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Guest Editorial

Special Issue: Data-Driven Methods in Biomechanics

Machine learning (ML) and artificial intelligence (AI) are impacting all engineering fields and biomechanical engineering is no exception. This special issue aims at showcasing some of the recent methods and applications of ML and AI specific to biomechanics. While ML and AI have had incredible success in their more traditional areas of application such as image processing and classification, new frontiers require the development of new tools or the repurposing of existing tools tailored to the unique types of data encountered in biomechanics problems. Furthermore, blind use of ML and AI techniques is likely to introduce biases, miss the mechanistic connection between physics and data, and ultimately lead to untrustworthy and inaccurate predictions. Integration of data-driven methods with in-depth knowledge and experience in biomechanics is paramount. This collection offers a timely snapshot of such integration. For example, solution of partial differential equations (PDEs) for fluid or solid mechanics is central to many biomechanics problems, prompting the development of physics-informed ML methods. Another class of problems in the field involves the dynamics of human motion, and in particular the role of electrical signaling for muscle activation, leading to specific instantiation of ML tools. Biological systems are inherently noisy, and this variability makes its way across temporal and spatial scales yielding patient-to-patient variation and heterogeneities even within the same tissue. Data-driven methods that can capture and propagate these uncertainties are also illustrated in this issue. Lastly, parallel to the development of new ML and AI tools, the creation of standards and benchmarks cannot be emphasized enough. The special issue also includes a paper that deals with this subject.

Several problems in biomechanics involve the solution of PDEs. Traditionally, numerical solution of PDEs has been done with the finite element (FE) method, and more recently with isogeometric analysis (IGA). These well-established techniques are likely to continue to be used in the future, they are reliable and accurate. However, one of the drawbacks of FE and IGA is that, especially for high-fidelity models, they are computationally expensive. ML tools such as artificial neural networks (ANNs) are powerful interpolators for very nonlinear functions in high-dimensions. As a result, they are able to learn input–output relationships coming out of PDE solvers. New methods to replace PDE solvers with ML surrogates are shown in this issue. For fluid mechanics problems, in particular blood flow in arterial bifurcations, the paper "Universal Solution Manifold Networks (USM-Nets): Non-Intrusive Mesh-Free Surrrogate Models for Problems in Variable Domains" illustrates how ANNs can be designed in such a way that they can generalize flow predictions to changing domains. In other words, given spatial samples of fluid velocity and pressure (from standard PDE solvers) in combination with geometric markers of individualized geometries, the ANN can make accurate predictions for the blood flow in a new patient geometry not seen in the training set. The paper "Neural Network Approaches for Soft Biological Tissue and Organ Simulations" also illustrates the use of ANN to replace both constitutive models of soft tissue as well as FE and IGA simulations of myocardium and heart leaflets. One of the main advantages of the ANN approach is that computational effort is invested in model training, yielding a desired reduction in computational time for a new prediction without loss of accuracy. The paper "A Physics-Guided Neural Operator Learning Approach to Model Biological Tissues from Digital Image Correlation Measurements" similarly tackles the use of ANNs as metamodels to learn full displacement fields for heterogeneous materials under biaxial loading, outperforming the computational cost of FE during model evaluation tasks. In addition to PDEs for solid and fluid mechanics, the solution of reaction-diffusion PDEs with data-driven methods is reported in "Data-Driven Simulation of Fisher–Kolmogorov Tumor Growth Models Using Dynamic Mode Decomposition." Reaction-diffusion models are important for problems in biomechanics involving growth and remodeling, e.g., tumor growth.

