A Robust Algorithm for a System Identification Approach to Digital Human Modeling: An Application to Multi-fingered Hand Movement

Kang Li, Sang-Wook Lee, and Xudong Zhang

University of Illinois at Urbana-Champaign, Urbana, IL 61801, USA
{kangli2,slee52,xudong}@uiuc.edu

Abstract. A recent study [2] proposed a forward bio-dynamic model of multi-fingered hand movement. The model employed a physics-based heuristic algorithm for system identification of the model parameters, and succeeded in replicating measured multi-fingered flexion-extension movement. However, while the model itself is general and readily applicable to other bodily movements, the heuristic algorithm required empirical adjustments to initial setups, and was therefore difficult to generalize. This paper introduces a rigorous and more robust parameter estimation algorithm to enhance the intended general modeling approach for digital human movement simulation. The algorithm is demonstrated by solving the same modeling problem posed in [2].

Keywords: hand movement, system identification, forward dynamics.

1 Introduction

Despite the successful applications of digital human modeling (DHM) and simulation in ergonomics analysis and workplace design, very little work has been done to enable designers to simulate hand and finger postures or movements. Existing collision-detection based posture prediction approaches, used in commercial software packages, are not capable of generating realistic hand representations. There is a need for computational models that reproduce naturalistic hand movements or postures. A recent study [2] proposed a forward bio-dynamic model of multi-fingered hand movement. The model employed a physics-based heuristic algorithm for system identification of the model parameters, and succeeded in replicating measured multi-fingered flexion-extension movement. However, while the model itself is general and readily applicable to other bodily movements, the heuristic algorithm required empirical adjustments to initial setups, and was therefore difficult to generalize. We hereby introduce a rigorous and more robust parameter estimation algorithm to enhance the intended general modeling approach for digital human movement simulation. We demonstrate the algorithm by solving the same modeling problem posed by Lee and Zhang [2].

V.G. Duffy (Ed.): Digital Human Modeling, HCII 2007, LNCS 4561, pp. 157–160, 2007.

2 Methods

The dynamics of a 3-segment, 3-DOF finger system can be represented by the following equations of motion:

$$M(\theta)\ddot{\theta} = V(\theta,\dot{\theta}) + G(\theta) + \tau \tag{1}$$

where θ is the three-joint-angle vector, $\tau \in \Re^{3\times1}$ is the torque vector at the joints, $M(\theta) \in \Re^{3\times3}$ is a positive definite mass matrix, $V(\theta,\dot{\theta}) \in \Re^{3\times1}$ is the centrifugal (square of joint velocity) and Coriolis force, and $G(\theta) \in \Re^{3\times1}$ is the gravitational component. The model did not consider the effect of the gravitational force $G(\theta)$.

It was assumed that all the joints (DIP, PIP and MCP) of digits 2-5 were controlled by torque actuators which could be modeled as proportional-derivative (PD) feedback controllers situated at the beginning of the joint movements, i.e. the torque at joint i, τ_i, could be computed by

$$\tau_i = -K_i^p(\theta - \theta_i^f) - K_i^d(\theta_i - \theta_i^f)) \quad \text{subject to } \tau_i \le M_i^{\max} \tag{2}$$

$$K_i^p \ge 0 \tag{3}$$

$$K_i^d \ge 0 \tag{4}$$

where K_i^p is the proportional gain of the joint actuator i affecting the movement speed; K_i^d is the velocity gain of the joint actuator i; $\theta_i^f, \dot{\theta}_i^f$ are the final joint angle and final angular velocity; $M_i^{\max}$ represents the relative magnitudes of the torque generated at joint i, which serves as an auxiliary parameter to control the initiation or the temporal coordination of finger segments.

An optimization problem minimizing the discrepancy between the model-predicted and measured angle profiles can be formulated to estimate the parameters (K_i^p, K_i^d, and $M_i^{\max}$) as follows:

$$min\int_0^{t_{max}} (\theta(t) - \tilde{\theta}(t))^2 dt \tag{5}$$

$$\text{s.t. } M(\theta(t))\ddot{\theta}(t) = V(\theta(t),\dot{\theta}(t)) + \tau(t) \tag{6}$$

$$\tau_i(t) = \min(M_i^{max}(\theta_i), -K_i^p(\theta_i(t) - \theta_i^f(t)) - K_i^d(\theta_i(t) - \theta_i^f(t))) \tag{7}$$

