Fast Adaptation to Super-Resolution Networks via Meta-Learning

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Abstract

Conventional supervised super-resolution (SR) approaches are trained with massive external SR datasets but fail to exploit desirable properties of the given test image. On the other hand, self-supervised SR approaches utilize the internal information within a test image but suffer from computational complexity in run-time. In this work, we observe the opportunity for further improvement of the performance of SISR without changing the architecture of conventional SR networks by practically exploiting additional information given from the input image. In the training stage, we train the network via meta-learning; thus, the network can quickly adapt to any input image at test time. Then, in the test stage, parameters of this meta-learned network are rapidly fine-tuned with only a few iterations by only using the given low-resolution image. The adaptation at the test time takes full advantage of patch-recurrence property observed in natural images. Our method effectively handles unknown SR kernels and can be applied to any existing model. We demonstrate that the proposed model-agnostic approach consistently improves the performance of conventional SR networks on various benchmark SR datasets.

1. Introduction

Super-resolution (SR) aims to increase the image size by recovering high-frequency details from a given low-resolution (LR) input image, and SR becomes a key feature in electrical goods, such as smartphone and TV; it has become popular as high-resolution (HR) screens are commonly available in our daily lives. The most basic methods utilize interpolation techniques (e.g. nearest and bicubic resizing) to fill in the missing pixels. These methods are efficient but produce blurry results. Moreover, dedicated hardware-equipped devices, such as jittering [2] and focal stack [23] cameras, allow the use of multiple images to solve the LR image problem. However, these specialized devices incur additional costs and cannot be used to restore images captured with conventional cameras in the past. To mitigate these problems, numerous single-image super-resolution (SISR) algorithms that restore high-quality images by using only a single LR image as input have been studied; in particular, optimization-based [9, 14] and learning-based [5, 21, 27, 18, 30, 33, 34] methods have been investigated intensively.

Since Dong et al. [5] demonstrated that a three-layered convolutional neural network could outperform the traditional optimization-based methods by a large margin, researchers have proposed numerous deep learning-based
methods for SISR. These methods aim to increase the performance of peak signal-to-noise ratio (PSNR) and structural similarity (SSIM) by allowing deeper networks to maximize the power of deep learning with large training datasets. In recent years, however, PSNR values have reached a certain limit, and more studies using perception metric [20, 22] have been introduced to focus on creating visually pleasing and human-friendly images.

Most of the current deep-supervised-learning approaches do not explicitly adapt their models during test time. Instead, fixed network parameters are used for all test images regardless of what we can learn more from the new test image. To fully utilize the additional information available from the given input test image (LR), we propose to extend this single fixed model approach by combining it with a dynamic parameter adaptation scheme. We find that the adaptive network results in better performance especially for unseen type of images. In particular, we can utilize patch-recurrence property if available in the input image, which can be described as self-supervised learning. The notion of exploiting patch-recurrence has been introduced in prior works [9, 40]. Recently, Shocher et al. [30] proposed a zero-shot SR (ZSSR) method employing deep learning; this study is the most related work to our proposed method. ZSSR trains a relatively small image-specific convolutional neural network (CNN) at test time from scratch, with training samples extracted only from the given input image itself. Therefore, ZSSR can naturally exploit the internal information of the input image. However, ZSSR has some limitations: (1) requirement of considerable inference time due to slow self-training step; (2) failure to take full advantage of using pre-trained networks learned by large amounts of external dataset;

Meta-learning can be a breakthrough for the above-mentioned problem. Meta-learning i.e., learning to learn, is gaining popularity in recent deep-learning studies [35, 31]. Meta-learning aims to learn quickly and efficiently from a small set of data available at test time. Several methods, such as recurrent architecture-based [10], and gradient-based methods [13, 26], have been proposed. In particular, model agnostic meta-learning (MAML) [7] is an example of a gradient-based method. We experimentally find that training a network with MAML results in the best initialization of the network parameter to perform well when fine-tuning with a small number of given input data.

