, a critical component of human posture prediction is the incorporation of joint torques with applied loads. However, there has been minimal work with actually considering external loads in computational predictions of human posture. Thus, the primary objectives of this paper are 1) to test the feasibility of incorporating applied loads in optimization-based posture prediction, and 2) to test basic toque-based human performance measures that provide the objective functions for optimization-based posture prediction. This work is intended as a pilot study for further development of posture prediction capabilities.

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*Literature review*

With regards to methods for predicting posture, there are two main approaches: data-based approaches and analytical inverse kinematics (IK) approaches. With data-based approaches, one uses prerecorded motion data, anthropometric data, and functional regression models (Beck and Chaffin, 1992; Zhang and Chaffin, 1996; Farraway, 1997; Chaffin *et al*, 1999; Chaffin, 2002). This approach tends to be resource intensive and can be limited by the database being used.

Analytical IK approaches predict posture by using analytical methods to simulate human motion. However, as the number of degrees of freedom (DOFs) increases, traditional analytical methods become intractable. In such cases, optimization-based methods become more prudent.

Zhao and Badler (Zhao *et al*, 1994) provide one of the earliest approaches that directly incorporate optimization for posture prediction. A gradient-based unconstrained optimization routine is used to minimize the weighted sum of components that model various factors, such as the position of the end-effector (a specified point, line, or plane) or the orientation of the hands. Riffard and Chedmail (Riffard *et al*, 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. These methods involve optimization algorithms for unconstrained problems, so constraints must be included in the objective function as penalty terms. Consequently, the extent to which one uses the objective function to model what drives human performance is limited. Yang *et al* (2004; 2006) provide an optimization-based approach that leverages constrained optimization and uses a relatively complex human model based on DH-method (Denavit and Hartenberg, 1955). This approach predicts posture in real time and allows for a relatively large number of DOFs. There is no difficulty in altering model parameters and seeing the consequences in the simulation.

With regards to analyzing postures once they have been predicted or simulated, currently available computational methods are limited. Because posture selection during forceful exertions has a strong relationship between hand-force and posture (Haslegrave *et al*, 1997), and because external forces are involved in almost any working posture, posture prediction with external loads and joint torques has become a significant frontier. The 3D Static Strength Prediction Program (3DSSPP) is one of the earliest models for calculating joint strength (Chaffin *et al*, 1991; Chaffin, 1997). This is involves a twelve-link model to determine static biomechanical estimates of joint moments, spinal compression forces, and balance for sequential static postures from motion models. It involves the analysis of a predetermined postures (actual posture prediction is not involved), and the skeleton model is relatively simple. OpenSim (Delp *et al*, 2007) is open source software that allows users to develop models of musculoskeletal structures and create dynamic simulations of a wide variety of movements. Variables such as joint torques and muscle forces are calculated with pre-recorded movement of a human body. This is only a simulation model, and it cannot predict posture or motion.

With regards to motion prediction, there has been a substantial amount of work completed. Recently, an optimization-based predictive dynamics method has matured for predicting dynamic motion with different tasks such as walking (Xiang *et al*, 2007), lifting (Xiang *et al*, 2008), and stair-climbing (Bhatt *et al*, 2008). However, although advancements have been made with dynamic motion prediction, relatively little work has been conducted with incorporating external loads in posture prediction.

Given that discomfort is often considered a primary factor in dictating human posture, it is a necessary consideration with any development of posture-prediction capabilities. In fact, some literature suggests that joint torque should be combined with posture prediction capabilities in order to predict human posture more accurately, and joint torques can only be calculated is applied loads are incorporated in the predictive models. Allread *et al* (1998) perform experiments to evaluate discomfort in manufacturing environments and find that overall total-body discomfort depends on external loads. 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. 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. Although much experimental work has been completed regarding joint torque and posture, there are currently no computational posture-prediction models involving joint torque.

In general, there has been no work to combine posture-prediction capabilities with applied loads. Physics based posture prediction is currently unavailable and is clearly needed. Although accurate for single subjects, data-based posture prediction lacks autonomy. Traditional analytical approaches to IK are impractical for complex human systems, and they are not physically accurate (static equilibrium is not considered). Currently available static analysis tools are not predictive. Consequently, there is a distinct need for a real-time computational approach to posture prediction that incorporates applied loads, calculates joint torques, and provides useful feedback.

