Inclusion of optical marker position data in optimal control simulations of a rigid body model of the human hand

Simon Heinrich[1], Birte Coppers[2,3], Anna-Maria Liphardt[2,3], Sigrid Leyendecker[1]

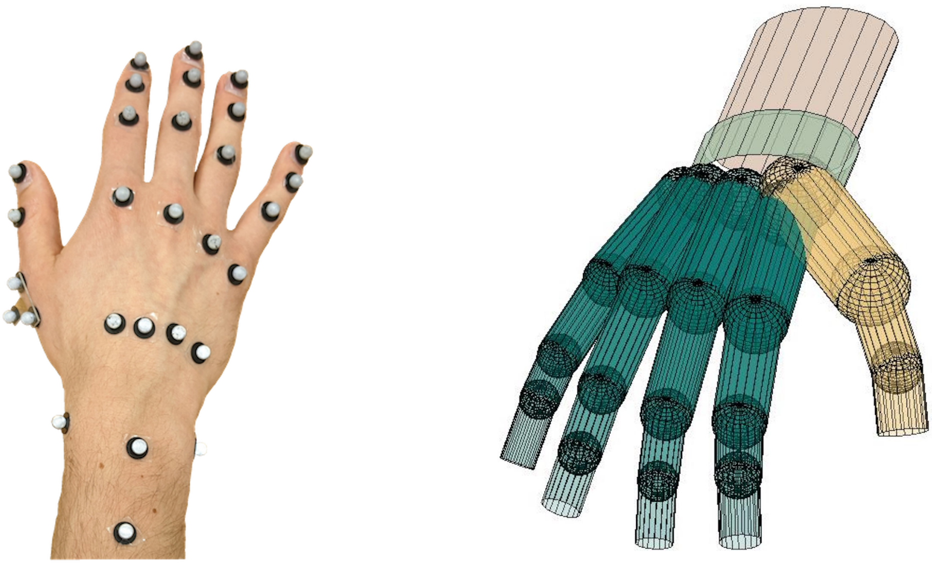
[1] Institute of Applied Dynamics
Friedrich-Alexander Universität Erlangen-Nürnberg (FAU)
Immerwahrstr. 1, 91058 Erlangen, Germany
[simon96.heinrich,sigrid.leyendecker]@fau.de

[2] Department of Internal Medicine 3 – Rheumatology & Immunology
University Hospital Erlangen & FAU
Ulmenweg 18, 91054 Erlangen, Germany
[anna-maria.liphardt,birte.coppers]@uk-erlangen.de

[3] Deutsches Zentrum für Immuntherapie
University Hospital Erlangen & FAU
Ulmenweg 18, 91054 Erlangen, Germany

EXTENDED ABSTRACT

Optimal control problem (OCP) simulations are an important tool in many areas, one of them is computational biomechanics, where a multibody model of rigid bones actuated with torque or muscle to predict realistic and potentially optimal movements can be used, see for example [1]. It can also be used to investigate immeasurable quantities during the movement of living humans, such as forces in joints and muscles. OCP simulations hereby utilize a physiologically motivated objective function together with constraints to obtain realistic results. However, the fundamental principles of human movement are not yet fully understood, because of the complexity of tissue involved (such as the nervous system or muscles), the number of different tasks and goals, inter-individual variation, and competing goals, for instance efficiency and performance [1]. Including measurements in these simulations has the potential to improve the efficiency of the numerical simulation and to trace the individuals' movements. The best way for data inclusion is highly dependent on the use case, type of data and the simulation. The state of the art position measurements in biomechanics use optical motion capturing with passive reflective markers [2] as in Fig. 1 a. Including the corresponding data in OCP simulations shall be investigated in more detail. We are continuing the investigations in [3] on arm movements and optical motion capture data. While the type of measurement is the same, the biomechanical model here is the human hand with its high number of degrees of freedom in a small volume and complex joints. We investigate the influence of including marker trajectories as part of the objective function compared to including the trajectories as constraints in Eq. (1) on computing performance and the obtained results.



(a) (b)

Figure 1: Hand with 6.5 mm spherical, reflective markers attached (a) and visualization of the hand model (b).

We model the hand, including the distal forearm, as a multibody model with simplified geometry for 21 rigid bodies with 33 degrees of freedom, with its visualization in Fig. 1 b. There are three different joint types used: one degree of freedom revolute joints, two degrees of freedom cardan joints and two degrees of freedom nino joints. The latter are a generalization of the cardan joint with axes that neither have to be intersecting nor orthogonal. It was proposed in [4] and validated to cover a reasonable range of motion in three dimensions [5]. The equations of motion, as well as the OCP for the system are formulated within the framework of discrete mechanics and optimal control for constraint systems (DMOCC) [6]. This framework provides a variational integrator with constant step size that preserves symplecticity and momentum maps, and has good energy behavior over exponentially long time ranges.

