Single Image Super-Resolution via a Dual Interactive Implicit Neural Network

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Abstract

In this paper, we introduce a novel implicit neural network for the task of single image super-resolution at arbitrary scale factors. To do this, we represent an image as a decoding function that maps locations in the image along with their associated features to their reciprocal pixel attributes. Since the pixel locations are continuous in this representation, our method can refer to any location in an image of varying resolution. To retrieve an image of a particular resolution, we apply a decoding function to a grid of locations each of which refers to the center of a pixel in the output image. In contrast to other techniques, our dual interactive neural network decouples content and positional features. As a result, we obtain a fully implicit representation of the image that solves the super-resolution problem at (real-valued) elective scales using a single model. We demonstrate the efficacy and flexibility of our approach against the state of the art on publicly available benchmark datasets.

1. Introduction

Single image super-resolution (SISR) is a fundamental low-level computer vision problem that aims to recover a high-resolution (HR) image from its low-resolution (LR) counterpart. There are two main reasons for performing SISR: (i) to enhance the visual quality of an image for human consumption, and (ii) to improve the representation of an image for machine perception. SISR has many practical applications including robotics, remote sensing, satellite imaging, thermal imaging, medical imaging, and much more [40, 39]. Despite being a challenging and ill-posed subject, SISR has remained a crucial area of study in the research community.

Recent deep learning approaches have provided high-quality SISR results [3, 37]. In perception systems, images are represented as 2D arrays of pixels whose quality, sharpness, and memory footprint are controlled by the resolution of the image. Consequently, the scale of the generated HR image is fixed depending on the training data. For example, if a neural network is trained to recover HR images of $\times 2$ scale then it only performs well on what it is trained for (i.e., performance will be poor on $\times 3$, $\times 4$, or other scales). Thus, instead of training multiple models for various resolutions, it can be extremely useful in terms of practicality to have a single SISR architecture that handles arbitrary scale factors. This is especially true for embedded vision platforms (e.g., unmanned ground/aerial vehicles) with multiple on-board cameras that must execute difficult tasks using limited computational resources.

The notion of an implicit neural representation, also known as coordinate-based representation, is an active field of research that has yielded substantial results in modeling 3D shapes [2, 5, 18, 30, 31]. Inspired by these successes, learning implicit neural representations of 2D images is a natural solution to the SISR problem since an implicit system can produce output at arbitrary resolutions. While this idea has been touched upon in several works [4, 33, 6, 26], in this paper we propose a more expressive neural network for SISR with significant improvements over the existing
state of the art, Figure 1. Our contributions are summarized as follows.

- We develop a novel dual interactive implicit neural network (DIINN) for SISR that handles image content features in a modulation branch and positional features in a synthesis branch, while allowing for interactions between the two.
- We learn an implicit neural network with a pixel-level representation, which allows for locally continuous super-resolution synthesis with respect to the nearest LR pixel.
- We demonstrate the effectiveness of our proposed network by setting new benchmarks on public datasets.

Our source code is available at [10]. The remainder of this paper is organized as follows. Related research is discussed in Section 2. In Section 3, we present a detailed description of our model for SISR at arbitrary scales using an implicit representation. Experimental results are presented in Section 4. The paper concludes in Section 5 and discusses future work.

2. Related Work

This section highlights pertinent literature on the task of SISR. First, we discuss deep learning techniques for SISR. Then, we provide an overview of implicit neural representations. Lastly, we cite the nascent domain of implicit representations for images. The SISR problem is an ill-defined problem in the sense that there are many possible HR images that can be downsampled to a single LR image. In this work, we focus on learning deterministic mappings, rather than stochastic mappings (i.e., generative models). In general, the input to an SISR system is an LR image, and the output is a super-resolved (SR) image that may or may not have the same resolution as a target HR image.

2.1. Deep Learning for SISR

Existing work on SISR typically utilizes convolutional neural networks (CNNs) coupled with upsampling operators to increase the resolution of the input image.

2.1.1 Upscaling + Refinement

SRCNN [11], VDSR [20], and DRCN [21] first interpolate an LR image to a desired resolution using bicubic interpolation, followed by a CNN-based neural network to enhance the interpolated image and produce an SR image. The refining network acts as a nonlinear mapping, which aims to improve the quality of the interpolation. These methods can produce SR images at arbitrary scales, but the performance is severely affected by the noise introduced during the interpolation process. The refining CNNs also have to operate at the desired resolution, thus leading to a longer runtime.

