Feature-based Adaptive Contrastive Distillation for Efficient Single Image Super-Resolution

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Abstract

Convolution Neural Networks (CNNs) have been used in various fields and are showing demonstrated excellent performance, especially in Single-Image Super Resolution (SISR). However, recently, CNN-based SISR has numerous parameters and computational costs for obtaining better performance. As one of the methods to make the network efficient, Knowledge Distillation (KD) which optimizes the performance trade-off by adding a loss term to the existing network architecture is currently being studied. KD for SISR is mainly proposed as a feature distillation (FD) to minimize L1-distance loss of feature maps between teacher and student networks, but it does not fully take into account the amount and importance of information that the student can accept. In this paper, we propose a feature-based adaptive contrastive distillation (FACD) method for efficiently training lightweight SISR networks. We show the limitations of the existing feature-distillation (FD) with L1-distance loss, and propose a feature-based contrastive loss that maximizes the mutual information between the feature maps of the teacher and student networks. The experimental results show that the proposed FACD improves not only the PSNR performance of the entire benchmark datasets and scales but also the subjective image quality compared to the conventional FD approach.

1. Introduction

Single image super-resolution (SISR) is a method of generating a high-resolution image from a given low-resolution image [8]. It is an important task that can be applied to a variety of computer vision tasks, such as medical imaging [30], pattern and object recognition [4, 11]. In the prior work, interpolation and image-based methods were applied to SISR task [33, 38, 42]. But, both methods show the limitation of performance. Relatively recently, the advent of CNN-based SISR networks such as SRCNN [6] has provided outperformed the traditional SISR works. Since then, numerous CNN-based SISR networks have been proposed [8, 20, 21], and the network parameters and computational complexity have been increased to obtain better performance.

The complex SISR model has limitations of practical applications such as resource-constrained devices. For this resource-limited environment such as mobile or IoT devices, the efficient and lightweight SISR model is needed. To meet this demand, the lightweight SISR model which derives more efficient performance trade-off is being studied [14, 16, 25, 29, 36, 41]. These studies can be largely divided into hardware-friendly network architecture design [7, 25] and advanced training approaches that optimize the performance trade-off by adding a loss term. Training approaches for lightweight networks consist of pruning [16, 41], quantization [2, 15, 26], and knowledge distillation (KD) [9, 14, 29, 36].

Among the above-mentioned methods, KD [9] methods have various advantages compared to other methods. Pruning, quantization, and hardware-friendly network design methods require more consideration of the structure and do not guarantee performance improvements. On the other hand, KD has the advantage of performance improvement without considering the network structure. Furthermore, KD can be combined with pruning and network de-
Noted that teacher and student networks are trained separately from scratch. sign methods by adding loss terms to result in more performance improvement [1, 19].

KD is mainly used for classification and detection tasks [4, 34, 37]. The student network is trained to minimize the distance between the labels of the student network and the soft labels of the teacher network in the classification task. However, for SISR task, this approach shows a limitation in performance improvement [29, 31]. Therefore, Feature-based Distillation (FD) has been mostly studied in the KD scheme. Feature Affinity-based KD (FAKD) [14] proposed transferring the feature knowledge of a larger teacher model to a lightweight student network. FAKD found that Teacher Supervision (TS) and Data Supervision (DS) helped improve the distillation performance. After that, Local-Selective Feature Distillation (LSFD) [29] proposed the feature attention method that selectively focuses on specific positions to extract feature information to improve the simple distance-based feature distillation of FAKD. Both methods have in common that they use L1 distance as a metric to transfer the feature knowledge from teacher to student. As shown in Fig. 1, neither method completely solves the disadvantages of distance-based loss such as the restoration of patterns and blurred images.

To address the limitation of L1 distance loss, contrastive loss on the image domain for SISR has been studied in the KD scheme [28, 36]. Contrastive Self-Distillation (CSD) [36] and [28] proposed the scheme to explicitly transfer the knowledge from teacher to student using contrastive loss in image domain and improved the distillation performance and restoration of texture. However, KD in image domain cannot fully utilize the rich information of feature maps and we experimentally found that the contrastive distillation on the image domain showed even worse performance over FD with L1 distance loss in the SISR task.

