Towards Bidirectional Arbitrary Image Rescaling: Joint Optimization and Cycle Idempotence

Abstract

Deep learning based single image super-resolution models have been widely studied and superb results are achieved in upscaling low-resolution images with fixed scale factor and downscaling degradation kernel. To improve real world applicability of such models, there are growing interests to develop models optimized for arbitrary upscaling factors. Our proposed method is the first to treat arbitrary rescaling, both upscaling and downscaling, as one unified process. Using joint optimization of both directions, the proposed model is able to learn upscaling and downscaling simultaneously and achieve bidirectional arbitrary image rescaling. It improves the performance of current arbitrary upscaling models by a large margin while at the same time learns to maintain visual perception quality in downscaled images. The proposed model is further shown to be robust in cycle idempotence test, free of severe degradations in reconstruction accuracy when the downscaling-to-upscaling cycle is applied repetitively. This robustness is beneficial for image rescaling in the wild when this cycle could be applied to one image for multiple times. It also performs well on tests with arbitrary large scales and asymmetric scales, even when the model is not trained with such tasks. Extensive experiments are conducted to demonstrate the superior performance of our model.

1 Introduction

In real world applications, it is common to rescale an image with arbitrary scale factors, either scaling up or down, for various purposes like display, storage or transmission. While recent deep learning based image super-resolution (SR) method have advanced the performance of image upscaling significantly, they are mostly optimized for fixed scale factors and known downscaling degradation kernels. Lately, there are growing interests in SR models that support arbitrary scale factors and great successes have been achieved, including arbitrary upscaling for scale factors in certain range [11], or learning a continuous image representation to resize it at any larger resolution [6], or asymmetric arbitrary upscaling where the vertical and horizontal scale factors could be different [26]. Like standard SR models, these methods are all optimized for the unidirectional upscaling process. In contrast, another line of image rescaling models [14, 25, 29] are developed to optimize the downscaling process together with the inverse upscaling and are able to improve accuracy on the upscaling task significantly comparing to unidirectional SR models of the same scale factors. Currently these bidirectional rescaling models are limited to a specific integer scale as far as we know.

Figure 1: Visual examples of quality degradation from multiple downscaling-to-upscaling cycles: IRN [29] and ours.
weight function (SVF) and a novel subpixel weight function (SWF) are introduced for subpixel splitting and merging respectively. Using ground-truth (GT) image as supervision for high-resolution (HR) reconstruction, plus a weak supervision in low-resolution (LR), the proposed model, jointly optimized for both upscaling and downscaling, is able to greatly advance performances in arbitrary image rescaling, including very large or asymmetric scales.

In addition, so far as we know, current models are only evaluated for a single application of the downscaling-to-upscaling cycle and the effects of multiple cycles have never been studied. Ideally, application of additional cycle should not introduce any further changes beyond the initial cycle. This ideal downscaling-to-upscaling process, by definition, is an idempotent operation. In other words, for a function \( f \) of variable \( x \), \( f \) is idempotent if \( \forall x, f(f(x)) = f(x) \). While an ideal idempotent rescaling cycle may not be feasible, it is desirable to have minimum additional degradation when multiple downscaling-to-upscaling cycles are applied. Here a proxy objective is studied for optimization of both weight function (SVF) and a novel subpixel weight function (SWF) are introduced for subpixel splitting and merging.

In summary, the main contributions of our work include:

- We are the first to consider bidirectional arbitrary image rescaling, both downscaling and upscaling, as one unified process and achieve SOTA performance in arbitrary image rescaling via joint optimization.
- A proxy objective that optimize both reconstruction accuracy and idempotence is investigated, and a newly proposed cycle idempotence test is conducted to demonstrate our method’s superior performance in model robustness after repetitive applications of the downscaling-to-upscaling cycle.
- The proposed method is also applicable to arbitrary asymmetric scales and large out-of-distribution scales and able to achieve SOTA in both tests.

2 Related Work

**Arbitrary Scale Super-Resolution.** Deep learning based image super-resolution have been studied extensively for the last few years [8, 15, 20, 32, 31], and these methods commonly train one model for one fixed scale factor. Lim et al. [20] was the first to propose a multi-scale SR model, which shares one feature learning backbone for different scales but still needs scale specific processing modules to handle the last step for multiple scales. Later, Li et al. [19] proposed a multi-scale residual network learn multi-scale spatial features using convolution layers with different kernel sizes. However, these methods are still limited to a fixed set of integer scale factors. Inspired by weight prediction techniques in meta-learning [18], Hu et al. [11] proposed a single Meta-SR model to solve SR at arbitrary scale factors by predicting weights of convolutional layers for arbitrary scale factors, not limited to a fixed set of integer ones. The newest ArbSR [25] proposed a plug-in module to further optimize existing SR models for arbitrary asymmetric SR where scale factors along horizontal and vertical directions could be different. These arbitrary SR works are often limited to a fixed maximum scale factor to maintain high performance. Most recently, Chen et al. [6] proposed to learn pixel representation features to replace pixel value features in previous methods. With a learned local implicit image function (LIIF), this model is able to predict pixel values at arbitrary large scales. Our work extends the idea of LIIF to be applicable for arbitrary downscaling and upscaling at the same time.

