Abstract

This paper reviews the 2nd NTIRE challenge on single image super-resolution (restoration of rich details in a low resolution image) with focus on proposed solutions and results. The challenge had 4 tracks. Track 1 employed the standard bicubic downscaling setup, while Tracks 2, 3 and 4 had realistic unknown downgrading operators simulating camera image acquisition pipeline. The operators were learnable through provided pairs of low and high resolution train images. The tracks had 145, 114, 101, and 113 registered participants, resp., and 31 teams competed in the final testing phase. They gauge the state-of-the-art in single image super-resolution.

1. Introduction

Example-based single image super-resolution (SR) targets the reconstruction of the lost high frequencies (rich details) in an image with the help of a set of prior examples of paired low resolution (LR) and high resolution (HR) images. This problem is ill-posed, for each LR image the space of plausible corresponding HR images is huge and scales up quadratically with the magnification factor.

In the recent years the research literature largely focused on example-based single image super-resolution. The performance achieved by the top methods [38, 32, 7, 16, 20, 31, 21] continuously improved.

The NTIRE 2017 challenge [31, 1] was a step forward in benchmarking SR. It was the first challenge of its kind with tracks employing standard bicubic degradation and ‘unknown’ operators (blur and decimation) on the 1000 DIV2K [1] dataset.

The NTIRE 2018 challenge builds upon NTIRE 2017 and goes further. In comparison with the previous edition, NTIRE 2018: (1) uses the same DIV2K [1] dataset; (2) has only one bicubic downscaling track with magnification factor ×8; (3) promotes realistic settings emulating camera acquisition pipeline through three tracks with gradually increased difficulty.
2. NTIRE 2018 Challenge

The objectives of the NTIRE 2018 challenge on example-based single-image super-resolution are: (i) to gauge and push the state-of-the-art in SR; (ii) to compare different solutions; and (iii) to promote realistic SR settings. **DIV2K Dataset** [1] employed by NTIRE 2017 SR challenge [31] is used also in our challenge. DIV2K has 1000 DIVerse 2K resolution RGB images with 800 for training, 100 for validation and 100 for testing purposes. The manually collected high quality images are diverse in contents.

2.1. Tracks

Access to data and submission of HR image results required registration on Codalab competition track. **Track 1: Classic Bicubic** ×8 uses the bicubic downscaling (Matlab imresize, default settings), the most common setting from the recent SR literature, with factor ×8. It is meant for easy deployment of recent proposed SR solutions. **Track 2: Realistic Mild** ×4 adverse conditions assumes that the degradation operators emulating the image acquisition process from a digital camera can be estimated through training pairs of LR and HR images. The degradation operators are the same (use the same controlling parameters) within each image space and for all the images in train, validation, and test sets. As in reality, the motion blur and the Poisson noise are image dependent and can introduce pixel shifts and scaling. Each ground truth (GT) image from DIV2K is downgraded (×4) to LR images. **Track 3: Realistic Difficult** ×4 adverse conditions is similar to Track 2, only the degradation is stronger. **Track 4: Realistic Wild** ×4 adverse conditions is similar to Tracks 2 and 3, the degradation operators are the same within an image space but different from one image to another. Some images are less degraded than other images. This setting is the closest to real ‘wild’ conditions. Due to increased complexity of the task 4 degraded LR images were generated for each HR train image. **Challenge phases** (1) Development phase: the participants got pairs of LR and HR train images and the LR validation images of the DIV2K dataset; an online validation server with a leaderboard provided immediate feedback for the uploaded HR results to the LR validation images; (2) Testing phase: the participants got test LR images and were required to submit super-resolved HR image results, code, and a factsheet for their method. After the end of the challenge the final results were released to the participants. **Evaluation protocol** The quantitative measures are Peak Signal-to-Noise Ratio (PSNR) measured in decibels [dB] and the Structural Similarity index (SSIM) [37], both full-reference measures computed between the HR result and the GT image. We report averages over sets of images.

As in [31] we ignore a boundary of 6 + s image pixels (s is the zoom factor). Because of the pixel shifts and scalings, for Tracks 2, 3, and 4 we consider all the translations ∈ [−40, 40] on both axes, compute PSNR and SSIM and report the most favorable scores. Due to time complexity, for Tracks 2, 3, and 4 we computed PSNR and SSIM using a 60 × 60px centered image crop during validation phase and a 800 × 800px centered image crop for the final results.

