Posture Reconstruction Method for Mapping Joint Angles of Motion Capture Experiments to Simulation Models

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Abstract. Motion capture experiments are often used in coordination with digital human modeling to offer insight into the simulation of real-world tasks or as a means of validating existing simulations. However, there is a gap between the motion capture experiments and the simulation models, because the motion capture system is based on Cartesian space while the simulation models are based on joint space. This paper bridges the gap and presents a methodology that enables one to map joint angles of motion capture experiments to simulation models in order to obtain the same posture. The posture reconstruction method is an optimization-based approach where the cost function is a constant and constraints include (1) the distances between simulation model joint centers and the corresponding experimental subject joint centers are equal to zeros; (2) all joint angles are within joint limits. Examples are used to demonstrate the effectiveness of the proposed method.

Keywords: digital human modeling, posture reconstruction, motion capture.

1 Introduction

Human modeling and simulation has gained momentum in recent years due to the advantages of incorporating digital human models into the design process early on. A new approach to design, human-centric design, focuses on the interactions between human beings and their environment. Recent advancements in technology enable a designer to first test a product in a virtual environment. Inside a virtual environment, a designer can subject the product to a series of virtual tests using the aid of a digital human. A digital human, in a general sense, is a software application that tries to replicate the human body in form and function. Through various virtual tests, it is possible for a designer to gather useful information for refining the design. Multiple testing scenarios incorporating digital humans of variable anthropometry are made possible in the digital human simulation environment. Therefore, it is a useful design tool, allowing a designer to stage virtual testing of a product that would have previously only been possible through prototype experiments. Digital human modeling reduces the need for prototype testing, thus saving money and reducing design times.

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Motion capture experiments are often a useful aid for digital human modeling simulations. In a typical motion capture experiment, reflective markers are placed on a subject's skin and the Cartesian position of each marker relative to the global coordinate system is tracked through the use of high-speed infrared cameras. As the subject carries out a given physical task, a history of each marker's position is recorded using an array of cameras. Typical output data of a motion capture experiment includes the Cartesian coordinate of each of the markers.

Motion capture experiments are often used in coordination with digital human modeling for enhancements of the simulation by three means. The first is that motion capture data often provides regression models for some commercial software such as Jack, Ramsis, and Safework. By capturing motion data for various subjects and tasks, a library of movements can be built and used to create fluid, realistic movements for digital humans. Combining several movements into one task can be accomplished rather easily and any holes in the animation can be smoothed by manipulating position, velocity, and acceleration profiles and interpolation. Many technical applications such as LifeMod, Anybody, and DI-Guy incorporate motion capture animation to simulate complex physical tasks such as running or dunking a basketball (Veloso et al., 2004; Rasmussen and Ozen, 2007; DI Guy, 2008).The second way motion capture is incorporated into digital human simulations is through the use of motion capture as a study aid for complex physical task simulations. Many physical tasks are difficult to model without the aid of motion capture. By studying the position, velocity, and acceleration profiles of a motion capture experiment, it is possible to gather useful information that can be incorporated into the mathematical simulations of complex movements. Using motion capture data often provides important details about initial conditions or constraints of movement. Incorporating this knowledge is often essential to the simulation of complex physical tasks, such as walking, running, or jumping. Zou et al., (2010) and Ozsoy et al., (2011) provide examples of digital human simulations where motion capture aids in the simulation of walking and jumping, respectively. Finally, the third way motion capture is used in coordination with digital human modeling is through validation. It is always necessary to ensure that digital human simulations mimic real-world scenarios closely. Otherwise, the usefulness of the simulation is lost. If a digital human is to be used for design of a product, the simulation must provide realistic results. Comparing digital human simulations to motion capture experiments often provides a means of validation. This paper is dedicated to developing a methodology map joint angles of motion capture experiments to simulation models in order to obtain the same posture.