2.1.2 Learning Features + Upscaling

Methods following this approach first feed an LR image through a CNN to obtain a deep feature map at the same resolution. In this way, the CNNs are of cheaper cost since they are applied at LR, which allows for deeper architectures. Next, an upsampling operator is used to produce an SR image. The most common upsampling operators are deconvolution (FSRCNN [12], DBPN [14]), and sub-pixel convolution (ESPCN [32], EDSR [23]). It is also possible to perform many iterations of learning features + upsampling and explicitly exploit the relationship between intermediate representations [14]. These methods only work with integer scale factors and produce fixed-sized outputs.

EDSR [23] attempts to mitigate these problems by training a separate upsampling head for each scale factor. On the other hand, Meta-SR [15] is among the first attempts to solve SISR at arbitrary real-valued scale factors via a soft version of the sub-pixel convolution. To predict the signal at each pixel in the SR image, Meta-SR uses a meta-network to determine the weights for features of a $(3 \times 3)$ window around the nearest pixel in the LR image. Effectively, each channel of the predicted pixel in the SR image is a weighted sum of a $(C \times 3 \times 3)$ volume, where $C$ is the number of channels in the deep feature map. While Meta-SR has a limited generalization capability to scale factors larger than its training scales, it can be viewed as a hybrid implicit/explicit model.

2.2. Implicit Neural Representations

Implicit neural representations are an elegant way to parameterize signals continuously in comparison to conventional representations, which are usually discrete. Chen et al. [7], Mescheder et al. [27], and Park et al. [28] are among the first to show that implicit neural representations outperform 3D representations (e.g., meshes, voxels, and point clouds) in 3D modeling. Many works that achieve state-of-the-art results in 3D computer vision have followed. For example, Chabra et al. [5] learned local shape priors for the reconstruction of 3D surfaces coupled with a deep signed distance function. A new implicit representation for 3D shape learning called a neural distance field was proposed by Chibane et al. [9]. Jiang et al. [18] leveraged voxel representations to enable implicit functions to fit large 3D scenes, and Peng et al. [30] increased the expressiveness of 3D scenes with various convolutional models. It also is possible to condition the implicit neural representations on the input signals [5, 8, 18, 30], which can be considered as a hybrid implicit/explicit model.
2.2.1 Implicit Neural Representations of 2D Images

Despite there being many uses of implicit neural representations in 3D computer vision, to the extent of our knowledge, it has been under-explored in the domain of 2D imaging. Parameterizing images implicitly via neural networks can be traced back to Stanley et al. [34] in 2007. Various types of signals, including images, are implicitly represented with neural networks using periodic activation functions by Sitzmann et al. [33]. Bemana et al. [4] learned representations of changes in view, time, and light using Jacobians of pixel positions to naturally interpolate images. Tancik et al. [35] showed that a coordinate-based multilayer perceptron (MLP) can implicitly synthesize 2D images with sharpness by transforming the coordinate inputs with a Fourier feature mapping. These works have limited generalizability to different instances, especially as the complexity of the data increases. Recently, Mehta et al. [26] proposed to modulate a synthesis network with a separate network whose inputs are local features, which enables generalization while maintaining high fidelity.

2.2.2 Implicit Neural Representations for SISR

Learning implicit neural representations of 2D images is immediately useful for SISR since it can sample the pixel signals at any location in the spatial domain. Chen et al. [6] proposed a local implicit image representation in which 2D deep feature maps of the input images coupled with an ensemble of local predictions ensure a smooth (i.e., continuous) transition between different locations. Ma et al. [24] extended [6] by enforcing sharpness constraints and additionally imposing multiple loss functions (including L1, perceptual [19], and generative adversarial [13] losses) versus the L1 loss in [6] to generate perceptually-pleasant de-
where $S_{(x,y)}$ is the SR predicted signal at $(x,y)$, $L$ is the LR image, $g_r(\cdot)$ is the encoder function parameterized by $\gamma$, $g_r(L)_{(x,y)}$ is the extracted features at $(x,y)$ (referred to as content features), $p$ is the positional features, and $f_p(\cdot, \cdot)$ is the implicit decoder function parameterized by $\theta$. Note that our method considers pixels of an image as squares rather than points and the location of a pixel references its center.

### 3.1. Encoder

The encoder supplies the decoder with a content feature representation associated with each query location within the image. The encoder used in our method could be a CNN, similar to those used in previous works [6, 15], without any upsampling module. The input is an LR image and its output is a deep feature map that preserves the spatial content of the image. With proper settings (e.g., kernel size, padding, etc.), the output has the same spatial size as the input image. Thus, given a set of coordinates for query locations, we can sample its corresponding features via interpolation.

