Santos the Virtual Soldier Predicts Human Behavior

Karim Abdel-Malek, Rajan Bhatt, Chris Murphy, and Marco Tena Salais
The University of Iowa, United States

Abstract

Human modeling and simulation environments have become sophisticated, providing capabilities for posturing the digital avatar, conducting dynamic tasks, assessing human performance, and obtaining scientific analysis. Physics-based analysis of human motion has also enabled capabilities for predicting the dynamics of the motion whereby the avatar is able to respond to external effects such as load conditions or the physical environment. However, the behavior of the avatar is typically the same. Indeed, the same input to the system yields the same output. This work is concerned with obtaining more realistic and different behaviors for the human while conducting a task in a physics-based environment.

While the Santos[1] digital human modeling (DHM) system has been successfully used in the analysis and prediction of human motion, the resulting behavior of a specific soldier is the same. An (avatar) individual doing a task will do the same task exactly the same way if the simulation is executed again. In reality, however, a soldier may adopt a different strategy to accomplish the same task.

This paper discusses the development of a rigorous scientific method using human performance functions as the driving force to induce different behavior.

The Santos platform uses 215 degrees of freedom to model a human. The research and development of this platform over the past 15 years has made significant strides in the development of *predictive dynamics*[2] as a methodology for predicting behavior and is physics-based. Rather than solving the highly complex and coupled algebraic-differential equations of motion governing the human's behavior, predictive dynamics uses optimization to solve for the behavior.

---

[1] Abdel-Malek, Karim, et al. "Santos: An integrated human modeling and simulation platform." *DHM and Posturography*. Academic Press, 2019. 63-77.

[2] Abdel-Malek, Karim, and Jasbir Singh Arora. *Human Motion Simulation: Predictive Dynamics*. Academic Press, 2013.

In this paper we use a new methodology that employs seed scenarios before executing predictive dynamics, thus allowing the system to provide variations in task execution. A tall person will execute a task differently than a short person, if height is an influencing factor.

The results of predictive dynamics are autonomous prediction of the motion while subject to the laws of motion (we use Lagrange's equations of motion). These results are not pre-recorded but rather a prediction of what a human can do. Depending on the task at hand, the soldier in the DHM environment will accomplish the task unaided by human analysis but subject to physics, biomechanics, physiology, and the constraints of the environment.

This paper will present the methodology for predictive behavior to affect various strategies. Results of this work will be presented.

Keywords: soldier, human performance, predicting behavior, physics-based

Introduction

The problem of the dynamic prediction of human motion is the subject of significant research this time because it is difficult to replicate human behavior in a digital format. This work aims to provide one methodology for such prediction using years of research into the modeling and simulation of human motion with the addition of a system for a computer to also select a strategy for an initial seed motion.

Dynamic motion prediction is a challenging problem because the equations of motion (EOM) are nonlinear and cannot be solved in a closed form. Robust nonlinear programming algorithms (NLP) have been developed and applied to solve the motion prediction problem. Inverse dynamics is usually adopted in the optimization formulation so that integration of the equations of motion is avoided. Sensitivity of the nonlinear dynamics equations with respect to the state variables is needed in the optimization process to solve the problem efficiently and accurately. Sohl and Bobrow (2001) developed a sensitivity algorithm of recursive Newton-Euler equations for branched or tree-topology systems. http://www.engineeringvillage2.org/controller/servlet/Controller?CID=quickSearchCitationFormat&searchWord1={Redhe,+M.}&section1=AU&database=1&startYear=1884&endYear=2005&yearselect=yearrangeKim *et al.* (1999) presented a class of Newton-type algorithms to analytically compute both the first and second derivatives of the dynamics equations with respect to arbitrary joint variables. Xiang *et al*. (2009a) carried out sensitivity analyses for dynamic motion prediction of a mechanical system by using the recursive Lagrangian formulation.

