ERC Advanced Grant 2023
Research proposal [Part B1]

Automated Model Discovery for Soft Matter Systems

DISCOVER

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Proposal Duration 60 Months

Soft materials play an integral role in many aspects of modern life including biomedicine, energy storage, and consumer goods, and their accurate modeling is critical to understand their unique properties and functions. However, the successful modeling of soft materials is limited to a few well-trained specialists in the field. My *long-term goal* is to democratize constitutive modeling through automated model discovery and make it accessible to a more inclusive and diverse community. The *overall objective* of this proposal is to establish a new family of constitutive neural networks that simultaneously and fully autonomously discover the model, parameters, and experiment that best explain a wide variety of soft matter systems. To train, test and validate these networks, I will perform tension, compression, and shear experiments on the heart, arteries, muscle, lung, liver, skin, brain, hydrogels, silicone, artificial meat, foams, and rubber, and quantify model uncertainties using a Bayesian approach. My *central hypothesis* is that automated model discovery will facilitate the exploration of a large parameter space of models, and provide unprecedented new insights into soft matter systems that are out of reach with traditional theoretical and numerical approaches today. My immediate *deliverable* is a fully documented open source scientific discovery platform that includes our new neural networks, experimental data, benchmarks, models, and parameters, freely available on GitHub. This discovery platform has the potential to induce a ground-breaking change in constitutive modeling and could forever change how we simulate materials and structures. This project will democratize constitutive modeling; stimulate discovery in soft matter systems; provide enabling deep-learning based tools to characterize, create, and functionalize soft matter; and train the next generation of civil, mechanical, and manufacturing innovators to adopt and promote these new technologies.

Section a: Extended Synopsis of the Scientific Proposal

I. OVERVIEW AND WORK PACKAGES.

Constitutive modeling and parameter identification are the cornerstones of the mechanics of materials and structures. For decades, the gold standard in constitutive modeling has been to *first* select a model and *then* fit its parameters to data. However, the scientific criteria for model selection remain poorly understood, and the success of this approach depends largely on user experience and personal preference. This limits the successful use of constitutive modeling—and with it the accurate design and analysis of engineering structures—to a few well-trained specialists in the field. ***My long-term goal is to democratize constitutive modeling through automated model discovery and make it accessible to a more inclusive and diverse community of students, scientists, and industries to accelerate the design of new functional materials and structures with tailored material properties***. The <u>overall objective</u> of this proposal is to establish, train, test, and validate a new family of constitutive neural networks that *simultaneously* and *fully autonomously* discover the model, parameters, and experiment that best explain the behavior of a wide variety of soft materials. This discovery platform has the potential to induce a paradigm shift in constitutive modeling and could forever change how we simulate materials and structures. My <u>*central hypothesis*</u> is that automated model discovery facilitates the exploration of a large parameter space of models and enables the identification of complex relationships between microstructure and properties that are not apparent from experimental data alone. Automating the process of model discovery will help us eliminate user bias, identify new phenomena in soft matter systems, lead to a deeper understanding of the mechanics of soft matter, and guide the creation of more accurate design tools. My <u>*deliverable*</u> is an open source discovery platform that features a new family of constitutive neural networks, a comprehensive benchmark library to train, test, and validate these networks for a wide variety of soft materials, and a comprehensive documentation to readily adopt this new technology for other soft matter systems. The <u>*rationale*</u> for embedding model discovery into a custom-designed network architecture is that this will allow us to reverse engineer our own neural networks from the modular building blocks of popular constitutive models and to efficiently screen a large parameters space to select the best model out of more than a million possible combinations of terms. This will provide unprecedented new insights into constitutive modeling that are out of reach with traditional theoretical and numerical approaches today. I plan to accomplished these goals in three <u>*work packages*</u> summarized Figure 1.

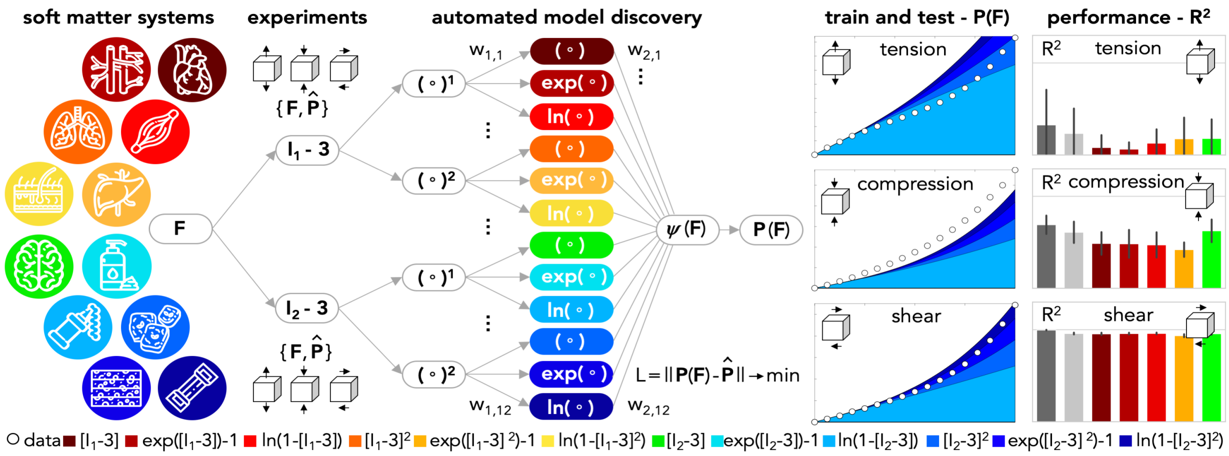


Figure 1. Automated model discovery. Discovering the best model, parameters, and experiment to explain a wide variety of soft matter systems including the heart, arteries, muscle, lung, liver, skin, brain, hydrogels, silicone, artificial meat, foams, and rubber. I will establish a new family of neural networks; train, test and validate them on tension, compression, and shear data; quantify their performance on new multiaxial experiments; and embed them into a Bayesian analysis to quantify uncertainty.

