Towards Learning Human-Seat Interactions for Optimally Controlled Multibody Models To Generate Realistic Occupant Motion

Niklas Fahse, Monika Harant, Michael Roller, Fabian Kempter,
Marius Obentheuer, Joachim Linn, Jörg Fehr

I. INTRODUCTION

Runtime-efficient human models with active musculature are required to analyse the wide range of future crash scenarios and varying human behaviours inside the vehicle. Human body models (HBMs) as digital twins of humans are a key tool for developing safe and ergonomic new mobility solutions. In accident scenarios, detailed Finite Element (FE) models are used to investigate the injury risk of passengers, while kinematic or multibody system (MBS) models of the human body are usually used to evaluate ergonomics. The popular kinematic ergonomics tool RAMSIS generates realistic postures with a probability-based model that relies on pre-recorded posture studies [1]. Especially in the biomechanics community, OpenSim [2] is a widely used tool for using inverse kinematics or dynamics to infer joint forces from pre-recorded subject motions. Although these tools are very useful in their application, they lack real-time applicability due to the high computational cost and/or rely on measured postures or movements from volunteer studies. This and the foreseeable increase of automated driving situations, and therefore the need for analysing the machine and the human not in isolation but in interaction, motivate the development of runtime-efficient human models with an active musculature.

This contribution proposes an approach to learn a surrogate model that describes the human-seat interaction by processing force distribution data of simulations with a detailed FE-HBM, i.e. THUMS [3]. Using an MBS modelling approach with active musculature – combined with *discrete mechanics and optimal control for constrained systems* (DMOCC) [4] – shows promise for predicting human-like motion [5] without the need for tracking volunteers in experiments. However, the human-seat interaction is crucial for applying those DMOCC-based HBMs in a vehicle interior to obtain meaningful results. Including the proposed surrogate model will lead to a run-time efficient active HBM that can interact with the car seat and will also enable simulations of longer, more complex low dynamic traffic scenarios.

II. METHODS

The overall methodology is separated into an offline and an online phase. In the offline FEM phase the interaction model is trained, while in the online phase the model is used in MBS simulations with the optimally controlled EMMA model [5] (see the schematic in Fig. 1). The interaction between the HBM and the vehicle seat is learned in the offline phase. Here, training data are generated by simulating the process of seating the human model in detailed passive FE simulations while varying parameters, such as the initial position of the HBM or the angle at which the seat is tilted. Then, contact regions for different body parts are defined and the force distributions of the detailed FE simulations are processed automatically to obtain the resultant forces and torques at every body part. To reduce the number of FE simulations required for training, the interaction is learned for each contact pair consisting of a body part and a seat part. This results in separate surrogate models per contact pair and, thus, a more general overall model that can be applied in a broader range of scenarios.

Two different approaches are presented, which differ in their processing of the data obtained from the FE simulations. *Approach 1* uses a surrogate model that approximates the interaction of a contact pair as a function of the relative kinematics of the two contacting bodies. *Approach 2* incorporates spheres that approximate the surface of the contact opponents (see Fig. 2) and then uses the intrusion of these spheres instead of the relative kinematics as the input for the surrogate models. This approach is assumed to prevent unphysical behaviour of the surrogate model to some extent and to simplify the learning process because the geometry is approximated by the spheres. After the automatic generation of training data, machine learning algorithms are utilised for training the surrogate model representing the interaction [6].

N. Fahse (e-mail: niklas.fahse@itm.uni-stuttgart.de; tel: +49 711 685 66560) is a Research Associate and Doctoral Student, F. Kempter is a former Doctoral Student and J. Fehr is a Professor at the Institute of Engineering and Computational Mechanics, University of Stuttgart, Germany. M. Harant, M. Roller and M. Obentheuer are Research Associates and J. Linn is Head of Department »Mathematics for the Digital Factory« at the Fraunhofer ITWM, Kaiserslautern, Germany.

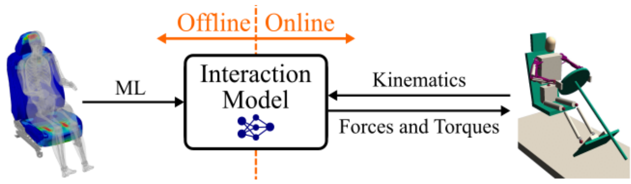

Fig. 1. Schematic of the methodology to formulate the human-seat interaction with a separation in an offline learning phase (left) and an online phase (right).

