# Validation of Predicted Posture for the Virtual Human Santos™

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**Abstract**. Digital human modeling and simulation plays an important role in product design, prototyping, and manufacturing: it reduces the number of design iterations and increases the safety and design quality of products. Posture prediction is one of the key capabilities. It is especially useful in the design of vehicle interiors for checking the reachability of buttons and determining comfort levels. This paper presents the validation of predicted posture for the virtual human Santos. The predicted posture is a physics-based model and is formulated as a multi-objective optimization (MOO) problem. The hypothesis is that human performance measures (cost functions) govern how humans move. We chose 12 subjects from four different percentiles, all Americans (female 5%, female 50%, male 50%, and male 95%). Four realistic in-vehicle tasks requiring both simple and complex functionality of the human simulations were chosen: reaching a point at the top of the A-pillar, the radio tuner button, the glove box handle, and a point on the driver's B-pillar seatbelt adjuster. The subjects were asked to reach the four target points, and the joint centers for wrist, elbow, and shoulder and the joint angle of elbow were recorded using a motion capture system. We used these data to validate our model. The validation criteria comprise R-square and confidence intervals. The results show that the predicted postures match well with the experiment results, and are realistic postures.

**Keywords:** Predicted posture, MOO, human performance measures, validation, virtual humans

## 1 Introduction

Posture prediction is an important component within the human modeling and simulation package. There are three major types of posture prediction. The first is an experiment-based method (empirical-statistical approach) in which the posture comes from experiments and statistic regression; this approach does not need to be validated. The second is an inverse kinematic method and the third is a direct optimization-based method, and other approaches. The approaches that are not directly from experiment do need to be validated.

The objective of this study is to validate in-vehicle optimization-based posture prediction using experiments. In this paper we present the details of the experimental protocol, criteria for validation, and a three-domain validation method.

In the empirical-statistical approach, data are collected either from thousands of experiments with human subjects or from simulations with three-dimensional computer-aided human-modeling software (Porter et al., 1990). The data are then analyzed statistically in order to form predictive posture models. These models have been implemented in the simulation software along with various methods for selecting the most probable posture given a specific scenario (Beck and Chaffin, 1992; Zhang and Chaffin, 1996; Faraway et al., 1999). This approach is based on actual human data and thus does not need to be verified in terms of realism.

The inverse kinematics approach to posture prediction, which uses biomechanics and kinematics as predictive tools, has received substantial attention. With this approach, the position of a limb is modeled mathematically with the goal of formulating a set of equations that provide the joint variables (Jung et al., 1995; Kee et al., 1994; Jung and Choe, 1996; Wang, 1999; Tolani et al., 2000). Zhang and Chaffin (2000) introduce an optimization-based differential inverse kinematics approach for modeling 3-D seated dynamic postures and validation. Griffin (2001) gives a review of the validation of biodynamic models. Park et al. (2004) present a memory-based human motion simulation. It uses an optimization method as the motion modification algorithm to fit the specific motion scenario. It also uses experiments to validate the model. Wang et al. (2005) demonstrate the validation of the model-based motion in the REALMAN project. However, all of these approaches are restricted to relatively simple models.

Yang et al. (2004) introduce a direct MOO-based posture prediction for a high-degree-of-freedom human model in real-time. This paper presents a three-domain method for validating the predicted posture. The validation scenario consists of the in-vehicle seated reaching tasks.

This paper is organized as follows. Section 2 briefly reviews Santos's kinematic model and the multi-objective optimization-based posture prediction model. Section 3 presents validation tasks, subject selection, experimental protocol, data collection and analysis, validation criteria selection, and the detailed validation process. Section 4 presents the conclusion and discussion.

## 2 MOO-based Posture Prediction

In this section we present the kinematic model for the virtual human Santos, determine the physics factors that affect human postures, derive the mathematical models (human performance measures) of these factors, and formulate the redundant inverse kinematics problem as a MOO problem.