WP 1. Establish a new family of constitutive neural networks that reproducibly discover the model, parameters, and experiment that best explain a wide variety of soft matter systems.

WP 2. Quantify the performance of our discovered models on previously unseen data for the heart, arteries, muscle, lung, liver, skin, brain, hydrogels, silicone, artificial meat, foams, and rubber.

WP 3. Quantify the uncertainty of our models, parameters, and experiments by embedding our networks into a Bayesian analysis to discover parameter distributions and credible intervals.

II. BACKGROUND AND STATE OF THE ART.

Soft materials are complex to understand and challenging to model. For decades, chemical, physical, and material scientists alike have been modeling the hyperelastic response of soft matter under finite deformations[7,58,60,72,94,103]. They have proposed numerous competing constitutive models to best characterize the behavior of natural and man-made soft materials and calibrated their model parameters using uniaxial tension, compression, shear, and biaxial tests[14,24,31,39,69,70,85]. ***With this proposal, I challenge the conventional wisdom and propose a radically different approach towards constitutive modeling*:** I abandon the common strategy to *first* select a constitutive model and *then* tune its parameters by fitting the model to data[33]. Instead, ***I propose to simultaneously and fully autonomously discover both the constitutive model and material parameters that best explain the experimental data*.** While constitutive models for stiff materials are well-studied and well-understood, soft materials typically undergo finite deformations[93,]; they are highly nonlinear[92], often incompressible[29], anisotropic[84], tension-compression asymmetric[10], and generally challenging to model. In the age of machine learning, this raises the question: Can we leverage the power of neural networks to systematically learn the best constitutive models for soft matter systems?

Classical neural networks interpolate data well, but ignore the underlying physics. In the most general form, constitutive equations in solid mechanics are tensor-valued tensor functions that define the relation between a stress, for example the Piola stress $\boldsymbol{P}$, and a deformation measure, for example the deformation gradient $\boldsymbol{F}$[2,33,92]. Conceptually, we could use any neural network[56] to learn the functional relation between $\boldsymbol{P}$ and $\boldsymbol{F}$ and many approaches in the literature actually do exactly that[35,55]. Interestingly, the first neural network that learned a stress-strain model from data was proposed for concrete more than three decades ago[25]. In the early days[36,83], neural networks served merely as regression operators and were commonly viewed as a black box. This lack of transparency is probably the main reason why these early approaches never really generated momentum in our mechanics community. Now, more than 20 years later, neural networks have advanced as a promising technology to support constitutive modeling[41,64,67]. They hold a tremendous potential to interpolate big data, especially when we have no prior information about the data[1,46]. However, they generally perform poorly on small data, they are at risk of overfitting[42], and fail to extrapolate or predict scenarios beyond their training regime[52]. More importantly, classical off-the-shelf neural networks entirely ignore our prior domain knowledge[5] and the functions $\boldsymbol{P}(\boldsymbol{F})$ that they learn often violate standard arguments of thermodynamics and widely-accepted physical laws[3,26,40,89]. ***With this proposal, I explore whether and how we can build our prior domain knowledge in soft matter physics into a neural network.***

Constitutive neural networks can be reverse-engineered from constitutive building blocks. To understand the art of modeling, it is insightful to perform a systematic comparison of classical popular constitutive models[85,96]. Strikingly, the most widely used constitutive models are made up of structurally and functionally similar building blocks[20,29]. They are either functions of the set of invariants[33,84], I_1, I_2, I_3, or of the set of principal stretches[57,60,96], λ_1, λ_2, λ_3, or more precisely, their equivalents in the undeformed reference configuration, $[I_1\text{-}3]$, $[I_2\text{-}3]$, $[I_3\text{-}1]$, or $[\lambda_1\text{-}1]$, $[\lambda_2\text{-}1]$, $[\lambda_3\text{-}1]$. These kinematic descriptors are then raised to linear, quadratic, or higher order powers, $(\circ)^1$, $(\circ)^2$,…, $(\circ)^n$, as in the neo Hooke[95], Blatz Ko[7], and Mooney Rivlin[58,72] models, and possibly further integrated into exponential or logarithmic functions, $[\exp(\circ)\text{-}1]$ or $[\ln(1\text{-}(\circ))]$, as in the Demiray[14], Gent[24], and Holzapfel[32] models. Coefficients of these models, or combinations of them, take the natural interpretation of the shear and bulk moduli μ and κ, or the Lamé constants L and G. ***With this proposal, I reverse engineer my own family of constitutive neural networks with activation functions that feature popular constitutive building blocks and network weights that translate into well-known engineering parameters.***

III. SCIENTIFIC APPROACH

Throughout this research, I will pursue a holistic scientific approach that seamlessly integrates theory, experiment, and computation to automatically discover the best model, parameters, and experiment that explain a wide variety of soft matter systems. My research methodology requires a deep knowledge in constitutive modelling, soft matter physics, machine learning, and artificial intelligence, and is designed around the following three work packages, as illustrated in Figure 1.

WP 1. Establish a new family of constitutive neural networks that reproducibly discover the model, parameters, and experiment that best explain a wide variety of soft matter systems.

