A STUDY OF DEEP PERCEPTUAL METRICS FOR IMAGE QUALITY ASSESSMENT

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ABSTRACT

Several metrics exist to quantify the similarity between images, but they are inefficient when it comes to measure the similarity of highly distorted images. In this work, we propose to empirically investigate perceptual metrics based on deep neural networks for tackling the Image Quality Assessment (IQA) task. We study deep perceptual metrics according to different hyperparameters like the network’s architecture or training procedure. Finally, we propose our multi-resolution perceptual metric (MR-Perceptual), that allows us to aggregate perceptual information at different resolutions and outperforms standard perceptual metrics on IQA tasks with varying image deformations. Our code is available at https://github.com/ENSTA-U2IS/MR_perceptual

Index Terms— Perceptual metric, Image quality assessment, deep neural networks

1. INTRODUCTION

Image Quality Assessment (IQA) plays an essential role in image-based applications [1, 2] where the acquisition systems or algorithms can introduce image quality variations. Although IQA is a well-known problem [3], it is difficult to define a metric directly linked to human perception. Indeed, for humans, IQA is intuitive and effortless [4]. Still, it remains a subjective measurement that is insufficient for validating algorithms or acquisition systems.

Several perceptual metrics have been investigated [2, 1] for IQA, such as the L2 Euclidean distance, or SSIM [5]. Yet, the human perception of image similarity relies on psychological vision mechanisms that are in a large extent unknown, then hard to implement. On the other hand, existing metrics only rely on estimating global or local variations between images.

Deep Learning-based perceptual metrics have been first proposed in [6], and [7] for the style transfer problem. It was followed by several applications, for the quality of super-resolution algorithms [6], semantic segmentation [8] task, or Generative Adversarial Network (GAN) [9] outputs quality. A perceptual metric is typically a L2 distance between features extracted from Deep Neural Networks (DNNs) after a forward pass of the input images. While some perceptual metrics like the Fréchet Inception Distance (FID) [10] are widely used to evaluate the quality of images generated by GANs, they are limited to the comparison of the estimated distribution of two set of images.

In this paper, we propose investigating IQA using Deep Learning-based perceptual metrics to compute the similarity between two images. Unlike previous studies [11, 12] that learn an image quality metric using DNN, we evaluate different DNNs and their associated hyperparameters (loss function, normalisation, resolution of input images, and the features extraction strategy), with the main goal of identifying a deep perceptual distance as general-purpose metric closer to human perception.

Our contribution is threefold: first, we empirically investigate different DNN perceptual metrics related to the network architecture. Next, we perform an ablation study highlighting the relationship between the training procedure of DNN parameters and the performances of deep perceptual metrics. Finally, we propose a perceptual metric that achieves the state-of-the-art results in unsupervised IQA by studying various hyperparameters impacting the computation of perceptual losses.

2. MULTI RESOLUTION PERCEPTUAL METRIC

2.1. Notations and formalism

We denote $D = \{x_i\}_{i=1}^n$ a dataset composed of $n$ images. Let $f_\omega(x_i)$ denote the output of the DNN $f$ with trainable parameters $\omega = \{\omega_k\}$ applied on image $x_i$.

DNNs can be decomposed into $B$ blocks applied sequentially. For example, we can decompose AlexNet [13], which comprises five convolutional layers, into $B = 5$ blocks, where each block is a convolutional layer. Let us denote $\{f_b^\omega(x_i)\}_{b=1}^B$ the set of the feature maps of the $B$ blocks output from image $x_i$. For $b \in [1, B]$, the feature map $f_b^\omega(x_i) \in \mathbb{R}^{H_b \times W_b \times C_b}$ is a three dimension tensor where $H_b$ and $W_b$ represent the height and width of the feature map and $C_b$ is the number of channels. We denote $f_b^\omega(x_i)[h, w, c]$ with $(h, w, c) \in [1, H_b] \times [1, W_b] \times [1, C_b]$ a particular value of the feature map.

2.2. Perceptual metric

The process of computing a perceptual metric can be divided into three stages: the deep feature extraction strategy from an
image given a DNN architecture, the normalization strategy of the feature space, followed by the dissimilarity measure to compare the features. We now present these different stages.

