Automated Customization of Human Multibody Models for Optical Motion Capture and Analysis

Santiago Beron, Urbano Lugrís, Florian Michaud, Javier Cuadrado

Laboratory of Mechanical Engineering
CITENI, Campus Industrial de Ferrol
University of La Coruña, 15403 Ferrol, Spain
[santiago.beron, urbano.lugris, florian.michaud, javier.cuadrado]@udc.es

EXTENDED ABSTRACT

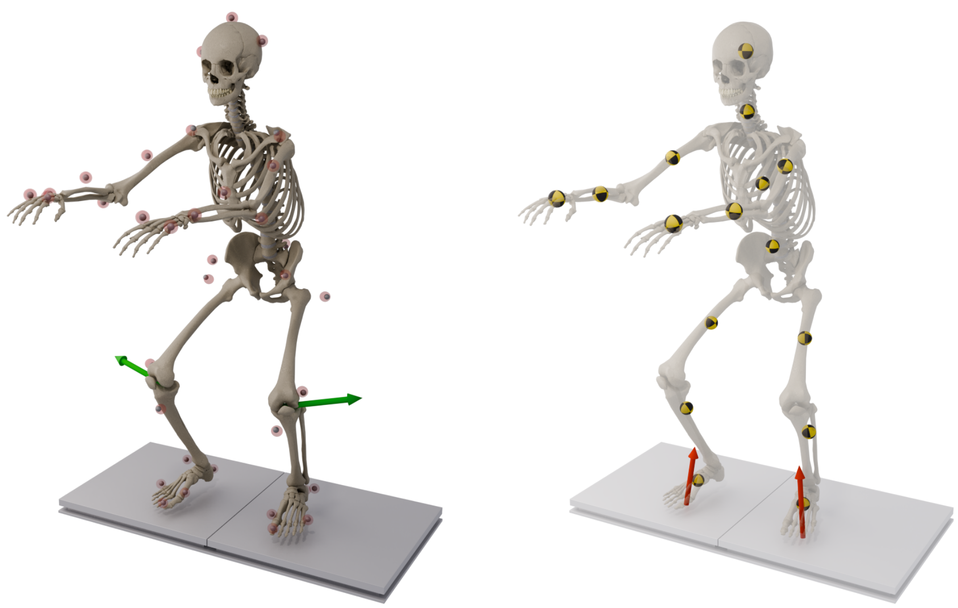
1 Introduction

When using motion capture to analyze human motion, the results are largely dependent on the quality of the underlying rigid–body model. Both its geometry and inertia parameters need to be properly estimated in order to obtain accurate results [1]. Although methods exist to experimentally measure these parameters, they are mostly based on medical imaging, so they are complex and require equipment that is not commonly available. For this reason, the most common approach is to resort to scaling and/or optimization techniques, both for estimating the geometry [2, 3] and the inertia parameters [4, 5].

In clinical settings, it is important that the model calibration prior to motion capture is as simple and short as possible, so that it is easy and straightforward to perform by clinical staff, and also does not subject the patient to a long and tedious measurement and calibration process. Since the existing estimation methods do not fulfill these requirements, this work aims to provide a fast and fully automated procedure to obtain an optimal model, by using only a few seconds of motion capture data, and without the need to perform any further measurements on the patient.

2 Parameter estimation method

The model geometry is estimated by solving a large–scale global optimization problem, using data from a single motion capture take. The optimization algorithm is based on the scaling procedure used in [6], with two main differences: firstly, it optimizes all the time steps simultaneously and, secondly, the vector of geometric parameters, along with the previously existing scaling factors, now also includes joint centers and rotation axes, as depicted in the left side of Figure 1.



(a) Geometry: knee rotation axes

(b) Inertia parameters: centers of gravity

Figure 1: Model performing a squat exercise, displaying some of the optimized parameters.

The first step in the process consists of having the patient perform some predefined movements, which are captured using the real–time reconstruction method also described in [6]. This provides a properly labeled set of marker trajectories, as well as an initial guess for the design variables $\mathbf{x}$ of the optimization. Said design variables include the independent coordinates of the model $\mathbf{z}_k$ at the n time steps comprising the motion capture take, along with a common set of geometric parameters $\mathbf{p}$, so the optimization problem is stated as follows:

$$\min_{\mathbf{x}} g(\mathbf{x}) = \sum_{k=1}^{n} [\mathbf{h}(\mathbf{z}_k, \mathbf{p}) - \mathbf{r}_k]^T \mathbf{W} [\mathbf{h}(\mathbf{z}_k, \mathbf{p}) - \mathbf{r}_k] \tag{1}$$

The function $\mathbf{h}(\mathbf{z}_k, \mathbf{p})$ returns the 3D coordinates of all the virtual markers, whose absolute positions at every time step k are determined by the current model configuration $\mathbf{z}_k$, along with the geometrical parameters $\mathbf{p}$. The vector $\mathbf{r}_k$ contains the positions of the corresponding physical markers measured by the cameras, and $\mathbf{W}$ is a diagonal weighting matrix. The size of the optimization problem can grow very quickly, since motion capture cameras normally provide output rates of 100 frames per second or above, and the model has 48 degrees of freedom. However, large–scale solvers such as Ceres [7] exploit the block structure of this kind of problems, achieving convergence in a few seconds in optimizations with hundreds of thousands of design variables.

After the geometrical parameters of the model $\mathbf{p}$ have been established, the same motion capture take is used to estimate the inertia parameters $\boldsymbol{\phi}$, using the standard identification method commonly employed in robotics. This requires the use of force plates to measure the net ground reactions $\mathbf{F}_k$ at every time step, in addition to the trajectories of the optical markers. The optimization procedure consists of rewriting the six equations of motion of the base body in such a way that they are linear with respect to the inertia parameters of the model $\boldsymbol{\phi}$:

$$\mathbf{M}_0(\mathbf{z}_k, \boldsymbol{\phi})\ddot{\mathbf{z}}_k + \mathbf{H}_0(\mathbf{z}_k, \dot{\mathbf{z}}_k, \boldsymbol{\phi}) = \mathbf{B}_0(\mathbf{z}_k)\mathbf{F}_k \implies \mathbf{Y}_0(\mathbf{z}_k, \dot{\mathbf{z}}_k, \ddot{\mathbf{z}}_k)\boldsymbol{\phi} = \mathbf{B}_0(\mathbf{z}_k)\mathbf{F}_k \qquad k = 1, \ldots, n \tag{2}$$

Here, $\mathbf{M}_0$ represents the six rows of the mass matrix corresponding to the base body (i.e. the pelvis), $\mathbf{H}_0$ is the associated vector of gravitational, centrifugal and Coriolis forces, and $\mathbf{B}_0$ is a matrix that maps the net ground reactions $\mathbf{F}_k$ into the six degrees of freedom of the pelvis. This equation can be stated at every time step k, and the least–squares solution to the resulting overconstrained linear system provides an optimal estimation of the inertia parameters. However, it is important to ensure that the recorded motion, also known as *excitation trajectory*, produces a sufficiently well–conditioned matrix [5], which is difficult to achieve if the optimization intends to estimate all the parameters. Therefore, a study is carried out to determine an optimal excitation trajectory, which allows obtaining the maximum number of parameters without requiring excessively long and complex movements.

3 Conclusion

The proposed procedure is well suited for its use in clinical environments. Once the optical markers are attached to the subject, the entire process of recording the calibration take and performing the sequence of optimizations takes less than a minute, thus providing a very simple and streamlined method for obtaining a fully customized model of the subject.

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