To this end, we introduce a method to apply the meta-learning (fast adaptation) algorithm to solve the SISR problem. Using a large number of degraded images generated with various SR kernels, our SR networks are trained not only to generalize over large external data but also to adapt fast to any input images with real SR kernels. Consequently, as shown in Table 1, the proposed method can efficiently improve the PSNR performance by using general information from external large dataset and information specific to the test image.

Our contributions can be summarized as follows:

- To our knowledge, fully exploiting supervision signals available from both external and internal data with an effective meta-learning method is successful for the first time.
- Most state-of-the-art SR networks can be improved with our meta-learning scheme without changing the predefined network architectures.
- Our method achieves the state-of-the-art performance over benchmark datasets.

2. Related Works

In this section, we review the most relevant SISR works. Also, methods for handling unknown SR kernel (i.e., blind SR) are briefly described.

An early example-based SISR method [8] learned the complicated relationships between LR and HR patches by learning how to use the external dataset. A locally linear embedding-based SISR method was introduced by Chang et al. [4]. Yang et al. [36] proposed a sparse coding-based algorithm assuming that a pair of LR and HR patches shares the same sparse coefficients with each distinct dictionary. Also, learning methodologies like random forest [17, 29, 28], hierarchical decision tree [16], and deep learning [5, 21, 27, 22, 18] have been proposed to boost the performance of SISR.

The self-similarity-based methods assume that a natural image contains repetitive patterns and structures within and across different image scales. Glasner et al. [9] proposed a unified framework that incorporates self-similarity-based approaches by exploiting patch-recurrence within and across different scales of a given LR input image. Huang et al. [14] handled transformed patches by estimating the transformations between the corresponding LR–HR patch pairs. Dong et al. [6] proposed the non-local centralized sparse representation to exploit the non-local self-similarity of a given LR image. Huang et al. [15] combined the benefits from both external and internal databases for SISR by employing a hierarchical random forest.

Recently, a study dealing with the unknown SR kernel has begun to draw attention. Mihae and Irani [25] exploit the nature of recurrence of small patches to handle unknown SR kernel. Yuan et al. [37] propose an unsupervised learning method with Cycle-GAN [39], and Gu et al. [11] estimate unknown SR kernel iteratively and additionally add a spatial feature transform (SFT) layers into the SR network for handling multiple blur kernels. Based on a simple convolutional neural network, ZSSR [30] deals with SR kernels.
given at test time by exploiting information from an input image itself.

In this work, we focus on overcoming the limitations of these conventional SISR methods. We observe that many existing deep learning-based methods fail to fully utilize the information provided in a given input image. Although ZSSR [30] utilizes both the power of deep learning and information from the input image at test time, it does not use pre-trained networks with large external dataset. Therefore, we start from training network to utilize the external examples. Then, we fine-tune the network with the input image to utilize the information captured by internal patch-recurrence and cover unknown SR kernels (given at test time) for the input. To obtain a well-trained network that can quickly adapt to the input image by using patch-recurrence, we integrate a meta-learning technique inspired by MAML [7] with conventional SISR networks without changing the network architectures. MAML aims to learn a meta-network that can swiftly adapt to new learning task and examples using a small number of iterations for fine-tuning. MAML is applicable in a variety of tasks, such as few-shot learning [19, 32] and reinforcement learning [12]. We apply the MAML method to fine-tune the pre-trained SR parameters to input images quickly and efficiently. We experimentally verify that our approach can boost the performance of state-of-the-art SISR by a large margin.

3. Meta-Learning for Super-Resolution

In this work, we introduce a new neural approach that integrates recent meta-learning techniques to solve the SISR problem by exploiting additional information available in the input LR image. The details of the proposed method will be given in the following sub-sections.

3.1. Exploiting patch-recurrence for deep SR

According to [9, 14, 30], small patches inside the natural image recur multiple times across the different scales of a given image. Therefore, unlike conventional learning-based methods which utilize large external datasets, we can find multiple HR patches corresponding to a given LR patch within a single-input image using patch-recurrence. However, these previous methods have been developed separately and handle external and internal datasets differently. Thus, we develop a new method that facilitates SR networks by utilizing both (large) external and (small) internal datasets to further enhance the quality of the restored images.