![Figure 1. Sample LR input images for Track 1,2,3, and 4, resp.](image)

3. Challenge Results

From ~110 registered participants on average per each track, 31 teams entered in the final phase and submitted results, codes/executables, and factsheets. Table 1 reports the final test results and rankings of the challenge, while in Table 2 the self-reported runtimes and major details are provided. The methods are briefly described in section 4 and the team members are listed in Appendix A. **Architectures and main ideas** All the proposed methods, excepting TSSR of UW18, are deep learning based. The deep residual net (ResNet) architecture [10] and the dense net (DenseNet) architecture [11] are the basis for most of the proposed methods. For fast inference, thus train and test time benefits, most of the teams conduct the major SR operations in the LR space. Several teams, such as UIUC-IFP, BMIPL-UNIST, Pixel_Overflow, build their methods based on EDSR [21], the state-of-the-art approach and the winner of the previous NTIRE 2017 SR challenge [31, 1]; while, other teams, such as Toyota-TI, HIT-VPC, DRZ, PDN, proposed new architectures for SR. **Restoration fidelity** The top 4 methods from ‘Classic Bicubic’ achieved similar PSNR scores (within 0.04dB). DeepSR entry, ranked 12th, is only 0.17dB behind the best PSNR score of Toyota-TI. On the realistic settings, Tracks 2, 3, and 4, due to the existence of noise and motion blur, the training strategy and the network architecture plays are equally important. Although UIUC-IFP ranked 7th on ‘Classic Bicubic’, below DRZ and Duke Data Science, it adopted a pre-alignment step for the training phase and achieved the best performance on the realistic tracks 2 and 3, significantly better than DRZ and Duke Data Science. PDN ranked 1st on Track 4, however, without submitted results for the other tracks we cannot tell if their solution/architecture is better than that of UIUC-IFP. **Ensembles and fusion** Most teams employ pseudo-ensembles [33]. The inputs are flipped/rotated and the HR results are aligned and averaged for enhanced prediction.
Table 1. NTIRE 2018 SR Challenge results and final rankings. Note that the ‘lpj008’ results are not ranked.

<table>
<thead>
<tr>
<th>Team</th>
<th>Author</th>
<th>PSNR</th>
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Baseline Bicubic | 23.703 | 0.6387 |

Table 2. Reported runtimes [s] per test image and details from the factsheets.

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<td>-</td>
<td>-</td>
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<td>Biplotation (s)</td>
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</table>

Runtime / efficiency: BOE-SBG reported the lowest runtime, 0.15s to super-resolve 8 × 8 one LR image on GPU, but ranked 17th on ‘Classic Bicubic’ 0.63dB lower than the best ranked method of Toyota-TI. Among the top 4 methods on ‘Classic Bicubic’ track, rainbow achieved the best trade-off between efficiency and performance. On a GTX 1080Ti GPU, it takes 6.75s for rainbow, while 35s are necessary for Toyota-TI per LR image to generate the HR image, including self-ensemble for both methods.

Train data: Data augmentation by scaling (only Track 1), flipping, and rotation [33] is another commonly used technique. Only a couple of methods, including Pixel_Overflow, used extra data for training. Pixel_Overflow used images from www.pexels.com, which is also the source of many DIV2K images. Hit-VPC used Track 1 images to estimate downgrading operators on Tracks 3 and 4, thus their ‘lpj008’ entry in Table 1 is just for reference and not ranked in the challenge.

Conclusions: By analyzing the settings, the proposed methods and their results we can conclude: (i) The proposed methods improve the state-of-the-art in SR. (ii) The top solutions are consistent across the realistic tracks, yet the top methods in ‘Classic Bicubic’ are not the top methods of the realistic tracks – domain specific knowledge (pre-alignment of train images) was critical. (iii) As expected, the realistic tracks are more challenging than the bicubic, reflected by the relatively lower PSNR (up to 2dB for the winners) of the results even if we compare 8 × 8 with 4 × 4. (iv) SSIM is more
correlated with PSNR on ‘Classic Bicubic’ than on realistic tracks. (v) High magnification factors and realistic settings pose the extra problem of (subpixel) alignment between HR results and ground truth. (vi) Other ranking measures are necessary (such as perceptual ones). (vii) Further realistic challenges could introduce non-uniform degradations.

