Structural Topology Optimization using a Convolutional Neural Network

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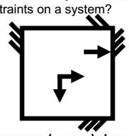
Objective

1.) What is the **optimal structural topology** for a given set of forces and fixed constraints on a system?



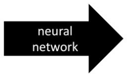
design space (square) showing forces (arrows), and fixed boundary nodes (hashing) in the system

topology which minimizes compliance of the system

2.) Given that topology optimization is a **computationally expensive tool**, can we stop the topology optimization early and use a neural network to predict the topology of the system?

diff. between iterations 4 and 5 of top. opt.

top. opt. stopped after 5 iterations (usually takes 100 to converge)



topology which minimizes compliance of the system

*Structure of problem and model inputs defined in [1].

Data and Features

'ToPy'[2] Generated Dataset

- 10,000 2D topology optimizations, each containing a unique set of input forces and boundary conditions:

iteration 5 | iteration 50 | iteration 100 (ground truth)

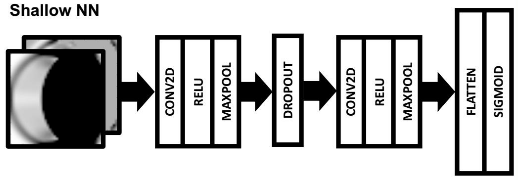
- 32,000 augmented examples added to training set:

original | horizontal flip | vertical flip | 90º flip CCW | 90º flip CW

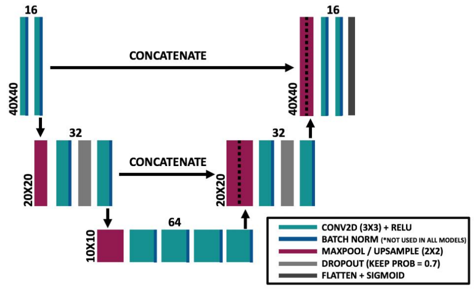
- 96% / 4% / 4% - training / dev / test set split with augmented data

Models

Shallow NN



Deep NN (U-Net[3] Architecture)



*Models were built and run in Python and Tensorflow on Google's Colaboratory platform and run off of a virtual machine using a GPU processor.

Results

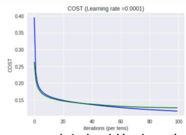
Evaluation Metrics

- Intersection over union:

$$IOU = \frac{1}{m}\sum_{i=1}^{m}\frac{Area\ of\ Intersection}{Area\ of\ Union}$$

- Binary pixel-wise accuracy:

$$Acc = \frac{1}{m}\sum_{i}^{m}\frac{\#\ correctly\ classified\ pixels}{total\ \#\ pixels}$$



un-regularized model (no dropout) showing train (blue) and dev (green) cost

Hyperparameters

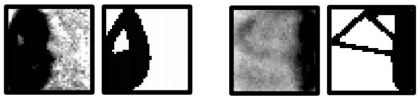
- Learning rate: 0.0001
- Epochs: 100
- Mini-batch size: 64
- Keep probability: 0.5

Model	Test Acc.	Test IOU
Shallow NN	84.9	91.8
Shallow NN w/ data augmentation	87.7	93.5
Deep NN	90.1	94.8
Deep NN w/ data augmentation	91.8	95.7

*Batch normalization was not used in final models due to decreased performance.

Discussion

- Batch normalization did not improve the accuracy or IOU on any of the models especially for topologies with small and detailed features (like the one at right)

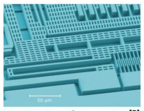


predicted structures w/ b.n. vs. ground truth labels

- The augmented training dataset performed about 1-2% better on both the shallow and deep neural networks
- The shallow neural network achieved decent accuracy and IOU (87.7% and 93.5%) compared with the deep neural network (91.8% and 95.7%) and trained about 4x faster

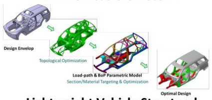
Future Work

- Determine if able to predict optimal structural topology with just the forces and fixed constraints as inputs to the model.
- Apply to a field like MEMS (microelectromechanical systems) where designs tend to be made up of typical shapes like rectangles and circles (shown right). This optimization is more complex because these are damped resonant structures, not static structures.



MEMS Accelerometer[5]

- More generally, determine if we can use AI / neural networks to help predict optimal structural topologies (ex: a car, shown right) or at least make the optimization process less computationally expensive.



Lightweight Vehicle Structural Optimization Process[6]

References

[1] Sosnovik, Ivan, and Ivan Oseledets. "Neural networks for topology optimization." *arXiv preprint arXiv:1709.09578*(2017).

[2] W. Hunter, et al., Topy - Topology Optimization with Python, https://github.com/williamhunter/topy (2017).

[3] Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." *International Conference on Medical image computing and computer-assisted intervention*. Springer, Cham, 2015.

[4] Sosnovik, Ivan, et al., Top – Wrapper for Topy, https://github.com/ISosnovik/top (2017).

[5] O'Brien, G. "BMA 250 Accelerometer." *Bosch.*

[6] "Lightweighting." *Optimal Inc. | Engineering for Electrification & Lightweighting*, www.optimalinc.com/lightweighting/.

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