Material Interface Reconstruction using Machine Learning

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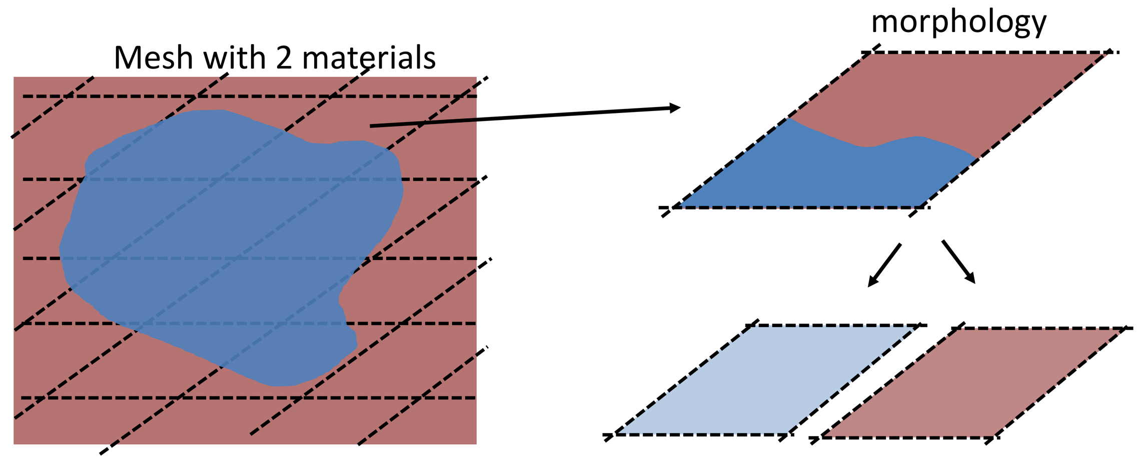
Problem

Consider simulating a fluid with multiple materials

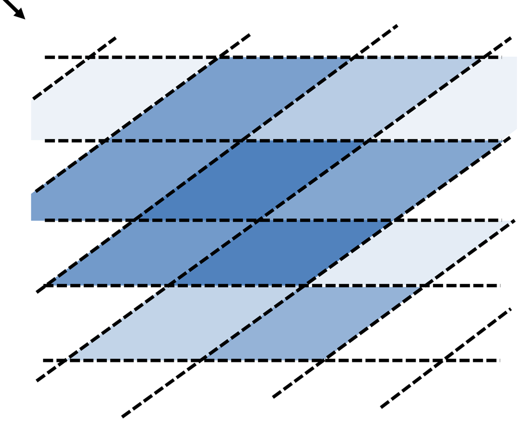
- How can a discrete mesh accurately represent the continuous boundary between the materials?
- What can go wrong?
- Can machine learning help in addressing this class of problems?