Recently, dynamic motion planning of digital humans has been solved using optimization, which requires sensitivity analysis of dynamics equations. Forward dynamics can be used to solve equations of motion in modeling human motion (Roussel et al., 1998; Chevallereau et al., 1998; Anderson & Pandy, 2001a). Anderson and Pandy (2001b) presented a model with 23 degrees of freedom (DOF) and 54 muscles for normal symmetric walking on level ground. The objective function was metabolic energy per unit distance, and the design variables were the muscle actuations. Equations of motion of the bio-system were integrated at each iteration in the optimization process. The parallel computation techniques were used to evaluate gradients by finite differences. The initial walking postures obtained from experiments were imposed as constraints in the formulation so that accurate kinetics data were recovered from the simulation. However, this approach suffers from high computation cost and availability of the motion capture data.

To circumvent these difficulties, alternative formulations may be used for the optimization problem, in which both forces and joint state variables are treated as unknowns. Equations of motion are either evaluated using inverse dynamics or simply imposed as equality constraints (Kim *et al*. 2008, Wang *et al*. 2007). Lo *et al*. (2002) presented a framework for human motion prediction incorporating inverse recursive Newton-Euler equations with analytical gradients. Saidouni and Bessonet (2003) used optimization to solve for cyclic, symmetric gait motion of a 9-DOF model that moves in the sagittal plane; the control points for the B-spline curves along with the time durations for the gait stages were optimized to minimize the actuating torque energy. Xiang *et al*. (2009b) presented the dynamic human walking prediction by using a 55-DOF skeleton digital human model. The joint angle profiles were treated as design variables, and the dynamic effort was minimized to generate the optimal symmetric walking motion. The simulation results matched well with the joint profiles, joint torques, and ground reaction forces obtained from experiments.

Optimization-based motion prediction has been widely used in biomechanics to synthesize control strategies, analyze muscle forces, predict optimal motion, and so on. However, the performance measure and necessary constraints are critical issues for predictive dynamics to simulate human motion. Marler et al. (2008) overviewed the computational approaches in digital human modeling. Schiehlen (1997) gave a review of multibody system dynamics in which optimal design of a mechanical system was discussed, especially the multicriteria optimization approach. Leboeuf et al. (2006) compared two performance criteria: the minimum effort cost and the minimum energy cost for predicting human handstand motion. It was concluded that the former tended to generate more natural motion and the latter gave a smoother motion. Vukobratović *et al*. (2007) derived a general model to simulate human and humanoid motions. The human was treated as a free spatial system, and particular tasks were considered as different contact problems between the human model and various objects. Bottasso et al. (2006) proposed a computational procedure for inferring the cost functions that underlie the experimentally observed human strategies. Although many performance measures have been studied for human motion prediction, there is limited work on constructing constraints for a bio-system for the optimization formulation.

The Method

The figure below shows the basic methodology behind predicting human behavior using predictive dynamics but incorporating seed scenarios. Seed scenarios allow for the consideration of variation in task execution among people.

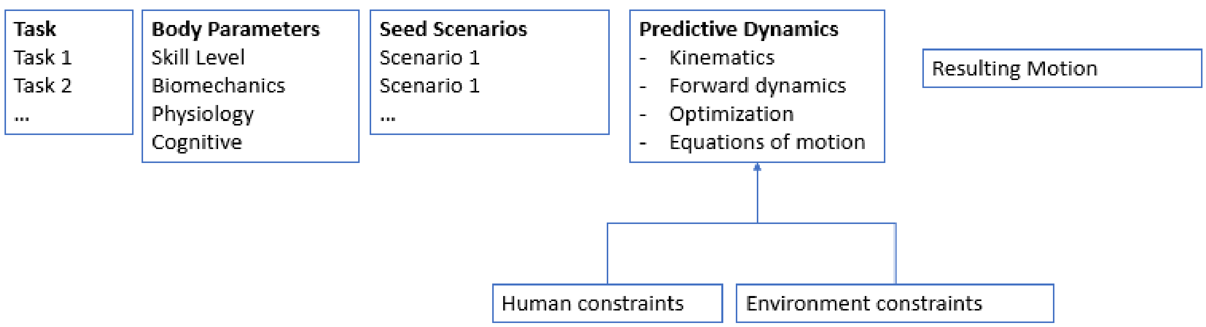

Figure 1. Methodology for predicting human behavior using predictive dynamics and incorporating seed scenarios

Below we define each element in this methodology.

