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A Validation Protocol for Predictive Human Locomotion

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ABSTRACT

A framework to validate the predicted motion of a computer human model (Santos) is presented in this work. The proposed validation framework is a task-based methodology. It depends on the comparison of selected motion determinants and joint angles that play major roles in the task, using qualitative and quantitative statistical techniques. In the present work, the validation of Santos walking will be presented. Fortunately, the determinants for normal walking are well defined in the literature and can be represented by (i) hip flexion/extension, (ii) knee flexion/extension, (iii) ankle plantar/dorsiflexion, (iv) pelvic tilt, (v) pelvic rotation, and (vi) lateral pelvic displacement. While Santos is an ongoing research project, the results have shown significant qualitative agreements between the walking determinants of Santos and the walking determinants of four normal subjects.

INTRODUCTION

Digital human modeling has attracted considerable attention in recent years, and this has heightened the need to model normal human locomotion due to its important role in many medical and industrial applications. There are many attempts in the literature to model human walking [1-3]. Approaches that attempt to solve for human walking motions based on performance optimization [4-6] are shown to be suitable for reproduction of realistic human motions. In this case, objective functions are used to represent human performance measures, and optimization schemes are developed to solve for the feasible joint motion profiles that extremize the performance measures [7-8]. The works in this category are important because the human motions are not artificially constrained and are dynamically feasible.

One interesting characteristic of the optimization-based techniques is their tendency to introduce more than one feasible solution; this behavior is consistent with natural human behavior where people do tasks in various manners. If well formulated, the methodology may present optimal solutions that can be very useful for many applications such as training. However, the solution space of the optimization-based approaches can be narrowed down to obtain a one task-based solution. For example, in normal walking, the ranges of joint angle movement are well defined and therefore can be imposed as constraints to achieve natural walking.

There have been several attempts in the literature to validate the motion of digital human models. Most of these human models are based on experimental and regression analysis that guide their motion, and traditionally the validation process is to show the statistical significance of these formulas.

There are many issues to be considered in validating the motion of human models. For example, people with different age, gender, race, and anthropometry may conduct the same task using different strategies. Also, muscle strength and subject fitness play significant roles in the resulting motion. Therefore, the latter issues should be included in the decision of the validation quality. In general, the expectation is that the model should be able to model the population in a statistical average sense.

There are additional problems to be considered in the validation process. For example, Faraway [9] showed the effect of a precise and consistent definition of movement start and end points, which are required for comparison of motions across and within participants and targets. Faraway and others [9-11] have studied the effect of the variability in the motion time between different subjects and within the same subject when they conducted a similar task, on the validation process. In this regard, they proposed a methodology to normalize the motion time and define t=0 to be the start of the motion and t=1 to be the end of the motion.

The challenge in the current work is to validate the motion of a predictive human model (Santos) whose motion is completely based on general equations of physics and some natural constraints. Besides the inertia forces, Santos's prediction is sensitive to the effects of the external forces. Therefore, it is very important to choose a comparable environment for the model and the subjects during the validation process. Additionally, due to the important role of the stance time and the swing time in the walking determinants, the proposed validation protocol is also designed to check the quality of the data within these intervals.

The objective of this article is to present the development of a framework of a validation protocol to test the capability of Santos to simulate normal human walking activities. Toward this end, a twelve-camera Vicon motion capture system was used to collect 3D motion data of four subjects walking normally inside the motion capture lab.

MOTION CAPTURE PROCESS

There are many techniques and devices on the market for measuring 3D motion data. Examples include electromagnetic sensors, optical sensors, fiber-optic-based sensors, and inertia sensors. Some of these devices, such as the electromagnetic sensors, may suffer from interference problems with other equipment in the testing environment; others, such as fiber-optic-based and inertia sensors, are normally capable of producing only local information and therefore may need to be supplemented with global positioning devices such as gyroscopes. The optical sensors approach is both effective and efficient for collecting objective data for 3D motion analysis. Today, optical systems have many applications in biomechanical studies [12-16]. These systems have been shown to be accurate, repeatable, and consistent [17], and, as an additional benefit, there is no pain or risk involved in using such systems. 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.

