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Data-Driven Computational Plasticity

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Abstract

The use of constitutive equations calibrated from data collected from adequate testing has been implemented successfully into standard solvers for successfully addressing a variety of problems encountered in SBES (simulation based engineering sciences). However, the complexity remains constantly increasing due to the more and more fine models being considered as well as the use of engineered materials. Data-Driven simulation constitutes a potential change of paradigm in SBES. Standard simulation in classical mechanics is based on the use of two very different types of equations. The first one, of axiomatic character, is related to balance laws (momentum, mass, energy...), whereas the second one consists of models that scientists have extracted from collected, natural or synthetic data. Data-driven simulation consists of directly linking data to computers in order to perform numerical simulations. These simulations will use universal laws while minimizing the need of explicit, often phenomenological, models. This work revisits our former work on data-driven computational linear and nonlinear elasticity and the rationale is extended for addressing computational inelasticity (viscoelastoplasticity).

Keywords: Computational plasticity, Computational inelasticity, Data-Driven, LATIN, Manifold learning

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1. Introduction

Big-data is becoming a key protagonist in our lives in many aspects, ranging from e-commerce to social sciences, mobile communications, healthcare, etc. However, very little has been done in the field of scientific computing, despite some very promising first attempts.

Advanced clustering techniques, for instance, not only help engineers and analysts, they become crucial in many areas where models, approximation bases, parameters, etc. are adapted depending on the local state (in space and time senses) of the system [1,2]. Machine learning needs frequently to extract the manifold structure in which the solution of complex and coupled engineering problems is living. Thus, uncorrelated parameters can be efficiently extracted from the collected data, the last coming from numerical simulations or experiments. As soon as uncorrelated parameters are identified (constituting the information level), the solution of the problem can be predicted at new locations of the parametric space, by employing adequate interpolation schemes [3,4]. On a different setting, parametric solutions can be obtained within an adequate framework able to circumvent the curse of dimensionality for any value of the uncorrelated model parameters [5].

This unprecedented possibility of directly determine knowledge from data or, in other words, to extract models from experiments in a automated way, is being followed with great interest in many fields of science and engineering. For instance, the possibility of fitting the data to a particular set of models has been explored recently in [6]. Closely related, Ortiz has developed a method that works without constitutive models, by finding iteratively the experimental data that best satisfies conservation laws [7]. In [8] authors followed a similar rationale extending the data-driven framework to nonlinear elasticity and inelasticity, where model-based simulations where replaced by data-driven simulations operating on a new kind of constitutive models defined directly from data. Thus, experiments become crucial because they are not only used for calibrating pre-assumed models (as it is the case in standard simulation approaches) but for driving directly simulations. Its main drawback is the huge amount of data required for running simulations. In the present work we will assume that all the needed data is available. We will not address the way of collecting data from adequate experiments and the use of eventual inverse techniques to enrich the behavior description, issues that will be reported in incoming works.

Usual model-based simulations proceeds by solving the equilibrium weak form defined in the domain Ω with boundary Γ

$$\int_{\Omega} \varepsilon\left(\mathbf{u}^*\right) : \sigma \ \mathrm{d}\mathbf{x} = \int_{\Gamma_t} \mathbf{u}^* \cdot \mathbf{t}_g \ \mathrm{d}\mathbf{x} \tag{1}$$

where $\Gamma = \Gamma_u \bigcup \Gamma_t$ ($\Gamma_u \bigcap \Gamma_t = \varnothing$) representing portions of the domain boundary where, respectively, displacements $\mathbf{u}_g$ (essential boundary conditions) and tractions $\mathbf{t}_g$ (natural boundary conditions) are enforced. In Eq. (1) $\mathbf{u}^*$ represents an arbitrary displacement field kinematically admissible (regular enough and satisfying the essential boundary conditions). In order to solve (1) a relationship linking kinematic and dynamic variables is required, the so-called constitutive equation. The simplest one, giving rise to linear elasticity, is known as Hooke's law (even if, more than a law, it is simply a model), and writes

$$\sigma = \lambda \mathrm{Tr}(\varepsilon)\mathbf{I} + \mu\varepsilon \tag{2}$$

where $\mathrm{Tr}(\bullet)$ denotes the trace operator, and λ and μ the two elastic coefficients. By introducing the constitutive model, Eq. (2), into Eq. (1), a problem is obtained that can be formulated entirely in terms of the displacement field $\mathbf{u}(\mathbf{x})$. By discretizing it, using for instance the standard finite element method, after performing numerically the integrals involved in Eq. (1), we finally obtain a linear algebraic system of equations, from which the nodal displacements can be obtained.

The biggest challenge could then be formulated as follows: *can simulation proceed directly from data by circumventing the necessity of establishing a mathematical expression of the constitutive model?*