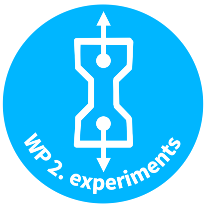
Soft materials play an integral role in many aspects of modern life including biomedicine, energy storage, and consumer goods, and their accurate modeling is critical to understand their unique properties and functions. A recent trend in soft material modeling is to entirely abandon existing constitutive models and fully replace them by neural networks. However, classical neural networks perform poorly on small data, they ignore the fundamental laws of physics, and their parameters have no physical interpretation. The ***objective*** of this work package is to build, train, and test *my own* family of constitutive neural networks that a priori satisfy the fundamental laws of physics through selective input, output, architecture, and activation functions. ***My hypothesis is that my new constitutive neural networks seamlessly integrate our prior domain knowledge in soft matter physics and autonomously discover the model and parameters that best explain a wide variety of soft materials***.

My ***scientific approach*** is to reverse-engineer a new family of constitutive neural networks from the functional building blocks of popular constitutive models and hardwire physical constraints into the network design. Specifically, I will combine our recent invariant-based[52-54,89] and principal-stretch-based[87] neural networks into a selectively connected feed-forward network architecture with two invariants, I_1 and I_2, and two principal stretches, λ_1 and λ_2, as input, two hidden layers, and seven activation functions per input, $(\circ)^1$, $(\circ)^2$, $(\circ)^n$, $\exp(\circ)^1$-1, $\exp(\circ)^2$-1, $\ln(1-(\circ)^1)$, $\ln(1-(\circ)^2)$, scaled by twelve weights. This will result in 4 x 7 = 28 individual terms and 4 x 12 = 48 network parameters, $\boldsymbol{w} = w_{ij}$. I will train the network on soft matter data including classical benchmark data for rubber[94], data from our collaborators for skin[54,89], arteries[59], and the heart[34], and our own data for human brain[10-13]. I will minimize the loss function, $L(\boldsymbol{w};\boldsymbol{F}) = ||\boldsymbol{P}(\boldsymbol{F}) - \boldsymbol{P}||^2 / n_{train} \rightarrow \min$, the error between model $\boldsymbol{P}(\boldsymbol{F})$ and data $\{\boldsymbol{F}, \boldsymbol{P}\}$ divided by the number of training points n_{train}, using the Adam optimizer. While our preliminary results[54] in Figure 1 suggest that we can robustly and repeatedly discovery a small subset of non-zero network weights that define model selection and parameterization, there is a chance that the discovery process identifies a large set of terms or becomes non-unique. To mitigate this limitation and reduce the risk of overfitting, I will apply L1 and L2 regularization, $L(\boldsymbol{w};\boldsymbol{F}) = ||\boldsymbol{P}(\boldsymbol{F}) - \boldsymbol{P}||^2/n_{train} + \alpha_1\, ||\mathbf{w}||_1 + \alpha_2\, ||\mathbf{w}||_2^2 \rightarrow \min$, by supplementing the loss function with the weighted L1 norm $||\mathbf{w}||_1$ or the weighted L2 norm $||\mathbf{w}||_2^2$. We have shown that increasing the parameters α_1 and α_2 reduces the number of non-zero weights and with it the number of activated terms[53,87]. The small subset of non-zero weights, the four blue terms in Figure 1, define the best model[53]. Our new 28-term network will discover this model from 2^{28} = 268,435,456 possible combinations of terms, from more than 250 million possible models! Importantly, our network weights naturally translate into meaningful parameters with physical units and a real physical interpretation. My rationale for using machine learning to automate model selection is that this allows us to rapidly screen millions of possible models, confirm existing models, and autonomously discover new combinations of terms, which are out of reach for conventional manual decision making today.

The ***deliverables*** of WP1 are: (i) a general concept to hardwire physical knowledge into a neural network design; (ii) a new family of constitutive neural networks for incompressible, hyperelastic materials; (iii) a set of mechanistically interpretable network weights that are intrinsically related to traditional invariant- and principal-stretch-based parameters; and (iv) a new open-source discovery platform to autonomously discover model, parameters, and experiments for soft matter systems that I will make publicly available on GitHub @LivingMatterLab. I expect that our custom-designed networks will induce a paradigm shift in constitutive modeling, from user-defined to fully automated, to make modeling accessible to a more inclusive and diverse community and accelerate scientific discovery and innovation.

WP 2. Train, test, and validate our discovered models on previously unseen data for the heart, arteries, muscle, lung, liver, skin, brain, hydrogels, silicone, artificial meat, foams, and rubber.

Benchmarking material models is critical to quantify their performance and accuracy against other models and evaluate their potential to solve real-world problems. To date, most constitutive neural networks are benchmarked against artificial synthetic data, but their true performance on noisy and incomplete real world-data remains insufficiently understood. The ***objective*** of this work package is to perform a series of tension, compression, and shear experiments on a variety of soft materials to train, test, and validate our model. ***My hypothesis is that our discovered models will outperform popular existing models and generalize robustly to previously unseen data in the spirit of continuous learning.***



