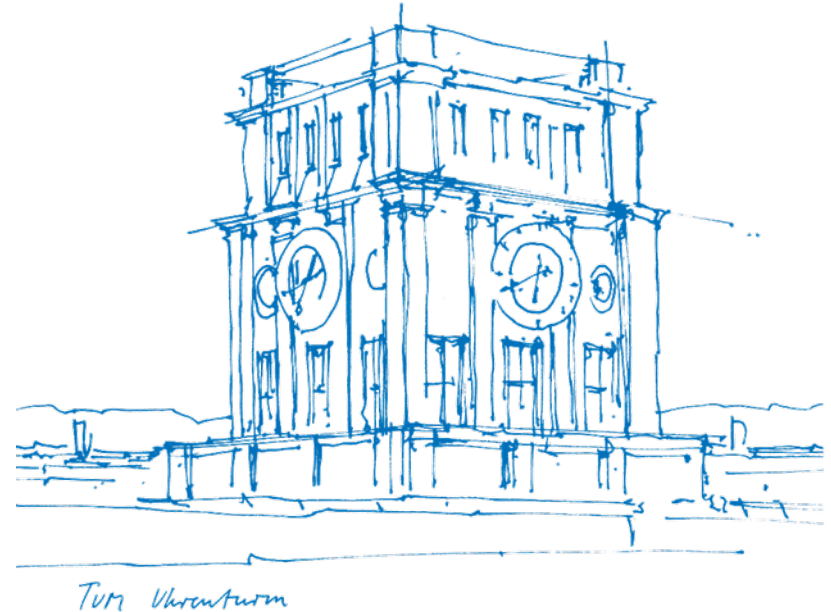


Deep Learning Methods for Reynolds-Averaged Navier-Stokes Simulations of Airfoil Flows

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



Introduction

TODO

Background – RANS

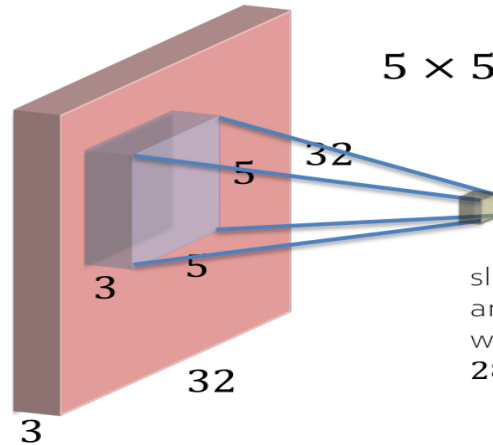
TODO

Background – RANS

TODO

Background – Convolutions

$32 \times 32 \times 3$ image

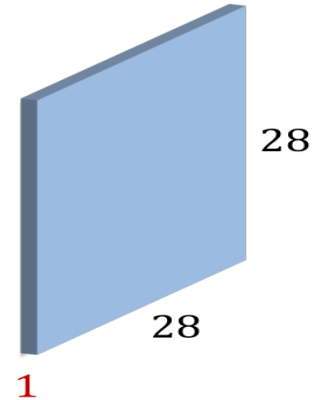


$5 \times 5 \times 3$ filter



slide over all spatial locations x_i
and compute all output z_i
w/o padding, there are
 28×28 locations

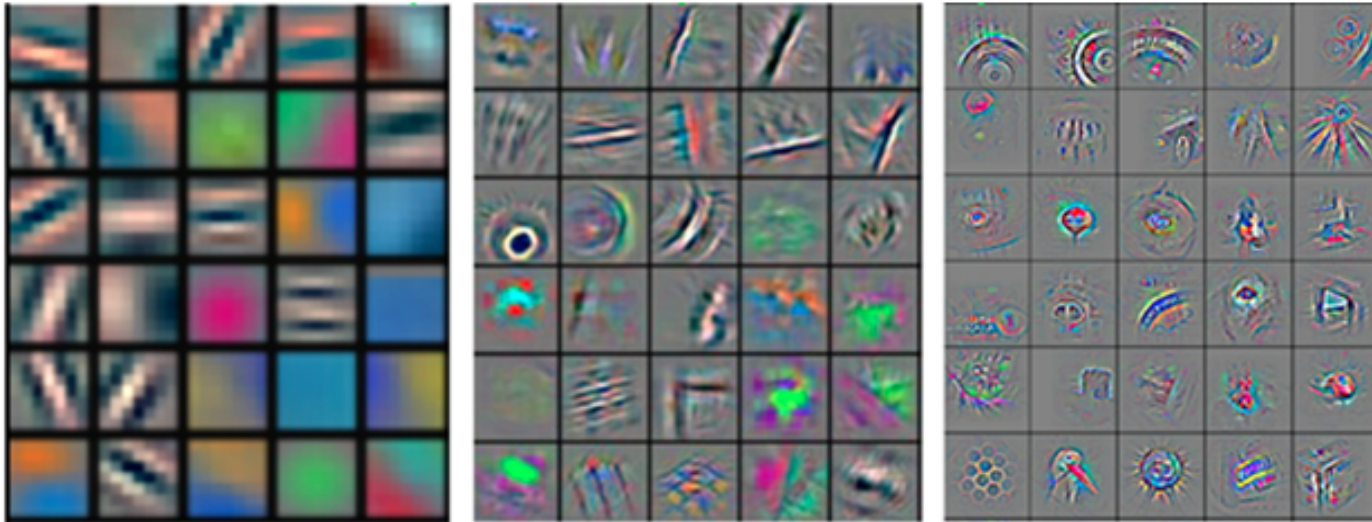
activation map
(also feature map)