4. Challenge Methods and Teams

4.1. Toyota-TI team proposed a deep back-projection networks (DBPN) [9] (see Fig. 2) which uses error feedbacks from the up- and down-scaling steps to guide the network to achieve optimal result. Unlike the previous methods which predict the SR image in feed-forward manner, DBPN adopts mutually connected up- and down-sampling stages to generate LR as well as HR features, and accumulate both up- and down-projection errors to predicting the final SR result. A group of LR features are firstly extracted from the input LR image. Then, back-projection stages are utilized to alternatively generate LR and HR feature maps $L_t$ and $H_t$, which further improved by dense connection where the input for each projection unit is the concatenation of the outputs from all previous units. At last, all the HR feature maps are utilized to reconstruct the final SR estimation $I_{sr} = f_{Rec}([H^1, H^2, \ldots, H^t])$.

The structure of the newly introduced up-projection and down-projection units are shown in Fig. 2(b). To deal with classic bicubic $\times 8$ downsampling SR problem, DBPN uses $12 \times 12$ convolutional layer with eight striding and two padding in the projection units, and 19 projection units (10 up- and 9 down-projection units) have been adopted for generating the SR result.

The network is trained on images from DIV2K with augmentation [33]. At training phase, the input patch size is set to $40 \times 40$ and the mini-batch size to 18. The model is trained with L1 loss using ADAM optimizer [18] with learning rate $1 \times 10^4$ and decrease by a factor of 10 for every $5 \times 10^4$ iterations for total $10^6$ iterations. In the testing phase, the authors adopt the self-ensemble strategy [33] to further improve the SR results.

4.2. Pixel_Overflow team [4] utilized the same network structure as EDSR [21]. To get better SR performance, external training data is adopted in the training phase. Pixel_Overflow uses Sobel filter to extract output and target image edges to emphasize loss on the edges and details.

4.3. rainbow team proposed a method based on EDSR [21] and SRDenseNet [11, 34] (Fig. 3). They employed a pyramid architecture to gradually generate the HR image. In order to trade-off the performance and the inference time, they adopted a two-step enlargement strategy. They trained the network with L1 loss and fine-tuned with L2 loss.

4.4. DRZ team proposed an asymmetric pyramidal structure for image SR [36] (see Fig. 4). Each level of the pyramid consists of a cascade of dense compression units (DCUs), and a sub-pixel convolution layer is utilized to generate the residual map to reconstruct the HR image. DCU consists of a smaller, modified densely connected block [11] followed by $1 \times 1$ convolution. Compared with the original densely connected block proposed for classification, the batch normalization (BN) layer has been removed in DCU.

In the training phase, curriculum learning [5] strategy has been adopted to achieve better SR performance and shorter training time. Specifically, DRZ firstly trains the $2 \times$ portion of the network and then gradually blend a new level of pyramid to reduce the impact on the previously trained layers. Curriculum learning adds an average of 0.07dB PSNR on the validation set of DIV2K for $2 \times 4 \times 8$ scales compared to 0.03dB using normal multiscale training.

4.5. UIUC-IFP team proposed a wide activation SR network (WDSR, see Fig. 5), which is a deep residual SR
network (two-layer residual blocks) similar to the baseline EDSR [21]. To improve the SR performance, WDSR modify the original EDSR in three aspects. Firstly, in comparison with EDSR, WDSR reduces the width of identity mapping pathway and increases the width of feature maps before the ReLU function in each residual block (see Fig. 5(a)). Their experiments showed that WDSR is extremely effective for improving accuracy. Secondly, UIUC-IFP follows recent works [8, 21, 31] which remove the BN layer in the residual blocks and adopts weight normalization in their WDSR approach, although the introducing of weight normalization in training SR networks may not help that much, it enables the authors to use higher learning rate to train the network. Thirdly, WDSR removes some convolution layers used in EDSR and directly generate the shuffled SR estimation (see Fig. 5(b)), such a strategy is able to improve the processing speed while not affect accuracy of SR network.

