

NTIRE 2019 Challenge on Image Enhancement: Methods and Results

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Abstract

This paper reviews the first NTIRE challenge on perceptual image enhancement with the focus on proposed solutions and results. The participating teams were solving a real-world photo enhancement problem, where the goal was to map low-quality photos from the iPhone 3GS device to the same photos captured with Canon 70D DSLR camera. The considered problem embraced a number of computer vision subtasks, such as image denoising, image resolution and sharpness enhancement, image color/contrast/exposure adjustment, etc. The target metric used in this challenge combined fidelity scores (PSNR and SSIM) with solutions' perceptual results measured in a user study. From above 200 registered participants, 13 teams submitted solutions for the final test phase of the challenge. The proposed solutions significantly improved baseline results, defining the state-of-the-art for practical image enhancement.

1. Introduction

Image restoration and image enhancement are among the fundamental computer vision problems aiming at the improvement of different image quality aspects, including its perceptual quality, resolution, color rendition, etc. With a wide range of practical applications and challenges, these topics have witnessed an increased interest from the vision

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Figure 1. The rig with the four DPED cameras.

and graphics communities over the recent years [28, 4, 1, 5, 9, 2, 22, 10]. One of the key real-world problems in this area is photo enhancement — as the popularity of mobile photography is rising constantly, there is an increasing need for improvement of photos captured with tiny mobile camera sensors, leading to a number of research works targeting image enhancement on smartphones [14, 16, 17, 6].

The problem of comprehensive image quality enhancement has emerged quite recently [14, 15], though significant progress has been achieved over the last years. A further development in this field was facilitated by the PIRM challenge on perceptual image enhancement on smartphones [17] that produced a large number of efficient solutions that have substantially improved the baseline results [25, 8, 30, 13, 20].

The NTIRE 2019 Image Enhancement challenge is a step forward in benchmarking example-based single image



Figure 2. The original iPhone 3GS photo (left) and the same image enhanced by the DPED network [14] (right).

enhancement. It uses a diverse DPED dataset [14] consisting of photos captured with several smartphones and Canon DSLR camera, and is taking into account both quantitative and qualitative visual results of the proposed solutions. In the next sections we describe the challenge and the corresponding dataset, present and discuss the results and describe the proposed methods.

2. NTIRE 2019 Enhancement Challenge

The objectives of the NTIRE 2019 Challenge on Single-Image Enhancement are to gauge and push the state-of-the-art in image enhancement, to compare different approaches and solutions, and to promote realistic image enhancement settings defined by the DPED dataset. The challenge consists of the following phases:

- i *development*: the participants get access to the data;
- ii *validation*: the participants have the opportunity to validate their solutions on the server and compare the results on the validation leaderboard;
- iii *test*: the participants submit their final results, models, and factsheets.

The goal of this challenge is to automatically improve the quality of photos captured with smartphones. For this, the participants were proposed to work with the DPED [14] dataset consisting of several thousands of images captured synchronously by three smartphones and one high-end DSLR camera (figure 1). Here we only consider a problem of mapping photos from a very old iPhone 3GS device into the photos from Canon 70D DSLR as this task is the most challenging one. An example of the original and enhanced DPED test images are shown in figure 2.

All solutions submitted by the participants were evaluated based on three measures:

- PSNR measuring fidelity score,

- SSIM, a proxy for perceptual score,
- MOS (mean opinion scores) by a user study for explicit image quality assessment.

Though SSIM scores are known to correlate better with human image quality perception than PSNR, they are still often not reflecting many aspects of real image quality. Therefore, during the final test phase we conducted a user study involving several hundreds of participants (using Amazon’s MTurk platform). The challenge participants submitted solutions for 10 full resolution test images and the user study participants were asked to rate the visual results of all submitted solutions by selecting one of five quality levels (definitely worse, probably worse, probably better, definitely better, excellent) for each method result in comparison with the original input image. The expressed preferences were averaged per each test image and then per each method to obtain the final MOS.