**Bidirectional Image Rescaling.** As pointed out above, most super-resolution models rely on LR-HR pairs where each LR image is downsampled from the corresponding HR using frequency-based kernels like Bicubic [22]. These models are trained for upscaling reconstruction only without taking the image downscaling method into joint consideration. To take advantage of the potential mutually beneficial reinforcement between downscaling and the inverse upscaling, Kim et al. [14] proposed an auto-encoder framework to jointly train image downscaling and upscaling together. Similarly, Sun et al. [25] proposed a new content adaptive-resampler based image downscaling method, which can be jointly trained with any existing differentiable upscaling (SR) models. More recently, Xiao et al. [29] proposed an invertible rescaling net (IRN) that has set the state-of-the-art (SOTA) for learning based bidirectional image rescaling. Based on the invertible neural network (INN) [2], IRN learns to convert HR input to LR output and an auxiliary latent variable \( z \). By mapping \( z \) to a case-agnostic normal distribution during training, inverse image upscaling is implemented by randomly sampling \( z \) from the normal distribution without need of the case specific \( z \). Current methods for bidirectional image rescaling are limited to a fixed integer scale factor like \( \times 4 \). As a contrast, we propose a bidirectional arbitrary rescaling approach in this work.

**Idempotent Image Processing.** For image processing, there are numerous examples of idempotent filters such as median filter [23], cascaded median filters [9] and basic morphological operations like opening and closing [10]. For
Figure 2: Proposed framework for a bidirectional arbitrary image rescaling network (BAIRNet) with magnified illustration of the subpixel splitting and merging process.

Many image processing applications, it is beneficial to have idempotent filters or processes for various reasons. In the case of image JPEG compression, an image could be compressed multiple times as it is not known for sure if an image in the wild is already compressed. To reflect the importance of repetitive image compression, there is a specific key feature of multi-generation robustness in the standardization process of JPEG XS [7]. Lately, it has been discovered that there is model instability issue in successive deep image compression that results in severe visual artifacts [16]. Here we will specifically study cycle idempotence of image SR and rescaling models after repetitive applications of the downscaling-to-upscaling process.

**Weak Supervision in Low Level Vision.** Weak supervision in a branch of supervised learning where supervision signals, like labels for image classification, are from either imprecise or noisy sources. While it has been widely studied in high level tasks like object detection [4] and semantic segmentation [13], its applications in low level vision tasks like image restoration and reconstruction, however, are not fully addressed. For image SR where LR-HR pairs are needed, LR images are often synthesized from HR using bicubic interpolation and they could be imprecise comparing to real world LR images. There have been efforts to co-collect true LR and HR images to build real-world SR dataset like RealSR [5] and DRealSR [28]. However, these pairs are subject to registration imprecision and/or local motion blur as LR and HR are taken sequentially using different lenses. For newest bidirectional rescaling models [14, 25, 29] that learn downscaling and upscaling jointly, although accuracy in inverse upscaling is the primary goal, a weakly supervised learning for downsampling is still needed. While the LR image from bicubic interpolation has been previously used as the downsampling reference, new forms of weak supervision are investigated in our study.

## 3 Proposed Method

### 3.1 Bidirectional Arbitrary Image Rescaling

The proposed framework for a bidirectional arbitrary image rescaling network (BAIRNet) is illustrated in Fig. 2. It is a bidirectional process, including downscaling to convert the GT image \( x \) to an LR image \( \tilde{x} \), and upscaling to restore a HR image \( \tilde{x} \) from \( \tilde{x} \). As illustrated on the left, each of the two directions consists of the same three steps: feature encoding, subpixel splitting and subpixel merging. These steps are denoted as

\[
\begin{align*}
\tilde{x} & = f_m(s, \omega) = f_m(f_s^D(z, \phi, \omega) = f_m(f_s^D(f_s^E(x, \phi), \omega)) \\
\hat{x} & = f_m(\tilde{s}, \tilde{\omega}) = f_m(f_s^U(\tilde{z}, \tilde{\phi}, \tilde{\omega}) = f_m(f_s^U(f_s^E(\tilde{x}, \tilde{\phi}), \tilde{\omega})
\end{align*}
\]