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

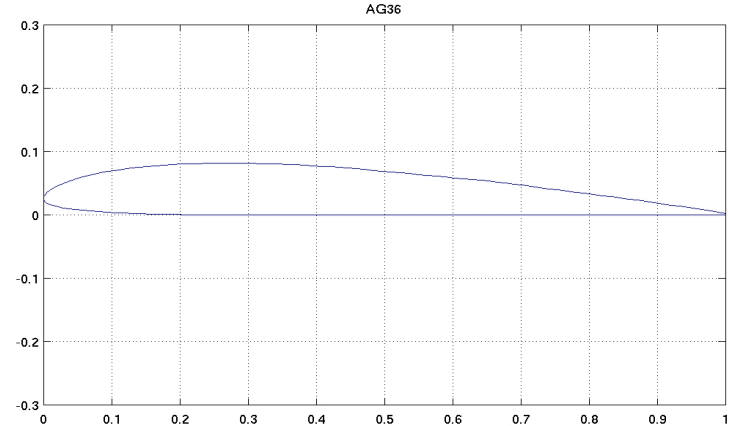
Airfoil shapes are provided by the UIUC database

Reynolds number: $[0.5, 5] \cdot 10^6$ (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

1. Bit mask representing airfoil shape
2. x velocity component
3. y velocity component

Reynolds number encoded as differently scaled
freestream velocity vectors wrt. their magnitude

Target channels

1. Pressure field
2. x velocity
3. y velocity

Data from the RANS solution

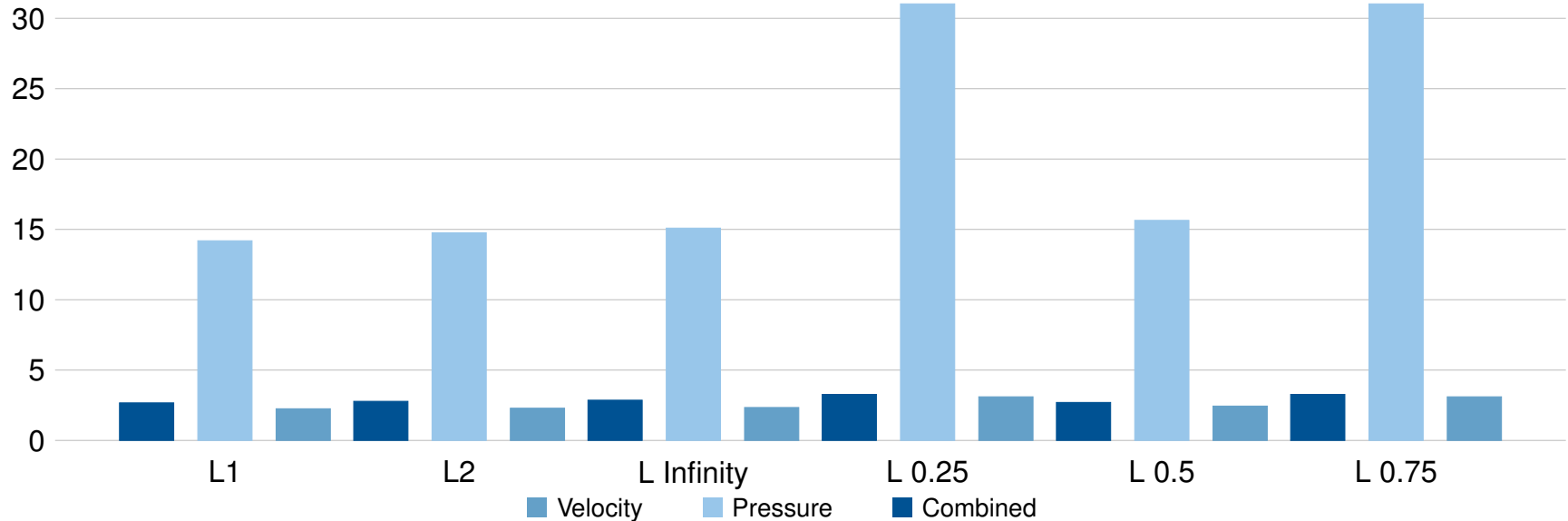
Pre-processing – Normalization

Pre-processing – Offset

Pre-processing – Evaluation

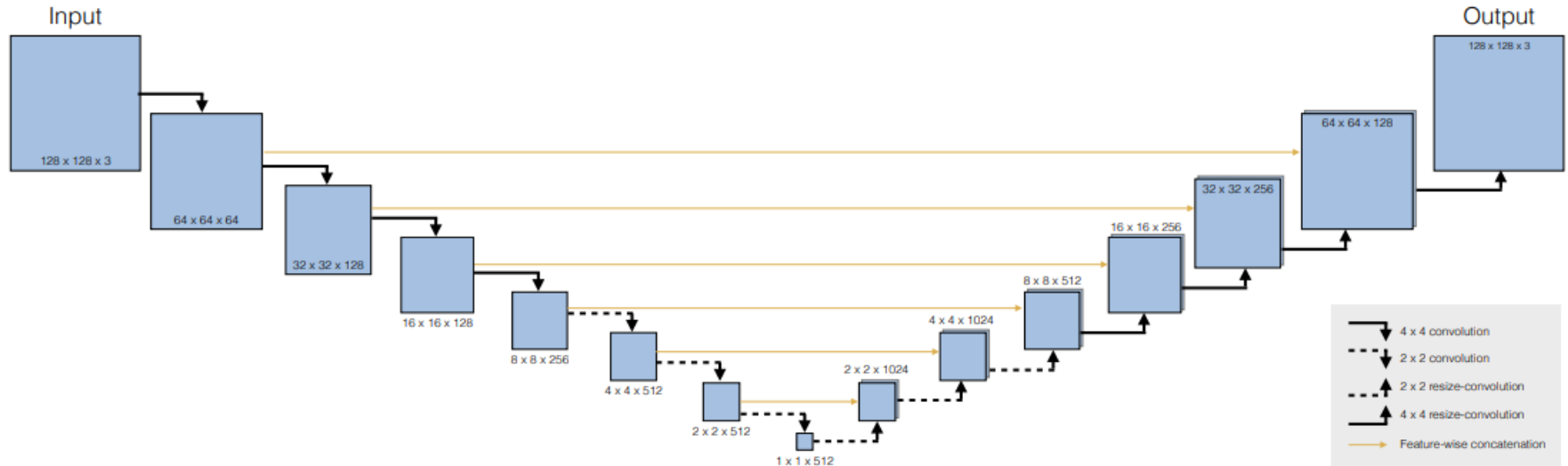
Vector norms used in pre-processing comparison wrt. error, L2 default (in %)