3. Challenge Results

From above 200 registered participants, 13 teams entered the final phase and submitted results, codes / executables, and factsheets. Table 1 summarizes the final challenge results and reports PSNR, SSIM and MOS scores for each submitted solution, as well as the self-reported runtimes and hardware / software configurations. The methods are briefly described in section 4, and the team members are listed in Appendix A.

3.1. Architectures and main ideas

All the proposed methods were relying on end-to-end deep learning-based solutions. The most common basic architectures were ResNet [12] and U-Net [26], which ideas and structures were used by the majority of methods. For faster training and inference and lower RAM consumption

<https://www.mturk.com/>

Team	Author	Framework	factsheet info		quantitative results		
			Hardware, GPU	Reported Runtime, ms	PSNR	SSIM	MOS
Mt.Stars	zxcg1120101037	PyTorch	GeForce GTX 1080 Ti	15	22.348760	0.790668	2.784
TeamInception	swz30	PyTorch	Tesla V100	109	22.414647	0.791206	2.595
BMIPL_UNIST_DW	Sprite	PyTorch	Titan V	1500	22.442052	0.802927	2.591
BOE-IOT-AIBD	BOE-IOT-AIBD	PyTorch	Titan X Maxwell	40	21.738756	0.781655	2.554
HIT-Xlab	zhwzhong	PyTorch	Tesla V100	520	22.143558	0.787604	2.529
TTI	iim lab	PyTorch	TITAN X	500	22.165396	0.762101	2.527
Geometry	Jie_Liu	PyTorch	GeForce GTX 1080 Ti	220	21.752385	0.782175	2.419
IVL	flavio	PyTorch	Titan X Pascal	6.5	21.369116	0.718913	2.402
HIT-UltraVision	UltraVision	PyTorch	GeForce GTX 1080 Ti	20000	21.921673	0.783971	2.394
ViPr	nelson1996	Keras / TensorFlow	GeForce RTX 2060	160	18.685189	0.729987	2.293
MENet	scape1989	TensorFlow	GeForce GTX 1080 Ti	12	18.397164	0.756864	2.253
Rainbow	zheng222	PyTorch	GeForce GTX 1080 Ti	500	22.663374	0.796817	n/a *
MiRL	KantiKumari	PyTorch	n/a	80	20.966558	0.744575	n/a *

Table 1. NTIRE 2019 Image Enhancement Challenge results and final rankings. * – Solutions from Rainbow and MiRL teams produced corrupted image results when running on full-resolution test photos.

(allowing to use larger batch sizes), most of the teams were doing image processing in low-resolution space. Another key benefit from image downsampling was the ability to introduce larger changes when working with compact feature representations, which is crucial for the considered image enhancement task as it often requires the content of the photos to be significantly altered. Other popular ideas were to use the attention mechanism [31] to improve the networks’ performance, to employ a self-ensemble strategy [29] often leading to higher PSNR / SSIM scores, and to process feature maps in parallel in different resolutions / scales, which allows to refine both content- and texture-based features. Almost all teams were using Adam optimizer to train deep learning models, and were implementing their solutions in PyTorch.

3.2. Performance

Mt.Stars is the best scoring team and the winner of the NTIRE 2019 Enhancement Challenge, while *TeamInception* and *BMIPL_UNIST_DW* are the runner-ups. These three methods achieved quite similar PSNR scores, though the solution proposed by *Mt.Stars* has demonstrated substantially higher MOS results measuring the target perceptual image quality. The highest PSNR scores were obtained by the method presented by *Rainbow* team, though unfortunately it was able to work only with small image patches, and on full-resolution photos it produced corrupted visual results. It should be also mentioned that many of the proposed approaches were producing various artifacts on the processed full-size images, which is a consequence of the task complexity — the larger the required image transformations, the more side-effects they are generally causing. Regarding the runtime, it is quite difficult to precisely compare the efficiency of the proposed methods as all measurements were done on different hardware configurations, though in general the fastest solutions were proposed by *IVL*, *Mt.Stars*, *MENet* and *BOE-IOT-AIBD* teams.