#### 3.1.1 Feature Unfolding

Following previous works [6, 15], before interpolation we enrich the feature map by applying feature unfolding with a kernel size of 3. That is, we concatenate the features of a $3 \times 3$ neighborhood around each pixel of the deep feature map, increasing the number of channels by 9. Since our implicit decoder handles continuous queries and the predictions are locally continuous, we choose nearest interpolation to avoid the additional smoothness constraint as well as artifacts that come with bilinear or bicubic interpolation. For any query location, the encoder effectively supplies the decoder with the nearest features in the deep feature map. As expressed in (1), $g_r(L)_{(x,y)}$ learns a feature map of $L$ and allows for querying content features (via nearest interpolation) associated with coordinates $(x,y)$.

### 3.2. Decoder

The decoder predicts the signal at every pixel in the SR image at a target resolution. Our implicit decoder uses both the content features (from the encoder) and the positional features for prediction. For SISR, the positional features of a query location typically contain information about its relative position to the nearest LR pixel (center) and some information about the scale factor [15]. We refer to the coordinates that reference the position of a pixel with respect to the center of the image as the ***global*** coordinates. Conversely, we refer to the coordinates that reference the position of a pixel with respect to its nearest LR pixel as the ***local*** coordinates. In our method, the ***global*** coordinates allow for uniquely identifying each pixel and computing its nearest LR pixel while the ***local*** ones are used as input to the decoder. Figure 3 shows examples of ***global*** and ***local*** coordinates.

#### 3.2.1 Modulated Periodic Activations Network

Recently, neural networks with periodic activation functions [33, 26] exhibit excellent performance in reconstructing high-fidelity images and videos. We use a similar dual MLP architecture, also known as a modulated periodic activations neural network [26], for our decoder with adjustments to address the SISR task. Our decoder of $N$ layers (i.e., $N$ layers of modulation and $N$ layers of synthesis) can be written recursively as

\begin{align}
    m_0 &= \text{ReLU}(w_0z + b_0), \\
    s_0 &= m_0 \odot \sin(w'_0p + b'_0), \\
    m_i &= \text{ReLU}(w_i[z_{i-1} z] + b_i), \\
    s_i &= m_i \odot \sin(w'_i[s_{i-1} z] + b'_i),
\end{align}

where $w, w', b,$ and $b'$ are the weights and biases, $z$ is the content features, and $p$ is the positional features. The last output of $s_i$ is then passed through a final dense layer (without activation) to output the predicted SR signal.

The two main differences between our method and [26] are the following.

(i) The $z$ vector in the image reconstruction experiment in [26] represents a patch while ours represents a pixel in the LR image. Typically, coarse-grain features are associated with higher levels of semantic information and thus may miss low-level details (e.g., edges, corners, etc.), which are crucial for SISR. Additionally, pixel-level representations have consistently performed well in the SISR literature [23, 15, 6]. Therefore, we opt for the finest-grain representation (i.e., pixel-level). The architecture of our encoder reflects this choice.

(ii) In (4), we use a concatenation of the output of the previous synthesis layer (instead of the previous modulation layer in [26]) and the latent feature vector as inputs for the latter modulation layer. We argue that the outputs of the synthesis network are progressively more refined toward different query locations and therefore provide better information to the modulation network while the latent feature vector serves as residual feedback. We show the benefits of our modification over [26] in Section 4.

Compared to the closest competing framework, LIIF [6], our method uses a more expressive neural network for the decoder, which leads to better performance. Unlike LIIF where the content features ($z$) and positional features ($p$) are
Table 1: A comparison against state-of-the-art SISR methods that allow for arbitrary scale upsampling at trained scales.