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

1. Activation – Leaky ReLu (0.2)
2. Convolution – Width down, Depth up
3. Batch normalization
4. Dropout (1%)

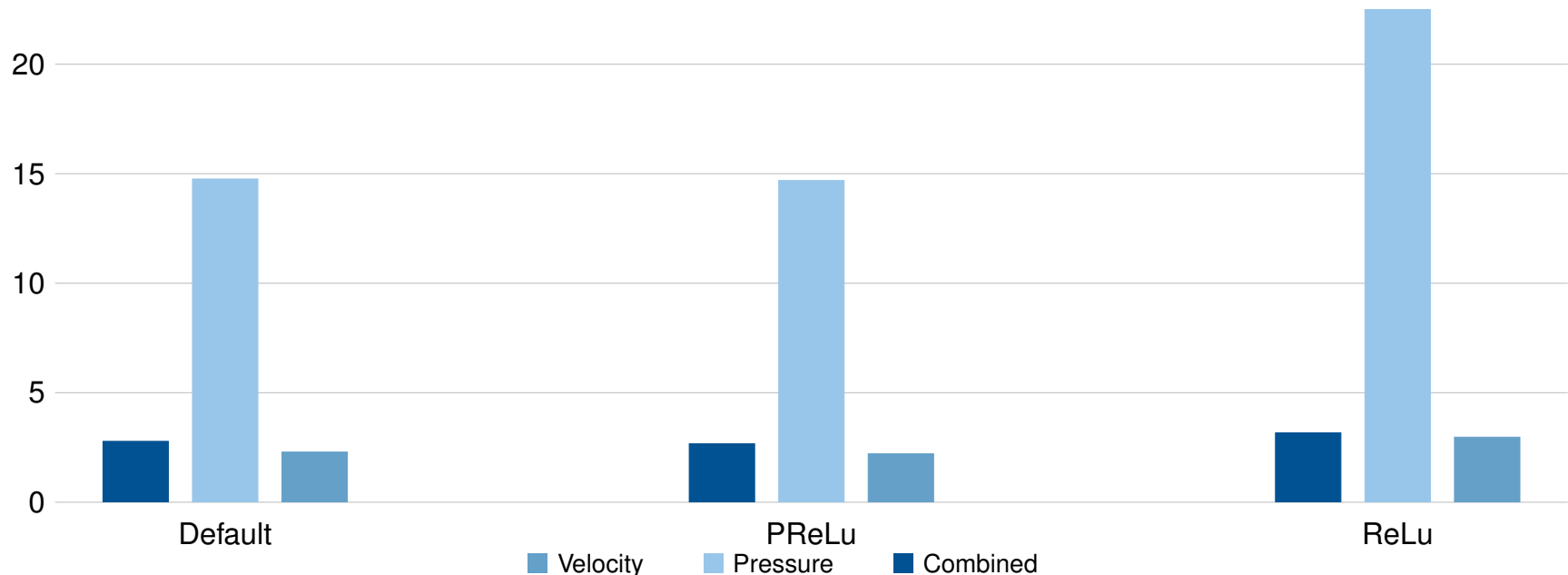
Decoder

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

Architecture – Evaluation

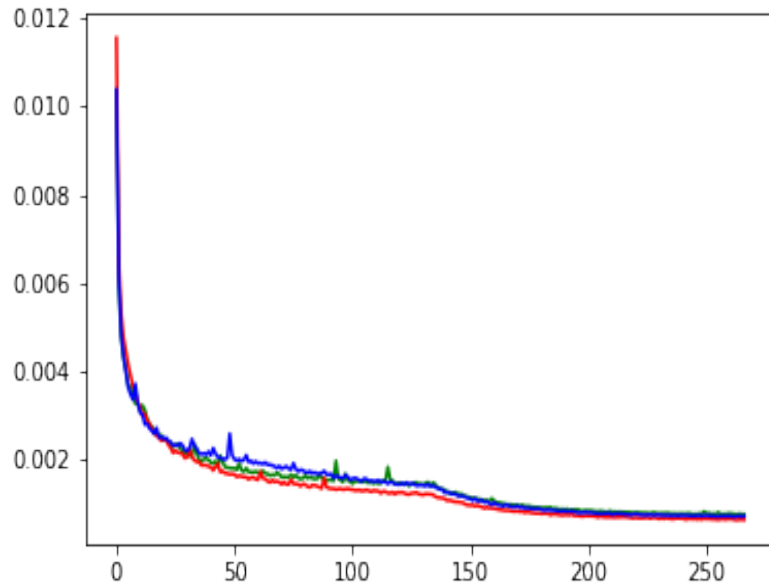
Error percentage of different activation functions after 160k iterations (266 epochs).

