Deep Learning for Efficient Riverine Bathymetry Inversion

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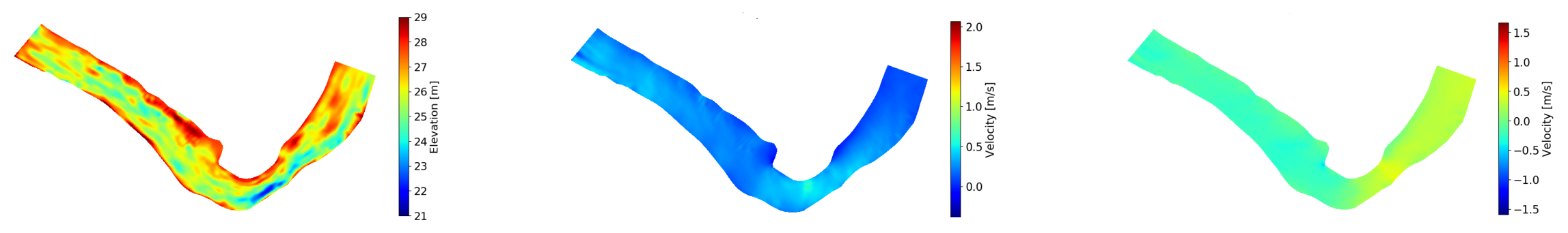
INTRODUCTION

- Shipping, navigation, and flood risk assessment for a river are assisted by having the river's bathymetry profile [2].
- Direct measurements and numerical methods based on more easily measurable data (e.g., surface velocity profiles) such as [2] are time-consuming and expensive.
- This project uses a combination of fully-connected and convolutional neural networks to improve the accuracy and runtime of the baseline method, PCGA (principal component geostatistical approach) [2].

DATASET

- Synthetic data generated by the U.S. Army Corps of Engineers' AdH library [1] on bathymetry profile of a section of the Savannah River.
- 851 samples: velocity and boundary conditions as inputs and depth profiles as outputs. Input data is reshaped for each architecture.
- 60/20/20 train/dev/test split.
- A sample of the true depth, surface velocity x, and surface velocity y:

