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Validation Methodology Development for Predicted Posture

Timothy Marler, Jingzhou Yang, Salam Rahmatalla, and Karim Abdel-Malek
Virtual Soldier Research (VSR) Program, Center for Computer Aided Design (CCAD), University of Iowa

Chad Harrison
Honda R&D Americas, Inc.

ABSTRACT

As predictive capabilities advance and human-model fidelity increases, so must validation of such predictions and models. However, subjective validation is sufficient only as an initial indicator; thorough, systematic studies must be conducted as well. Thus, the purpose of this paper is to validate postures that are determined using single-objective optimization (SOO) and multi-objective optimization (MOO), as applied to the virtual human Santos™. In addition, a general methodology and tools for posture-prediction validation are presented. We find that using MOO provides improvement over SOO, and the results are realistic from both a subjective and objective perspective.

INTRODUCTION

As the field of human modeling and simulation builds momentum and as applications expand, increasing fidelity and autonomy becomes critical. It is no longer sufficient to work with the simple likeness of a human either in regards to appearance or function. Realism is now paramount. The video game industry is addressing the issue of visual realism. Thus, the demand for functional realism falls on the engineering-research community. This trend begs the question of what constitutes being real? What is acceptable with respect to fidelity? The answer is validated predictive capabilities.

A virtual human has many components and aspects that must be modeled, ranging from skin, to muscles, to cognition. Ultimately, all of these aspects must be checked for realism; they must be validated. When considering the complete human system, not just one section or organ, a fundamental component of any virtual human is posture prediction and analysis. This is especially true given the expanse of current applications with vehicle analysis and design. The Virtual Soldier Research (VSR) Program at The University of Iowa has pushed forward the field of posture prediction with the development of Santos™, a new kind of virtual human (Yang *et al*, 2005; Yang *et al*, 2006b).

With respect to posture and motion, Santos™ is *predictive*. This means posture and motion are not based on prerecorded motion or data that must be updated with alterations in the virtual environment or with new desired types of motion. Rather, Santos™ actually predicts how people strike various poses and how they move. Such predictive capabilities afford the model considerable autonomy and stem in large part, from our *optimization-based* approach to human modeling. Joint angles (one for each degree of freedom) provide the design variables that are determined by minimizing human performance measures such as discomfort, joint displacement, vision, and energy. This computational optimization problem is solved while satisfying constraints that are used to model various tasks and anthropometric limitations. This approach is extremely fast, allowing Santos™ to operate in *real time*, in most cases. Because of our use of optimization, the number of degrees of freedom (DOF) used for the human model does not significantly impact computational speed. Thus, our skeletal model currently includes 109 degrees of freedom, and it can easily be expanded without significant computational detriment. This model can be modified to represent any anthropometric cross section. The *high fidelity* of the Santos™ model is also reflected in its appearance. Santos™ is not a cartoon. His realism is superior, and this allows Santos™ to act as an actual design aid, a virtual human that can ultimately train and work with real humans.

The performance measures, which serve as objective functions in the optimization problem, govern the motion and posture. These performance measures are *physics-based*, meaning they represent physically significant quantities; they are not functions derived from sets of data. What governs one's motion depends on the task being completed, and with the proposed approach, one is able to exchange performance measures, and thus model different kinds of behavior with what we call *task-*

based prediction. A single performance measure can be used in a single-objective optimization (SOO) problem, or multiple performance measures can be combined using multi-objective optimization (MOO). When modeling a task or class of tasks, we formulate a hypothesis as to which performance measure or combination there of governs that particular type of motion. Then, the simulation is run and validated (the hypothesis is tested), and if necessary, the performance measure is modified (the hypothesis is refined). The outcome is a general model that is not only complete enough to explain what drives a particular type of motion and how the human body works, but is also robust enough to accommodate modifications in the task scenario.

The purpose of this paper is first to validate in-cab predicted upper-body postures that are obtained using Santos™. In general, there are essentially three stages to validation. Stage 1 involves subjective visual analysis of simulated results. Stage 2 involves basic motion-capture studies with a limited number of human subjects. Stage 3 involves extensive experimental studies and statistical analysis. This work involves Stages 1 and 2. Unless the initial hypothesis and consequent simulation are perfect, which rarely occurs in any scientific process, modifications must be made based on initial tests. Thus, a second goal for this paper is to walk through the process of modifying performance measures, of using MOO, and of comparing SOO and MOO results. Finally, this paper provides initial steps towards developing a systematic protocol for validating posture-prediction with a high-fidelity human model. In this context, protocol does not just include experimental procedures; it involves methods for aggregating data and metrics for indicating successful simulations.

Throughout this study, there are two primary assumptions. First, we work only with an upper-body model that does not include hip motion. Secondly, there is no cognitive model that might incorporate why one completes a task and might consequently refine how one completes a task.

LITERATURE REVIEW

Marler (2005), Marler *et al* (2005a), and Marler *et al* (in press) provide detailed reviews of optimization-based methods for posture prediction. To date, there is no work that rigorously compares SOO results and MOO results. With regard to predictive capabilities in general, much research has been conducted concerning applications to human modeling, and most predictions are, as a matter of the scientific method, validated or tested. However, especially with regards to real-time high-fidelity models that use a large number of degrees of freedom, few thorough systematic validation studies have been conducted with posture prediction. In addition, there has been little effort to devise a systematic methodology (sets of procedures and tools) for aggregating experimental and simulation data. Here, we review some of the work that has been completed with validating 3-dimensional posture-prediction methods.

A common approach to reaching-motion prediction involves using prerecorded motion, anthropometric data, and functional regression models in terms of joint angles (Farraway, 1997; Zhang and Chaffin, 1997; Chaffin *et al*, 2000; Chaffin, 2002). This provides analytical expressions for joint-angles as a function of time, from which individual postures can be extracted. Conceptually, because the output motion with these approaches is based on prerecorded motion, validation is not critical and is not discussed extensively. Technically, however, this approach is not always accurate with respect to constraints in Cartesian space and thus may not satisfy subjective validation reviews (Chaffin, 2002). Consequently, Faraway *et al* (1999) provide a modification to this general approach that applies to posture prediction. A posture is selected that is as close as possible to the initial data-based prediction, while satisfying restrictions in Cartesian space modeled with traditional inverse kinematics. The translation between joint space and Cartesian space is completed using traditional inverse kinematics (using a pseudoinverse of the Jacobian). The approach is validated using one human subject and a seven-DOF model for upper-body reach. Visual validation is conducted using a stick-figure diagram, and objective validation is conducted by comparing joint-center locations.