Zone averaging

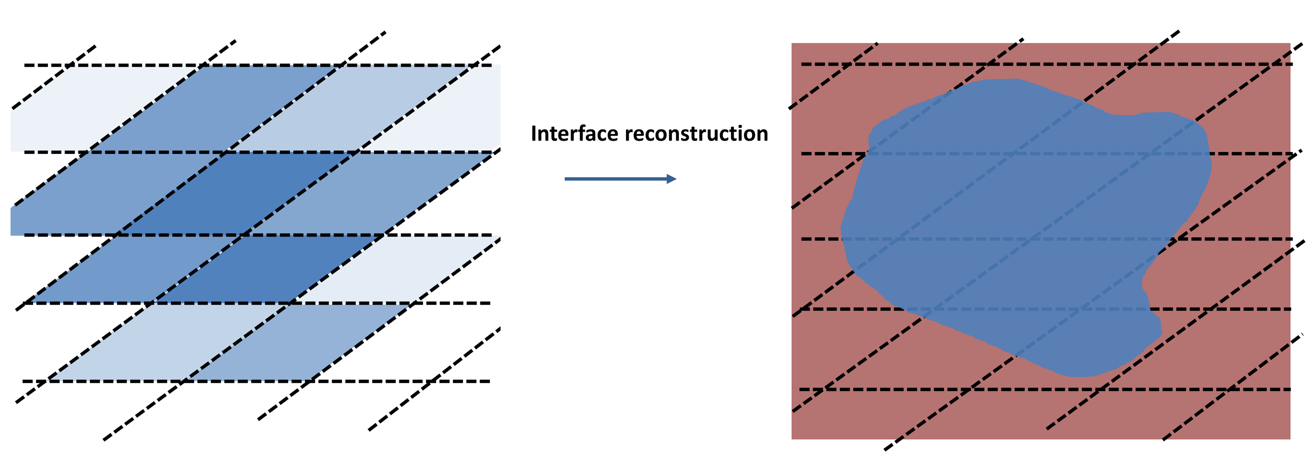


Zone averaging causes interface to be lost

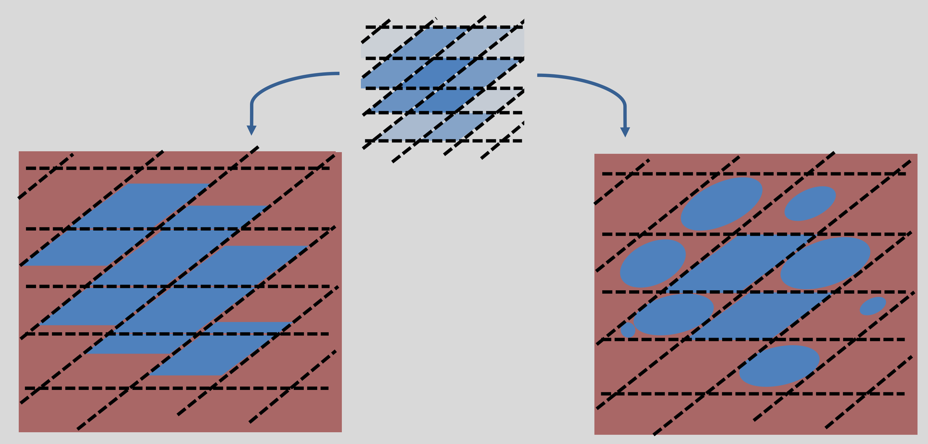
Interfaces are important for correct advection



Research objective: Use machine learning to reconstruct interface morphology from volume averages

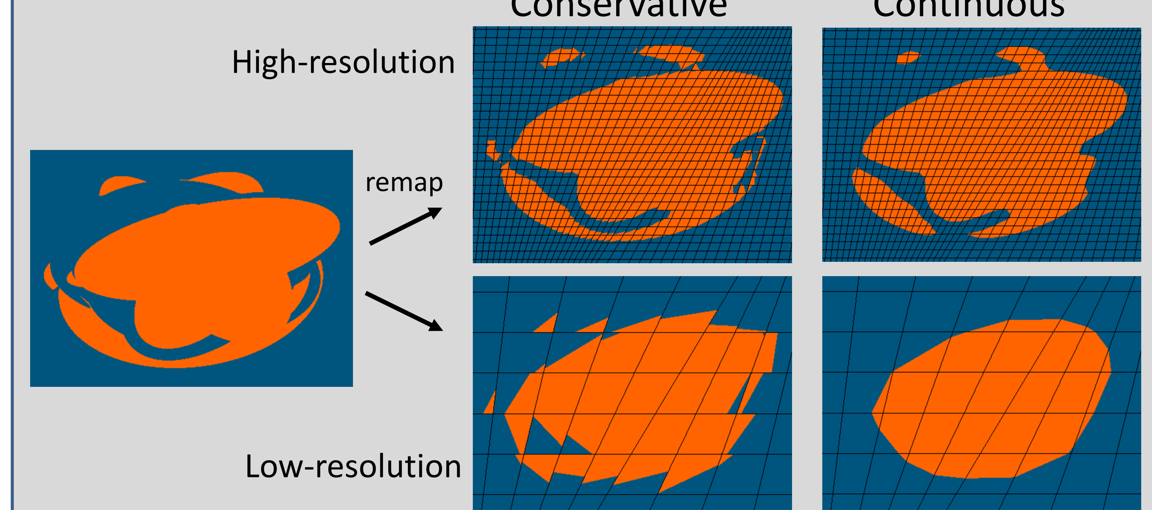


Challenges



Reconstruction is highly under-constrained

Difficult to achieve both conservation and continuity
Especially for low resolution