3.3. Discussion

The NTIRE 2019 Image Enhancement Challenge promoted realistic settings for the image enhancement task — instead of using synthetic datasets capturing only a very limited amount of image quality aspects, the participants were proposed to improve the quality of real photos captured with low-end mobile cameras, and were provided with the DPED dataset containing paired and aligned photos captured with smartphones and a high-end DSLR camera. A diversity of proposed approaches surpassed the baseline methods defined in [14] and demonstrated improved visual results. We conclude that the challenge through the proposed solutions defined the state-of-the-art for the practical image enhancement task.

4. Challenge Methods and Teams

This section describes solutions submitted by all teams participating in the final stage of the NTIRE 2019 Image Enhancement Challenge.

4.1. Mt.Stars

Mt.Stars team proposed a CNN architecture that had a U-Net-based structure with removed skip connections, and contained an encoder module, a multiscale downsampling module, two modified HRNet [27] modules, and a decoder. The encoder consisted of three convolutional layers and *leaky ReLU* activation functions. A convolution with stride 2 was used for image downsampling in the corresponding multiscale downsampling module that produced $\times 2$, $\times 4$ and $\times 8$ downscaled feature maps. These maps were then fed as inputs to the HRNet modules, where batch normalization layers were replaced with instance normalization layers. Every branch of the considered HRNets contained three residual blocks, and the networks produced three outputs of the same size as the input feature maps. A transposed convolution was used for performing the upsampling

operation: the smallest feature map was upsampled by a factor of 2, summed with the second feature map, then upsampled again and summed with the largest feature map, and the result was passed to the decoder module consisting of three convolutional layers. The last layer was followed by a \tanh activation function. The network was trained with a combination of L1, GAN, VGG, MS-SSIM and total variation losses with the following weights: 1500, 100, 0.001, 500 and 1, respectively.

4.2. TeamInception

TeamInception proposed to recursively improve the color contrast of the input image with a recursive attention network (RAN) depicted in figure 3.

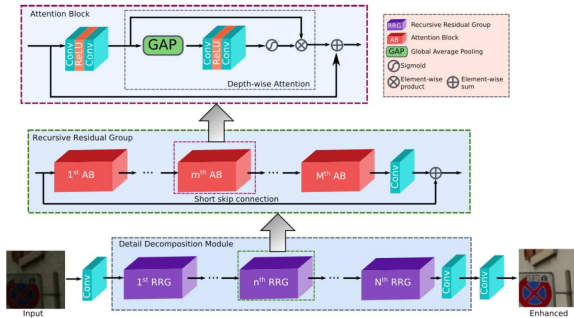


Figure 3. Recursive Attention Network (RAN).

At the entry point of the RAN network, the authors employed a convolutional layer that takes a low-contrast image as an input and extracts low-level features. The features are fed to the detail decomposition module (DDM), which contains 5 recursive residual groups (RRGs). The goal of RRG is to progressively improve the information related to the desired enhanced image from the low-contrast input image. Each RRG further employs 10 attention blocks (ABs). Features that are less important get suppressed at the AB, and only useful information is propagated onward. To discern such features, the authors applied a depth-wise attention branch that models the relationships among channels and adaptively rescales the feature responses. It does so by first applying a global average pooling (GAP) operation to the input tensor of size $H' \times W' \times C'$ to obtain a global descriptor of size $1 \times C'$. Next, a convolutional layer is applied to the global descriptor that reduces its channel dimension by a factor of 16. The descriptor then passes through a channel-upscaling convolutional layer that yields a descriptor of size $1 \times C'$ that is activated with a sigmoid gating function. Finally, the descriptor enriched with channel statistics is used to rescale the input tensor.

In each AB, the features belonging to the latent enhanced image are bypassed via skip connections while other features go through subsequent ABs for further detail decomposition. The last convolutional layer of the network re-

ceives deep features from the last RRG (after convolution) and yields the final enhanced image having the same resolution as the input image.

