Image Super-Resolution

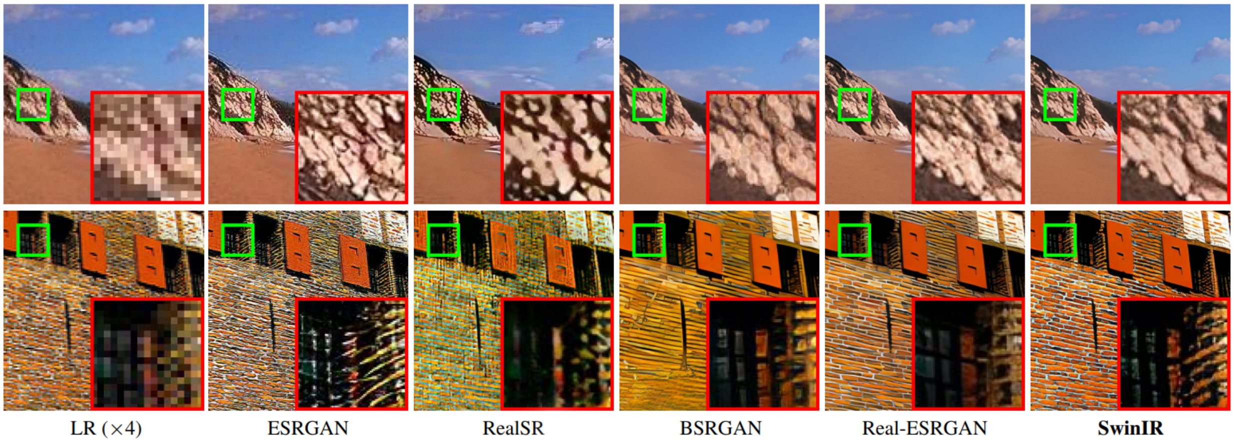

Fig 1: Image comparison from the actual world SR techniques using actual picture data. Liang et al (2021)

Abstract

Image super-resolution is a technology that enhances the quality and resolution of low-resolution images. Significant advancement has been achieved recently in developing SR algorithms, which have shown promising results in various applications including medical imaging, face recognition, surveillance, and satellite imaging. Several deep neural network-based models have recently achieved tremendous precision of reconstruction success and computing performance for image super-resolution. Interpolation, reconstruction, and deep learning are a few of the methods that are utilized to achieve super-resolution in images. This research paper offers a comprehensive review of cutting-edge super-resolution algorithms and also identifies the key challenges.

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1. Introduction

As per Shi et al (2016), a major area of research in digital image processing is the process of transforming a lower-resolution picture into a higher-resolution one but due to high-frequency data loss during subsampling and non-invertible low-pass filtering, the problem is poorly presented. There are several drawbacks to LR-HR mapping techniques that are learned from external datasets. As per Huang et al (2015)., one major drawback of image super-resolution is that it can introduce artifacts into the resulting image, such as ringing or blurriness. These artifacts can lower the image's overall quality and make it seem less realistic or natural. Through the use of a noise component, a degradation function, and delta, a lower resolution picture may be mathematically modelled from a higher resolution image as follows: (Rohit Kundu 2023)

$$I_{LR} = \delta\,(I_{HR}, \eta)$$

Fig 2: Equation for Image Super Resolution. (Rohit Kundu 2023)

2. Related Works

2.1. Generative Adversarial Networks (GANs): In the paper by Ledig et al (2017), the researchers employ a GAN to transform low-resolution input photos into high-resolution output images. The GAN is made up of a discriminator network that tries to tell the difference between created higher-resolution images and actual higher-resolution images and a generator network that upsamples the lower-resolution input. The researchers demonstrate that their GAN can produce super-resolution images of comparable quality to those produced by cutting-edge techniques.