| Dataset | Scale | Method       | PSNR | SSIM | LR-PSNR | PSNR | SSIM | LR-PSNR | PSNR | SSIM | LR-PSNR |
|---------|-------|--------------|------|------|---------|------|------|---------|------|------|---------|
| DIV2K   | ×2    | Bicubic      | 31.06| 0.8937| 40.38   | 28.26| 0.8138| 39.45   | 26.7 | 0.753 | 38.68   |
|         |       | Meta-SR [15] | 34.64| 0.938 | 57.13   | 30.91| 0.8736| 54.93   | 28.89| 0.8173| 53.19   |
|         |       | LIIF [6]     | 34.46| 0.9367| 53.63   | 30.81| 0.8724| 52.23   | 28.88| 0.8163| 50.95   |
|         |       | DIINN (ours) | 34.63| 0.938 | 55.96   | 30.93| 0.8740| 53.56   | 28.98| 0.8193| 52.52   |
| B100    | ×2    | Bicubic      | 28.27| 0.8316| 38.54   | 25.88| 0.7171| 38.19   | 24.64| 0.6411| 37.93   |
|         |       | Meta-SR [15] | 29.23| 0.8651| 41.5    | 27.51| 0.7823| 48.6    | 25.94| 0.701  | 47.36   |
|         |       | LIIF [6]     | 30.66| 0.8891| 52.27   | 27.68| 0.7862| 51.67   | 26.17| 0.7097| 50.61   |
|         |       | DIINN (ours) | 30.69| 0.8896| 52.62   | 27.73| 0.7873| 52.36   | 26.22| 0.7119| 50.82   |
| Set5    | ×2    | Bicubic      | 31.81| 0.9097| 40.77   | 28.63| 0.8385| 38.79   | 26.7 | 0.7739| 37.29   |
|         |       | Meta-SR [15] | 35.68| 0.9439| 57.21   | 31.6 | 0.8878| 48.82   | 29.95| 0.8605| 53.79   |
|         |       | LIIF [6]     | 35.5 | 0.9427| 54.06   | 32.15| 0.9008| 52.61   | 29.92| 0.8601| 50.52   |
|         |       | DIINN (ours) | 35.67| 0.9438| 56.38   | 32.26| 0.9002| 54.2    | 30.06| 0.8631| 51.89   |
| Set14   | ×2    | Bicubic      | 28.33| 0.8437| 38.25   | 25.74| 0.7413| 37.18   | 24.24| 0.6648| 36.57   |
|         |       | Meta-SR [15] | 30.9 | 0.8987| 52.93   | 27.65| 0.8005| 46.51   | 26.25| 0.7383| 50.61   |
|         |       | LIIF [6]     | 31.5 | 0.8919| 51.57   | 28.04| 0.8083| 50.43   | 26.34| 0.7407| 49.22   |
|         |       | DIINN (ours) | 31.29| 0.8937| 53.92   | 28.14| 0.8101| 51.53   | 26.43| 0.7437| 50.33   |
| Urban100| ×2    | Bicubic      | 25.44| 0.8284| 35.54   | 23.01| 0.7151| 35.02   | 21.69| 0.6334| 34.64   |
|         |       | Meta-SR [15] | 29.32| 0.907 | 47.53   | 25.53| 0.8152| 42.79   | 24.12| 0.7507| 48.35   |
|         |       | LIIF [6]     | 30.02| 0.9147| 48.92   | 26.29| 0.8296| 48.34   | 24.29| 0.7555| 47.33   |
|         |       | DIINN (ours) | 30.29| 0.9176| 51.2    | 26.46| 0.8337| 49.67   | 24.49| 0.7624| 48.75   |

Table 2: A comparison against state-of-the-art SISR methods that allow for arbitrary scale upsampling on the DIV2K dataset at “inter”-scales.

| Scale | Method       | PSNR | SSIM | LR-PSNR | PSNR | SSIM | LR-PSNR |
|-------|--------------|------|------|---------|------|------|---------|
| ×2.5  | Bicubic      | 29.41| 0.8514| 39.89   | 27.39| 0.781 | 39.02   |
|       | Meta-SR [15] | 31.36| 0.8898| 46.1    | 29.21| 0.8305| 47.18   |
|       | LIIF [6]     | 32.29| 0.9036| 52.93   | 29.73| 0.8427| 51.62   |
|       | DIINN (ours) | 32.34| 0.9046| 53.43   | 29.82| 0.845 | 52.39   |

Table 2: A comparison against state-of-the-art SISR methods that allow for arbitrary scale upsampling on the DIV2K dataset at “inter”-scales.

4. Experiments

In this section, we present an experimental evaluation of DIINN for SISR. We give an overview of the datasets and metrics used in Section 4.1, along with the training details in Section 4.2. In Section 4.3, we highlight our benchmark results on popular datasets and provide a comparison with state-of-the-art methods. We discuss and illustrate our qualitative results on various image scales in Section 4.4. Finally, we present an ablation study in Section 4.5.
| Scale | Method  | ×6  | ×8  | ×10 | ×15  |
|-------|---------|-----|-----|-----|------|
|       | PSNR  | SSIM | LR-PSNR | PSNR  | SSIM | LR-PSNR | PSNR  | SSIM | LR-PSNR |
|       | 24.87 | 0.6761 | 37.75 | 23.75 | 0.6326 | 37.14 | 22.95 | 0.6056 | 36.72 | 21.63 | 0.57 | 36.02 |
|       | 26.53 | 0.7294 | 49.51 | 25.13 | 0.6704 | 46.64 | 24.18 | 0.633 | 45.16 | 22.63 | 0.5819 | 43.27 |
|       | 26.65 | 0.7368 | 49.3 | 25.32 | 0.6865 | 48.3 | 24.38 | 0.6527 | 47.55 | 22.82 | 0.6038 | 46.49 |
|       | 24.38 | 0.6527 | 47.55 | 22.89 | 0.6063 | 47.55 | 25.41 | 0.6898 | 49.17 | 22.82 | 0.6038 | 46.49 |
|       | 24.46 | 0.6557 | 48.48 | 24.87 | 0.6761 | 48.7 | 25.32 | 0.6865 | 49.3 | 24.38 | 0.6527 | 47.55 |
|       | 25.32 | 0.6865 | 48.3 | 25.25 | 0.6865 | 49.3 | 24.38 | 0.6527 | 48.7 | 24.38 | 0.6527 | 47.55 |