The first efforts with predicting posture without observed data involved the pseudo-inverse method of inverse kinematics. Liegeois (1977), and Klein and Huang (1983) apply this approach to simple robots and thus need no validation. Jung *et al* (1995) apply this approach to human reach-posture prediction with an eight-DOF model. It is validated using five human subjects. Stick figures representing some of the subjects and corresponding predictions are compared subjectively. Mean values for the elbow and shoulder joint angles, and for the location of the joint centers are validated objectively. Zhang *et al* (1998) incorporate optimization in a weighted pseudo-inverse approach with a seven-DOF human model, whereby the weights are determined such that the predicted motion approximates empirical data (prerecorded motion). This approach depends on a specified hand motion trajectory. Different schemes for setting the weights are evaluated, and the results seem to be validated using the same empirical data that are used for developing the model. Predicted and experimental joint-angle profiles (motion) are compared subjectively. Zhang and Chaffin (2000) use this same approach and model, with a more extensive validation effort. The authors use ensemble errors averaged over time (over the complete motion) and over multiple joint angles. These errors represent angle, velocity, and displacement, and they provide a method for aggregating motion-prediction data for the complete human model. In addition, joint-angle profiles are compared subjectively. Reed *et al* (2000) 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. The proposed method is validated subjectively against the Cascade prediction model (CPM), using stick figures. Predicted eye locations are validated objectively with experimental data.

Wang and Verriest (1998), and Wang (1999) propose a geometric algorithm for arm posture prediction and apply it to a 4-DOF and 7-DOF model respectively. The models are validated by comparing the distance between the predicted position of the elbow and the actual/experimental position.

Zhao and Badler (1994) provide one of the earliest works with the direct independent use of optimization for posture prediction, with a 22-DOF full-body virtual human. Riffard and Chedmail (1996) use a similar approach with a seven-DOF arm. However, these works do not involve any formal validation, just subjective visual evaluation. Mi *et al* (2002) use direct optimization as well with a 15-DOF upper-body model. Subjective validation is conducted by comparing simulation results with photographs of a single human subject. To date, the proposed optimization-based method used with Santos™ has been validated by subjectively comparing simulated results with single-subject motion-capture data (Farrell *et al*, 2005; Marler *et al*, 2005a; Marler *et al*, 2006).

Much of the current literature involves models with relatively small numbers of DOFs. There are few consistent systematic methodologies for aggregating visual postures as well as objective simulation data. Although most predictive studies involve validation of some sort, there are few extensive validation efforts and little consensus regarding tenants for evaluating predictive results. Finally, there is little discussion of the anthropometric cross sections considered in the experimentation.

With respect to optimization-based posture prediction, to date, validation for the proposed approach has been limited to visual inspection and motion-capture experiments with a small number of subjects. In addition, although MOO has been used, the details of how various performance measures should be combined, has not been investigated. Although Marler *et al* (in press) compare various MOO results with SOO results using subjective visual comparison of predicted postures, a more extensive validation effort is needed.

OVERVIEW OF THE PAPER

In this paper, we first summarize the human model, initial baseline simulations, and the motion-capture experimental protocol. Then, simulation results using SOO are compared to experimental results, and the motivation for using MOO is highlighted. The process used to determine which performance measures should be combined is outlined, and the consequent simulation results using MOO are studied and compared to those from SOO. Although only examples of results are shown, all results are discussed. More extensive discussions of statistical analysis are provided in a companion paper (Yang *et al*, 2007). In conclusion, we present the significant findings with respect to validating predicted posture, and we itemize data-analysis tools and metrics. Finally, we summarize potential areas for future work.

HUMAN MODEL

This section summarizes our human model (Figure 1) and our approach to posture prediction, both of which are discussed by Yang *et al* (2006a) and Abdel-Malek *et al* (2006).

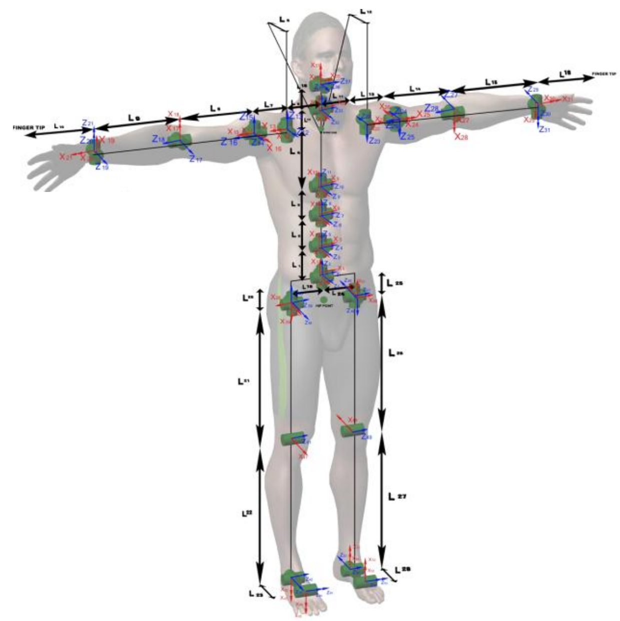

Figure 1: The Virtual Human Santos™

SKELETAL MODEL

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 2.

q_i is a *joint angle* and represents the rotation of a single revolute joint with respect to a local coordinate system. 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. 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 essentially allows one to work with either joint space or Cartesian space.

With this study, a 35-DOF model for the human torso, right arm, left arm, and neck is used as shown in Figure 1, where each cylinder represents a rotational DOF.

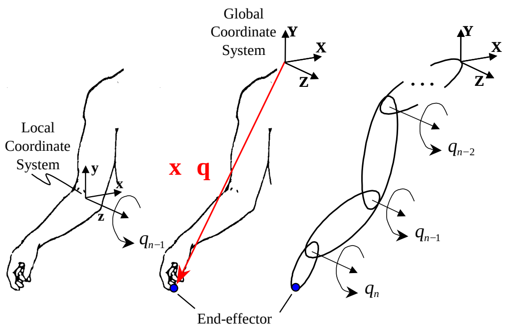

Figure 2: A Kinematic Chain of Joints

POSTURE-PREDICTION APPROACH

The posture of the above-described 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 for q_i, and q_i^L represents the lower limit. These limits are derived from anthropometric data. Given the nature of the DH-method and transformation matrices used therein, it s also possible to constrain the orientation of various local coordinates systems.