2.2.1. Deep Feature Extraction

The deep feature extraction is the initial step that allows representing the data into a new feature space. Contrary to handcrafted features like GLCM [14], we can use a trained DNN to extract features at different levels of the network.

If in some cases DNNs parameters are obtained from pretrained general purpose networks like ImageNet [15], some DNNs are finetuned to achieve better performances in a dataset tailored to the evaluation of perceptual metrics [11].

Also, in previous works, features were extracted from the image at the original dimension (×1). However, we also explore the feature results after upscaling by two the image, thanks to a bilinear interpolation (×2). Let us denote φ(i) the latent representation of the image xi.

Given extracted features at different levels of a DNN, a straightforward strategy, termed as linear features, takes all the feature maps containing the perceptual and contextual information at different resolutions, and concatenate them. It is defined as follows:

\[ \phi_1(x_i) = [f_1^B(x_i), \ldots, f_B^B(x_i)] \] (1)

An alternative strategy consists in combining features, using the Gram matrix as proposed in [7], allowing to extract new features termed as quadratic features. The Gram matrix \( G_{\omega}^b \) of the layer \( b \) is a square matrix of size \( C_b \times C_b \). Let \( (c_1, c_2) \in [1, C_b]^2 \). The Gram matrix’s coefficient at position \( (c_1, c_2) \) defined for a feature map \( f_{\omega}^b(x_i) \) is given by:

\[ G_{\omega}^{c_1,c_2}(x_i) = \sum_{h, w} f_{\omega}^b(x_i)[h, w, c_1] f_{\omega}^b(x_i)[h, w, c_2]. \]

We can now define the quadratic features of an image \( x_i \) as:

\[ \phi_2(x_i) = [G_{\omega}^{c_1,c_1}(x_i), \ldots, G_{\omega}^{c_2,c_2}(x_i)] \] (2)

On the one hand, the linear features are directly linked to the content (layout) of an image and to the first moments of the feature maps. On the other hand, quadratic features are linked to the style of an image [7], and capture stationary information related to the second moment, i.e. the covariance.

2.2.2. Features Normalization

Because the values vary in magnitudes between feature maps, it is essential to normalize them to homogenize all the layers and their importance. This work compares two normalization strategies. Current solutions consider an \( L_2 \) normalization, that divides each value by the \( L_2 \) norm of the feature map. Yet it is also possible to normalize with \( L_1 \) or with a sigmoid function. We propose to normalize using a sigmoid function, bounding all values of the feature map within [0, 1]. Another operation which can be done is to use the ReLu function before normalising.

2.2.3. Dissimilarity measure

In order to quantify the difference between the latent representation of two images, we need to define a dissimilarity measure \( D \) in the feature space, not necessarily limited to distance metrics. We expect that \( D \) associated with the extracted features is linked to human perceptual dissimilarity metric.

Typically perceptual loss uses the \( L_2 \) norm (MSE) between features. In addition, we propose to use different dissimilarities such as the \( L_1 \) norm (MAE), and the binary cross-entropy (CE).

2.3. MR-Perceptual loss

Classically the perceptual loss [11] is composed of VGG [16] linear features, followed by a \( L_2 \) normalization and the dissimilarity metrics is the MSE. In the rest of the paper we will refer to this loss as the classical perceptual loss.

Based on these three main stages, we propose to change this classical perceptual loss [11] by first proposing a multi-scale and multi-statistic feature space. Our feature space is multi-scale because instead of extracting the feature at just one resolution, we extract the descriptor at two resolutions (×1 and ×2). Our descriptor is also multi-statistic since we concatenate quadratic and linear features for the standard resolution. We use the sigmoid function as a normalization function and then use a Binary cross-entropy as a dissimilarity measure. The full process is illustrated in Fig. 1.

3. EXPERIMENTS

In this section, we first introduce the used dataset (Sec. 3.1), then compare different feature spaces from different architectures (Sec. 3.2). Next, we discuss the importance of how to learn the representation (Sec. 3.3), and finally we perform an ablation study with our technique (Sec. 3.4).

