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An artificial intelligence approach to model nonlinear continua by intelligent meta-elements

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A data-driven "intelligent" meta-element that reduces the dimensionality and accelerates nonlinear finite element computations is demonstrated on an elastoplastic continuum frame.

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1 Introduction

Celebrating groundbreaking successes in pattern recognition and autonomous driving, methods from artificial intelligence have inspired research directions in the field of computational mechanics, such as surrogate models [1–3] and intelligent elements [4–8]. Current variants of intelligent elements can be classified into three categories: intelligent constitutive models [4], multiscaling [6, 9] and meta-elements [5, 7, 8]. Intelligent constitutive models focus on the integration points and approximate the material response. They excel at the low order curve-fitting problem of nonlinear material behavior, but do not accelerate simulations by dimensionality reduction. Intelligent multiscaling and smart elements introduce neural network surrogates for the micro models [6, 9]. Intelligent meta-elements approximate the response of entire continua and reduce the model dimensionality, but have been limited to linear and elastic problems so far [5, 7]. In the present contribution, a deep learning approach for intelligent meta-elements is demonstrated on a path-dependent elastoplastic problem.

2 Intelligent nonlinear meta-elements

Densely-connected feedforward neural networks are computational graphs of consecutive layers (l) implemented as

$$\boldsymbol{a}^{(l)} = \mathrm{f}^{(l)}\left(\boldsymbol{W}^{(l)}\boldsymbol{x}^{(l)} + \boldsymbol{b}^{(l)}\right) , \tag{1}$$

where $\boldsymbol{x}^{(l)}$ is the layer input, $\boldsymbol{a}^{(l)}$ the layer output, and $\mathrm{f}^{(l)}$ a usually non-linear activation function. In this work, the layer weight $\boldsymbol{W}^{(l)}$ and bias $\boldsymbol{b}$ parameters are trained using supervised learning. More advanced architectures share parameters by introducing convolutions for spatial or recursions for temporal problems. One convolutional-recurrent neural network architecture, the Time-distributed Recurrent U-Net, has been successfully employed for path-dependent problems [8].

The intelligent element IE is a neural network with L layers that maps element boundary displacements $\boldsymbol{u}^{\partial\Omega_e}_{t+1}$ to the internal displacement response $\boldsymbol{u}^e_{t+1}$, stress field $\boldsymbol{\sigma}^e_{t+1}$, and restoring force $\boldsymbol{f}^e_{t+1}$:

$$\mathrm{IE}: \quad \boldsymbol{u}^{\partial\Omega_e}_{t+1} \quad \xrightarrow{\boldsymbol{\theta}} \quad \left[\boldsymbol{u}^e_{t+1}, \quad \boldsymbol{\sigma}^e_{t+1}, \quad \boldsymbol{f}^e_{t+1}\right]^\mathsf{T} \quad \text{with} \quad \boldsymbol{\theta} = \left\{\left(\boldsymbol{W}^{(l)}, \boldsymbol{b}^{(l)}\right) \quad \forall\, l = 1 \dots L\right\} . \tag{2}$$

The meta-element stiffness is computed a priori with a Craig-Bampton approach [5, 7, 8]. By directly computing the integrated restoring force for a large continuum patch, the number of degrees of freedom of the finite element model is reduced. Pre- and postprocessing of the inputs and outputs involved a grid-encoding of the discretized element [8], feature standardization, iteration cycling [8], and sequence masking.

3 Numerical demonstration

Independent of the general loading and assembled geometry, the intelligent meta-element is trained on randomly generated single-element samples subjected to generalized loading cases [8]. Training followed the same strategy and algorithms, as outlined in [8]. It resulted in mean square errors in the order of $7 \cdot 10^{-4}$ for the training, validation, and test sets. The training was only performed on the training set, the validation set was used to tune the hyperparameters of the learning algorithm, and the test set was evaluated only after training and tuning were complete. Neither data set included samples from the following case study, ensuring a generalized intelligent meta-element applicable to a wide variety of problems.

