Symposium on

Perspectives of multibody systems towards data-based methods and AI

February 21 – 22, 2025

Book of Abstracts

University of Innsbruck
Department of Mechatronics
Technical Campus
Technikerstr. 13, 6020 Innsbruck, Austria

Schedule

Friday, Feb. 21, 2025

Time slot	author	
09:00-09:30	**Negrut**	
09:30-10:00	**Orzechowski**	
10:00-10:30	**Möltner**	
Break		
11:00-11:30	**Choi**	
11:30-12:00	**Mikkola**	
12:00-12:30	**Manzl**	
Lunch		
14:00-14:30	**Naets**	
14:30-15:00	**Pieber**	
15:00-15:30	**Zwölfer**	
Break		
16:00-16:30	**Malczyk**	
16:30-17:00	**Rodríguez**	
17:00-17:30	**Negrut 2**	
17:30-18:00		
Social program		

An overview of Chrono Support for Using Simulation to Facilitate Research in Embodied AI

Nevindu Batagoda, Bo-Hsun Chen, Bret Witt, Luning Bakke, Radu Serban, and **Dan Negrut**

This presentation outlines support that facilitates the use of simulation in designing intelligent autonomous systems. The focus is on robots, and to that end, we will overview support for simulation robots, their sensors, the terrains in which they operate, and the virtual worlds that are sensed during the robot operation. The simulation infrastructure support ROS2 integration and allows one to carry out software-in-the-loop, human-in-the-loop, and hardware-in-the-loop analysis. The software-in-the-loop component is tied to testing any component of an autonomy stack, e.g., computer vision, state estimation, and mapping algorithms. For human-in-the-loop, since the infrastructure can run, under certain conditions, in real time, one can investigate the human-autonomy interplay. Finally, for hardware-in-the-loop, one can use the simulator in embodied AI applications to verify is the on-board chip provides the compute power to ensure the safe operation of the agent.

Prediction and control in heavy mobile machinery applications

Grzegorz Orzechowski, and Aki Mikkola

The integration of machine learning (ML) techniques with heavy mobile machinery simulations holds significant potential for advancing prediction and control systems. Time-delayed neural networks and long short-term memory (LSTM) networks have proven highly effective in modeling nonlinear dynamical systems, including hydraulic systems, by capturing the complex temporal dependencies inherent in their operation. Additionally, multi-fidelity modeling offers a robust framework for balancing computational efficiency, data requirements, and predictive accuracy, enabling the efficient handling of nonlinear problems. Reinforcement learning (RL) further expands the scope of ML by facilitating adaptive, autonomous control and optimizing machinery performance in dynamic and uncertain environments. Together, these advancements underscore the transformative role of ML in enhancing the efficiency, reliability, and operational safety of heavy mobile machinery.

Evaluation of Large Language Models using a Virtual Multibody Dynamics Lab

Tobias Möltner, Michael Pieber, Peter Manzl, and Johannes Gerstmayr

Artificial intelligence, particularly large language models (LLMs), is revolutionizing engineering tasks, enabling broader accessibility to complex domains such as multibody dynamics (MBD). LLMs have already shown the potential to generate simulation code for MBD systems. However, automated evaluation of the capability of LLMs in simulation code generation remains underexplored.

To address this issue, we introduce a lab in the loop that systematically evaluates the ability of LLMs to perform virtual MBD experiments. More specifically, the LLM constitutes a suitable validation for a specific MBD system and proposes a corresponding conjecture, which is subsequently validated through simulation. As a simple example, the LLM could assume that an MBD system has two degrees of freedom. Primarily, we provide the LLM with context to create a Python simulation model which it uses to extract the results after simulation. The virtual experiment is ultimately validated with the initially stated conjecture and the simulation results in a fully automated manner, leading to the generation of synthetic but validated multibody knowledge base. Furthermore, closing the loop with the validation allows a statistical evaluation of the performance of the LLM for virtual experiments and code generation.

Preliminary tests indicate that the lab in the loop offers a promising approach for automated assessment of LLM capabilities in validating, generating, and simulating MBD systems. Furthermore, the data generated through these evaluations can serve as a foundation for fine-tuning LLMs. The validation processes for each step in framework could replace traditional reinforcement learning with human feedback for fine-tuning tasks in the future.