for downscaling and upscaling respectively. For the three steps, feature encoding \( f_s^E \) is shared for both directions and subpixel merging \( f_m \) is the same definition too. For subpixel splitting though, different subpixel value function (SVF) are trained, denoted as \( f_s^D \) and \( f_s^U \) respectively. For variables, \( z/\tilde{z} \) are feature vectors, \( s/\tilde{s} \) are subpixel values, \( \phi/\tilde{\phi} \) are subpixel coordinates, and \( \omega/\tilde{\omega} \) are subpixel weights used in merging. Each pair has the same definition and \( \sim \) is used to differentiate upscaling from downscaling.

To illustrate the subpixel splitting and merging process, a magnified illustration is included in Fig. 2 on the right. One pixel \( i \) of the input is split to one or more subpixels first, and after remapping, a new set of subpixels is merged to one pixel \( j \) in the rescaled image. A subpixel \( k \) in the intermediate step is defined as one rectangle in the image space that reside wholly inside one original pixel as well as inside one rescaled pixel, and its boundaries are aligned with the boundaries of input and/or rescaled pixels. Here we use \( p_i, s_k \) and \( r_j \) to represent values of pixels \( i, j \) and \( k \) respectively. In the illustrated downscaling example, pixel \( i \) is split to four subpixels and this mapping relationship is denoted as
Let \( \mathbb{P}_i = \{i_1, i_2, i_3, i_4\} \). To merge subpixels to rescaled pixels, a remapping process is needed to associate groups of subpixels with rescaled pixels. In the example in Fig. 2, output pixel \( j \) is merged from 4 pixels and it is denoted as \( \mathbb{R}_j = \{j_1, j_2, j_3, j_4\} \). Lastly, as illustrated in the downscaled pixel \( j \), its central, top-left and bottom-right coordinates are denoted as \((h^c_j, v^c_j), (h^t_j, v^t_j)\) and \((h^b_j, v^b_j)\) respectively.

For input pixel \( i \) and subpixel \( k, k \in \mathbb{P}_i \), defining \( \phi^i_k \) as relative coordinates of \( k \) in reference to \( i \): \( \phi^i_k = (h^i_k - h^c_i, v^i_k - v^c_i, h^k_h - h^c_i, v^k_v - v^c_i) \), the process to predict subpixel values \( s_k \) during subpixel-splitting is denoted as
\[
s_k = f_s(z_i, \phi^i_k)
\]
where \( f_s \) is the SVF function and \( z_i \) is the feature vector of pixel \( i \). This process is the same for both downscaling and upscaling but separate SVFs are trained and denoted differently in Eq. 1 for distinction.

The value of pixel \( j \) at subpixel-merging is computed as
\[
r_j = \sum_{k \in \mathbb{R}_j} \omega^j_k s_k / \sum_{k \in \mathbb{R}_j} \omega^j_k
\]
where \( \omega^j_k \) is the weight of subpixel \( k \) during merging of pixel \( j \). For the subpixel merging weights in upscaling, \( \omega^j_k \) is simply defined as the area of subpixel \( k \). As the majority of upsampled pixel \( j \) consists of just one subpixel \( k \), and the others have either 2 or 4, the area based weights are sufficient to represent the significance of each subpixel. While in the case of downscaling, each pixel \( j \) may include a large number of subpixels and the impact of each subpixel should depend on both its size and location. Here we propose a subpixel weight function (SWF) module to learn the subpixel weights for merging during the end-to-end training, denoted as \( \omega^j_k = f_w(\psi^j_k) \). Similar to \( \phi^i_k, \psi^j_k \) is defined as \( (h^k_h - h^c_i, v^k_v - v^c_i, h^c_i, v^c_i) \).

While this framework has some resemblance with two prior works, that is, IRN [29] and LIIF [6], there are some substantial differences between our proposed and the previous two. First, IRN is limited to one fixed integer scale \( N \) consists of just one subpixel \( k \), and the others are set as 1, 2 or 4, the area based weights are sufficient to represent the significance of each subpixel. While in the case of downscaling, each pixel \( j \) may include a large number of subpixels and the impact of each subpixel should depend on both its size and location. Here we propose a subpixel weight function (SWF) module to learn the subpixel weights for merging during the end-to-end training, denoted as \( \omega^j_k = f_w(\psi^j_k) \). Similar to \( \phi^i_k, \psi^j_k \) is defined as \( (h^k_h - h^c_i, v^k_v - v^c_i, h^c_i, v^c_i) \).