### 2.1 Santos's Kinematic Model

The human body is a complex system that includes bones, muscles, tendons, and nerves. The human skeletal model can be simplified as a mechanism with rigid links connected by kinematic joints. One anatomy joint could have one or more kinematic joints. For example, the shoulder joint has three revolute kinematic joints, while the elbow joint entails only one revolute joint. Therefore, we can model the human as a system with high degrees of freedom (DOF). Fig. 1 shows a 109-DOF Santos kinematic model (Yang et al., 2005, 2006). It has five open loops starting from the root at the hip point to the right hand, left hand, head, left leg, and right leg.

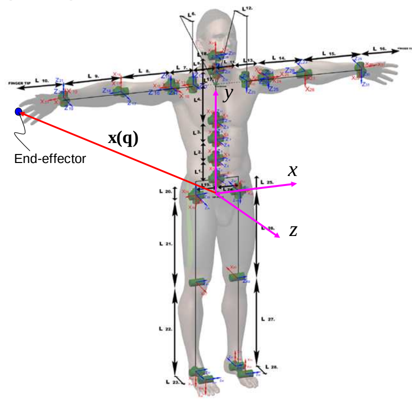



Fig. 1 Santos's kinematic model

The end-effector, or point of interest, is the fingertip, toe, or a point on the head. The position vector of the end-effector with respect to the global frame attached to the hip point $\mathbf{x(q)}$ is defined by the following:

$$\begin{bmatrix} \mathbf{x(q)} \\ 1 \end{bmatrix} = {}^{0}\mathbf{T}_{1}{}^{1}\mathbf{T}_{2} \cdots {}^{n-1}\mathbf{T}_{n} \begin{bmatrix} \mathbf{x}_{n} \\ 1 \end{bmatrix} \quad (1)$$

where ${}^{i-1}\mathbf{T}_{i}$ is a $(4\times4)$ transformation matrix from frame $i$ to frame $i-1$ determined by the Denavit-Hartenberg method (Denavit and Hartenberg, 1955). $\mathbf{q} = \begin{bmatrix} q_1 & \cdots & q_n \end{bmatrix}^T$ is the joint angles from the hip to the end-effector. $\mathbf{x}_n$ is the end-effector vector with respect to frame $n$.

### 2.2 Posture prediction

Posture prediction is defined as follows. We try to find the configuration (joint angles) of a human when he or she reaches for a target point using the fingertip or other end-effector (point of interest on body). Because the human model has a high number of DOFs, this problem has multiple solutions, or is a redundant problem. We have proposed a MOO-based method (Yang et al., 2004) in which physics factors govern how humans move. This approach ensures autonomous movement regardless of the scenario and can be implemented in real time.

There are many physics factors that govern human postures. The first is that human posture gravitates to a "neutral posture," and there are different task-related neutral postures. For example, when humans stand to achieve a task, the neutral posture is one in which the arms are straight down at the side, and the neck, torso, and legs remain straight in the frontal plane. When humans sit, the neutral position is one in which the torso leans on the seat back, knees bend, feet rest on the floor, and arms are on the arm rests of the seat. The second factor that governs human posture is potential energy. Humans use one posture instead another to save energy. For example, humans use the arm before the torso or clavicle because the mass of the arm is much smaller than the mass of the torso. The third factor is that initial posture affects the predicted posture, and the fourth is that joints with tendons try to avoid stretching those tendons. The fifth factor is vision; humans try to see a target as they reach for it.

Based on these physics factors, we developed several mathematical cost functions (human performance measures). They are joint displacement, effort, change of potential energy, visual displacement, and discomfort (Yang et al., 2004; Marler, 2005, Marler et al., 2006). The MOO-based approach is different from traditional inverse kinematic methods or the experiment-based approach. It enforces human performance measures to drive the posture. Therefore, this approach is more generic and can be used in all different scenarios. This MOO problem is formulated as follows:

*To find*: $\mathbf{q}$
*to minimize*: Human performance measures
*subject to*: Constraints
where constraints include the requirement that the end-effector should touch the target point and the requirement that joint angles should be within their limits.