A Task

A task in this context is defined as an action that is needed to be accomplished. Several tasks can be queued to accomplish an entire motion scenario. A task, for example, could be defined as jump from a high platform to the ground. Another task could be to push a lever with a specific force.

Body Parameters

There are several characteristics that define this set of parameters, including but not limited to skill level (level of training) and the biomechanics of the person (body height, weight, distribution, dimensions, anthropometry, etc.). The physiology of the human is also included in terms of strength, fatigue levels, metabolics, etc.

Seed Scenarios

We have adopted this methodology to include the acquisition of a number of scenarios that are executed by humans as a seed scenario for the predictive dynamics. This is where the variation between one person and another comes into play. A tall person will execute a task differently than a short person.

Acquiring motions requires the actual physical execution of a task by someone. The figure below shows the actual execution of a task (deadlift) while motion tracked.

Figure 2. Execution of a deadlift task while motion tracked

The number of seed scenarios to record is determined by observing the execution of the task. It is not scientific. In some cases, females execute the task differently than males. Tall people execute differently than short people, if the task required is affected by height.

For the tasks that we observed, on average, we had to record two to four seed scenarios.

Predictive Dynamics

The predictive dynamics approach was successfully applied to simulate digital human walking (Xiang et al. 2009b) and stair climbing (Bhatt et. al. 2008) tasks and was then further developed. The problem statement for the prediction of motion for dynamics tasks can be stated as “Given task-based parameters, human anthropometry, segment inertial properties, physical joint motion and actuation limits, and desired time for completion of task, generate visually appealing and dynamically consistent task simulations that minimize human performance.” Such a description of the problem statement lends itself to an optimization formulation.

Joint angle profiles, $\mathbf{q}(\mathbf{t})$, are approximated as linear combinations of cubic B-spline basis functions. Thus, the control points representing the B-splines are the design variables for the optimization problem. Corresponding joint angle, joint velocity, and joint acceleration values are calculated at each iteration from these control point values.

The dynamic effort, which is defined as the time integral of squares of joint torques, is chosen as the objective function to be minimized for the general human motion prediction as in Equation (1).

$$J = \int_0^T \boldsymbol{\tau}^{\mathrm{T}} \boldsymbol{\tau} dt \quad (1)$$

The general constraints are categorized into physical constraints and task-based constraints. Physical constraints include the joint angle limits, joint torque limits, and equations of motion to impose law of physics as depicted in the following equations:

$$\mathbf{q}^L \le \mathbf{q}(t) \le \mathbf{q}^U \quad (2)$$

$$\boldsymbol{\tau}^L \le \boldsymbol{\tau}(t) \le \boldsymbol{\tau}^U \quad (3)$$

$$\boldsymbol{\tau} - f(\mathbf{q}, \mathbf{t}) = \mathbf{0} \quad (4)$$

The common task-based constraints being used to generate predictions for all tasks include ground penetration, dynamic stability, and self/collision avoidance. These constraints have been discussed in detail for dynamic walking prediction (Xiang et al. 2009b). The EOMs are calculated using recursive Lagrangian dynamics, and the analytical gradients are provided to the optimization solver. The dynamic stability of the digital human model is calculated from these equations of motion. The predicted motions are verified using determinants obtained from motion capture experiments. Well-accepted determinants based on literature are used if available. If the determinants are not available, new determinants are selected such that they characterize the motion being predicted. The formulation also showed high fidelity in predicting joint torques and ground reaction forces.

This paper presents the recent advances of predictive dynamics to simulate human motion including box lifting, running, throwing, and sideways walking. In addition, the new approach of segment-based collision avoidance and its applications in predictive dynamics is also addressed. It is noted that many dynamic tasks share same objective functions and constraints in the optimization formulation. Therefore, only those task-based constraints that feature the characteristics of each task are emphasized in the following section.