3.2 Idempotent Image Rescaling

The rescaling cycle defined in Eq. 1 can be simplified as \( \hat{x} = f(x) \). Without considering constraints in LR, the primary goal to optimize this cycle is to minimize its reconstruction loss, but it is also desirable to learn an idempotent one. These two objectives could be defined separately as
\[
f = \min_f \mathcal{L}(x, f(x))
\]
\[
\hat{f} = \min_{\hat{f}} \mathcal{L}(f_\text{ref}(x), f_\text{ref}(f_\text{ref}(x)))
\]
As these two objectives may conflict, an empirical proxy objective is proposed to learn a compromise between the two. In practice, the model is trained to minimize reconstruction error after \( n \) cycles, described as
\[
f = \min_{f_\text{ref}} \mathcal{L}(x, f_\text{ref}(x)), n \in [1, N]
\]
where \( f_\text{ref} \) means \( f_0 \) is applied \( n \) times. When \( N \) is set as 1, this proxy objective is equivalent to the primary task of 1-cycle reconstruction. In our experiments, different \( N \) are investigated to compare the trade-off between two objectives: reconstruction accuracy and cycle idempotence.

3.3 Weak Supervision in LR

Considering the multi-cycle optimization as in Eq. 5 and the need to generate visually coherent LR images, the overall loss for training our model is defined as
\[
\mathcal{L} = \lambda_1 \mathcal{L}_\text{rec}(x, \hat{x}^n) + \lambda_2 \mathcal{L}_\text{ref}(x, \hat{x}^n)
\]
where \( \mathcal{L}_\text{rec} \) is the reconstruction loss for HR, \( \mathcal{L}_\text{ref} \) is the reference loss in LR, and \( \hat{x}^n \) and \( \hat{x}^n \) are the LR and HR outputs after \( n \)-cycles respectively. Although it is possible to train it fully self-supervised by setting \( \lambda_2 = 0 \), it will lead to
with ReLU activation and hidden dimensions of 256 is used. For the downscaling SWF, a 5-layer MLP with hidden dimensions of 16 is used. With a batch size of 8, all models are trained using Adam [17] optimizer. In order to conduct ablation studies efficiently, a pretrained model is generated after 500 epochs, 300 iteration each, from an initial learning rate of 0.0001. The learning rate decays by half after every 100 epochs. For this stage, \( \lambda_1 \) is set as 0.2, \( \lambda_2 \) and \( \lambda_3 \) are set as 3 and the final model is denoted as BAIRNet + SWF.

For fair comparison with previous works like LIIF and IRN, the same methods in bold are used for distinction.

### Table 1: Quantitative comparison of SOTA SR and rescaling methods with the best two results highlighted in red and blue respectively (methods in bold require multiple models and additional interpolations to achieve arbitrary scales).

| Method       | Scale | Set5  | Set14 | BSD100 | Urban100 | Manga109 | DIV2K  |
|--------------|-------|-------|-------|--------|----------|----------|--------|
| Bicubic      | ×2.5  | 31.76/0.898 | 28.52/0.819 | 28.13/0.878 | 25.43/0.837 | 28.56/0.895 | 29.40/0.850 |
| RCAN [31]    | ×2.5  | 36.05/0.943 | 31.69/0.881 | 30.47/0.850 | 30.42/0.899 | 36.59/0.964 | 32.72/0.907 |
| Meta-SR [11] | ×2.5  | 36.18/0.944 | 31.90/0.884 | 30.47/0.850 | 30.57/0.900 | 36.55/0.969 | 32.77/0.906 |
| LIIF [29]    | ×2.5  | 35.98/0.943 | 31.64/0.881 | 30.45/0.851 | 30.42/0.899 | 36.39/0.963 | 32.78/0.909 |
| ArbSR [20]   | ×2.5  | 36.21/0.948 | 31.99/0.883 | 30.51/0.856 | 30.68/0.902 | 36.67/0.964 | 32.77/0.903 |
| CAR [25]     | ×2.5  | 37.33/0.954 | 33.78/0.916 | 32.53/0.920 | 32.19/0.930 | 37.63/0.971 | 34.32/0.930 |
| IRN [29]     | ×2.5  | 39.78/0.974 | 36.39/0.953 | 35.56/0.954 | 33.99/0.958 | 39.33/0.986 | 36.60/0.960 |
| BAIRNet†     | ×2.5  | 40.11/0.966 | 36.62/0.946 | 36.29/0.956 | 36.62/0.967 | 40.26/0.983 | 37.46/0.962 |