*Overview of the Paper*

This paper leverages success at The University of Iowa's Virtual Soldier Research (VSR) Program in developing Santos[TM], a highly realistic predictive human model (Abdel-Malek *et al*, 2006; Yang *et al*, 2007). Santos uses an optimization-based approach to posture prediction, and this paper presents a new method for incorporating equations of static equilibrium in this approach. First, an overview of optimization-based posture prediction is provided. Then, a detailed optimization formulation is developed for an upper-body model, which incorporates applied loads, static equilibrium, and torque-based performance measures (objective functions). Basic examples are run with loads applied to both hands simultaneously. The results are evaluated quantitatively in terms of numerical output, and qualitatively in terms of visual outputs. Finally, contributions are summarized, high level issues and challenges are discussed, and future work is presented.

## OPTIMIZATION-BASED POSTURE PREDICTION

This section provides an overview of the current optimization-based approach to posture prediction. The human skeletal system is highly redundant from a kinematics perspective, meaning there are infinitely many postures one can assume in order to contact a single target point. This means there are infinitely many solutions to most inverse kinematics problems (determine human joint angles necessary to contact specified Cartesian points) involving the human body. However, it is possible to determine a single realistic posture by using optimization.

Simulating human posture depends largely on how the human skeleton is modeled. We view a skeleton as 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, as shown in Figure 1.

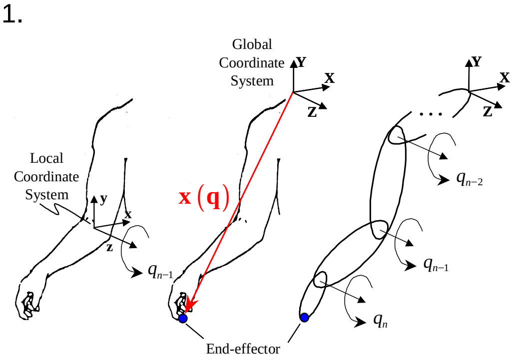


Figure 1: A kinematic chain of joints

$q_i$ 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, or more 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 with respect to the global coordinate system. For a given set of joint angles $\mathbf{q}$, $\mathbf{x}(\mathbf{q})$ is determined using the Denavit-Hartenberg (DH)-method (Denavit and Hartenberg, 1955). The DH-method uses a series of transformation matrices to translate from joint space to Cartesian space.

With this pilot study, a 55-DOF model for the human torso, right arm, left arm, and neck is used as shown in Figure 2, where each cylinder represents a rotational DOF. This also includes six global DOFs, three for translation of the hip point and three for rotation about the hip point. The posture of this model is determined by solving the optimization problem developed at VSR and formulated in this section. The design variables for the problem are $q_i$, measured in units of radians.

The first constraint, called the *distance* constraint, requires the end-effector to contact a target point. In addition, each joint angle is constrained to lie within predetermined limits. $q_i^U$ represents the upper limit, and $q_i^L$ represents the lower limit. These limits are derived from anthropometric data.

The basic benchmark performance measure represents joint displacement (Jung *et al*, 1994; Mi *et al*, 2002). This performance measure is proportional to the deviation from a *neutral position*, which is selected as a relatively comfortable posture, typically a standing position with arms at one's sides. $q_i^N$ is the neutral position of a joint. Because some joints articulate more readily than others, a weight $w_i$ is introduced to stress the relative stiffness of a joint. Additional performance measures can also be used, such as musculoskeletal discomfort (Yang *et al*, 2004; Marler *et al*, 2005), potential energy (Yang, *et al*, 2004; Marler, 2005), and visual displacement (Marler *et al*, 2006; Smith *et al*, 2008).