To solve these issues, in this paper, we propose a Feature-based Adaptive Contrastive Distillation (FACD) that transfers the feature knowledge from a teacher using contrastive loss. Firstly, we noted that the efficiency of distillation lies in the feature rather than the image domain, and contrastive loss rather than L1 distance loss. Therefore, we focus on feature distillation with the contrastive loss for SISR. Our Feature-based Contrastive Distillation (FCD) can solve the reconstruction of edges and patterns, and provide improvement of distillation performance by maximizing mutual information between intermediate features of teacher and student networks.

In addition, FAKD and LSFD using three intermediate feature maps for FD do not consider the attention at the feature map level. In case of LSFD, they pay attention to specific pixel location of feature. On the other hand, we assign the different importance (attention) to each feature map according to their location in the network and demonstrate that it is experimentally useful in Section 5. We noted that since CNN-based SR network has a cascading structure, the inappropriate distillation of upper part sequentially affects the lower part of network.

Finally, as shown in Fig. 2, we noted that the output patches of teacher network do not always outperform those of the student due to the incorrect inference results of teacher network. Based on our analysis, the inappropriate output patches of the teacher are occupied up to 5 and 11% in the case of EDSR and RCAN networks, respectively. Since inappropriate patches can transfer erroneous knowledge to the student network, we adaptively apply FCD or not according to the state of patch during training and we will describe the efficiency of the adaptive distillation in the Section 5. Combined with the feature-based contrastive loss, layer attention, and adaptive distillation, FACD achieves state-of-the-art performance over FD and excellent qualitative results. Our main contributions can be summarized as follows:

1. We propose the FCD that provides higher performance than the traditional FD methods by transferring the teacher’s intermediate feature knowledge to the lightweight student network based on the contrastive loss. FD with L1-distance loss provides only the upper bound of knowledge, whereas the contrastive loss provides both the lower and upper bounds, enabling efficient knowledge transfer to students. By this approach, our FCD solves the reconstruction of texture that occurs with the conventional FD approach. FCD which maximizes the mutual information of the teacher and student feature maps increases the efficiency of FD.

2. We experimentally found that inappropriate teacher’s knowledge interfered with student learning. For the efficiency of distillation, we propose an algorithm called feature-based adaptive contrastive distillation (FACD) that selectively applies FCD according to the comparison of output patches derived from teacher and student networks.
networks and ground-truth.

3. We demonstrate the FACD achieves state-of-the-art performance on distance-based FD and excellent qualitative results. Especially, in qualitative results, FACD confirmed outperformed edge and pattern reconstruction results.

2. Related Works

2.1. Efficient Super Resolution Network

At first, the CNN-based SR model stacks more deep layers to improve performance, but this architecture caused a gradient vanishing. After that, VDSR [20] and DRCN [21] networks used deeply stacking residual blocks [13] to solve this issue. In addition, EDSR [24] demonstrated that Batch-Normalization (BN), which showed outperformed performance in the classification task, leads to normalization of the output of the SISR model. Furthermore, EDSR [24] uses the residual-scaling method to enhance stable training caused by removing BN. Recently, RCAN [40] and SAN [5] provide significant improvement in performance by adopting the channel-attention mechanism.

However, deeper layer, stacking blocks, and attention mechanism require the huge memory and computational cost during inference due to numerous parameters, spatial and non-local operation and is limited in application to resource-constrained devices such as mobile or IoT devices. For practice with these devices, designing an efficient network structure and optimization of training scheme is essential [10]. Since optimizing performance by only designing an efficient network structure is limited, the advanced training scheme work which consist of pruning, quantization, and KD is more important for resource-limited devices. Among them, KD has the advantage of optimizing the performance trade-off without structure modification compared to another approach. Details of this approach are described in the next section.

2.2. Feature-based Distillation for SISR

KD is a method of transferring knowledge from the teacher model to a lightweight structure of student networks [9]. Distillation with the label domain (same as the image domain in SISR) shows the outperformed performance in the classification problem. However, in the regression problems such as SISR, since the teacher network generates image with characteristics similar to GT images except in specific cases, image information of teacher is not sufficient for distillation [32]. Therefore, FD mainly proposed to be trained with L1-distance loss between features of student and teacher networks [14,23,29,31].