Table 3: A comparison against state-of-the-art SISR methods that allow for arbitrary scale upsampling on the DIV2K dataset at "outer"-scales.

| Output size | Method | Runtime (ms) |
|-------------|--------|--------------|
| (128 × 128) | Bicubic | 0.11         |
|             | Meta-SR [15] | 50.27         |
|             | LIIF [6] | 73.36         |
|             | DIINN (ours) | 56.6          |
| (256 × 256) | Bicubic | 0.15         |
|             | Meta-SR [15] | 69.27         |
|             | LIIF [6] | 185.42        |
|             | DIINN (ours) | 95.51         |
| (512 × 512) | Bicubic | 0.49         |
|             | Meta-SR [15] | 162.22        |
|             | LIIF [6] | 693.27        |
|             | DIINN (ours) | 243.59        |

Table 4: A runtime comparison in milliseconds. The input is a single RGB image of size (48 × 48). We report the average runtime of the forward pass for each method and SR size over 100 runs on a single NVIDIA Quadro RTX 3000. Bicubic is for reference only.

4.1. Datasets and Metrics

The DIV2K dataset [1], released for the NTIRE 2017 challenge on SISR [36], consists of 1000 HR images each of which has a height or width equal to 2040. Our model is trained using a split of 800 HR images. We do not retrain and we preserve all hyperparameters when testing the model on the following four standard benchmark datasets: DIV2K validation set (100 HR images), Set5, Set14, BSDS100 [25], and Urban100 [16]. The results are evaluated using the peak signal-to-noise ratio (PSNR) [17] and the structural similarity index measure (SSIM) [38]. Additionally, we evaluate the LR consistency by measuring the LR-PSNR. LR-PSNR is computed as the PSNR between the downsampled SR image and the downsampled ground-truth HR image with the same bicubic kernel.

4.2. Training Details

Our training procedure is similar to [15, 6]. For each scale factor \( s \in \{2, 3, 4\} \) and HR image in the minibatch, we randomly cropped a \( 48s \times 48s \) patch and downsample it using bicubic interpolation via the `resize` function available in `Torchvision` [29]. We randomly applied horizontal, vertical, and/or diagonal flips, each with a probability of 0.5. A minibatch of 4 HR images was used, which resulted in 12 pairs of LR and HR images across the three scales. We trained our model for 1000 epochs, where each epoch is a full pass through 800 HR images in the DIV2K training set, using the Adam [22] optimizer with the default hyperparameters provided by `PyTorch` [29]. The learning rate was initialized at \( 10^{-4} \) and halved every 200 epochs. To ensure a fair comparison, we followed previous works [15, 6] and used the L1 loss to train our network.

4.3. Benchmark Results

We compared DIINN against other methods that allow for arbitrary scale upsampling, namely, Meta-SR [15] and LIIF [6]. We retrained Meta-SR and LIIF under the same settings. In Tables 1-3, we show the results on the upsampling scales that the models were trained with (e.g., \( \times 2, \times 3, \) and \( \times 4 \)), "inter"-scales (e.g., \( \times 2.5 \) and \( \times 3.5 \)), and the "outer"-scales (e.g., \( \times 6, \times 8, \times 10, \) and \( \times 15 \)). The HR images were downsampled by each scale to be used as inputs and the SR images are of the same size as the HR images.

For the scales that the models were trained with (Table 1), we observe that in terms of PSNR and SSIM, DIINN only underperforms Meta-SR in two settings (\( \times 2 \) scale for DIV2K and Set5) while it outperforms both Meta-SR and LIIF in all other settings. For both "inter"-scales (Table 2) and "outer"-scales (Table 3), DIINN consistently beats both Meta-SR and LIIF across all settings. In addition, we report the inference time of all the methods with the same input and output sizes in Table 4. The results confirm that our framework is competitive with the state of the art in both performance and generalizability.

