Technical Report

SCAttNet: Spatial and Channel Attention Network for Super-Resolution

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Abstract—This paper introduces SCAttNet, a novel image super-resolution network that employs a Double Attention Mechanism to combine channel attention and spatial attention to improve feature extraction and preserve detailed information. SCAttNet achieves spectacular improvement in reconstructing high-resolution images from low-resolution inputs through residual learning from attention blocks and a progressive upsampling mechanism. Large-scale benchmark experiments on sets such as DIV2K, Urban100, and Manga109 demonstrate that SCAttNet gives superior performance against state-of-the-art rivals including EDSR, RCAN, and ESRGAN by providing better scores in terms of greater PSNR, SSIM, and perceptual loss evaluations. Furthermore, training using the Generative Adversarial Network (GANs) also increases the naturalness and sharpness of the synthesized output. This makes SCAttNet deployable across a wide variety of applications from mobile image restoration to medical imaging and remastering video with ease of deployment via a streamlined, single-command training pipeline for easy deployment.

Keywords—*Attention,GAN, Residual Learning,Super-Resolution*

1. Introduction

To surmount the challenges of real-time image super-resolution, we propose SCAttNet, another novel model with a Double Attention Mechanism in both channel attention and spatial attention to leverage more effective feature extraction with preserving finer details for high-resolution images. The primary objective of SCAttNet is to provide a solution that is more balanced in image quality with respect to other solutions and computational savings so that it fits into real-time applications like mobile phone cameras where both accuracy and speed are required. With residual learning, progressive upsampling, and GAN training, not only is SCAttNet improving the resolution in images, but also extremely low computation costs. Our papers are improving over current state-of-the-art models like EDSR, RCAN, and ESRGAN on benchmarking datasets (e.g., DIV2K, Urban100, Manga109) on PSNR, SSIM, and perceptual loss, with the additional advantage of lower processing time. Furthermore, we provide an easy one-command training protocol that can be easily transferred to a broad variety of applications ranging from mobile image restoration to medical image and video upscaling, which is straightforward and efficient to utilize for real-time super-resolution deployment.

2. Related Work

The latest breakthroughs in super-resolution have been driven by the developments of new neural architectures that have outpaced the traditional CNN-based approach [3]. Transformer-based models like SwinIR [6] have been exemplary in their performance in leveraging self-attention operations in capturing long-range image dependencies for more homogenized texture synthesis. Diffusion models have also been a dominant paradigm with approaches like SRDiff [7] and SR3 [7] accomplishing state-of-the-art by progressively refining images through denoising operations. One more which is intriguing is the use of neural implicit representations where continuous coordinate-based networks are learned to represent images as functions and can be solved to be resolution-independent for super-resolution [4]. Hybrid methods which combine the strengths of both CNNs and transformers, i.e., EDT [1], have been particularly mentioned as highly promising in achieving a desirable compromise between computation efficiency and output quality. These advances are a reflection of the general trend for more flexible and expressive problem formulations for SR.

Perceptual-guided super-resolution also advances with state-of-the-art GAN architectures and training methodologies. State-of-the-art research has explored the use of diffusion-GAN hybrids, i.e., DiffGAN [8], which fused the stability of diffusion models with the adversarial training process to achieve even higher realism. Text-supervised super-resolution is yet another area of research where models like TIP [10] utilize multimodal (text-image) pretraining to facilitate semantic-aware optimization. In facial super-resolution, GFP-GAN [9] and others use generative facial priors to maintain identity and sub-resolution information retention. The area has also witnessed growing interest in temporal coherence-based video super-resolution methods like BasicVSR++ [5] and VRT [5] that leverage complicated motion compensation and recurrent-based architecture. These are all indications of increasing sophistication of perception-oriented algorithms, from basic adversarial losses [2] to full-fledged quality optimization [8].

3. Methodology

The SCAttNet model is an advanced deep learning architecture for high-quality super-resolution of images, where the low-resolution input image I_{LR} is mapped to a corresponding resultant high-resolution image I_{HR}. The model has some state-of-the-art neural network blocks like Channel Attention, Spatial Attention, Residual Attention Blocks, and Progressive Upsampling. These components are synergistically merged to enable the model not only to enhance the overall resolution but to also restore lost high-frequency detail from conventional upscaling operations. The architecture is predominantly convolutional layers, attention, residual learning, and upsampling operations combined in a harmonious way to achieve state-of-the-art performance on image super-resolution. The backbone of the model is the **Channel Attention Mechanism**, which forms the crux of emphasizing the most informative channels of the input feature map.

