Robust Reference-based Super-Resolution via $C^2$-Matching
Supplementary File

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In this supplementary file, we will explain the network structures (i.e. Contrastive Correspondence Network and Restoration Network) and training details in Section A. Then we will introduce training losses we used in Section B. In Section C, the model size will be analyzed. In Section D, we will provide more visual comparisons with state-of-the-art methods. Finally, we will show more visual comparisons of ablation study in Section E.

A. Network Structures and Training Details

A.1. Contrastive Correspondence Network

**Network Structure.** Table 1 shows the detailed feature extractor structure of contrastive correspondence network. Since the resolutions of input image and reference image are different, we adopt two feature extractors for LR input image and HR reference image, respectively.

Table 1. The feature extractor structure of contrastive correspondence network. The kernel size of convolution layers is $3 \times 3$ and the MaxPool operation is with kernel size of $2 \times 2$.

| #   | Layer name(s)                          |
|-----|---------------------------------------|
| 0   | Conv (3, 64), ReLU                     |
| 1   | Conv (64, 64), ReLU                    |
| 2   | MaxPool (2 × 2)                        |
| 3   | Conv (64, 128), ReLU                   |
| 4   | Conv (128, 128), ReLU                  |
| 5   | MaxPool (2 × 2)                        |
| 6   | Conv (128, 256)                        |

**Training Details.** To enable teacher-student correlation distillation, a teacher contrastive correspondence network should be first trained. The hyperparameters for the training of teacher model are set as follows: the margin value $m$ is 1.0, the threshold value $T$ is 4.0, the batch size is set as 8, and the learning rate is $10^{-3}$. We use the pretrained weights of VGG-16 to initialize the feature extractor. Then the student contrastive correspondence network is trained with the teacher network fixed. The margin value $m$, threshold value $T$, batch size and learning rate are the same as the teacher network. The temperature value $\tau$ is 0.15, and the weight $\alpha_{kl}$ for KL-divergence loss is 15.

A.2. Restoration Network

**Network Structure.** The restoration network consists of dynamic aggregation module and restoration module. For each image, three reference features (i.e. pretrained VGG relu3_1, relu2_1, relu1_1 feature [3]) are aggregated by dynamic aggregation module, and the aggregated reference features are denoted as Aggregated Reference Feature1, Aggregated Reference Feature2 and Aggregated Reference Feature3, respectively. The structure of restoration module is illustrated in Table 2.

Table 2. The structure of restoration module. The kernel size of convolution layers is $3 \times 3$. PixelShuffle layers are $2 \times$. RB denotes residual block. Aggregated Reference Feature denotes the reference feature aggregated by the dynamic aggregation module.

| #   | Layer name(s)                          |
|-----|---------------------------------------|
| 0   | Conv(3, 64), LeakyReLU                 |
| 1   | RB [Conv(64, 64), ReLU, Conv(64, 64)] × 16 |
| 2   | Concat [#1, Aggregated Reference Feature1] |
| 3   | Conv(320, 64), LeakyReLU               |
| 4   | RB [Conv(64, 64), ReLU, Conv(64, 64)] × 16 |
| 5   | ElementwiseAdd(#1, #4)                |
| 6   | Conv(64, 256), PixelShuffle, LeakyReLU |
| 7   | Concat [#6, Aggregated Reference Feature2] |
| 8   | Conv(192, 64), LeakyReLU               |
| 9   | RB [Conv(64, 64), ReLU, Conv(64, 64)] × 16 |
| 10  | ElementwiseAdd(#6, #9)                |
| 11  | Conv(64, 256), PixelShuffle, LeakyReLU |
| 12  | Concat [#11, Aggregated Reference Feature3] |
| 13  | Conv(128, 64), LeakyReLU               |
| 14  | RB [Conv(64, 64), ReLU, Conv(64, 64)] × 16 |
| 15  | ElementwiseAdd(#11, #14)              |
| 16  | Conv(64, 32), LeakyReLU                |
| 17  | Conv(32, 3)                            |

**Training Details.** The learning rate is set as $10^{-4}$. For the training of the network with adversarial loss and perceptual
loss, we adopt the same setting as [8] (i.e. the network is trained with only reconstruction loss for the first 10K iterations).