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

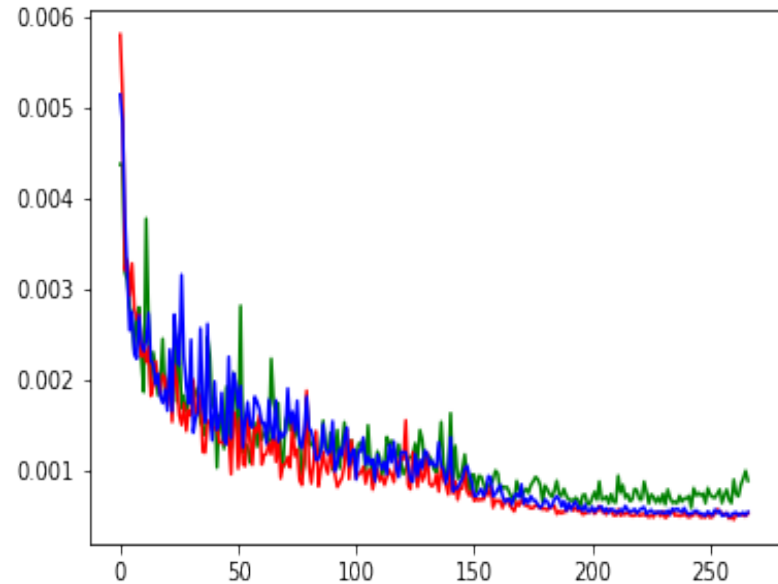


Architecture – Evaluation

Training loss



Validation loss

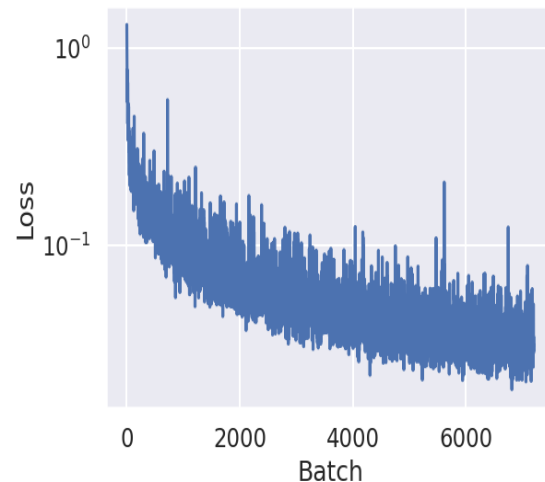
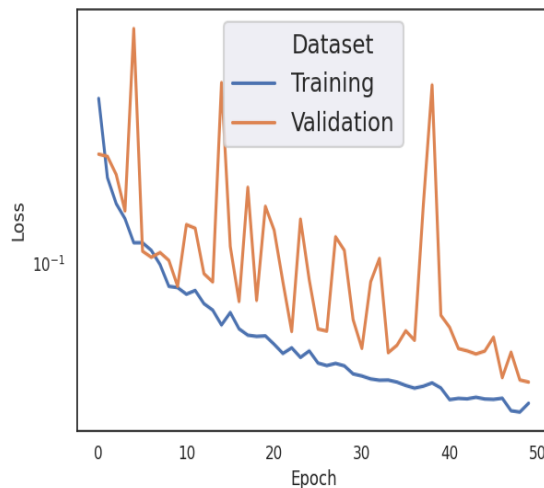
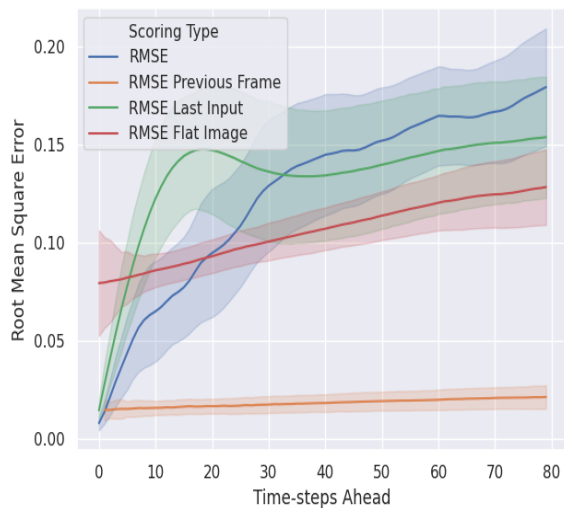