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

$$\text{Find: } \mathbf{q} \in R^{DOF} \tag{1}$$

$$\text{To minimize: } f_{JointDisplacement}(\mathbf{q}) = \sum_{i=1}^{n} w_i \left( q_i - q_i^N \right)^2$$

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

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

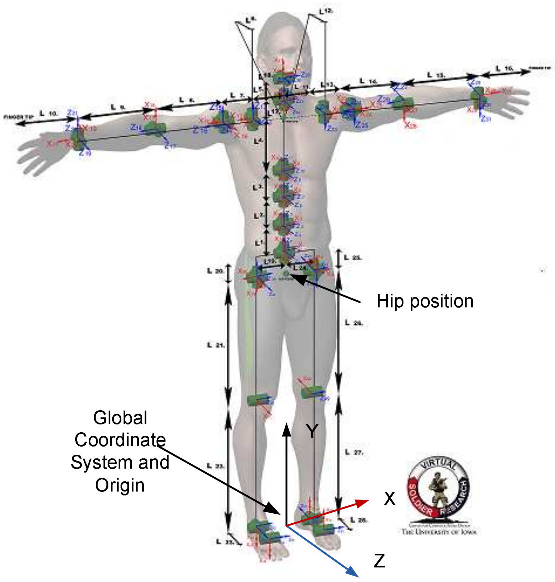


Figure 2: Santos™ and global coordinates and origin

where $\varepsilon$ is a small positive number that approximates zero and *DOF* is the total number of degrees of freedom. (1) is solved using the software SNOPT (Gill *et al*, 2002), which uses a sequential quadratic programming (SQP) algorithm. Analytical gradients are determined for all objective functions and for all constraints.

The formulation in (1) involves kinematic posture prediction only. It provides the foundation for predicting posture with applied loads, which includes static equilibrium constraints as well as new objective functions that include joint torque.

## OPTIMIZATION FORMULATION FOR APPLIED LOADS

This section presents a new optimization formulation for posture prediction, and it involves two primary contributions: constraints to enforce static equilibrium, and objective functions that incorporate joint torque and its effects on human posture. As with (1), the design variables are joint angles. Given the joint angles, a critical component of the formulation is the calculation of joint torques and ground reaction forces.

*Joint Torques*

The torque calculated at each joint is an actuation torque, not a reaction torque. It is essentially the torque that is necessary to keep the system in static equilibrium. These torques are calculated as follows:

$$\boldsymbol{\tau} = -\sum_i \mathbf{J}_i^T m_i \mathbf{g} - \sum_k \mathbf{J}_k^T \begin{bmatrix} \mathbf{F}_k \\ \mathbf{M}_k \end{bmatrix} \tag{2}$$

where the first term in (2) represents the joint torques due to gravity. $m_i$ is the mass of link *i*, and **g** is the gravitational acceleration vector. The second term represents the joint torques due to the summation of multiple external loads. $\mathbf{F}_k$ and $\mathbf{M}_k$ are the external force and moment, respectively, as applied to a point on link *k*. $\mathbf{J}_k$ is the Jacobian matrix, and it is defined as follows:

$$\mathbf{J}_k(\mathbf{q}) = \begin{bmatrix} \mathbf{J}_{k,1}(\mathbf{q}) & \cdots & \mathbf{J}_{k,i}(\mathbf{q}) & \cdots & \mathbf{J}_{k,k}(\mathbf{q}) \end{bmatrix}_{6\times k} \tag{3}$$

The $i^{th}$ column vectors for revolute and prismatic joints are, respectively,

$$\mathbf{J}_{k,i}^{revolute}(\mathbf{q}) = \begin{bmatrix} \dfrac{\partial\, {}^0\mathbf{T}_k(\mathbf{q})}{\partial q_i}\, {}^k\mathbf{r}_k \\ {}^0\mathbf{z}_{i-1}(\mathbf{q}) \end{bmatrix}_{6\times 1} \tag{4}$$

$$\mathbf{J}_{k,i}^{prismatic}(\mathbf{q}) = \begin{bmatrix} \dfrac{\partial\, {}^0\mathbf{T}_k(\mathbf{q})}{\partial q_i}\, {}^k\mathbf{r}_k \\ \mathbf{0}_{3\times 1} \end{bmatrix}_{6\times 1} \tag{5}$$

${}^0\mathbf{T}_k(\mathbf{q})$ is a homogeneous transformation matrix used in the DH-method, ${}^k\mathbf{r}_k$ is the local coordinate of the point of force application in {*k*} local reference frame, and ${}^0\mathbf{z}_{i-1}\ (i=1,...,k)$ is the local z-axis vector of {*i*} local reference frame expressed in terms of the global coordinate frame.

In general, joint torque represents the force of a group of muscles acting on or around a joint, and the torque limits represent strength. Theoretically, changes in such limits with time would represent fatigue (Xia and Frey-Law, 2008).