B. Loss Functions

Reconstruction Loss. The $\ell_1$-norm is adopted to keep the spatial structure of the LR images. It is defined as follows:

$$L_{rec} = \| I^{HR} - I^{SR} \|_1.$$  

Perceptual Loss. The perceptual loss [1] is employed to improve the visual quality. It is defined as follows:

$$L_{per} = \frac{1}{V} \sum_{i=1}^{C} \| \phi_i(I^{HR}) - \phi_i(I^{SR}) \|_F,$$  

where $V$ and $C$ denote the volume and channel number of feature maps. $\phi$ denotes the relu5_1 features of VGG19 model [3]. $\| \cdot \|_F$ denotes the Frobenius norm.

Adversarial Loss. The adversarial loss [2] is defined as follows:

$$L_{adv} = -D(I^{SR}).$$  

The loss for training discriminator $D$ is defined as follows:

$$L_D = D(I^{SR}) - D(I^{HR}) + \lambda \| \nabla D(\hat{I}) \|_2 - 1)^2.$$  

where $\hat{I}$ is the random convex combination of $I^{SR}$ and $I^{HR}$.

C. Comparison of Model Size

The comparison of model size (i.e. the number of trainable parameters) is shown in Table 3. Our proposed $C^2$-Matching has a total number of 8.9M parameters and achieves a PSNR of 28.24dB. For a fair comparison in terms of model size, we build a light version of $C^2$-Matching, which has fewer trainable parameters. The $C^2$-Matching-light is built by setting the number of residual blocks of layer #9 and layer #14 to 8 and 4, respectively, and removing the Aggregated Reference Feature. The $C^2$-Matching-light has a total number of 4.8M parameters. The light version has fewer parameters than TTSR [5] but significantly better performance.

Table 3. Model sizes of different methods. PSNR / SSIM are adopted as the evaluation metrics.

| Method               | Params | PSNR/SSIM |
|----------------------|--------|-----------|
| RCAN [7]             | 16M    | 26.06 / .769 |
| RankSRGAN [6]        | 1.5M   | 22.31 / .635 |
| CrossNet [9]         | 33.6M  | 25.48 / .764 |
| SRNTT [8]            | 4.2M   | 26.24 / .784 |
| TTSR [5]             | 6.4M   | 27.09 / .804 |
| $C^2$-Matching-light | 4.8M   | 28.14 / .839 |
| $C^2$-Matching       | 8.9M   | 28.24 / .841 |

D. More Visual Comparisons with State-of-the-art Methods

In Fig. 1 and Fig. 2, more visual comparisons with ESRGAN [4], RankSRGAN [6], SRNTT [8] and TTSR [5] are provided. The images restored by our proposed $C^2$-Matching have better visual quality.

E. More Visual Comparisons of Ablation Study

In this paper, the proposed $C^2$-Matching consists of three major components: Dynamic Aggregation Module (Dyn-Agg), Contrastive Correspondence Network (Contras) and Teacher-Student Correlation Distillation (TS Corr). On top of the baseline model, we progressively add the Dyn-Agg module, Contras network and TS Corr distillation. In Fig. 3, we show more visual comparisons with these proposed modules progressively added.

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Figure 1. **More visual comparisons.** We compare our results with ESRGAN [4], RankSRGAN [6], SRNTT [8], and TTSR [5]. All these methods are trained with GAN loss. Our results have better visual quality with more texture details.
Figure 2. **More visual comparisons.** We compare our results with ESRGAN [4], RankSRGAN [6], SRNTT [8], and TTSR [5]. All these methods are trained with GAN loss. Our results have better visual quality with more texture details.
Figure 3. More visual comparisons of ablation study. On top of the baseline model, Dynamic Aggregation Module (Dyn-Agg), Contrastive Correspondence Network (Contras) and Teacher-Student Correlation Distillation (TS Corr) are progressively added.