Transfer

TODO

Transfer

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

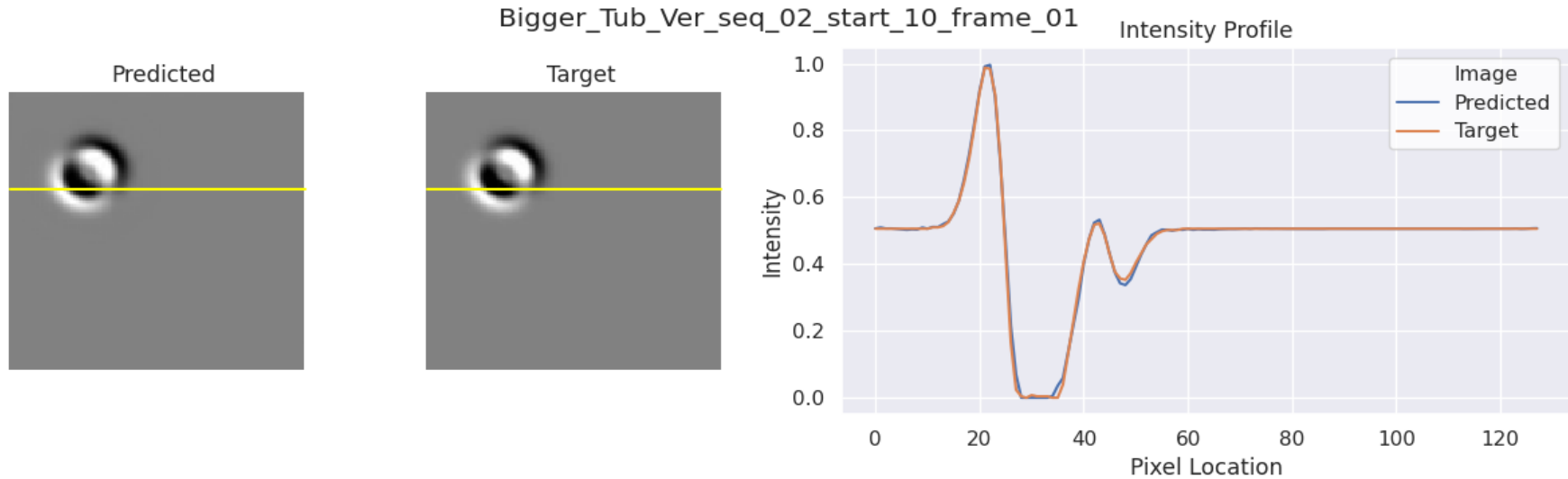


All plots in Transfer were made with https://github.com/stathius/wave_propagation

Transfer

Wave propagation prediction

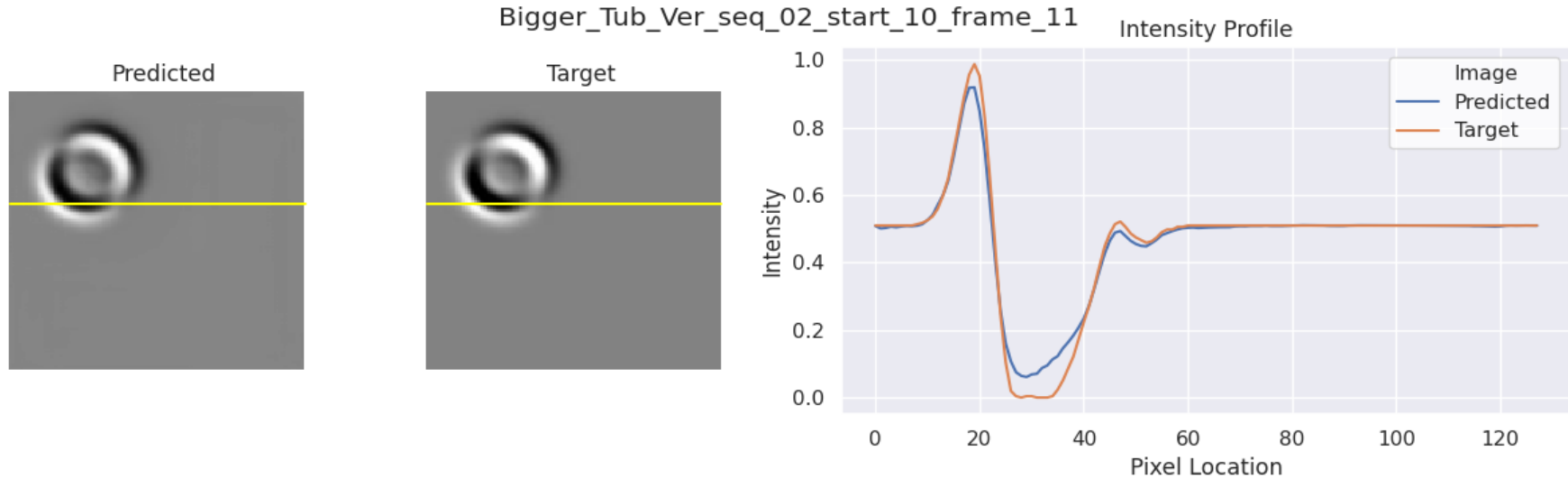
Intensity profile on scanline – Frame 1



Transfer

Wave propagation prediction

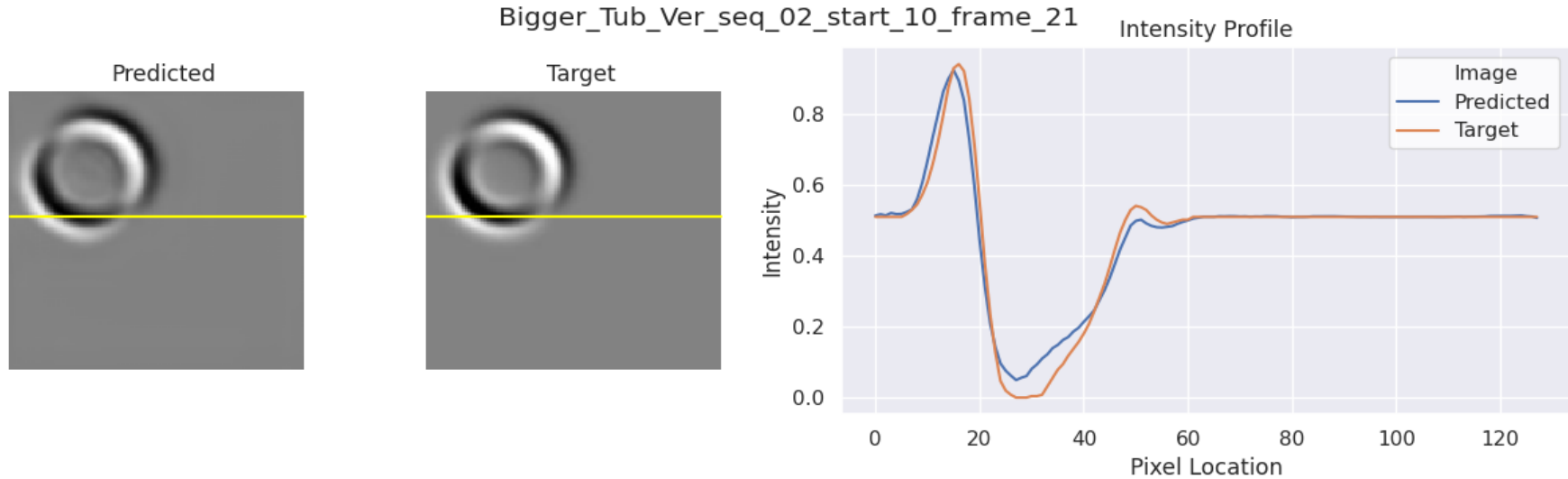
Intensity profile on scanline – Frame 11