Models and Methods

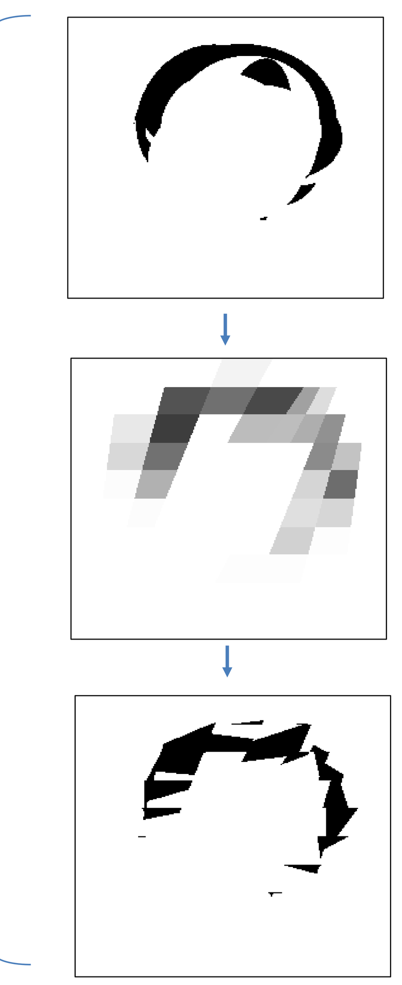
Image-based approach using **supervised learning**

Domain "snapshot"
Image pixel values determined by material composition at pixel's location → **ML Network** → **Image representing probable interface morphology** → **Map image to domain**

Preliminary investigation of two materials
Trained using synthetic as well as simulation (shock tube) data

Data generation procedure

Pairs of "ground truth" and conventional reconstruction images

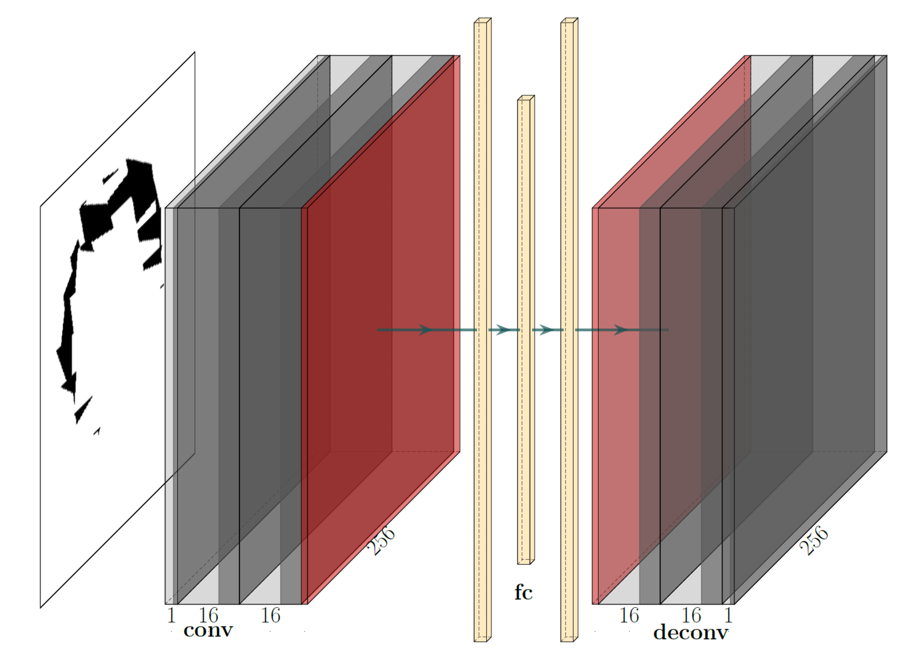


Convolutional Autoencoder

Symmetric layers of convolution/deconvolution

Fully-connected layers learn sparse representation

Input: image
Output: image



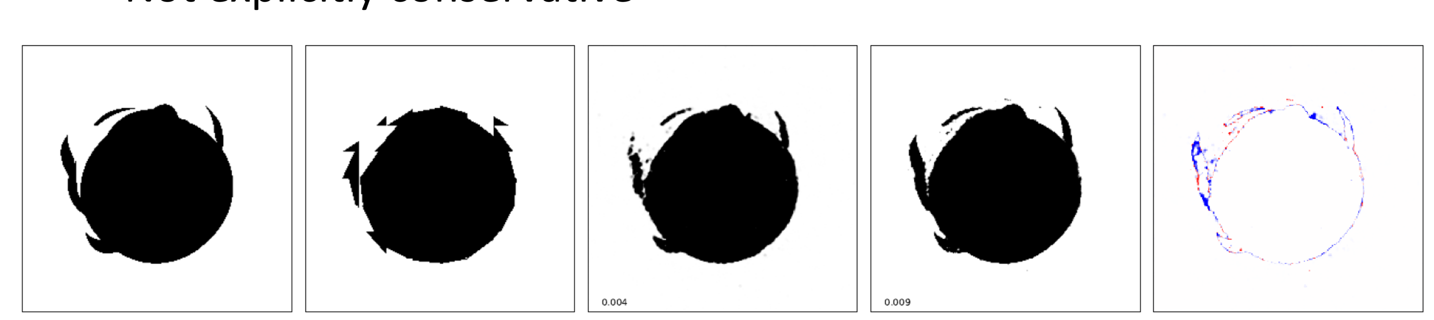
Schematic of network architecture. The network is divided into three sections: convolution→dense→deconvolution. Each section has three layers. Red denotes batch normalization.