A big experimental study including a measurement campaign was conducted within the collaborative research center 1483 (EmpkinS). Optical motion capture measurements of hand movement were recorded in 70 healthy male and female study participants with an age range of 20 to 80 years. We used a camera setup with calibrated, synchronized, high speed, high resolution cameras (nine Oqus7+, Qualisys AB Sweden) on an aluminum frame. The marker protocol is based on [7] with markers of 6.5 mm diameter and a T-cluster with three connected markers on the thumb instead of three individual markers, shown in Fig. 1 a. Simple movement tasks and functional tests for hand function were executed and measured with a capture rate of 300 Hz. The raw measurement data are processed by assigning unique identifiers to the different markers, removing timeframes with occluded markers, and filtering markers with a low-pass filter to remove noise and exporting the data to be used for the simulations in Matlab (The MathWorks, Massachusetts).

Applying the direct transcription method DMOCC to the OCP results in a finite dimensional constrained optimization problem in the form of Eq. (1). Here, $(\mathbf{u}, \boldsymbol{\tau})$ represent the approximated trajectories of state and control. The objective function J can represent any measure of optimality. The DEL approximate the dynamics of the system, $\mathbf{s}$ are boundary constraints for initial and final state and $\mathbf{h}$ are path constraints. On the one hand, the measurement data can be included in the objective function J to minimize the summed up, squared distance between measured and simulated marker positions. On the other hand, the measurement data can be included as a constraint in $\mathbf{h}$, such that the distance between measured and simulated markers is within a certain bound.

$$\begin{aligned} \min_{\mathbf{u},\boldsymbol{\tau}} \quad & J(\mathbf{u}, \boldsymbol{\tau}) \\ \text{s.t.} \quad & \mathrm{DEL}(\mathbf{u}, \boldsymbol{\tau}) = \mathbf{0} \\ & \mathbf{s}(\mathbf{u}, \boldsymbol{\tau}) = \mathbf{0} \\ & \mathbf{h}(\mathbf{u}, \boldsymbol{\tau}) \leq \mathbf{0} \end{aligned} \tag{1}$$

The results on the performance of the simulation are compared with the results in [3], as their investigation is comparable, but limited due to the simpler system and only having measurements from a single subject. We want to investigate how to include marker data into optimal control simulations of biomechanical systems and provide an approach to verify this for other systems. Even though the insight given here is very likely transferable, the results still have to be verified on a broader scale. This is of course not limited to biomechanical systems nor optical motion capture data.

Further investigations will include the complete data set, other more complex motions, other data types and the effect of different objective functions in combination with a reduced number of markers and/or a reduced measurement frequency.

Acknowledgments

This work was supported by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Grant SFB 1483 – Project-ID 442419336
We would like to thank the German Research Foundation (DFG) for funding the major instruments at the Institute of Applied Dynamics, Friedrich-Alexander Universitaät Erlangen-Nürnberg used in this study - reference number INST90 / 985-1 FUGG.

References

[1] B. R. Umberger, R. H. Miller. Optimal Control Modeling of Human Movement. In: Handbook of Human Motion, Springer, Cham, 2017

[2] D. A. Winter. Biomechanics and Motor Control of Human Movement. Wiley, 2009

[3] R. Hoffmann, B. Taetz, M. Miezal, G. Bleser, S. Leyendecker. On optical data-guided optimal control simulations on human motion. Multibody Syst Dyn 48, 105-126, 2020

[4] A. Hollister, W. L. Buford, L. M. Myers, D. J. Giurintano, A. Novick. The Axes of Rotation of the Thumb Carpometacarpal Joint, J. Orthop. Res, 1992

[5] U. D. Phutane, M. Roller, S. Björkenstam, J. Linn, S. Leyendecker. Kinematic Validation of a Human Thumb Model. Proceedings of the ECCOMAS Multibody Dynamics Conference, 2017

[6] S. Leyendecker, S. Ober-Blöbaum, J. E. Marsden, M. Ortiz. Discrete Mechanics and Optimal Control for Constrained Systems. Optim Control Appl Methods 31, 505-528, 2010

[7] J. L. Sancho-Bru, N. J. Jarque-Bou, M. Vergara, A. Perez-Gonzalez, Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine, 228(2): 182.189, 2014