Transfer

Wave propagation prediction

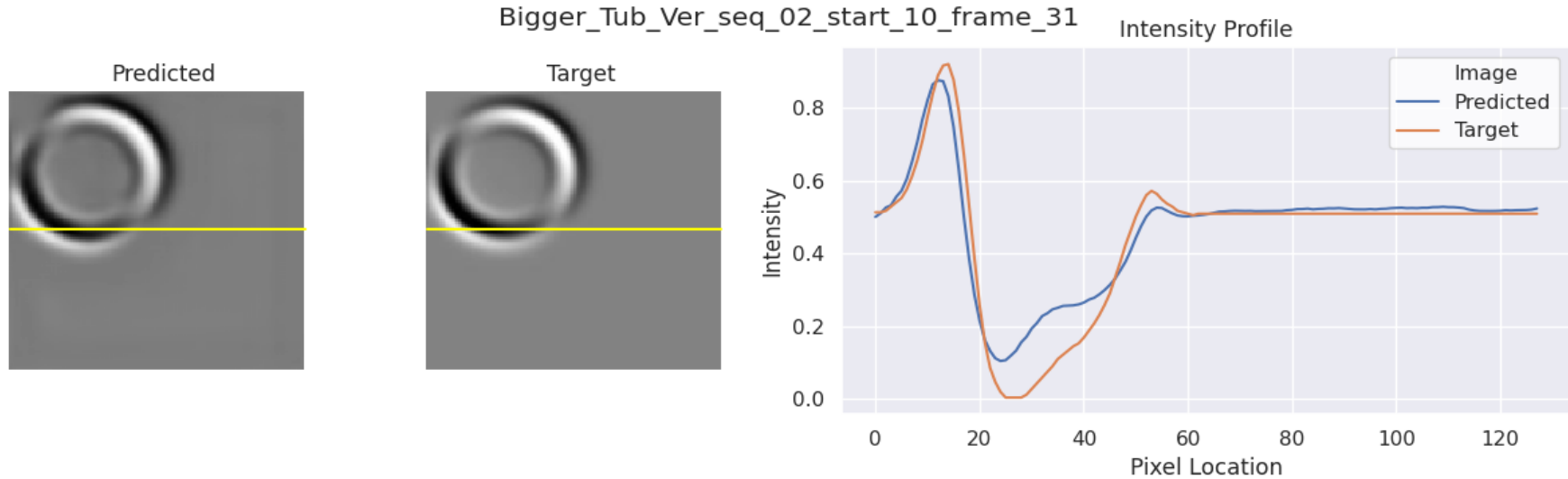
Intensity profile on scanline – Frame 21



Transfer

Wave propagation prediction

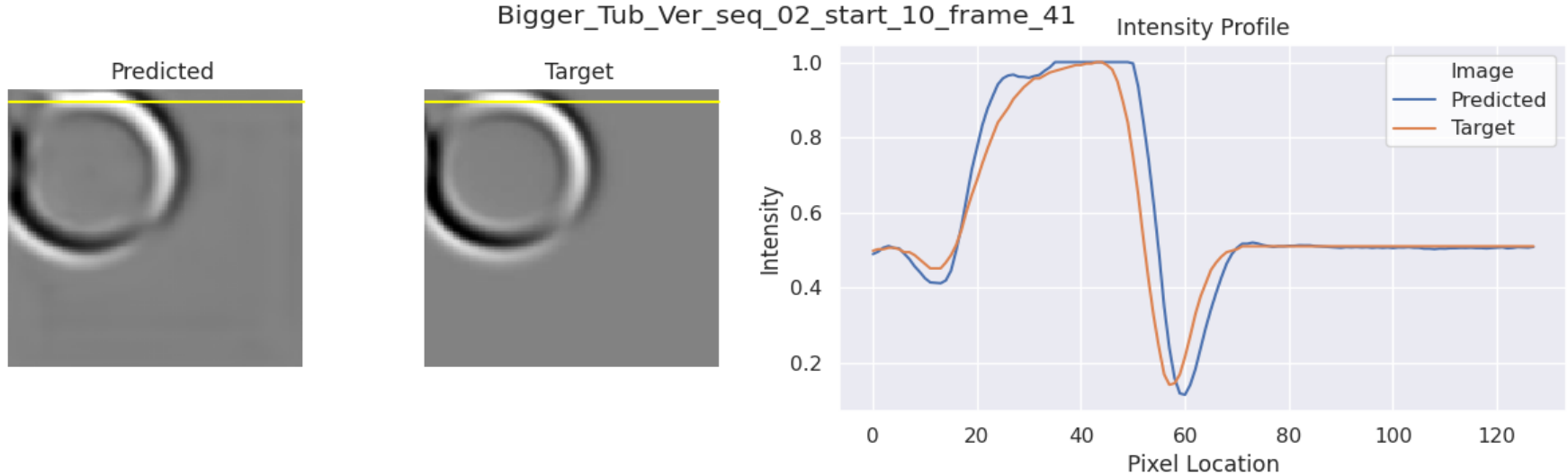
Intensity profile on scanline – Frame 31



