Deep Learning for Fluid Sculpting in Microfluidic Platforms

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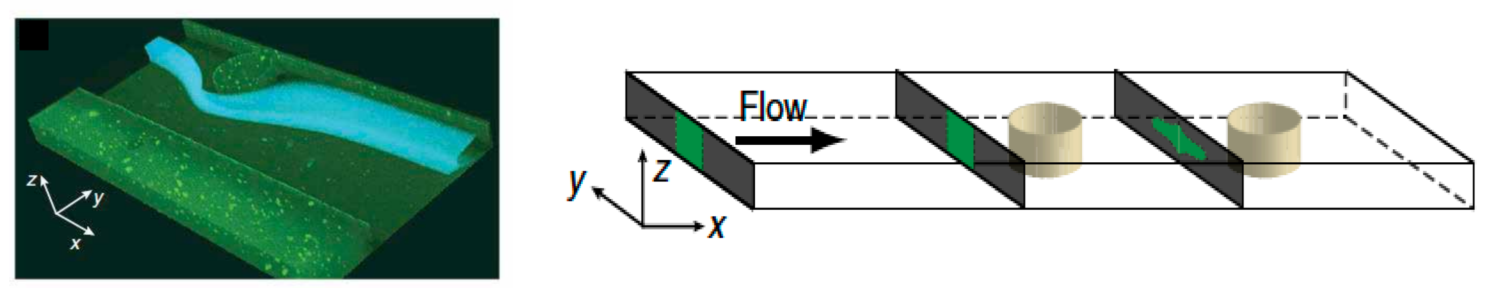
Abstract

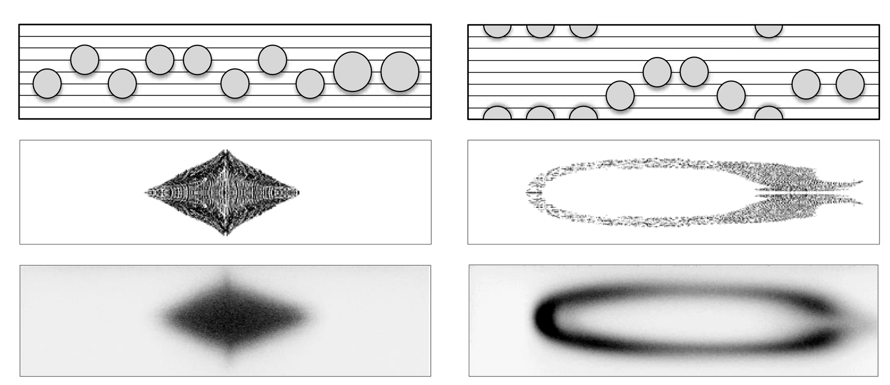
- Controlling the shape and location of a fluid stream provides a fundamental tool for creating structured materials, preparing biological samples, and engineering heat and mass transport.
- Recent work has demonstrated the concept of sculpting fluid streams in a microchannel using a set of pillars that individually deform a flow in a predictable pre-computed manner [1].
- These pillars are placed in a defined sequence within the channel, whereby the composition of their individual flow deformations form complex user-defined flow shapes [2].
- Creating user-defined flow shapes important for practical applications currently requires laborious trial and error design iterations, or time consuming evolutionary algorithms prohibitive to real-time design.
- We explore the applicability of machine learning models using GPU acceleration to serve as a map between user-defined flow shapes and the corresponding sequence of pillars.

Motivation

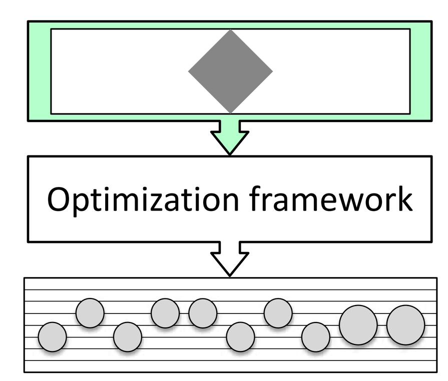
- Current methods that tackle the inverse design problem in pillar programming are successful [3], but require many hours – perhaps days – of heavy computation, thus making their utility in real-time suspect.
- Our goal is to develop CAD tools (like splice) that enables engineer to rapidly design fluid flow profiles for their applications without full-scale Navier-Stokes simulations and experiments.



Left: single-pillar deformation. Right: "pillar programming", with multiple pillars.