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 the *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. The final joint displacement is given as follows:

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

Additional performance measures are also used. In fact, the primary performance measure for this study is discomfort (Marler *et al*, 2005a), which is loosely based on joint displacement. It models musculoskeletal discomfort and involves three factors: the tendency to gravitate to a reasonably comfortable position, the tendency to move body segments in sequence (i.e. move the arm, then the torso if necessary, and then the clavicle), and the tendency to avoid postures where ligaments and/or tendons are stretched. We also use visual displacement, which essentially models the tendency to align one's line of site with the object being touched or used (Marler *et al*, 2006). Finally, we consider potential energy, with the datum for each body segment defined separately as the height of that segment when the body is in the neutral position (Marler (2005).

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

Find: $\mathbf{q} \in R^{DOF}$ (2)

to minimize: $\text{Performance Measure}(\mathbf{q})$

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

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

where ε is a small positive number that approximates zero. (2) is solved using the software SNOPT (Gill *et al*, 2002), which uses a sequential quadratic programming algorithm. Analytical gradients are determined for all objective functions and for all constraints.

BASELINE SIMULATION STUDY

The first part of the overall validation effort is a baseline study to verify that predictive results are visually reasonable and to provide a baseline of SOO-based predicted postures to which additional results are compared. Reach targets that represent common scenarios in an automotive cab are used for posture prediction and are shown in Figure 3.

Target 1 represents the A-pillar. Target 2 represents the radio. Target 3 represents the glove box. Target 4 represents the B-pillar, where a seat belt is typically found. Discomfort is used as the performance measure in equation (2). Data are recorded in terms of joint angles, visual postures, and location of markers on Santos's™ skin. With regards to the markers, the intent is to experiment with leveraging Santos's™ highly realistic skin model. Only the right arm is considered. Anthropometry (in the form of skeletal dimensions) is used that represents approximately a 50th percentile male. Selected views of visual results with all of the targets are shown in Figure 4. The small dots indicate points on the avatar's skin where position is recorded. The larger dot represents the target.

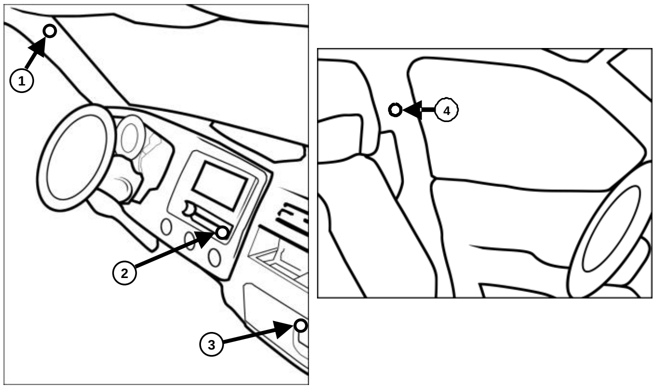

Figure 3: Target Points in an Automotive Cab

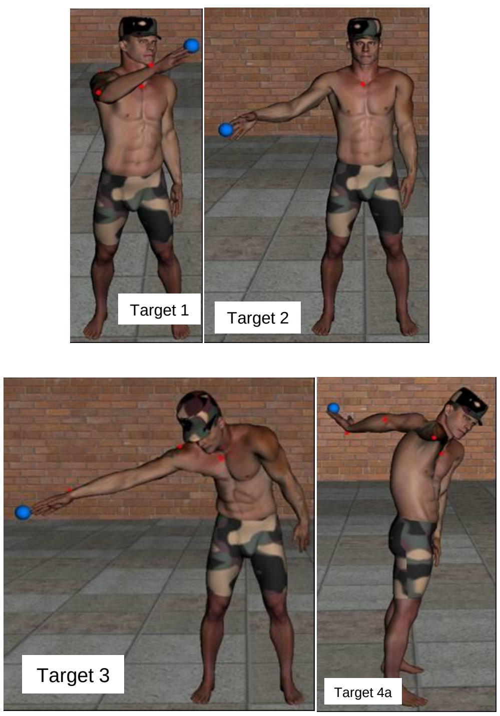

Figure 4: Visual Results for Baseline Study, using Discomfort

In general, the visual results suggest that the postures predicted using Santos^{TM} are realistic, and using discomfort for the given targets is appropriate. Although results with target 4 are different from what one might expect, they are reasonable given the nature of the discomfort model. That is, the predicted postures yield a relatively comfortable position, but they do not incorporate one's tendency to see what one is working with. Initial use of MOO to combine vision with discomfort improves the results (Figure 5) and provides motivation for investigating further use of MOO with this study.

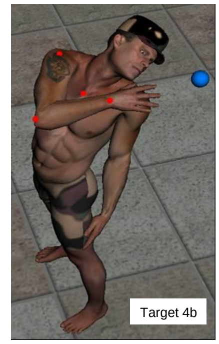

Figure 5: Using MOO to Combine Discomfort and Vision

We find that tracking markers on the avatar's skin is problematic. Transferring marker location between different avatars or between avatars and experimental subjects is impractical. Initial results suggest it is easier to track the locations of joint centers.

This baseline study sheds light on the following components that are not factored in the simulation model and thus require either a more extensive model or additional boundary conditions applied to the model: 1) the tendency to strive to see what one is working with, 2) the tendency to move one's hip, and 3) the cognitive awareness of why one reaches for a particular target.

MOTION-CAPTURE EXPERIMENTS

Given the successful results with Stage 1 validation, we proceed with Stage 2 validation, which involves experimental motion-capture studies. These experimental results provide the gold standard for this study, to which subsequent simulations are compared. The fundamentals of the experimental protocol are outlined as follows.

Thirteen subjects are used in a modified cab. Their postures are recorded using motion-capture as they reach for the four targets. Neck and head motion is not recorded, although it is shown in photographs. The subjects represent the following anthropometric cross sections: fifth percentile females, fiftieth percentile males, fiftieth percentile females, and ninety-fifth percentile males. At the beginning of each test, the subject is instructed to sit in the seat, buckle a two-point belt, adjust the seat in a comfortable location, and put his/her feet on the brake and gas pedals. The subjects first place their hands on the "ten and two" positions of the steering wheel. This also provides the final position for the arms (after a specified target has been touched).

Each test condition (a specific subject reaching for a specific target) is repeated for five trials. Thus, a total of 20 trials are run (five trials for each of four targets). The subjects are provided 1 minute breaks between repeated test conditions in an attempt to minimize fatigue and changes in awareness between conditions. For each subject, the average (over all trials) position (x-, y-, and z-components) of the joint centers, and the average elbow angle are determined. It was found that the five tests for each subject produced similar results, suggesting that with studies such as this, extensive repetitions are not necessary. For data analysis, one of the five cases was selected randomly.

Throughout the validation efforts, the subjects are labeled to indicate the gender, percentile, and subject number. For example, S05F1 represents 5th percentile female subject number one.