The whole network was trained with a combination of L1, MS-SSIM and VGG-based losses with weights 0.136, 0.714 and 0.15, respectively, for 300 epochs with Adam optimizer with a learning rate of 10^{-3} decreased by half after every 40 epochs. At the inference time, a self-ensemble strategy [29] is employed: for each input image, the authors created a set of the following 8 images: original, flipped, rotated 90, 180 and 270 degrees; flipped and rotated by 90, 180 and 270 degrees. Next, these transformed images were passed through the proposed model to obtain the enhanced outputs. Then the above transformations were undone, and all obtained images were averaged to obtain the final output image.

4.3. BMIPL_UNIST_DW

BMIPL_UNIST_DW team used the architecture illustrated in figure 4. The proposed network first downsampled the input color image of size $W \times H \times 3$ to the feature maps of size $W/2 \times H/2 \times 64$ that were fed into the backbone network and residual in residual (RIR) skip connection to yield the initial feature maps (figure 4 b). A residual channel attention network (RCAN) [32] was used as a backbone of the proposed network. Then the obtained features were up-scaled, combined together with the input image and passed to the second module (figure 4 a) that produced the final output. A more detailed overview of the proposed approach can be found in [24]

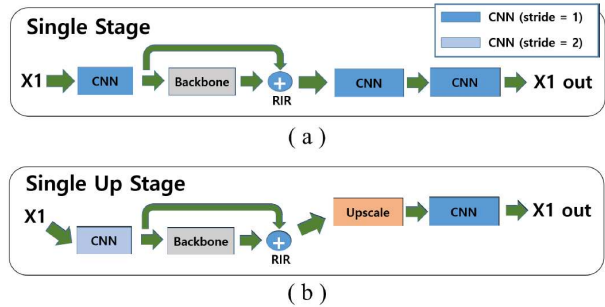


Figure 4. Architecture proposed by BMIPL_UNIST_DW team.

For image downscaling, a convolutional layer with stride 2 was used. The network was trained for 300 epochs with Adam optimizer with a learning rate of $0.5 \cdot 10^{-5}$ reduced by half every 100 epochs. Random crops, horizontal and vertical flips were utilized for data augmentation. A self-ensemble strategy described in [29] was additionally used during inference.

4.4. BOE-IOT-AIBD

BOE-IOT-AIBD presented a solution based on the Iterative Back-Projection (IBP) algorithm [18]. The new multi-scale architecture was designed with the aim to solve general image enhancement problems based on previous work on image super-resolution [23]. The general definition of the system is depicted in figure 5: The *Analysis* and *Synthesis* modules convert an image into a feature space and vice versa using convolutional networks. The *Upscaler* and *Downscaler* modules are composed of convolutional layers and strided (transposed) convolutions.

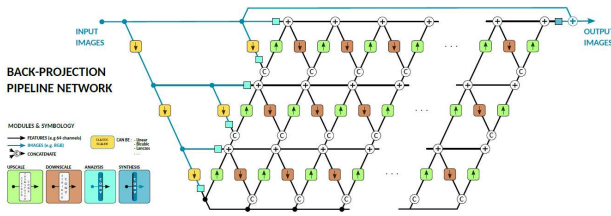


Figure 5. Architecture proposed by BOE-IOT-AIBD.

4.5. HIT-XLlab

HIT-XLlab team proposed a deep dense-in-dense network which use a multi-scale attention mechanism to further improved the network performance. To ease the training of deeper network and to alleviate gradient vanishing problem we incorporate the short skip connection in each local dense block and a long skip connection to let the network to learn the residual mapping rather than original mapping. Each feature generated from different local dense block were concated and utilized to reconstructed the final result.

During the training phase, the input size is set to 32×32 and the mini-batch size is to 64. The model was trained with L1 loss and Gradient loss using Adam optimizer with the initial learning rate 1×10^4 and decrease by half it every 10 epochs, our network was stopped until the loss was unchanged.