Firstly, FitNet [31] proposed the distillation in both image and feature domains. For FD, they use a simple regressor which is composed of 1 × 1 convolution layers due to the channel size of the teacher and student network is different. PISR [23] proposed using an autoencoder for intermediate feature maps of teacher and student networks in the distillation stage. For more efficient distillation, FAKD proposes a feature affinity-matrix-based KD framework by distilling the structural knowledge from a bigger teacher model. Furthermore, teacher supervision (TS) loss between the output super-resolution images of teacher and student is considered. In addition, LSFD proposed a feature attention method that adaptively focuses on the specific pixel to extract feature maps. Merging FD with the adaptive functional attention mechanism, LSFD showed improved performance compared to other FD algorithms such as FAKD. However, these approaches did not completely solve the limitation of the L1-distance loss in subjective image quality.

2.3. Contrastive Learning

Contrastive loss is mainly proposed in self-supervised learning [18, 22] and is to train images such that positive pairs stay close to each other, while negative pairs are far away [34, 36]. By maximizing the Kullback-Leibler (KL) divergence of the positive and negative pairs, the mutual information is maximized in the positive pair while clearly distinguishing both distributions. In other words, contrastive loss in KD optimized performance by maximizing mutual information between teacher and student while minimizing uncertainty between both networks. It means that the teacher and student networks become more similar. Especially, in this approach, Contrastive representation distillation (CRD) achieves state-of-the-art (SOTA) results in the classification task by distillation with contrastive loss [34].

Furthermore, contrastive loss with KD is proposed for SISR, and they have a slight performance improvement over other distillation approaches [1,28,36]. However, we experimentally find that contrastive loss-based distillation performs better in the feature domain than the image domain (described in the ablation study section). Therefore, we propose an FD with the contrastive loss for the SISR task and introduce a new way to adaptively apply KD approach.

3. Proposed Method

In this section, we describe the loss function of the proposed FACD. The pipeline of our proposed FACD framework is shown in Fig. 3. As shown in Fig. 3, proposed FACD is performed distillation on both image and feature domain. In the image domain, output images of the teacher and ground-truth (GT) are used to KD for the student network, respectively. On the other hand, in the feature domain, FACD performs with contrastive learning between the intermediate feature maps of the teacher and student [14,29]. In Section 3.1, we describe the decision approach of adaptively applying distillation per sample in mini-batch In Sec-
In the section, we describe the adaptive KD for efficient transfer knowledge from teacher networks. We propose a simple adaptive distillation method for optimizing distillation performance in both the image and feature domain. As shown in Fig. 2 and Section 1, interestingly, the output of the teacher network does not always guarantee better performance than students. We found that 5% and 11% of worse cases occur in EDSR and RCAN on average, respectively, in the training patches. We have experimentally found that these worse patches decrease the efficiency of distillation and will be described in Section 5. The indicator of adaptive KD is formulated as:

$$\alpha_i = \begin{cases} 0 & \text{if } \|SR_i^S - GT\|_1 < \|SR_i^T - GT\|_1, \\ 1 & \text{else.} \end{cases}$$  (1)

where $\alpha$ is the indicator of appropriate samples, and $i$ is the index of the batch sample. If the distance from GT is farther from the teacher, the parameter of appropriate samples $\alpha_i$ is set to 0. Here, 0 value means that the patch is not used for distillation.

3.2. Contrastive Adaptive Distillation

In the section, we propose the feature-based adaptive contrastive distillation to transfer intermediate feature knowledge from teacher to student network. For the total loss function of FACD as in Eq. (4), the L1 distance and contrastive loss are performed in the image and feature domains, respectively. We describe the loss function for each domain separately in this section.

Firstly, the loss function in the image domain using the indicator of adaptive KD ($\alpha_i$) is formulated as:

$$L_{SR} = \frac{1}{2N} \sum_{i=1}^{N} (2 - \alpha_i)\|SR_i^S - GT\|_1 + \alpha_i\|SR_i^T - SR_i^T\|_1$$  (2)

where $SR_i^S$, $SR_i^T$, and $GT$ are the output images of the student network, the teacher network, and ground-truth, respectively. $N$ is the number of batch size. The former of $L_{SR}$ means the L1 loss with GT, which is the loss term of the conventional SISR, and the latter means that distillation in the image domain.

In order to use the contrastive loss on feature domain, we need to decide how to construct the positive and negative pairs, and which similarity measures (e.g. L1, dot-product, and cosine similarity (CS)) to use in the loss function. Our contrastive loss is similar to InfoNCE loss, which uses a dot-product operation as a similarity measure. Instead, we use a L1-distance operation and will show an experimental comparison of each similarity measure in the Section 5. In addition, for a fair experimental comparison, FACD configured the three matching points of the intermediate features to compare with the conventional FD [1, 14, 29].

