No-Reference Metrics for Standard Dynamic Range and High Dynamic Range Image Content

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Why Do We Need Metrics?

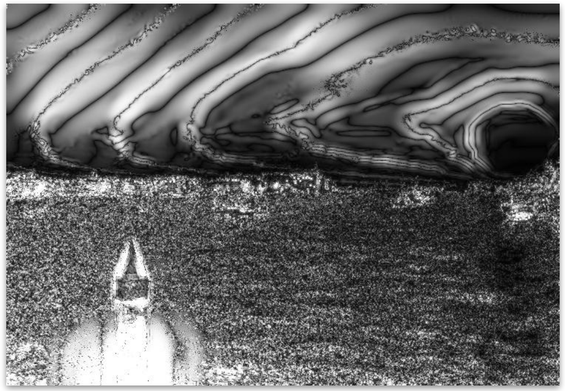
- In HDR/SDR Imaging, we need to determine and to understand what is happening during different steps of the pipeline:
  - **Acquisition**: we want to understand if there are artifacts due to acquisition or single image reconstruction;
  - **Compression**: we want small file size at maintaining high-quality;
  - **Tone mapping**: we want to adapt content for different display while keeping quality as it was “scene-referred”.

Reference Metrics

Reference Image

Distorted Image

Reference Metric



Probability Map

Q = 42.0

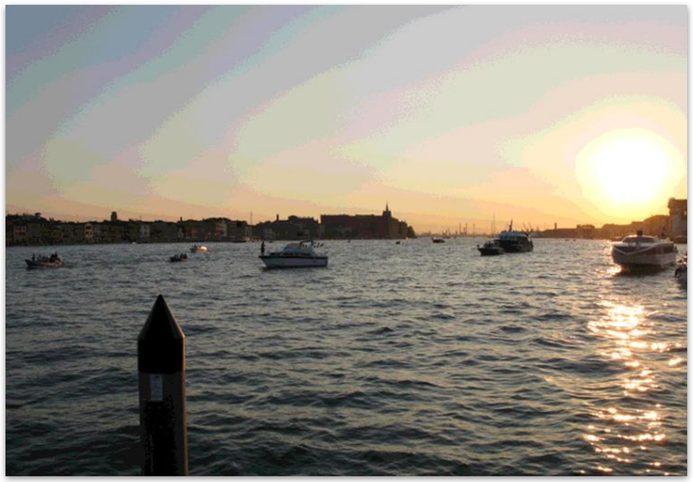
Quality Value

Reference Metrics: Current Limitations

- These models are very complex:
  - Difficult to port to GPUs with ease.
- They are computationally expensive; e.g., minutes of computations for a full HD image.
- Do we need a distortion map?
  - For most tasks we just need **a single value**!