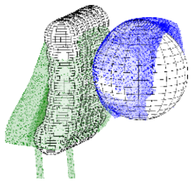

Fig. 2. Exemplary placement of spheres for the head-headrest contact pair. The FE nodes are shown in green (headrest) and blue (head).

To interact with the learned surrogate model in both the online and offline phases, (i) the partitioning into body parts, (ii) the definition of the respective coordinate systems and (iii) the positioning of the spheres are shared between the FE and MBS models. In the online phase motions of the HBM are generated using an approach by Roller *et al.* [5]. There, optimal control searches for an optimal actuation of the MBS model with respect to specific objective functions. The continuous optimal control problem (OCP) is discretised by the DMOCC approach and solved with the interior point method [5][7]. Since the human-seat interaction obtained from the surrogate model appears in the constraints of the OCP that ensure compliance with the multibody dynamics, the surrogate must be formulated in algebraic form to allow the calculation of gradients. This restricts the applicable algorithms for the data-driven contact model.

III. INITIAL FINDINGS

Based on the PIPER framework [8], suitable coordinate systems (COS) were introduced in both FE and MBS human models to describe their kinematics. A crucial factor was finding a suitable translation between the kinematics of the FE model and the low degree-of-freedom MBS model, which combines several anatomical bodies, i.e. vertebrae, into one lumped rigid body segment. In the first step, the resultant interaction forces $\boldsymbol{f}_i^{\text{res}}$ and torques $\boldsymbol{\tau}_i^{\text{res}}$ at COS i were formulated as a function of the human kinematics $\boldsymbol{r}_i$ relative to the seat: $\boldsymbol{f}_i^{\text{res}} = \boldsymbol{f}_i^{\text{res}}(r_i)$; $\boldsymbol{\tau}_i^{\text{res}} = \boldsymbol{\tau}_i^{\text{res}}(\boldsymbol{r}_i)\ \forall i \in \mathbf{I}$. So far, an interaction model has been trained that maps the relative kinematics to the interaction forces for the head-headrest contact pair. Subsequently, this model was used in an optimally controlled MBS simulation, confirming the surrogate's runtime efficiency, and showing the applicability of the overall approach. Furthermore, spheres that approximate the surface of the contact opponents were defined for the head-headrest contact pair in the FE and MBS model and first attempts to use the sphere intrusions instead of the relative kinematics look promising.

IV. DISCUSSION

As shown, the relevant characteristics of the human-seat interaction were extracted from FE simulations to form an interaction model that can be applied to an MBS simulation. The surrogate model is a computationally efficient representation of the human-seat interaction. It also enables the use of efficient optimal control algorithms in MBS simulations of an HBM and ultimately leads to a framework to generate realistic human movements while interacting with the seat. This is especially useful because motion capturing of a person sitting in a vehicle is difficult. In addition, the automatic generation of realistic movements of a vehicle occupant can enable car manufacturers to integrate active occupant behaviour into an iterative and holistic design process.

The approach of approximating the surfaces by spheres may have advantages in terms of scaling to other anthropometries or avoiding unphysical behaviour but it introduces additional complexity in the offline as well as the online phase. The implications of this approach need further investigation and are part of our current work.

Moreover, the use of a surrogate model to represent human-seat interaction in optimally controlled MBS simulations introduces additional discrepancies that require careful validation of the generated motions.

V. REFERENCES

[1] Bubb, *et al.*, *IJHFMS*, 2006.
[2] Delp, *et al.*, *IEEE Trans Biomed Eng*, 2007.
[3] Daichi, *et al., IRCOBI*, 2018.
[4] Leyendecker, *et al.*, *Optim Control Appl Methods*, 2010.
[5] Roller, *et al.*, ECCOMAS, 2017.
[6] Kneifl, *et al.*, *Int J Numer Methods Eng*, 2021.
[7] Björkenstam, *et al.*, *J Comput Nonlinear Dyn*, 2018.
[8] "piper-project.org" Internet: [www.piper-project.org], 2022-04-26 [2023-05-19].

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