For motion-capture, an 8-camera Vicon Motion Analysis System is used. Passive markers are attached to the subject and to the surrounding environment (steering wheel, seat, target points, etc.). Because of the complexity of the scenario, a marker protocol was developed with approximately 50 markers and substantial redundancy, in order to track motion and to identify joint-center locations.

Numerical data are recorded in terms of the location of joint centers for the wrist, elbow, and shoulder, as well as the angle in the elbow. Visual results are also recorded for each posture.

Anthropometry for the simulation model represents each individual subject, and the approximate anthropometry for each subject is determined using the motion capture system.

SINGLE-OBJECTIVE SIMULATION STUDY

Given an outline of the experimental procedure, this section describes the simulation procedure and the results. This constitutes the first test of the hypothesis that optimization-based posture prediction can be used with discomfort as a performance measure (in equation (2)), to predict in-cab reaching postures. With each subject, the predicted postures are compared to the experimental postures using visual comparison; joint center location for the clavicle, shoulder, elbow, and wrist; and elbow angle. These specific quantities were selected judiciously to represent the posture of the complete upper body without having to track every joint angle and every joint center location. This represents a key premise of this work, that posture can be validated using a limited number of parameters.

Examples of quantitative results are shown in Figures 6 through 9 for a few different subjects. The plots indicate the difference between the experimental and simulated values for the elbow angle, and for the Cartesian positions for the various joint centers. An example of visual results is shown with Target 4 in order to highlight issues surrounding discomfort.

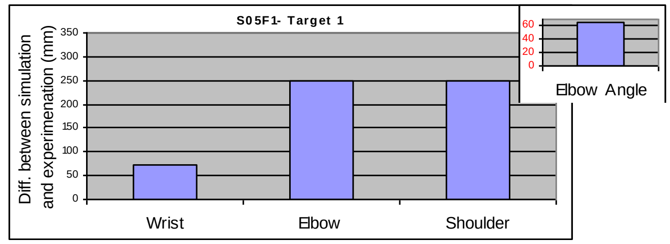

Figure 6: SOO Results for Target 1 with a 5th Percentile Female

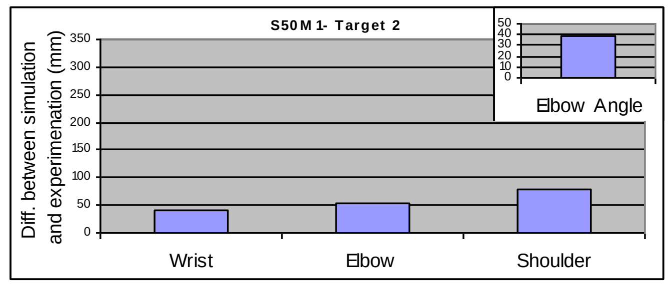

Figure 7: SOO Results for Target 2 with a 50th Percentile Male

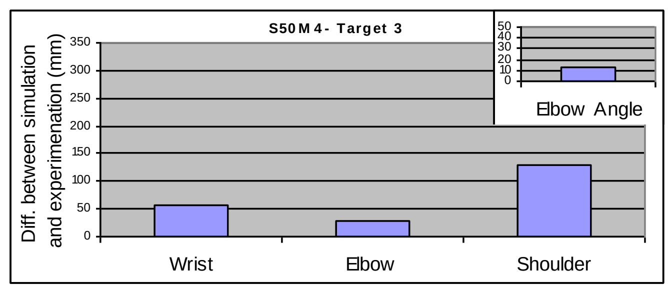

Figure 8: SOO Results for Target 3 with a 50th Percentile Male

Based on qualitative analysis, especially with Targets 1 through 3, all of the predicted postures using discomfort appear to be reasonable relative to the experimental postures. That is, with most cases, Santos™ used a posture similar to that of the corresponding subject.

Based on quantitative analysis, as demonstrated with the plots above, differences between experimental and predicted results are significant. This reinforces the idea that subjective validation, although necessary, is not sufficient for developing a robust predictive model. The differences are attributed to the following issues, some of which surfaced with Stage 1 validation as well. First, there are minor inaccuracies in anthropometry, stemming both from the model itself and from the inability to extract precise joint-center data from any motion-capture system. Secondly, a lack of hip motion contributed to cases where Santos™ was not able to contact the target. Finally, there are differences between modeling discomfort, which is the only performance measure used thus far, and modeling actual human performance, which may involve vision and cognition. This is especially evident with Target 4. As discussed with respect to Stage 1 validation, using MOO to combine discomfort with additional performance measures, especially vision, will yield improved results.

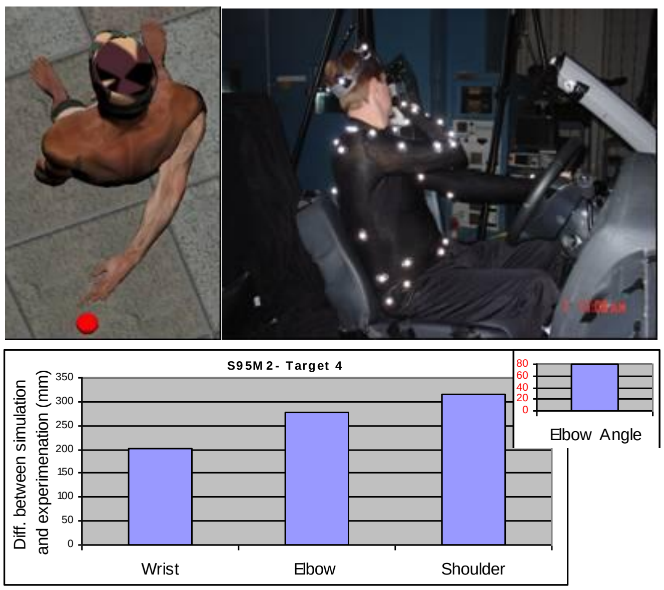

Figure 9: SOO Results for Target 4 with a 95th Percentile Male

This validation study highlighted the following topics for future work:

1) With all motion-capture systems, there is inherent error when translating anthropometric data from human subjects, to motion-capture systems, and then to simulation models. Improvements in this process will likely require significant research and development efforts.
2) Joint torque should eventually be incorporated in the discomfort model.
3) New methods for aggregating experimental and prediction data are needed.
4) The subjects' environment should be incorporated in the simulation as much as possible. Where components of the environment are not modeled, appropriate boundary conditions must be incorporated in the human model. Although we only use an upper-body mode, it is insufficient to have Santos™ standing when modeling seated tasks.