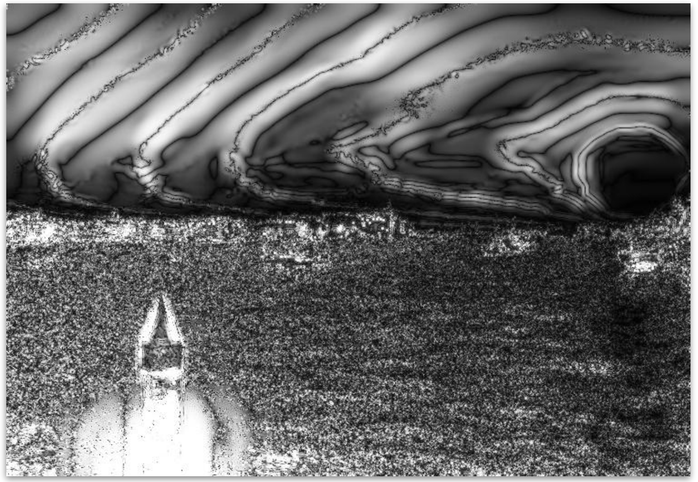
Going No-Reference

No-Reference Metrics



Distorted Image

No-reference Metric



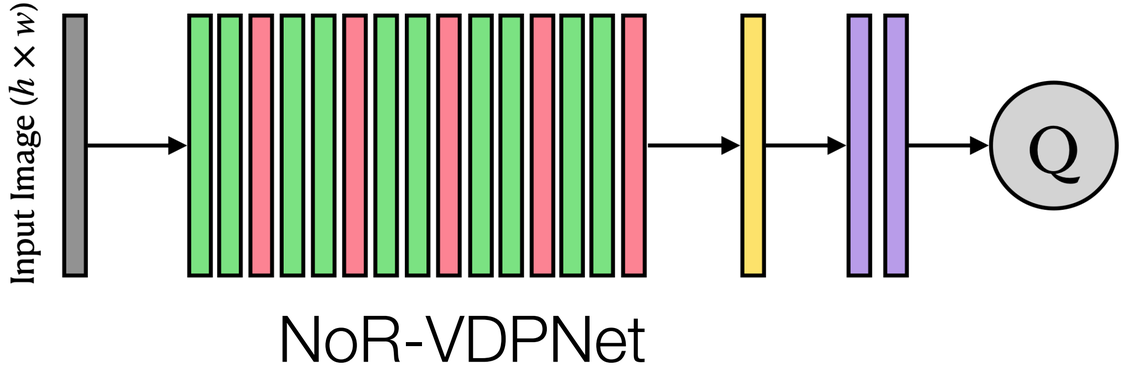
Probability Map

Q = 42.7

Quality Value

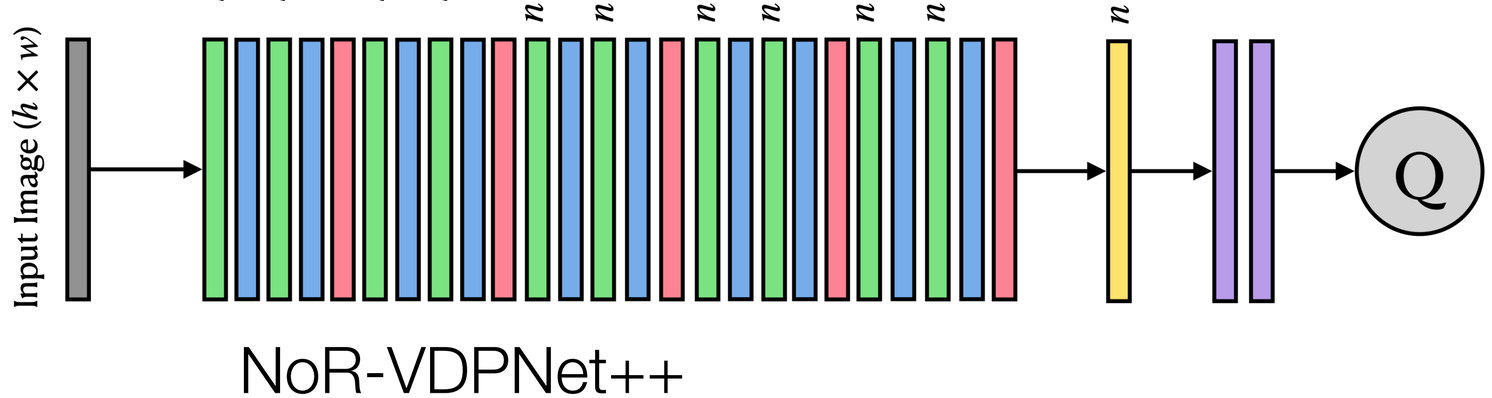
NoR-VDPNet(++): Architecture

Distorted Image

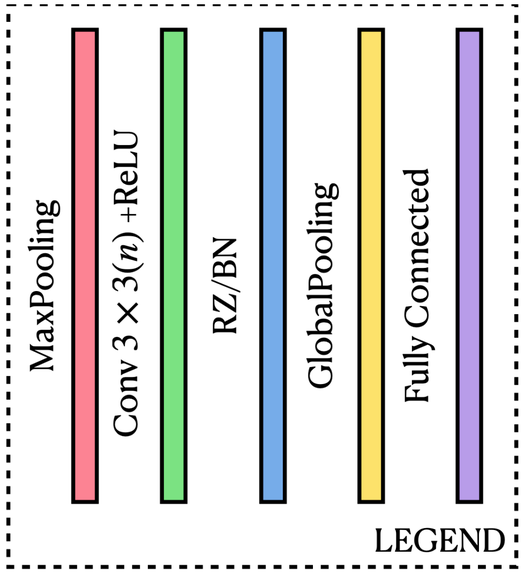


NoR-VDPNet

Distorted Image



NoR-VDPNet++



Training Set

Distorted Image

Reference Image

FR Metric

Q=49

Quality Value

TRAINING SAMPLE

Q=49

Input
Distorted Image

Target
Quality Value

NoRVDPNet(++): HDR-VDP2.2/TMQI Datasets

	TRAINING SET	VALIDATION SET	TEST SET	TOTAL
HDR-C (HDR-VDP2.2)	49.602	6.216	6.216	62.034
SDR-D (HDR-VDP2.2)	80.244	10.025	10.044	100.313
TMO (TMQI)	106.290	13.320	13.320	132.930
ITMO (HDR-VDP2.2)	106.290	13.320	13.320	132.930

NoR-VDPNet(++): SDR-D Dataset

REFERENCE SDR IMAGE

BLUR DISTORTION

NOISE DISTORTION

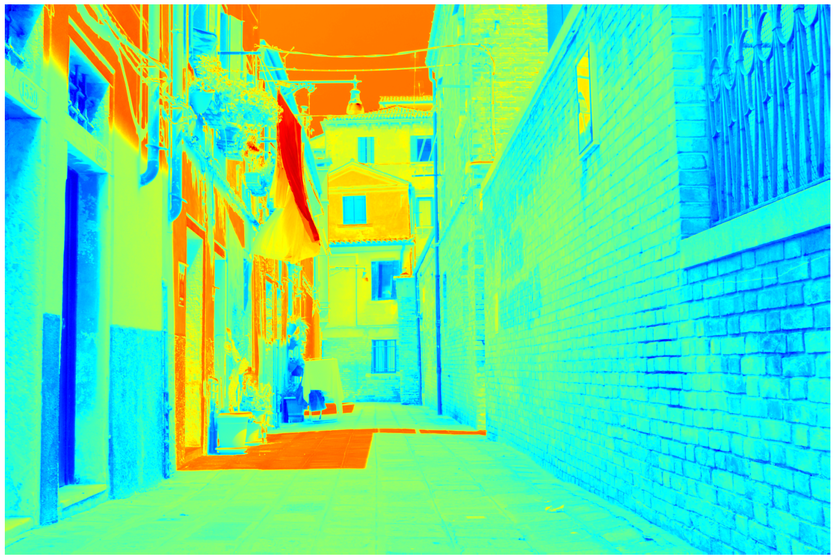
NoR-VDPNet(++): SDR-D Dataset

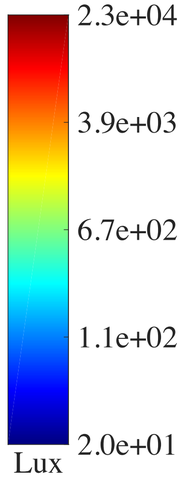
REFERENCE SDR IMAGE

QUANTIZATION DISTORTION

SIN GRATE DISTORTION

NoR-VDPNet(++): HDR-C Dataset





HDR Image

JPEG-XT:

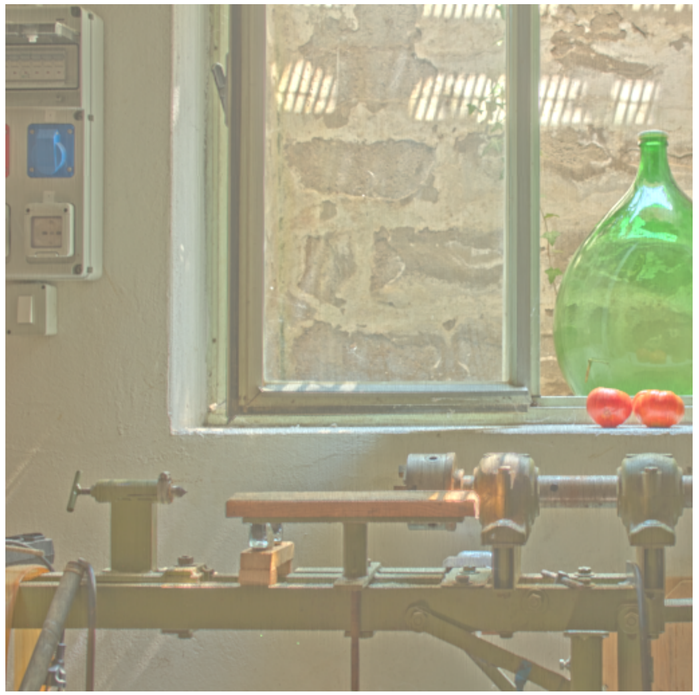
- Random Profile
- Random Residual Compressione

8-bit Layer

METADATA

NoRVDPNet(++): TMO Dataset

Drago et al. 2003



Durand and Dorsey 2002

Reinhard et al. 2002

18 tone mapping operators from the HDR-Toolbox: https://github.com/banterle/HDR_Toolbox/