My ***scientific approach*** to test this hypothesis is to perform a comprehensive series of benchmark experiments to generate new, previously unseen data for network training, testing, and validation. We will train ourselves in multiaxial soft tissue testing during research visits to Professor Gerhard Holzapfel's group at TU Graz. I will then purchase the same triaxial testing device (Zwick/Roell, Ulm, Germany) to perform *new* tension, compression, and shear experiments on up to 5x5x5mm^3 large cubic specimens of both natural and man-made soft materials following our previous protocols[10-12]. As Figure 1 indicates, I will expand our existing benchmark library for rubber[52], skin[47,54], and brain[53] on GitHub @LivingMatterLab, and successively add new experimental data on the heart[34,76], arteries[51,59], muscle[73-75,102], lung[17,18], liver, hydrogels, silicone, artificial meat, and foams. To address the limitation of incompressibility and isotropy of our networks from WP1, I will now add the third, fourth, and fifth invariants[29,84], I_3, I_4, I_5, to our network architecture[54], and discover the best model, parameters, and experiments across all data in our open source library. For comparison, I will then constrain all but a few selected network weights to zero, and use our network to learn the best parameters of popular constitutive models including neo Hooke[95] with $\psi = ½\,\mu\,[I_1\text{-}3]$, Demiray[14] with $\psi = ½\,a/b\,[\exp(b[I_1\text{-}3])\text{-}1]$, Gent[24] with $\psi = \text{-}½\,\alpha/\beta\,\ln(1\text{-}(\beta[I_1\text{-}3]))$, Holzapfel[32] with $\psi = ½\,a/b\,[\exp(b[I_4\text{-}3])^2\text{-}1]$, and Blatz Ko[7] with $\psi = ½\,\mu\,[I_2\text{-}3]$. I will quantify the performance of model discovery using the coefficients of determination and normalized root mean squared errors, and compare our discovered models against these and other popular existing models. The goodness of fit R^2 in Figure 1 suggests that our newly discovered model in grey consistently outperforms these models, in dark red, red, light red, orange, and green[53]. The rationale for systematic benchmarking with traditional models is that this will confirm successful existing models, identify shortcomings in others, and build trust in our newly discovered models.

The ***deliverables*** of WP2 are: (i) a comprehensive experimental data sets of soft matter systems including the heart, arteries, muscle, lung, liver, skin, brain, hydrogels, silicone, artificial meat, foams, and rubber; (ii) a suite of newly discovered models and parameters for natural and man-made soft materials; (iii) a quantitative performance evaluation of our newly discovered models compared to existing traditional models; and (iv) new mechanistic insight into the fundamental building blocks of constitutive models for soft matter systems. I expect that our open source benchmark library, with dozens of new data sets, models, and parameters, will become a standard go to reference that will increase collaboration, reusability, transparency, and learning opportunities that will benefit both individual soft matter modelers and the mechanics community at large.

WP 3. Quantify the uncertainty of our models, parameters, and experiments by embedding our networks into a Bayesian analysis to discover parameter distributions and credible intervals.

Neural networks have been successfully used to fit stress-stretch curves to data; yet, to date, no unified concept exists to interpret the data, model, and parameters in view of uncertainty quantification. The ***objective*** of this work package is to establish a family of Bayesian constitutive neural networks to discover models, parameters distributions, and credible intervals for uncertainty quantification. ***My hypothesis is that by embedding our networks into a Bayesian framework, our deterministic models, and parameter point estimates from WP1 and WP2 will seamlessly translate into probabilistic models and parameter distributions for uncertainty quantification.***

My ***scientific approach*** to test this hypothesis is to embed our trained neural networks into a Bayesian analysis[37,38,50,81,82] and iteratively improve them by gradually adding new data. Specifically, the Bayesian analysis will infer the best probabilistic model, posterior parameter distributions, $p(\boldsymbol{\vartheta}|\boldsymbol{P}) = p(\boldsymbol{P}|\boldsymbol{\vartheta}) \,/\, \mathrm{p}(\boldsymbol{\vartheta}) \,.\, \mathrm{p}(\boldsymbol{P})$, and experiment to explain our previous data[45]. This discovery step will inform the design of new experiments with the highest possible degree of information. We will perform these discovered experiments, use the new data to update our prior probability distributions, $\mathrm{p}(\boldsymbol{\vartheta})$, and start a new learning cycle. Our Bayesian approach is a form of continuous learning[45] that inherently provides uncertainty quantification[6,48,61,77]. My rationale is that the weights of our Bayesian networks represent well-defined physical parameters with means and credible intervals that will progressively narrow as more data become available. I will successively add our new experimental data, probabilistic models, and parameter distributions to our open source library on GitHub @LivingMatterLab, and, ultimately, integrate all knowledge into a single universal material subroutine for finite element simulations.

The ***deliverables*** of WP3 are: (i) a novel iterative technology to seamlessly integrate experiment and computation using Bayesian constitutive neural networks; (ii) a suite of newly discovered probabilistic models and parameter distributions for a wide variety of natural and man-made soft materials; (iii) a fully trained, tested, and validated continuously learning discovery platform for soft matter systems; and (iv) a universal material subroutine for finite element simulations that will replace dozens of individual material-specific subroutines. I expect that our discovery platform will not only accurately reproduce and predict the behavior of soft material systems in complex real-life situations, but also provide a more complete picture of model uncertainties and support a more robust and reliable decision making.