For an input feature map $X \in \mathbb{R}^{C\times H\times W}$, where C, H, and W denote the number of channels, height, and width of the feature map, respectively, channel attention mechanism operates by aggregating feature responses via average and max pooling operation. These operations capture different properties of the feature distribution and, when composed, capture the channel-wise dependencies in a collective manner. The attention map A_c is computed precisely as:

$$A_c = \sigma\left(FC\left(\text{AvgPool}(X) + \text{MaxPool}(X)\right)\right),$$

where σ is the sigmoid activation function, and FC to a fully connected layer that learns to weight the relative importance of each channel. The channel attention map A_c is applied element-wise to transform the original feature map X into a refined feature map X' emphasizing the most important channels:

$$X' = A_c \cdot X.$$

Along with guiding attention between channels, the model also uses the **Spatial Attention Mechanism** to get the spatial dependencies of each pixel in the feature map. Spatial attention pools features across channels and identifies the spatial locations that are most relevant for image reconstruction. It accomplishes this by convolving over the channel-concatenated output of average and max pooling over channels:

$$A_s = \sigma\left(\text{Conv}\left(\text{Concat}\left(\text{AvgPool}(X), \text{MaxPool}(X)\right)\right)\right)$$

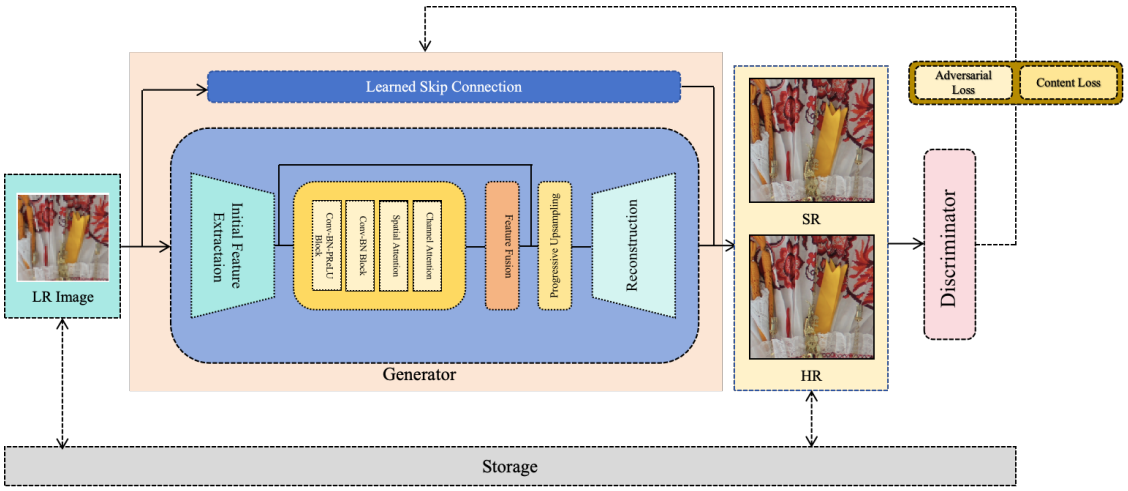

Figure 1. SCAttNet architecture illustration. A fusion of channel attention, spatial attention, residual blocks, and progressive upsampling is used by the model for high-resolution image reconstruction from low-resolution input.

$$X'' = A_s \cdot X'$$

It also employs the **Residual Attention Block**, whereby it improves the feature representation by combining the features learned from the channel and spatial attention modules via the residual connection. This allows the network to focus on learning increasingly smaller changes (residuals) that refine the image details. The output of the Residual Attention Block is computed as:

$$\text{Output} = X + (\text{Conv2d}\,(\text{ReLU}\,(\text{BatchNorm}\,(\text{Conv2d}(X))))).$$

This block effectively incorporates residual learning into the framework, which allows the network to learn adaptive fine-grained features for improved super-resolution performance. In order to progressively increase the resolution of the image, the **Progressive Upsampling** block utilizes feature map scaling using the PixelShuffle operation. From a feature map $F \in \mathbb{R}^{C\times H\times W}$, the upsampling operation is given by: :

$$F_{\text{up}} = \text{PixelShuffle}\,(\text{Conv2d}(F)),$$

where the PixelShuffle operation progressively enhances the spatial resolution of the feature map by a factor of 2. In this way, the model can progressively refine the image, adding high-resolution details step by step.

