SAR Image Enhancement using Deep Learning

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Abstract: In remote sensing, Synthetic Aperture Radar (SAR) images are well known for their all time and weather capabilities. SAR is a coherent radar imaging technology which is capable of producing high resolution images of targets and landscapes. Radar imaging applications are also susceptible to radar design constraints on bandwidth, acquisition time, number of antennas which affects the image resolution, this issues make the processing and interpretation of SAR images very difficult for human interpreters and computer vision systems. Single image super resolution (SISR), a greatly challenging task of computer vision and machine learning, attempts to reconstruct a high-resolution (HR) image from corresponding low image resolution. While image Super resolution (SR) is an ill-posed inverse procedure, since there exists a multitude of solutions for any LR input. To tackle this inverse problem, plenty of image SR algorithms have been proposed. Deep learning methods such as CNNs and GANs are being used to perform super resolution with results competitive to the state of the art. In this project will investigate whether the Deep learning (GANs & CNNs) can be used to achieve super resolution in SAR image.

I. INTRODUCTION

In remote sensing, Synthetic Aperture Radar (SAR) images are well-known for their all-time and all-weather capabilities. SAR is a coherent radar imaging technology which is capable of producing high-resolution images of targets and landscapes. Due to its ability to capture images both at night and in bad weather conditions, SAR imaging has several advantages compared to optical and infrared systems. However, SAR images are often difficult to interpret because they are contaminated by multiplicative noise known as speckle and the processed SAR images are often grayscale and they do not contain any colour information. Additionally, radar imaging applications are also susceptible to radar design constraints on bandwidth, acquisition time, number of antennas and antenna separation, which affect the image resolution. These issues often make the processing and interpretation of SAR images very difficult for both human interpreters and computer vision systems.

Single image super resolution (SISR), a greatly challenging task of computer vision and machine learning, attempts to reconstruct a high-resolution (HR) image from a low-resolution (LR) image. recover any kinds of high resolution image from corresponding low-resolution image. SISR is used in various computer vision tasks, such as security and surveillance imaging, medical imaging, and image generation. Other application areas include Satellite imaging (remote sensing) where several images of a single area are available, security and surveillance where it may be required to enlarge a particular point of interest in a scene (such as zooming on the face of a criminal or the numbers of a license plate), computer vision where it can improve the performance of pattern recognition and other areas such as facial image analysis, text image analysis, biometric identification, fingerprint image enhancement, etc.

While image Super Resolution (SR) is an ill-posed inverse procedure, since there exists a multitude of solutions for any LR input. To tackle this inverse problem, plenty of image SR algorithms have been proposed, including interpolation based, reconstruction-based, and learning-based methods. Conventional methods for achieving super-resolution such as image priors, interpolation, sparse coding require a lot of pre/post processing and optimization. Recently, deep learning methods such as Convolution Neural Networks (CNNs) and Generative Adversarial Networks are being used to perform super-resolution with results competitive to the state of the art.

In recent years, the significant increase in data size and computational resources leads to a considerable boost in deep learning. Especially the development of Deep Convolution Neural Networks (DCNNs) radically changed the research approach in the field of image processing. Generative adversarial networks (GANs) are a recent branch and are considered as the state-of-the-art in image generation tasks. Moreover, a variant of GANs, conditional generative adversarial networks (cGANs), was recently introduced for image-to-image translation such as natural image super-resolution, medical image correction and in painting.

One advantage of GANs is the adversarial loss component that allows it work well with multi-modal outputs, e.g., in image generation tasks where an input can have multiple acceptable correct answers. Traditional machine learning methods use pixel-wise mean squared error as the optimization objective and are hence not able to produce multiple correct outputs. GANs excel in tasks which require generating samples resembling a particular distribution. One such task is super-resolution where from a low-resolution image, a high-resolution equivalent has to be estimated, and multiple high-resolution images corresponding to a low-resolution image are possible.

A. Image Quality metrics

Image quality can degrade due to distortions during image acquisition and processing. Examples of distortion include noise, blurring, ringing, and compression artifacts.

Efforts have been made to create objective measures of quality. For many applications, a valuable quality metric correlates well with the subjective perception of quality by a human observer. Quality metrics can also track unperceived errors as they propagate through an image processing pipeline, and can be used to compare image processing algorithms.

If an image without distortion is available, you can use it as a reference to measure the quality of other images. For example, when evaluating the quality of compressed images, an uncompressed version of the image provides a useful reference. In these cases, you can use full-reference quality metrics to directly compare the target image and the reference image.

If a reference image without distortion is not available. you can use a no-reference image quality metric instead. These metrics compute quality scores based on expected image statistics.

II. METHOD

A. SYSTEM ARCHITECTURE

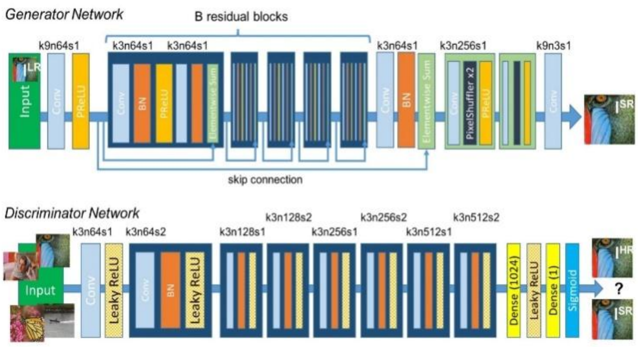

Figure 3.1: system architecture

Above is the network design for the generator and the discriminator. It mostly composes of convolution layers, batch normalization and parameterized ReLU (PReLU). The generator also implements skip connections similar to ResNet.