There are many advantages to using optical motion capture systems to collect motion data. First, the markers are passive sensors, meaning that they are merely reflective surfaces and can be attached easily to any area on the body of the subject without requiring wires to connect them to a data collection system. Second, theoretically, only three markers are required to define the three-dimensional velocity and acceleration of each body segment. In this work, the time history of the location of the reflective markers was collected at a rate of 100 frames per second. Power spectrum analyses were conducted on the accelerometers' signals and a cut-off frequency of 8Hz was identified for subsequent data smoothing.

MARKER PLACEMENT PROTOCOL

The Santos Marker Placement Protocol (Fig.1), developed by CCAD researchers, was used to prepare the subjects for the normal walking motion capture. In this protocol, markers were placed on the subjects to highlight bony landmarks and identify segments between joints in line with previously identified guidelines and suggestions [18-19]. The marker placement protocol was defined based on the skeleton of the virtual human Santos, which is based on the Denavit-Hartenberg (DH) method, in which 4×4 homogeneous transformation matrices relate two adjacent coordinate systems [20]. The skeleton of Santos includes the major joints present in the human body with the number of spine joints reduced to four. Inverse kinematics problem or vector analysis is normally used to solve for various joint angles.

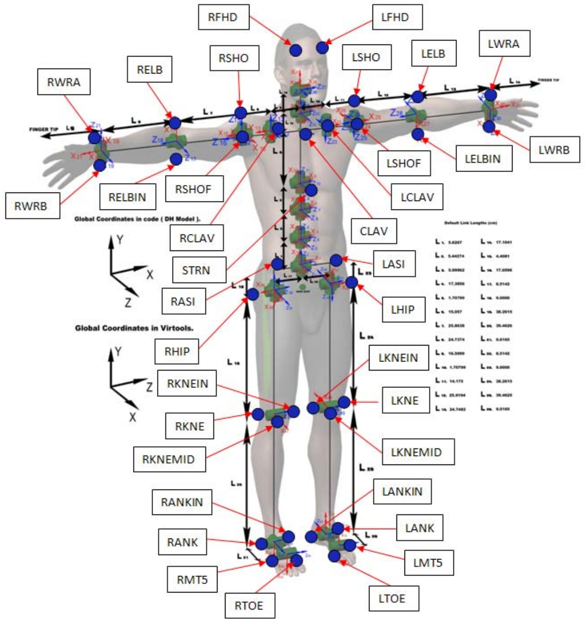

Figure 1: Santos marker placement protocol

In the protocol, markers were placed around joint centers to determine the center of motion. For example, three markers were placed around the knee. One marker was placed directly on the medial epicondyle, another on the lateral epicondyle, and the third on the central anterior patellar surface. Each of these marker positions was identified as an anatomical landmark by Cappozzo et al. [18] with the terminology coming from the well-defined, classic standards used by Gray and Lewis [21]. Various research efforts verify that these described anatomical landmarks can be easily used to identify the geometric center of the knee. A similar technique was used for the remaining joints of the subject.

WALKING DETERMINANTS

After developing a protocol for collecting and processing the data, the next important phase in the validation process is to determine the minimum number of parameters that define a given motion; these parameters are identified to be the determinants of the motion. If Santos has the ability to predict each of these determinants within a statistically acceptable range, then he can execute the task in a natural way that is characteristic of human motion. Based on the literature and a strong understanding of human gait, six angles and displacements were chosen to define forward walking [22]. These determinants look to the lower extremities and pelvic motion of the human and include hip flexion/extension, knee flexion/extension, ankle plantar/dorsiflexion, pelvic tilt, pelvic rotation, and lateral pelvic displacement. With the exception of lateral pelvic displacement, each of the gait determinants is the time history of a joint angle. Joint angles are dimensionless, so they become an intrinsic measurement of motion; they are independent of anthropometry. Fig. 2 provides a physical representation of some of the lower extremity determinants [23]. Below each pictorial representation of the determinant is the accepted time history curve as presented in the literature [24]. Pelvic motion, which we defined to include pelvic tilt, pelvic rotation, and lateral pelvic displacement, is not consistently identified in the literature; however, we include them in this validation because of their significant involvement in normal human walking.