NoRVDPNet(++): ITMO Dataset

Input SDR Image

Eilertsen et al. 2017
(tonemapped)

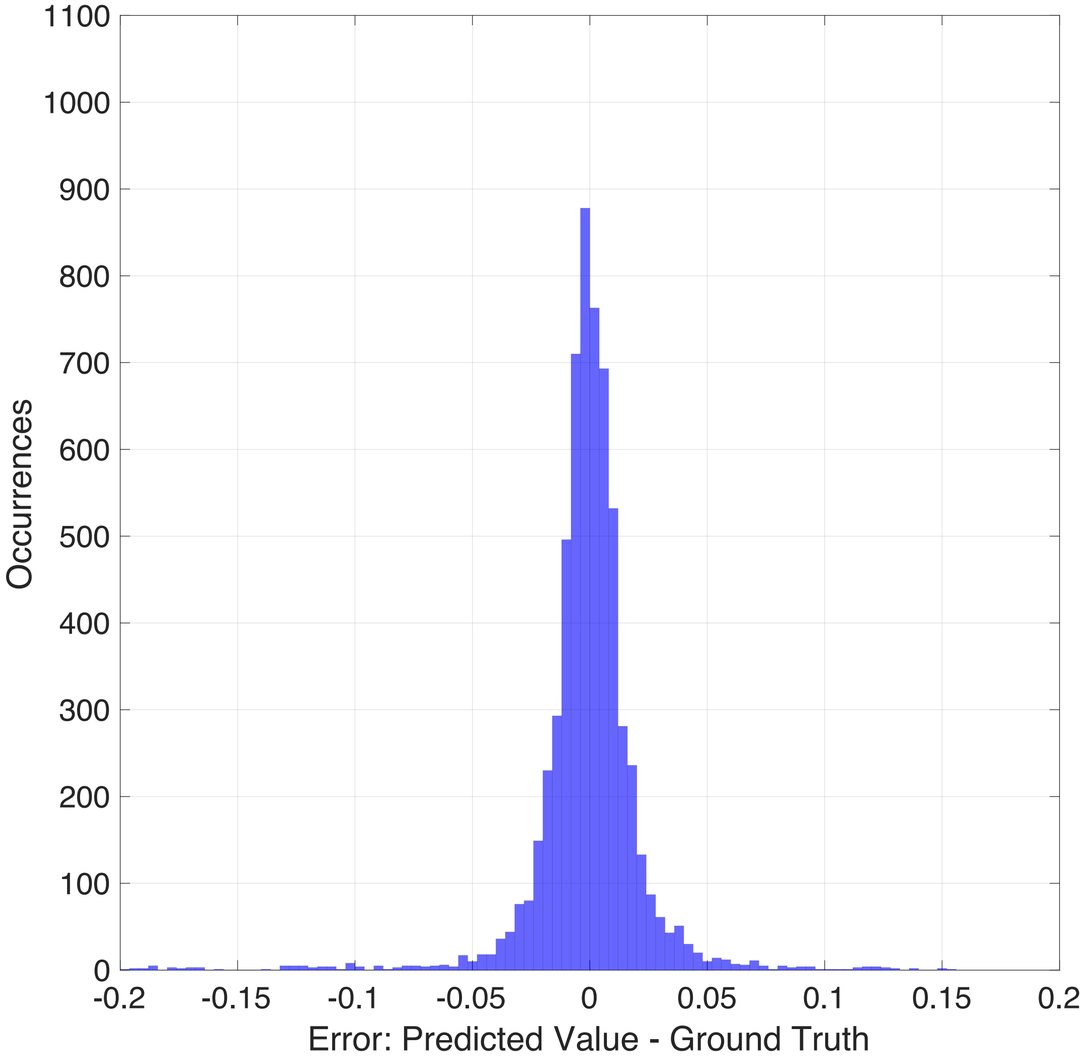
Santos et al. 20202
(tonemapped)

6 inverse tone mapping operators 4 available in the HDR-Toolbox: https://github.com/banterle/HDR_Toolbox/

