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Super Resolution Generative Adversarial Network Model parameter optimization to improve the quality of geostationary meteorological satellite images

Harimino Andriamalala RAJAONARISOA[1,*], Solonjaka RAKOTONASY[2], Fanilo RANDRIAMAHALEO[3], Adolphe Andriamanga RATIARISON[4]

[1] Dynamic laboratory of Atmosphere, Climate, and Ocean, Physics and Applications, University of Antananarivo, Madagascar
Email: hariminondriamalala@gmail.com
[2] Mathematics and Computer Science Mention, Faculty of Science, University of Antananarivo, Madagascar
Email: rakotonasys@gmail.com
[3] Mathematics and Computer Science Mention, Faculty of Science, University of Antananarivo, Madagascar
Email: fanilo.randriamahaleo@univ-antananarivo.mg
[4] Dynamic laboratory of Atmosphere, Climate, and Ocean, Physics and Applications, Sciences and Technologies, University of Antananarivo, Madagascar
Email: adolphe.ratiarison@univ-antananarivo.mg

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Abstract

The purpose of this study was to determine the "batch size" and "epoch" parameters of the SRGAN (Super Resolution Generative Adversarial Network) Model that best improve the quality of images from the Second Generation Geostationary Meteorological Satellites. The datasets used for training the model consisted of two hundred images from this satellite, including one hundred low-resolution images and one hundred corresponding high-resolution images. The images were captured by the same meteorological satellite at the same moments but in two different resolutions (low and high resolution). 80 pairs of images were used for model training, and the remaining 20 pairs were used for testing. For each combination of batch size and epoch parameters, the trained model generated an image, which was then compared to the expected high-resolution image using the PSNR metric. The PSNR evolution curves as a function of these parameters taken independently (the other parameters of the SRGAN model were set to default) helped find the optimal values for batch size and epoch.

Keywords

Artificial Intelligence, Batch size, Epoch, PSNR, SRGAN, Upscaling.

1. Introduction

The improvement of image quality through artificial intelligence techniques has been trendy in recent years. The application of these techniques covers various fields. In particular, in the field of meteorology, tracking small-scale weather phenomena requires high-resolution satellite imagery. Indeed, there are two types of meteorological satellites: geostationary and polar-orbiting [1]. Polar-orbiting satellites, due to their lower altitude, have the advantage of providing high-resolution images but do not offer the opportunity to periodically monitor the same region. On the other hand, geostationary satellites provide the opportunity to monitor the same region of the Earth. Their disadvantages are their inability to see Polar Regions and the low resolution of images as they are positioned at an altitude of 36,000 km [2].

For example, in the case of geostationary meteorological satellites like MSG, the resolution of satellite images is 3 km² for the infrared channel [3]. However, small-scale weather phenomena can have an area much smaller than the smallest detectable element by this satellite. Therefore improving the quality of these images, would allow for better tracking of small-scale weather phenomena.

In recent years, various artificial intelligence techniques have been trendy for improving the quality of images. Some algorithms such as EDSR [4] [5], LAPSRN [6], SRGAN [7], etc can be mentioned. In the context of this study, the SRGAN model was chosen. The issue at hand was the parameters of the SRGAN model leading to a better improvement in image quality.

To address this issue, an approach that involved identifying the key parameters of the SRGAN model was followed to achieve better image resolution from a low-resolution image.

2. Materials and Methods

2.1. Datasets

In the context of this research, two hundred color images from EUMETSAT, including one hundred low-resolution images [8] and one hundred corresponding high-resolution images [9] were used to train the SRGAN model. In other words, the experimental data consisted of one hundred pairs of images taken by the same geostationary satellite but in two different resolutions.