MULTI-OBJECTIVE SIMULATION STUDY

PROCEDURE

Typically, any validation effort involves refinement in the model. Therefore, the general focus of this portion of the validation effort is the simulation. Based on the results discussed above, we now refine the posture-prediction model and consider the following issues. 1) Santos™ is placed in an actual vehicle with his left hand holding the steering wheel, thus allowing him to interact with the environment. This involves the use of a 35-DOF upper-body model that includes both arms (Farrell *et al*, 2005). That is, posture prediction is completed for the torso, neck, left arm, and right arm simultaneously. 2) Methods for aggregating experimental and posture-prediction data are developed. 3) MOO is used to combine additional performance measures with discomfort.

The following primary steps are taken with this portion of the study.

1) Individual performance measures are tested. This is done subjectively by comparing predicted postures using default anthropometry, with general posture strategies indicated by motion-capture. These tests are run using discomfort, joint displacement, and energy with all of the targets.
2) Joint limits and neutral positions are tested. This is done subjectively by comparing experimental results for subject S50M3 to simulation results that are obtained using two different sets of joint limits and two different neutral positions, with each target. The first set of joint limits represents the original default limits for Santos™. The second set of limits are determined based on a combination of published data (Rothstein *et al*, 1998), input from an expert in physical therapy and rehabilitation science, and experimentation with the current avatar. The two neutral positions represent a relaxed stance and a seated position.
3) Using subject S50M3 with fixed joint limits and a fixed neutral position from step 2), subjective experiments are run to determine which weights are most effective when using MOO to combine discomfort, visual displacement, and energy; and again when combining joint displacement, visual displacement, and energy. Discomfort and joint displacement are not combined, because discomfort is based in part on joint displacement (Marler *et al*, 2005a).
4) Posture prediction results are recorded for the following subjects using the weights determined for each target in step 3): S50M3, S05F3, S50F3, and S95M1.

MOO BASICS

MOO is a subfield of optimization that addresses the issue of how one considers multiple objective functions simultaneously. It has been incorporated with the VSR approach to posture prediction with in various capacities. Marler *et al* (in press) use it to develop performance measure and to combine performance measures with no articulation of preferences. Marler *et al* (2005b) use MOO with *a posteriori* articulation of preference, depicting Pareto optimal sets with posture prediction. Here, a priori articulation of preferences is used to indicate to what extent various performance measures are considered.

There are many methods for combining objectives and articulating preferences as to which objectives are more important (Marler and Arora, 2004). We use the following global criterion, based on work by Marler (2005):

$$F(\mathbf{q}) = \left\{ \left[w_1 \left(\frac{f_1}{f_1^{Max}} \right) + 1 \right]^2 + \left[w_2 \left(\frac{f_2}{f_2^{Max}} \right) + 1 \right]^2 + \cdots + \left[w_i \left(\frac{f_i}{f_i^{Max}} \right) + 1 \right]^2 \right\}^{\frac{1}{2}} \quad (3)$$

f_i represents a performance measure, and a superscript of *Max* indicates the maximum possible value for the performance measure. Note that the maximum value of a performance measure depends on the target and the distance constraint in equation (2). Thus, in this case, the maxima are determined analytically considering the complete reach envelope (all possible targets). w_1 and w_2 are weights representing the relative importance of the two performance measures.

RESULTS

Step 1 – Test Individual Performance Measures

The primary outcome from the tests on the individual performance measures was a modification to the discomfort model. First, the penalty that is applied as joints reach their limits, in cases when ligaments or tendons are stretched, was modified. Secondly, the sequence in which different body segments are articulated was altered. Initially, the model was designed such that one moves their arm to touch a target. If necessary, one then articulates the spine. Finally, one extends the clavicle. However, we find that a critical component of modeling upper body posture is proper modeling of the shoulder system. The motion and the joint limits in the shoulder joint and clavicle joint should be coupled, and changes in the discomfort model compensate for the lack of coupling. Thus, the *new discomfort* function models the following sequence of segment motion: arm, forward motion in the clavicle, back, upward motion in the clavicle.

Step 2 – Test Joint Limits and Neutral Positions

Given refined performance measures, the joint limits and the neutral positions are tested. The comparison of the two sets of joint limits suggests that the new joint limits should be used. We find that the two neutral positions (seated and standing) result in similar predictions, so we continue to use the standing neutral position.

Step 3 – Weights for Multi-objective Optimization

Using subject S50M3, MOO weights are determined. Then, in the next step these weights are used with additional subjects. The ideal MOO weights using discomfort are determined as follows for Targets 1, 2, 3, and 4 respectively: (d,v,e)=(1,1,0), (d,v,e)=(1,1,.01), (d,v,e)=(1,1,0), (d,v,e)=(.6,1,0), where *d* represents the weight for discomfort, *v* represents the weight for vision, and *e* represents the weight for energy. The ideal weights using joint displacement were determined as follows, again for Targets 1, 2, 3, and 4 respectively: (jd,v,e)=(1,.03,0), (jd,v,e)=(1,.15,0), (jd,v,e)=(1,1,1), (1d,v,e)=(1,1,1), where *jd* represents joint displacement.

In general, the best combination of performance measures included a weight of 1 for discomfort, a weight of 1 for visual displacement, and a small weight (approximately 0.01) for energy. The most effective weights were similar for all targets, with the exception of Target 4, which requires boundary conditions that are not yet considered in the model.

In order to compare the results with different performance measures and combinations there of, we compiled data using what we call *method plots*. These plots are given in Figures 10 through 13. Each bar in each plot indicates the distance between the joint center determined with experimentation, and the joint center determined with simulation. The smaller plots indicate the difference between the elbow angles determined with experimentation and the elbow angle determined with simulation.