For Track 1, UIUC-IFP utilized similar training parameters as EDSR, the only difference is that weight normalization enables UIUC-IFP to increase the learning rate 10× to 0.001. After training with L1 loss, the model is finetuned with PSNR loss, directly. The finetune step leads to around 0.03dB PSNR improvement on the DIV2K validation set. For Tracks 2, 3 and 4, UIUC-IFP utilized a pre-align step to alleviate the random shift effects between the LR and HR images. Specifically, the HR images are shifted up to 40 pixels, and then bicubic downsampled HR images are compared with given realistic LR images to find coarse aligned HR images for each LR image.

In the testing phase, a self-ensemble inference strategy has been adopted to improve SR performance [33].

4.6. **PDN team** proposed the PolyDenseNet (PDN) (see Fig. 6) for image SR. The basic building block of PDN is PolyDense Block (PDB), which is motivated by PolyNet [42] and DenseNet [11]. Each PDB contains three 5-layer dense block and use three parameters $\alpha_1$, $\alpha_2$ and $\alpha_3$ to combine the dense block outputs $D_1$, $D_2$ and $D_3$ to get the output. PDN team investigated also a PDN variant by building skip connections between adjacent PDBs (see Fig. 6(b)). The results by the two variants are ensembled at test time. In the training phase, the authors upsample the LR images and calculate the best shifting parameters w.r.t. ground truth based on PSNR. For brightness scaling, the authors adjust the pixel mean of LR images by the mean of its corresponding ground-truth image.

4.7. **BMIPL_UNIST team** decomposed the original problem of NTIRE 2018 challenge into subproblems (SR at various scales and denoising / deblurring) and proposed an efficient module-based single image SR network [27] (EM-BSR, see Fig. 7). For an individual module network on SR, they proposed EDSR-PP which integrated pyramid pooling into the upsampling layer of EDSR [21] for better utilizing both the global and local context information. For a module network on denoising / deblurring, they proposed a residual convolution network (DnResNet) which replaced convolution blocks of DnCNN [40] by residual blocks with BN and
scaling. A pre-processing step aligning the input and target images have been adopted in the training process of DnResNet, which is reportedly critical for good performance.

4.8. HIT-VPC team utilized different strategies for solving the bicubic and realistic experimental settings. For Track 1 ‘Classic bicubic’ ×8, HIT-VPC proposed an inverse multi-level wavelet convolutional neural network (iMwCNN). As shown in Fig. 8(a), iMwCNN is designed as pyramid structure with multi-level wavelet packet transform (WPT) [22]. The input LR image is firstly bicubic interpolated by a scale factor 2, and the DWT coefficients of the interpolated image are the network input. To get a scale factor of 8, 3-level networks have been adopted for estimating the inverse DWT coefficients. Between each level of networks, a fixed inverse wavelet transform is adopted to transform the coefficients back to the image space. Each level of network contains 8 convolutional layers, and feature map number for the three levels are set as 256, 256 and 128, respectively. In the training phase, the loss is defined on each scale of estimations.

For the realistic settings (Tracks 2, 3, and 4), HIT-VPC utilized different strategies for solving the bicubic and realistic experimental settings. For Track 1 ‘Classic bicubic’ ×8, HIT-VPC proposed an inverse multi-level wavelet convolutional neural network (iMwCNN). As shown in Fig. 8(a), iMwCNN is designed as pyramid structure with multi-level wavelet packet transform (WPT) [22]. The input LR image is firstly bicubic interpolated by a scale factor 2, and the DWT coefficients of the interpolated image are the network input. To get a scale factor of 8, 3-level networks have been adopted for estimating the inverse DWT coefficients. Between each level of networks, a fixed inverse wavelet transform is adopted to transform the coefficients back to the image space. Each level of network contains 8 convolutional layers, and feature map number for the three levels are set as 256, 256 and 128, respectively. In the training phase, the loss is defined on each scale of estimations.