Transfer

Wave propagation prediction

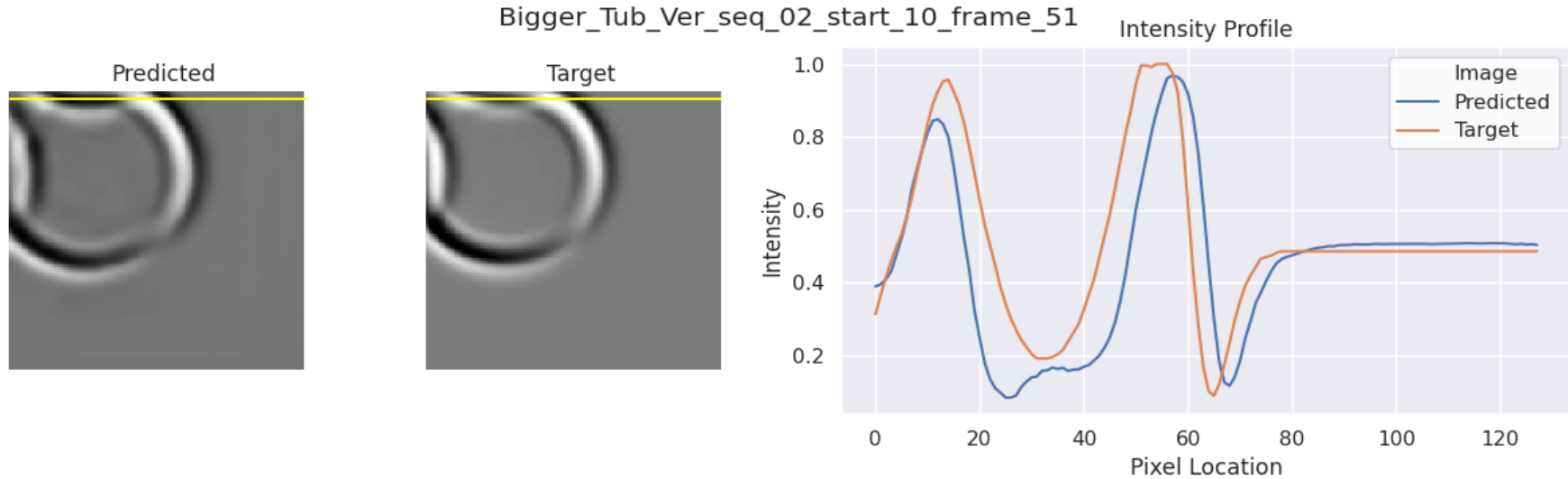
Intensity profile on scanline – Frame 41



Transfer

Wave propagation prediction

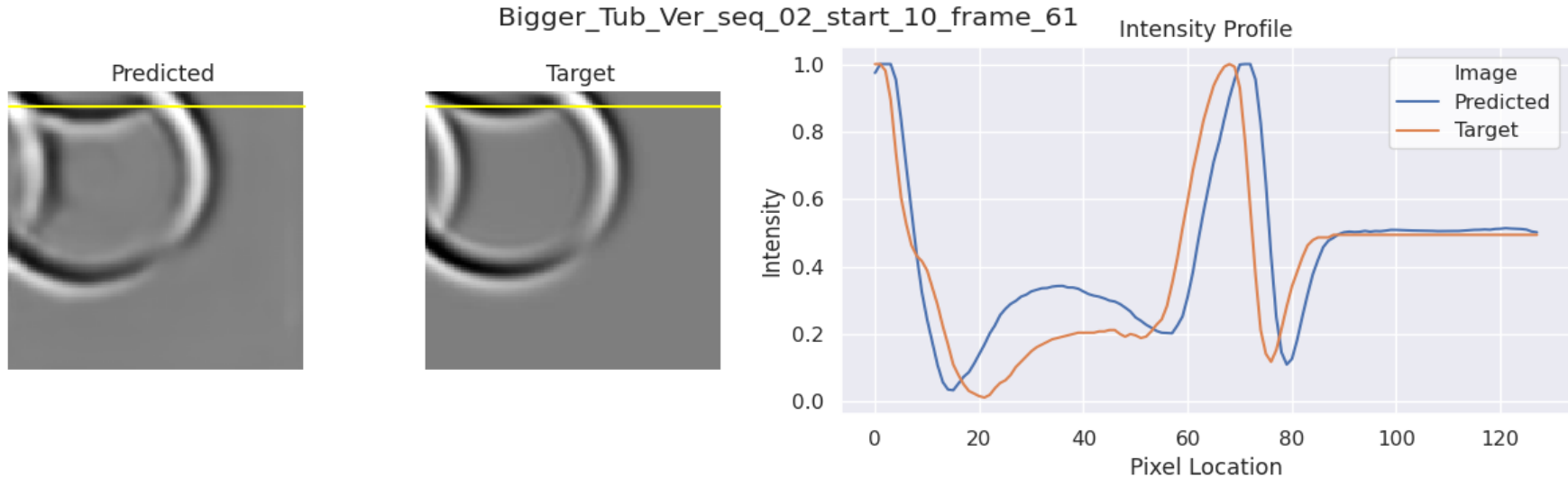
Intensity profile on scanline – Frame 51