## 3 Validation of Postures

In this section, we will describe the validation tasks, subject selection, data collection using a motion capture system, experimental protocols, experiment data variation analysis, validation criteria, and the three-domain approach to the validation.

### 3.1 Tasks to validate

This study focuses on the in-car environment. We selected realistic in-vehicle tasks that test both the simple and the complex functionality of the human simulations. Fig. 2 shows the four tasks that were chosen for the experiment. Task 1 requires reaching the point at the top of the A-pillar, a simple reach task. Task 2 requires reaching the radio tuner button, a slightly difficult reach task. Task 3 requires reaching the glove box handle, a difficult reach task. Task 4 requires reaching a point on the driver's B-pillar seatbelt adjuster. This is a complex task that requires reaching across the body and turning the head to see the target. The general procedure for achieving a task is as follows: the subject holds the steering wheel using both hands for the initial posture, then maintains the left handhold and uses the right-hand index finger to touch the target point.

### 3.2 Subject selection

To cover a larger driver population, auto designers choose a range of percentiles from 5% female to 95 % male. Therefore, in our experiment, we chose four different populations, all Americans: 5% female, 50% female, 50% male, and 95% male. Also within percentiles, three subjects are selected.

### 3.3 Data collection and experimental protocol

Optical systems have many applications in biomechanical studies (Hagio et al., 2004; Robert et al., 2005; Rahmatalla et al., 2006). In the motion capture process, a number of reflective markers are attached over bony landmarks on the participant's body, such as the elbow, the clavicle, or the vertebral spinous processes. As the participant walks or carries out a given physical task or function, the position history of each marker is captured using an array of infrared cameras. A potential problem with passive markers, though, is *occlusion*, where the markers do not appear in enough of the camera shots due to blockage of the line of sight between the marker and the cameras by objects in the scene or by other parts of the subject's body. In this work, redundant markers (more than the minimum required) were used to compensate for occluded markers. The time history of the location of the reflective markers was collected using a Vicon motion capture system with eight cameras at a rate of 200 frames per second.

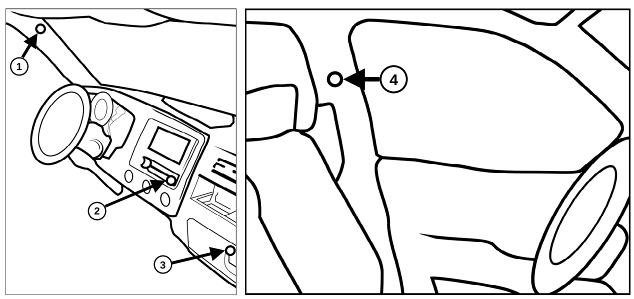


Fig. 2 Four in-vehicle tasks

Several marker placement protocols have been introduced in the literature for studying various types of motion. Among these protocols, plug-in gait is a typical protocol that has been adopted by systems such as Vicon and LifeMOD. In the plug-in gait protocol, markers are attached to bony landmarks on the subject's body to establish local coordinate systems on various segments of the body. Joint centers and joint profiles can then be obtained using these coordinate systems. Methodologies for calculating joint center locations and link lengths of humans are available and have been somewhat successful (Halvorsen et al., 1999). However, because of the occlusion problem, it is very hard to accomplish this goal with a high degree of accuracy for people in seated positions with the existence of obstacles in the environment. In this work, due to the complexity of the capturing environment for a seated person inside a car and due to the limited number of cameras available at the time of the experiments (eight), redundant markers were attached to the upper part of the subject's body to estimate joint center locations and to compensate for the missing markers, as shown in Fig.3. The marker placement protocol was designed to facilitate the process of obtaining the location of the joint centers of the upper part of the subject's body (right wrist, right elbow, right shoulder, and hip joint) during the experiments. In the marker placement protocol, one marker was attached to the end effecter (the end of the middle finger), three markers were attached to the wrist joint, and three markers were attached to the elbow joint. The shoulder joint is very complicated, so four markers were used to estimate the location of this joint center, and two markers were used to estimate the location of the clavicle (one on the clavicle and one on the T4). In all cases, the joint center location was estimated by the intersection of the lines connecting the markers on each joint.