For the realistic settings (Tracks 2, 3, and 4), HIT-VPC built upon their recently proposed super-resolution network for multiple degradations (SRMD) [39]. As illustrated in Fig. 8(b), SRMD takes the parameterized degradation map as well as LR image as the network inputs, and utilizes 20 convolution + BN + ReLU blocks to estimate the HR sub-images. In order to apply SRMD to tracks 2, 3 and 4, the blur kernel of which is unknown, HIT-VPC centers the blur kernels based on the largest values to align the LR image and HR image, and calculates the mean (aligned) degradation maps for each track. Then, the mean degradation maps for each track is used for super-resolve images from the corresponding tracks.

HIT-VPC∗ (‘lpj008’, not ranked) submitted additional results of a single SRMD model for Tracks 3 and 4. They used Track 1 images for degradation operator estimation and showed the advantages of non-blind SRMD: (i) it can handle Tracks 3 and 4 in a single model while (ii) producing better results with accurate blur kernel than the blind SRMD.

4.9. Faceall_Xlabs team’s architecture is based on EDSR [21]. The filter number for each convolution layer has been changed to 256, and 80 residual blocks were used.

4.10. Duke Data Science team [4] also adopted different strategies for the bicubic and realistic settings. For the bicubic setting, they utilized EDSR [21] with a different training strategy. Warm restarts and cosine annealing approach has been introduced to allow the network to jump out the local minima.

For the realistic settings, the authors firstly trained a DnCNN [40] and an EDSR [21] for denoising and SR separately, and then finetuned the two networks in tandem.

4.11. SIA team reproduced EDSR [21] and used Charbonnier loss instead of L1 loss, as suggested in [19]. To take full advantage of convolution operation for the full image, the CPU was used at test time. For Tracks 2, 3, and 4, the train pairs were first aligned based on PSNR.

4.12. KAIST-VICLAB team [15] designed, for Track 1, a 43-layer CNN (see Fig. 9) for progressively upscaling the input RGB image to the final target resolution. Two sub-pixel convolution layers are inserted after the 20-th and the 40-th convolution layer to enlarge the feature maps by 2 and 4, resp. The network is trained in a coarse-to-fine manner: first for 2× upscaling, then for 4×, and finally for 8×.

For Tracks 2, 3 and 4, KAIST-VICLAB developed a solution comprised from: 1) Four 5×5-sized filters are learned between LR and HR training sub-images, which are applied to create noise-reduced and luminance-corrected intermediate images of HR sizes. 2) Aligned HR training images are generated by aligning original HR training images with the intermediate images. 3) A 58-layered CNN with 2M parameters is trained using the noisy LR training images and the newly aligned HR training images. Specifically, residual learning, residual units and two subpixel convolution layers are adopted in the network.

4.13. Haiyun_XMU team [6] adopted different strategies for the bicubic and realistic settings. For Track 1 an EDSR [21]-based model with 50 residual blocks were trained to reconstruct the HR image. While, for the realistic settings, Haiyun_XMU design the persistent memory
block [30] in two ways and then embed it into EDSR [21]. First, for MemEDSR, the authors replace the body part of EDSR with a memory block with 4 residual blocks, and each memory module links to the gate unit, which adaptively selects the features needed to store. Second, for IRMem, the authors design a memory block with an IR-CNN [41] block, which delete all the BN layer and add residual factor assigned 0.1, and embedded this memory block into EDSR [21]. The MemEDSR is adopted in Tracks 2 and 3, while the IRMem is adopted in Track 4.

4.14. Ajou-LAMDA-Lab team proposed progressive CARN [3] which apply progressive training [14] based on the CARN [2]. Specifically, the structure of the CARN module is shown in Fig. 10 (b), the local and global cascading modules are expected to extract multi-level representations. Upon this, three-stage of CARN modules are progressively trained to reconstruct the ×8 HR image as depicted in Fig. 10 (a). In the training process, extra CARN module is added at the end of the stage and replace the previous reconstruction layers with the one that produces the image in double resolution. Further, learning rate of pre-trained modules is decayed ten times to stabilize overall training.

![](https://example.com/fig10.png)

Figure 10. Ajou-LAMDA-Lab’s networks.

4.15. srFans team improved EDSR [21] in two aspects: (i) the number of residual blocks have been changed to 30 for generating sharper details, and (ii) the first convolution layer in each res-block has been changed to dilated convolution with size 2. srFans adopted a pre-processing step to align the LR and HR image pairs before training.