In this section, we conduct a simple experiment to improve the performance of existing deep SR networks without changing their network architectures by using the patch-recurrence from a given LR test image. To achieve such goal, we re-train (fine-tune) the fully trained SR networks, such as RCAN [38], IDN [18] and ENET [27] with a new training set consisting of LR test image and its down-scaled version. Note that, RCAN is currently state-of-the-art SR network. By updating the network parameters using the gradient descent, the PSNR values of SR networks increase. Also note that we can further increase PSNR values without using the ground truth HR image, because we utilize additional information obtained from the patch-recurrence of down-scaled training set (Figure 1). The PSNR values in Figure 1 are obtained by calculating the average of the updated PSNR values on the Urban100 dataset [14]. The PSNR values tend to increase until 50 iterations, then decrease because the networks are over-fitted with a small training set at test time. The performance RCAN drops relatively quickly due to huge number of parameters used in the network.

This experiment demonstrates that there is still room to improve the performance of conventional SR networks while keeping their original network architectures, and patch-recurrence property is the key to boost the performance by adapting parameters of the fully pre-trained networks.

3.2. Handling unknown SR kernel for deep SR

![Figure 1. Increasing PSNR values of RCAN [38], IDN [18] and ENET [27] with fine-tuning process during the testing phase. Solid and dashed lines show the performances of the fine-tuned SR networks and original SR networks respectively.](image)

|         | Set5   | Set14  | BSD100 | Urban100 |
|---------|--------|--------|--------|----------|
| IDN [18]| 28.24  | 26.29  | 26.28  | 23.49    |
| IDN-Finetune | 31.52  | 28.91  | 28.47  | 25.93    |

Table 2. Average PSNR for scale factor $\times 2$ dealing with unknown SR kernel. Down-scaled images are generated using a non-bicubic kernel provided and used in ZSSR [30].

SR in unknown degradation settings (i.e., unknown SR kernel) is more challenging than conventional SR in ideal setting using the bicubic interpolation. According to [25],
the performance of the conventional SR networks trained with only bicubic kernel deteriorates significantly when it comes to the non-bicubic and real SR kernels in real scenario [30]. That is, generalization capability of the networks which can handle newly seen SR kernel during test phase is restricted in real situation. However, many conventional SR networks still assume ideal and fixed (bicubic) SR kernel, and thus cannot handle real non-bicubic SR kernels.

In this section, we perform a simple experiment to see whether this problem can be also alleviated with patch-recurrence property. We first degrade input LR image with a non-bicubic SR kernel to generate a new training set consisting of LR image and its down-sized image, and then evaluate the performance of the original IDN and its fine-tuned version with the down-sized training set. Note that the original IDN is initially trained with only bicubic SR kernel on the DIV2K [1] dataset, and our IDN with fine-tuning (IDN-Finetune) is further optimized for 1000 iterations with the gradient update. In Table 2, we observe that IDN-Finetune can handle the images degraded by non-bicubic SR kernel much better on numerous benchmark datasets compared to the original IDN trained with bicubic SR kernel. Thus, we can see that patch-recurrence property still holds and can be also used to improve SR performance by handling unknown SR kernels.

3.3. Proposed Method

In previous sections, we have shown that patch-recurrence property can be used not only to improve the performance of SR networks but also to deal with non-bicubic SR kernels. However, to update and adapt the pre-trained network parameters at test time to the specific input image, naive fine-tune-based update with SGD optimizer requires large number of iterations and takes much time. To solve this problem, we integrate a meta-learning technique [7] with the SR networks to facilitate use of patch-recurrence and boost the speed of the adaptation procedure at test time.

We define each task as super-resolving one specific LR image. We want the network to perform well on this specific image given some information within the image. Unfortunately, unlike conventional few-shot problems which can be solved by meta-learning, our new SR task does not provide the ground-truth data (HR image) corresponding to the LR input image for learning at test time. Thus, it is difficult to directly apply the meta-learning algorithms to our new learning task for SR.