Few things to note from network architecture:

Residual blocks: since deeper networks are more difficult to train. The residual learning framework eases the training of these networks, and enables them to be substantially deeper, leading to improved performance. 16 residual blocks are used in generator.

A. **Pixel Shuffler x2**: this is featue map up scaling 2 sub-pixels CNN are used in generator. Up scaling or up sampling are same. There are various ways to do that. In code keras in built function has been used.
B. **Prelu (Parameterized Relu)**: we are using Prelu in place of Relu or LeakyRelu. It introduces learn-able parameter that makes it possible to adaptively learn the negative part coefficient.

K3n64s1 this means kernel 3, channels 64 and strides 1.

A. **Loss function**: this is most important part. As discussed we will using perceptual loss. It comprises of content (reconstruction) loss and adversial loss.

$$l^{SR} = \underbrace{\underbrace{l^{SR}_{\mathrm{X}}}_{\text{content loss}} + \underbrace{10^{-3} l^{SR}_{Gen}}_{\text{adversarial loss}}}_{\text{perceptual loss (for VGG based content losses)}}$$

B. **Adversial loss**: this pushes our solution to the natural image manifold using a discriminator network that is trained to differentiate between the super-resolved images.

$$l^{SR}_{Gen} = \sum_{n=1}^{N} -\log D_{\theta_D}(G_{\theta_G}(I^{LR}))$$

C. **Content loss**: Content loss we are using so that we can keep perceptual similarity instead of pixel wise similarity. This will allow us to recover photo-realistic textures from heavily down sampled images. Instead of relying on pixel-wise losses we will use a loss function that is closer to perceptual similarity. We define the VGG loss based on the ReLU activation layers of the pre-trained 19 layers VGG network. VGG loss is defined as the Euclidean distance between the feature representations of a reconstructed image and the reference image.

$$l^{SR}_{VGG/i.j} = \frac{1}{W_{i,j}H_{i,j}} \sum_{x=1}^{W_{i,j}} \sum_{y=1}^{H_{i,j}} (\phi_{i,j}(I^{HR})_{x,y} - \phi_{i,j}(G_{\theta_G}(I^{LR}))_{x,y})^2$$

B. GAS BASIC ARCHITECTURE

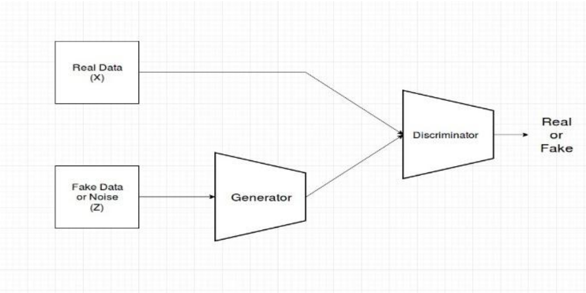

Figure 3.2: GAN basic architecture

A. Generative adversarial Networks

How GANs Work

One neural network, called the generator, generates new data instances, while the other, the discriminator, evaluates them for authenticity. i.e. the discriminator decides whether each instance of data that it reviews belongs to the actual training dataset or not.

Meanwhile, the generator is creating new, synthetic images that it passes to the discriminator. It does so in the hopes that they, too, will be deemed authentic, even though they are fake. The goal of the generator is to generate passable hand-written digits: to lie without being caught. The goal of the discriminator is to identify images coming from the generator as fake.

Here are the steps a GAN takes:

- The generator takes in random numbers and returns an image.
- This generated image is fed into the discriminator alongside a stream of images taken from the actual, ground-truth dataset.
- The discriminator takes in both real and fake images and returns probabilities, a number between 0 and 1, with 1 representing a prediction of authenticity and 0 representing fake.

III. RESULTS

Figure 4.1: High resulotion imageand Super resolution image

IV. CONCLUSION

A. Summary

The proposed approach, GAN, learns an end-to-end mapping between low- and high-resolution images, with little extra pre/post-processing beyond the optimization. With a lightweight structure, the GAN has achieved superior performance than the state-of-the-art methods. We have focused image super resolution and introduced SRGAN, which augments the content loss function with an adversarial loss by training a GAN. We conjecture that additional performance can be further gained by exploring more filters and different training strategies. Besides, the proposed structure, with its advantages of simplicity and robustness, could be applied to other low-level vision problems, such as image de blurring or simultaneous. One could also investigate a network to cope with different up scaling factors.

B. Suggestions for Future Extensions to Project

The Super-Resolution Generative Adversarial Network (SRGAN) is a seminal work that is capable of generating realistic textures during single image super-resolution. However, the hallucinated details are often accompanied with unpleasant artifacts. To further enhance the visual quality, we thoroughly study three key components of SRGAN – network architecture, adversarial loss and perceptual loss, and improve each of them to derive an Enhanced SRGAN (ESRGAN). In particular, we introduce the Residual-in-Residual Dense Block (RRDB) without batch normalization as the basic network building unit. Finally, we improve the perceptual loss by using the features before activation, which could provide stronger supervision for brightness consistency and texture recovery. Benefiting from these improvements, the proposed ESRGAN achieves consistently better visual quality with more realistic and natural textures than SRGAN and won the first place in the PIRM2018-SR Challenge (region 3) with the best perceptual index.

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