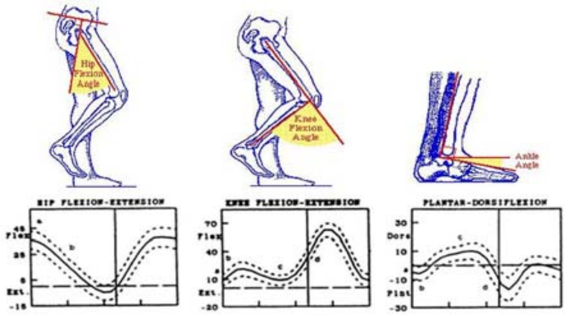

Figure 2: Pictorial depictions of the lower extremity gait determinants. From left to right: hip flexion/extension, knee flexion/extension, ankle plantar/dorsiflexion

SUBJECT POPULATION

The subject population was comprised of four healthy male subjects. The subjects had no history of musculoskeletal problems and were reasonably fit. Their participation was voluntary, and each subject signed a consent form before beginning the experiment. The mean height of the subject population was 5'7" with a mean weight of 143 lbs. The average age of the participants was 34 years old.

SUBJECT PREPARATION AND DATA COLLECTION

When a subject came in to the motion capture lab, he/she put on the motion capture suit and markers were placed on his/her body according to the previously defined marker placement protocol. Bony landmarks were carefully located and corresponding markers were placed accordingly. Our methods for joint center calculations are defined based on anatomical detail, so it is important that marker positions reflect these anatomical reference points [19, 25].

The subjects were instructed to take several practice walks until they were comfortable with the camera setup and were showing consistency in their self-selected speed. All of the subjects demonstrated normal walking patterns during the experiment.

The normal walking trial was set up so that the subject walked forward at a comfortable speed, stopped, and walked backwards to return to the starting position. On average, the subjects took 4-5 steps forward depending on preferred step length. The first and final steps were considered acceleration and deceleration, respectively. The middle stride was analyzed as a steady state gait cycle for normal forward walking.

The trials were repeated to ensure that the results were usable and to examine the consistency of the velocities chosen by the subjects. In addition, every trial began and ended with the subject in the same position. This position is known as the T-pose, and it corresponds to the initial joint angles and segment locations of the skeleton. Fig. 3 is a photograph of a subject standing in the T-pose. The reflective markers seen on the subject correspond to the Santos Marker Placement Protocol.


[redacted]

Figure 3: Subject standing in T-pose

VALIDATION

COMPARISON PROTOCOL

The experimental protocol used to compare the simulation of Santos to the normal human walking trials contains the parameters that must be considered for a direct comparison of the data. These parameters include the starting position and leading foot of the gait cycle. In addition, the time of the gait cycle must be normalized to match the simulation and the initial point of comparison must be defined. The time history of a steady state gait cycle was used to represent the cyclic motion of walking for each subject. According to the literature, the gait cycle begins with the left heel strike; this position was used as the starting point of the gait cycle for the experimental and simulated data [24].

QUALITATIVE COMPARISON

Santos determinant curves as shown in Fig. 4 have general trends that closely follow the data that represent normal human walking determinants. If we consider each individual determinant (Fig.4), then the Santos curve will have significant similarity with the human population, and it can be shifted horizontally or vertically to get better agreement. However the difficulty with normal walking is that the determinants are coupled and, in order to achieve normal walking, the Santos curves should follow the curves of all the determinants at the same time. Even with this requirement, the Santos curves have qualitatively similar behaviors to that of human population. With a closer look, we can recognize some differences in the magnitude of simulated flexion/extension in the lower extremities of Santos that take place in parts of the gait cycle. The curve predicted for pelvic displacement shows a shift between the simulated and experimental data, but the magnitude and nature of the curves are consistent. Santos's predicted dynamics model shows competency for computing the pelvic rotation of normal human walking.

QUANTITATIVE COMPARISON

During the walking trials, each subject walked at a self-selected speed. As a result, the time for completion of one gait cycle varied between subjects, and a direct frame-by-frame comparison of the determinants was not realistic. Therefore, experimental data for each subject was normalized by dividing the cycle time by the maximum time to directly evaluate the determinants at a percentage of a gait cycle. For each subject, the time scale was normalized such that the initial left heel strike occurred at time $t = 0$ and the subsequent left heel strike occurred at time $t = 1$ [9].