### 3.4 Trial-to-trial and subject-to-subject data variation

As described in above section, we obtained the joint centers for the right wrist, elbow, and shoulder and the right elbow angles using a motion capture system. The objective was to correlate the relationship between the simulation results and experiment results. However, we had to transform all data to the same coordinate system. In this study, we used Santos Spine1 above the hip joint as the common coordinate system.

When we did the experiment, each subject reached one target point for five trials. For trial-to-trial variation, we use subject S95M3 to illustrate the results. For subject-to-subject variation, we demonstrate variation within one percentile (the three S95M subjects). The results are shown in Fig. 4. The vertical axis denotes the variation from the mean value of the distance from the target point to the origin, and the horizontal axis represents the four tasks. As shown in Fig. 4, a single subject's trial-to-trial variation is small and within $\pm 10\text{mm}$ and $\pm 3\text{degrees}$. Subject-to-subject variation within percentiles is only slightly larger than trial-to-trial variation. The variation values are within $\pm 25$ mm and $\pm 6$ degrees. Therefore, it is appropriate to average the data from all five trials and reasonable to choose a representative subject within the percentiles.

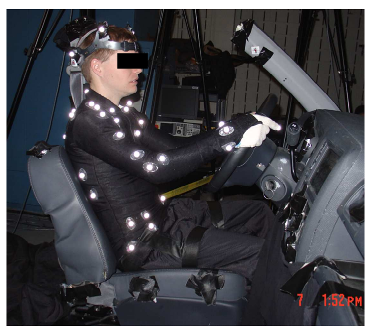


Fig. 3 Experiment markers

### 3.5 Validation Criteria

There are several criteria for validation, though they are not independent. In this section, we summarize the criteria for general model validation, which are $R^2$, confidence intervals of mean, regression, and other statistic values.

The coefficient of determination $R^2$ is *the relative predictive power of a model*. Generally, *the closer it is to one, the better the model is*. However, $R^2$ is not an absolute measure for a good model. There are different factors that affect the values of $R^2$, such as the range of X values, different patterns of X values, average values of X, and randomness. Therefore, when $R^2$ is close to 1, it does not necessarily mean that the model is good; it only indicates that the model can represent the experiment data very well. Likewise, when $R^2$ is small, it does not necessarily mean that the model is not good. We have to carefully study the data themselves and also check whether the slope is close to 1. The 45 degree line with respect to the X axis denotes that the experiment and simulation values are the same. This is another important parameter for validating the model.

A confidence interval gives an estimated range of statistic values that is likely to include an unknown population ρ, the estimated range being calculated from a given set of sample data. Confidence intervals are calculated at a confidence level (a certain percentage), usually 95% ($\alpha$ =0.05), but we can also produce 90%, 99%, 99.9%, and other confidence intervals for the unknown parameter ρ. Confidence intervals are more informative than the simple results of hypothesis tests because they provide a range of plausible values for the unknown parameter. Confidence intervals of mean, regression, and slope of the linear regression are used for validation of the model.