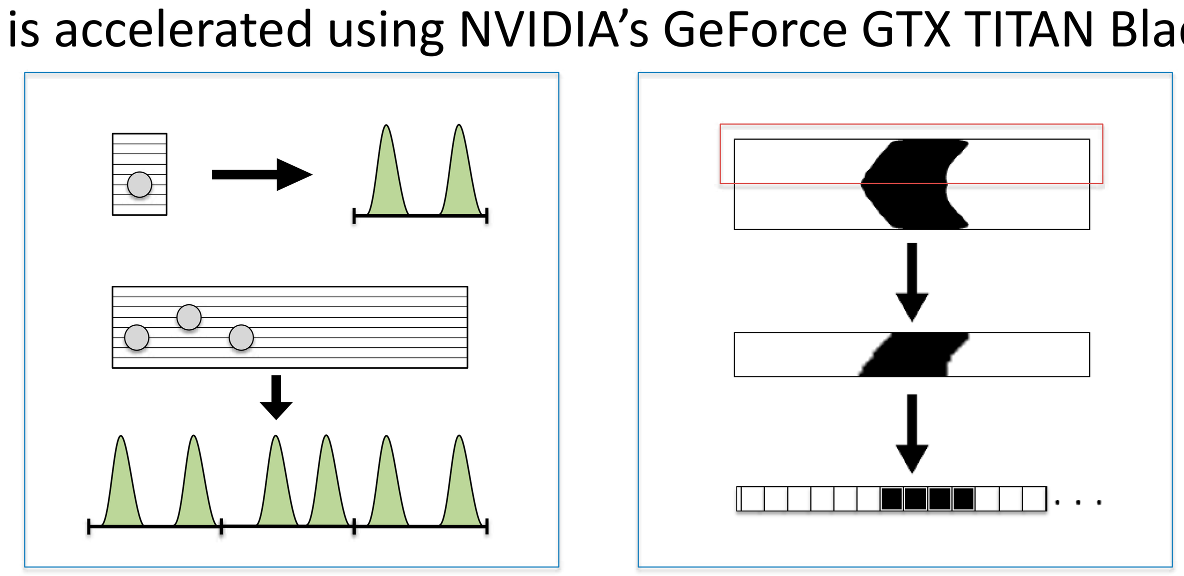
Pillar programs (top row), simulations (middle row) and experimental validation (bottom row).



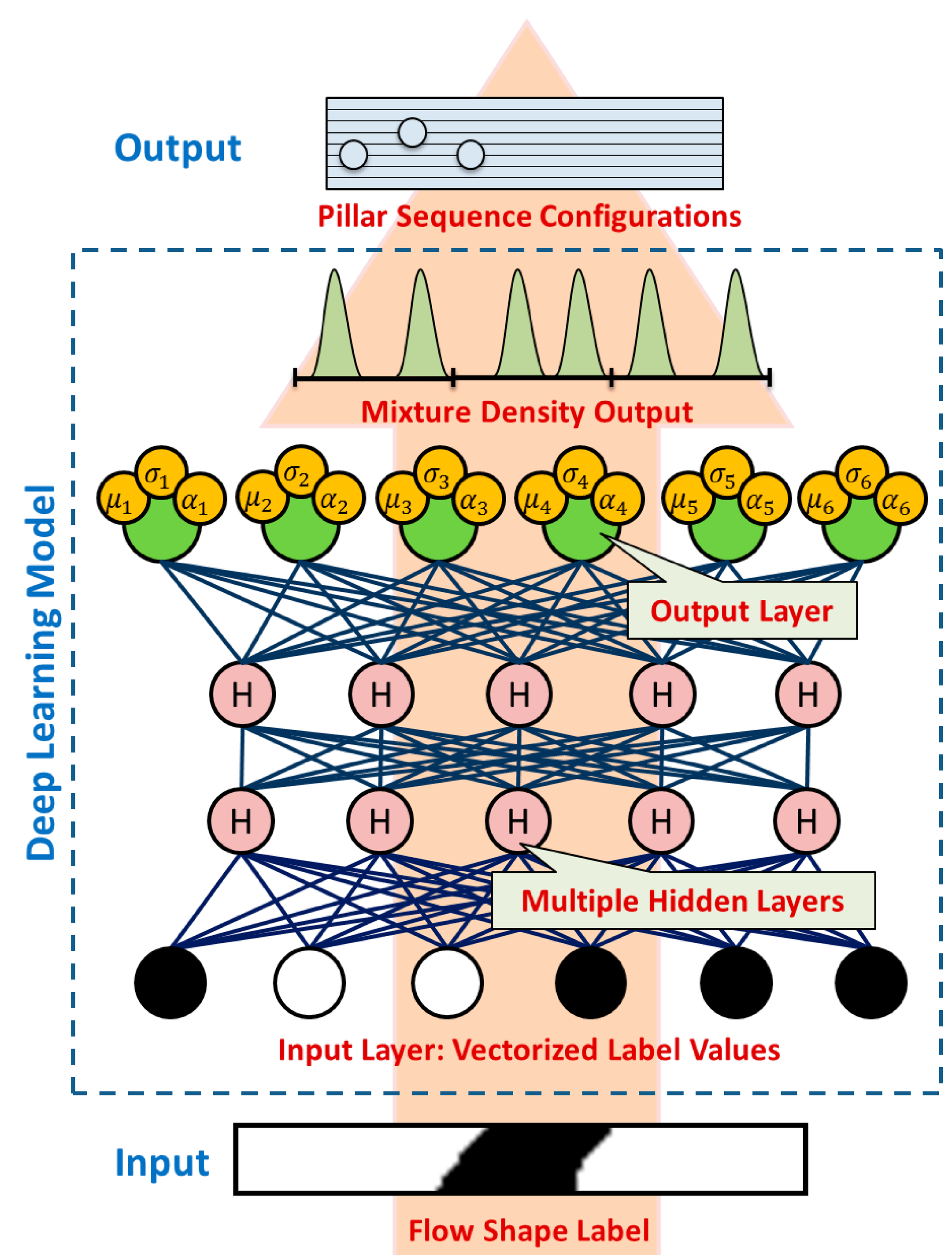
The goal of inverse design.