IV. GROUND-BREAKING NATURE AND HIGH-RISK/HIGH-GAIN ASSESSMENT

Soft matter systems are neither traditional solids nor liquids. They exhibit complex and tunable behaviors, which make them highly suitable for a wide range of applications in biomedicine, pharmaceutics, food science, energy storage, soft robotics, and wearable electronics. ***This project addresses the critical need to understand the unique behavior of soft materials through automated model discovery, a ground-breaking new paradigm to autonomously discover the model, parameters, and experiment that best explain soft matter systems***. Clearly, this is a timely but very ambitious, high-risk goal that would have been unthinkable several years ago: It integrates cutting-edge developments in constitutive modelling and soft matter physics[20,21,35,66,89] with recent discoveries in deep learning and artificial intelligence[1,41,46,52,67,71,90]. Throughout my career, I have pioneered technologies to test, model, and simulate soft materials[15,16,19,27,28,43,44,79,91,97,98,102] and fit these models to data[9-13,22,23,30,62,65,78,80,86,99-101]. However, it is becoming increasingly clear that this approach provides only limited insight into the complex behavior of soft materials. To gain a more holistic understanding, I propose to establish an open source discovery platform that I will share with students, scientists, and industries across all disciplines to advance our collective understanding of soft matter systems. As a founding member of the Living Heart Project, an open source translational research initiative to revolutionize cardiovascular science through realistic simulation, I have a successful track record in partnering with more than 400 participants from research, medicine, industry, and regulatory agencies from more than two dozen countries[4,22,23,62,63,68,76,77,78,86,91]. Similar to the Living Heart Project, ***this project has the potential for high gain, as it aims to enable everyone—not just a few well-trained specialists—to accurately model and simulate soft matter systems.*** To mitigate the potential high risk that this project is too visionary to work, I have prototyped my scientific approach for rubber[52], skin[54,89], and human brain[53,87]. I envision that generalizing this concept to other soft materials is conceptually feasible and straightforward. ***To ensure high gain and translate the results of this project into practise, I have partnered with Abaqus FEA/Simulia to create a single universal user material subroutine that will replace dozens of individual model-specific subroutines.*** This new subroutine takes our network output as input and entirely eliminates the critical step of model selection in a finite element analysis. To address the high risk that this subroutine does not generalize well to other materials, I will crowdsource a large lay audience of potential users in engineering classes, workshops, and summer schools. I am confident that integrating science and education by crowdsourcing will gradually make our discovery platform more robust and user-friendly, and create a broader and more inclusive user community. ***This project has the potential to induce a ground-breaking change in constitutive modeling—from user-defined model selection to automated model discovery—which would forever change how we simulate materials and structures.***

V. REQUESTED RESOURCES

I am currently the Robert Bosch Chair of Mechanical Engineering at Stanford University. This ERC Advanced Grant will allow me to gradually transition back to Europe: During the first two years, I will spend half of my time, sabbaticals and teaching-free summers, at the FAU Erlangen. In year three, my family plans to return to Europe fulltime. This project requests part-time support for myself, two postdocs, a part-time staff member, a triaxial testing device (Zwick/Roell, Ulm, Germany), and research visits to the TU Graz to collaborate with Professor Gerhard Holzapfel on soft tissue testing and modelling.

Literature [Kuhl's students and postdocs underlined]

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80. Schafer A, Chaggar P, Thompson TB, Goriely A, **Kuhl E** (2021) Predicting brain atrophy from tau pathology: a summary of clinical findings and their translation into personalized models. Brain Multiphysics. 2: 100039.
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82. Schafer A, Chaggar P, Goriely A, **Kuhl E** (2022) Correlating tau pathology to brain atrophy using a physics-based Bayesian model. Engineering with Computers 38: 3867-3877.
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90. Thakolkaran P, Joshi A, Zheng Y, Flaschel M, De Lorenzis L, Kumar S (2022) NN-EUKLID: Deep-learning hyperelasticity without stress data. Journal of the Mechanics and Physics of Solids 169: 105076.
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103. Zopf C, Kaliske M (2017) Numerical characterisation of uncured elastomers by a neural network based approach. Computers and Structures 182: 504-525.

Section b: Curriculum vitae

Personal Information

Family name, First name	Kuhl, Ellen	
Researcher unique identifiers	Google Scholar	jjQDKYYAAAAJ
	ORCID	0000-0002-6283-935X
	Researcher ID	G-4444-2011
	Scopus ID	7004398913
	Research Gate	Ellen-Kuhl
Date of birth, Nationality	15.08.1971, German	
URL for web site	https://livingmatter.stanford.edu	

Education

2004	Habilitation	Mechanical Engineering, Technical University of Kaiserslautern, Germany
2000	PhD	Civil Engineering, University of Stuttgart, Germany
1995	MS	Civil Engineering, Leibniz University of Hannover, Germany
1993	BS	Computational Engineering, Leibniz University of Hannover, Germany

Current Positions

2021 -	Walter B. Reinhold Professor in the School of Engineering, Stanford University, Stanford
2019 -	Robert Bosch Department Chair of Mechanical Engineering, Stanford University, Stanford
2016 -	Professor of Mechanical Engineering and Bioengineering, Stanford University, Stanford

Previous Positions

2010 - 2016	Associate Professor of Mechanical Engineering, Stanford University, Stanford, California
2011 - 2011	Professor of Mechanical and Process Engineering, ETH Zurich, Switzerland
2007 - 2009	Assistant Professor of Mechanical Engineering, Stanford University, Stanford, California
2002 - 2006	Assistant Professor of Mechanical and Process Engineering, TU Kaiserslautern, Germany
2001 - 2002	Habilitation Researcher, Mechanical and Process Engineering, TU Kaiserslautern, Germany
2000 - 2001	Postdoctoral Researcher, Aerospace Engineering, TU Delft, the Netherlands
1996 - 2000	Graduate Researcher, Civil Engineering, University of Stuttgart, Germany
1995 - 1996	Graduate Researcher, Civil Engineering, Leibniz University of Hannover, Germany