| Bicubic      | ×3.5  | 29.30/0.874 | 26.52/0.732 | 26.50/0.700 | 23.70/0.685 | 25.83/0.820 | 23.38/0.782 |
| RCAN [31]    | ×3.5  | 33.47/0.913 | 29.24/0.814 | 28.42/0.773 | 27.61/0.838 | 32.74/0.938 | 30.13/0.851 |
| Meta-SR [11] | ×3.5  | 33.59/0.916 | 29.60/0.810 | 28.42/0.772 | 27.71/0.836 | 32.75/0.937 | 30.18/0.854 |
| LIIF [29]    | ×3.5  | 33.41/0.913 | 29.20/0.813 | 28.39/0.771 | 27.60/0.834 | 32.60/0.932 | 30.16/0.857 |
| ArbSR [20]   | ×3.5  | 33.63/0.914 | 29.58/0.817 | 28.41/0.774 | 27.69/0.836 | 32.84/0.939 | 30.14/0.858 |
| CAR [25]     | ×3.5  | 34.98/0.930 | 31.38/0.864 | 30.14/0.826 | 29.97/0.881 | 35.00/0.950 | 31.88/0.886 |
| IRN [29]     | ×3.5  | 37.12/0.956 | 33.65/0.919 | 32.54/0.907 | 31.84/0.927 | 36.86/0.960 | 33.84/0.928 |
| BAIRNet†     | ×3.5  | 36.85/0.947 | 32.97/0.907 | 32.36/0.898 | 32.71/0.938 | 36.98/0.967 | 33.87/0.926 |

The table shows the PSNR (dB) and SSIM values for different methods and scales, with the best two results highlighted in red and blue, respectively. The methods include Bicubic, RCAN, Meta-SR, LIIF, ArbSR, CAR, IRN, and BAIRNet. The performance is evaluated on various datasets such as Set5, Set14, BSD100, Urban100, Manga109, and DIV2K.

### 4 Experiments

#### 4.1 Data and Settings

For fair comparison with previous works like LIIF and IRN, the same 800 HR images from DIV2K [1] are used for training. For quantitative evaluation, we use HR images of five commonly used benchmark datasets, including Set5 [3], Set14 [30], BSD100 [20], Urban100 [12] and Manga109 [12], plus 100 HR images from the DIV2K validation set. Following previous practices like LIIF, we take the peak noise-signal ratio (PSNR) and SSIM [27] on the luminance channel for the 5 benchmark sets, but use the same metrics in RGB color space for DIV2K validation set.

The are \( B \) 200×200 input HR patches in one batch, each with a random scale sampled from a uniform distribution of \( U(1, 4) \). For individual modules, we use RDN [32] minus its upsampling module as the feature encoder, which generates a feature map with the same size as the input image. For both downscaling and upsampling SVF, a 5-layer MLP with ReLU activation and hidden dimensions of 256 is used. For the downscaling SWF, a 5-layer MLP with hidden dimensions of 16 is used. With a batch size of 8, all models are trained using Adam [17] optimizer. In order to conduct ablation studies efficiently, a pretrained model is generated after 500 epochs, 300 iteration each, from an initial learning rate of \( 10^{-4} \). The learning rate decays by half after every 100 epochs. For this stage, \( L_{rec} \) is set as a pixel-level L1 loss and \( L_{ref} \) is set as \( L_2 \), and no SWF module is included. The pretrained one is further trained for 500 epochs get the base model BAIRNet, with downscaling SWF included, and \( L_{ref} \) is set as \( L_2 \) for the mean pixel value per color channel. \( \lambda_1 \) and \( \lambda_2 \) are set as 3 and the final model is denoted as BAIRNet† used for distinction.

#### 4.2 Arbitrary Rescaling Performance

To assess the performance of our proposed method for arbitrary rescaling, we compare rescaled HR images using a set of arbitrary scales. For each fixed scale, the resolution of LR images are kept the same for all methods for fair comparison.
Figure 3: Visual examples of arbitrary rescaling from Urban100 and DIV2K at two scales: \( \times 2.5 \) and \( \times 3.5 \) (Best viewed for online version).

Figure 4: Cross-scale performance comparison for arbitrary rescaling testing \( (\times 1.1 - \times 4) \) on DIV2K validation set.