The current digital human employed by the Human-Centric Design Research Laboratory (HCDRL) has 49 degrees-of-freedom (DOF) based on human anatomy. The movement of the digital human is tied to a kinematic joint chain that represents the human skeletal system. Thus, a single posture is uniquely defined by a single set of real numbers, or joint angles. When motion capture is used as a method of validation, it is necessary to be able to directly compare the results of the simulation with results from the motion capture experiments. The experimental data obtained through motion capture is typically the Cartesian coordinates of the markers with respect to the global coordinate system. Thus, it is necessary to map the experimental data from Cartesian position space to joint angle space. The motion capture software has the capability to transfer Cartesian space to joint space, but the error is large. To better compare the experimental data to simulation results, a posture reconstruction algorithm has been developed. Posture reconstruction involves calculating the necessary joint angles that will recreate the experimental posture with the digital human. Once the joint angles are calculated, they can be directly compared to predicted joint angles from the simulation of the same task or posture. Since predicting human posture is a redundant problem, the posture reconstruction algorithm is formulated as an optimization problem. This paper develops a posture reconstruction algorithm to directly compare digital human simulations to motion capture experimental data by mapping the experimental data from Cartesian space to joint space. Several examples of posture reconstruction are provided to demonstrate the algorithm's effectiveness for various subjects and tasks.

This paper is organized as follows: Section 2 describes the posture reconstruction formulation, Section 3 details the motion capture experiments and equipment, Section 4 provides examples of posture reconstruction through examples of four subjects performing three different tasks and validation, and Section 5 contains discussion of the posture reconstruction algorithm and extended applications.

2 Posture Reconstruction Formulation

The idea behind posture reconstruction is the same as posture prediction, albeit with considerably more end-effectors. In a posture prediction simulation, typically only a human's natural end-effectors (hands, feet, and head) are prescribed to a certain point in Cartesian space. Typically the other joints in the body are free to move according to joint limits or some other criteria. In our previous work, digital human movement is dictated by human performance measures, such as joint displacement, joint torque, musculoskeletal discomfort, visual displacement, and delta-potential energy (Yang et al., 2004). Posture prediction is formulated as an optimization problem with human performance measures serving as objective functions in the optimization problem. A typical posture prediction problem formulation is as follows:

- Find: joint angles that represent a specific posture
- Minimize: human performance measures
- Subject to: distance constraints on multiple end-effectors

Human performance measures are combined into a single weighted multi-objective function in the multi-objective optimization (MOO) problem described by Yang et al., (2004). A typical posture prediction problem is described in detail as part of previous work (Gragg et al., 2010a). In a general sense, there are user-defined constraint functions and objective function(s). The objective functions, constraint functions, and function gradients are defined and the optimization problem is solved by SNOPT. SNOPT is a general purpose system that solves constrained optimization problems (Gill et al., 2002). The posture reconstruction algorithm expands upon the posture prediction formulation by adding more end-effectors in a highly-constrained optimization problem.

The digital human employed by the HCDRL is controlled through movement of a kinematic joint chain that represents a human's skeletal system. Deformable skin is attached to the skeleton to aid in visualization, but the kinematics of the digital human are only associated with the skeletal structure (Gragg et al., 2010b). The skeletal structure is constructed according to the Denavit-Hartenberg (DH) convention

(Denavit and Hartenberg, 1955). All joints in the chain are single DOF revolute joints described by a single real number, or joint angle. For the i^{th} joint, we associate the joint variable, q_i, and rigidly attach a local coordinate system. Each subsequent joint is connected by a link of varying length. This does not cause loss of generality, as physical human joints with multiple associated DOFs can be represented as multiple DH joints connected by a link of length zero. The set of all joint angles, $\mathbf{q} = [q_1 \ \cdots \ q_n]^T \in R^n$, represents a specific posture. $\mathbf{x}(\mathbf{q}) \in R^3$ is the position vector in Cartesian space that describes the location of an end-effector with respect to the global coordinate system. $\mathbf{x}(\mathbf{q})$ is determined using the DH method and expressed as the product of the individual transformations associated with each joint. The 4x4 transformation matrix $\mathbf{T}_j^i$ denotes the position and orientation of joint i with respect to joint j. $\mathbf{x}(\mathbf{q})$ and $\mathbf{T}_j^i$ are expressed mathematically as follows:

$$\mathbf{x}(\mathbf{q}) = \left(\prod_{i=1}^{n} \mathbf{T}_i^{i-1} \right) \mathbf{x}_n \tag{1}$$

$$\mathbf{T}_i^{i-1} = \begin{bmatrix} \cos\theta_i & -\cos\alpha_i \sin\theta_i & \sin\alpha_i \sin\theta_i & a_i \cos\theta_i \\ \sin\theta_i & \cos\alpha_i \cos\theta_i & -\sin\alpha_i \cos\theta_i & a_i \sin\theta_i \\ 0 & \sin\alpha_i & \cos\alpha_i & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2}$$

$\mathbf{x}_n$ is the position of the end-effector with respect to the n^{th} frame and n is the number of DOFs. The rotational displacement q_i changes the value of θ_i. The constants α, a, and d are the DH parameters link twist, link length, and link offset and along with θ are used to define the geometric relationships between the joint $i-1$ and joint i.