The percentage of the gait cycle at some time t signifies the progression of the subject through the walking cycle. This was used as our standard for comparison of the experimental and simulated data. The six determinants were plotted against percentage of the walking cycle for each subject and the simulation. The results are shown in Fig. 4.

In the plots of the determinants versus the percentage of the walking cycle, the red line represents the joint angle or displacement history predicted by Santos. The remaining curves correspond to the experimental data. The number of frames required to complete one walking cycle differed between subjects and between trials of one subject so an unequal number of points was used to describe the motion of each subject. Consequently, the normalization method previously described produced a walking cycle from 0-100% for each subject, but the increment between successive data points varied between subjects based on execution time of the gait cycle. As a result, the data points vary between subjects, and this makes it very hard to average the values at each data point to find the mean or central tendency of the experimental data. Therefore, the data was fitted to a nonparametric model using the B-spline fitting technique.

Splines are piecewise polynomial functions that are constrained to join at points called knots. We chose cubic B-splines for the basis because of their well-known stability for numerical calculations in contrast to polynomials. Cubic B splines are made to be smooth at the knots by forcing the first and second derivatives of the functions to agree at the knots. The cubic degree allows for continuous first and second derivatives, which is important if velocity and acceleration are needed.

Let $y(t) = (y_1(t), ... y_4(t))$ be angle curves, given m+1 knots t_j with $t_0 \le t_1 \le t_2 \le \cdots \le t_m$.

We represent the joint angle curve for the ith subject as linear combinations of basis functions

$$y_i(t) = \sum_{j=0}^{m-4} p_{ij} B_{j,3}(t) + \varepsilon_i(t), t \in [t_3, t_{m-3}] \ ,$$

where the cubic B-spline basis function is defined using the Cox-de Boor recursion formula as

$$B_{j,0}(t) = \begin{cases} 1 & t_j \le t < t_{j+1} \\ 0 & otherwise \end{cases}$$

$$B_{j,3}(t) = \frac{t - t_j}{t_{j+3} - t_j} B_{j,2}(t) + \frac{t_{j+4} - t}{t_{j+4} - t_{j+1}} B_{j+1,2}(t).$$

The control points p_{ij} are found by minimizing

$$\int_0^1 (y_i(t) - \sum_{j=0}^{m-4} p_{ij} B_{j,3}(t))^2 dt \ .$$

Let $B = [B_1, \cdots B_{m+1}] = \begin{bmatrix} B_1(0) & \cdots & B_{m+1}(0) \\ \vdots & \vdots & \vdots \\ B_1(100) & \cdots & B_{m+1}(100) \end{bmatrix}$

$$y(t) = [B_1(t), \cdots B_{m+1}(t)]p = B(t)p$$

$$y = [y(0), \cdots y(100)] = Bp.$$

The variance of spline function values is given by

$$V\text{ar}(y) = Var[Bp] = BVar[\hat{P}]B',$$

where $Var[\hat{P}]$ is the variance-covariance matrix of the vector of estimates of $\hat{P}$. The 95% point-wise confidence interval is $B\hat{p} \pm Z_{\alpha/2}(BVar[\hat{P}]B')^{\frac{1}{2}}$.