For models trained for integer scales only, like RCAN and IRN, evaluation on arbitrary scales is implemented as upscaling LR using the closest oversampled integer scale (use \( \times 3 \) for any scales between 2 and 3) before resampling using bicubic interpolation to target size. For bidirectional CAR [25] and IRN, HR inputs are also pre-upscaled accordingly. As listed in Table 1, PSNR and SSIM results from three scales (\( \times 1.5/2.5/3.5 \)) are compared. It shows that our BAIRNet\(^\dagger\) outperforms others by a comfortable margin for \( \times 1.5 \) and \( \times 2.5 \), and it is the best in \( \times 3.5 \) tests for the 3 large test sets out of 6 while trailing slightly behind IRN for the other 3. Visually as shown in Fig. 3 bidirectional methods like IRN and ours are the best overall. Between the two, IRN is more blurry in \( \times 2.5 \) and its color is off in the second example of \( \times 3.5 \). Results of continuous scales between \( \times 1.1 \) and \( \times 4 \) (sampled every 0.1) are also illustrated in Fig. 4 to compare our model with others. For arbitrary upscaling models like Meta-SR, LIIF and ArbSR, they are essentially equivalent to RCAN and with each other for scales above \( \times 2 \). Bidirectional models CAR and IRN improves performances in larger scales greatly but their performances suffer at small arbitrary scales. BAIRNet\(^\dagger\) is clearly the best overall, at the top for all scales except trailing slightly behind IRN for scales above \( \times 3.5 \), plus the spike at \( \times 2 \), where no extra interpolation needed is needed for IRN.

4.3 Cycle Idempotence

A cycle idempotence test is defined as the assessment of \( \mathcal{L}(x, f^n(x)) \) for different number of cycles, where \( f^n \) means the rescaling cycle \( f \) is applied \( n \) times. Here we use the PSNR value in place of \( \mathcal{L} \) for test assessment. For the first set of test, defined as closed test, the downscaling function is fixed as the one best matches its upscaling one. So for RCAN, Meta-SR, ArbSR and LIIF, matlab_imresize [24] is used for its equivalence with the Matlab one. For other
bidirectionally trained models, their own corresponding downscaling process are applied respectively. For the open test, which means the downscaling is set freely, cv2.resize with INTER_AREA interpolation is picked for its wide application, and it is used for all methods for fair comparison.

Figure 5: PSNR results from closed and open idempotence tests for 1-5 cycles on DIV2K validation set (×4).

To avoid extra interpolation for RCAN and IRN, a ×4 scale is chosen here for testing on the DIV2K validation set and the results are compared in Fig. [5]. For the closed test, BIL-NN (bilinear for downsampling and nearest-neighbour for upsampling) is included as a perfectly idempotent reference. IRN has the best performance at cycle 1 with its bidirectional learning and invertible network structure. However, there is a drastic drop from cycle 2 and hereafter, probably caused by the random latent variable sampling during the upscaling process. For our method, both BAIRNet and BAIRNet† are included to show the improvement in idempotence of BAIRNet†, which is fine-tuned from BAIRNet using the proxy objective of multiple-cycle losses. At cycle 1, both are closely behind IRN, and their additional quality losses from multiple cycles are gradual. After 5 cycles, both are still significantly better than upscaling-only models at cycle 1, and BAIRNet† is clearly better than BAIRNet. This shows the advantage of our method in robustness to repetitive rescaling cycles in closed settings, and the effectiveness of multi-cycle losses. For open tests on the right, while all models are subject to significant performance losses at cycle 1 comparing to closed tests, our models have a much slower degradation for multiple cycles. Due to page limitation, more visual examples of cycle idempotence tests are included as supplementary materials.

Table 2: PSNR improvements over base BAIRNet after fine-tuning using $N$-cycle losses (Eq. 5), testing 5 cycles each for 3 scales.

| Cycle | $N = 1$ | $N = 3$ | $N = 5$ |
|-------|---------|---------|---------|
|       | ×4 | ×3 | ×2 | ×4 | ×3 | ×2 | ×4 | ×3 | ×2 |
| 1     | 0.09 | 0.09 | 0.09 | 0.08 | 0.10 | 0.13 | 0.05 | 0.08 | 0.13 |
| 2     | 0.14 | 0.16 | 0.21 | 0.16 | 0.21 | 0.33 | 0.15 | 0.21 | 0.34 |
| 3     | 0.21 | 0.24 | 0.32 | 0.27 | 0.36 | 0.56 | 0.28 | 0.39 | 0.60 |
| 4     | 0.29 | 0.34 | 0.42 | 0.40 | 0.54 | 0.78 | 0.44 | 0.60 | 0.86 |
| 5     | 0.38 | 0.43 | 0.49 | 0.54 | 0.73 | 1.00 | 0.61 | 0.82 | 1.11 |