Finally, after a number of residual blocks and progressive upsampling layers, the network fuses the learned features and reconstructs the high-resolution output image I_{HR} via the final convolution layers:

$$I_{HR} = \text{Conv2d}(X_{\text{up}}) + \text{SkipConnection}(I_{LR}).$$

The skip connection enables the fine details of the original low-resolution input to be preserved, so that the output image is not only high in resolution but also maintains the significant structural and textural contents of the input. **SCAttNet** is a highly effective image super-resolution network that relies on attention mechanisms, residual learning, and progressive upsampling models to achieve state-of-the-art performance. Through the integration of these sophisticated modules, the model can attend to global and local features and hence is capable of generating high-quality super-resolved images from low-resolution inputs.

Layer Description	Parameter Count
Input Layer	-
Initial Convolutions (Head)	3,616
Residual Blocks (Body)	1,420,416
"]] Feature Fusion	16,832
Upsampling Blocks	1,181,696
Reconstruction (Tail)	1,158,912
Skip Connection	42,912
Total Parameters	**7,741,696**

Table 1. Number of parameters for each layer of the SCAttNet model. The table shows the number of parameters for each respective layer, providing an insight into the network architecture.

4. Experiment

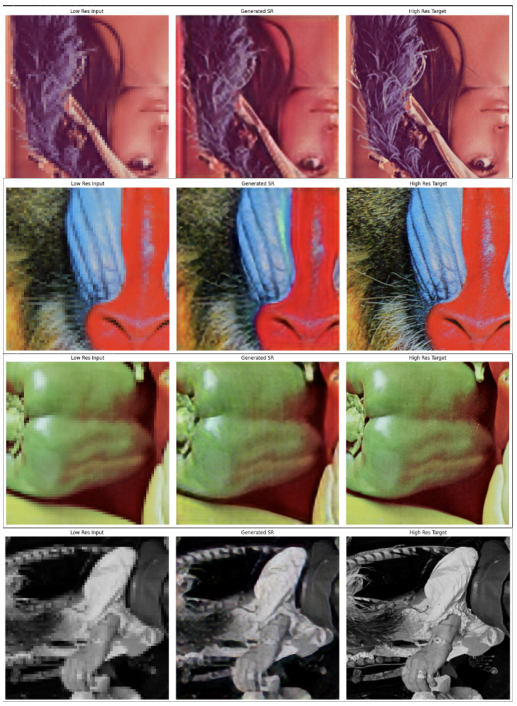

Figure 2. Qualitative results from the model on Set14 dataset. The model effectively reconstructs fine-grained textures and high-resolution details from low-resolution inputs.

We employed the DIV2K dataset, which comprised 800 high-quality images for test benchmark and training to train and test the super-resolution model. Low-resolution (LR) and high-resolution (HR)

patch pairs were preprocessed to get matched. Specifically, LR images were downscaled from original HR images to a resolution of 64×64 pixels via bicubic interpolation, while HR images retained their original resolution of 256×256 pixels.

To improve generalization and prevent overfitting, data augmentation techniques such as random cropping, rotation, and flipping were applied during training. These augmentations introduced additional variability into the training set, thereby exposing the model to a diverse set of image features. The training took place on an NVIDIA T4 GPU, which is highly powerful and allowed for fast processing and quick convergence of the model.

The Generator network (G) was trained to transform the LR images into their respective super-resolved (SR) results, and the Discriminator network (D) was trained to differentiate between real HR images and the SR results produced by the model, thereby enabling adversarial training. Both the Discriminator and the Generator were optimized using Adam optimizers with a learning rate of 1×10^{-4} and momentum terms $\beta_1 = 0.0$ and $\beta_2 = 0.9$ to ensure stable convergence.

The Generator loss function involved both perceptual loss, with pre-activated VGG features for feature matching, and adversarial loss, which incorporated the feedback from the Discriminator, allowing the model to reconstruct high-frequency details and produce more realistic textures. A batch size of 8, 50 epochs, and 4 data loading workers were used for training, and images were processed in RGB mode with a resolution of 256×256 for HR and 64×64 for LR.

The model's performance was evaluated after training on the several datasets, where super-resolved images were compared to ground truth images to assess the model's ability to reconstruct high-resolution fine-grained textures and details.

