

Efficient, Automated Parameter Optimization Method for Marker-Based Human Motion Capture

Urbano Lugrís*, Santiago Beron*, Florian Michaud*, Javier Cuadrado*

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

Abstract

Optical motion capture is one of the most widely used tools for analyzing human motion. This technique is based on reconstructing the motion of an underlying rigid body model of the subject which, due to the many uncertainties involved in the process, is very difficult to characterize accurately. This is a relevant problem, since the results of the analysis are particularly sensitive to the geometry of the model [1], so it is of great importance to identify its parameters as best as possible.

After several prior efforts that either treated bodies separately [2], required body segments to be previously scaled [3], or focused on individual joints [4], Reinbolt et al. [5] developed a method that allowed simultaneous estimation of optimal motion, scaling factors and joint parameters. However, it required very long CPU times, since it needed to solve two nested optimization problems. Subsequently, the authors improved it by proposing instead a single optimization, in which the motion was parameterized by B-splines [1]. Andersen et al. [6] used a constrained optimization approach, including the local coordinates of the markers as design variables, to obtain a fitting method that did not require the use of B-splines to reduce the dimension of the problem. More recently, Ziegler et al. [7] showed that very fast computation times could be obtained for periodic motion by parameterizing it using Fourier series instead of B-splines.

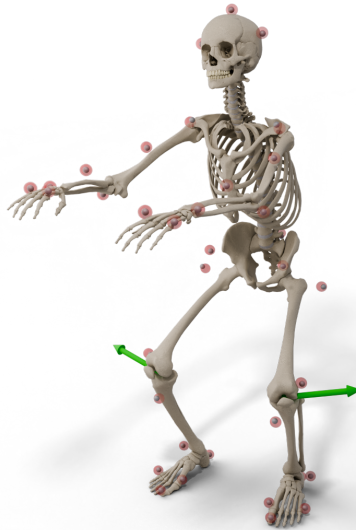


Figure 1: Squat exercise displaying estimated knee rotation axes.

This work presents a highly efficient large-scale global optimization method designed to estimate all the geometric parameters of the model by capturing some predefined movements, and then carrying out a single optimization, which is able to converge in a matter of seconds. The algorithm is based on the scaling procedure used in [8], with two main differences: firstly, it optimizes all 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.

The first step of the process is to capture the motion of the subject, using the human model and real-time EKF described in [8]. This generates a properly labeled set of marker trajectories and, moreover, provides a good initial guess for the optimization problem. Then, the model is refined by fitting a set of n_p geometric parameters \mathbf{p} . At every time step f , the model state is defined by a vector of n_z independent

coordinates z_f , consisting of the joint angles, along with the absolute translation and rotation of the pelvis. The vector of design variables \mathbf{q} of the optimization problem contains the n_z coordinates of the model at every frame, along with the geometric parameters \mathbf{p} , which are common to all the time steps:

$$\mathbf{q} = [z_1^T \quad z_2^T \quad \cdots \quad z_{n_f}^T \quad \mathbf{p}^T]^T \quad (1)$$

According to this definition of the design variables, the fitting problem is stated as shown in Eq. (2):

$$\min_{\mathbf{q}} g(\mathbf{q}) = \sum_{f=1}^{n_f} [\mathbf{h}(z_f, \mathbf{p}) - \mathbf{r}_f]^T \mathbf{W} [\mathbf{h}(z_f, \mathbf{p}) - \mathbf{r}_f] \quad (2)$$

where $\mathbf{h}(z, \mathbf{p})$ is a function that returns, for a given set of coordinates z and model parameters \mathbf{p} , the 3D coordinates of all n_m virtual markers, \mathbf{r}_f is a vector containing the positions of the corresponding experimental markers at time step f , and \mathbf{W} is a diagonal weighting matrix.

The size of the optimization problem can grow very quickly, since \mathbf{q} is a vector of dimension $n_z \times n_f + n_p$, and motion capture cameras normally provide output rates of 100 frames per second or above. However, being an unconstrained nonlinear least squares problem (NLLS), it can be very efficiently solved by the Levenberg–Marquardt algorithm. This method has a fast convergence when the initial guess is reasonably good, as is the case, since the EKF results are available. The solver is further accelerated by taking advantage of the high sparsity of the Jacobian matrix, which, in turn, is computed analytically. Preliminary tests with the scaling method described in [8], but using all frames simultaneously as proposed here, show that such a large problem can be solved in a few seconds, speeding up the whole motion capture process considerably.

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