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

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EXTENDED ABSTRACT

1 Introduction

Human body models (HBM) are an important tool for developing safe and ergonomic new mobility solutions. In accident scenarios, detailed Finite-Element-Models (FE models) are used to investigate the injury risk of the passengers while for evaluating ergonomics usually kinematic or multibody system (MBS) models of the human body are used. The widely used kinematic ergonomics tool RAMSIS generates realistic postures with a probability-based model that relies on prerecorded 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 prerecorded 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. To analyze the wide range of future crash scenarios and varying human behaviors inside the vehicle, runtime-efficient human models with active musculature are required. This is especially the case due to the foreseeable increase of automated driving situations and therefore the need for analyzing the machine and the human not in isolation but in interaction. Multibody systems (MBS) modeling the human body with discrete mechanics and optimal muscular control show promise for predicting human-like motion [3]. However, the human-seat interaction is crucial for the application in a vehicle interior to obtain meaningful results. This contribution proposes an approach to learn a surrogate model which describes the interaction between human and seat by processing force distribution data of simulations with detailed FE-HBMs. This leads to a run-time efficient active human body model that can interact with the car interior and enable simulations of longer, more complex traffic scenarios. Additionally, by including optimal muscular control, the model can generate realistic (occupant) movements without the need of tracking volunteers in real-world experiments.

2 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, see schematic on the left in Figure 1.

The interaction between the HBM and the vehicle interior is learned in the offline phase. Here, training data is generated by simulating the process of seating the human model under the influence of gravity in detailed 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 amount of FE simulations needed for training, the interaction is learned for every contact pair of one body part and one seat part. This results in a separate surrogate model for each 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 optained 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 (relative position as well as relative velocity) of the two contacting bodies. *Approach 2* incorporates spheres that approximate the surface of the contact opponents and then uses the intrusion of these spheres instead of the relative kinematics as the input for the surrogate models. An exemplary placement of spheres for the head and headrest is shown on the right in Figure 1. This approach is assumed to prevent – to some extent – unphysical behavior of the surrogate model and simplifies the learning process because the geometry is approximated by the spheres. Additionally, this approach could lead to a contact model that can be scaled to new anthropometries or adapted to other seat geometries. Furthermore, the authors expect that the surrogate model will generalize better to seating positions that were not part of the training data. After the automatic generation of training data, model order reduction (MOR) and machine learning (ML) algorithms are combined for pre-processing and training the surrogate model representing the interaction [4].

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 digital human model are generated by an approach proposed by Roller et al. [3]. There, optimal control searches for an optimal actuation of the MBS model with respect to specific objective functions. The continuous optimal control problem is discretized by the *discrete mechanics and optimal control for constrained systems* (DMOCC) [5] approach and solved with the interior point method [6, 3]. Since the human-seat interaction obtained from the surrogate model appears in the constraints of the optimal control problem that ensure compliance with the multibody dynamics, the surrogate model must be formulated in an efficient algebraic form. This further restricts the applicable algorithms for the data-driven contact model.

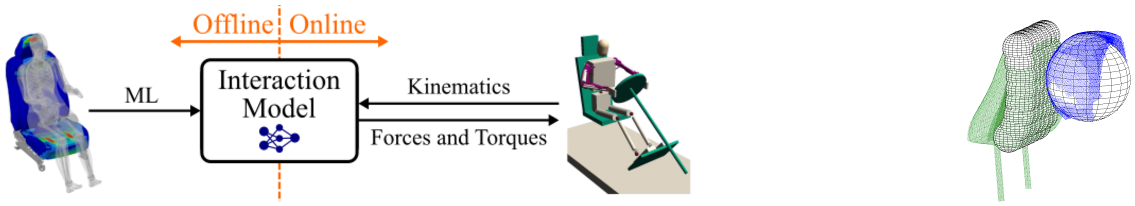

Figure 1: Schematic of the methodology to formulate the human-seat interaction with a separation in an offline learning phase with detailed FE simulations and an online interaction phase (left). Exemplary placement of spheres for the head-headrest contact pair (right). The FE nodes are shown in green (headrest) and blue (head).

3 Results and Discussion

Suitable coordinate systems (COS) are introduced in both FE and MBS human models to describe their kinematics. A crucial factor is 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 are formulated as a function of the human kinematics $\boldsymbol{r}_i$ relative to the seat

$$\boldsymbol{f}_i^{\text{res}} = \boldsymbol{f}_i^{\text{res}}(\boldsymbol{r}_i) \text{ and } \boldsymbol{\tau}_i^{\text{res}} = \boldsymbol{\tau}_i^{\text{res}}(\boldsymbol{r}_i) \;\; \forall i \in \mathrm{I}\,. \tag{1}$$

So far, an interaction model was 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. These simulations confirm the runtime-efficiency of the surrogate and show 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 both the FE and MBS model and first attempts to use the intrusion of these spheres with the opponents' spheres instead of the relative kinematics look promising.

As shown, the relevant characteristics of the human-seat interaction are extracted from the virtual FE simulations to an interaction model which can be applied to a MBS simulation. The surrogate model not only is a computationally efficient representation of the human-seat interaction, but it enables using efficient optimal control algorithms in the MBS simulation 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 and time-consuming. Additionally, the automatic generation of realistic movements of a vehicle occupant can enable car manufacturers to integrate the active behavior of the occupant into the iterative development process.

The mentioned approach of approximating the surfaces by spheres may have advantages in terms of scaling to other anthropometries or avoiding unphysical behavior but 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.

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