4.4. Qualitative Results

In Figure 4, we show a qualitative comparison between bicubic interpolation (first column), Meta-SR (second column), LIIF (third column), and DIINN (last column). SR predictions are obtained across all methods from the same LR input (downsampled via bicubic interpolation by a factor of \( 2 \pi \approx 0.28 \)) at increasing scale factors. We denote the size of the images for each row and the method for each column. As expected, bicubic interpolation only smooths the LR image and is unable to recover sharp details. SR images
predicted by Meta-SR have artifacts, especially around the boundary locations corresponding to the edges of LR pixels. We observe significantly better results from LIIF and DIINN, which shows the benefits of implicit decoders for SISR.

Compared to LIIF, DIINN produces sharper edges and details. Note that if we zoom in on the results of our method, we can see similar artifacts to those of Meta-SR, but much less distinguishable. LIIF overcomes these types of artifacts by averaging their predictions over a small window, which is termed “local ensemble”. However, as we observe in the third column in Figure 4, the “local ensemble” introduces blunter edges at a higher computational cost. We also note that the aforementioned artifacts do not appear visually with DIINN when the LR input is of higher quality (e.g., downsampled HR image at a factor of 4 or less).

4.5. Ablation Study

To more closely examine the design choices of our architecture, we performed an ablation study on variations of the
 dual implicit decoder. In Table 5, we summarize the quantitative results of six variations on the Urban100 dataset. Note that model (f) is our final model, which we used to report the results in the previous tables.

### 4.5.1 Modulation Inputs

First, we adjust the inputs to the modulation network in following three ways.

1. For models (a) and (b), each subsequent modulation layer takes only the output of its previous modulation layer as input and the residual connections to the content features \((z)\) are removed. The following equation is used in place of (4):

   \[
   m_i = ReLU(w_i m_{i-1} + b_i). \quad (6)
   \]

2. For models (c) and (d), each subsequent modulation layer takes a concatenation of the output of its previous modulation layer and the content features \((z)\) as input, as proposed in [26]. The following equation is used in place of (4):

   \[
   m_i = ReLU(w_i [m_{i-1} \ z] + b_i). \quad (7)
   \]

3. For models (e) and (f), each subsequent modulation layer takes a concatenation of the output of the previous synthesis layer and the content features as input, as expressed in (4).

Comparing models (a) and (c), or models (b) and (d), we observe that the addition of the skip connections to the content features \((z)\) increases the SISR performance similar to the observation in [26] on image reconstruction. This performance boost comes with additional parameters in the modulation networks. Nonetheless, comparing models (c) and (e), or models (d) and (f), we find that by simply using the output of the previous synthesis layer instead of the previous modulation layer, we can increase the PSNR and SSIM performance at no additional cost. We note that the consistency of the SR images with respect to the LR inputs, measured by the LR-PSNR, is better with models (c) and (d) compared to models (e) and (f) at larger scale factors.

### 4.5.2 Positional Features

Next, we explore a way to connect the positional features with the neighborhood around the corresponding LR pixels introduced by the feature unfolding operation (Section 3.1). We attempt to do this by adding an initializing dense layer with a sine activation at the beginning of the decoder \((i.e., \text{before we perform (2)}\)). The following equations are used to transform both the positional and the content features:

\[
p \leftarrow \sin(w_i p + b_i), \quad (8)
\]

\[
z \leftarrow p \odot z. \quad (9)
\]

Intuitively, we want this initializing layer to decide the weights for each LR pixel in the corresponding neighborhood, which could be seen as a learnable distance weighting function. As shown in Table 5, we observe no improvement across the three variations (Section 4.5.1) despite allowing for more flexibility with additional parameters in our model.

### 5. Conclusion

In this paper, we leveraged the learning of implicit representations to develop a dual interactive implicit network for SISR. Our approach allows for arbitrary scale factors without the need to train multiple models. Through extensive experimental evaluations across many settings and datasets, we empirically showed that DIIIN achieves state-of-the-art results. Exploring ways to transform our architecture to a larger receptive field along with improved interactions between the encoder and the decoder will be left for future work. We will also consider adapting our method to learn a space of predictions to address the ill-posed nature of SISR.

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| Scale | ×3.14 | ×4 | ×8 |
|-------|-------|----|----|
| Model | MI   | IP | PSNR | SSIM | LR-PSNR | PSNR | SSIM | LR-PSNR | PSNR | SSIM | LR-PSNR |
| (a)   | \[m\] | Yes | 25.67 | 0.8105 | 47.5 | 24.07 | 0.7465 | 47.25 | 20.68 | 0.5643 | 45.75 |
| (b)   | \[m\] | No  | 25.78 | 0.814 | 47.93 | 24.17 | 0.7506 | 48.02 | 20.74 | 0.5673 | 46.42 |
| (c)   | \[m, z\] | Yes | 25.89 | 0.8168 | 47.83 | 24.26 | 0.7538 | 48.26 | 20.77 | 0.5704 | 46.26 |
| (d)   | \[m, z\] | No  | 26.07 | 0.8218 | 49.11 | 24.42 | 0.7598 | 48.88 | 20.87 | 0.5762 | 47.05 |
| (e)   | \[s, z\] | Yes | 25.93 | 0.8179 | 48.58 | 24.3 | 0.7555 | 48.12 | 20.8 | 0.5725 | 45.95 |
| (f)   | \[s, z\] | No  | 26.14 | 0.8233 | 49.4 | 24.49 | 0.7624 | 48.75 | 20.91 | 0.5798 | 46.23 |

