

Deep Learning Methods for Reynolds-Averaged Navier-Stokes Simulations of Airfoil Flows

Julian Hohenadel Technical University of Munich Chair of Computer Graphics and Visualization Munich, 11. May 2020





Introduction





Background – RANS

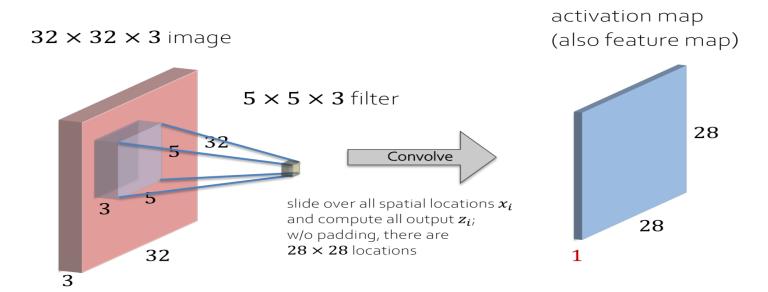




Background – RANS



Background – Convolutions

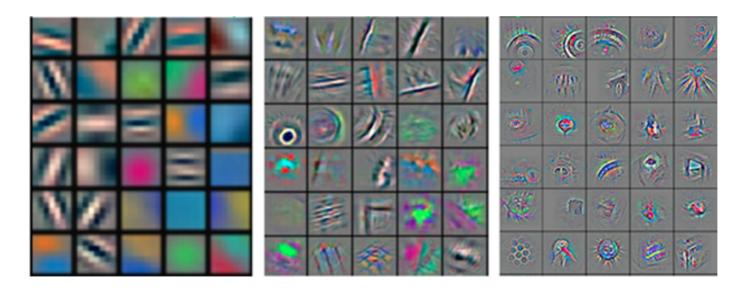


Taken from I2DL WS19/20 (TUM)



Background – Convolutions

Low-Level Features, Mid-Level Features, High-Level Features: each filter captures different characteristics



Taken from https://arxiv.org/pdf/1311.2901.pdf





Data Generation

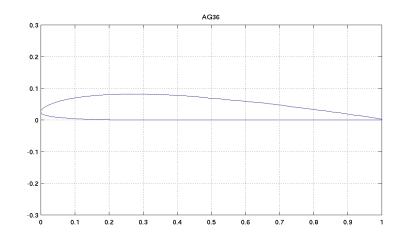
Airfoil shapes are provided by the UIUC database

Reynolds number: [0.5,5] · 10⁶ (highly turbulent)

Angle of attack: [-22.5, 22.5]

Ground truth generated with OpenFOAM (pressure, x velocity, y velocity)

Training data resolution: $3 \times 128 \times 128$





Pre-processing – Data

Input channels	Target channels
1. Bit mask representing airfoil shape	1. Pressure field
2. x velocity component	2. x velocity field
3. y velocity component	3. y velocity field
Reynolds number encoded as differently scaled freestream velocity vectors wrt. their magnitude	Data from the RANS solution



Pre-processing – Normalization

Motivation: Flatten space of solutions, accelerate learning by simplifing the learning task for the NN

Normaliztion of target channels by division with freestream magnitude (vector norm, default: L2): This makes pressure and velocity dimensionless

$$ilde{v_o} = rac{v_o}{\|v_i\|}, \quad ilde{p_o} = rac{p_o}{\|v_i\|^2}$$
 – important to remove quadratic scaling of pressure

For a better understanding:

Pressure: $[p]_{Sl} = 1Pa = 1\frac{kg}{m \cdot s^2}$

Density: $[\rho]_{SI} = 1 \frac{kg}{m^3}$ – constant in incompressible flow

Velocity: $[v]_{SI} = \frac{m}{s}$



Pre-processing – Offset removal & value clamping

Motivation: eliminate ill-posed learning goal & improve numerical precision

Spatially move pressure distribution into the origin

$$\hat{p_o} = \tilde{p_o} - p_{mean}$$

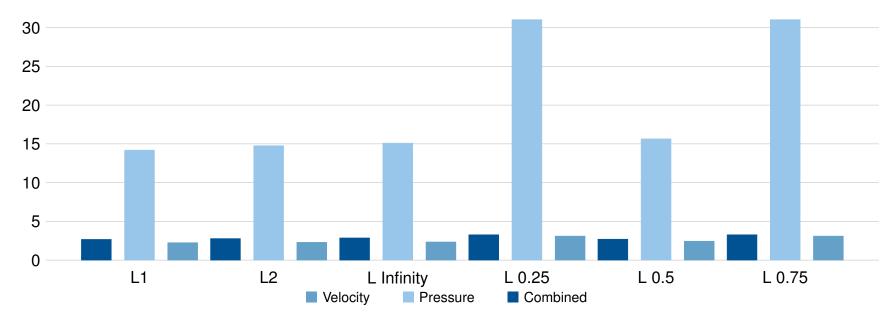
Clamp both input and target channels into [-1,1] range by diving by the maximum absolute value