In the posture reconstruction formulation, each physical joint center of the human body is treated as an end-effector. That is, every joint center that represents the position of a physical joint in the human body is prescribed to some point in Cartesian space, the same position of the corresponding joint center position from the motion capture experiment. Joints like the shoulders, clavicles, and elbows are now considered as "end-effectors" and thus have an associated distance constraint. Each of the following joint centers is an end effector: four spinal joints, two clavicle joints, two shoulder joints, two elbow joints, two wrist joints, two hand joints, three neck/head joints, one hip-point, two hip joints, two knee joints, two ankle joints, and two foot joints. **Fig. 1** shows each of the joints whose position is prescribed.

As seen in Fig. 1, each physical joint in the human body is an end-effector. For joints where there are multiple DOFs, such as the hip, the first DH joint in the kinematic chain is the end-effector joint. There are 26 joint centers that are considered end-effectors. There are a total of 55 DOF for the digital human, 49 human DOF, and 6 global DOF that describe the position and orientation of the hip point in Cartesian space. Since the amount of distance constraints, equal to the number of end-effectors, is almost half the total DOF of the system, the problem is considered highly-constrained. Thus, for computational efficiency, there are no human performance measures to minimize in the optimization formulation. The objective function is given as a constant with the objective gradient with respect to all angles thus being zero. Since there is no minimization of a human performance measure, the optimization solver is merely trying to find a feasible solution. If a human performance measure is used in the optimization problem, the computational cost of the simulation will increase. Digital human simulations typically strive to be as close to real-time simulations as possible to enhance the benefits of using digital human modeling as a design tool. A typical posture prediction problem can be solved in less than half a second, thus able to claim real-time simulation capability. The posture reconstruction formulation is defined as follows:

- Find: $\mathrm{x} = \begin{bmatrix} q_0 & q_1 & \cdots & q_{\mathrm{m}} \end{bmatrix}$
- Minimize: $\mathrm{f} = 1$
- Subject to: $\mathrm{g}_j = \left(x_j - TP_x\right)^2 + \left(y_j - TP_y\right)^2 + \left(z_j - TP_z\right)^2,\ j = 1,\ldots,M$

$$-\infty \le \mathrm{g}_j \le \varepsilon$$

$$q_i^L \le q_i \le q_i^U$$

where $m = 55$, $M = 26$, and $\varepsilon = .001$. x_j, y_j, and z_j are the x, y, and z position of the individual joint. TP_x, TP_y, and TP_z are the x, y, and z position of the joint's target position. Since the units associated with the simulation are meters, each of the joint centers is required to be within 1mm of the experimental position of the joint center. Since all of the physical human joint centers' positions are prescribed, the result is a posture that fully recreates the experimental posture.

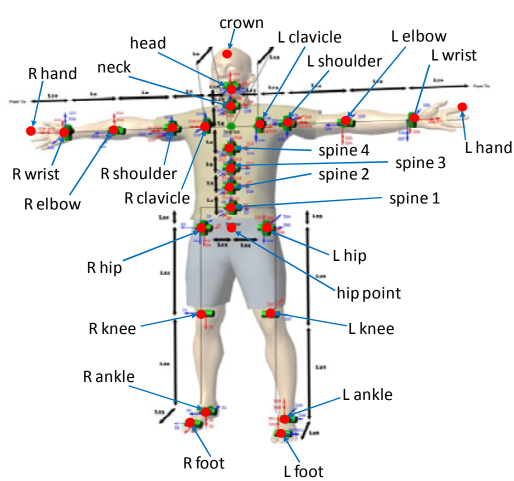

Fig. 1. Important joint centers for posture reconstruction

The output of the posture reconstruction simulation is the joint angles for the experimental posture. These joint angles can then be directly compared to predicted joint angles from a simulation for purpose of validation. This is why the posture reconstruction simulation is said to map the joint angles from motion capture experiments to the digital human.