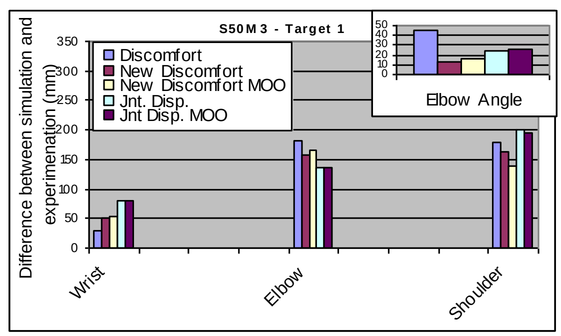

Figure 10: Optimization Method Plot for Target 1

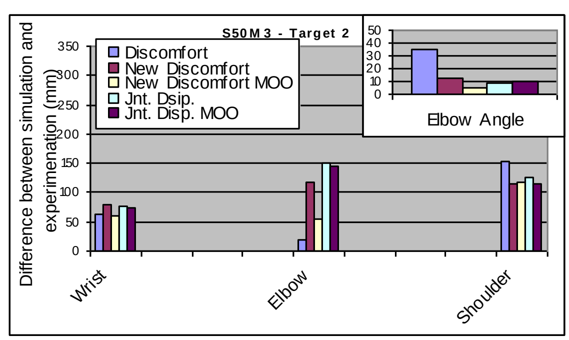

Figure 11: Optimization Method Plot for Target 2

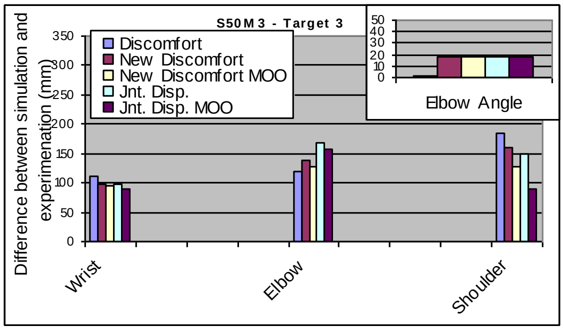

Figure 12: Optimization Method Plot for Target 3

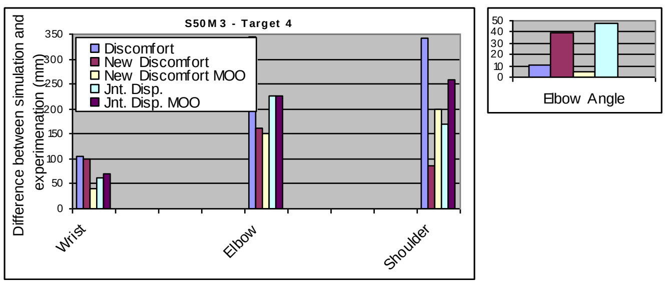

Figure 13: Optimization Method Plot for Target 4

There is a quantitative and qualitative improvement in the predicted postures when the new discomfort function is used with MOO. In addition, using MOO with discomfort provides superior result to using MOO with joint displacement. The method plots indicate that the position of the joint center for the wrist most closely matches the experimental results. This is because the wrist is relatively close to the end-effector. Consequently, we find that it is more appropriate to track only joint centers that are further away from points affected by constraints (i.e. the constraint that requires the end effector to contact the target).

Because the best results are obtained using the new discomfort function with MOO, the corresponding postures are given in Figures 14 through 17. The pictures determined using the new discomfort function with MOO also include a line of site. These results are compared to the SOO results involving the previous version of discomfort, and to the experimental results.

The following issues were noted with the experiments under step 3. Using energy lowered the elbow to a more realistic position, but using too much energy resulted in too much bend in the wrist. Thus, the overall strategy in setting the weights was to start with the discomfort weight at 1, increase vision as much as possible, and then increase energy until the wrist orientation became unrealistic.

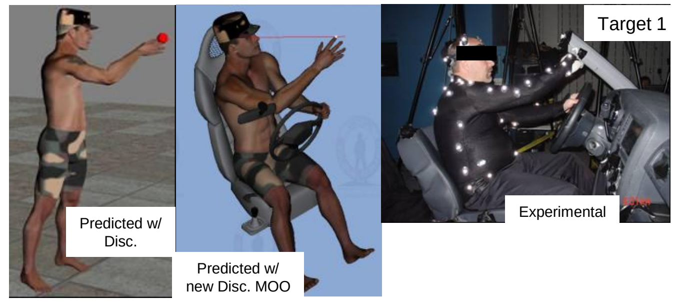

Figure 14: Visual Results for Target 1

Figure 15: Visual Results for Target 2

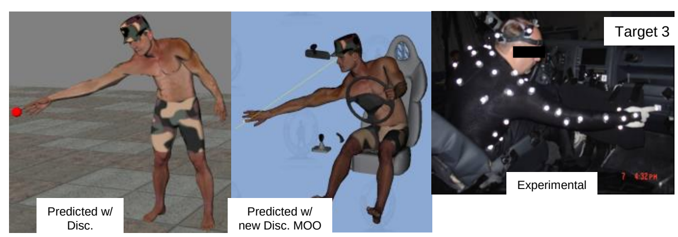

Figure 15: Visual Results for Target 3

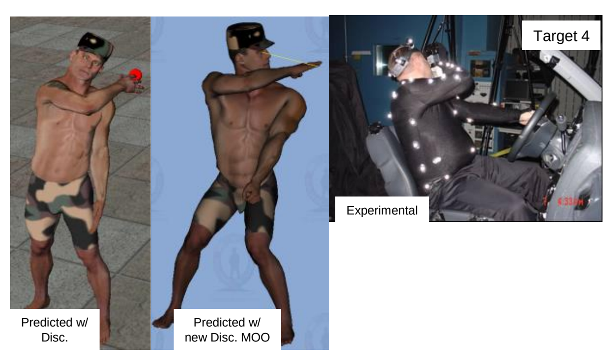

Figure 16: Visual Results for Target 4

With Target 2, using discomfort alone resulted in an elbow that was too high and a shoulder that was too far forward. Correcting both errors is impossible. This is because with a constant target location, moving the shoulder back tends to raise the elbow. Joint displacement provided results similar to those obtained with discomfort but with excessive arm rotation.

With Target 3, considering that there is no hip motion in the simulation, the posture-prediction problem no longer concerns finding the optimal posture. Rather, it simply involves finding a feasible posture. Therefore, changing the weights has only subtle effects on the consequent posture. With every case/method, the elbow angle is always at its minimum value.

With Target 4, using a vision weight of 1 results in the eyeball contacting the target. This suggests that focal length should be incorporated in the vision model. It is especially evident with Target 4 that discomfort is sensitive to the joint limits, since a penalty is applied as joints approach their perspective limits.

Step 4 – Test MOO Settings with Additional Subjects

The weights determined with step 3 are applied to additional subjects, and the same improvement that using the new discomfort function with MOO provided in step 3) was seen with the additional subjects. Method plots were compiled for each subject-target test, although they are not included here.

During the motion-capture experiments, it was noted that the smaller subjects (fifth percentile and fiftieth percentile females) tended to rotate the steering wheel, thus moving their left hand downward. They also rotated their hips considerably when reaching for Target 4. Thus, in the corresponding simulations, the left hand was not constrained to the steering wheel. Essentially, a boundary condition was altered.

In many instances, the simulated vision ray, which indicates where exactly Santos™ is looking, does not intersect the target precisely, although it always comes close. This is because visual displacement is used as an objective function, which may or may not obtain its absolute minimum value when incorporated in a MOO formulation. This suggests that visual discomfort should be tested as a constraint.