*Ground Reaction Forces*

For the ground reaction forces (GRF) distribution, we use the algorithm proposed by Xiang *et al*. (2007), which depends on the concept of the Zero Moment Point (ZMP). The ZMP is the point on the ground at which the horizontal components of the net moments are zero (Vukobratović and Borovac, 2004). For a standing posture, the ZMP is located between the two supporting feet, and a linear relationship is used to distribute GRF to each foot. Let points 1 and 2 the center points of the middle joints of the feet. Let $d_1$ and $d_2$ the distances from the ZMP to points 1 and 2, respectively. Note that there are only normal moment $M_y$ and resultant force $\mathbf{R}$ ($R_x$, $R_y$, $R_z$) at ZMP, as $M_z$ and $M_x$ vanish due to the definition of ZMP. The GRF is linearly decomposed to the central points as follows:

$$M_{y1} = \frac{d_2}{d_1+d_2} M_y\,; \quad \mathbf{R}_1 = \frac{d_2}{d_1+d_2}\mathbf{R} \tag{6}$$

$$M_{y2} = \frac{d_1}{d_1+d_2} M_y\,; \quad \mathbf{R}_2 = \frac{d_1}{d_1+d_2}\mathbf{R} \tag{7}$$

To implement the above idea, first, given current joint variables (angles and global translations), the static equilibrium equation for the whole body is used to calculate torques without GRF. The resulting global forces in the virtual branch (the branch/link that describes the global position and orientation of the human model in terms of DH-method) are not zero because the GRF is excluded. Second, considering the equilibrium of the global forces and moments in the virtual branch with the ground reaction forces and moments, the GRF are then applied to the corresponding central points, and the updated joint torques are recovered from the static equilibrium equation (Figure 3).

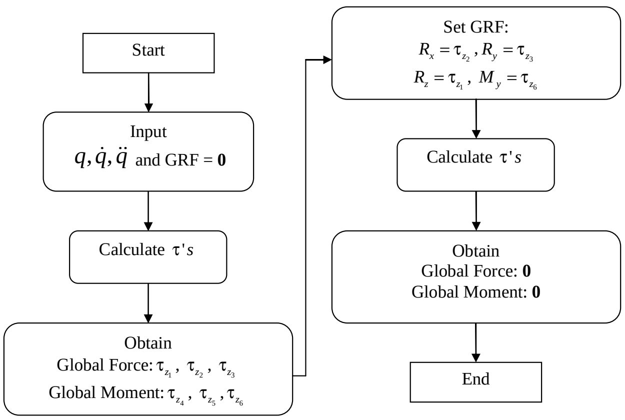


Figure 3: Flowchart of calculating GRF

*Complete Formulation*

Given joint torques and GRFs, posture is determined by solving the following optimization problem:

Find: $\mathbf{q} \in R^{DOF}$
to minimize:

$$f_{MaxNormalizedTorqueSquared}\left(\tau(\boldsymbol{q})\right) = \left(\sum_{i=1}^{DOF}\left(\left(\frac{\tau_i}{\tau_i^{\lim}}\right)+1\right)^p\right)^{\frac{1}{p}}; \; p = 100 \tag{8}$$

subject to:

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

$$\text{Sum of forces} = \sum_{i=1}^{DOF} F_i\left(\tau(\boldsymbol{q})\right) \le \varepsilon \tag{9}$$

$$\text{Sum of moments} = \sum_{i=1}^{DOF} M_i\left(\tau(\boldsymbol{q})\right) \le \varepsilon \tag{10}$$

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

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

where $\varepsilon$ is a small positive number that approximates zero. $\tau_i$, $\tau_i^L$, and $\tau_i^U$ represent the joint torque, lower torque limit, and upper torque limits respectively.

The torque-based objective function in *equation reference goes here* minimizes the maximum normalized joint torque. This approach to formulating a min-max problem is based on the work from Marler (2005). Each torque is normalized by dividing each term by $\tau_i^{\lim} = \tau_i^U - \tau_i^L$. The sum of joint torques and the sum of normalized joint torques were also initially tested as objective functions, but they resulted in unrealistic postures.

The constraint in equation (9) represents static equilibrium for all forces and includes gravitational forces, GRF, and externally applied forces. Equation (10) represents static equilibrium for all moments including moments produced by gravity, joint torques, and externally applied moments.