For our FACD loss, as shown in Fig. 3, we consider the feature of the student network ($F_{ij}^S$) and its feature of the teacher network ($F_{ij}^T$).
teacher network ($F_{T}^j$) as a positive pair ($d_{pos}$ in Fig. 3) in the same sample. On the other hand, negative pairs ($d_{neg}$ in Fig. 3) consisted of the feature maps between different index of samples in mini-batch ($F_{ij}^S, F_{kj}^{Neg}$). In other words, given a batch-size $N$, it consists of $N$ positive pairs and $\frac{N^2-N}{2}$ negative pairs. The detailed loss function of FACD is formulated as:

$$L_{FACD} = \sum_{i=1}^{N} \sum_{j=1}^{3} w_j \sum_{k=1}^{K} \alpha_i \| DR(F_{ij}^S) - F_{ij}^T \|_1 + \frac{1}{K} \sum_{k=1}^{K} \| DR(F_{kj}^S) - F_{kj}^{Neg} \|_1$$

(3)

where $w_j$ is the attention weight of each feature matching point, DR refers to the deep regressor which consists of five $1 \times 1$ convolution layers with PReLU activation [12], $N$ is the number of batch sizes, and $K$ is the number of negative pairs. As in Eq. (2), FD is not performed on inappropriate samples in positive pairs. By minimizing this $L_{FACD}$, the distance of the positive pair is made close, and the contrastive loss is performed by making the distance of the negative pair farther away. Through this approach, the mutual information between the feature maps of the teacher and student networks can be maximized. The effectiveness of contrastive loss on each domain is described in our ablation study.

### 3.3. Overall Loss Function

The overall loss function of our FACD is constructed by image and feature domain contrastive distillation, which can be formulated as Eq. (4):

$$L_{total} = L_{SR} + \lambda L_{FACD}$$

(4)

where $\lambda$ is a hyper-parameter for balancing $L_{SR}$ and $L_{FACD}$

### 4. Experiments

In this section, we explain the details of our experimental network settings and analyze the experimental results both quantitatively and qualitatively.

#### 4.1. Experimental Settings

Following the previous work [5, 14, 24, 29, 36, 40], we use the 800 split set images from the DIV2K dataset [35] for training. On the other hand, we test with RGB-PSNR our FACD on four benchmark datasets such as Set 5 [3], Set 14 [39], BSD 100 [27], and Urban 100 [17]. For comparison to previous KD algorithms, we performed experiments on existing SISR networks, EDSR [24] and RCAN [40]. Table 1 demonstrated the configuration of distillation models, which consist of teacher and student networks. The configuration of distillation models same as the previous works for fair experimental comparison. While EDSR decreases the number of residual blocks (ResBlocks) and channel size of the convolutional, RCAN keeps the number of residual groups (ResGroups), which contain multiple ResBlocks, but only decreases the number of ResBlocks. EDSR is compressed about 30 times through this distillation and RCAN about 3 times in terms of the number of parameters.

Our FACD is implemented by PyTorch 1.8.0 with NVIDIA TITAN RTX GPU. All the student networks using distillation are trained using ADAM optimizer with default hyperparameter in Pytorch. In the 200 [14] or [29] 300 epochs with the previous work setting, FACD loss is not sufficiently saturated. Therefore, batch sizes and total epochs are set to 16 (same as in previous work) and 600 epochs, respectively. The initial learning rate is set to $2 \times 10^{-4}$, and is halved at 150 epochs. In addition, the patch size is set to $48 \times 48$ for network input, and default data augmentation (e.g. horizontal flip, vertical flip, and random rotation) is applied. These experimental settings for reproduced results are equally applied to FAKD [14] and LFD [29] which are main comparison works in this paper.

Finally, the hyperparameter of the $\lambda$ is set to 4 for $L_{SR}$, which is the balancing weight of FD, and the layer-attention parameter $w_j$ is set to $[0.5, 0.3, 0.2]$.

#### 4.2. Quantitative Results

The quantitative results of PSNR are shown in Table 2. FACD achieves the best performance on almost benchmark datasets and scale factors except for the Set 5 dataset on EDSR x4. The average performance improvement of EDSR and RCAN is about 0.1dB over conventional FD. The performance improvement of RCAN is better than that of EDSR. The biggest difference between EDSR and RCAN is the presence or absence of feature-attention blocks. This means that it is effective to make the features more similar in RCAN using the feature attention scheme. In other words, the knowledge of teachers can be better utilized in RCAN than EDSR on feature domain.