However, we have shown that a pair of images composed of LR input and its down-scaled version (LR ↓) can be used as a training sample for our new SR task due to patch-recurrence property of the natural image. Thus, we propose a Meta-Learning for SR (MLSR) algorithm which learns to adapt the pre-trained SR networks to the given test image. In particular, we employ the recent model-agnostic meta-learning (MAML) approach. MAML can be well generalized to a new task with only a small number of gradient update steps [7], so we can boost the speed of our test-time learning task which originally requires large number of gradient update steps without meta-learning scheme (i.e. naive fine-tune).

In Figure 2, a sketch of the overall flow of the proposed method is illustrated. During training, we first initialize the conventional SR networks with large external train datasets. Next, we start meta-learning using MAML which optimizes the initialized SR parameters to enable quick adaptation to the new LR test image. Finally, during test phase, we adapt the meta-learned SR parameters with the given test image, and restore the HR image by using the adapted SR parameters.

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**Algorithm 1: MLSR training algorithm**

Require: \( p(I) \): Distribution (e.g. uniform) over images

Require: \( \alpha, \beta \): Hyper-parameters (step-size)

1. Initialize \( \theta \)
2. while not converged do
3. Sample a batch of images \( \{I_i\} \sim p(I) \)
4. Generate \( \{HR_i\}, \{LR_i\}, \{LR_i \downarrow\} \) from \( \{I_i\} \)
5. foreach \( i \) do
6. Evaluate \( \nabla_{\theta} L(f_{\theta}(LR_i \downarrow), LR_i) \) using \( L \)
7. Compute adapted parameters with SGD:
   \[ \theta_i \leftarrow \theta - \alpha \nabla_{\theta} L(f_{\theta}(LR_i \downarrow), LR_i) \]
8. Update \( \theta \leftarrow \theta - \beta \nabla_{\theta} \sum_i L(f_{\theta}(LR_i), HR_i) \)

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**Algorithm 2: MLSR inference algorithm**

Require: \( I \): Given image

Require: \( \alpha \): Hyper-parameter (step-size)

Require: \( n \): Number of gradient updates

1. Initialize \( \theta \) with meta-trained parameter
2. Generate \( LR, LR \downarrow \) from \( I \)
3. \( i \leftarrow 0 \)
4. while \( i < n \) do
5. Compute adapted parameters with SGD:
   \[ \theta \leftarrow \theta - \alpha \nabla_{\theta} L(f_{\theta}(LR \downarrow), LR) \]
6. \( i \leftarrow i + 1 \)
7. Compute \( f_{\theta}(LR) \)

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Specifically, we formulate the proposed method more concretely. Our SR model \( f_{\theta} \) which is initialized with parameter \( \theta \) renders an HR image from a given LR image by
minimizing the loss $L$, and it yields,

$$L(f_\theta(LR), HR) = ||f_\theta(LR) - HR||^2_2,$$

(1)

and our aim of meta-learning is to optimize the network parameter $\theta$ to be quickly adapted to $\theta_i$ at test time with given input image $LR_i$ and its down-scaled image $LR_i \downarrow$. Therefore, the adaptation formulation when using one gradient step (can be multiple steps, but for simplicity) is given as follows:

$$\theta_i \leftarrow \theta - \alpha \nabla_\theta (f_\theta(LR_i \downarrow), LR_i),$$

(2)

where a hyper-parameter $\alpha$ controls the learning rate of the inner update procedure. Notably, to generate the down-scaled image $LR \downarrow$ we can use any SR kernel if available. Then, the parameter $\theta$ can be further optimized with $\theta_i$ as suggested in [7], and it is given by,

$$\theta \leftarrow \theta - \beta \nabla_\theta \sum_i L(f_\theta(LR_i), HR_i),$$

(3)

where $\beta$ controls the meta update step. These update procedures in meta-learning are repeated until convergence, and can be easily applicable to any differentiable SR networks. The details of our MLSR algorithm is given in Algorithm 1.

In general, we can use multiple iterations for the adaptation in (2), but it increases computational cost in calculation of high-order derivatives in (3). To alleviate this problem, we can simply employ the first-order approximation methods [7, 26], which is known to give competitive result compared to the original algorithm with lower computational cost. In our experiments, we use the first-order MAML suggested in [7].

