TOWARDS THE LEARNING OF HUMAN-SEAT INTERACTIONS FOR RUNTIME-EFFICIENT HUMAN MODELS BASED ON PRESSURE DISTRIBUTIONS

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Introduction

Human body models (HBM) are an important tool for developing safety systems and evaluating ergonomics. Especially in accident scenarios, detailed Finite-Element-Models (FEM) are used to investigate the injury risk of the passengers. The high computational cost of these simulations prevents the analysis of the wide range of future crash scenarios and varying human behaviors inside the vehicle. These aspects and the requirements arising from the foreseeable increase of automated driving situations motivate the creation of runtime-efficient human models with active musculature. Multibody systems (MBS) modeling the human body with discrete mechanics and optimal muscular control show promise for predicting human-like motion [1]. However, for the application in a vehicle interior, the human-seat interaction is crucial to obtain valid results. In this contribution, we propose 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 including realistic occupant movement.

Methods

The interaction between the HBM and the vehicle interior is learned in an offline phase. Therefore, contact regions for the different body parts are defined and the pressure (force) distributions of the detailed FE-simulations are processed in an automatic fashion to obtain the resultant forces and torques. Subsequently, model order reduction (MOR) and machine learning (ML) algorithms are combined for pre-processing and training the surrogate model representing the interaction [2]. Figure 1 shows a schematic of this procedure.

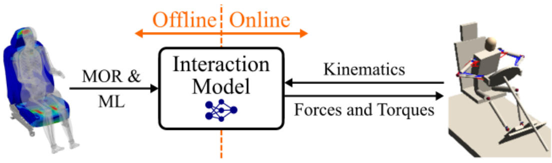

Figure 1: Schematic of the methodology to formulate the human-seat interaction with a separation in an offline learning phase with detailed FE simulations (left) and an online interaction phase (right).

Results

Suitable coordinate systems (COS) are introduced in both FE and MBS human models to describe their kinematics and to allow the transfer of the identified interaction model. A decisive factor there is, to find a suitable translation between the kinematics of the FE model and the low-degree of freedom MBS model which combines several anatomical bodies, e.g. vertebrae, into one lumbed rigid body segment. Thus, the resultant interaction forces $\boldsymbol{f}_i^{\mathrm{res}}$ and torques $\boldsymbol{\tau}_i^{\mathrm{res}}$, at the COS i can be formulated as a function of the human kinematics of the corresponding body $\boldsymbol{r}_i$ relative to the seat

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

So far, we have categorized the body into 8 contact-regions and learned the interaction properties based on force-controlled virtual experiments performed in nonlinear FE simulations.

Discussion

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. This will allow the runtime-efficient human model to interact with different interiors without the need to model them as an MBS and perform a contact-based approach to calculate the corresponding interaction forces. The normally expensive interaction procedure is replaced by simple matrix vector multiplications.
Furthermore, the approach is formulated in a way that additional experimental data can be easily integrated into the training data of the interaction model. Thus, the data basis for training is enlarged and real-world transferability is improved.

References

1. Roller et al, Adv Transdiscipl Eng, 11:269-276, 2020.
2. Kneifl et al, Int J Numer Methods Eng, 122: 4774-4786, 2021.

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