Transfer

Wave propagation prediction

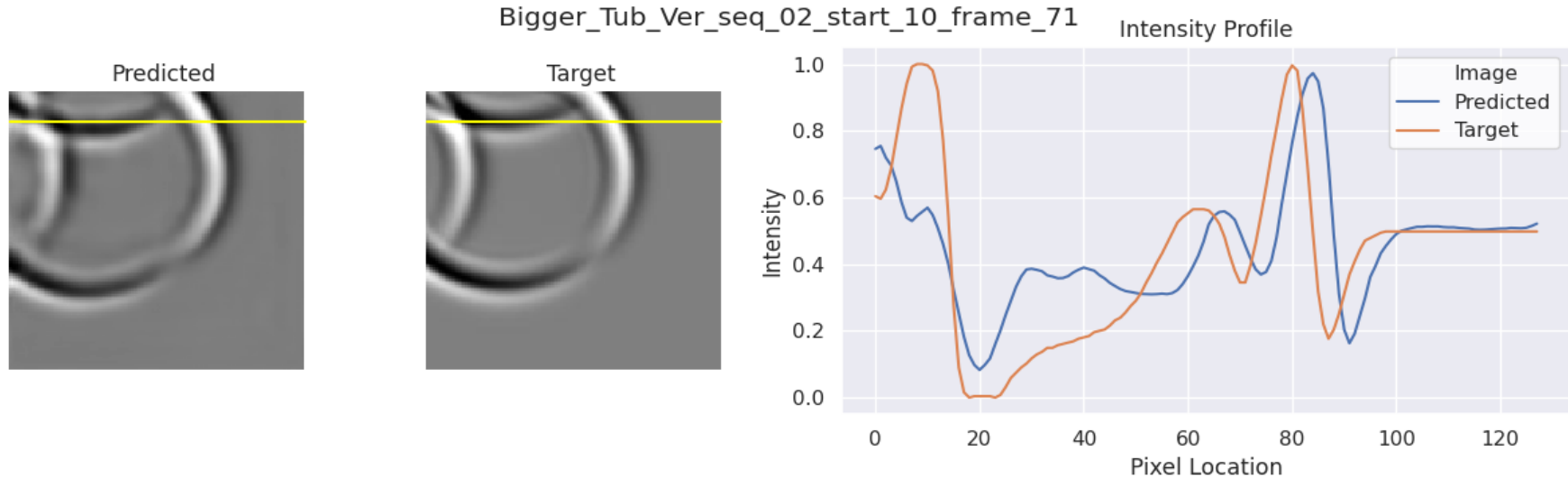
Intensity profile on scanline – Frame 61



Transfer

Wave propagation prediction

Intensity profile on scanline – Frame 71

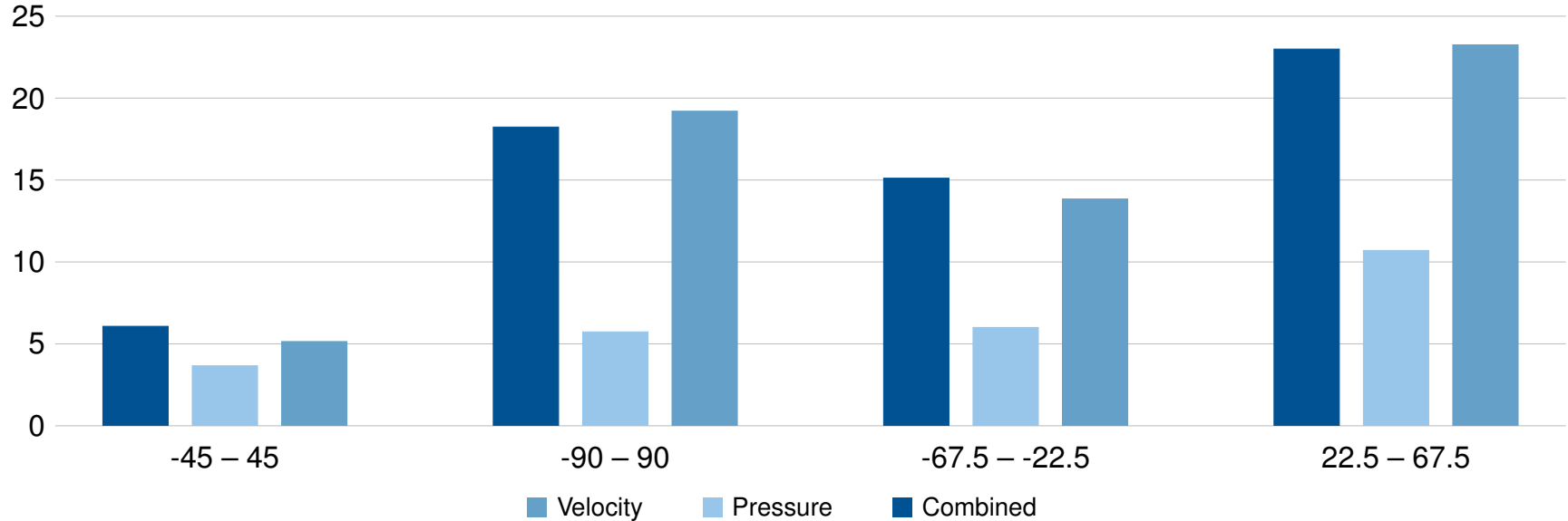


Generalization

TODO

Generalization

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



Discussion

TODO

Discussion

Positiv

Punkt 1

Punkt 2

Punkt 3

Punkt 4

Negativ

Punkt 1

Punkt 2

Punkt 3

Punkt 4

Summary

TODO

Backup slides

TODO