4.16. DeepSR team proposed a deeply progressive memory network (DPMN). Specifically, the authors utilized convolution, summation, concatenation and deconvolution layers to build the DPMN block, and used 5 DPMN blocks to deal with the SR problem (see Fig. 11). Each convolution layer is followed by a leaky rectified unit (LReLU).

4.17. reveal.ai team proposed a network structure based on the DenseNet [11] (see Fig. 12). reveal.ai also introduced dense connections across dense blocks. Furthermore, each layer inside the dense-block is changed to a convolution + ReLU + convolution layer, which is similar to EDSR [21].

4.18. ISP Team used blur maps to improve the SR results in realistic conditions. Specifically, after estimating the blur map of testing image, ISP Team puts the blur map as well as the LR image into the SR-net to reconstruct the HR image.

4.19. BOE-SBG team developed a multi-scale SR system (see Fig. 13), for zooming factor 8 and 4, 3 and 2 levels of ×2 network are utilized to progressively upscale a LR image. In each scale of upsampling network, the authors adopted a multi-grid version of iterative back-projections [13, 35] in the latent space (e.g. features within a network) to further improve the SR performance. The authors utilized the learned upscale and downscale layers to improve the SR estimation with the LR residuals. In the upscale and downscale steps, the stride convolution/deconvolution operations and the newly proposed Muxout and TransposedMuxout [26, 24, 25] layers have been adopted for track 1, 3 and 2, 4, respectively.

4.20. MCML team proposed a network architecture [17] based on MDSR [21]. To improve the performance of MDSR [21], they proposed enhanced upscaling module (EUM) shown in Fig. 14. Compared with the original upscaling layer in MDSR, which uses only one convolution layer without an activation function to increase the number of features, they introduce four residual modules and concatenate the outputs of the modules to increase the number of feature maps. The proposed EUM has the advantages that it can handle nonlinear operations and exploit skip con-
connections. They proposed a novel deep residual network for super-resolution (EUSR) by utilizing the EUM and multi-scale learning ($\times 2$, $\times 4$, and $\times 8$), whose structure is illustrated in Fig. 14.

For track 1, they used 48 residual blocks and 2 residual blocks in each residual module for feature extraction and upscaling, respectively. They used a single EUSR for the other three tracks, which exploit the information of multiple degradation processes (mild, difficult, and wild) instead of the multiple scales. They used 64 residual blocks and 2 residual blocks in each residual module for feature extraction and upscaling, respectively. They also used three additional feature maps as input, which are obtained by a residual module consisting of three residual blocks. The self-ensemble strategy [33] is adopted for track 1 at testing.

4.21. SRFun team divided the $8 \times$ SR problem into 3 $2 \times$ SR problems [12]. A modified version of ResNet and DenseNet deep autoencoder has been utilized to estimate the residual between target HR image and a pre-defined upsampled image.

4.22. APSARA team used the LR image to estimate the wavelet coefficients of HR image. Since each sub-band map of HR wavelet coefficients are with the same size of LR image, the proposed network (see Fig. 15) do not need deconvolution or subpixel layers. The network uses the first 32 residual blocks and a $1 \times 1$ convolution layer to compute the detail coefficients of HR image and utilize another 32 residual blocks to compute the approximation coefficients of HR image. Then, the two component are combined together to generate the final HR reconstruction.

4.23. CEERI team proposed an improved residual based gradual upscaling network (IRGUN) [29]. The IRGUN has a series of up-scaling and enhancement blocks (UEB) connected end-to-end and fine-tuned together to give a gradual magnification and enhancement. The up-scaling network is a 6 layer architecture, which contains 3 convolutional layers followed by 3 de-convolutional layers. While the enhancement network contains 10 layer residual enhancement network (RED-10) [23]. The authors repeated the UEB until they reach the required SR factor.

4.24. UW18 team proposed a two-step SR (TSSR) approach (see Fig. 16) which utilizes two successive resolution enhancement operation to super-resolve the input LR image. In the first step, a set of rough filters, which is based on the hash mechanism proposed in RAISR [28], is utilized to generate a coarse SR result. Then, a set of refined resolution enhancement filters are applied to yield the final HR patches.

