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

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### Abstract
In this work, we present a simple and effective way to obtain efficient no-reference metrics by using a simple strategy to transfer the knowledge of well-known and respected reference metrics into no-reference metrics that work on the GPU. In our work, we show that a simple neural network is sufficient to transfer knowledge and it is effective.

### Keywords
High Dynamic Range Imaging, Image Quality Assessment, No-Reference Metrics,

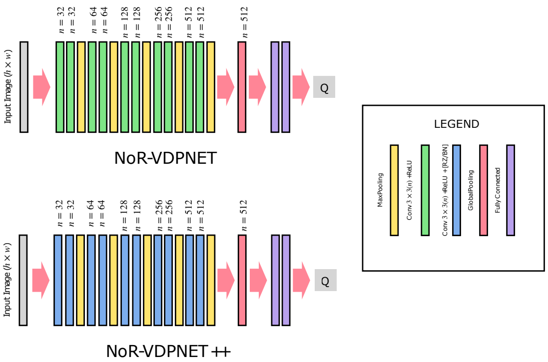


**Figure 1:** The network architecture of NoR-VDPNet e NoR-VDPNet++.

## 1. Introduction

Objective image quality metrics are extremely important to evaluate the quality of modern imaging algorithms such as deblurring, colorization, super-resolution, denoising, etc.

A widely used metric for both Standard Dynamic Range (SDR or 8-bit) content and High Dynamic Range (HDR) images and videos is HDR-VDP[1]. This metric is a reference-based metric that mimics how the human visual system behaves at different stimuli. Although this metric produces high-quality results it has two main issues: i) it requires a reference which is not always available; ii) it is MATLAB only and it requires a lot of computational time for HD or 4K content.

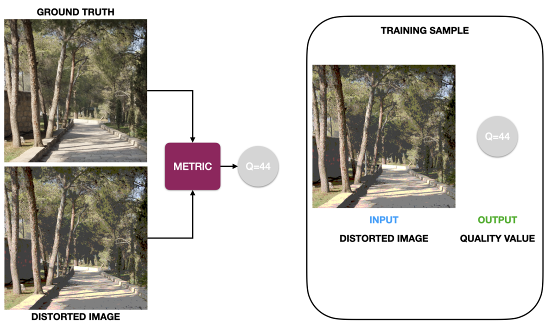


**Figure 2:** A training dataset is generated by processing ground truth and distorted images using a reference metric. Then, the training sample for our NoR-VDPNet or NoR-VDPNet++ is composed of the distorted image only and the quality value is computed by the metric.

In this work, we present NoR-VDPNet [2] and NoR-VDPNet++ [3] two metrics that transfer the knowledge of HDR-VDP into a simple CNN metric to achieve no-reference metrics for both SDR and HDR content.

## 2. Method

NoR-VDPNet and NoR-VDPNet++ use a simple neural network architecture composed of different convolutional layers with max-pooling; see Figure 1. The difference between the two architectures is that NoR-VDPNet++ introduces the use of normalization. However, from early experiments[3], we found out that BatchNor-

*Ital-IA 2023: 3rd National Conference on Artificial Intelligence, organized by CINI, May 29–31, 2023, Pisa, Italy*
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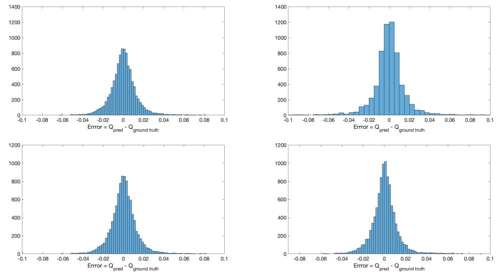

**Figure 3:** The histogram of the error between the prediction and the ground truth for the test datasets for our tasks (HDR-C and SDR-D): On the top left, the results of NoR-VDPNet for the HDR-C task. On the top right, are the results of NoR-VDPNet++ for the HDR-C task. On the bottom left, are the results of NoR-VDPNet for the SDR-D task. On the bottom right, are the results of NoR-VDPNet++ for the SDR-D task.

malization [4] and Residuals are not effective. We found out that ReZero [5] is the most computationally efficient and effective mechanism for our task.

We collected a medium-small dataset of SDR and HDR images and their relative distortions for which we computed HDR-VDP quality values; see Figure 2 for training generation. In particular, we tested our metric for two specific tasks:

- SDR-D: SDR distortions such as blur, noise, quantization, jpeg, etc.
- HDR-C: HDR compression using JPEG-XT standard[1].

Table 1 reports more information about our dataset.

| Dataset | Training | Validation | Test | Total |
|---|---|---|---|---|
| **SDR-D** | 80,244 | 10,025 | 10,044 | 100,313 |
| **HDR-C** | 49,602 | 6,216 | 6,216 | 62,034 |

**Table 1**
The employed datasets for two tasks.

## 3. Results

We implemented our architectures using PyTorch. We trained and tested both on an NVIDIA DGX Server employing a single NVIDIA A100 GPU with 40 GB of memory (CUDA 11.3).

Figure 3 shows our results for the test datasets for both SDR-D and HDR-C. We can notice that both NoR-VDPNet and NoR-VDPNet++ achieve a low error; note that Hanji et al.[6] showed that there are perceptual differences when the difference error is greater than 0.075 for inverse tone mapping tasks. Overall NoR-VDPNet++ provides a better advantage in terms of resulting quality.

In terms of computational efficiency, both NoR-VDPNet and NoR-VDPNet++ can process 8-Mpixel images in less than 0.05 seconds; i.e., they achieve real-time performance.

## 4. Conclusions

In conclusion, we have presented an efficient architecture for converting computationally expensive reference metrics into computationally efficient metrics that work without the need for a reference. This is very handy when it comes to assessing the image quality of live streams such as sports or other events.

[1] https://jpeg.org/jpegxt/

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