2.2. Methods

The approach established was as follows:

Step 1: Preprocessing of image data ;

Step 2: Training of the SRGAN model ;

Step 3: Testing of the SRGAN model ;

Step 4: Selection of SRGAN model parameters.

a) Step 1: Preprocessing of image data

The first operation of image data preprocessing was is resizing. Indeed, the low-resolution and high-resolution image data downloaded directly from the link [10] had the same dimension of 3712*3712. This dimension was reduced to 128*128 for the high-resolution image and 32*32 for the low-resolution image. By reducing the dimension of the images, a significant amount of time was saved during the execution of the SRGAN model training. It was then possible to approach the maximum possible value of "epoch" during the model training. Another advantage of reducing the dimension of the images before processing was the increase in the sharpness difference between the low-resolution and high-resolution images. With this difference, the model training was more effective. The second operation of the image data preprocessing was the separation of images used for model training and testing. Therefore, eighty pairs of resized high-resolution and low-resolution images were used for model training, and the remaining twenty pairs of images were used to test the model.

b) Step 2: Training of the SRGAN model

The training of the SRGAN model with the eighty pairs of resized low-resolution and high-resolution images was carried out in two steps:

- Set the batch size parameter to 1 and vary the number of epochs from 10 to 50 in increments of 10;

- Fix the epoch parameter and vary the batch size parameter from 1 to 20 in increments of 5.

b.1) The principle of the SRGAN model

The SRGAN model is a model that enhances the resolution of any image. This model consists of two deep neural networks: a generator and a discriminator.

❖ **The generator of the SRGAN model**

As Figure 1 indicates, the generator takes a low-resolution image as input and generates a corresponding high-resolution image. The SRGAN generator can be composed of multiple layers of convolution, batch normalization, and non-linear activation functions. It can also utilize residual blocks to facilitate the learning of residual features between low-resolution and high-resolution images.

The parameters of the SRGAN model's generator are:

- **Convolution layers :** The SRGAN generator consists of multiple convolution layers. Key parameters of these layers include filter size, the number of filters, the convolution stride, and the padding type.

These parameters determine how features from the low-resolution image are extracted and how the image is progressively upsampled.

- **Normalization layers :** The generator can use normalization layers, such as Batch Normalization, to stabilize learning by normalizing intermediate activations.
- **Activation function :** Activation functions, such as ReLU (Rectified Linear Unit) or LeakyReLU, are used to introduce non-linearity into the model. They determine how values are transformed across the layers.

❖ **Discriminator of the SRGAN model**

The discriminator is used to distinguish the high-resolution images generated by the generator from real high-resolution images in the training dataset. It is a binary convolutional neural network that takes an image as input and predicts whether it is real (from the training dataset) or generated by the generator. The primary goal of the discriminator is to learn to reliably discriminate between real high-resolution images and images generated by the generator. At the same time, the generator is trained to deceive the discriminator by generating images that appear real.

The parameters of the discriminator are as follows:

- Convolution Layers: The SRGAN discriminator also consists of several convolution layers that extract features from the input image. Key parameters include filter size, the number of filters, the convolution stride, and the padding type.
- Normalization Layers: Similar to the generator, the discriminator can use normalization layers to stabilize learning.
- Activation Functions: Activation functions are used to introduce non-linearity into the discriminator model.
- Output Size: The size of the discriminator's output depends on how it is configured. In general, it can be a single value (binary classification) or a map of values that represent the probability that the input image is real or generated. Figure 1 summarizes the principle of the SRGAN model.

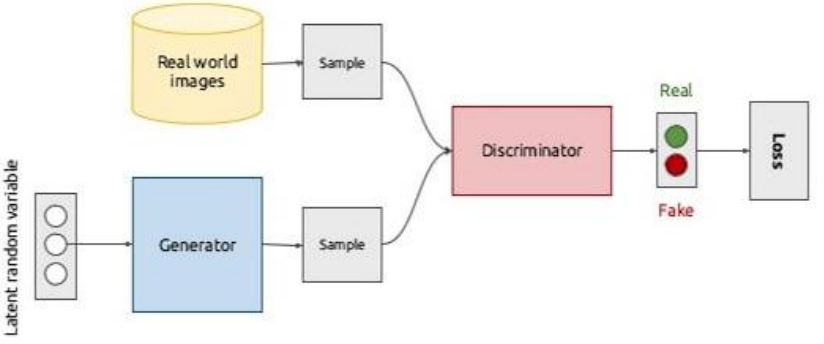

Figure 1: The principle of SRGAN model (Source: https://dev.to/manishdhakal/super-resolution-with-gan-and-keras-srgan-38ma)

b.2) The learning parameters of the SRGAN model

The main learning parameters of the SRGAN model are:

Learning rate;

Loss function;

Batch size;

Number of training iterations (epochs).