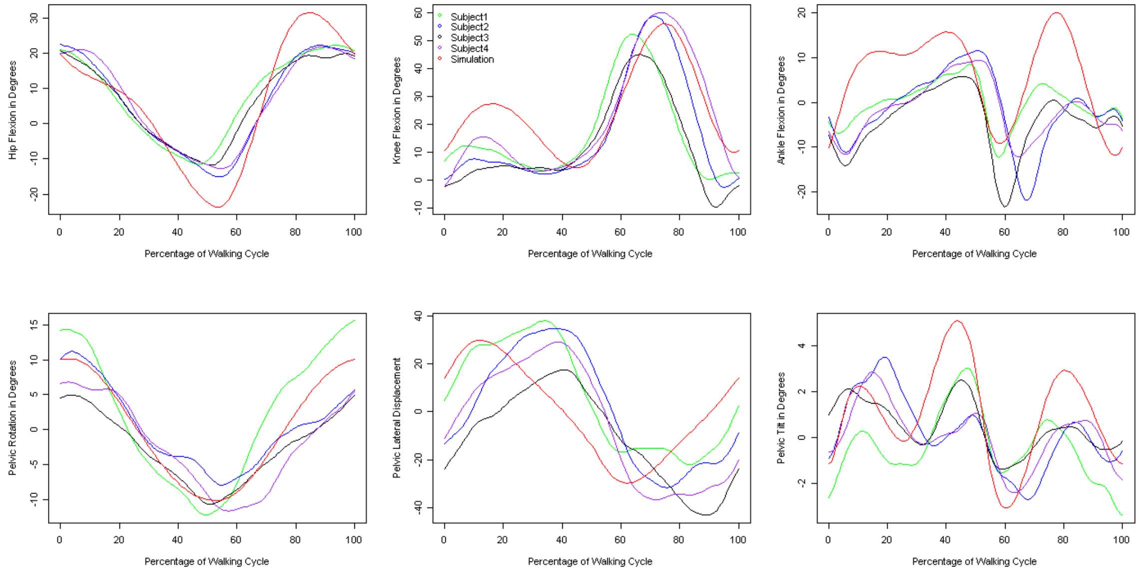

Figure 4: Normalized walking cycle for four human subjects and Santos

STATISTICAL ANALYSIS

The variability of a data set can be measured in standard deviations or how far each data set lies from the mean. In general, if the simulation falls within two standard deviations of the mean, then it can be considered agreeable and representative of the motion being analyzed [26-27]. We are interested in whether or not the digital human model of Santos is capable of predicting forward walking that is in agreement with the normal population. Interval of confidence provides limits such that there is a high level of confidence that a large proportion of values of the variable will fall within them. In our case, we want to be 95% confident that the entire proportion of values of each determinant of Santos will fall within the tolerance limits. The two standard deviation bands correspond to the 95% tolerance bands for all the fitted values.

The comparison between the experimental results obtained from motion capture and the predicted results made by the virtual human Santos are presented in Figure 5. If the simulation lies within the region of the upper and lower bounds of the interval of confidence, then a strong agreement is shown between the simulation and normal human walking. In other words, if the predicted values lie within the region, we can be 95% confident that Santos's digital model is capable of reliably representing normal forward walking.

The analyses have shown that Santos's hip flexion/extension time history reaches greater maximum and minimum peaks than the subject population. It still shows a correlation to normal forward walking, but some improvement is needed. Knee flexion/extension lies within the region; however, the curve of the simulation differs from normal human motion during the period from 10-40% of the gait cycle. There is a lesser degree of correlation between the ankle and normal human motion, and there may be some constraint that has not been considered in the simulation. From the plots, we see that the pelvic rotation of Santos corresponds to the pelvic rotation seen in humans during normal forward walking. The general trend line of the pelvic tilt seems to agree with the experimental curves. The pelvic tilt falls outside the 95% confidence interval from 35% to 50% of the gait cycle when the ANOVA test shows that $P<0.001$. In terms of lateral pelvic displacement, the simulation provides a relatively normal curve, but the peak values occur at different percentages of the gait cycle than were seen in the subject population.