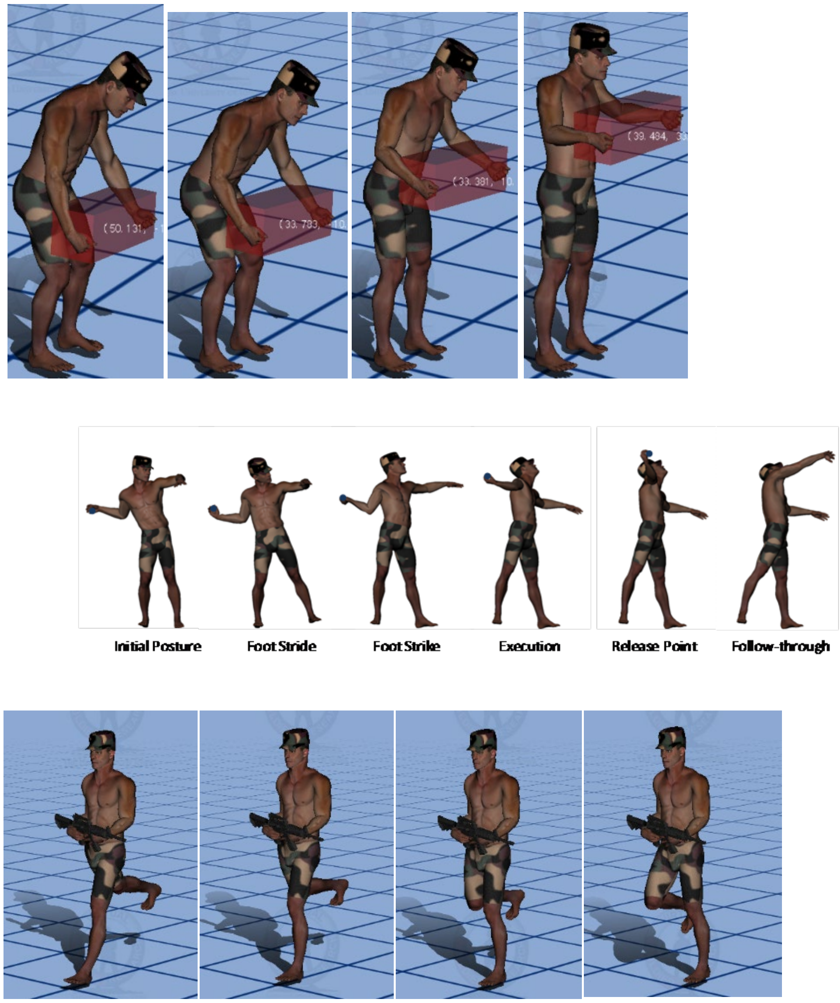

Figure 3. Santos executing the tasks of box-lifting, throwing, and walking while carrying

Constraints

The feasible set of solutions for the problem is an important issue for predictive dynamics. An infeasible set will result in a null solution space for the system. This situation should always be avoided while formulating a predictive dynamics problem. For a bio-system, feasibility of all the constraints can be tested by solving the predictive dynamics problem with a constant objective function as follows:

$$\begin{aligned}
\min_{\mathbf{q},\,\boldsymbol{\tau}} \quad & J(\mathbf{q}, \boldsymbol{\tau}, \mathbf{t}) \equiv c \\
s.t.: \quad & \boldsymbol{\tau}\text{-}\boldsymbol{f}(\mathbf{q}, \mathbf{t}) = \mathbf{0} \\
& \mathbf{g}(\Upsilon) \leq \mathbf{0} \\
& \mathbf{q}^{L} \leq \mathbf{q} \leq \mathbf{q}^{U} \\
& \boldsymbol{\tau}^{L} \leq \boldsymbol{\tau} \leq \boldsymbol{\tau}^{U} \qquad (6)
\end{aligned}$$

where c is a constant.