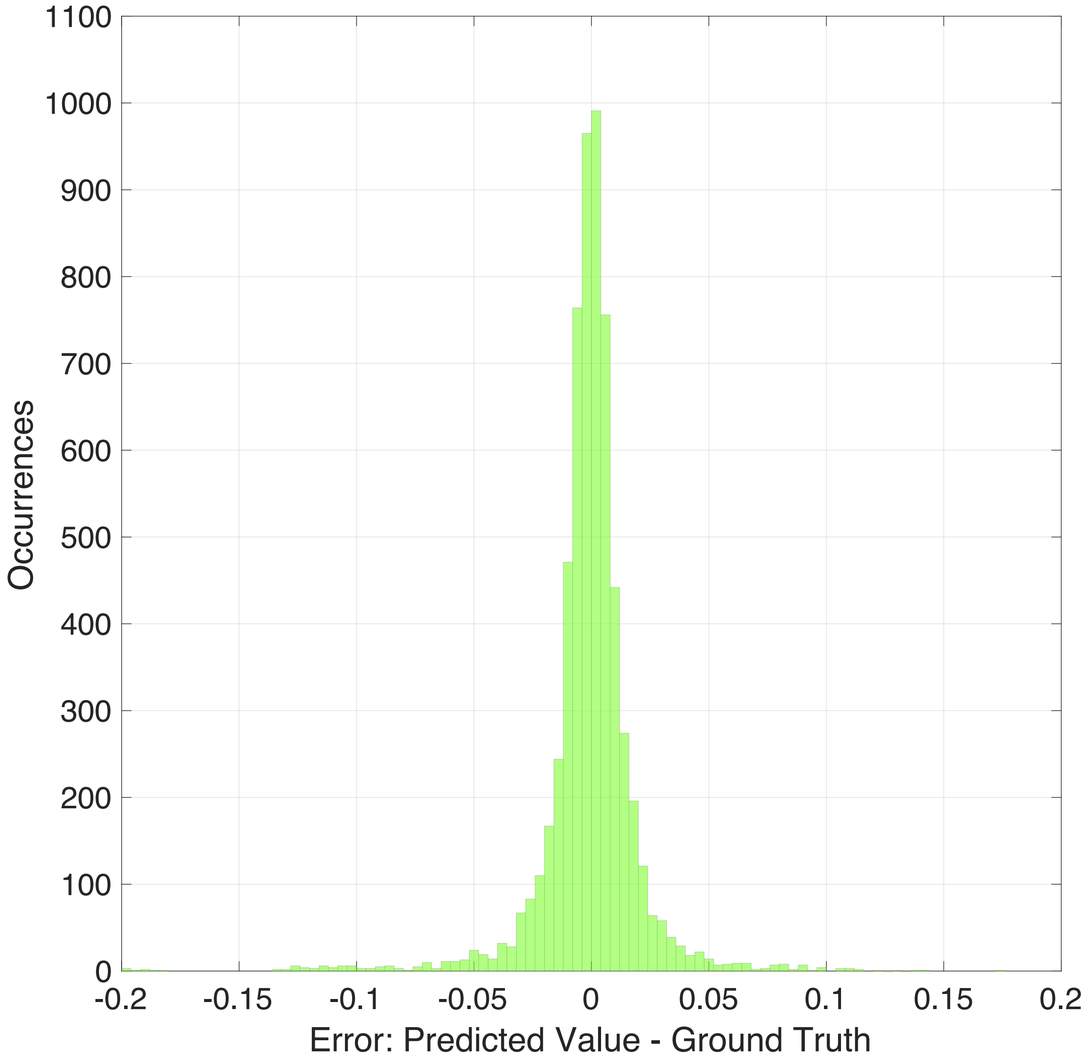
NoR-VDPNet(++): Loss and Encoding

- Loss is a classic MSE; it works well for predicting quantitative values:
- Encoding:
  - SDR Images: linear scaling to fit the range $[0,1]$
  - HDR Images: $\log_{10}(x+1)$