To study the effectiveness of various $N$ in Eq. 5, the base BAIRNet model is trained for another 200 epochs using $N = 1, 3, 5$ respectively. As shown in Table 2, the improvements in PSNR for three fine-tuned models are compared for 1-5 cycles at 3 different scales. There are consistent improvements across scales and cycles even when $N = 1$, indicating the base BAIRNet is not fully trained. For $N = 3$, it is shown to improve PSNR more significantly after multi-cycles, especially for smaller scales, while only trailing by 0.01 at 1-cycle for ×4. For $N = 5$, the corresponding gain at multi-cycles is larger, but there is trade-off of accuracy at 1-cycle. Overall, it is demonstrated that the proposed proxy objective is effective at increasing model robustness in cycle idempotence while maintaining high performance at the primary goal of 1-cycle reconstruction accuracy.
Table 3: PSNR results achieved for both symmetric and asymmetric scale factors (methods in bold require extra interpolations).

| Method      | Set5 | Set14 | BSD100 | Urban100 | Manga109 |
|-------------|------|-------|--------|----------|----------|
| ArbSR       | 35.90| 35.90 | 35.85  | 36.24    | 35.14    |
| IRN         | 38.66| 38.55 | 38.80  | 39.78    | 34.87    |
| BAIRNet     | 39.40| 39.05 | 38.34  | 40.03    | 36.00    |
| BAIRNet‡     | 40.06| 40.42 | 40.11  | 40.16    | 36.33    |

Figure 6: Visual examples of arbitrary asymmetric rescaling from Urban100 test set (Best viewed for online version).

4.4 Out-of-distribution Assessment

While our model is trained with symmetric scale factors randomly distributed between $\times 1 - \times 4$ and mainly tested using such in-distribution settings, there is no such limitation in the capacity of the proposed method. For assessment, as shown in Table 3 and 4 respectively, our model is compared with ArbSR for asymmetric scales and with LIIF for large scales. In both cases, BAIRNet is used as is for upsampling by simply changing the output resolution and using corresponding $\phi$ as in Eq. 1. These out-of-distribution tests further demonstrate robustness of our proposed method.

For asymmetric scales $\times s_v \times s_h$ where $s_v$ is the vertical scale and $s_h$ is for horizontal, comparisons of 5 benchmark test sets are shown in Table 3. Results from ArbSR are included as a SOTA baseline for unidirectional models where only upsampling is le. For bidirectional IRN, although additional interpolations are needed for both downscaling and upsampling as only $\times 2$ and $\times 4$ models are available, its performance is far more superior comparing to the ArbSR baseline. For our base BAIRNet, pre-interpolation is only needed for the downscaling stage, where the input GT image is resampled using bicubic interpolation with a $s_v/s_h$ vertical scale and a $s_h/s_v$ horizontal scale. Here $s_h = \sqrt{s_v s_h}$, which will convert the asymmetric scale to symmetric scale of $s_v s_h$ for downscaling, while keeping the number of input pixels approximately the same as GT for fair comparison. It is shown in Table 4 that BAIRNet is better than IRN with the exception of $\times 3.6$, similar to the observation from Fig. 4 that IRN is slightly better than BAIRNet for scales larger than $\times 3.5$. Unlike IRN that is limited to training data with symmetric scales, BAIRNet could be further trained using data with asymmetric scales and the fine-tuned model is denoted as BAIRNet‡. It no longer needs the initial symmetric conversion step and shows further significant improvements in asymmetric tests, while subjects to slight degradation in symmetric test for only 2 out 5 test sets. Visual examples in Fig. 4 clearly show that BAIRNet‡ is able to reproduce more fine details at random asymmetric scales.

For tests of large scales as shown in Table 4 although all models are trained from images with scales up to $\times 4$, LIIF is much more robust for large scales up to $\times 30$ comparing to ArbSR. For testing BAIRNet at scale $s$, the GT image is pre-downscaled by a scale of $s/4$ using bicubic so the downscaling step in BAIRNet is capped at $\times 4$. This is a reasonable choice as this reduces the number of pixels used for the time-consuming step of downsampling feature encoding. It is shown that BAIRNet is consistently much better than LIIF quantitatively. For visual examples in Fig. 5, BAIRNet is clearly able to recover sharper details comparing to the others. All LR inputs, either from bicubic resizing as in LIIF and ArbSR or downsampling by BAIRNet, have the same low resolution and are included in Fig. 5 for reference.