4.6. TTI

TTI team proposed the architecture that was also inspired by the Deep Back-Projection Networks [11]. The authors constructed iterative down-up projection units based on the following assumption: down-projection unit can be used to produce the predicted low-resolution image which is represented in the feature domain. Then, the up-projection unit is used to upscale the feature-maps back to the original resolution. The authors used error feedbacks from the up- and down-scaling steps to guide the network to achieve optimal results as shown in figure 6.

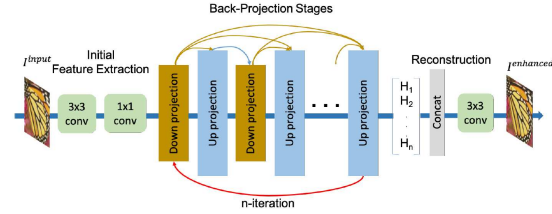


Figure 6. TTI's network structure.

4.7. Geometry

Geometry team used a weakly-dense convolution network (figure 7) with residual blocks to catch more information from the long-range feature maps. The network was trained to minimize MAE and SSIM losses with Adam optimizer.

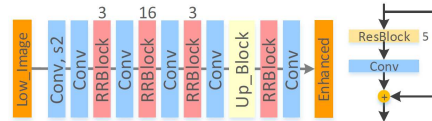


Figure 7. A weakly-dense convolution network.

4.8. IVL

IVL team used a global color transformation-based approach to enhance DPED images [3]. The proposed method (figure 8) is composed of two different neural networks: the first one performs global enhancement by estimating the coefficients of the global color transformation (in the form of a continuous piecewise function), which is later applied to the input image. The second network performs local enhancement and estimates the best spatial filters to be applied to further improve the image.

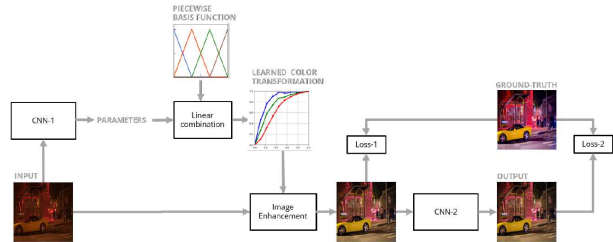


Figure 8. Global color transformation approach used by IVL.

4.9. HIT-UltraVision

HIT-UltraVision team proposed a multi-level wavelet residual network (MWRN) by incorporating MWCNN [21] with multiple residual blocks (figure 9). Similar to MWCNN, MWRN adopts discrete wavelet transform (DWT) as a downsampling operator in the second and third

levels of the encoder, and inverse wavelet transform (IWT) as an upsampling operator in the corresponding decoder. MWRN uses 10 residual blocks in each level to enhance feature representations and speed-up the training. Adam algorithm and L2-norm are utilized to optimize the network's parameters.

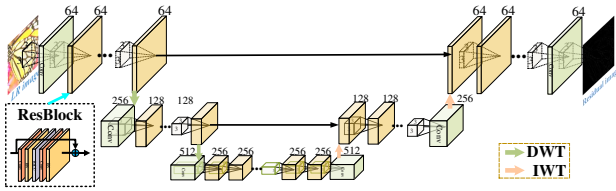


Figure 9. A multi-level wavelet residual network.

4.10. ViPr

ViPr team used unsupervised learning in this task, and deployed a 2-way GAN architecture that was based on CycleGAN. The generator depicted in figure 10 was taking images converted to HSV colorspace and enhancing them, while the discriminator was learning to distinguish between the *enhanced* and *real DSLR* images. The ViPr proposed solution is fully described in [7].

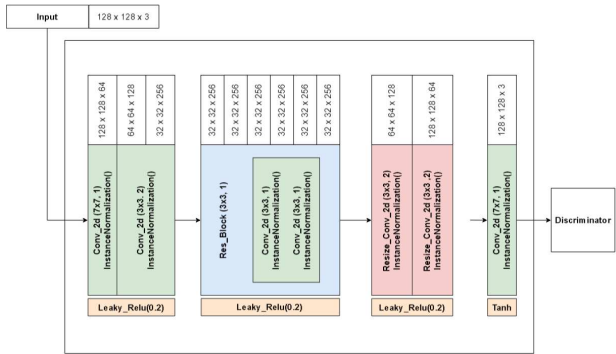


Figure 10. Generator architecture proposed by ViPr.