Although this formulation applies to a 55-DOF model, the global DOFs (at the hip point) and the DOFs for the lower body were constrained (frozen) to simplify this initial study. As with (8), this problem is solved using SNOPT. Again, analytical gradients are determined for the objective functions and for all constraints.

## RESULTS

A series of test were run using the formulation from the previous section, and test conditions are summarized in Table 1. The global coordinate system (origin) to which all target points and loads are referenced, is shown in Figure 2. The left- and right-hand end-effectors are located at the respective joint centers for the wrists.

Tests 1, 2, and 5 involve only the kinematic formulation shown in (1) and provide a baseline to which results from the new formulation are compared. With Tests 2 and 5, although torques are not considered in the constraints or objective functions, loads are applied in order to calculate torques that would result without any torque limits and without any torque-based objective function. Computational results are given in Table 2. The predicted postures for Tests 1, 2, and 5 are identical and are shown in Figure 3. The predicted postures for Tests 3, 4, and 6 are shown in Figures 4 through 6.

The results in Table 2 were obtained using an Intel Xeon CPU, a 3.06 GHz processor, and 3.00 GB of RAM. The *Number of Major Iterations* indicates the number of iterations necessary for the SQP algorithm to converge. The *Number of Iterations* indicates the cumulative number of minor iterations necessary to find a search direction for each major iteration. Each major iteration involves multiple minor iterations in order to find a single search direction. The zeros in the last column (Time for Objective Function) indicate the objective-function calculations required less than 0.005 second.

Table 2 lists the minimum objective-function (performance measure) value, the number of optimization iterations, and the necessary computational time. The last two columns indicate how much time was used for evaluating constraints and the objective function respectively. As expected, including applied loads requires additional computational time. This decrease in speed becomes more substantial when higher loads are applied, as with Test 6. Much of this computational time is dedicated to evaluating constraints, because as loads are increased, more torque limits become active. Nonetheless, with reasonable loads, the approach is relatively fast.

Figure 4: Predicted posture for Tests 1, 2, and 5

In Figure 4, because torque is not actually considered in the objective function of in the constarints, the predicted postures simply gravitate towards the neutral position while still satisfying the distance cosntraints (end-effectors must contact the target points), based on the joint-displacement performance measure in (1). However, when joint torque is considered, the predicted posture change substantially, as shown in Figures 5 through 7.

In Figure 5 and 7, Santos™ bends the spine backward in order to support loads that are applied downward. Alternatively, in Figure 6, Santos™ bends forward to support loads that are applied upward. In Figure 7, Santos™ bends the spine backward more than he does in Figure 5, because the external loads have been increased from 40N to 100N. In general, these results are reasonable and show expected deviation from the results of basic kinematic posture prediction. Note that although the loads seem symmetrical, the resulting posture is not. This is because the application points for the two loads are not symmetrical, as indicated in Table 1. Because the load on the right hand is further from the torso, Santos™ leans to the right to stay balanced and minimize joint torque.

Figure 8 shows the actual torque values for Tests 5 and 6, along with the joint torque limits. These limits are based on the Maximum Voluntary Torque (MVT) data reported by Javier Gonzalez et al. (2002) and have been adjusted to fit into the kinematic structure of our human model. Recall that with Test 5, torques are simply calculated from equations of static equilibrium but are not included in the objective function.