4.5 Ablation Study

To assess the effectiveness of modules like SWF and different LR supervision strategies, the pretrained model is trained for an additional 200 epoch using different settings as shown in Table 5. For settings of $L_{ref}$, $L_2$ means $L_2$ loss at pixel level, $L_2^c$ means $L_2$ for $C_b$ and $C_r$ channels only, and $L_2^v$ refers to using mean pixel value per color channel. Note that for $L_2^v$, $L_2$ is set as 2. It is shown clearly in Table 5 that the SWF module in downsampling step is beneficial across different scales. For $L_{ref}$, it is obvious that weaker supervision leads to improved restoration accuracy overall, and the
Table 4: PSNR results for large out-of-distribution scales.

|       | ×6 | ×12 | ×18 | ×24 | ×30 |
|-------|----|-----|-----|-----|-----|
| Bicubic | 24.82 | 22.27 | 21.00 | 20.19 | 19.59 |
| LIIF    | 27.02 | 23.95 | 22.40 | 21.40 | 20.71 |
| ArbSR   | 26.61 | 23.07 | 21.45 | 20.49 | 19.81 |
| BAIRNet | 29.29 | 25.55 | 23.84 | 22.75 | 21.97 |

Table 5: PSNR results for different model and training settings.

|         | D-SWF | DIV2K | Lref       | Lc         | Lm       | Lrec     | Ls       | L1       |
|---------|-------|-------|------------|------------|----------|----------|----------|----------|
| ×4      | 31.19 | 31.42 | 31.78      | 32.12      | 32.13    | 32.14    |          |          |
| ×3      | 34.24 | 34.42 | 34.66      | 35.13      | 35.12    | 35.10    |          |          |
| ×2      | 38.89 | 39.42 | 39.32      | 40.11      | 40.15    | 39.93    |          |          |

Figure 7: Examples of large scale factors (×30) with ↑ pointing to corresponding LR inputs (Best viewed when zooming in).

weak $L_m^m$ is effectively the same as no supervision in LR at all. For $L_{rec}$, as images of various scales are included in each batch of model training, it is expected that those with lower scales have smaller reconstruction losses naturally. Intuitively, a simple scale-normalization, $L_s = L_1 / s$ where $s$ is the rescaling factor, is used in the training of BAIRNet. For comparison, the model is also trained without such loss normalization, and as shown in the table, it is equivalent with the primary model using $L_s$ for larger scales, but suffers from performance loss at smaller scales.

Table 5: PSNR results for different model and training settings.

For the specific $L_c^m$, it is designed and tested as a measure to suppress false-color artifacts noticed in downsampled LR from bidirectional models like IRN and ours. As shown in Fig. 8, the LR images from bicubic downsampling and the learned bidirectional models like IRN and BAIRNet are hardly differentiable in normal display resolution. However, when magnified, there are noticeable moiré-like and false color artifacts from both models. Comparing to BAIRNet trained with $L_m^m$ in LR, BAIRNet trained with the newly designed $L_c^m$ loss is able to successfully suppress false color artifacts as shown in Fig. 8, while sacrificing the overall restoration quality slightly as listed in Table 5.

4.6 Limitations

The main limitation of our method is its lower speed and large memory consumption for downscaling. Though it is slightly faster than LIIF in upscaling without using the feature unfolding option, it slows down both inference and training for downscaling as the same feature encoder is applied to a larger number of pixels in the HR inputs. For very large scale factors though, as demonstrated in Section 4.4, it is not necessary to use the full resolution as input and a pre-downscaling could be applied to reduce number of input pixels and increase efficiency in downscaling feature encoding. One potential future improvement is to optimize the feature encoding module in downscaling for higher efficiency while maintaining accuracy. Lastly, only the default RDN backbone is used in our model. A RCAN backbone is expected to further improve performance, as demonstrated in ArbSR, but not tested here as it is slower than RDN.

5 Conclusion

Current deep learning based image SR and arbitrary SR models are all subject to one or multiple limiting factors in related to downscaling degradation kernel and scale factors. Modeling arbitrary downscaling and upscaling as one
unified subpixel splitting and merging process, a bidirectional arbitrary image rescaling network (BAIRNet) is shown to improve upscaling accuracy significantly by jointly optimizing arbitrary upscaling and downscaling. Cycle idempotence tests are also used to test robustness of various models when the downscaling-to-upscaling cycle is applied multiple times, including closed test where the downscaling is limited to model assumptions or training settings, and open test where the downscaling is not limited. For closed and open tests overall, BAIRNet is the best with great performance at cycle 1 and no sudden drop in accuracy for following cycles. Additionally, a proxy objective that minimize multi-cycle losses is demonstrated to further improve model robustness in cycle idempotence. It is also shown that, even when BAIRNet is only trained for random symmetric scales between $\times 1 - 4$, it achieves impressive results for rescaling at asymmetric or large scales, outperforming SOTA methods LIIF and ArbSR with substantial margins.

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