Table 5: A quantitative ablation study on the Urban100 dataset. “MI” stands for the modulation inputs \((i.e., \text{the inputs to the subsequent modulation layers})\) and “IP” stands for the initialization of the positional features \((p)\).
References

[1] Eirikur Agustsson and Radu Timofte. Ntire 2017 challenge on single image super-resolution: Dataset and study. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, pages 126–135, 2017.

[2] Matan Atzmon and Yaron Lipman. Sal: Sign agnostic learning of shapes from raw data. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 2565–2574, 2020.

[3] K Bai, X Liao, Q Zhang, X Jia, and S Liu. Survey of learning based single image super-resolution reconstruction technology. Pattern Recognition and Image Analysis, 30(4):567–577, 2020.

[4] Mojtaba Bemana, Karol Myszkowski, Hans-Peter Seidel, and Tobias Ritschel. X-fields: Implicit neural view-, light- and time-image interpolation. ACM Transactions on Graphics, 39(6):1–15, 2020.

[5] Rohan Chabra, Jan E Lenssen, Eddy Ilg, Tanner Schmidt, Julian Straub, Steven Lovegrove, and Richard Newcombe. Deep local shapes: Learning local sdf priors for detailed 3d reconstruction. In Proceedings of the European Conference on Computer Vision, pages 608–625, Springer, 2020.

[6] Yinbo Chen, Sifei Liu, and Xiaolong Wang. Learning continuous image representation with local implicit image function. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 8628–8638, 2021.

[7] Zhiqin Chen and Hao Zhang. Learning implicit fields for generative shape modeling. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 5939–5948, 2019.

[8] Julian Chibane, Thimo Alldieck, and Gerard Pons-Moll. Implicit functions in feature space for 3d shape reconstruction and completion. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 6970–6981, 2020.

[9] Julian Chibane, Aymen Mir, and Gerard Pons-Moll. Neural unsigned distance fields for implicit function learning. In Proceedings of the Advances in Neural Information Processing Systems, pages 21638–21652, 2020.

[10] https://github.com/robotic-vision-lab/Dual-Interactive-Implicit-Neural-Network.

[11] Chao Dong, Chen Change Loy, Kaiming He, and Xiaoou Tang. Image super-resolution using deep convolutional networks. IEEE Transactions on Pattern Analysis and Machine Intelligence, 38(2):295–307, 2015.

[12] Chao Dong, Chen Change Loy, and Xiaoou Tang. Accelerating the super-resolution convolutional neural network. In Proceedings of the European Conference on Computer Vision, pages 391–407. Springer, 2016.

[13] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. Proceedings of the Advances in Neural Information Processing Systems, 27, 2014.

[14] Muhammad Haris, Gregory Shakhnarovich, and Norimichi Ukita. Deep back-projection networks for super-resolution. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 1664–1673, 2018.

[15] Xuecai Hu, Haoyuan Mu, Xiangyu Zhang, Zilei Wang, Tieniu Tan, and Jian Sun. Meta-sr: A magnification-arbitrary network for super-resolution. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 1575–1584, 2019.

[16] Jia-Bin Huang, Abhishek Singh, and Narendra Ahuja. Single image super-resolution from transformed self-exemplars. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 5197–5206, 2015.

[17] Michal Irani and Shmuel Peleg. Motion analysis for image enhancement: Resolution, occlusion, and transparency. Journal of Visual Communication and Image Representation, 4(4):324–335, 1993.

[18] Chiyu Jiang, Avneesh Sud, Ameesh Makadia, Jingwei Huang, Matthias Nießner, Thomas Funkhouser, et al. Local implicit grid representations for 3d scenes. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 6001–6010, 2020.

[19] Justin Johnson, Alexandre Alahi, and Li Fei-Fei. Perceptual losses for real-time style transfer and super-resolution. In Proceedings of the European Conference on Computer Vision, pages 694–711. Springer, 2016.

[20] Jiwon Kim, Jung Kwon Lee, and Kyoung Mu Lee. Accurate image super-resolution using very deep convolutional networks. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 1646–1654, 2016.

