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TOPOLOGY OPTIMIZATION BY PREDICTING SENSITIVITIES BASED ON LOCAL STATE FEATURES

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Topology optimization attempts to find the optimal distribution of material within a design space, providing the basic layout and shape of a structure. The problem of identifying regions which should contain material and those that should contain void can be efficiently solved by utilizing analytical sensitivity information. However, in engineering optimization problems this information is not generally available, for example when attempting to design crashworthiness structures. In such cases non-gradient approaches or finite difference gradient estimations may be used, however these become prohibitively expensive in typical topology optimization problems. Therefore, we propose a heuristic alternative for topology optimization in which regression models are trained in order to replace predefined analytic sensitivities: Topology Optimization by Predicting Sensitivities (TOPS). With TOPS it is possible to drastically reduce the number of quality evaluations required, compared to finite difference gradient estimation.
Density-based methods [1], assign a continuous variable to each cell of a finite element representation of the design space. Using this representation, TOPS combines finite differencing with the assumption that Local State Features (LSF) associated with each design variable can be used for predicting its corresponding sensitivity. After evaluating the initial structure, a random subset of the variables is chosen and their sensitivities are estimated separately using finite differencing. The LSF of these variables and the according sensitivity estimate are stored in a database of sensitivity samples and subsequently a regression model is trained. The regressor predicts sensitivity estimates for the variables which were not selected for finite differencing, using their respective LSF. Based on the sampled and predicted sensitivities the design is updated using a gradient-based optimizer. The new design is accepted if its quality constitutes an improvement, otherwise additional sensitivity samples are collected, added to the database and the model is improved. In this way, TOPS iteratively trains a model, which represents a strategy for updating the design. The process of predicting sensitivities and updating the design is repeated until the quality of the design cannot be improved any further.

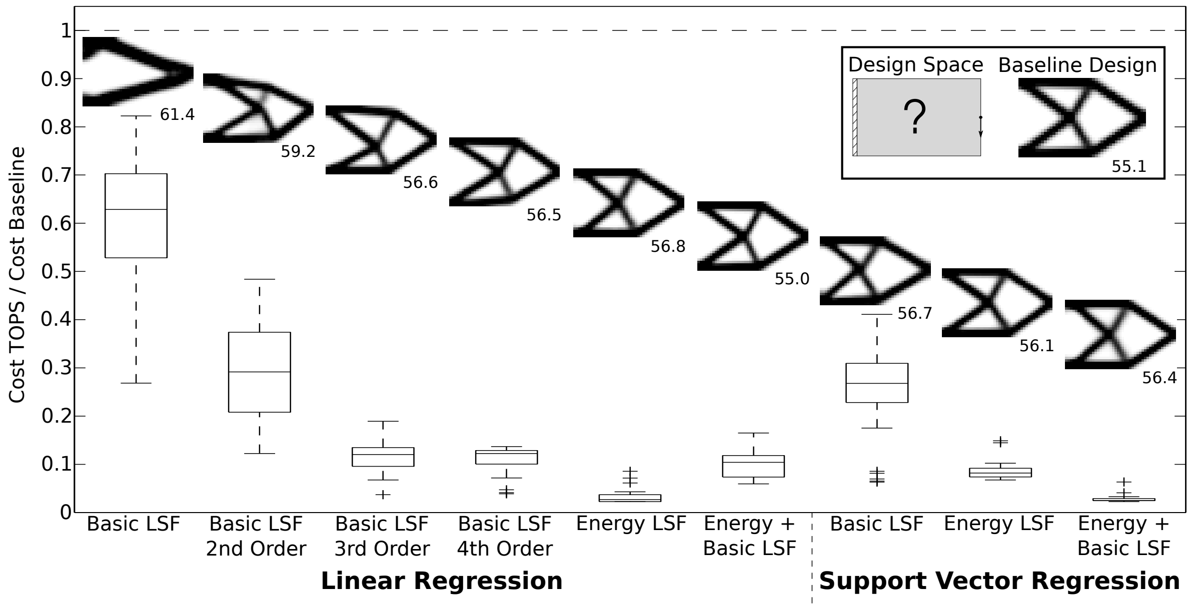

Figure 1: The cost of TOPS for different feature sets and predictors normalized to the baseline cost is plotted. For each variant of TOPS also the design resulting from the run with the median quality is shown. In addition the number next to each design provides the corresponding objective value. The box in the upper right corner shows the design space with boundary conditions and the baseline solution.

In order to evaluate the proposed method and to compare the results to known solutions, it was applied to the problem of optimizing a minimum compliance cantilever in a rectangular design space. Different variants of TOPS, using linear and non-linear predictors [2] and different sets of features were evaluated. Basic LSF are the elemental displacement vector and the density of the element to which the design variable is associated. Sets of LSF with increasing quality were constructed by utilizing higher order products of the basic LSF and by including the elemental strain energy as LSF. The results of a statistical evaluation are compared to a baseline obtained by naive finite difference gradient estimation in terms of quality and computational cost. Fig. 1 provides an overview of the main results. For more descriptive LSF, the solution quality is improving while the computational cost, measured by number of finite element analysis simulations, is decreasing. In most experiments, designs very similar to the baseline design are obtained, while the cost is reduced significantly compared to the baseline (by 97.6% in the best case).
The proposed algorithm is a novel heuristic for topology optimization, not requiring analytical sensitivity information and was demonstrated to generate feasible topological solutions. As performance and cost depend on the quality of the predictions, we provide recommendations for the choice of model and LSF based on the conducted experiments.

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