Awards and Fellowships

2021	Ted Belytschko Applied Mechanics Award; American Society of Mechanical Engineers (ASME)
2017	Fellow; American Society of Mechanical Engineers (ASME)
2016	Humboldt Research Award; Alexander von Humboldt Foundation
2014	Fellow; American Institute for Medical and Biological Engineering (AIMBE)
2014	Midwest Mechanics Seminar Speaker
2010 - 2014	CAREER Award; National Science Foundation (NSF)
2009	Hellman Faculty Scholar
2001 - 2004	Habilitation Research Award; German National Science Foundation (DFG)
1996 - 1999	Graduate Research Fellowship; German National Science Foundation (DFG)

Supervision of Graduate Students and Postdoctoral Fellows

2002 – 2023 Doctorates: 14 completed and 6 ongoing; Postdoctorates: 9 completed and 1 ongoing

Teaching Activities (Selection)

2007 - 2023	Statics, Finite Element Analysis, Continuum Mechanics, Introduction to Neuromechanics, Mechanics of the Cell, Mechanics of the Brain, Mechanics of Growth; Data-Driven Modeling of Covid-19, Automated Model Discovery; Stanford University, California
2017, 2019	Introduction to Neuromechanics; FAU Erlangen Nuremberg, Germany
2011	Mechanics I; ETH Zurich, Switzerland
2001 - 2006	Mechanics II Strength of Materials, Linear and Nonlinear Continuum Mechanics, Linear and Nonlinear Finite Element Methods, Biomechanics; TU Kaiserslautern, Germany
2012, 2018	Modeling of Living Matter; 5th and 8th Summer School on Biomechanics; TU Graz, Austria

2017	Growth and Remodeling; 23rd CISM-IUTM International Summer School; Udine, Italy
2003	Open Systems and Growth, Commas Summer School; University of Stuttgart, Germany

Institutional Responsibilities (Selection / Most Recent)

2022 -	Member, Bio-X Leadership Council; Stanford
2021 -	Member, Wu Tsai Human Performance Alliance Executive Committee; Stanford
2019 -	Chair, Department of Mechanical Engineering; Stanford
2019 -	Member, School of Engineering Executive Committee; Stanford
2014 -	Member, Department of Mechanical Engineering, Advisory Committee; Stanford
2020 - 2022	Chair, Department of Mechanical Engineering Strategic Planning Committee; Stanford
2018 - 2019	Chair, Department of Mechanical Engineering Graduate Admission Committee; Stanford
2017 - 2018	Chair, Department of Mechanical Engineering Graduate Curriculum Committee; Stanford
2017 - 2018	Member, Stanford University Long-Range Planning Steering Group Research; Stanford
2016 – 2017	Member, Stanford University Leading the Biomedical Revolution; Stanford
2015 – 2017	Fellow, Stanford University; Stanford
2015 - 2016	Chair, Department of Mechanical Engineering Faculty Search Committee; Stanford

Professional Service (Selection / Most Recent)

2020 -	Member-Elect, Expertengremium für Exzellenzstrategie, German Science Foundation (DFG)
2018 -	Chair, US National Committee on Biomechanics (USNCB)
2018 -	Member-Elect, World Council of Biomechanics (WCB)
2020 - 2022	Chair TTA Data-Driven Modeling, US Association for Computational Mechanics (USACM)
2016 - 2018	Member-at-Large, US Association for Computational Mechanics (USACM)
2016 - 2018	Vice Chair, US National Committee on Biomechanics (USNCB)
2016 - 2018	Member, NIH IMAG Interagency Modeling Analysis Group Steering Committee (IMAG)
2015 - 2019	Chair TTA Biological Systems, US Association for Computational Mechanics (USNCM)
2014 - 2016	Secretary and Treasurer, US National Committee on Biomechanics (USNCB)

Review Activities (Selection)

2018	German National Science Foundation (DFG) ING Excellence Initiative Panel
2017	German National Science Foundation (DFG) ING Excellence Initiative Panel
2012	German National Science Foundation (DFG) ING Excellence Initiative Panel
2012 - 2018	National Institutes of Health (NIH) Mod Anal Bio Systems (MABS) Study Section Member
2012 - 2014	American Heart Association (AHA), Bioengieering , Basic Sciences, Peer Review Study Group
2012 -	Qatar National Research Fund (QNRF) Division of Engineering
2011 -	National Science Foundation (NSF) CMMI Biomech Model Mechanobio (BMMB) CAREER
2010 -	National Science Foundation (NSF) CMMI Mech Materials Structures (MOMS) CAREER
2009 -	Stanford Bio-X Interdisciplinary Initiative Seed Grants (Bio-XIIP) V-X; Rounds I and II
2009 -	Swiss National Science Foundation (SNF) Divisions of Med, Eng Sci, Math Nat Sci, …
2009 -	Israel National Science Foundation (ISF) Division of Engineering
2007 -	National Science Foundation (NSF) BMMB, MOMS, CBET, CDSE, DMS, DCI, ENG, PHY, EFRI, …
2006 -	German National Science Foundation (DFG) Divisions of Eng Sci, Life Sci, SFB 926, …

Membership of Professional Societies

APS	American Physical Society
ASME	American Society of Mechanical Engineers
BMES	Biomedical Engineering Society
ESB	European Society of Biomechanics
EUROMECH	European Mechanics Society (EUROMECH), Member
IACM	International Association for Computational Mechanics
USACCM	US Association for Computational Mechanics

Other

2018 –	All American Triathlete
2019 - 2023	Ironman Word Championship Qualifier; Kailua Kona, Hawaii
2009 - 2023	Marathon Runner; Berlin, Boston, Chicago, New York, San Francisco, Zurich