3 Motion Capture Experiment

Several technologies are available on the market that allow for measuring 3D motion data. Some technologies are: electromagnetic sensors, optical sensors, fiber-optic-based sensors, and inertia sensors. The in-house motion capture system is an optical motion capture system that employs reflective markers and infrared cameras that capture the reflected light from the markers. Optical systems have proven both effective and efficient at collecting objective data for 3D motion analysis, as the systems have shown to be accurate, repeatable, and consistent (Miller et al., 2002). Currently, optical systems have also been employed in many applications in biomechanical studies (Hagio et al., 2004; Robert et al., 2005).

The in-house motion capture system is an eight Eagle-4 camera system (Motion Analysis®). Each camera in the system has 4 megapixel resolution, shutter speeds from 0-2000 μs, focal lengths ranging from 18 mm to 52 mm, and a maximum of 500 frames per second. The eight cameras are set up to enclose a 10 x 10 ft square envelope and a height of 9 ft. For position tracking, it is necessary for three cameras to see a marker so that the position can be triangulated in Cartesian space. Therefore, the cameras are set up in an array surrounding the capture volume in such a way that it is possible for each marker on the body to be in range of at least three cameras.

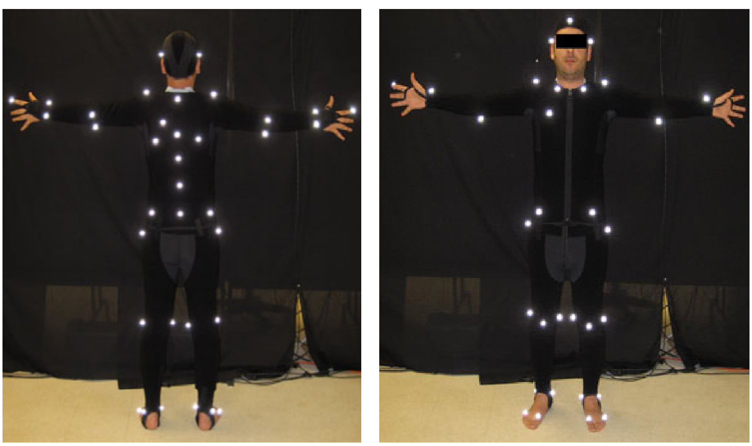

Fig. 2. Marker placement protocol

Marker placement is an important aspect of any motion capture experiment. Proper marker placement is essential for quality results. Several protocols have been introduced in the literature, with plug-in gait being a typical protocol that has been adopted by systems such as Motion Analysis, VICON, and Life MOD. According to plug-in gait protocol, markers are attached to bony landmarks on the subject's body.

The physical markers are then related to joint centers by virtual markers. For instance, to find the joint center position of the wrist, it is necessary to place two markers on the end of the radius and ulna bones. The position of the joint center is then taken to be halfway in between these two physical markers. A virtual marker is then established in the software which represents the position of the joint center. Fig. 2 details the marker placement protocol. The total number of physical markers on the subject is 48, with additional markers for target points.

The position of each joint center is approximated by using two or three physical markers for each important joint center. The position is approximated relative to the position of the real markers, so error is introduced into the system. Thus, it could happen that a posture captured by the motion capture experiment cannot be completely recreated by the digital human. In some instances the posture reconstruction algorithm will fail to meet the distance requirements fully, instead minimizing the error.

4 Posture Reconstruction Examples

Four subjects were chosen for demonstration of the posture reconstruction algorithm: a 5% female, two 50% males, and a 95% male. The first subject, Subject 1, is a 50% male subject required to perform two standing tasks, a right-hand reach and a left-hand reach. This example demonstrates the algorithm's capability of handling a single subject with multiple tasks. The second demonstration requires Subject 2, Subject 3, and Subject 4, a 5% female, a different 50% male, and a 95% male, respectively, to perform a seated reaching task. This example demonstrates the algorithm's capability of handling multiple subjects with the same task. Together these examples demonstrate the posture reconstruction algorithm's versatility in handling multiple subjects and multiple tasks.