**Impact on scale factor:** Table 3 summarizes the evaluation results of Table 2. PSNR performance improvement average the difference between FACD and the overall FD performance in the Table 2. As shown in Table 3, we confirmed that the efficiency of performance improvement of FACD
Table 2. Quantitative results (PSNR) on EDSR and RCAN networks. FAKD* and FitNet indicates LSFD paper results, FAKD** and LFD* indicate our reproduced results with our experimental settings. Except for them, the results indicate the results of its paper. The best performance in the same experimental settings is marked in bold.

| Methods      | Scale | Set5  | Set14 | B100  | Urban100 |
|--------------|-------|-------|-------|-------|----------|
| Teacher      | x2    | 38.190| 33.857| 32.351| 32.873   |
| Student      |       |       |       |       |          |
| FAKD*        |       |       |       |       |          |
| FAKD**       | x2    | 37.919| 33.439| 32.102| 31.728   |
| LFD          | x2    | 37.975| 33.520| 32.149| 31.920   |
| LFD*         | x2    | 37.984| 33.547| 32.156| 31.896   |
| LSFD         | x2    | 37.986| 33.528| 32.159| 31.935   |
| FACD (ours)  | 38.043| 33.588| 32.188| 32.072|          |

| Methods      | Scale | Set5  | Set14 | B100  | Urban100 |
|--------------|-------|-------|-------|-------|----------|
| Teacher      | x3    | 34.547| 30.435| 29.167| 28.470   |
| Student      |       |       |       |       |          |
| FAKD*        |       |       |       |       |          |
| FAKD**       | x3    | 34.272| 30.266| 29.044| 27.959   |
| LFD          | x3    | 34.347| 30.300| 29.073| 28.000   |
| LFD*         | x3    | 34.348| 30.287| 29.068| 27.999   |
| LSFD         | x3    | 34.333| 30.301| 29.077| 28.022   |
| FACD (ours)  | 34.394| 30.333| 29.103| 28.125|          |

Table 3. Evaluation results on average PSNR improvement over other FD approach. Performance improvement over 0.1dB is marked in underlined.

| Model | scale | Set5  | Set14 | B100  | Urban100 |
|-------|-------|-------|-------|-------|----------|
| EDSR  | x2    | +0.061| +0.061| +0.033| +0.153   |
|       | x3    | +0.040| +0.036| +0.031| +0.112   |
|       | x4    | +0.017| +0.038| +0.028| 0.085    |
| RCAN  | x2    | +0.052| +0.123| +0.068| +0.209   |
|       | x3    | +0.093| +0.076| +0.052| +0.226   |
|       | x4    | +0.078| +0.070| +0.026| +0.133   |

Over other FD decreases as the scale factor increases. In general, the performance improvement efficiency of scale x2 is about two times better than that of scale x4. As the scale factor increases, the texture restoration becomes more difficult, and limits the upper bound of the performance of the teacher network. This means that the knowledge to be transmitted from the teacher is limited in a bigger scale factor.

**Performance on Urban100:** Benchmark datasets for SISR each have their own data characteristics. For instance, Set5 and 14 are samples of basic objects, and BSD100 has various characteristics from natural images to complex textures. Urban100 dataset has a variety and repetitive of patterns and edges that arise from the complex architecture of buildings. As shown in Table 2 and Table 3, FACD has better quantitative performance, especially on the Urban100 dataset compared to other datasets. This means that our FACD has an advantage over other FD approach for the reconstruction of textures. Our FACD achieves 0.66dB, 0.34dB, and 0.17dB PSNR improvement over baseline student, FAKD, and LSFD on scale 2 in RCAN network, respectively.

**Performance on feature domain:** PSNR performances of the feature are shown in Table 4. In Eq. (3), we described the feature matching point of previous work and FACD. For the evaluation, we measured the average PSNR between features of teachers and students at these three matching points. In addition, in the case of EDSR, since the number of channels between teacher and student is different, it is not possible to do fair comparison with previous work that does not use deep regressors. Therefore, we evaluate the performance in feature domain on RCAN only. Our FACD achieves the best performance on all of benchmark datasets and scale factors. The average performance improvement of the feature is about 0.5dB in terms of PSNR. It means that the feature-based contrastive loss makes intermediate features more similar to teachers.
Table 4. Evaluation results on average PSNR between the features of student and teacher in RCAN. FAKD* and LFD* indicate our reproduced results with our experimental settings. The best performance in the same setting is marked in **bold**.