Pre-processing – Evaluation

Vector norms used in pre-processing comparision wrt. error, default: L2 (in %)

L1 normalization achieves the best error rates (p, vel, combined: 14.19%, 2.251%, 2.646% – L2: 14.76%, 2.291%, 2.780%)

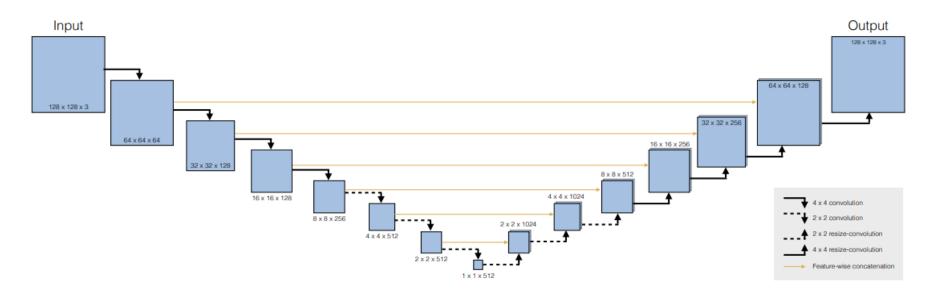






Architecture

U-Net derivative proposed in the paper:



Taken from https://arxiv.org/pdf/1810.08217.pdf



Architecture – Convolutional blocks

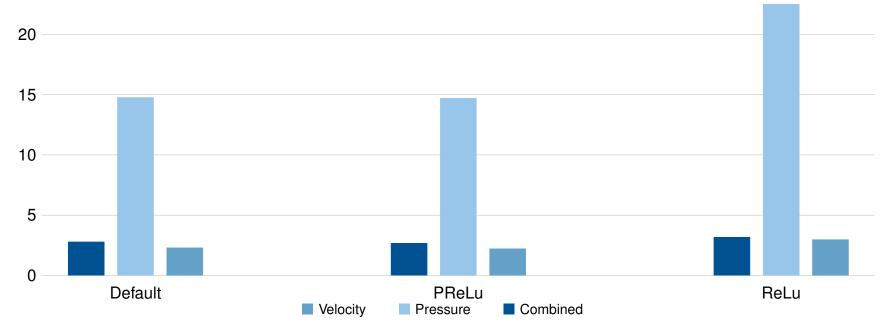
Encoder	Decoder
1. Activation – Leaky ReLu (0.2)	1. Activation – ReLu
2. Convolution – Width down, Depth up	2. Upsampling – linear (2.0)
3. Batch normalization	3. Convolution – Width up, Depth down
4. Dropout (1%)	4. Batch normalization
	5. Dropout (1%)



Architecture – Evaluation

Error percentage of different activation functions after 160k iterations (266 epochs).

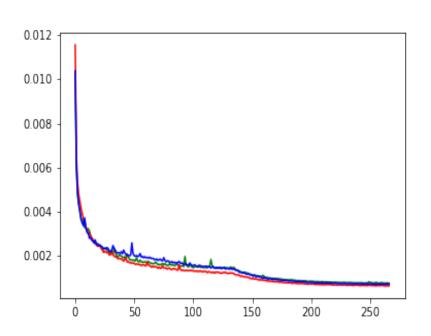
PReLu achieves the best error rates (p, vel, combined: **14.69**%, **2.216**%, **2.676**% – Default: 14.76%, 2.296%, 2.787%)