Given the large amount of data collected for step 4, the question arises as to how one consolidates this data and how one develops metrics for validation. With step 3) we introduced *method plots* as one tool for validation. With step 4), we use two additional new tools for validation. The first is a set of *joint plots* given in Figures 17 through 20, in order to aggregate validation data and compare it to simulation data. The first three plots involve the Cartesian coordinates for three joint centers, and the fourth plot involves elbow angle. One subject was selected randomly from each percentile, and all targets were considered with the resulting four subjects.

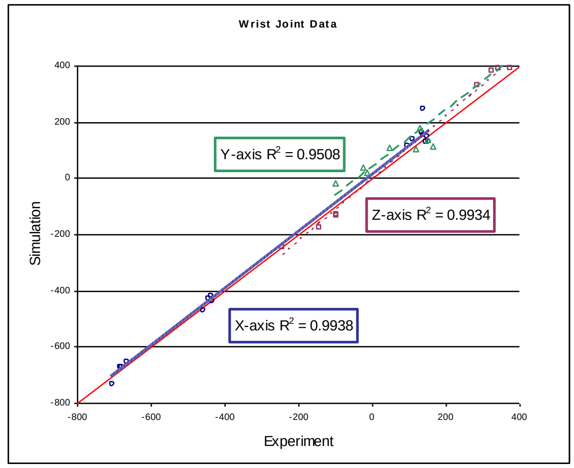

Figure 17: Joint Plot for Wrist Data

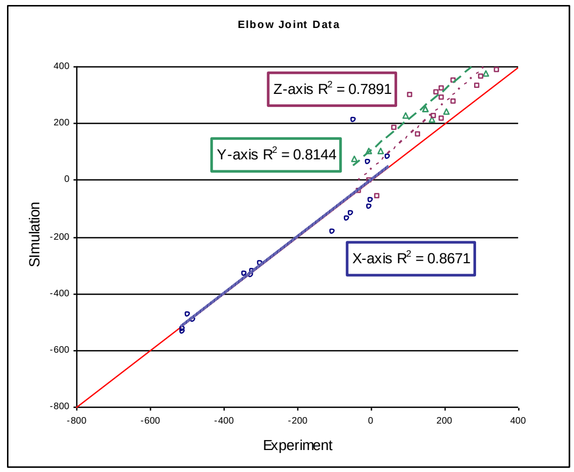

Figure 18: Joint Plot for Elbow Data

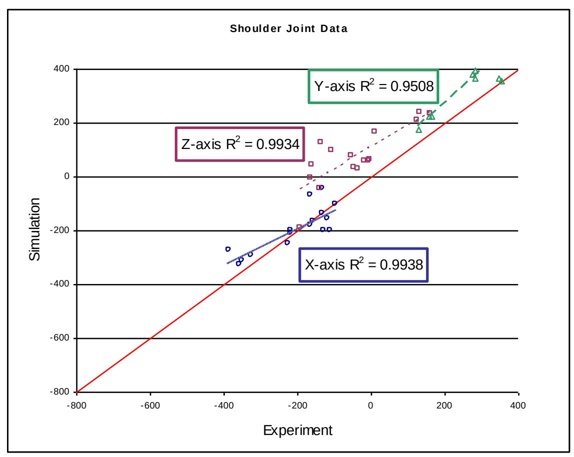

Figure 19: Joint Plot for Shoulder Data

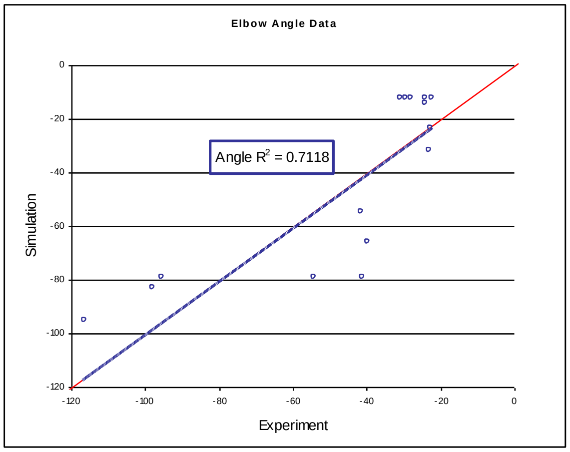

Figure 20: Joint Plot for Elbow-Angle Data

These plots contain a wealth of information. The degree of scatter around any given trend line (there is one trend line for each coordinate) indicates the degree of precision, and R^2 is a metric for such precision. We strove for $R^2>0.7$, and this requirement is satisfied in all cases. The correlation of a trend line with the red 45-degree line indicates accuracy. A trend line that is parallel to the 45-degree line suggests that although the data may not be completely accurate, the simulation is consistent across all targets and all subjects. Alternatively, a trend line that is skewed relative to the 45-degree line suggests that there are inconsistencies in the simulation between various targets and/or various subjects. Currently, there are no hard-and-fast limits for the correlation of trend lines to the 45-degree line, but subjective evaluation of such correlation provides significant insight.

In general, the joint plots suggest successful validation of posture prediction capabilities. In the cases when there is some lack of accuracy, it tends to be because simulated Y- and Z-values are too high. Note that the Y-axis points from the hip up towards the head, and the Z-axis points from the hip forward away from the body. Predictions along the X-axis are relatively accurate. The wrist joint is the most accurate. This is because the wrist joint-center is closest to the end-effector and essentially follows the end-effector, and the end-effector is constrained to contact the target. The trend lines for the elbow joint center are offset from the 45-degree line, but they are parallel to the 45-degree line. Although there is some inaccuracy, the predictions are consistent. Alternatively, the trend lines for the shoulder are somewhat skewed relative to the 45-degree line, suggesting inconsistencies in the model. In fact, as discussed earlier, coupling of the motion and limits in the shoulder system constitutes critical future work.

Often, regression analysis can be misleading. However, rather than provide extensive statistical analysis, the intent here is to develop methods for aggregating data. Yang *et all* (2007) provide a more extensive consideration of statistical analysis issues, and discuss confidence intervals associated with the regression analysis.

In addition to the method plots and joint plots discussed above, we also develop a method for testing the overall posture strategy using what we call *task plots*. Example task plots are shown for Target 2 in Figures 21 through 23. While the joint plots are used to aggregate numerical data, these plots are used essentially to aggregate visual postures. These plots average the joint-center positions for multiple subjects, showing arm postures from different views. As with the joint plots, one subject was randomly selected from each percentile, and all targets are considered with the resulting four subjects.

The coordinates for the joint centers, shown in the plots, are averages of values that have been normalized by the height of the subjects. The data are normalized so that the plots can represent multiple subjects. However, because the coordinates were normalized, the dimensions indicated with the axes in the plots have no physical significance. Nonetheless, these plots are useful for comparing posture strategies.