4.11. MENet

MENet team proposed a network consisting of 4 residual dense blocks (see Figure 11). Each block was composed of densely connected, local feature fusion (LFF) and local residual learning layers, leading to a contiguous memory (CM) mechanism. All convolutional layers in the image enhancement network were additionally regularized by spectral normalization. For GAN's part of the total loss, the authors used a relativistic average discriminator with the same architecture as in [14].

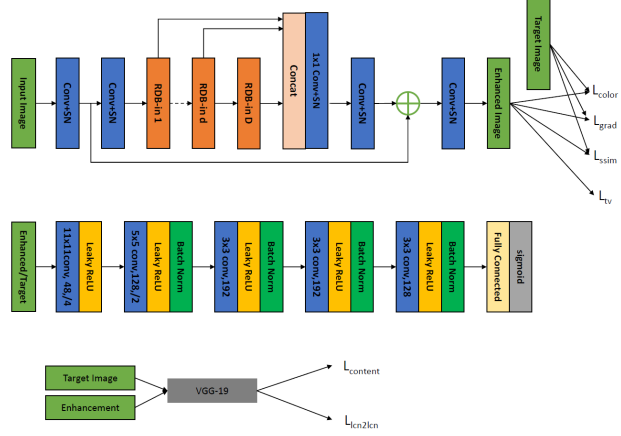


Figure 11. Residual Dense Network used by MENet team.

4.12. Rainbow

Rainbow team based their solution on EDSR architecture [19] with a fusion block presented in figure 12. This block was used to construct 32 residual in residual fusion blocks (RRFB) that were operating with input data down-scaled by a factor of 4 with two strided convolutional layers.

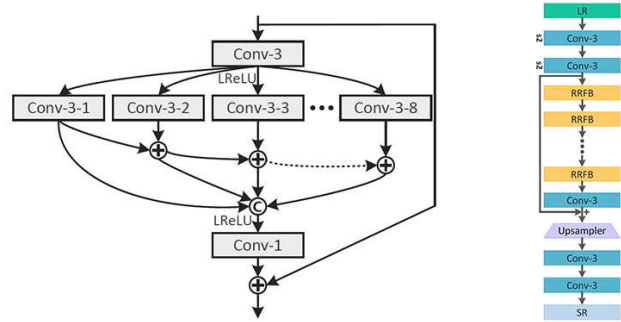


Figure 12. A fusion block and the overall CNN architecture proposed by Rainbow team.

4.13. MiRL

MiRL team proposed the idea of using an ensemble of three different networks(see Figure 13): one U-Net-based CNN for plain image-to-image translation, one network for content-aware image improvement, and one for image denoising. The outputs of these networks were summed to get the final image.

Acknowledgements

We thank the NTIRE 2019 sponsors: HUAWEI Technologies Co. Ltd., OPPO Mobile Corp., Ltd., NVIDIA Corp., SAMSUNG Electronics Co., Ltd., Amazon.com,

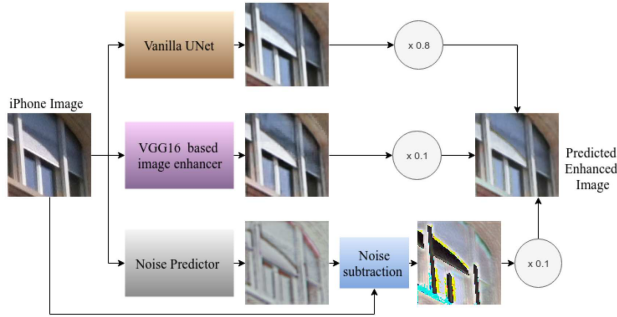


Figure 13. An ensemble of three networks proposed by MiRL.

Inc., MediaTek Inc., and ETH Zurich (Computer Vision Lab).

A. Appendix 1: Teams and affiliations

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