4.25 NMH team improved EDSR [21] by expanding the number of feature maps before the last convolution layer to 512 and introducing an $1 \times 1$ convolution layer to generate the HR reconstruction.

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A. Teams and affiliations

NTIRE2018 team

**Title:** NTIRE 2019 Challenge on example-based single image super-resolution  
**Members:** Radu Timofte $^{1,2}$ (radu.timofte@vision.ee.ethz.ch), Shuhang Gu $^{1}$, Jiqing Wu $^{1}$, Luc Van Gool $^{1,3}$, Lei Zhang $^{4}$, Ming-Hsuan Yang $^{5}$  
**Affiliations:**  
1 Computer Vision Lab, ETH Zurich, Switzerland  
2 Merantix, Germany  
3 ESAT, KU Leuven, Belgium  
4 The Hong Kong Polytechnic University, China  
5 University of California at Merced, US

Ajou-LAMDALab

**Title:** Image Super-resolution via Progressive Cascading Residual Network  
**Members:** Namhyuk Ahn (aa0dfg@ajou.ac.kr), Byungkon Kang, Kyung-Ah Sohn  
**Affiliation:** Ajou University, Republic of Korea

APSARA

**Title:** Single Image Super Resolution based on Wavelet  
**Members:** Ming Qiu (mingqiu@xmu.edu.cn), Liting Jing, Jiehang Zeng, Ying Wang  
**Affiliation:** Software School of Xiamen University, China

BMIPL,UNIST

**Title:** Efficient Module based Single Image Super Resolution for Multiple Problems  
**Members:** Dongwon Park (dongl@unist.ac.kr), Kwanyoung Kim, Se Young Chun  
**Affiliation:** School of Electrical and Computer Engineering, Ulsan National Institute of Science and Technology (UNIST), Republic of Korea

BOE-SBG

**Title:** Multi-Grid Back-Projection Networks for Image SuperResolution  
**Members:** Pablo Navarrete Michelini (pnavarre@boe.com.cn), Dan Zhu, Hanwen Liu  
**Affiliation:** BOE Technology Group Co., Ltd.

CEERI

**Title:** Improved residual based gradual upscaling network (IRGUN)  
**Members:** Manoj Sharma, Rudrabha Mukhopadhyay, Avinash Upadhyay, Srijan Koundinya, Ankit Shukla, Santanaa Chaudhury  
**Affiliation:** CSIR-CEERI, India

DeepSR

**Title:** Deeply Progressive Memory Network for Image Restoration  
**Members:** Yan Zhao (N161127032@fzu.edu.cn), Wei Deng  
**Affiliation:** Fuzhou University, China

DRZ

**Title:** A Fully Progressive Approach to Single-Image Super-Resolution  
**Members:** Yifan Wang $^{1,2}$ (yifan.wang@disneyresearch.com), Federico Perazzi$^{1}$, Brian McWilliams$^{1}$, Alexander Sorkine-Hornung$^{3}$, Olga Sorkine-Hornung$^{2}$, Christopher Schroers  
**Affiliation:**  
1 Disney Research,  
2 ETH Zurich, Switzerland  
3 Facebook Oculus

Duke Data Science

**Title:** CosEDSR  
**Members:** Alexandru Damian (ad315@duke.edu), Nikhil Ravi, Sachit Menon  
**Affiliation:** Duke University, US

Faceall_Xlabs

**Members:** Jinchang Xu (sjc1@bupt.edu.cn), Yijiao Liu, Fengye Xiong, Yuan Dong, Hongliang Bai  
**Affiliation:**  
Beijing University of Posts and Telecommunications, China  
Beijing Faceall Technology Co., Ltd, China

Haiyun_xmu

**Title:** Persist Memory Residual Network for Super Resolution
Members: Rong Chen (chenrong.mail@qq.com), Kun Zeng, Jinkang Guo, Yanyun Qu, Cuihua Li
Affiliation: Xiamen University, China

HIT-VPC
Title: Learning a Single Convolutional Super-Resolution Network for Multiple Degradations
Members: Kai Zhang (cskaizhang@gmail.com), Pengju Liu, Wangmeng Zuo, Shi Guo, Jiye Liu
Affiliation: School of Computer Science and Technology, Harbin Institute of Technology, Harbin, China