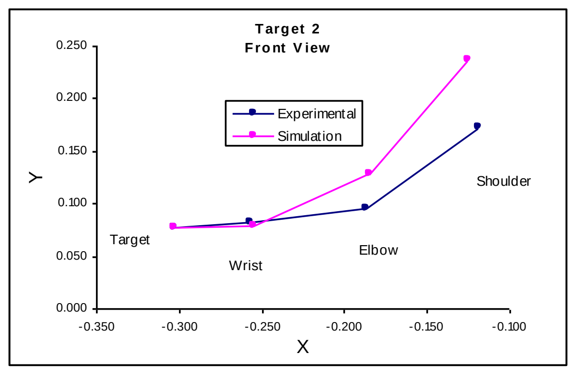

Figure 21: Task Plot for Target 2, Front View

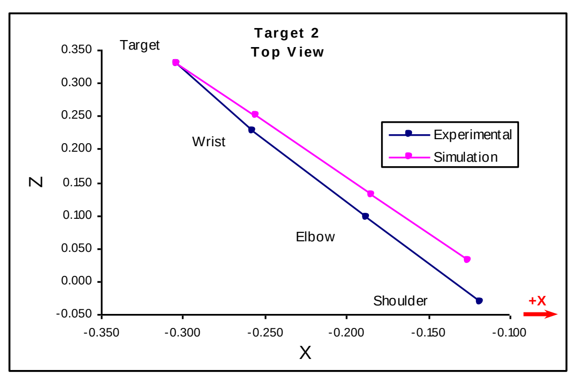

Figure 22: Task Plot for Target 2, Top View

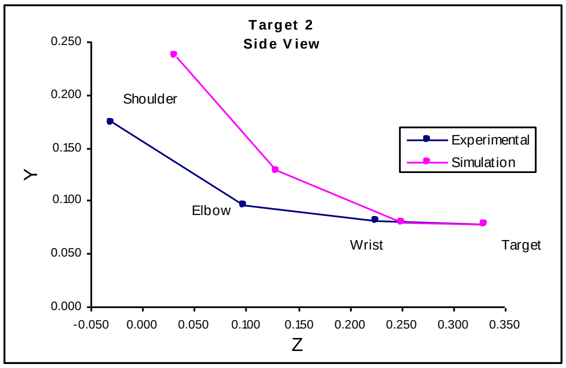

Figure 23: Task Plot for Target 2, Side View

Generally, the simulations and experimental results indicate similar posture strategies, with all targets. With Target 1, however, the elbow is predicted to be slightly higher than the shoulder. With Target 3, the arm is predicted as being nearly fully extended. As discussed previously, because there is no hip motion in the simulation model, touching Target 3 is a matter of simply determining a feasible posture rather than an optimal posture; there is little redundancy in the system.

CONCLUSION

In this paper, we have outlined an approach to validating predicted postures. This involves an overall methodology, experimental protocol, and tools for aggregating data. This approach was used with upper-body reach-type posture prediction an automotive cab, with SOO-based and MOO-based posture prediction.

Some of the primary contributions of this study are findings, development of tools, and identification of metrics relevant to validation of posture prediction. These components are listed as follows:

1) We have shown that human posture can be validated using a few select markers or components, rather than tracking every joint or every degree of freedom.
2) It is best to track joint angles and the location of joint centers, not markers on the skin. Joint centers that are not tied, directly or indirectly, to constraints in the model are preferable.
3) The markers and components that are tracked depend on the task. For instance, validating walking requires different markers than validation for upper-body reaching.
4) Posture can not be validated precisely because of inaccuracies in model and motion-capture systems and, more importantly, because of inherent variability in human performance. The latter stems from personal history and cognitive differences. However, one can ensure that predicted postures are within a reasonable range, an envelope of acceptability. In addition, one can validate posture strategy.
5) One should use both subjective and objective tools for validation. As useful as quantitative metrics are, there is no substitute for visually comparing postures.
6) In addition to visually comparing postures, the following new tools have been developed for aggregating posture-prediction and experimental data: method plots, joint plots, and task plots.
7) Solid criteria relating to the method plots and relating to the trend lines' relationship to the 45-degree line on the joint plots need to be developed. R^2 should be greater than 0.7 with the joint plots. As are the visual postures, the task plots are for subjective evaluation.

Throughout this work the idea of boundary conditions surfaced with respect to the human model. In cases of product design, it is not sufficient to model just the human body; one must consider how the human body interacts with the environment. This in turn requires that one clearly define what exactly is modeled, and what constitutes the system being studied. Boundary conditions define the boundaries of the model. They approximate behavior of components that are not actually modeled.

Another key component of human modeling that often requires approximations is anthropometry. If one intends to validate predicted postures precisely, there must be a precise match between the anthropometry of the human subject(s) and the simulation model. However, because of current limitations in motion-capture technology, such precision is not possible. Thus, one should use subjective validation simply to validate posture strategies and general approaches to various tasks. Objective validation should be completed with the understanding that results must fall within a margin of error.

When determining appropriate weights for MOO, the issue of how one distinguishes a "task" surfaced. The premise of task-based simulation is that we are able to model the differences in behavior that different tasks demand. This is done by using different performance measures. However, if hypotheses must be tested and optimization formulations must be altered too often, the advantages of actually predicting posture subside. With this work, we view the task being addressed as *reaching*. Each target does not constitute a different task. In fact, the MOO weights were similar for most of the targets.

This work focused primarily on analysis across percentiles. That is, with the joint plots and task plots, all targets were considered for subjects from all of the percentiles. As future work, we will also consider multiple subjects from the same percentile, thus adding a second dimension to the analysis. Finally, it will be necessary to consider joint plots for a single target, adding the third and final dimension to the validation work. Yang *et al* (2006) summarizes this idea of *multi-dimensional validation*.

Based on the consideration of various boundary conditions and the idea that model modification must typically accompany validation, a variety of potential areas for future work have surfaced with regard to the human model. In terms of experimentation, a gold standard of some sort, external to this study, needs to be identified for comparison with both experimental and simulation results. With respect to the human model, hip motion should be incorporated, and the shoulder model must be extended to involve coupled motion and limits between the shoulder and clavicle. Cognitive modeling must also be considered, although the application of cognitive modeling to gross human posture and motion is just now beginning to see progress. The vision model should be augmented so that focal length is considered and so that vision can be modeled as a constraint rather than just a performance measure. Obstacle avoidance and self-avoidance capabilities must be developed further. Finally, the accuracy with which joint-center positions can be extracted from motion-capture data must be improved. All of this work is ongoing at VSR.

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