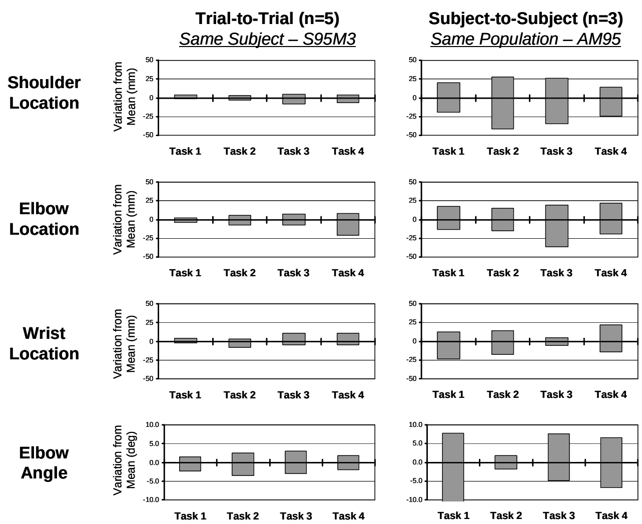



Fig. 4 The variation in the mean values for the distance between the target and the origin

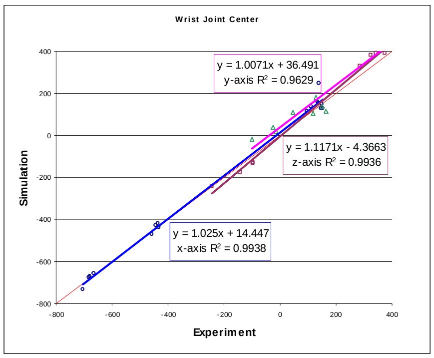
### 3.6 Three-domain approach

In this study we have developed a three-domain approach to validate the predicted posture. This approach validates the predicted posture in three domains: across percentiles, within percentiles, and with respect to Task 2.

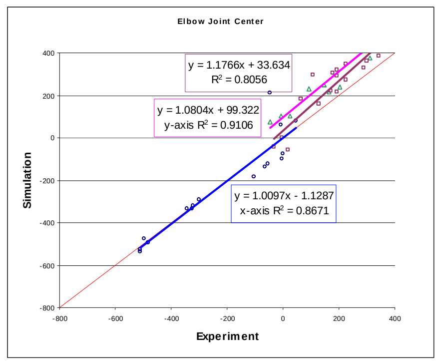
We have selected one representative subject for each percentile. That means there is one subject from each of these percentiles: 5% female, 50% female, 50% male, and 95% male. Therefore, across percentiles we consider only four subjects and consider all tasks together. We first illustrate the coefficient of determination $R^2$ . Then, we demonstrate only the confidence intervals for the elbow joint angles. Figs. 5 (a)-(c) are regression plots of Cartesian coordinates of x, y, and z for the joint centers of the right wrist, elbow, and shoulder, respectively. Fig. 5(d) is the right elbow joint angle regression plot. The red straight line is at

45 degrees with respect to the X axis. All $R^2$ values satisfy $R^2 \geq 0.7$, and the slopes of all regressions are close to 1.

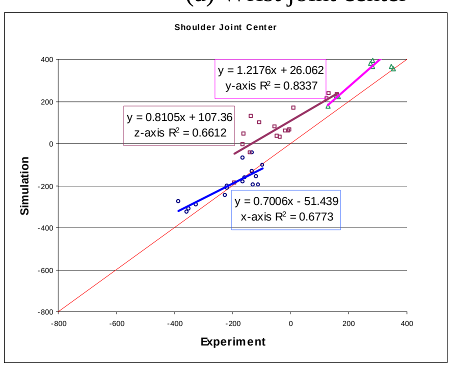
For confidence intervals, we demonstrate only the elbow joint angle in this paper; however, the procedure to determine the confidence intervals is the same as for other joint centers. The confidence interval of regression for the elbow joint angle with a 95% confidence level is $0.1115 \leq \rho^2 \leq 0.7967$. The confidence interval for the slope of the regression of the elbow joint angle with a 95% confidence level is within $(0.7033, 1.3038)$. The confidence interval for mean with 95% confidence level is shown in Fig. 6 (a).