A Data-Driven Dynamic Analysis for Flexible Multi-Body Systems through Data-Integrated Model-Driven Simulation

Juhwan Choi, Seongsu Kim, and **Jin H. Choi**

The field of Multi-Body Dynamics (MBD), which traditionally focused on understanding the motion of rigid bodies, has evolved into Multi-Flexible-Body Dynamics (MFBD) by integrating Finite Element Analysis (FEA) techniques that account for deformations. MFBD has become a powerful tool for analyzing complex systems comprised of rigid and flexible bodies. In addition, MFBD can be useful for Digital Twin (DT) because of its effective way of converting a real complex system into a digital system.

However, to construct an applicable digital twin system for a real application model, we require a solver capable of real-time solutions for the digital application model. Real-time analysis for the MFBD model is exceptionally challenging due to nonlinearities and high degrees of freedom. Therefore, a major challenge that dynamics analysis software must address in the future is developing a fast and robust analysis technique for MFBD systems. Nonetheless, existing analysis methods based on the formulation of governing equations of motion have limitations. To address these limitations, data-driven analysis techniques based on machine learning (ML) and artificial intelligence (AI) are actively under research. This study presents an effective method for real-time system dynamics analysis, which is required for expansion into various application fields. It is the Data-Integrated Model-Driven Simulation (DIMDS) technique, which combines existing formalization techniques for governing equations of motion with data-driven techniques. It is expected that the presented technique will allow MFBD models to be analyzed quickly and more effectively.

Application of Multibody System Dynamics to Fatigue Analysis of Welded Structures

Aki Mikkola

This study examines the application of multibody system dynamics in predicting fatigue damage in welded steel structures. Welded structures are particularly prone to fatigue due to material heterogeneity, residual stresses introduced during the welding process, and stress concentrations at weld joints. These factors make welded structures more vulnerable to fatigue damage by accelerating crack initiation. Dynamic loading, such as repeated cyclic stresses, further exacerbates this issue. Given their susceptibility to damage, it is essential to predict how welding-related fatigue evolves over time.

Accurate fatigue prediction requires a thorough understanding of the material properties, the geometry of the welded joints, and the forces acting on the structure. However, determining these forces in real-world applications is a significant challenge, particularly for structures subjected to dynamic loads. This research addresses these challenges by employing real-time flexible multibody system dynamics, actuator models, and realistic environmental conditions. The study focuses on high-strength steel, which facilitates the design of lightweight and slender structures but increases vulnerability to dynamic loading and fatigue.

Machine Learning Applications for Industry and Teaching

Peter Manzl, Alexander Humer, Qasim Khadim, and Johannes Gerstmayr

Deep learning based methods have shown great potential for dynamic analysis of mechanical systems. In this work, we investigate the use of various neural network architectures to estimate the dynamic response of multibody systems. Based on benchmark problems, we show application and performance of the transformer, recurrent neural networks (RNN), convolutional neural networks (CNN), and the classical feedforward neural network (FNN). Using supervised learning, training and validation datasets are generated through simulation with the multibody simulation code Exudyn, enabling an analysis of the trade-offs between larger datasets and training compute. Training and testing results are analyzed for the models regarding the trained neural network's performance on the validation set, training compute, and model sizes.

It is shown how the different architectures can be applied in the SLIDE method, a method that exploits the damping of multibody systems and a sliding window approach, to estimate time series of varying lengths.

Exploiting physical measurement data to improve (flexible) multibody simulation

Simon Vanpaemel, Thijs Willems, Martijn Vermaut, and **Frank Naets**

Flexible multibody simulation has presented itself as a powerful to tool to analyse various kinds of complex dynamic machine interactions. Historically there has been a close link between how body deformations are described in a reduced order fashion and experimental methods like experimental modal analysis. However, on the level of capturing measurement data on full machines, and how to exploit that data to improve the fidelity of flexible multibody models, only limited efforts have been undertaken. In order to fully leverage the potential here, an holistic approach needs to be considered which accounts for effective ways to measure on moving systems (e.g. through camera based measurement), how to model the various unknown components, and how to infer the most representative parameters. In this talk we will present several approaches to measure dynamic phenomena in real-life machines, and how those measurements can be exploited to improve the representativeness of the flexible multibody simulations for those systems.