Appendix: All on-going grants and submitted grants applications of the PI (Funding ID)

On-going grants

Project Title	Funding source	Amount (Euros)	Period	Role of the PI	Relation to current ERC proposal
1663671 SI2-SSI Collaborative Research: The SimCardio open source multi-physics cardiac modelling package	National Science Foundation NSF	$1,431,169	6 years -2023	Co-Principal Investigator	None: Project develops open source software package for physics-based multi-scale cardiac simulations in health and disease from medical images
Wu Tsai Performance Alliance; Moonshot 1: The Digital Athlete	Joe and Clara Tsai Foundation	Public-private partner-ship supported through a total donation of $220M	10 years -2031	Co-Principal Investigator	None: Project creates open source predictive computer models to guide training and treatment for athletes to better understand human health

Submitted grant applications

Project Title	Funding source	Amount (Euros)	Period	Role of the PI	Relation to current ERC proposal
Mechanics of Bioinspired Soft Slender Actuators	National Science Foundation NSF	$650,000	3 years	Principal Investigator	None: Project would seek to understand soft biomimetic robots inspired by the elephant trunk through modeling, simulation, and experiment
Automated Model Discovery for Soft Matter	National Science Foundation NSF	$400,000	3 years	Principal Investigator	None: Project would prototype different strategies for model discovery; it could inform Aim 1 of this project, but there would be no direct overlap

Section c: Ten years track-record

Top 10 publications since 2013 (Google Scholar h-index 5/23: 77, 19,000 citations in total)

1. Budday S, Nay R, de Rooij R, Steinmann P, Wyrobek T, Ovaert TC, Kuhl E. Mechanical properties of gray and white matter brain tissue by indentation. J Mech Behavior Biomed Mat 2015; 46: 318-330; 568 citations
2. Budday S, Sommer G, Birkl C, Langkammer C, Hayback J, Kohnert J, Bauer M, Paulsen F, Steinmann P, Kuhl E, Holzapfel GA. Mechanical characterization of human brain tissue. Acta Biomat 2017; 48: 319-340; 433 citations.
3. Goriely A, Geers MGD, Holzapfel GA, Jayamohan J, Jerusalem A, Sivaloganathan S, Squier W, van Dommelen JAW, Waters S, Kuhl E. Mechanics of the brain: Perspectives, challenges, and opportunities. Biomech Modeling Mechanobio 2015; 14: 931-965; 350 citations.
4. Linka K, Peirlinck M, Sahli Costabal F, Kuhl E. Outbreak dynamics of COVID-19 in Europe and the effect of travel restrictions. Comp Meth Biomech Biomed Eng 2020; 23: 710-717; 343 citations.
5. Baillargeon B, Rebelo N, Fox DD, Taylor RL, Kuhl E. The Living Heart Project: A robust and integrative simulator for human heart function. Eur J Mech A/Solids 2014; 48: 38-47; 290 citations.
6. Alber M, Buganza Tepole A, Cannon W, De S, Dura-Bernal S, Garikipati K, Karniadakis G, Lytton WW, Perdikaris P, Petzold L, Kuhl E. Integrating machine learning and multiscale modeling: Perspectives, challenges, and opportunities. npj Digital Medicine 2019; 2:115; 289 citations.
7. Budday S, Steinmann P, Kuhl E**.** Physical biology of human brain development. Front Cell Neurosci 2015; 9: 257.1-17; 287 citations.
8. Budday S, Ovaert TC, Holzapfel GA, Steinmann P, Kuhl E. Fifty shades of brain: A review on the material testing and modeling of brain tissue. Arch Comp Mth Eng 2020; 27: 1187-1230; 229 citations.
9. Budday S, Steinmann P, Kuhl E**.** The role of mechanics during brain development. J Mech Phys Solids 2014; 72: 75-92; 219 citations.
10. Sahli Costabal F, Yang Y, Perdikaris P, Hurtado DE, Kuhl E. Physics-informed neural networks for cardiac activation mapping. Front Physiology 2020; 8: 42; 210 citations.

Book Publications

1. Kuhl E. Computational Epidemiology – Data-Driven Modeling of COVID-19, Springer Nature New York, ISBN 978-3-030-82889-9, 2021.
2. De S, Wang W, Kuhl E. (Eds.) Multiscale Modeling in Biomechanics and Mechanobiology, Springer Science + Business Media Dordrecht. ISBN 978-1-4471-6598-9, 2015.

Plenary Lectures since 2013 (Selection from > 250 Scientific Presentations)

1. Mechanics meets Machine Learning – What can we learn? Plenary Lecture, 92nd Annual Meeting of the Int'l Association of Applied Mathematics and Mechanics (GAMM), 16/08/2022, Aachen, Germany.
2. Opportunities for Machine Learning in Computational Mechanics. Semi-Plenary Lecture, 15th World Congress on Computational Mechanics (WCCM-XV), 02/08/2022, Yokohama, Japan.
3. Mechanics meets Machine Learning: What can we learn? Plenary Lecture, 11th European Solid Mechanics Conference (ESMC), 06/07/2022, Galway, Ireland.
4. Data-Driven Modeling and Physics-Based Learning in the Biomedical Sciences. Plenary Lecture. 19th US National Congress on Theoretical and Applied Mechanics (USNCTAM), 21/06/2022, Austin, Texas.
5. Data-Driven Modeling of Neurodegeneration. Plenary Lecture. 7th Int'l Symposium on Computer Methods in Biomechanics and Biomedical Engineering (CMBBE2021), 07/09/2021, Bonn, Germany.
6. The Multiphysics of Neurodegeneration. Plenary Lecture. 16th U.S. National Congress on Computational Mechanics (USNCCM), 28/07/2021, Chicago, Illinois.
7. Neuromechanics: Challenges and Opportunities. Plenary Lecture, InterPore 2017, 09/05/2017, Rotterdam, the Netherlands.
8. Neuromechanics: Perspectives, Challenges, and Opportunities. Plenary Lecture, Engineering Mechanics Institute (EMI) 2017 Conference, 20/03/2017, Rio de Janeiro, Brazil.
9. Neuromechanics: Challenges and Opportunities. Semi-Plenary Lecture, 12th World Congress on Computational Mechanics (WCCM), 26/07/2016, Seoul, Korea.
10. Mechanics of the Developing Brain. Plenary Lecture, Computer Methods in Biomechanics and Biomedical Engineering (CMBBE), 13/10/2014, Amsterdam, the Netherlands.