Results: HDR-C Test Set

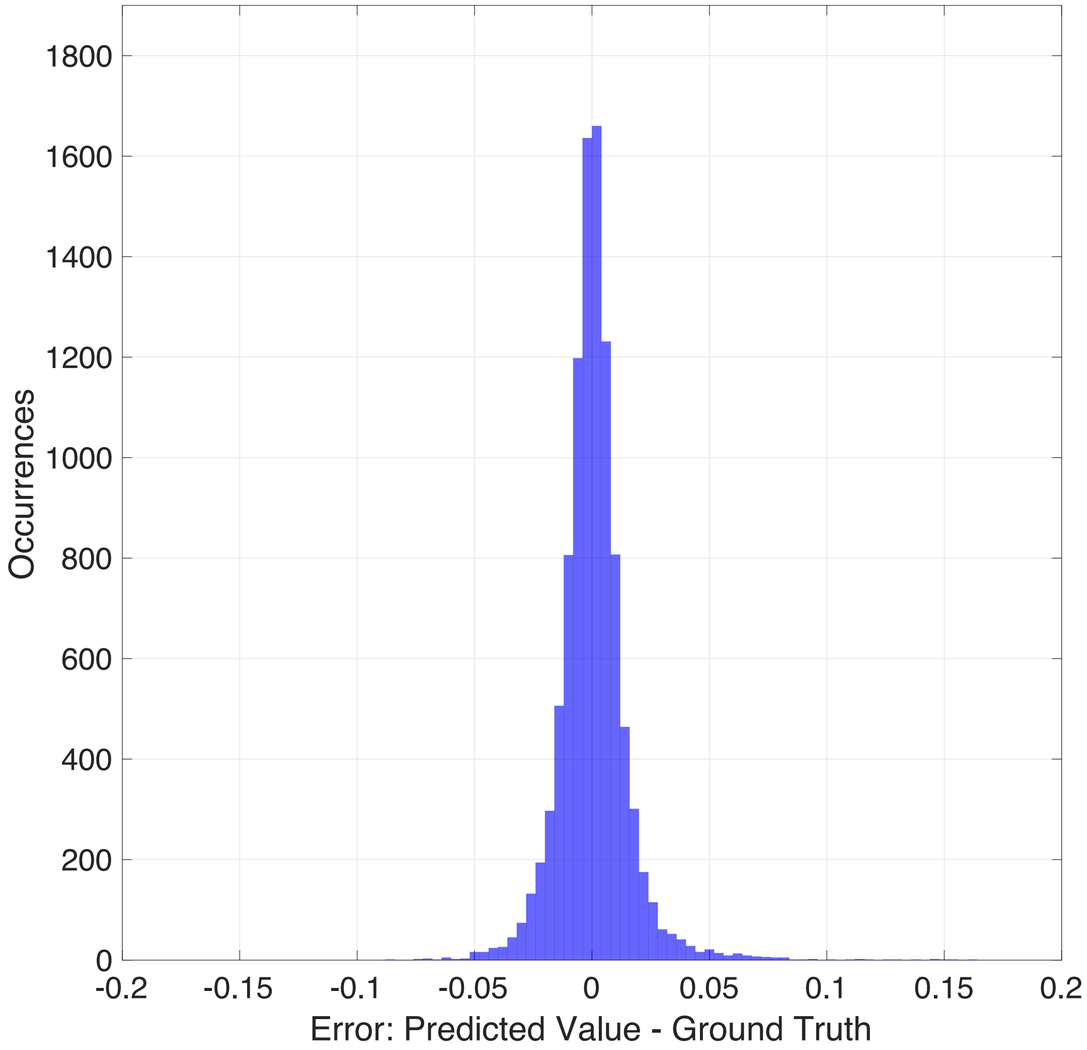


NoRVDPNet

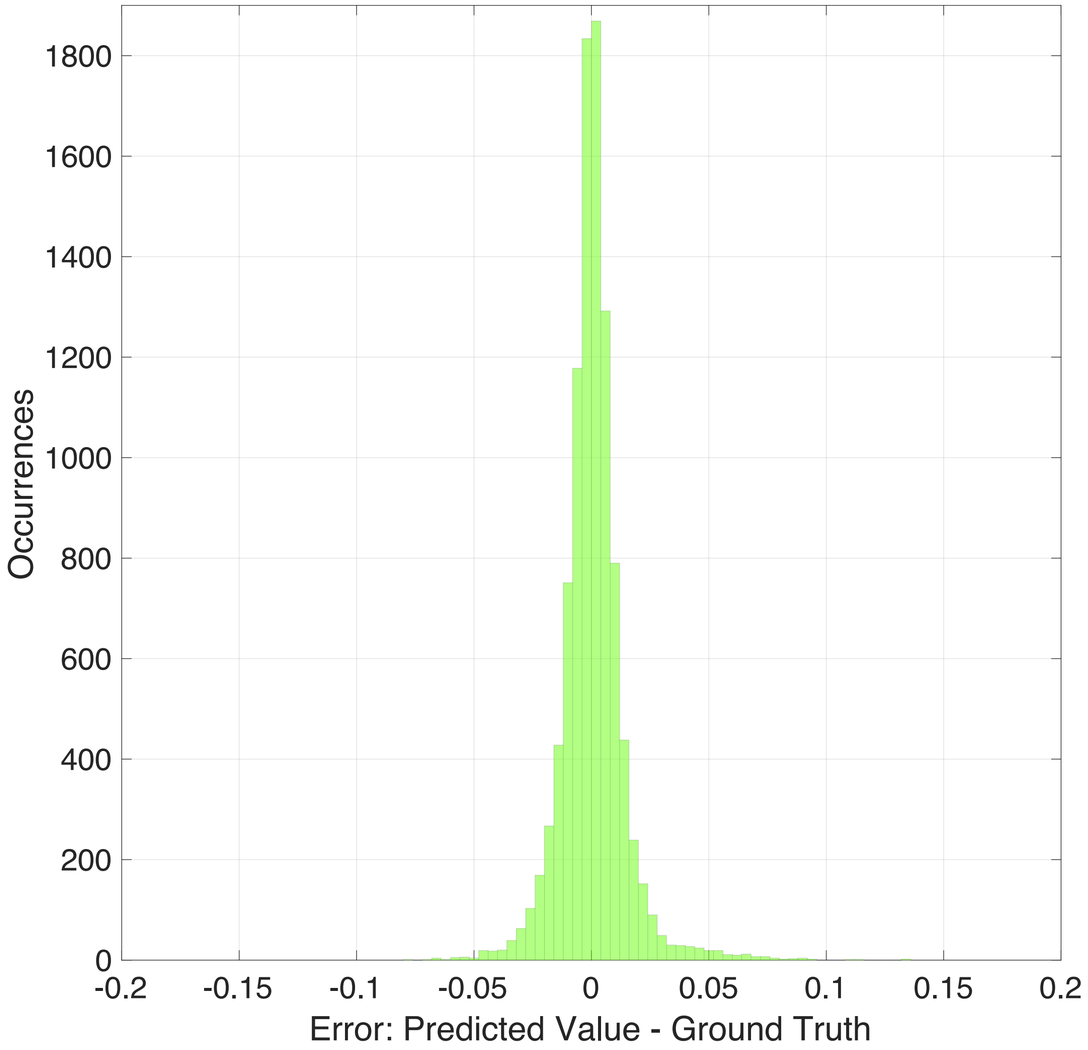


NoRVDPNet++

Results: SDR-D Test Set

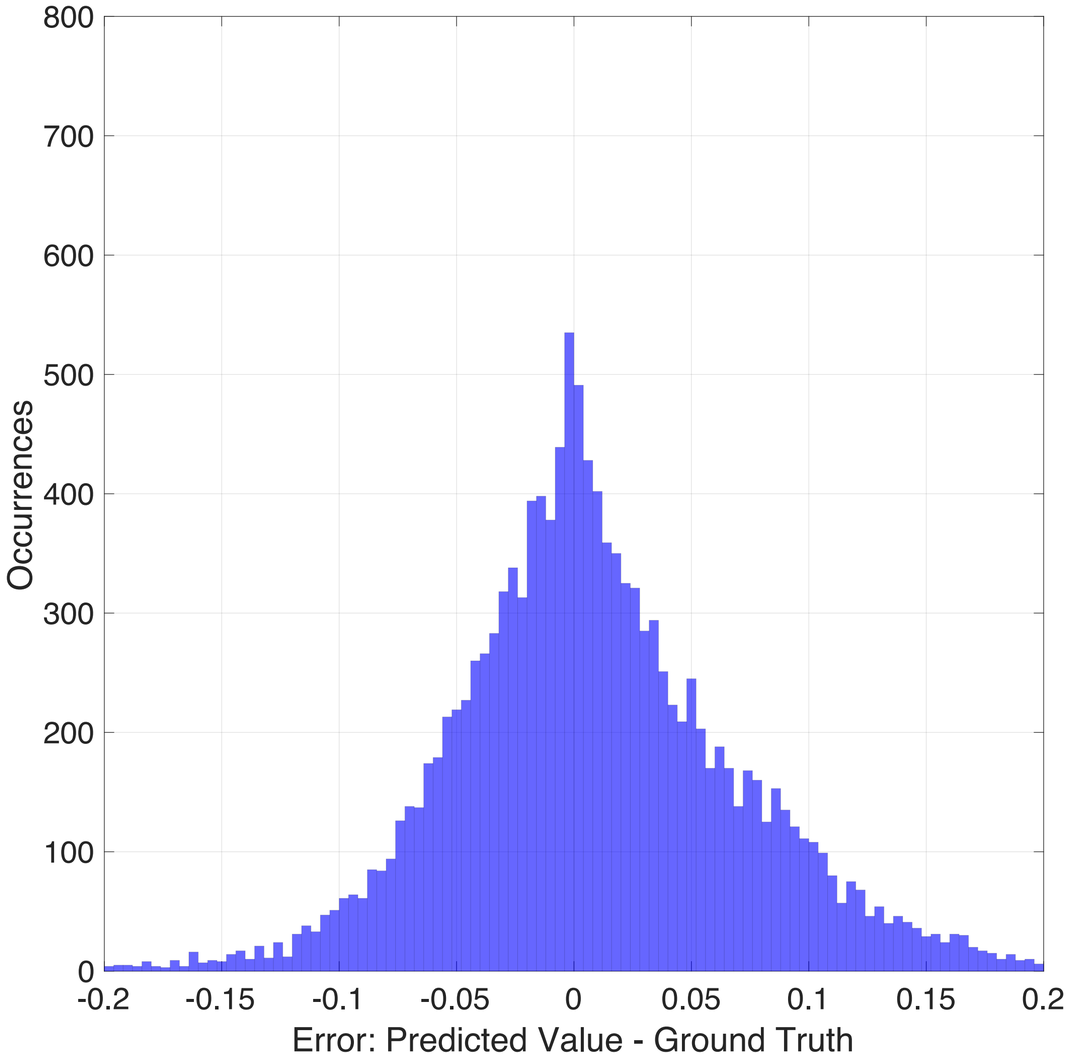


NoRVDPNet

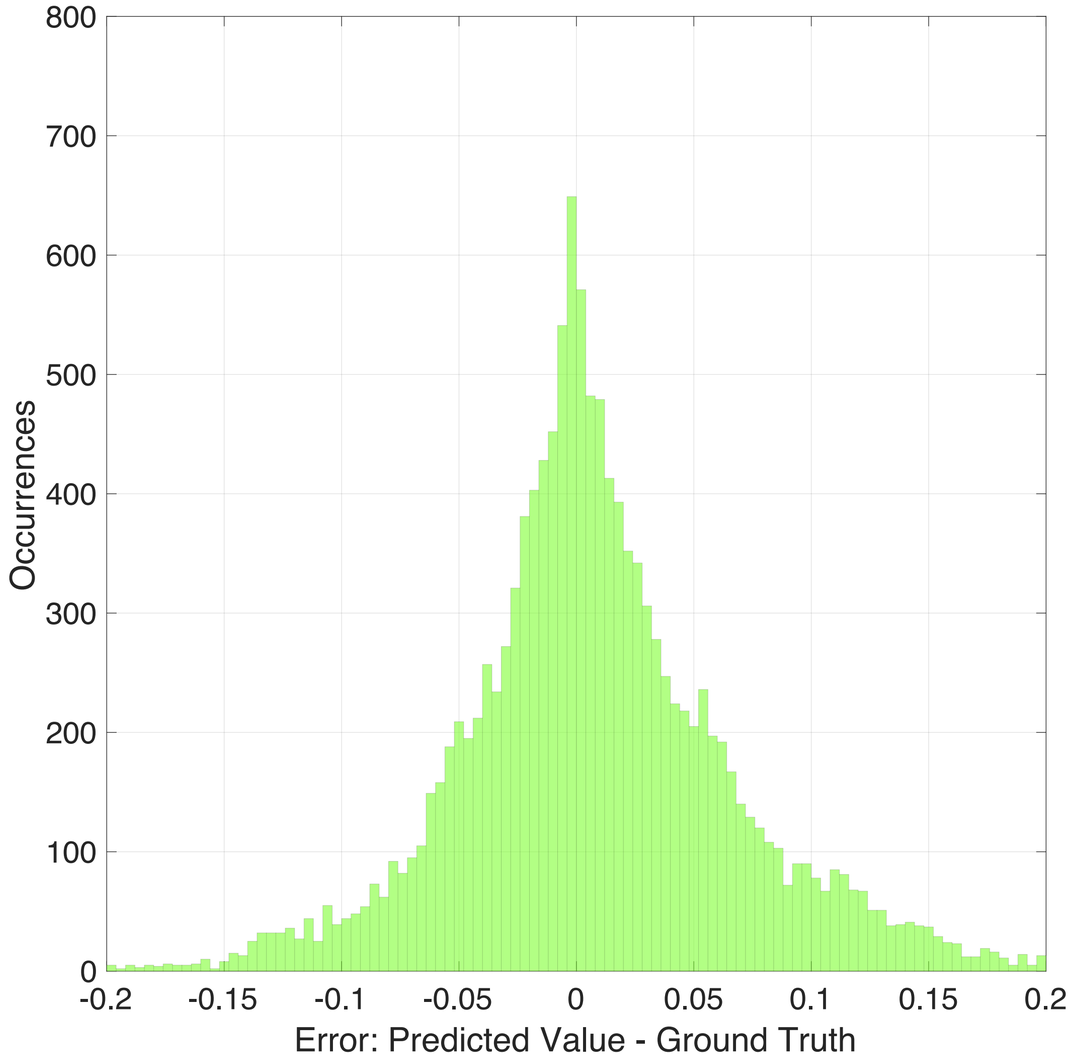


NoRVDPNet++

Results: ITMOS Test Set

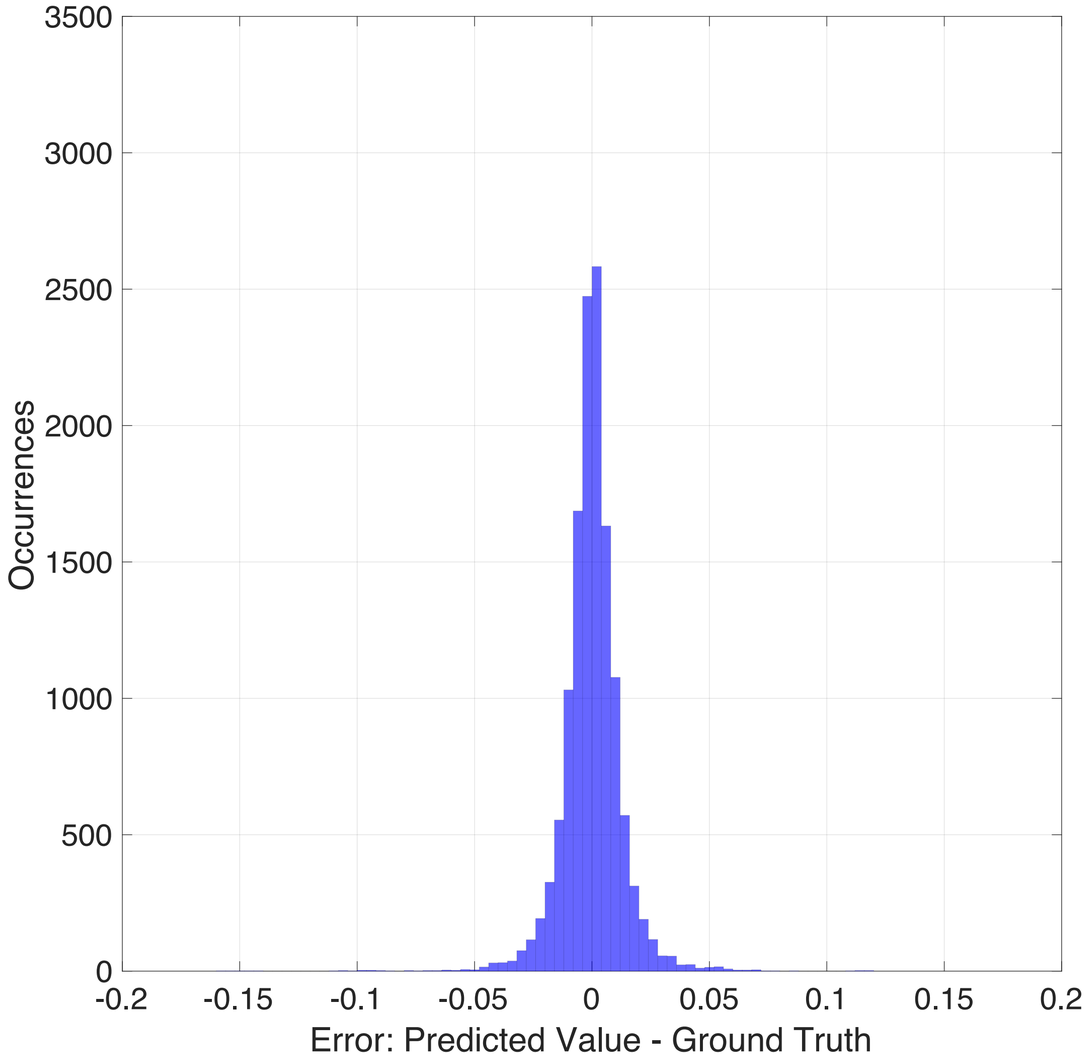


NoRVDPNet

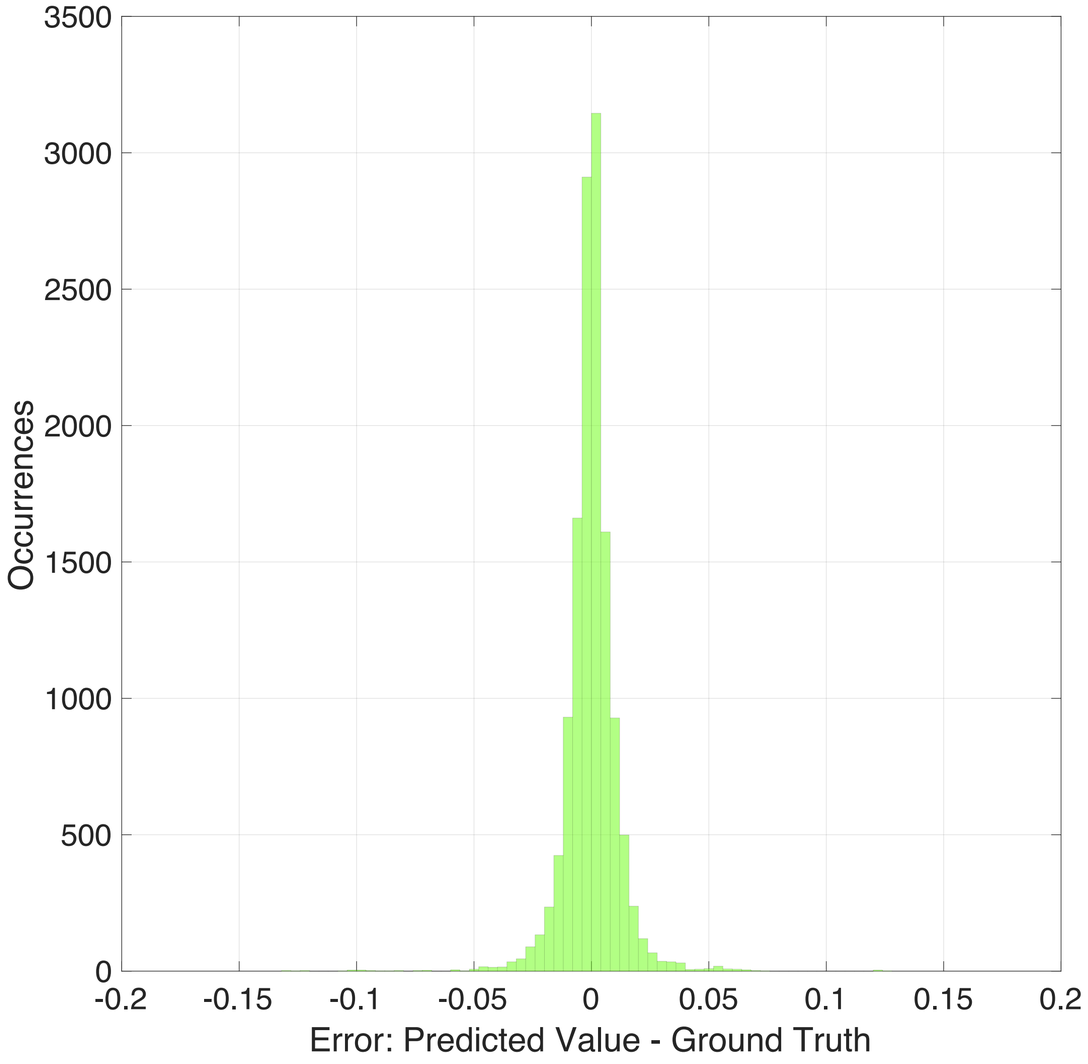


NoRVDPNet++

Results: TMOS Test Set

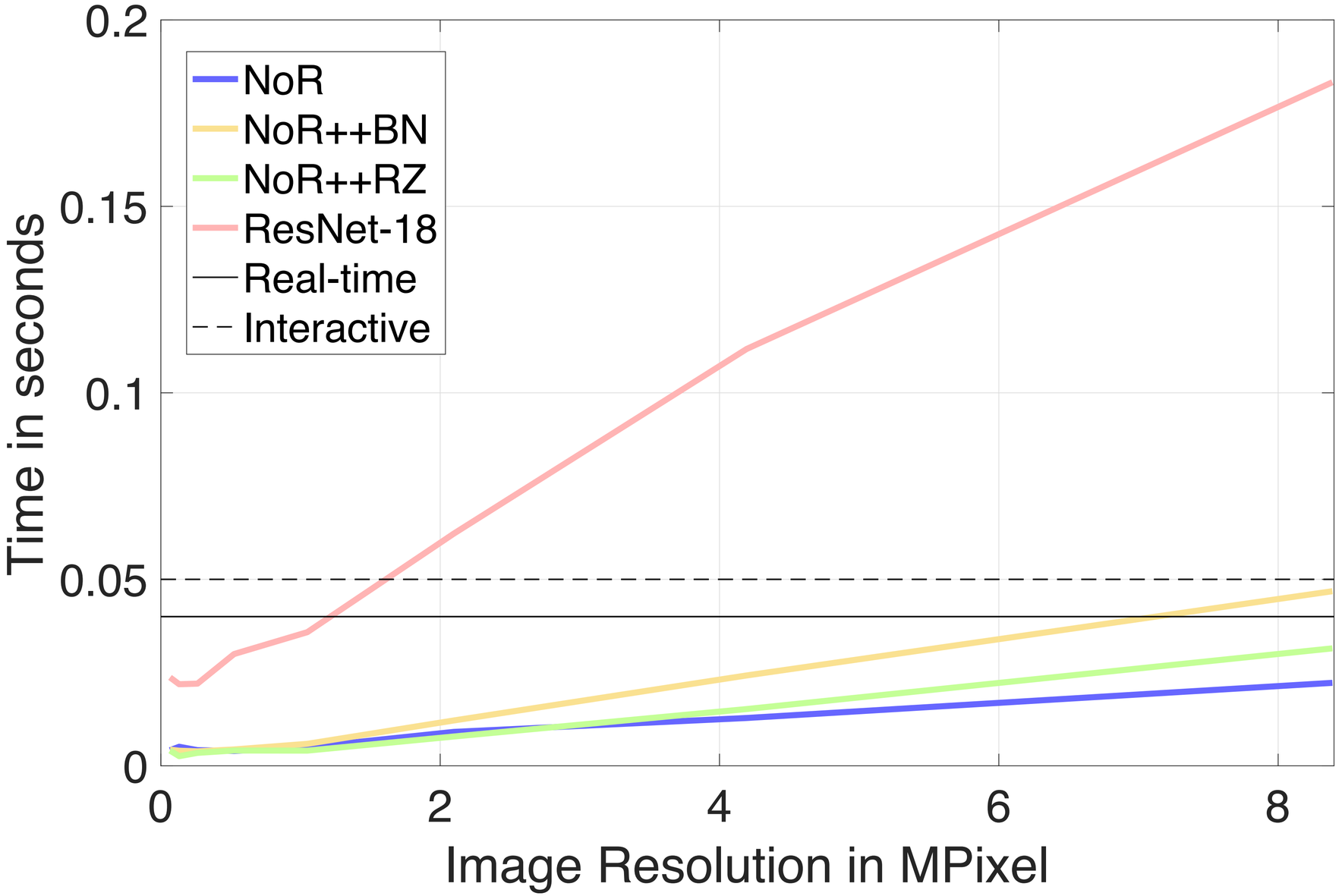


NoRVDPNet



NoRVDPNet++

Timings


0.2
0.15
0.1
0.05
0
Time in seconds
NoR
NoR++BN
NoR++RZ
ResNet-18
Real-time
Interactive
0
2
4
6
8
Image Resolution in MPixel