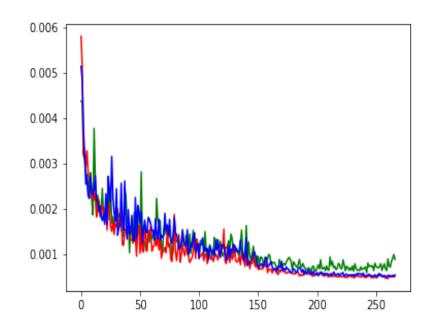


Architecture – Evaluation

Training loss



Validation loss

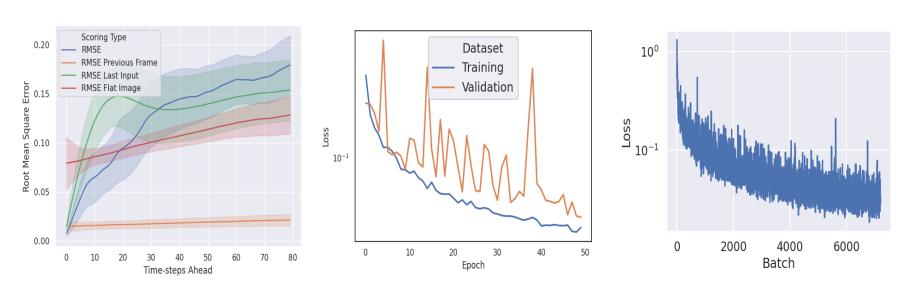






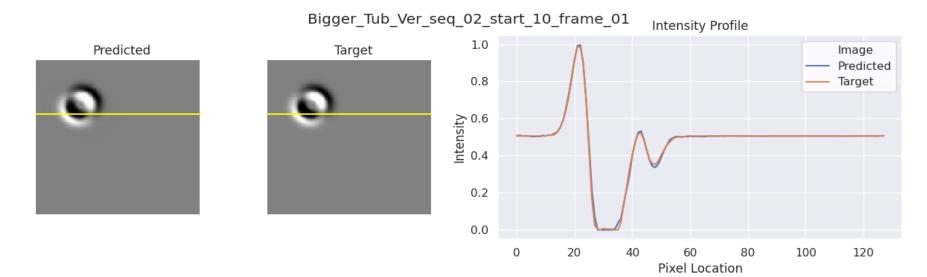


RMSE with variance, validation loss and batch loss on Bigger Tub environment:

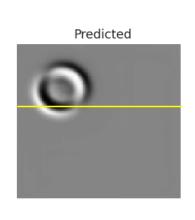


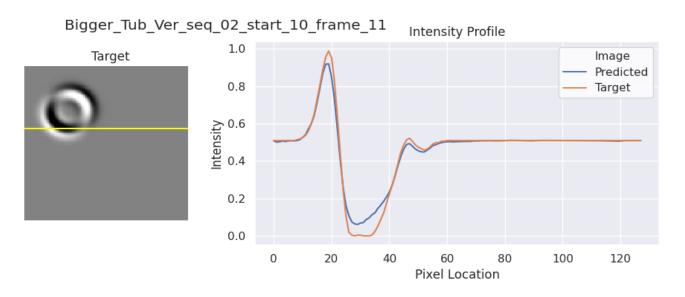
All plots in Transfer were made with https://github.com/stathius/wave_propagation