3.1. Dataset

To evaluate the performances of perceptual metrics, we use the Two-Alternative Forced-Choices (2AFC) dataset [11].
The test sets include 36.3K triplets composed of one reference image and two distorted images associated with their scores in [0, 1] defining the ground truth perceptual dissimilarity. According to a human panel, the score reflects the proportion of votes for the chosen image for each tuple. Specifically, a ground truth will have a score of 0 if all the testers wave chosen the first image and 1 if all the testers wave chosen the second image.

The dataset is organized into six groups according to the transformations applied to the distorted images as follows: 
- **Tred** uses photometric and geometric transformations.
- **CNN** uses transformations coming from DNN, like denoising autoencoders.
- **SuperRes** uses super resolution algorithms on images coming from the NITRE 2017 challenge [17].
- **Deblur** uses image extracted from video clips [18], with video deblurring algorithms.
- **Color** uses the output of image translation algorithms for image colorization applied on ImageNet [19].
- **FrameInterp** uses different frame interpolation algorithms applied on the Davis Middlebury dataset [20].

### 3.2. Link between the IQA and the architectures

To evaluate the deep feature from different networks, we extracted linear feature from AlexNet [13], SqueezeNet [21], VGG [16], ResNet [22] and VIT [23]. All theses networks are pretrained on imagenet [19].

These architectures are organized in convolutional blocks followed by dense layers. Similarly to [11], we use the output of the five convolution blocks to extract features, except for SqueezeNet of which we use seven blocks.

Table 2 presents the results of a handcrafted technique (SSIM) and classical perceptual losses on different DNN architectures. The first result is that perceptual losses highly outperform SSIM, which supports the hypothesis of a better representation of human similarity perception. Moreover, the AlexNet feature space seems to perform better than other architectures. Our interpretation is twofold: first, ImageNet accuracy is not necessarily linked to the quality of the feature space since the tasks are different; secondly, the deeper an architecture is, the worse it performs. This might be linked to the propagation of the perceptual information throughout all the layers, such that all layers are initially trained for the ImageNet task.

### 3.3. Link between the IQA and the training procedure

In Section 3.2, first experiments focused on the impact of the architecture against a classical perceptual metric. Now, we focus our experiments on the strategy to train a DNN for an optimal representation for perceptual queries. For this purpose, we consider a ResNet50 architecture trained on ImageNet and the following training strategies: a supervised training, DeepCluster [24], Dino [25], MoCo v2 [26], OBoW [27], SimCLR [28], SwAV [29], and finally a random initialization of the parameters. In Table 3, we compare the performance of ResNet50 with the different pretrained parameters, and we observe that our supervised training outperforms the others in most of the tasks. This shows that a supervised procedure helps to inject in the network useful information for the perceptual task.

### 3.4. Importance of the different components for IQA

Based on previous results in Sections 3.2 and 3.3, AlexNet trained on ImageNet in a supervised manner is the best to quantify the perceptual dissimilarity. We studied in the table 4 the performance according to the extracted features and observed that features extracted from 4th and 5th layers are the best for the Tred set. But features extracted from the 2nd and 3rd outperform on CNN, SuperRes, Deblur and Color distortions.

This suggests that some layers might focus on particular details in the distorted images which provides clues for being invariant to some distortions.

Table 1 shows an ablation study to evaluate the relevant hyperparameters for designing a novel perceptual metric as detailed in Section 2.2. We consider the features extraction strategies, the type of dissimilarity metric in the feature space, the normalization strategy, and finally, the resolution. Multi-resolution seems to be the key to improving performances. In addition, Multi statistic seems to improve also the performances for certain distortions.

As shown in Tab. 5, the classic perceptual metric setup is outperformed in all the distortions; this remains true for all the networks, including Watching [30], Split-brain [31], Puzzle [32] and BiGAN [33].

### 4. CONCLUSIONS

We empirically investigated general-purpose deep perceptual metrics w.r.t. different experimental settings on an IQA task. First, we show that it is unnecessary to use deeper DNN with complex architecture; a simple AlexNet is sufficient for perceptual metrics. Despite convincing results of self-supervised, we show that a supervised strategy remains the best choice. Finally, we confirm that combining features at different resolutions is relevant as it forces the DNN to be more robust against various types of distortion. Future work would involve combining this new perceptual metric and image-to-image translation DNNs to improve the quality of generated images.