NoR-VDPNet(++): Conclusions

- We can go from reference to no-reference;
- When we model several distortions we have a larger error than a single distortion;
- Layer normalization increases quality;
- This scheme works for TMQI-I (SSIM-based);
- Still real-time performance.

Applications

Applications: TMO Optimization Task

Input HDR image

TMO

Tone Mapped Image

DEEP NR-METRIC

Q

Q > Thr

NO

YES

Tone Mapped Image

Applications: Optimized TMO

TMO without optimized parameters

TMO with optimized parameters

Video Courtesy of Jan Fröhlich - Stuttgart HDR Video Dataset

Application: Optimized TMO

(a) $\hat{Q} = 0.903$ /$Q = 0.885$

(b) $\hat{Q} = 0.906$/$Q = 0.930$

(c) $\hat{Q} = 0.933$ /$Q = 0.914$

(d) $\hat{Q} = 0.918$/$Q = 0.903$

(e) $\hat{Q} = 0.902$/$Q = 0.889$

(f) $\hat{Q} = 0.841$/$Q = 0.771$

(g) $\hat{Q} = 0.951$/$Q = 0.831$

(h) $\hat{Q} = 0.875$/$Q = 0.909$

(i) $\hat{Q} = 0.951$/$Q = 0.967$

(j) $\hat{Q} = 0.958$/$Q = 0.974$

(k) $\hat{Q} = 0.967$/$Q = 0.976$

(l) $\hat{Q} = 0.997$/$Q = 0.979$

Applications: JPEG-XT Compression Task

Input HDR image

TMO

Tone Mapped
+
Metadata

Reconstructed
HDR Image

DEEP
NR-METRIC

Q

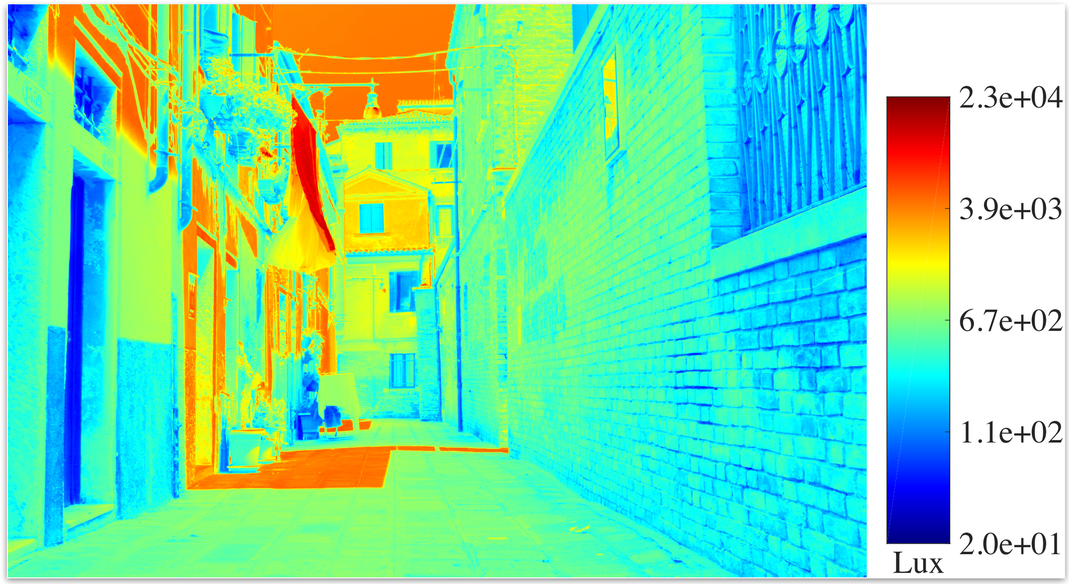
Q > Thr

NO

YES

Tone Mapped
+
Metadata

Applications: Results JPEG-XT Compression



Input HDR image