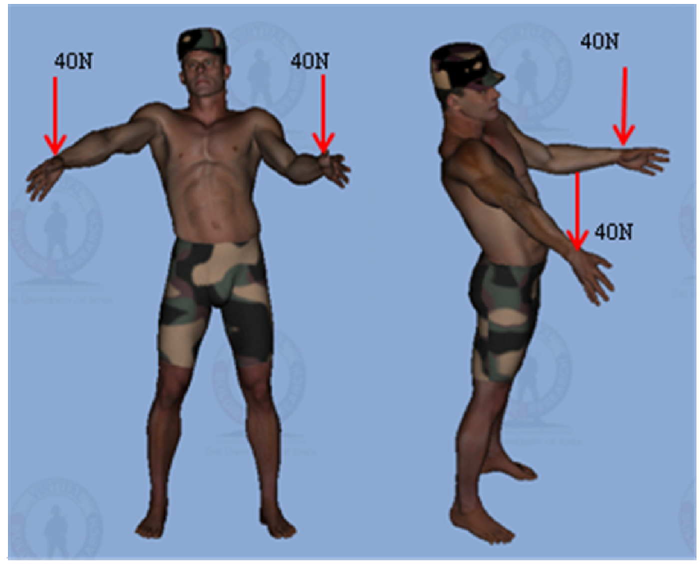


Figure 5: Predicted posture for Test 3

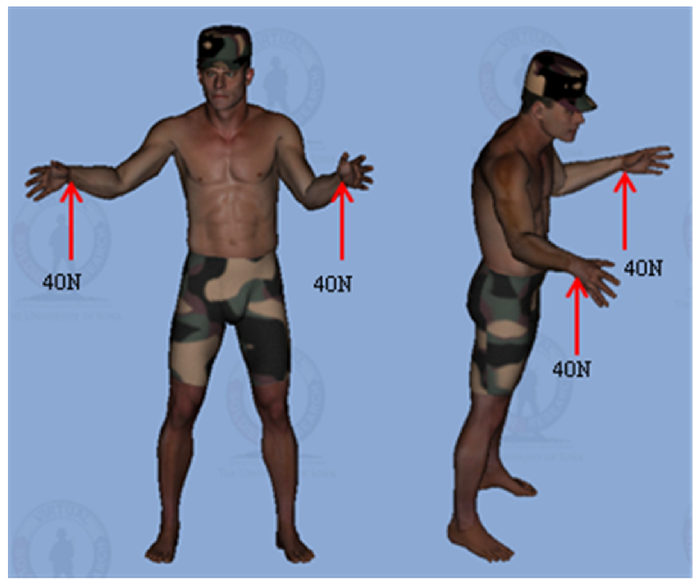


Figure 6: Predicted posture for Test 4

Clearly, the new formulation (used with Test 6) reduces the joint torques. With the kinematic posture prediction approach, joint torques may exceed their limits, especially in the spine and clavicle regions. When the new formulation is used, the highest joint-torques arise in the lower spine and in the shoulders, as one would expect with the given loading conditions. Given the nature of the applied loads, this is as one would expect. Because no loads are applied to the head or neck, the torques in the neck are nearly zero and result only from the mass of the body segments.

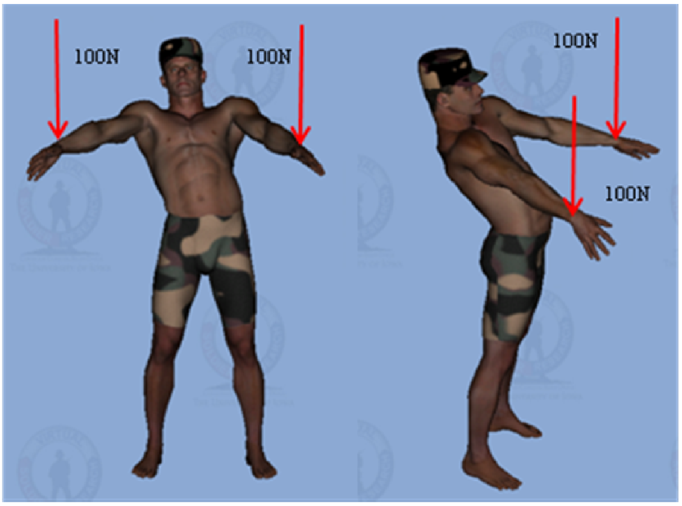


Figure 7: Predicted posture for Test 6

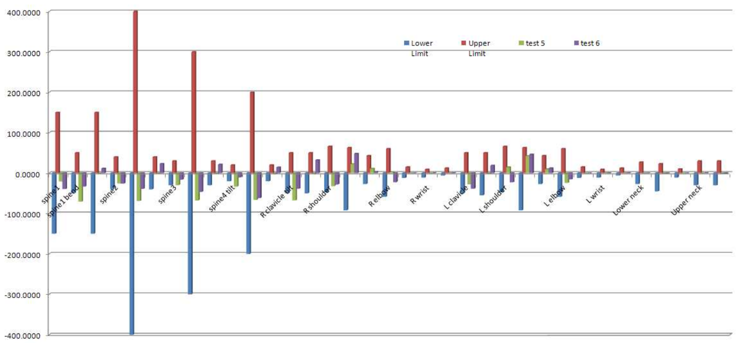


Figure 8: Actual joint torque for Tests 5 and 6

## DISCUSSION AND CONCLUSION

Although currently available posture-prediction tools are helpful, much of human posture depends on applied loads, reaction forces, and actuation torques at the joints. It is not sufficient to determine these quantities a posteriori; they must be involved in the prediction process. Consequently, in this paper, we have presented a new optimization-based approach to posture prediction with applied loads. Initial steps have been taken to calculate joint torques, satisfy equations of static equilibrium, and include joint torques in a performance measure that drives human posture. Subjective evaluation of visual results and quantitative results suggests that the approach is reasonably accurate.