$$K_i^p \ge 0 \tag{8}$$

$$K_i^d \ge 0 \tag{9}$$

where t is time, $\theta(t)=\left[\theta_1(t)\quad \theta_2(t)\quad \theta_3(t)\right]^T$ is the angle vector at time t; $\tilde{\theta}(t)=\left[\tilde{\theta}_1(t)\quad \tilde{\theta}_2(t)\quad \tilde{\theta}_3(t)\right]^T$ is the observed values at time t; $\ddot{\theta}(t)=\left[\ddot{\theta}_1(t)\quad \ddot{\theta}_2(t)\quad \ddot{\theta}_3(t)\right]^T$ is the angle acceleration vector at time t; $\dot{\theta}(t)=\left[\dot{\theta}_1(t)\quad \dot{\theta}_2(t)\quad \dot{\theta}_3(t)\right]^T$ is the angle velocity vector at time t; $\tau(t)=\left[\tau_1(t)\quad \tau_2(t)\quad \tau_3(t)\right]^T$ is the torque vector at time t.

This problem is essentially a simulation-based optimization problem [4]. It aims to find reasonable values for $K_i^{\,p}$, $K_i^{\,d}$ and $M_i^{\max}$ so that the system, (5) and (6), can replicate the given angular trajectories $\tilde{\theta}(t)$. However, because of non-linearity and non-smoothness of the constraints and high dimensionality of the system model, the gradient and Hessian of the system are difficult if not impossible to obtain or even to approximate, which may exclude the feasibility of using derivative-based methods in our study. Thus the most favorite method to solve this problem may be the direct search (DS) method [3]. This method is able to find optimal solution without computing derivative but evaluating function values. The method of implementing the DS follows a standard approach using the generalized pattern search (GPS) [3] algorithm for bound constrained problems. The same initial guess of the parameter in [2] was employed as the initial value of the GPS algorithm. The maximum iteration was selected to be 150. The parameter, *Complete poll*, was set to *on*, i.e. the algorithm polled all the mesh points at each iteration. The parameters, *tolerance on mesh size (TolMesh)*, *tolerance on function (TolFun)*, *tolerance on variable (TolX)*, and *tolerance on constraints (TolCon)*, were all set to be 1e-8.

The same experimental database employed by Lee and Zhang [1], [2] was used to test this parameter estimation approach. Twenty-eight subjects performed simulated grasping tasks. Reflective markers were placed on the dorsum of the subjects' right hands and the three-dimensional (3D) marker coordinates were recorded by a five-camera Vicon 250 system (Oxford Metrics, UK) at a sampling frequency of 120 Hz to calculate joint angles.

3 Results

The simulated grasping movement, based on the estimated parameters yielded from the GPS algorithm, successfully replicated the measured angular profiles. The

Table 1. Mean and standard deviation of RMSE values (unit: °)

Joint	Digit			
	2	3	4	5
DIP	3.39 (2.10)	4.26 (3.25)	3.92 (3.19)	3.26 (2.39)
PIP	2.63 (1.73)	2.48 (1.86)	2.91 (2.37)	2.80 (1.96)
MCP	2.19 (0.92)	2.80 (1.70)	2.59 (1.84)	2.76 (1.65)

root-mean-square error (RMSE) values for the pair-wise difference between the simulated and measured angular profiles ranged from 2.19 to 4.25° (Table 1). The grand mean of the RMSE values across 28 subjects was 3.00°. In comparison with the results from the heuristic search [2], there was marked improvement in terms of RMSE: the GPS algorithm resulted in smaller RMSE than the heuristic algorithm in 9 out of the 12 joints and smaller grand mean of the RMSE values.

4 Discussion

This was a preliminary study aimed to apply the GPS algorithm to finger movement modeling. The results indicated that the model was able to fit the experimental data closely. However, while the GPS algorithm outperformed the heuristic algorithm in estimating the model parameters, the improvement came at a cost: it took the new algorithm longer to converge on a solution.

The major advantage of the GPS algorithm is that it is not movement-dependent and could be further generalized to the highly nonlinear and non-smooth constrained problems and other difficult optimization problems; the parameter estimation approach could therefore become a very versatile tool in digital human modeling. Studies are underway to explore adapting the proposed algorithm along with the modeling framework itself for other human movements of a higher level of complexity.

Acknowledgments. This work is supported by Centers for Disease Control and Prevention and National Institute of Occupational Safety and Health.

References

1. Lee, S.-W., Zhang, X.: Development and validation of an optimization-based model for power-grip posture prediction. J BIOMECH 38, 1591–1597 (2005)
2. Lee, S.-W., Zhang, X.: Biodynamic modeling and system identification of multi-finger movements. Submitted to J BIOMECH (2006)
3. Torczon, V.: On the convergence of pattern search algorithms. SIAM J OPTIMIZ 7, 1–25 (1997)
4. Kolda, T.G., Lewis, R.M., Torczon, V.: Optimization by direct search: New perspectives on some classical and modern methods. SIAM REV 45, 385–482 (2003)