| Methods     | scale | Set5  | Set14 | B100  | Urban100 |
|-------------|-------|-------|-------|-------|----------|
| FAKD*       | x2    | 34.766| 35.651| 36.360| 35.824   |
| LFD*        |       | 35.345| 36.566| 37.255| 36.811   |
| FACD (ours) |       | **36.060**| **37.019**| **37.740**| **37.441**|
| FAKD*       | x3    | 34.454| 35.318| 36.100| 35.685   |
| LFD*        |       | 34.712| 35.572| 36.332| 36.213   |
| FACD (ours) |       | **35.039**| **36.136**| **36.757**| **36.477**|
| FAKD*       | x4    | 33.149| 34.422| 34.818| 34.768   |
| LFD*        |       | 34.266| 35.609| 36.057| 36.038   |
| FACD (ours) |       | **34.465**| **35.908**| **36.297**| **36.281**|

4.3. Qualitative Results

As shown in Fig. 4, we compare our FACD with other previous work on Urban100 benchmark dataset in terms of qualitative results. To compare the difference in the restoration of detailed patterns, we compared them to a relatively small cropped images. PSNR scores are calculated only by consideration of cropped images. In general, as shown in qualitative results, PSNR performance is proportional to subjective image quality. We clearly confirmed that our FACD performs better PSNR and qualitative results than other FD approach. Especially for the restoration of textures (e.g. patterns, blur), we can be seen that the more clear texture by the FACD are more similar to both the teacher and HR images than other FD. In the case of scale x3 images (092 from Urban 100), PSNR performance of FACD and LFD is not significantly different, but it shows a bigger difference in the reconstruction of patterns that has distorted from the conventional student networks. In other cases (076 from Urban 100, x4), it shows a difference in the sharpness of the line and the straightness.

5. Ablation Study

This section demonstrates the effectiveness of the proposed FACD approach and we conduct an ablation study to analyze the contrastive loss, effectiveness of each loss component, and adaptive distillation.

**Impact on contrastive loss domains:** To show the contrastive loss efficiency in the feature domain, we compared the contrastive loss results in the feature and image domains. The composition of contrastive loss such as the formation of the equation and the decision mechanism of positive and negative pairs is the same except for the applied domain. As shown in Table 5, our FACD achieves better results than IACD. Feature-based contrastive loss achieves 0.04dB PSNR improvement over the image domain contrastive loss.

**Impact on contrastive loss formulation:** InfoNCE loss has been mainly used in contrastive learning on self-supervised learning. Similarity measure of contrastive loss in InfoNCE loss used the dot-product operation. In other hands, our FACD used the L1-distance loss as a similarity measure for contrastive loss. As shown in Table 6, FACD achieves better results than InfoNCE loss. L1 loss-based contrastive loss achieves 0.04dB PSNR improvement enhancement over the InfoNCE loss.

**Impact on each loss component:** In order to confirm the effect on the performance of each loss component, the loss component is turned on/off and tested. L1_GT is the conventional distance-base L1 loss over GT images and LT_T is the image domain distillation loss. Using the all of loss component match the FACD in this paper. The overall results in
Nevertheless, the combination of all loss components achieves the best evaluation results on various benchmark datasets. Table 7 in 4th row shows that training also works well for the independent application of distillation without L1_GT. Nevertheless, the combination of all loss components achieves the best evaluation results on various benchmark datasets.

**Impact on adaptive KD:** In this Section 3.1, we describe the effectiveness of worse cases of the teacher networks. In order to confirm the effect of performance with worse samples of teacher networks, we compared the quantitative results of our FACD with feature-based contrastive distillation (FCD) without an adaptive distillation approach. As shown in Table 8, except for Set5 and 14 in scale 4 (EDSR), our distillation approach achieved significant performance improvement on all benchmark datasets.

**Impact on feature attention:** This paper is composed of the three intermediate feature matching points for FD. In order to compare the effect of each feature, we compared the evaluation results of attention of each feature point. The only difference between each method is the composition of the \( w_j \) in Eq. (3). As shown in Table 9, FCD with our attention version (FAU) achieves the best PSNR performance over the attention of other feature matching points. This means that the upper part has a more impact on the distillation performance than the lower part due to the cascading architecture of the CNN-based SR network.

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