In general, the constraints represent boundary conditions for the optimization problems that either enforce conditions that are beyond the scope of the model (i.e. constraining joint limits because collision detection between bones is not modeled), represent physical laws (i.e. static equilibrium), or enforce requirements for analysis (i.e. touching a specific target. Alternatively, the objective function(s) model what drives human posture. The proposed formulation allows one to test the effects of joint torque when studying what governs human posture. It is observed that minimizing maximum normalized joint torque provides natural postures when evaluated subjectively. At this point, the proposition made at the beginning of this paper is clear that the joint torques should be included in the optimization cost function for load-based posture prediction problem.

Although this pilot study was successful in testing a new approach to posture prediction, there a few areas of ongoing additional research. First, the whole-body model that includes global DOFs for the hip point and DOFs for the legs will be tested. Concurrently, a constraint will be added to represent the zero-moment-point and its effects on stability. Additional hypotheses can be tested regarding what drives human posture, including methods for multi-objective optimization, which can combine multiple objective functions (performance measures). In particular, how joint torque contributes to discomfort will be studied. In addition, once reaction forces (between the human and contact points) are included as design variables, it will be possible to determine what types of postures avoid impractical or uncomfortable reaction forces. Finally, validation studies will be completed using motion capture, to ensure the predicted postures reflect what real humans actually do.

## ACKNOWLEDGEMENTS

The authors would like to thank all other research members at VSR for their help.

Table 1: Hand end-effector positions and external loads

| Test # | Perf. Measure | End Effector | Target point | External loads | |
|---|---|---|---|---|---|
| | | | | Direction | Magnitude |
| 1 | Jnt. Displace | LH | (0.3,1.15,0.3) | - | 0 |
| | | RH | (-0.5,1.15,0.3) | - | 0 |
| 2 | Jnt. Displace | LH | (0.3,1.15,0.3) | (0,-1,0) | 40N |
| | | RH | (-0.5,1.15,0.3) | (0,-1,0) | 40N |
| 3 | Max Torque | LH | (0.3,1.15,0.3) | (0,-1,0) | 40N |
| | | RH | (-0.5,1.15,0.3) | (0,-1,0) | 40N |
| 4 | Max Torque | LH | (0.3,1.15,0.3) | (0,1,0) | 40N |
| | | RH | (-0.5,1.15,0.3) | (0,1,0) | 40N |
| 5 | Jnt. Displace | LH | (0.3,1.15,0.3) | (0,-1,0) | 100N |
| | | RH | (-0.5,1.15,0.3) | (0,-1,0) | 100N |
| 6 | Max Torque | LH | (0.3,1.15,0.3) | (0,-1,0) | 100N |
| | | RH | (-0.5,1.15,0.3) | (0,-1,0) | 100N |

Table 2: Performance-measure values and optimization time

| Test # | Perf. Measure | Opt. Obj. Value | Number of Iterations | Number of Major Iterations | Time for solving the problem | Time for constraint function | Time for Objective function |
|---|---|---|---|---|---|---|---|
| 1 | Jnt. Displace | 2.63100 | 455 | 42 | 1.2s | 1.08s | 0.00s |
| 2 | Jnt. Displace | 2.63100 | 455 | 42 | 1.2s | 1.08s | 0.00s |
| 3 | Max Torque | 1.06127 | 267 | 46 | 4.56s | 4.28s | 0.23s |
| 4 | Max Torque | 1.04367 | 127 | 24 | 1.67s | 1.57s | 0.13s |
| 5 | Jnt. Displace | 2.63100 | 455 | 42 | 1.2s | 1.08s | 0.00s |
| 6 | Max Torque | 1.15898 | 314 | 80 | 16.08s | 15.13s | 0.81s |

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