Former Trainees and Current Academic Affiliations

Swantje Bargmann	Professor	University of Wuppertal	Wuppertal, Germany
Silvia Budday	Professor	FAU Erlangen-Nuremberg	Erlangen, Germany
Adrian Buganza Tepole	Associate Professor	Purdue University	West Lafayette, Indiana
Hüsnu Dal	Associate Professor	Middle East Technical University	Ankara, Turkey
Mona Eskandari	Assistant Professor	University of California	Riverside, California
Nele Famaey	Professor	KU Leuven	Leuven, Belgium
Martin Genet	Assistant Professor	Ecole Polytechnique, Palaiseau	Paris, France
Serdar Göktepe	Associate Professor	Middle East Technical University	Ankara, Turkey
Maria Holland	Assistant Professor	University of Notre Dame	South Bend, Indiana
Julia Mergheim	Professor	FAU Erlangen-Nuremberg	Erlangen, Germany
Lise Noël	Assistant Professor	Technical University of Delft	Delft, The Netherlands
Mathias Peirlinck	Assistant Professor	Technical University of Delft	Delft, The Netherlands
Manuel Rausch	Associate Professor	University of Texas	Austin, Texas
Pablo Saez	Assistant Professor	UPC Catalunya	Barcelona, Spain
Francisco Sahli Costabal	Assistant Professor	Pontificia Universidad Catolica	Santiago, Chile
Alkiviadis Tsamis	Assistant Professor	University Western Macedonia	Kozani, Greece
Johannes Weickenmeier	Assistant Professor	Stevens Institute of Technology	Hoboken, New Jersey

Service as Editor

2015 -	Journal of the Mechanics and Physics of Solids, Associate Editor
2015 -	Annals of Biomedical Engineering, Associate Editor
2012 - 2016	ASME Applied Mechanics Reviews, Associate Editor

Service as Editorial/Advisory Board Member

2022 -	Computer Methods Applied Mechanics Engineering, Editorial Advisory Board Member
2020 -	Computational Mechanics, Editorial Advisory Board Member
2020 -	Brain Multiphysics, Editorial Board Member
2015 -	Biomechanics and Modeling in Mechanobiology, Editorial Board Member
2013 - 2015	Journal of the Mechanics and Physics of Solids, Editorial Advisor
2012 -	Journal of Computational Surgery, Editorial Board Member
2011 -	Int'l Journal for Numerical Methods in Biomedical Engineering, Editorial Board Member
2011 -	Computer Methods in Biomechanics and Biomedical Engineering, Editorial Board Member
2011 -	Acta Mechanica Sinica, Editorial Board Member

Guest-Editor of Special Issues: Computational Mechanics, Current Opinion in Biomedical Engineering, Computer Methods in Applied Mechanics and Engineering, Annals of Biomedical Engineering, Journal of the Mechanical Behavior of Biomedical Materials, Mechanics Research Communications, International Journal of Multiscale Computational Engineering, Philosophical Transactions of the Royal Society London, Computer Methods in Biomechanics and Biomedical Engineering

Conference Organization (Selection)

23-28/08/20	Special Session Epidemiology of Covid-19, Virtual Physical Human (VPH2020); Paris, France
19-24/07/20	Minisymposia MS87, MS319, 13th World Congress Comp Mech (WCCM); Paris, France
23-24/10/19	Integrating Machine Learning with Multiscale Modeling, Conference Chair; NIH, Maryland
04-09/06/18	Symposium B-11; 16th Comp Meth Biomech Biomed Engineering (CMBBE); New York
04-09/06/18	Minisymposium MS361; 18th US Nat Congress Theor Mech (USNC/TAM); Chicago, Illinois
24-29/07/16	Minisymposia MS6, MS10, MS17, 12th World Congress Comp Mech (WCCM); Seoul, Korea
14-19/02/16	New Challenges in the Physics of the Brain; Ecole de Physique des Hoches, France
01-07/11/15	Workshop 1545 Mathematics of Growth; Math Research Center Oberwolfach, Germany
20-25/07/15	Minisymposium MS102, 13th US Nat Congress Comp Mech (USNCCM); San Diego, California
20-25/07/14	Minisymposia MS7,MS97,MS106,11th World Congress Comp Mech (WCCM); Barcelona, Spain
06-11/07/14	World Congress of Biomechanics (WCB) Track: Organ Biomechanics; Boston, Massachusetts
13-14/02/14	Multiscale Methods and Validation in Medicine and Biology II (MMVMB); Berkeley, California
22-24/05/13	Euromech 545: Frontiers in Finite-Deformation Electromechanics; Dortmund, Germany