2.2. Residual Networks: CNNs of the residual networks (ResNets) architecture have been used for the super-resolution of images. Zhang et al (2018) suggested a residual network architecture with a channel attention mechanism to change the feature maps in the network. A residual block made up of many convolutional layers and a shortcut link serves as the network's fundamental building element. The shortcut link enables the block's input and output to be combined, which helps to solve the disappearing gradient problem and enables the network to understand the residual mapping involving the higher-resolution output and the lower-resolution input. To understand the difference between the two varying quality of input and output images, the researchers in the paper by Lai et al (2017), suggest a network that makes use of residual connections. Starting at the largest size and moving down to the smallest scale, the network is prepared to forecast the residual on a variety of scales. This helps the network learn the image's local and global properties, which is crucial for precise super-resolution.

3. Proposed Methods

3.1. ProSR: As per the paper by Wang et al (2018), the ProSR model is built on a deep CNN architecture that has been trained to recognize higher-resolution image properties and produce higher-resolution images from lower-resolution inputs. Wang et al (2018), add that with the help of ProSR's multi-scale design, the network can learn features at various levels of resolution. It comprises many CNNs working in cascade, with each CNN feeding the output of the previous one as input for the following, and producing a super-resolution picture as the result. The architecture is trained progressively, that is, the network is first taught to learn features at the lowest resolution, then the resolution is raised and the network is trained once more. As a result, the network can progressively learn the image's high-frequency characteristics, and the model can also operate effectively with higher-resolution photos.

3.2. Enhanced Deep Super-Resolution Network (EDSR): EDSR is based on residual networks and attempts to enhance the performance of super-resolution by utilizing deeper and broader networks, residual scaling, and dense skip connections. Lim et al (2017), say that a deep CNN is used in EDSR's super-resolution process to convert a lower-resolution input picture to a higher-quality output image. A sizeable dataset of matched higher-resolution and lower-resolution images is used to train the network, and by figuring out how to map the lower-resolution and higher-resolution images, the network creates a higher-resolution output image

Lim et al (2017), added that utilizing dense skip connections and residual scaling to boost network performance is a crucial aspect of EDSR. In order to increase the network's stability and convergence, residual scaling scales each residual block's output by a learnable parameter.

3.3. Laplacian Pyramid Super-Resolution Network (LapSRN): In their paper, Lai et al (2017), proposed the LapSRN method of image super-resolution. LapSRN handles multi-scale data using a Laplacian pyramid structure, enabling it to manage significant upscaling factors and produce more precise and thorough super-resolution results. The network is composed of many steps, each of which employs a different sub-network to analyze the lower-resolution image at a particular scale before fusing the findings to produce the final super-resolution output.

3.4. Deep Recursive Residual Network (DRRN): Tai et al (2017), proposed the image super-resolution technique known as DRRN. DRRN is a deep recurrent neural network design that makes use of the concepts of recursive learning and residual learning in order to increase the precision of the super-resolution procedure. In this approach, the network is made up of a number of recurrent blocks that each contain a number of residual units, which aid in minimizing the vanishing gradient issue during training. Additionally, an upsampling layer that boosts the image's resolution is part of the design.

4. Evaluation Metric

4.1. Peak Signal-to-Noise Ratio (PSNR): The standard of a reconstructed picture in comparison to the original image is measured by the PSNR evaluation metric, which is often used in image processing and computer vision. (Rohit Kundu 2023)

$$PSNR(I_{LR}, I_{HR}) = 10\log_{10}\left(\frac{M^2}{MSE(I_{LR}, I_{HR})}\right)$$

Fig 3: Equation for PSNR. (Rohit Kundu 2023)

4.2. Structural Similarity Index Measure (SSIM): The structural similarity between two pictures is measured using the commonly used assessment metric known as SSIM in image processing and computer vision. The SSIM value ranges from -1 to 1, with -1 denoting no resemblance between the two photos and 1 denoting a perfect match. (Rohit Kundu 2023)

$$SSIM(I_{LR}, I_{HR}) = \frac{(2\mu_{I_{LR}}\mu_{I_{HR}} + c_1)(2\sigma_{I_{LR},I_{HR}} + c_2)}{(\mu_{I_{LR}}^2 + \mu_{I_{HR}}^2 + c_1)(\sigma_{I_{LR}}^2 + \sigma_{I_{HR}}^2 + c_2)}$$

