Optimization of the specimen geometry for one-shot discovery of material models

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Abstract

We recently proposed an approach for Efficient Unsupervised Constitutive Law Identification and Discovery (EUCLID), which exploits machine learning tools such as sparse regression [1–4], Bayesian learning [5], or neural networks [6] to automatically discover material laws independent of stress data, but solely based on full-field displacement and global force data obtained from mechanical testing. The displacement field can be measured on the surface of a target specimen via digital image correlation (DIC).

An important feature of the approach is that, in principle, the discovery of the material law can be performed in a one-shot fashion, i.e., using only one experiment. However, this capability heavily relies upon the richness of the measured displacement data, i.e., their ability to probe the stress-strain space (where the stresses depend on the constitutive law being sought) to an extent sufficient for an accurate and robust discovery process. The richness of the displacement data and the robustness of the discovery process are in turn governed by the specimen geometry.

In the present study, we aim to optimally design the geometry of the target specimen via density-based topology optimisation approach. In this fashion, we perform automatic specimen design by maximising the robustness of the solution, i.e., the identified material parameters, given noisy displacement measurements from DIC. In this contribution, we shed light on the objective function, the topology optimisation framework, and a range of optimised topologies for orthotropic elasticity (see Fig. 1).

Keywords: Optimised specimen geometry; topology optimisation; discovery of material models; one-shot discovery.

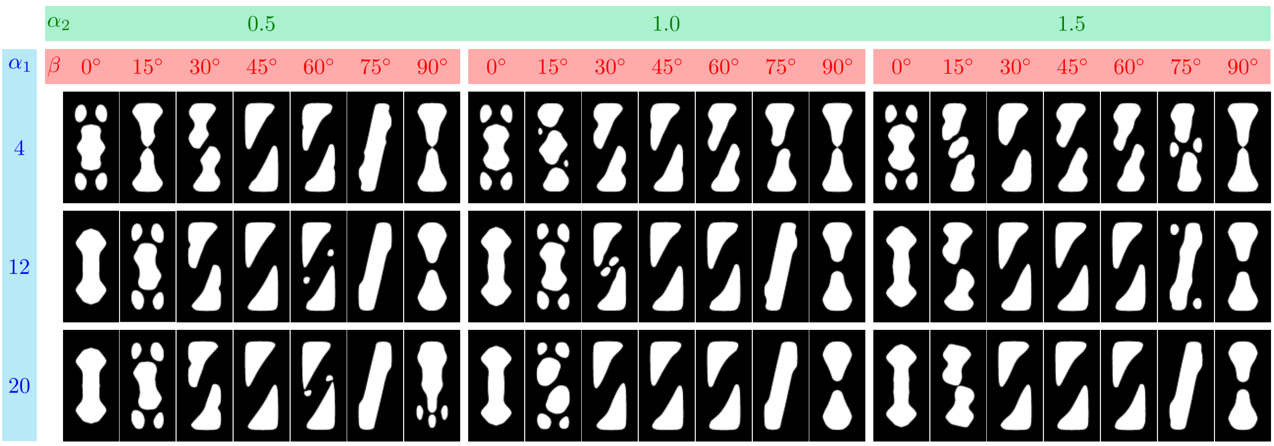

Fig. 1. Optimised topologies for different input orthotropic materials. Here, β is the anisotropy orientation, $\alpha_1 = E_{xx}/E_{yy}$ is the fibre-to-transverse Young's moduli ratio, and, $\alpha_2 = G_{xy}/G_{xy}^{sv}$ is the ratio of the shear modulus to the Saint-Venant's approximation $1/G_{xy}^{sv} = 1/E_{xx} + 1/E_{yy} + 2\nu_{xy}/E_{xx}$.

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