ISP Team
Members: Xiaowang Cai (460571930@qq.com), Fang Huang, Yueshu Xu
Affiliation:

Juan Luis Gonzalez
Title: Receptive Field ESPCN
Members: Juan Luis Gonzalez (juanluisgb@kaist.ac.kr)
Affiliation: KAIST, Republic of Korea

KAIST-VICLAB
Title: Track 1: A Progressive Super-resolution Method using Convolutional Neural Networks
Track 2, 3, 4: Convolutional Neural Networks for Alignment and Super-Resolution
Members: Soo Ye Kim (sooyekim@kaist.ac.kr), Jae-Seok Choi, Sehwan Ki, Soomin Seo, Hyeonjun Sim, Saehun Kim, Munchurl Kim
Affiliation: Korea Advanced Institute of Science and Technology (KAIST), Republic of Korea

MCML
Title: Deep residual network using enhanced upscale modules for super-resolution
Members: Jun-Hyuk Kim (junhyuk.kim@yonsei.ac.kr), Jong-Seok Lee
Affiliation: Yonsei University, Republic of Korea

NMH
Members: Lingzhi Fu (lexuszhi1990@gmail.com)

PDN
Title: Deep Poly-Dense Network for Image Super-Resolution
Members: Xintao Wang¹ (wx016@ie.cuhk.edu.hk), Ke Yu¹, Tak-Wai Hui¹, Chao Dong², Liang Lin², Chen Change Loy¹
Affiliation: ¹The Chinese University of Hong Kong, ²SenseTime Research

Pixel Overflow
Title: x8 super-resolution, explored the effect of edge loss using Sobel filter
Members: Shijia Hu (sh395@duke.edu), Webster Bei Yijie
Affiliation: Duke University, US

Rainbow
Title: Image Super-Resolution via Deep Pyramidal Residual Network (DPRN)
Members: Zheng Hui (zheng_hui@stu.xidian.edu.cn), Xiao Jiang, Yanan Gu, Jie Liu
Affiliation: School of Electronic Engineering, Xidian University, China

Reveal.ai
Title: Denseption for Single-Image Super Resolution
Members: Sibt Ul Hussain (sibhtul.hussain@nu.edu.pk), Muneeb Aadil, Rafia Rahim
Affiliation: National University of Computer & Emerging Sciences, Islamabad, Pakistan

SIA
Title: Reproducing EDSR
Members: Junghoon Seo (sjh@satreci.com), Taegyun Jeon, Jamyoung Koo, Seunghyun Jeon
Affiliation: R&D Center, Satrec Initiative
srFans

Title: Dilated Deeper Residual Network for Super Resolution
Members: Yuan Yuan
(yuyuan13@ualberta.ca), Jiawei Zhang, Jiahao Pang, Xiangyu Xu
Affiliation: Electrical and Computer Engineering, University of Alberta, Canada

SRFun

Title: Densely Connected High Order Residual Network for Single Frame Image Super Resolution
Members: Yiwen Huang
(nickgray0@gmail.com)
Affiliation: Wenhua College, China

Toyota-TI

Title: Deep Back-Projection Networks
Members: Muhammad Haris
(mharis@toyota-ti.ac.jp), Greg Shakhnarovich, Norimichi Ukita
Affiliation: 1 Toyota Technological Institute
2 TTI-Chicago, US

UIUC-IFP

Title: Wide Activation and Weight Normalization for Accurate Image SuperResolution
Members: Jiahui Yu
(jyu79@illinois.edu), Yuchen Fan, Jianchao Yang, Ning Xu, Zhaowen Wang, Xinchao Wang, Thomas S. Huang
Affiliation: 1 University of Illinois at Urbana-Champaign, US
2 Snap Inc.,
3 Adobe Research,
4 Stevens Institute of Technology, US

UW18

Title: TSSR(Two-Step Super Resolution)
Members: Zhe Zhang
(zhangzsmg@gmail.com), Yu Hen Hu
Affiliation: 1 Dept. Electrical and Computer Engineering, University of Wisconsin-Madison, Madison, US
2 MOE KLINNS Lab, Institute of Integrated Automation, School of Electronic and Information Engineering, Xian Jiaotong University, China

References