Subject 1 performs two standing tasks, a right-hand reach and left-hand reach. The subject is required to touch the same point with first the right hand and then the left hand without moving the feet to get closer. Fig. 3 shows the results for the right hand reach and left hand reach standing tasks. Table 1. compares the x, y, and z positions (in *m*) of each of the joint centers for the motion capture data and posture reconstruction data for the right hand reach and left hand reach standing tasks. The motion capture figure shows both the positions of the physical markers, depicted as colored dots, and the positions of the virtual markers, depicted as dark blue crosshairs. The colored lines represent relationships between physical markers. In order to distinguish individual markers, relationships are built that determine which marker is which based on the distance to other markers. For example, the two right elbow markers are about the same distance from each other throughout the entire experiment, so the software can distinguish these markers from the wrist markers based on proximity. The digital human is shown without skin in order for direct comparison to the motion capture view.

The second example requires three subjects to touch a point with their right index finger while seated. Each subject is required to touch the same point with the chair in the same position for each trial. Fig. 4 shows the results for Subject 2, Subject 3, and Subject 4 seated tasks. Table 2 gives the difference between the x, y, and z positions (in *m*) of each of the joint centers for the motion capture data and posture reconstruction data for Subject 2, Subject 3, and Subject 4.

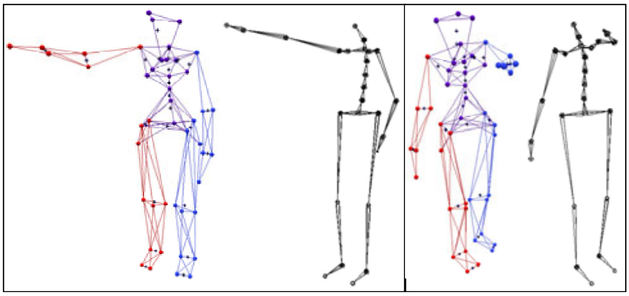

Fig. 3. Subject 1: (a) right hand reach- motion capture posture and reconstructed posture (b) left hand reach- motion capture posture and reconstructed posture

Table 1. Motion capture vs. Posture Reconstruction- Subject 1: (a) right hand reach; (b) left hand reach

(a)

	Motion Capture			Posture Reconstruction			Difference
	x	y	z	x	y	z	d
hippoint	0.0000	0.0000	0.0000	0.0161	0.0155	-0.0026	0.0005
spine 1	0.0720	0.0004	-0.0090	0.0515	0.0003	-0.0030	0.0007
spine 2	0.0765	0.1657	-0.0103	0.0635	0.1646	-0.0004	0.0005
spine 3	0.0791	0.2400	-0.0211	0.0721	0.2300	0.0036	0.0005
spine 4	0.0720	0.4001	-0.0105	0.0720	0.4176	0.0142	0.0005
Rclavicle	0.0008	0.3000	-0.0505	0.0000	0.3799	-0.0602	0.0015
Rshoulder	-0.0130	0.3054	-0.1252	-0.0082	0.3077	-0.1200	0.0005
Relbow	-0.2478	0.0017	-0.3054	-0.2285	0.0025	-0.3005	0.0019
Rwrist	-0.0000	0.4756	-0.0620	-0.0021	0.4048	-0.4561	0.0007
Lclavicle	0.0215	0.3002	0.0033	0.0000	0.3506	0.0015	0.0018
Lshoulder	0.0290	0.3671	0.1210	0.0295	0.3631	0.1303	0.0003
Lelbow	0.0616	0.0066	0.2275	0.0604	0.0705	0.2334	0.0001
Lwrist	-0.0565	-0.1206	0.2726	-0.0738	-0.1205	0.2606	0.0006
neck	-0.0375	0.4576	0.0251	0.0380	0.4342	0.0296	0.0032
head	-0.0004	0.5600	-0.0173	-0.0201	0.5803	0.0140	0.0046
Rhip	-0.0140	-0.0015	-0.1422	0.0062	0.0195	-0.1452	0.0005
Rknee	0.0231	-0.5174	-0.0571	-0.0152	-0.4909	-0.1350	0.0006
Rankle	0.0467	-0.0095	-0.1026	0.0145	-0.0709	-0.1282	0.0005
Rfoot	-0.0795	-0.9406	-0.1181	-0.1001	-0.9218	-0.1057	0.0005
Lhip	0.0137	0.0010	0.1309	0.0266	0.0100	0.1363	0.0005
Lknee	0.0294	-0.5204	0.1017	-0.0003	-0.5042	0.0593	0.0006
Lankle	0.0532	-0.0007	0.1111	0.0121	-0.0020	0.0653	0.0005
Lfoot	-0.0691	-0.9400	0.1070	-0.1111	-0.9317	0.0752	0.0005