At test time, we first adapt the parameters ($\theta$) of meta-learned SR networks with the input low-resolution image ($LR$) and its down-sized image ($LR \downarrow$), then restore the HR image using the adapted SR parameters as elaborated in Algorithm 2.

4. Experimental Results

In this section, we perform extensive experiments to demonstrate the superiority of the proposed method, and show quantitative and qualitative comparison results. Our source code will be publicly available upon acceptance, and please see our the supplementary material for more results.

4.1. Implementation details

For our experiments, we first initialize conventional SR networks (SRCNN [5], ENET [27], IDN [18] and RCAN [38]) with DIV2K [1] dataset. For initialization, we use publicly available pre-trained parameters for IDN and RCAN (TensorFlow versions), and use our own parameters trained from scratch for SRCNN and ENET. We optimize SR networks by minimizing L2 loss between the ground-truth HR images and corresponding LR images. Next, we start meta-learning for these SR networks in accordance with iterative steps in Algorithm 1. For meta-learning, we still use DIV2K dataset, and use 5 inner gradient update steps for (2) (line 7 in Algorithm 1). We set $\alpha = 10^{-5}$, $\beta = 10^{-6}$, train patch size to $512 \times 512$, and mini-batch size to 16.

4.2. MLSR with fixed bicubic SR kernel

First, we assume fixed bicubic SR kernel (scale factor $\times 2$), and compare PSNR values of our SR networks on Urban100 and BSD100 [24] datasets. For the comparison on DIV2K, test set of DIV2K is used since our networks are trained with DIV2K. Results are shown in Table...
we evaluate differently trained IDNs, and IDN trained on Urban100 with meta-learning algorithm outperforms other models as we expect. Note that PSNR value of meta-trained IDN (IDN-ML) is relatively low at first (before adaptation), but improves dramatically with only 5 gradient updates (0.3dB gain). This proves that our MLSR method can learn better on images with rich patch-recurrence in urban scenes. More qualitative comparison results are shown in Figure 5, and the test images are particularly well restored with our network trained with meta-learning algorithm since specific patterns are repeated over the image itself while smoothly changing scales. Moreover, results by parameter adaptation with more gradient update steps render visually much better results.

Moreover, in Figure 3, we show how PSNR value changes when the number of gradient steps in (2) increases during meta-learning and test phases. As shown, our meta-learned model (IDN-ML) can quickly adapt SR parameters at test time, and achieves competitive results with only few gradient updates. Indeed, only 5 gradient updates can produce results which can be obtainable with ∼15 iterations of IDN with naive fine-tuning.

In Figure 4, we can also see that the difference of PSNR values before and after gradient updates during meta-learning procedure becomes larger and produces higher PSNR values as shown in Figure 3. The result indicates that the fully meta-learned model can well adapt to input image and exploit information within the input more thoroughly at test time.
Figure 3. Comparing IDN and IDN-ML trained on DIV2K w.r.t. gradient update steps. IDN-ML’s PSNR rises faster than base IDN.

Figure 4. Difference of PSNR values between before and after 5 gradient updates during meta training done in Table 4.

4.3. MLSR with unseen SR kernel

In this section, we further conduct experiments to see the capability of the proposed MLSR algorithm in dealing with new and unseen SR kernel during test phase. We carry out meta-learning in Algorithm 1 with randomly generated $5 \times 5$ SR kernels on the DIV2K dataset and train for 30k iterations. Moreover, We generate 40k $5 \times 5$ SR kernels as in [3], and use 38k kernels for training, 1k for validation, and 1k for test.

In Table 2, unlike fine-tuning with bicubic SR kernel, we need a large number of iterations ($\sim 1000$) to achieve the highest PSNR value in dealing with non-bicubic SR kernel. However, our IDN-ML trained with many different SR kernels learnt the way to be quickly adapted to the new SR kernel given at test time, and it shows competitive results with only few gradient updates with the new kernel. Notably, we assume that the SR kernel is given or can be estimated with conventional methods as in [25, 30]. In Figure 6, we can see that results with only 5 gradient updates are similar to the results from 350 iterations using the naive fine-tune without our meta-learning.