Machine Learning Applications for Industry and Teaching

Michael Pieber, Peter Manzl, Stefan Holzinger, and Johannes Gerstmayr

Machine learning offers opportunities for multibody systems in both industry and teaching, as demonstrated in this work. In the first application, we use neural networks to approximate high-fidelity models in multibody systems. Specifically, we address the following questions: Can machine learning methods provide computationally efficient and accurate approximations of high-fidelity models that can be used in multibody system simulations at the component level? How well do they integrate with numerical techniques such as the Newton method, and how do they compare with classical approaches like polynomial fitting? We demonstrate the performance and show how issues with PyTorch can be resolved, leading to accuracy and computational performance comparable to the other methods investigated. In the second application, we classify operating states in the cutting process of a real system using labeled measurements, such as the condition of the shredder blade, based on purely unfiltered, highly dynamic acceleration signals. This task is challenging due to the limited number of datasets and the raw, unprocessed nature of the data. We demonstrate that machine learning can successfully classify these operating states. Finally, examples from teaching are shown, where state-of-the-art CNNs are applied to the task of image classification together with pixel-based image processing methods. By applying transfer learning with pre-trained neural networks good performance is reached with training sets in the order of few hundred images. The applications presented underscore the suitability of machine learning for computational efficiency, accuracy, and practical applicability in multibody systems.

Data-Driven Model Reduction for Flexible Multibody System Dynamics

Andreas Zwölfer

Multibody system dynamics simulations are powerful tools to realistically analyse real-world devices in their intended operating environment. However, simulations of engineering relevance include often numerous components and degrees of freedom, especially when the bodies' flexibility needs to be taken into account. This computational burden typically necessitates the use of model order reduction techniques—especially when real-time applications, such as the control of humanoid robots, are required. Furthermore, the inherently non-linear governing equations are often (at least partially) unknown, e.g., contact and damping terms, and cannot be easily reduced with classical projection-based reduction techniques. To address these challenges, data-driven approaches offer a promising alternative. This presentation will focus on combining data-driven and classical methods for the non-linear model order reduction of mechanical system dynamics.

Data-Driven Forward and Inverse Dynamics of Multibody Systems

Pikuliński Maciej, and **Malczyk Paweł**

Traditionally, building forward or inverse dynamics models to predict or control the motion of a multibody system (MBS) involves deriving the formulations from first principles. Such physics-based representations lead to ordinary differential or differential-algebraic formulations, which extrapolate well by design and are usually preferred in model-based control strategies.

Nevertheless, it is often that parameters or the structure of the model remain unknown. With recent advancements, data-driven techniques to identify dynamics directly from data are quickly growing. The emerging method, dynamic mode decomposition, seems to be a highly versatile and powerful approach to discovering dynamics from time-series recordings or numerical simulations. We propose directly deriving the forward and inverse MBS dynamics models from data samples. The models are updated online as new measurements are acquired during system operation. In this talk, we will also show the applications of the methods in the simulation and control of a real robotic system.

Data-driven prediction of subsystem dynamics for explicit co-simulation

Maciej Pikuliński, Paweł Malczyk, **Antonio J. Rodríguez**, and Francisco González

Explicit co-simulation is an efficient means to couple subsystem dynamics in multiphysics environments, allowing each subsystem to integrate its dynamics independently from the others and keeping the dynamics consistency via the exchange of a reduced set of coupling variables at discrete-time communication points. Hardware/Human- and System-in-the-Loop interfaces also need to couple physical and virtual components through explicit, noniterative schemes. Such a solution suffers from interface discontinuities that compromise the accuracy of the integration, and can sometimes lead to instability. Polynomial extrapolation has traditionally been used to predict future subsystem inputs with the aim to alleviate interface discontinuities. Extrapolation, however, does not reflect the physical behaviour of the subsystems, which is often unknown to the rest of the environment because the only information about subsystem internals is the one contained in the coupling variables. We present a data-driven prediction of subsystem dynamics based on dynamic mode decomposition, which only uses information exposed to its environment by the subsystem. The method has been tested with nonlinear and multirate benchmark problems.

Three Case Studies in Using Chrono Simulation to Enable Research in Robotics

Harry Zhang, Sriram Ashokkumar, Huzaifa Unjhawala, Luning Bakke, Radu Serban, and Dan Negrut

This presentation shows three examples that illustrate how Chrono is used to enable embodied AI. In the first one, we show how large multi-modal models, which combine text and images, are deployed on a robot that can carry out requests made by a human, while operating in unstructured environments such as a house. The second example focuses on the task of comparing different control strategies that can be used to guide an off-road autonomous robot. Lastly, we show how fast simulation models come into play in training Reinforcement Learning agents for deploying on an autonomous robot that engages in bulldozing operations.