Mini Review
Volume 17:3, 2023

Journal of Generalized Lie Theory and Applications

ISSN: 1736-4337 Open Access

EUCLID Allows for the Automated Discovery of Generalized Standard Material Models

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Abstract

The general case of a material belonging to an unknown class of constitutive behavior is the focus of our recently developed EUCLID method for unsupervised automated discovery of material laws. To this end, we influence the hypothesis of summed up standard materials, which envelops a plenty of significant constitutive classes including flexibility, thickness, versatility and erratic blends thereof. That's what we show, dependent just upon full-field kinematic estimations and net response powers, EUCLID can naturally find the two scalar thermodynamic possibilities, to be specific, the Helmholtz free energy and the dissemination potential, which totally characterize the way of behaving of summed up standard materials.

Keywords: Inverse limit • Natural extension • Hénon family • Lozi family • Strange attractor

Introduction

Construction stability and thermodynamic consistency of the discovered model are guaranteed by the a priori enforced constraint of convexity on these potentials; In place of the availability of labeled pairs for stress and strain, the balance of linear momentum serves as a fundamental constraint; sparsity advancing regularization empowers the programmed determination of a little subset from a conceivably enormous number of up-and-comer model elements and subsequently prompts a miserly, i.e., straightforward and interpretable, model. Importantly, sparse regression automatically induces a sparse selection of the few internal variables required for an accurate but straightforward description of the material behavior because model features are associated with the correspondingly active internal variables. In order to achieve a user-defined balance between model accuracy and simplicity, the hyperparameter controlling the weight of the sparsity promoting regularization term is selected through a procedure that is completely automated. We show that EUCLID can automatically identify the true hidden material model from a wide range of constitutive classes, including elasticity, viscoelasticity, elastoplasticity, viscoplasticity, isotropic and kinematic hardening, by testing the method on synthetic data with artificial noise [1].

Literature Review

In solid mechanics, the traditional method of mathematically describing a material's response is to select an a priori material model based on a limited number of tunable parameters and calibrate these parameters using experimental data. The calibrated material model can then be used in numerical (for example, finite element) simulations to predict the mechanical response of material components of any shape to external influences by describing the relationship between stresses and strains and possibly other material state variables [2].

The most fragile part of this system lies in the deduced choice of a reasonable model, which is to a great extent founded on experience. Failure to identify a set of material parameters that enable the model to accurately represent the experimental data is inevitable when an inappropriate initial choice is made; In such a scenario, the initial choice must be altered and the procedure must be repeated, possibly multiple times, resulting in an iterative process that is both time-consuming and prone to error. Data-driven approaches, frequently based on machine learning tools, are increasingly being investigated for applications in solid mechanics, particularly material modeling, facilitated by the enormous amount of data made available by recent advances in experimental mechanics [3,4].

Choosing a parametric material model ansatz that is as general as possible, i.e., with a large number of tunable parameters, is a common method for mitigating the negative effects of an inappropriate a priori model selection. Splines, neural ordinary differential equations and neural processes are all examples. These kinds of model ansatz are less likely to fail to accurately interpret the observed data because they have a greater number of trainable parameters and functions that describe the material response. The performance of the resulting material models can be further enhanced by combining traditional and machine learning components. The recent trend of adding physics-based constraints to machine learning models is motivated by the recognition that constitutive models should not violate any well-known physical requirements. These are implemented either by development or from a frail perspective by acquainting extra regularization terms with the misfortune capability that punish the infringement of actual regulations. Convexity or polyconvexity in hyperelasticity, as well as the second law of thermodynamics for dissipative materials, are examples of constraints [5].

The referenced works show that the authorization of material science limitations enjoys the extra benefit of further developing the extrapolation force of AI based models. So-called (material) model-free data-driven approaches aim to solve boundary value problems by replacing the material model with experimental data, thereby avoiding the fitting of a parametric material model entirely. Here the displaying parts are restricted to the energy balance condition and the expected kinematics and hence are diminished to a base. See how an inverse formulation of the same problem can be used to recover stress fields from kinematic measurements [6].

Discussion

The current study opens the door to a number of intriguing new applications. The thermodynamic potentials model library could be expanded to include additional phenomena like anisotropy, heterogeneity, softening (which would need to take into account gradient terms), coupled thermo- or electromechanical effects and so on. This would be an important step in the right direction. Consider a self-adaptive library that automatically adds more features to the two thermodynamic potentials as long as the fitting accuracy is insufficient in order to automate the augmentation of the model library within the framework of generalized standard materials. As the inverse problem's constitutive equations become more complex with an increasing number of unknown parameters, improving computational efficiency is another important goal for the future. Using automatic differentiation

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Received: 20 May, 2023, Manuscript No. glta-23-105717; **Editor Assigned:** 22 May, 2023, PreQC No. P-105717; **Reviewed:** 13 June, 2023, QC No. Q-105717; **Revised:** 19 June, 2023, Manuscript No. R-105717; **Published:** 26 June, 2023, DOI: 10.37421/1736-4337.2023.17.393

would be helpful in easing the implementation of the constitutive equation solver for a large library of thermodynamic potentials.

Conclusion

However, as this paper explains, automatic differentiation currently implies a decrease in overall computational efficiency and necessitates regularization of the potentials. This issue could be addressed in the future. Last but not least, one important goal for the future would be to test EUCLID on experimental data.

Acknowledgement

None.

Conflict of Interest

No conflict of interest.

References

1. Perlis, Roy H. "A clinical risk stratification tool for predicting treatment resistance in major depressive disorder." *Biol Psychiatry* 74 (2013): 7-14.
2. Chekroud, Adam Mourad, Ryan Joseph Zotti, Zarrar Shehzad and Ralitza Gueorguieva, et al. "Cross-trial prediction of treatment outcome in depression: A machine learning approach." The Lancet Psychiatry 3 (2016): 243-250.
3. Hu, Chien-An, Chia-Ming Chen, Yen-Chun Fang and Shinn-Jye Liang, et al. "Using a machine learning approach to predict mortality in critically ill influenza patients: A cross-sectional retrospective multicentre study in Taiwan." *BMJ* 10 (2020): e033898.
4. Liu, Jialin, Jinfa Wu, Siru Liu and Mengdie Li, et al. "Predicting mortality of patients with acute kidney injury in the ICU using XGBoost model." *Plos One* 16 (2021): e0246306.
5. Heldt, Frank S., Marcela P. Vizcaychipi, Sophie Peacock and Mattia Cinelli, et al. "Early risk assessment for COVID-19 patients from emergency department data using machine learning." *Sci Rep* 11 (2021): 4200.
6. Jalil, Bushra, Giuseppe Riccardo Leone, Massimo Martinelli and Davide Moroni, et al. "Fault detection in power equipment *via* an unmanned aerial system using multi modal data." *Sensors* 19 (2019): 3014.

How to cite this article: Fischer, Véronique. "EUCLID Allows for the Automated Discovery of Generalized Standard Material Models." *J Generalized Lie Theory App* 17 (2023): 393.