MACHINE LEARNING DERIVED GRADED LATTICE STRUCTURES CONSIDERING ANISOTROPY

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Abstract

To further improve the performance of the designed lattice structures and accelerate the design process, Machine Learning (ML) has been applied to lattice design in several attempts. For example, the use of clustering[1] algorithm helps to cluster the elements into different cell clusters. The employment of Neural Network (NN) accelerates the property prediction of lattice unit cells[2], [3], enables the inverse design of spinodoid metamaterial[4], and even help with the sensitivity analysis of TO[4].

Herein, we propose a new lattice generation strategy that is computationally cheaper and produces high quality geometric definition based on Machine Learning (ML) when compared to traditional methods. To achieve the design of high-performance unit cells, firstly, the optimal mechanical property for each cell region is derived according to the loading condition and the reference density obtained utilising a conventional topology optimisation result. Next, a Neural Network (NN) is employed as an inverse generator which is responsible for predicting the cell pattern for the optimal mechanical property. Training data were collected from Finite Element (FE) analysis with varied cell parameters and then fed to the NN. With the help of ML, the time spent in building the inverse generator is significantly reduced. Furthermore, the ML-based inverse generator can handle different cell types rather than one specific type which facilitates the diversity and optimality of lattices.

More specifically, the 2D lattice unit cell is parameterised by the nodal parameters (4 parameters) and its mechanical properties are represented using the elasticity compliance matrix (6 independent components). A Neural Network (NN) is employed as an inverse generator which can output the representative parameters of lattice unit cells with the input elasticity properties. Training dataset with a size of 500 are collected from FE analysis of voxelised cells with varied cell parameters and then fed to the NN. To implement the lattice generation strategy, firstly, optimal density distribution is obtained from TO result as the reference elemental densities. Secondly, the optimal elasticity properties are determined based on the reference elemental density and the elemental stress condition. Finally, the NN-based inverse lattice generator is used to generate corresponding lattice unit cells from the optimal elasticity properties.

Furthermore, through a series of sub-problems, the anisotropic properties for each element can be optimised. Based on the optimised anisotropic elasticity properties, lattice cells will be predicted through the developed inverse generator. To conclude, the lattice generation strategy consists of three steps: i) produce the greyscale structure using SIMP; ii) generate anisotropic properties for each cell region based on the greyscale SIMP result; iii) use the inverse lattice generator to output lattice unit cells from the anisotropic properties and form the final lattice structure.

To enhance the performance of the lattice further a simple material anisotropy is considered aligned with the member axis of the lattice. It is expected that incorporating this material anisotropy will provide superior performance to the structures explored earlier.

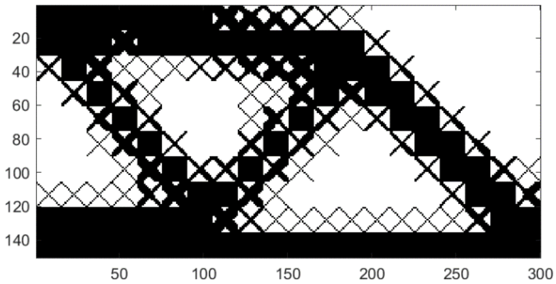

Figure 1: Lattice structure generated by new strategy

References

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