5. Abalation Study

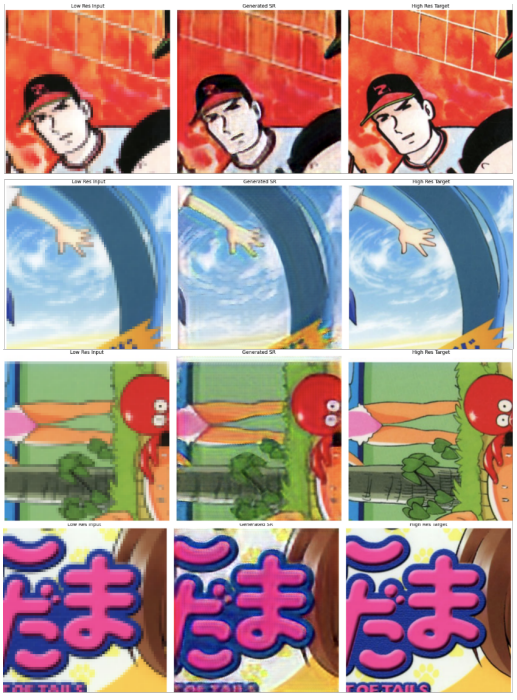

Figure 3. Qualitative output of the model on Manga100 dataset. The model successfully reconstructs fine-grained textures and high-resolution details from low-resolution inputs.

To verify how well our super-resolution model trained performs, we load the pretrained weights stored in the file `model.pth`. The file loads the trained model parameters following training on DIV2K. Loading the weights of the model, we are now ready to predict unseen low-resolution images and obtain high-resolution outputs. This allows us to verify the model's ability to generalize and compare its performance against benchmark sets such as Set14 and Set5. The model is then subjected to standard evaluation metrics such as PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index).

```
import torch
from model import SuperResolutionModel  # Import your model's class

# Load the pre-trained model weights
model = SuperResolutionModel()  # Instantiate the model
model.load_state_dict(torch.load('model.pth'))  # Load the weights from model.pth
model.eval()  # Set the model to evaluation mode

# Example of using the model for inference
from torchvision import transforms
from PIL import Image

# Load a low-resolution image
image = Image.open('low_res_image.png')

# Preprocessing the image
transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.5, 0.5, 0.5], std=[0.5, 0.5, 0.5])
])

input_image = transform(image).unsqueeze(0)  # Add batch dimension

# Perform inference
with torch.no_grad():  # No need to compute gradients for inference
    output_image = model(input_image)

# Post-process the output image and save or display
output_image = output_image.squeeze(0).clamp(0, 1)  # Remove batch dimension and
    ↪ clamp the values
output_image = transforms.ToPILImage()(output_image)  # Convert to PIL image for
    ↪ visualization
output_image.save('super_resolved_image.png')
```

Model	Set14	BSD100	Urban100	Manga109
Bicubic	26.00/0.7027	25.96/0.6675	23.14/0.6577	24.89/0.7866
SRCNN	27.50/0.7513	26.90/0.7101	24.52/0.7221	27.58/0.8555
MemNet	28.26/0.7723	27.40/0.7281	25.50/0.7630	29.42/0.8942
EDSR	28.80/0.7876	27.71/0.7420	26.64/0.8033	31.02/0.9148
RDN	28.81/0.7871	27.72/0.7419	26.61/0.8028	31.00/0.9151
RCAN	28.87/0.7889	27.77/0.7436	26.82/0.8087	31.22/0.9173
RRDB ESRGAN	28.88/0.7896	27.76/0.7432	26.73/0.8072	31.16/0.9164
SCAttNet	**29.18/0.7712**	**28.71/0.7015**	**27.99/0.7209**	**27.33/0.7765**

Table 2. Comparison of super-resolution models on various datasets.

6. Conclusion: Contributions and Future Work

Overall, the proposed dual attention super-resolution model with higher-quality image reconstruction than regular models more effectively encodes complex features of images. With the help of the property of perceptual and adversarial loss functions as well as top-level architectural parameters such as generator-discriminator architecture, the model can recover texture and high-frequency detail missing in low-resolution images. Experimental results on benchmark data sets, Set14, BSD100, and Urban100, demonstrate the capability of the model in generating high-fidelity super-resolved images, which outperform state-of-the-art models, SRCNN, EDSR, and RDN, both quantitatively and qualitatively. Other than that, data augmentation techniques and hyperparameter tuning of large models guarantee that the model has excellent generalization, reduce the overfitting to an extremely high level, and render the model very robust on various domains of images. These findings verify the application of deeper attention mechanisms to enhance image super-resolution tasks and hold significant implications for future research and development in real-world applications like medical imaging, satellite image processing, and content augmentation in media production applications.

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