(b)

	Motion Capture			Posture Reconstruction			Difference
	x	y	z	x	y	z	d
hippoint	0.0000	0.0000	0.0000	0.0120	0.0143	0.0120	0.0005
spine 1	0.0092	0.0076	0.0301	0.0177	0.0050	0.0009	0.0006
spine 2	0.0334	0.1786	0.0401	0.0051	0.1702	-0.0029	0.0005
spine 3	0.0309	0.2064	0.0536	-0.0004	0.2029	-0.0157	0.0007
spine 4	0.0105	0.3232	0.0500	-0.0361	0.3194	-0.0418	0.0005
Rclavicle	0.0334	0.3002	-0.0050	-0.0000	0.3243	-0.1547	0.0018
Rshoulder	0.1021	0.3407	-0.0950	0.0595	0.3451	-0.1603	0.0005
Relbow	0.2027	0.0054	-0.0007	0.2067	0.0946	-0.0905	0.0004
Rwrist	0.2000	-0.1000	-0.1005	0.2536	-0.1404	-0.1709	0.0005
Lclavicle	-0.0050	0.3954	0.0005	-0.1235	0.3451	-0.0047	0.0010
Lshoulder	-0.1237	0.3939	0.0104	-0.1530	0.3017	-0.0574	0.0003
Lelbow	-0.3640	0.4156	-0.1645	-0.0052	0.3211	-0.2245	0.0007
Lwrist	-0.0967	0.4507	-0.3076	-0.5413	0.3132	-0.4201	0.0005
neck	-0.0076	0.4662	-0.0655	-0.0622	0.4054	-0.1169	0.0022
head	-0.0532	0.5405	-0.1202	-0.0065	0.4522	-0.1075	0.0031
Rhip	0.0756	-0.0091	-0.1073	0.0037	0.0008	-0.1061	0.0009
Rknee	0.0341	-0.5227	-0.0013	0.0370	-0.5057	0.0114	0.0005
Rankle	0.0575	-0.0901	-0.0937	0.1570	-0.0654	0.0909	0.0006
Rfoot	-0.0007	-0.9510	-0.1145	0.0529	-0.9408	0.0070	0.0005
Lhip	-0.0021	0.0027	0.1140	-0.0645	0.0207	0.1291	0.0005
Lknee	-0.0036	-0.5241	0.0959	0.0435	-0.4677	0.2200	0.0015
Lankle	0.0613	-0.0006	0.1209	0.1674	-0.0201	0.2076	0.0006
Lfoot	-0.0909	-0.9509	0.1424	0.0640	-0.9027	0.3100	0.0005

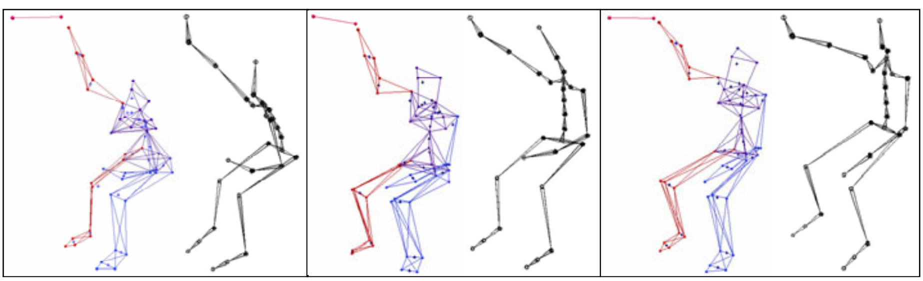

Fig. 4. Seated right hand reach: (a) Subject 2- motion capture posture and reconstructed posture; (b) Subject 3- motion capture posture and reconstructed posture; (c) Subject 4- motion capture posture and reconstructed posture

As seen in Fig. 3, the posture reconstruction algorithm is able to handle a subject performing a variety of tasks with high accuracy. Fig. 4 demonstrates the ability of the algorithm to handle multiple subjects performing the same task. Error introduced through the approximation of the joint centers by virtual markers accounts for slight differences in the positions of the corresponding joint centers, but all joint centers fall within a maximum of 5 mm from the joint center positions from the motion capture experiments. The posture reconstruction algorithm provides a useful tool to obtain the joint angles from motion capture experiment corresponding to the simulation model.