The solution of Equation (6) implies that the output set $(\mathbf{q}^{f}, \boldsymbol{\tau}^{f})$ satisfies all linear and nonlinear constraints but does not optimize any performance measure for the biosystem. This is a feasible solution of the predictive dynamics problem. There are two purposes for obtaining a feasible solution for the system: one is to test the feasibility of all the constraints, and the other is to get a solution that might be used as a good initial guess for the predictive dynamics with a physical performance measure.

Minimal set of constraints

It is obvious that the more information about the biosystem that is available, the more accurate the predictive dynamics solution is. As an extreme case, all the displacement and force histories can be available in the time domain $\Omega \cup \Gamma$. However, in most cases, only minimal information about the biosystem is available, so predictive dynamics seeks the minimal constraint set $\mathbf{g}(\Upsilon_{minimal})$ and an appropriate performance measure to simulate the applied force and response histories for the biosystem, as follows:

$$\begin{aligned}
\min_{\mathbf{q},\,\boldsymbol{\tau}} \quad & J(\mathbf{q}, \boldsymbol{\tau}, \mathbf{t}) \\
s.t.: \quad & \boldsymbol{\tau}\text{-}\boldsymbol{f}(\mathbf{q}, \mathbf{t}) = \mathbf{0} \\
& \mathbf{g}(\Upsilon_{minimal}) \leq \mathbf{0} \\
& \mathbf{q}^{L} \leq \mathbf{q} \leq \mathbf{q}^{U} \\
& \boldsymbol{\tau}^{L} \leq \boldsymbol{\tau} \leq \boldsymbol{\tau}^{U} \qquad (7)
\end{aligned}$$

The minimal constraint set depends on the complexity of the biosystem and the motion to be simulated. For a simple motion, boundary conditions alone might be enough to reveal the entire motion; in this case, the minimal constraint set includes only boundary conditions. In contrast, for a complex motion, some state responses between the boundaries need to be known to simulate the real motion. Therefore, these state responses have to be included in the minimal constraint set.

Resulting Motion

We have experimented with this methodology using a number of prescribed tasks. Examples include climbing over a box, lifting a box, and several others.

The presentation at DHM will share some of these results as videos.

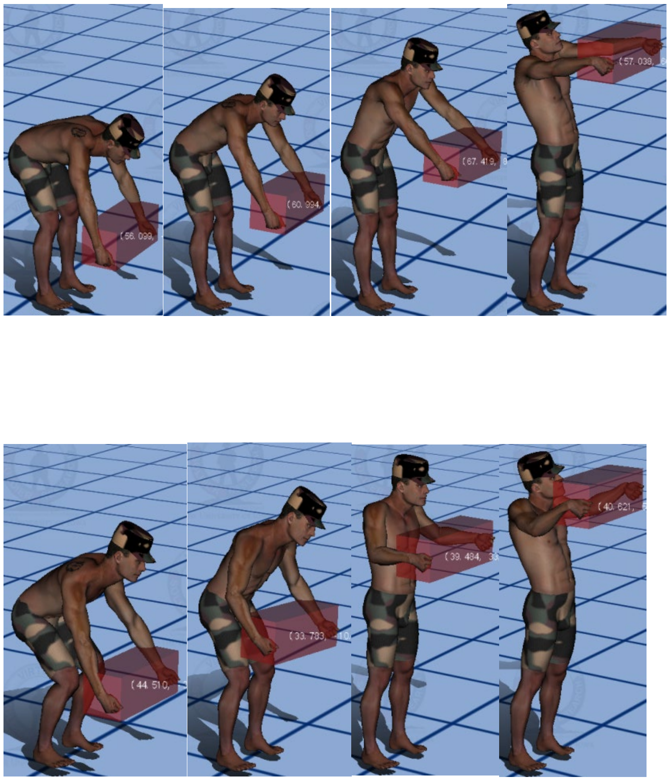

Figure 4: Two instances of Santos executing a box-lifting task

While this methodology shown merit for the prediction of behavior and for accounting for the variation in task execution among people, this is only a start, and significantly more work is needed.

References

Anderson, F.C., and Pandy, M.G. Static and dynamic optimization solutions for gait are practically equivalent. *Journal of Biomechanics*, v 34, 2001 a, p 153-161.