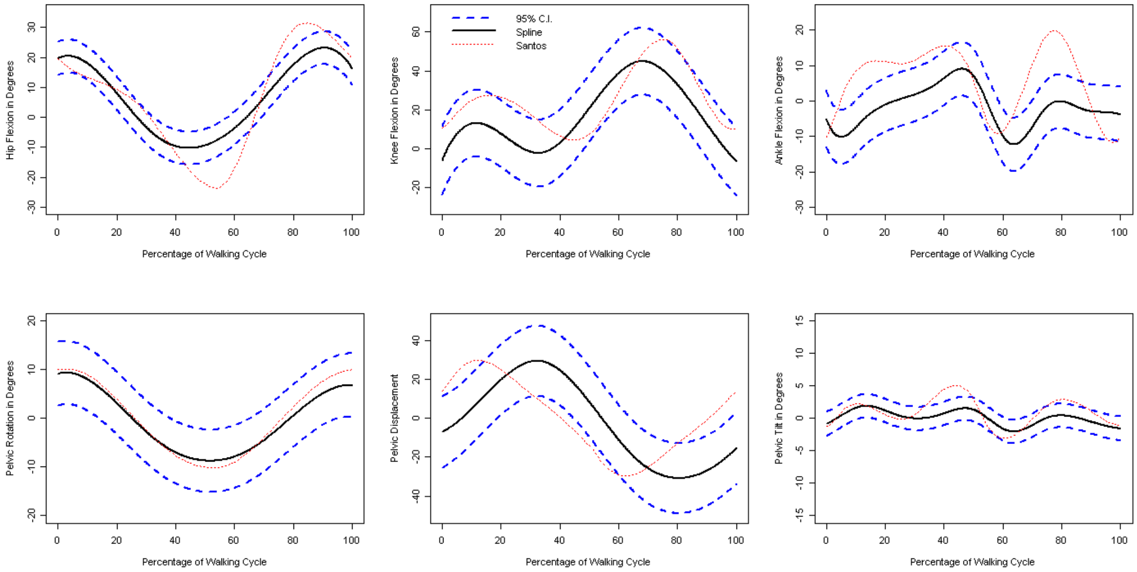

Figure 5: Subjects mean and 95% interval of confidence with Santos determinants using B-spline fitting

CONCLUSIONS AND DISCUSSIONS

After obtaining the experimental data, the graph of each determinant was plotted against frame number (which represents the time). We noticed that there was a difference in the cycle time within the individual subjects and when the subjects repeated the trial. While the latter is natural behavior and depends on how fast the subjects walk during the experiment, it is important in this work to have a standard time scale so that the data can be used adequately in the comparison process during the statistical analysis. Therefore, the first task we addressed was how to normalize (standardize) these data sets for comparison to the simulation on a set time interval. Also, due to the difference in the starting position of each subject and the simulation, the data was shifted so that each subject was compared from the left heel strike to the subsequent left heel strike.

At first, we tried performing shifts in the x and y-directions; however, it became apparent that this was altering the appearance of the data. Instead, the determinants were found and the initial zero degree angles of the subject in the T-pose were subtracted to match the subject's initial position to the simulation data and the zero degree position of Santos. This accounted for individual variation in joint limits and initial position and was a more useful normalization of the data.

Once the normalization was performed, the experimental and simulated gait determinants were plotted together for comparison. At this point, the determinants were examined qualitatively and quantitatively. Differences between the simulated and expected data were observed and noted so that further improvements could be made. Statistical analysis involved fitting the data using a cubic B-spline curve, finding the mean and the 95% interval of confidence, and using ANOVA tables for the analysis of the variance.

The statistical analyses have shown that Santos's hip flexion is a very good indicator of normal human motion and lies mostly within the tolerance interval in Fig. 5. There is no significant difference in terms of the overall mean joint angles of Santos during the gait cycle. (P=0.6564). We noticed that the first 40% of the simulated gait cycle agrees very well; however, the predicted curve lies outside the tolerance interval from approximately 45% to 55% and from 80 to 100% when the supporting leg is changing and the center of gravity is shifting. For these periods, P<0.001, suggesting improvement is needed.

Knee flexion is simulated well by the digital human model except for the period between 10% and 40% of the gait cycle. This is knee flexion during the stance phase of the gait cycle, and P<0.001 in the variance analysis, suggesting there is a statistically significant difference between the simulated and experimental data.

Analysis of the ankle shows similar discrepancies during the stance phase of the gait cycle and some improvement may be necessary in the modeling of these joints.

The general trend line of the pelvic tilt seems to agree with the experimental curves. Pelvic tilt falls outside the 95% confidence interval from 35% to 50% of the gait cycle when the ANOVA test shows that $P<0.001$. This represents a significant difference. Pelvic rotation, on the other hand, is modeled very well by Santos. It falls within the 95% tolerance band for the entire gait cycle and lies close to the mean of the experimental data. Lateral pelvic displacement falls outside the tolerance interval from 40% to 60% of the gait cycle when the ANOVA test shows that $P<0.001$. This represents a significant difference; however, from qualitative analysis it is clear that there is a shift between the data sets, and the displacement of Santos occurs before that of normal human subjects.

This study has provided the initial validation of normal walking predicted by the virtual human model Santos. More importantly, it provided a logical and systematic approach to virtual human validation. The proposed method of validation is essential to the use and dependability of the model, so while it may be improved and expanded upon in the future, it has provided the foundation for predictive motion validation. Now that a systematic process has been defined and completed, it will be used to validate other dynamic human motions predicted by Santos.

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