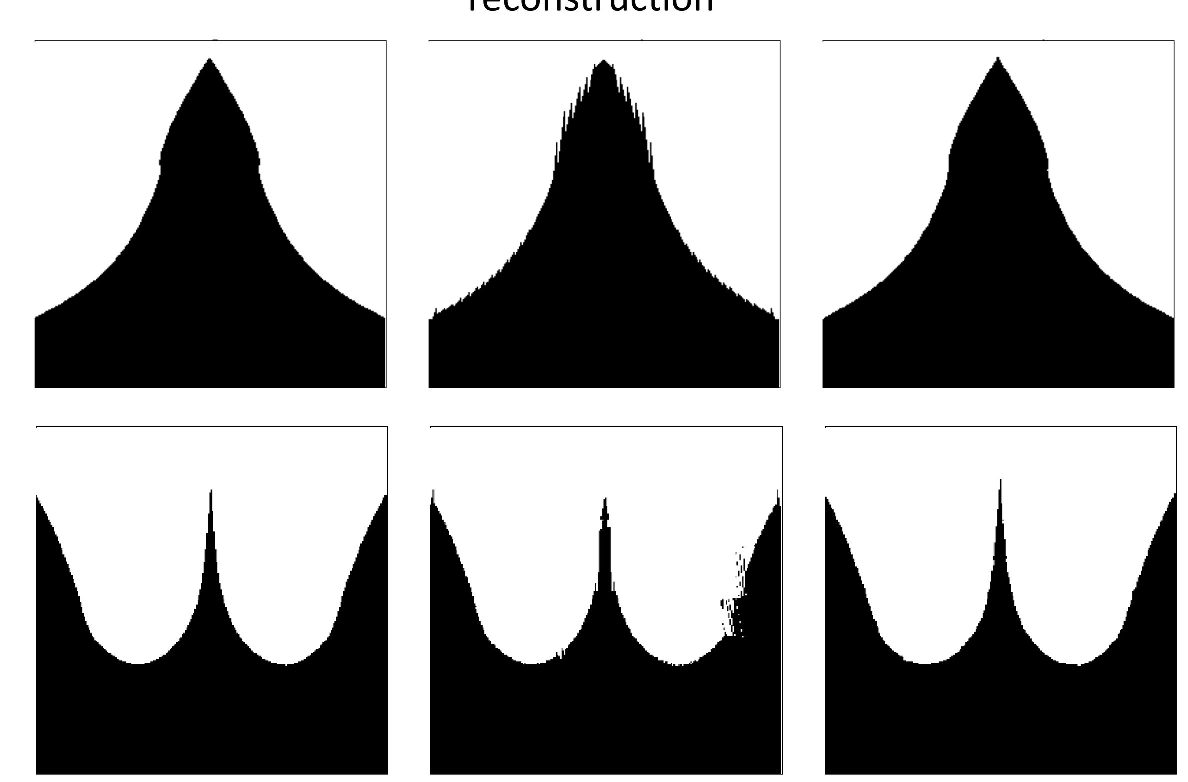
Loss: pixelwise MSE
Two implementations:
- All pixels weighted equally (baseline)
- Pixels in mixed zones weighted more heavily (modified)

Results/Discussion

Key results
- **Good performance with both synthetic and simulation data**
- **Continuous reconstructions**
- **Most morphological features preserved**
- **Modified loss function improves results**

Limitations
- Some difficulty with long thin structures
- Only considered two materials
- Not explicitly conservative





Conclusions

- Network can reproduce most morphological features
- Outputs are typically smooth
- Improve performance by training only on regions containing interfaces

Future Work

- Additional interface morphologies
- More than 2 materials
- Incorporate additional mesh variables

Contact Information

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