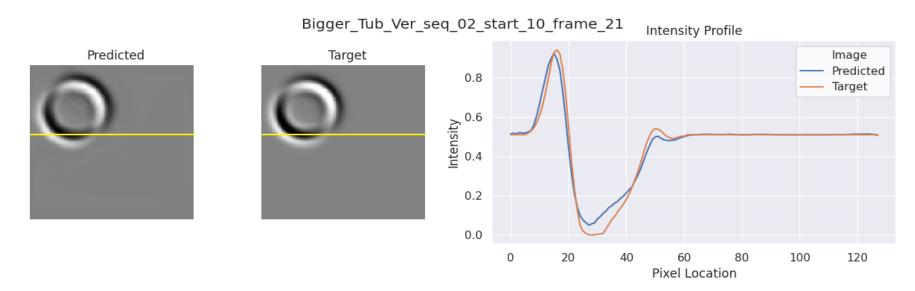




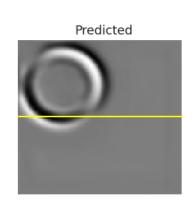


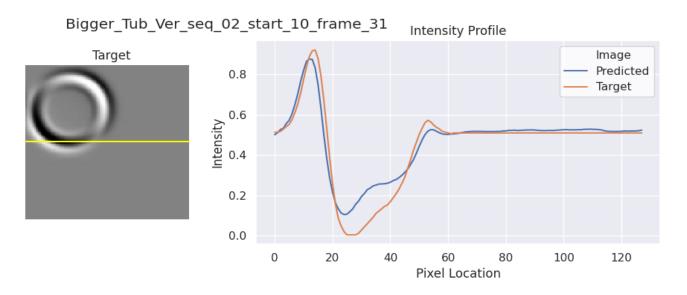




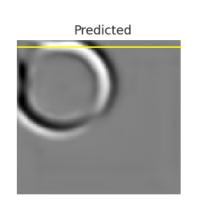


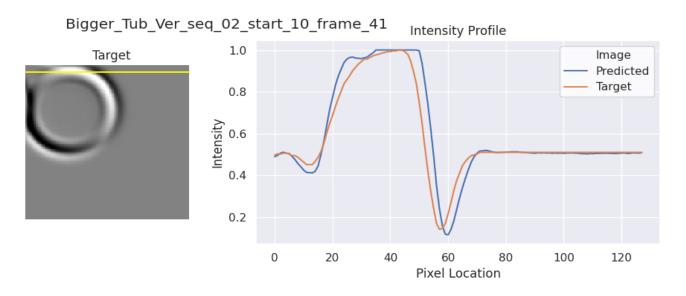




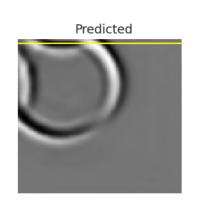


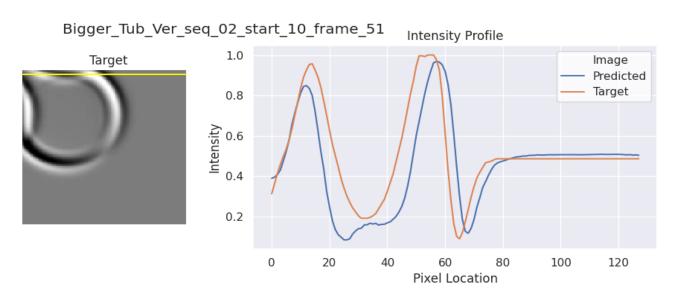




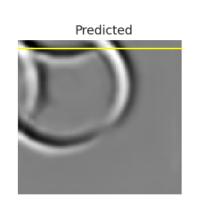


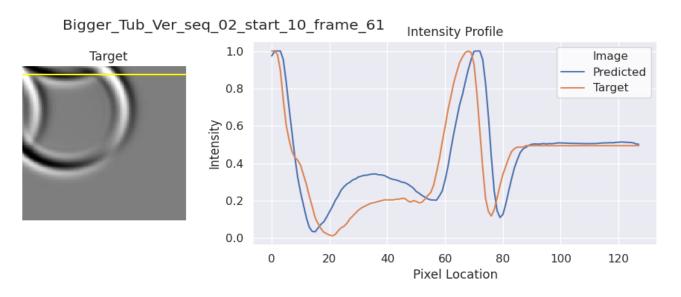




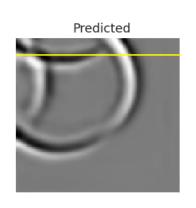


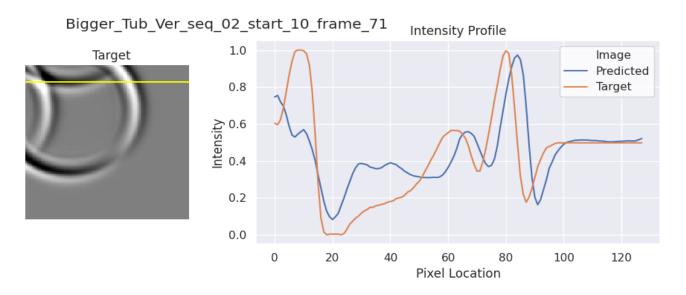












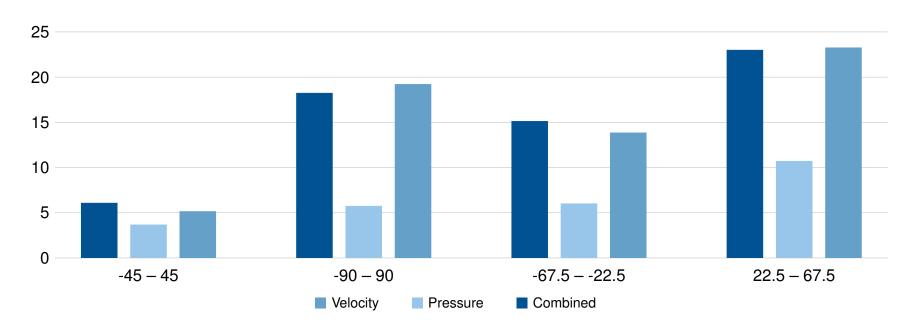


Generalization



Generalization

Error percentage of different angle of attack intervals wrt. ground truth [-22.5, 22.5]





Discussion



Discussion

Positiv	Negativ
Punkt 1	Punkt 1
Punkt 2	Punkt 2
Punkt 3	Punkt 3
Punkt 4	Punkt 4



Summary



Backup slides