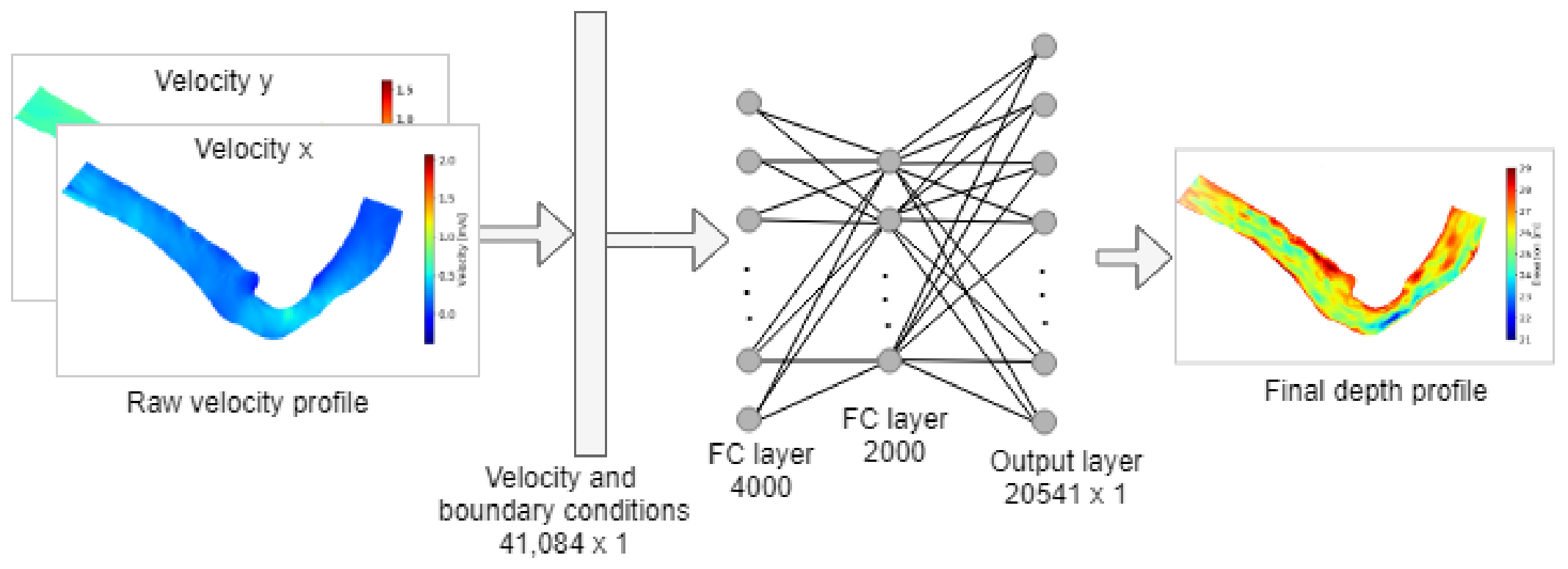


FEATURES

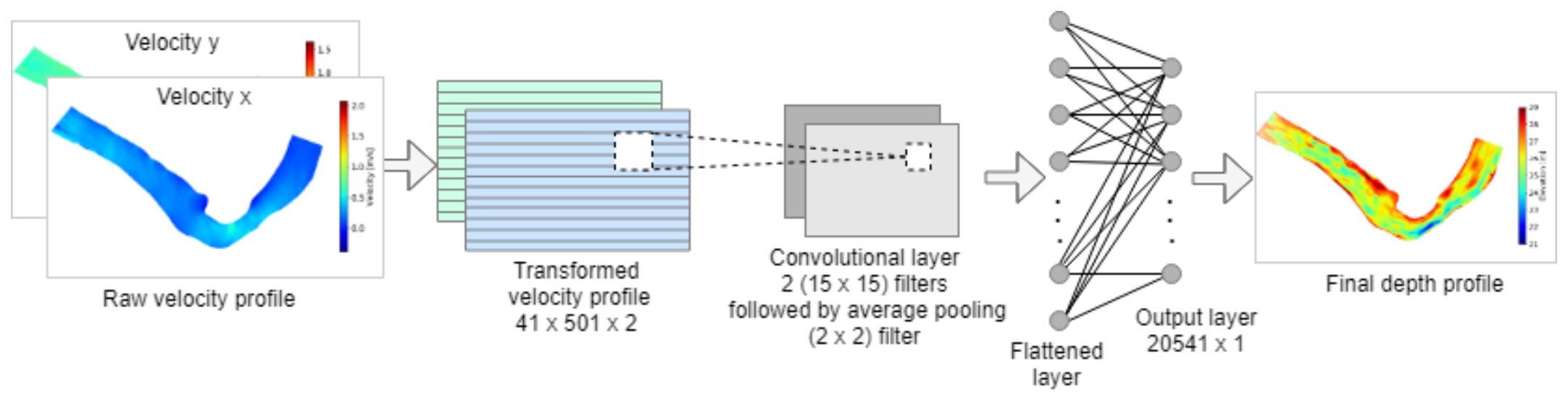
- ***mesh* (20541 x 2 matrix)**: x and y coordinates of depth and velocity measurements.
- ***Z* (20541 x 1 vector)**: Depth at each *mesh* point.
- **$velocity_{prof}$ (41082 x 1 vector)**: x and y surface velocity components at each *mesh* point with white Gaussian noise added.
- **Q_b (scalar)**: Volumetric flow.
- **z_f (scalar)**: Free surface elevation.