Methods

- We use a Deep Learning based framework to extract pertinent nonlinear features from flow shape images as well as learn a density estimator with pillar configurations as the target distributions.
- As the forward problem of generating simulated flow shapes for a certain pillar configuration is computationally inexpensive, we generate a large set (on the order of millions) of labeled images for training.
- The training process uses Deep Neural Networks [4] (pretrained with a Deep Belief Network) in Theano's deep learning framework [5][6] that is accelerated using NVIDIA's GeForce GTX TITAN Black.



Left: Pillar sequences are converted to distributions by mapping pillar diameter and position as Gaussian distributions, which will be used in the neural network input layer. **Right:** Flow simulations are reshaped into binary vectors, which will be the labels used in the neural network input layer.



Prediction Results

Initial results provide significant credibility to the hypothesis regarding usefulness of the proposed Deep Learning framework for flow sculpting. The network consists of five hidden layers, each with 500 hidden units.

Flow based on actual (top) and predicted (bottom) pillar sequences

Pixel Match Rate = 96.6%

$$\text{Match Rate} = 1 - \frac{\|Label - Prediction\|_1}{\text{Total Number of Pixels}}$$

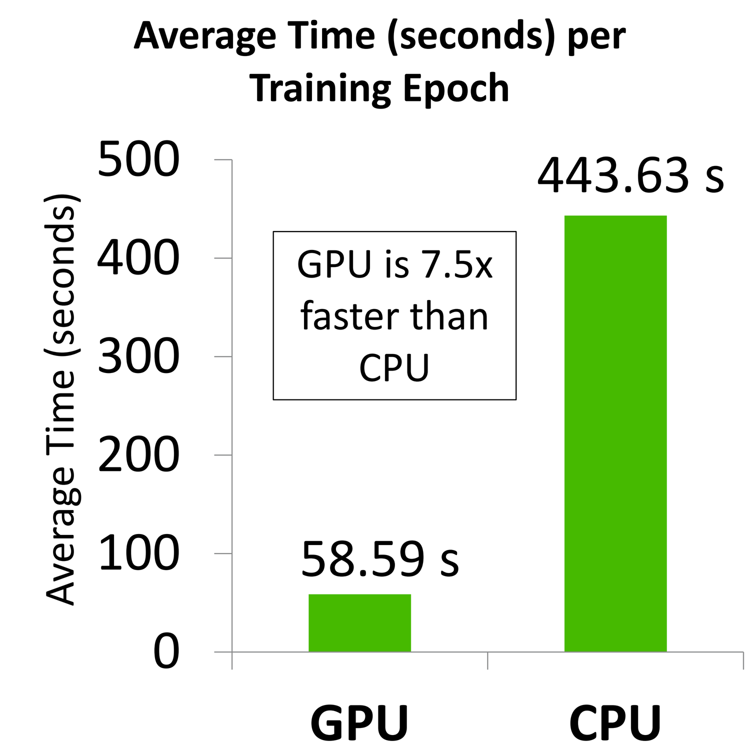


Table 1: Prediction Performance

	Match Rate Statistics	
Resolution	**12 x 100**	**24 x 200**
Min	55.00%	55.15%
Mean	82.74%	82.79%
Median	83.75%	83.98%
Max	98.83%	98.90%

Table 2: Threshold Scores

Resolution	12 x 100	24 x 200
Match Rate	**Test Examples**	
75% and above	82.86%	82.43%
80% and above	66.48%	67.42%
85% and above	43.36%	44.77%
90% and above	18.87%	19.00%
95% and above	2.76%	2.83%

Future Work

- Use higher resolution images
- Test scaling on multiple GPUs
- Explore different inlet configurations
- Improve data generation to cover the sample space more evenly
- Explore other types of deep learning networks and error metrics

References and Acknowledgement

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