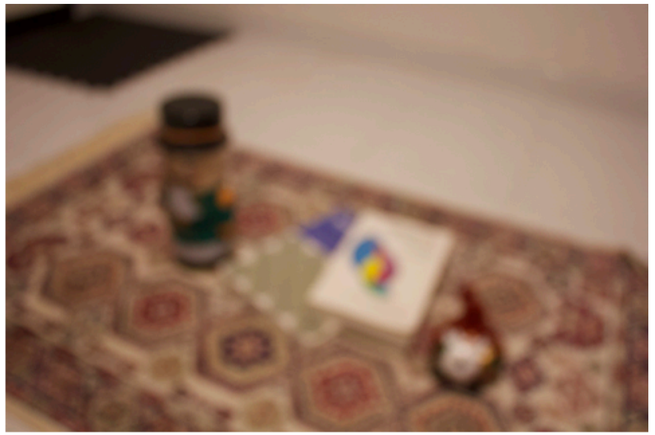
Reinhard et al.'s TMO
optimized with NoRVDPNet

Tone Mapped HDR image
for JPEG-XT

Applications: Photo Selection

Q=86.99

Q=86.92



Q=56.46

Q=91.39

Q=76.26

Q=59.9

Applications: Photo Selection

Q=86.99

Q=86.92

Q=56.46

Q=91.39

Q=76.26

Q=59.9

Future Directions

Future Directions

- Going in the temporal domain.
- Extend approaches to perceptual uniform domains.
- Mix perceptual experiments results and metrics.

Thank you for your attention!

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https://deepacamera.org.cy http://vcg.isti.cnr.it

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