Human motion and muscle activation dynamics fall within another major area in biomechanics that is also represented in this special issue. Data in this area are unique compared to those data of interest for the PDE modelers. On the other hand, analogous to the PDE case, while standard ML methods are able to interpolate the nonlinear dynamics of muscle activation and human motion, using ML tools as a black box leads to limited generalization of the method. Given that there is extensive knowledge of muscle physiology, imposing these physics and biological constraints into ANNs enables accurate predictions outside the training set, as shown by Taneja et al. in "A Feature-Encoded Physics-Informed Parameter Identification Neural Network for Musculoskeletal Systems." One of the key innovations by Taneja and coauthors is the consideration of Fourier features rather than time domain data. This insightful change of variables is a noteworthy example of how physics-informed ML methods require unique considerations that might not be important in other fields of application. The work "Generating Human Arm Kinematics Using Reinforcement Learning to Train Active Muscle Behavior in Automotive Research" also trains a deep learning model on a physics-based model of the human arm, including the physiological model of muscle activation and the resulting motion of the arm from the combined activation and coupled biomechanics of all the relevant muscles, bones, and joints. The challenge tackled by the authors was the learning of the muscle activation signals needed for the production of desired motions, which then they used to investigate how a controller trained on a limited set of tasks performed in tasks not seen during training. The third example of human motion biomechanics included in this issue is "Gait Phase Detection in Walking and Stairs Using Machine Learning," which shows how data-driven methods for gait biomechanics can be trained and applied to real-world human gait data.

An important feature of biological systems that hinders our ability to make accurate predictions with physics-based models is the presence of uncertainty. One main example is the variability in tissue and organ systems geometry and mechanical properties from one patient to another. Additionally, one of the challenges to deal with this uncertainty is that measurements in realistic clinical scenarios are usually imperfect and the exact material parameters and geometry for an individual are not directly available. Therefore, there is a need to use prior information (e.g., population data), as well as physics constraints to solve the inverse problem of identifying individualized parameters from noisy measurements. In the paper "Bayesian Inference With Gaussian Process Surrogates to Characterize Anisotropic Mechanical Properties of Skin From Suction Tests," the authors rely on high-fidelity FE simulations of skin suction tests using detailed material models and parameter ranges from ex vivo skin biaxial tests in the literature. They then use Gaussian process (GP) surrogates to replace the high-fidelity model, and use the surrogate in a Bayesian framework to infer the material parameters for a new dataset consisting only of suction test results. A similar idea is explored in "Reducing Geometric Uncertainty in Computational Hemodynamics by Deep Learning-Assisted Parallel-Chain MCMC," where the authors tackle the problem of identifying individualized vessel geometries and flow features from noisy MR data by constraining the data on a physics solver. The setup in this second paper is also Bayesian, whereby the output is not a single geometry and flow profile, but rather a probabilistic prediction. Because the forward physics solver is computationally expensive, it is essential to replace it with a deep learning surrogate. Yet one more example of inverse parameter estimation from noisy MR data of blood flow is shown in "Feasibility of Vascular Parameter Estimation for Assessing Hypertensive Pregnancy Disorders." The last example dealing with prediction under uncertainty is shown in "Multi-Fidelity Gaussian Process Surrogate Modeling of Pediatric Tissue Expansion," where the authors use a multifidelity GP surrogate to combine a low-fidelity scalar model of skin growth with a FE model of tissue expansion. The authors inform the parameters for skin mechanics and biological response from literature data on human and porcine skin, and use the surrogate to propagate the uncertainty in these data to make probabilistic predictions for a new patient.

Unlike other fields in which ML and AI have thrived, one of the main limitations in biomechanical engineering is the lack of data. This is, at the same time, the reason why many efforts in biomechanics complement experimental observations with physics-based modeling as a way to mitigate the gaps in the data with first principles. Yet, this lack of data also poses question of how to properly benchmark new methods against existing ones. We view open sharing of ML and AI code and corresponding data as an essential requirement to guarantee the continuous progress in data-driven models in biomechanics, as well as to ensure that their future use will indeed improve clinical outcomes and quality of life. Important work in this direction has been done in "Enhancing Mechanical Metamodels With a Generative Model-Based Augmented Training Dataset." This paper not only generates a dataset to benchmark reaction-diffusion and hyperelasticity ANN solvers, it also explores the idea of generative models to produce new data that can used to benchmark deep learning models in fields where real data is scarce, such as in biomechanical engineering.

In summary, this special issue not only presents a representative collection of latest research on data-driven methods in bioengineering but also provides some useful in-depth insights to the community. Finally, we thank all the authors contributing to this special issue and the editors for this opportunity.

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