[21] Jiwon Kim, Jung Kwon Lee, and Kyoung Mu Lee. Deeply-recurcive convolutional network for image super-resolution. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 1637–1645, 2016.

[22] Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In Proceedings of the International Conference on Learning Representations, 2015.

[23] Bee Lim, Sanghyun Son, Heewon Kim, Seungjun Nah, and Kyoung Mu Lee. Enhanced deep residual networks for single image super-resolution. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 136–144, 2017.

[24] Cheng Ma, Peiqi Yu, Jiwen Lu, and Jie Zhou. Recovering realistic details for magnification-arbitrary image super-resolution. IEEE Transactions on Image Processing, 2022.

[25] David Martin, Charless Fowlkes, Doron Tal, and Jitendra Malik. A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics. In Proceedings of the IEEE/CVF International Conference on Computer Vision, volume 2, pages 416–423, 2001.

[26] Ishit Mehta, Michäel Gharbi, Connelly Barnes, Eli Shechtman, Ravi Ramamoorthi, and Manmohan Chandraker. Modulated periodic activations for generalizable local functional representations. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 14214–14223, 2021.

[27] Lars Mescheder, Michael Oechsle, Michael Niemeyer, Sebastian Nowozin, and Andreas Geiger. Occupancy networks:
Learning 3d reconstruction in function space. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 4460–4470, 2019.

[28] Jeong Joon Park, Peter Florence, Julian Straub, Richard Newcombe, and Steven Lovegrove. Deepsdf: Learning continuous signed distance functions for shape representation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 165–174, 2019.

[29] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kopf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. Pytorch: An imperative style, high-performance deep learning library. *Proceedings of the Advances in Neural Information Processing Systems*, 32:8024–8035, 2019.

[30] Songyou Peng, Michael Niemeyer, Lars Mescheder, Marc Pollefeys, and Andreas Geiger. Convolutional occupancy networks. In *Proceedings of the European Conference on Computer Vision*, pages 523–540. Springer, 2020.

[31] Eduard Ramon, Gil Triginer, Janna Escur, Albert Pumarola, Jaime Garcia, Xavier Giro-i Nieto, and Francesc Moreno-Noguer. H3d-net: Few-shot high-fidelity 3d head reconstruction. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 5620–5629, 2021.

[32] Wenzhe Shi, Jose Caballero, Ferenc Huszár, Johannes Totz, Andrew P Aitken, Rob Bishop, Daniel Rueckert, and Zehan Wang. Real-time single image and video super-resolution using an efficient sub-pixel convolutional neural network. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 1874–1883, 2016.

[33] Vincent Sitzmann, Julien Martel, Alexander Bergman, David Lindell, and Gordon Wetzstein. Implicit neural representations with periodic activation functions. *Proceedings of the Advances in Neural Information Processing Systems*, 33:7462–7473, 2020.

[34] Kenneth O Stanley. Compositional pattern producing networks: A novel abstraction of development. *Genetic Programming and Evolvable Machines*, 8(2):131–162, 2007.

[35] Matthew Tancik, Pratul P. Srinivasan, Ben Mildenhall, Sara Fridovich-Keil, Nithin Raghavan, Utkarsh Singhal, Ravi Ramamoorthi, Jonathan T. Barron, and Ren Ng. Fourier features let networks learn high frequency functions in low dimensional domains. *Proceedings of the Advances in Neural Information Processing Systems*, 2020.

[36] Radu Timofte, Eirikur Agustsson, Luc Van Gool, Ming-Hsuan Yang, and Lei Zhang. Ntire 2017 challenge on single image super-resolution: Methods and results. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, pages 114–125, 2017.

[37] Wei Wang, Yihui Hu, Yanhong Luo, and Tong Zhang. Brief survey of single image super-resolution reconstruction based on deep learning approaches. *Sensing and Imaging*, 21(1):1–20, 2020.

[38] Zhou Wang, A.C. Bovik, H.R. Sheikh, and E.P. Simoncelli. Image quality assessment: From error visibility to structural similarity. *IEEE Transactions on Image Processing*, 13(4):600–612, 2004.

[39] Jianchao Yang and Thomas Huang. Image super-resolution: Historical overview and future challenges. In *Super-Resolution Imaging*, pages 1–34. CRC Press, 2017.

[40] Linwei Yue, Huanfeng Shen, Jie Li, Qianguang Yuan, Hongyan Zhang, and Liangpei Zhang. Image super-resolution: The techniques, applications, and future. *Signal Processing*, 128:389–408, 2016.

[41] Yulun Zhang, Yapeng Tian, Yu Kong, Bineng Zhong, and Yun Fu. Residual dense network for image super-resolution. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2018.