METHODS

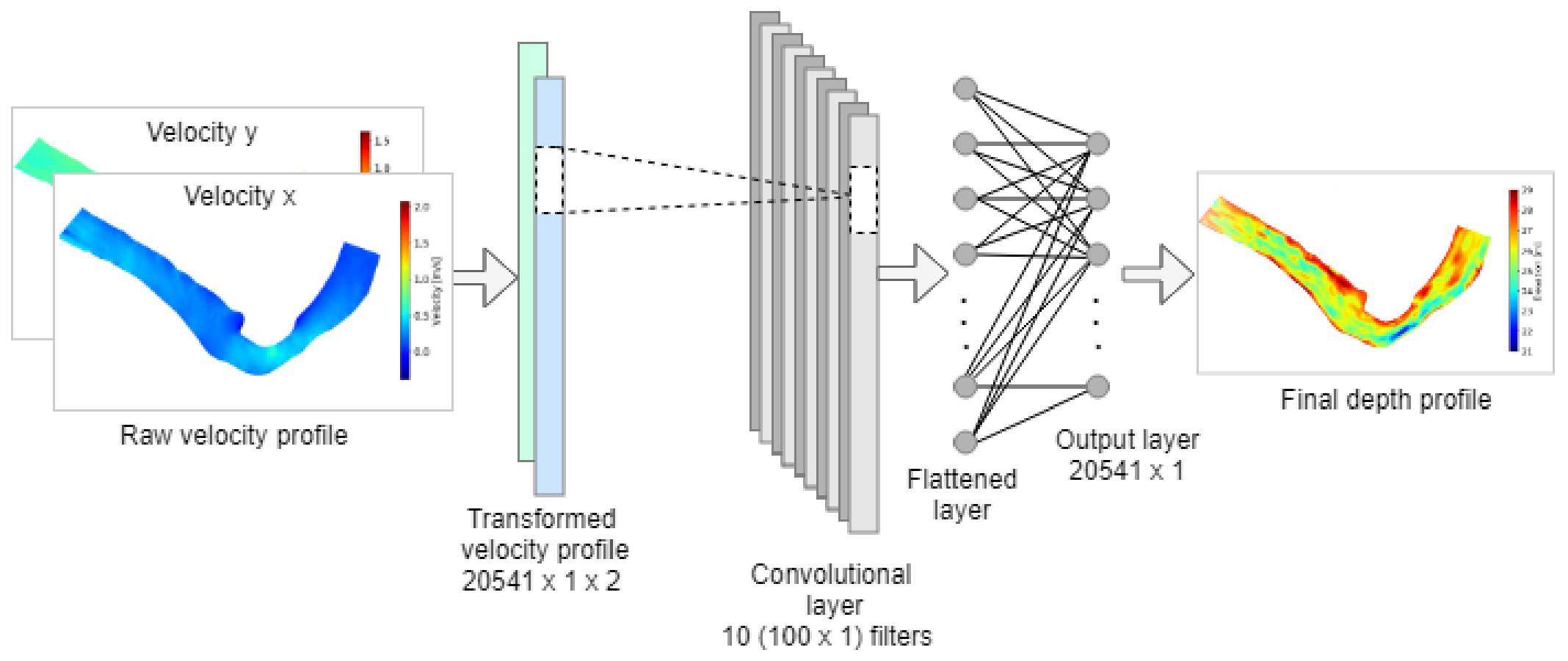
- Metrics
  - RMSE: $J(x) = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{m}}$
  - Prediction time
- Loss function: **MSE**
  - Exception: **MAE** superior for 1D convolution.
- Three architectures investigated:
  - Fully Connected



  - 2D Convolution



  - 1D Convolution



DISCUSSION

- All 3 architectures exceeded PCGA accuracy baseline (0.7 m RMSE) [2] by 61% or more.
- All 3 exceeded PCGA prediction speed baseline (1 hour) by **4 orders of magnitude**.
- Unlike numerical/analytics solutions, boundary conditions were mostly irrelevant.
- All 3 architectures roughly equivalent in accuracy, but fully-connected architecture was fastest.

RESULTS

Architecture	Train RMSE (m)	Dev RMSE (m)	Test RMSE (m)	Training Time (s)	Prediction Time Per Sample (s)
Fully connected	0.388	0.584	0.268	593.701	0.121
2D convolutional	0.378	0.570	0.258	911.767	0.139
1D convolutional	0.254	0.563	0.271	1131.783	0.133
PCGA (baseline)	-	-	0.7	-	1 hour

Table 1: Best results for each architecture

Figure 1: 1) True depth profile with 2) a good (low RMSE) prediction.

Figure 2: 1) True depth profile with 2) a poor (high RMSE) prediction.

FUTURE WORK

- Need to iterate architectures on a machine with more memory to overcome hyperparameter tuning limits.
- Training should be performed on larger synthetic datasets.
- Training should be performed on noisier real-world data, and the resulting models deployed for field use.

REFERENCES

[1] Adaptive Hydraulics, https://chl.erdc.dren.mil/chladh, Accessed: October 6, 2019.

[2] Lee, Jonghyun & Ghorbanidehno, Hojat & Farthing, Matthew & Hesser, Tyler & Darve, Eric & Kitanidis, Peter. (2018). Riverine Bathymetry Imaging With Indirect Observations. Water Resources Research. 54. 10.1029/2017WR021649.