Table 2. Motion capture vs. Posture Reconstruction- Subject 2

	Difference		Difference		Difference
	d		d		d
hippoint	0.0006	hippoint	0.0011	hippoint	0.0005
spine 1	0.0001	spine 1	0.0010	spine 1	0.0005
spine 2	0.0002	spine 2	0.0005	spine 2	0.0002
spine 3	0.0003	spine 3	0.0006	spine 3	0.0002
spine 4	0.0001	spine 4	0.0002	spine 4	0.0013
Rclavicle	0.0012	Rclavicle	0.0012	Rclavicle	0.0055
Rshoulder	0.0005	Rshoulder	0.0005	Rshoulder	0.0020
Relbow	0.0051	Relbow	0.0040	Relbow	0.0054
Rwrist	0.0026	Rwrist	0.0034	Rwrist	0.0046
Lclavicle	0.0015	Lclavicle	0.0003	Lclavicle	0.0013
Lshoulder	0.0004	Lshoulder	0.0013	Lshoulder	0.0002
Lelbow	0.0005	Lelbow	0.0017	Lelbow	0.0005
Lwrist	0.0005	Lwrist	0.0039	Lwrist	0.0005
neck	0.0027	neck	0.0008	neck	0.0051
head	0.0017	head	0.0024	head	0.0066
Rhip	0.0006	Rhip	0.0011	Rhip	0.0003
Rknee	0.0005	Rknee	0.0038	Rknee	0.0004
Rankle	0.0007	Rankle	0.0035	Rankle	0.0005
Rfoot	0.0007	Rfoot	0.0046	Rfoot	0.0003
Lhip	0.0005	Lhip	0.0014	Lhip	0.0005
Lknee	0.0013	Lknee	0.0047	Lknee	0.0005
Lankle	0.0003	Lankle	0.0082	Lankle	0.0005
Lfoot	0.0005	Lfoot	0.0073	Lfoot	0.0005

5 Conclusion

When simulating human movement in a digital environment, it is necessary to validate the predicted posture or motion to ensure realistic simulations. One means of validation is provided by the use of motion capture experiments for comparison with predicted results. The current digital human simulations predict a set of joint angles that represents a physical posture. The in-house motion capture equipment provides only Cartesian coordinates of various joint centers during a task. Therefore, a posture reconstruction algorithm has been developed that maps the motion capture data from Cartesian space to joint space, allowing for direct comparison of digital human simulations and motion capture experiments.

With the posture reconstruction algorithm, it is now possible to validate any future digital human simulations to ensure reliability. Once a particular task is simulated, a series of experiments can be run with subjects of varying anthropometry and the results can be directly compared to predicted values of joint angles. After comparison, if the predicted results are unacceptable, alterations can be made to the simulations, providing higher accuracy and realism to the digital human simulation and virtual environment.

Future work with posture reconstruction will be dedicated to comparing the current algorithm with two alternate methods. The first alternate method is to incorporate a human performance measure such as joint displacement into the optimization formulation. The second alternate method is to implement a two-stage approach to posture reconstruction. The first stage will consist of the current algorithm. The results from the first stage will be used as an initial guess for the second stage. The second stage will incorporate a human performance measure into the optimization formulation as well as lowering the distance tolerance, and the initial joint angle guess will come from the first stage. The three methods will be compared according to accuracy and run-time. Other future work includes using the newly developed algorithms to validate past simulations. Digital human simulations have proven useful as an aid in design, reducing the need for prototypes, reducing costs, and shortening design time to market. Validation of digital human simulations is important to ensure that the simulations provide realistic, reliable results. This posture reconstruction algorithm will provide a means to validate current and future digital human simulations at the HCDRL.

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