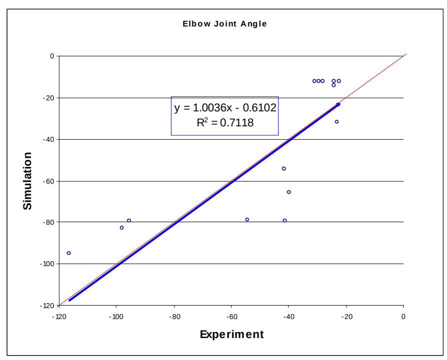

(a) Wrist joint center




(b) Elbow joint center




(c) Shoulder joint center

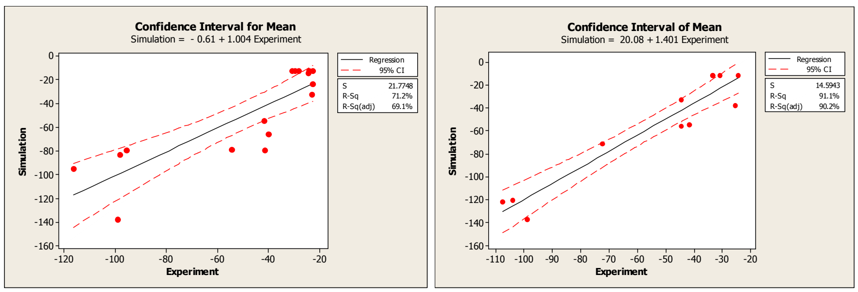



(d) Elbow joint angle

Fig. 5 Regression plots across percentiles

Within 50% male category, we analyze the regression similar to the cases across percentiles. All $R^2$ values satisfy $R^2 \geq 0.7$, except in the case of Shoulder x. The confidence intervals are straightforward, as in the examples above. In this case, the confidence interval of regression for the elbow joint angle (95% confidence level) is $0.4999 \leq \rho^2 \leq 0.9509$. The confidence interval for the slope of the regression of the elbow joint angle (95% confidence level) is within $(1.075, 1.727)$. It is obvious that one is not within this range, which means the accuracy is not as good as it is across percentiles. The confidence interval for mean with 95% confidence level is shown in Fig. 6(b).

Regarding to Task 2, most $R^2$ values are very small. Does this tell us that the model is not good? The answer is NO. In these plots, most data points are clustered together. This shows the property of “pure randomness.” That means it is not appropriate to validate our model in this domain. However, this also tells us that our posture prediction model does not capture the properties of gender because we can use one set of data from male 50% to replace the data from female 50% because there is no significant difference.




(a) Cross percentile (b) Within a percentile

Fig. 6 Confidence interval for mean

## 4. Conclusions and Discussions

This study presents a systematical validation procedure of the predicted posture. In general, although there were errors from all different sources, such as the motion capture system, the method that transforms markers on the skin to joint centers or joint angles, the human model, and the posture prediction model, the validation process was successful and the predicted postures were within the required error limit. Human postures can be validated using a few selected key markers, and every degree of freedom does not need to be tracked. The results show that it is best to track key joint angles and the location of joint centers, not the markers on the skin. We used a three-domain approach to validate the predicted postures, and all plots contain a wealth of information. Generally, $R^2$ is a metric for the degree of precision of the model. The slope of the regression is another criterion to indicate the accuracy of the model. However, because we used a limited number of samples, it was necessary to investigate confidence intervals to predict the range of values that was likely to indicate the unknown population.

The results show that regression with respect to a task is not appropriate for validating the posture because it is a pure randomness problem. They also show that there are some areas in which our model could be improved. The posture prediction model could be improved in the following areas: (1) an advanced shoulder model considering coupled degrees of freedom and coupled joint limits; (2) gender within the model; (3) hip movement; (4) neck and head model that is connected to the spine; (5) cognitive modeling aspects. In the meantime, we should do further experiments with an increased population.

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