ABSTRACT

Machine Learning based Acceleration of Multi-Resolution Topology Optimization with Transition Elements

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With the recent development of high-performance structural design and additive manufacturing technologies, the manufacturability of complex structural configurations has increased, leading to a growing need for topology optimization to obtain high-resolution structural layouts with superior performance under a limited amount of material. In particular, density-based topology optimization can generate novel structural configurations independent of initial design shapes by discretizing the design domain into finite elements and assigning material density design variables to each element. However, high-resolution topology optimization requires a large number of design variables and degrees of freedom, and the computational cost of finite element analysis, which must be repeatedly performed at every optimization iteration, increases significantly. This computational burden becomes a major limitation in applying topology optimization to large-scale structural problems or problems requiring detailed representation of thin members.

In this thesis, a learning-based multiresolution topology optimization method using

static condensation analysis based on transition elements and hierarchical shape functions is proposed to reduce the analysis cost while maintaining a high-resolution density distribution. In the proposed method, the boundary displacement of an analysis cell is represented using hierarchical shape functions, and the internal fine-scale degrees of freedom are eliminated through static condensation. The transition elements connect the hierarchical analysis degrees of freedom on the analysis-cell boundary with the fine-grid degrees of freedom inside the cell, enabling higher-order boundary displacement representation and fine-scale internal responses to be integrated into a single analysis-cell formulation. As a result, numerical shape functions and a reduced stiffness matrix are constructed at the analysis-degree-of-freedom level. The internal response components, which vary according to the density distribution inside the analysis cell, are not directly computed at every iteration but are predicted using a machine learning model trained offline.

The performance of the proposed method is verified through compliance minimization problems and compliant mechanism design problems. The numerical results show that the use of higher-order hierarchical boundary representation tends to alleviate artificial patterns that may appear in low-order analysis and provides more consistent optimized layouts for high-resolution density distributions. It is also confirmed that, when a large filter radius is used, the internal response reconstructed by interpolation from a lower displacement subdivision number shows results similar to those obtained by direct computation. Finally, the proposed method was applied to a large-scale Half MBB beam problem with approximately 4.32 million elements and 43.23 million degrees of freedom, demonstrating its potential to reduce repeated analysis costs in high-resolution multiresolution topology optimization.