This case study demonstrates the use of intelligent meta-elements in a continuum model of a frame with width $4\,\mathrm{mm}$, height $3\,\mathrm{mm}$, and section width $1\,\mathrm{mm}$. Perfect elastoplastic material behavior under plane strain and small deformations are assumed. A combined maximum displacement of the top of $u_1^{\mathrm{top}}(t=1) = 3.5 \cdot 10^{-3}\,\mathrm{mm}$ horizontal and $u_2^{\mathrm{top}}(t=1) = -3 \cdot 10^{-3}\,\mathrm{mm}$

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vertical is applied using a linear ramp, before unloading linearly to $u_1^{\text{top}}(t=2) = u_2^{\text{top}}(t=2) = 0\,\text{mm}$. The finite element problem is solved implicitly with an initial Newton-Raphson solver. Figure 1 compares the results of the reference finite element solution to the intelligent element solution. On the left side, the plots compare the forces summed over all nodes at the top of the frame over the average displacements in both directions. On the right side, the von Mises stress fields are compared at maximum deformation ($t = 1$). The reference model has 585 degrees of freedom, while the intelligent element model has 193 degrees of freedom. Both models were computed on the CPU, resulting in a speed-up factor of 3.327.

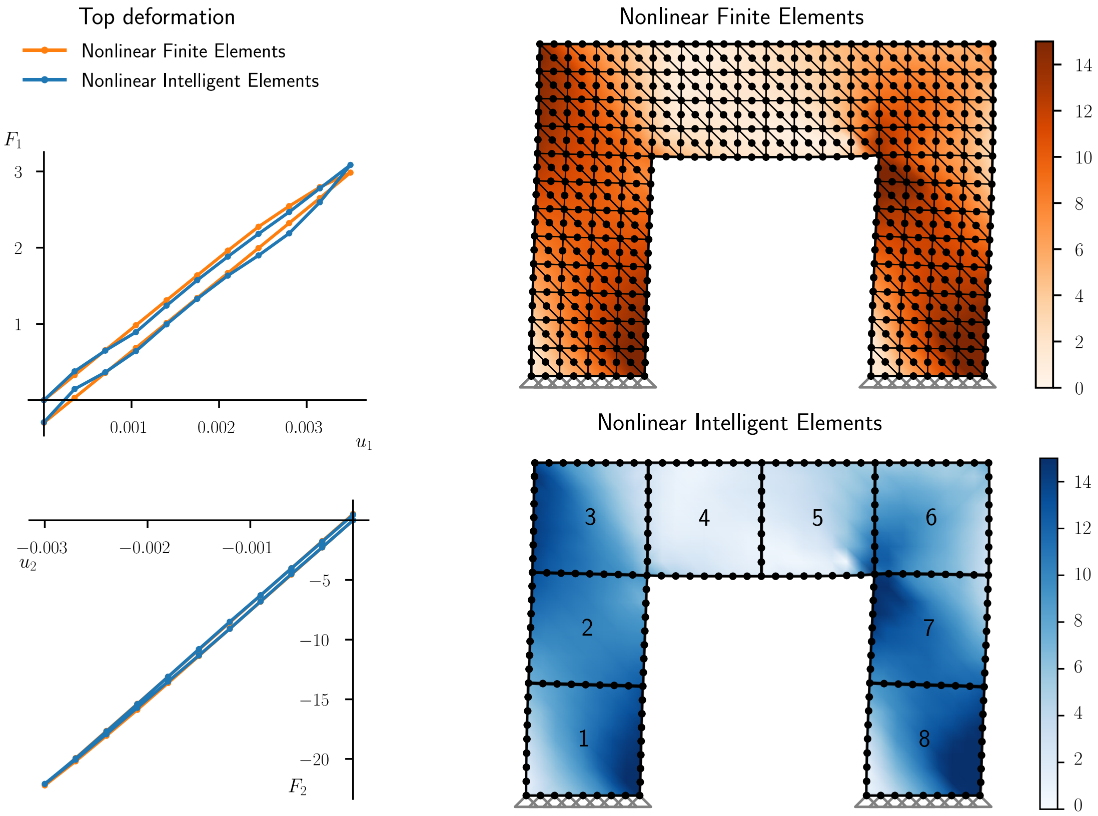

Fig. 1: Elastoplastic frame subjected to linearly increasing-decreasing combined pressure and shearing at the top. (Left) Load-displacement curves of the top boundary of the frame. (Top right) Finite element reference solution showing the von Mises stress field and scaled displacement response at maximum absolute frame displacement. (Bottom right) Intelligent meta-element solution for comparison. The load-displacement hystereses, stress fields, and displacement responses are in good agreement. The intelligent model has a considerably smaller dimensionality.

4 Conclusions

The intelligent meta-element model exhibits a considerable speed-up, which falls between speed-ups demonstrated by intelligent surrogate [1, 2] and constitutive models. As opposed to surrogate models, the intelligent meta-element can be employed flexibly as part of various finite element models without retraining.

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