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Table 1. Ablation study on AlexNet [13] pretrained on ImageNet with a supervised strategy.

| Dataset     | SSIM | Alexnet | VGG | SqueezeNet | ResNet18 | ResNet50 | ResNet101 | VIT |
|-------------|------|---------|-----|------------|----------|----------|-----------|-----|
| **Top1**    |      |         |     |            |          |          |           |     |
| **AlexNet** | 73.6 | 65.3    | 62.3 | 59.0       | 56.7     | 52.6     | 49.7      | 45.9 |
| **CNN**     | 75.8 | 71.2    | 68.7 | 65.2       | 62.4     | 59.0     | 55.7      | 51.8 |
| **SuperRes**| 73.3 | 69.0    | 66.5 | 63.8       | 60.6     | 57.2     | 53.9      | 50.0 |
| **Deblur**  | 71.7 | 66.6    | 64.2 | 61.5       | 58.3     | 55.0     | 51.7      | 48.8 |
| **Color**   | 69.4 | 64.0    | 61.5 | 58.7       | 55.5     | 52.2     | 49.0      | 45.1 |
| **FrameInterp** | 67.2 | 62.8    | 60.0 | 57.3       | 54.1     | 51.0     | 47.8      | 44.0 |
| **AVERAGE** | 70.2 | 66.0    | 63.5 | 60.6       | 57.3     | 53.9     | 50.6      | 47.1 |

Table 2. Comparative results of different DNN architectures linear features. The first rows denote the 2AFC score. The last row shows the Top1 accuracy on ImageNet [19].

| Dataset | Supervised Deepcluster Dino MoCo Obow SimCLR SwA V |
|---------|----------------------------------------------------|
| **Top1** | 70.5 | 68.1 | 65.4 | 62.8 | 60.2 | 57.6 | 54.9 | 52.2 |
| **AlexNet** | 73.6 | 71.2 | 68.7 | 65.2 | 62.4 | 59.0 | 55.7 | 51.8 |
| **CNN** | 75.8 | 71.2 | 68.7 | 65.2 | 62.4 | 59.0 | 55.7 | 51.8 |
| **SuperRes** | 73.3 | 69.0 | 66.5 | 63.8 | 60.6 | 57.2 | 53.9 | 50.0 |
| **Deblur** | 71.7 | 66.6 | 64.2 | 61.5 | 58.3 | 55.0 | 51.7 | 48.8 |
| **Color** | 69.4 | 64.0 | 61.5 | 58.7 | 55.5 | 52.2 | 49.0 | 45.1 |
| **FrameInterp** | 67.2 | 62.8 | 60.0 | 57.3 | 54.1 | 51.0 | 47.8 | 44.0 |
| **AVERAGE** | 70.2 | 66.0 | 63.5 | 60.6 | 57.3 | 53.9 | 50.6 | 47.1 |

Table 3. Comparative results showing the impact of supervised training on 2AFC [11] with ResNet 50 [22] architecture. We run a linear feature extraction with different pretraining conditions.

| Dataset | Block 1 | Block 2 | Block 3 | Block 4 | Block 5 | All |
|---------|---------|---------|---------|---------|---------|-----|
| **Top1** | 70.5 | 68.1 | 65.4 | 62.8 | 60.2 | 57.6 |
| **AlexNet** | 73.6 | 71.2 | 68.7 | 65.2 | 62.4 | 59.0 |
| **CNN** | 75.8 | 71.2 | 68.7 | 65.2 | 62.4 | 59.0 |
| **SuperRes** | 73.3 | 69.0 | 66.5 | 63.8 | 60.6 | 57.2 |
| **Deblur** | 71.7 | 66.6 | 64.2 | 61.5 | 58.3 | 55.0 |
| **Color** | 69.4 | 64.0 | 61.5 | 58.7 | 55.5 | 52.2 |
| **FrameInterp** | 67.2 | 62.8 | 60.0 | 57.3 | 54.1 | 51.0 |
| **AVERAGE** | 70.2 | 66.0 | 63.5 | 60.6 | 57.3 | 53.9 |

Table 4. Comparative results showing the impact the chosen layer on 2AFC [11] with AlexNet [13] architecture. The bolded results show the best results among blocks.

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