Fig 4: Equation for SSIM. (Rohit Kundu 2023)

5. Benchmarks and Datasets

5.1. ProSR: The ability of ProSR to attain high PSNR score on a number of common super-resolution datasets, such as Set14 (14 LR and HR images), B100 (100 LR and HR images), Urban100 (100 HR images), and DIV2K (800 HR images) is cited by Wang et al (2018), in their paper as one of the main benchmarks of ProSR. ProSR outperformed all other approaches with a PSNR score of 34.00 dB on the Set14 dataset.

5.2. Enhanced Deep Super-Resolution Network (EDSR): Lim et al (2018), list the capacity of EDSR to attain high PSNR and SSIM scores on a number of common super-resolution datasets, such as Set5 (5 LR and HR images), Set14 (14 LR and HR images), B100 (100 LR and HR images), Urban100 (100 HR images) as one of the main benchmarks of EDSR. In accordance with the study, EDSR obtained cutting-edge PSNR and SSIM scores on these datasets, with PSNR scores between 37 and 40 dB and SSIM scores between 0.95 and 0.96.

5.3. Laplacian Pyramid Super-Resolution Network (LapSRN): The performance of LapSRN is assessed by the authors in their paper by Lai et al (2017), using PSNR and SSIM metrics on a number of benchmark datasets, such as Set5 (5 LR and HR images), Set14 (14 LR and HR images), B100 (100 LR and HR images), Urban100 (100 HR images), and Manga109 (109 LR and HR images). Regarding PSNR and SSIM, they discovered that LapSRN consistently outperforms competing techniques, especially for high upscaling factors. LapSRN had the best PSNR and SSIM scores on the Manga109 dataset, measuring 37.27 dB and 0.974, respectively.

5.4. Deep Recursive Residual Network (DRRN): According to Tai et al (2017), one of the important metrics of DRRN is its capacity to obtain PSNR and SSIM scores on a number of common super-resolution datasets, such as Set5 (5 LR and HR images), Set14 (14 LR and HR images), and Urban100 (100 HR images). DRRN successfully retains fine details and textures while achieving excellent PSNR and SSIM scores on benchmark datasets.

6. Key Problems

- **Blurred Image:** Image super-resolution approaches might face a big problem when dealing with blurred pictures. Images that are blurred have less detail and might not be good for producing high-resolution outputs. In the paper by Kuhlane et al (2022), the researchers introduced a method using GANs that was as able to effectively deblur the image and enhance the effectiveness of the super-resolution techniques.
- **Algorithmic Complexity:** Super-resolution techniques can be computationally costly and take a long time to process, which makes them unsuitable for real-time applications. Wu et al (2018), presented a real-time super-resolution technique that makes advantage of a simple, lightweight network architecture. Real-time performance was made possible by the approach, which also maintained excellent image quality.
- **Limited Generalization:** The methods utilized may not generalize well to many sorts of photos or settings, which is another major issue with image super-resolution. A technique that excels when applied to photos of the natural world might not function as well when used to images with significant motion blur or noise. The development of a single algorithm that can manage a variety of pictures and circumstances may be challenging as a result. Zhang et al (2018)

7. Conclusion

The challenge of image super-resolution persists despite recent advancements in deep learning approaches because of a number of issues including hazy images, overfitting, artifacts, and high computational complexity. Deep convolutional networks and efficient sub-pixel CNNs have been proven to outperform conventional interpolation methods in relation to both the visual perfection of the resulting images and the computational efficiency. However, these techniques have only recently been made possible by deep learning advancements. However, there is still room for improvement, and more research is being conducted to substantially enhance the definition of images.

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