The 26th Computational Engineering Conference of JSCES

特別講演・計算工学大賞 2020 授賞式

The JSCES Grand Prize 2020 Lecture and Ceremony

2020 年度計算工学大賞を受賞された米国・カリフォルニア大学の J. S. Chen 教授の特別講演ビデオをオンライン放送します。多数のご視聴とご参加をお待ちしております。

日 時 / Date　２０２１年５月２７日（木）１５：０５－１５：５５*（終了後、授賞式に移行します）
形 式 / Form　司会による紹介の後，J. S. Chen 先生の特別講演ビデオを放送します。
司 会 / Chair　Junji Kato (Nagoya University)

Deep Autoencoders Enhanced Manifold Learning for Digital Twin Application to Musculoskeletal Systems

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Abstract

The goal of this research is to develop a two-scale Digital Twin which integrates cellular scale musculoskeletal (MSK) models with structural scale system dynamics model for simulating human behavior under different environments, conditions, and constraints. The cellular scale models combine the image based physical models augmented with data-driven computing and learning algorithms for simulating muscle mechanics. Under this framework, the data-driven modeling is a hybrid approach that integrates universal physical laws with sensor data directly to circumvent the necessity of using phenomenological constitutive models. A robust data-driven simulation approach based on manifold learning based locally convex data-driven (LCDD) computing, is formulated under the image based RKPM framework. The proposed approach reconstructs a local material manifold with the convex hull based on the nearest experimental data to the given state, and seeks for the optimum solution via the projection onto the associated local manifold. An autoencoder is introduced to extract a low-dimensional representation (embedding) of data and addresses the "dimensionality curse" emerging from other conventional manifold learning-based methods. The data embeddings learned by the encoders provide enhanced noise filtering and extrapolation generalization. A local convexity-preserving scheme based on Shepard interpolation is introduced for the data-driven local solution to enhance numerical stability.

The cellular scale models are upscaled with the reduced order approach for coupling with the component and whole-body system dynamics models. The system dynamics models are calibrated with the motion tracking data by solving an optimization problem. This framework is formulated by enhancing Deep Neural Networks (DNNs) with physics-based constraints such as residuals of the governing equations. Adding the physics-based residual as a regularization term to the loss function of DNNs allows for a robust system identification procedure. The approach is further enhanced with modern machine learning architectures to yield a computationally efficient framework for system parameters and function identification. The future work in integrating various data streams of the subject including motion capture data (position, velocity, and acceleration) and wearable sensor data (kinetic and kinematic data of the muscle groups) for a better solution accuracy and connecting the system identification of the multi-body dynamics of the MSK DT to the patient specific muscle mechanical properties, is also highlighted.

* 予定時刻となります。

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