After meta-training, we compare our model on Set5, Set14, BSD100 and Urban100 datasets. In the inference stage, an SR kernel that has not been shown during training stage, and an LR image degraded with the SR kernel are provided. The results Figure 6 for various datasets show consistent improvements as the number of gradient update steps increase. Specifically, the performances raise strikingly ($\sim 1$dB) at around 5 iterations, and it verifies that the network can quickly adapt to the given image and SR kernel at test time with small number of updates. Notably, result on Urban100 is slightly different from others. Performance of the fine-tuned network on Urban100 improves more rapidly than fine-tuned networks on other datasets as rich patch-recurrence with urban scenes really helps to handle newly seen SR kernels at test time.

In Table 5, we also compare ours with ZSSR on numerous dataset with SR kernels used in ZSSR, and our proposed method with 20 gradient updates shows competitive results compared to ZSSR, and significantly outperforms ZSSR when adapted for 100 iterations. Notably, ours with 100 iterations takes only 6 minutes to restore 100 urban images, but ZSSR requires more than 3 hours in GeForce RTX 2080Ti.
Figure 6. Performance curve of PSNR values on various test datasets. Random $5 \times 5$ SR kernels are used for down-scaling the HR images. Performance of the original IDN can be improved, and improving pace boomed with our meta-learning.

Figure 7. PSNR of IDN with scale $\times 3$, $\times 4$ on the Urban100 dataset. Right and left sides of the y-axis indicate the PSNR values with respect to the upscaling factor $\times 3$ and $\times 4$, respectively.

In Figure 8 and Figure 9, we compare visual results by naive fine-tuning, meta-learning and ZSSR. We see that the quality improves dramatically within few iterations with our MLSR, while improves slowly at the boundaries with fine-tuning as iteration goes. Moreover, artifacts normally shown on the results by ZSSR are not produced with the proposed method.

**4.4. SR with large scaling factor**

Finally, we study the validity of the patch-recurrence property with large SR scaling factor. Unfortunately, as shown in Figure 7, patch-recurrence property does not hold any longer when scaling factor is large (i.e. $\times 3$ or $\times 4$). Maximal performance gained by fine-tuning with large SR factors are around 0.04dB which are negligible. Therefore, to produce large images with large scaling factors, we can employ multi-scale (coarse-to-fine) approaches embedded into the conventional SR methods with small scale factor.

Figure 8. The “butterfly” image from Set5 dataset with upscaling factor $\times 2$. Input LR image is downscaled with a non-bicubic $5 \times 5$ SR kernel. Unlike ZSSR, our result shows higher PSNR value, also is free from the checkerboard artifacts.

Figure 9. The “102061” image from BSD100 dataset with upscaling factor $\times 2$. LR image is generated using a non-bicubic kernel used in ZSSR. Our method achieves higher performance than naive fine-tuning with the same number of inner updates at runtime.

(e.g. $\times 1.25$) which also exploit self-similarity nature of the given test images [9, 14, 30].

**5. Conclusion**

In this work, we introduced a new SR method which utilizes both the power of deep learning with large external dataset and additional information available from the input image at test time. To this end, we proposed a novel Meta-Learning for SR (MLSR) algorithm which enables quick adaptation of SR parameters using only input LR image during the test phase. MLSR can be combined with conventional SR networks without any architecture changes, and can utilize the patch-recurrence property of the natural image, which can further boost PSNR performance of deep learning-based methods that have recently reached
their limits. In addition, MLSR can handle non-bicubic SR kernel that exists in real world because meta-trained networks can be adapted to the specific input image. In experiments, we show that our MLSR can greatly boost up the performance of existing SR networks, with a few gradient updates. Also, it was demonstrated experimentally that MLSR takes advantage of the patch-recurrence well, by showing the most performance improvements in the Urban100 dataset, where patch-recurrence occurs frequently. The proposed MLSR was also validated with the unseen non-bicubic SR kernel and showed that MLSR required less gradient updates than naive fine-tuning. We believe that the proposed method can be applied not only to SR but also to various types of reconstruction and low-level vision tasks.

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