Anderson, F.C., and Pandy, M.G. Dynamic optimization of human walking. *Journal of Biomechanical Engineering*, v 123(5), 2001 b, p. 381-390.

Bhatt, R., Xiang, Y., Kim, J., Mathai, A., Penmatsa, R., Chung, H-J., Kwon, H-J., Patrick, A., Rahmatalla, S., Marler, T., Beck, S., Yang, J., Arora, J. S., Abdel-Malek, K., & Obusek, J.P. (2008, June). Dynamic optimization of human stair-climbing motion. Paper presented at the SAE Digital Human Modeling Conference, Pittsburgh, PA.

Bottasso, C. L., Prilutsky, B.I., Croce, A., Imberti, E., and Sartirana, S. A numerical procedure for inferring from experimental data the optimization cost functions using a multibody model of the neuro-musculoskeletal system. *Multibody System Dynamics*, v 16, 2006, p. 123-154.

Chevallereau, C., Formal'sky, A., and Perrin, B. Low energy cost reference trajectories for a biped robot, *Proceedings of IEEE International Conference on Robotics and Automation*, Leuven, Belgium, v 2, 1998, p. 1398-1404.

Kim, H.J., Wang, Q., Rahmatalla, S., Swan, C.C., Arora, J.S., Abdel-Malek, K., and Assouline, J.G., Dynamic motion planning of 3D human locomotion using gradient-based optimization. *International Journal of Biomechanical Engineering*, 2008; 130(3):031002.

Kim, J.G., Baek, J.H., and Park, F.C. Newton-type algorithms for robot motion optimization. *Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems,* v 3, 1999, p. 1842-1847.

Leboeuf, F., Bessonnet, G., Seguin, P., and Lacouture, P. Energetic versus sthenic optimality criteria for gymnastic movement synthesis. *Multibody System Dynamics*, v 16, 2006, p. 213-236.

Lo, J., Huang, G., and Metaxas, D. Human motion planning based on recursive dynamics and optimal control techniques. *Multibody Sys. Dyn*, v 8(4), 2002, p. 433-458.

Marler, T., Arora, J., Beck, S., Lu, J., Mathai, A., Patrick, A., and Swan, C. Computational approaches in DHM, in *Handbook of Digital Human Modeling for Human Factors and Ergonomics*, Vincent G. Duffy, Ed., 2008.

Roussel, L., Canudas-de-Wit, C., and Goswami, A. Generation of energy optimal complete gait cycles for biped robots, *Proceedings of IEEE International Conference on Robotics and Automation*, Leuven, Belgium, v 3, 1998, p. 2036-2041.

Schiehlen, W. Multibody system dynamics: roots and perspectives. *Multibody System Dynamics*, v 1, 1997, p. 149-188.

Saidouni, T., and Bessonnet, G. Generating globally optimized sagittal gait cycles of a biped robot. *Robotica*, v 21(2), 2003, p 199-210.

Sohl, G.A., and Bobrow, J.E. A recursive multibody dynamics and sensitivity algorithm for branched kinematic chains. *ASME J. Dyn. Syst., Meas., Control*, v123, 2001, p. 391-399.

Vukobratović, M., Potkonjak, V., Babković, K., and Borovac, B. Simulation model of general human and humanoid motion, *Multibody System Dynamics*, v 17, 2007, p. 71-96.

Wang, Q., Xiang, Y., Arora, J.S., and Abdel-Malek, K. Alternative formulations for optimization-based human gait planning, *48th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference*, Honolulu, Hawaii, Apr. 23 – 26, 2007.

Xiang, Y., Arora, J.S., and Abdel-Malek, K. Optimization-based motion prediction of mechanical systems: sensitivity analysis. *Structural and multidisciplinary optimization*, v 37(6), 2009a, p. 595-608.

Xiang, Y., Arora, J.S., Rahmatalla, S., and Abdel-Malek, K. Optimization-based dynamic human walking prediction: one step formulation. *International Journal for Numerical Methods in Engineering*, 2009b (in press, DOI: 10.1002/nme.2575).