- **Learning rate**

This is the rate at which the network's weights are updated during training. Too high a learning rate can lead to instability, while too low a rate can slow down learning. In this study, the default learning rate value of the SRGAN model was used.

- **Loss function**

The SRGAN model typically uses a loss function that includes components for content loss (for similarity between the generated image and the real high-resolution image) and adversarial loss (for GAN training). In this research, the default loss function of the SRGAN model was used.

- **Batch size**

The batch size determines the number of training examples used at each iteration during training. It can impact training stability and memory requirements.

- **Number of training iterations**

The SRGAN model typically requires a large number of training iterations to converge to good performance. In this study, only the batch size and the number of training iterations were variable parameters. The other parameters of the SRGAN model were set to the default values according to the original architecture of the SRGAN model in Figure 2.

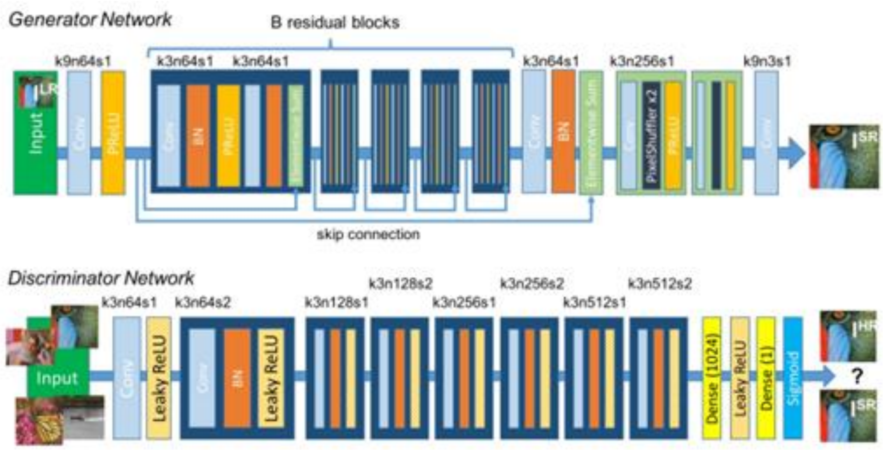

Figure 2: Original architecture of the SRGAN model [15]

c) Step 3: Testing of the SRGAN model

In this research, the SRGAN model that was trained with the selected datasets was tested using 20 pairs (low and high resolution) of image sequences that were not used during training. To ensure a more objective evaluation of the model, the difference between the high-resolution image (expected output) and the image generated by the model (from a low-resolution image) was assessed using the Peak Signal-to-Noise Ratio (PSNR) metric [16]. It is worth noting that higher PSNR values correspond to a better fidelity.

The following formula was used to calculate this metric:

$$PSNR = 10\ log_{10}\left(\frac{MAX^2}{MSE}\right) \tag{1}$$

Where *MAX* is the maximum possible intensity of the image

$$MSE = \frac{\sum_{i=1}^{n}(y_i - x_i)^2}{n} \tag{2}$$

x_i and y_i denote the intensity values of the high-resolution image and the image predicted, respectively.

n is the number of pixels.

d) Step 4: Selection of the SRGAN model parameters

The selection of the batch size and the number of iterations (epochs) is based on the PSNR metric's evolution curve concerning these parameters taken individually.

The selection process takes place in two steps:

- Set the batch size value to 1 and vary the epoch from 1 to 50. Then select the epoch value that maximizes the PSNR.
- Keep the epoch value from the previous step that resulted in the highest PSNR and vary the batch size parameter from 1 to 20 in increments of 5. The batch size value corresponding to the maximum PSNR is chosen.

After these two steps, the desired values for the SRGAN model's batch size and epoch parameters are obtained.

3. Results

3.1. The result of the PSNR evolution with respect to the epoch for a fixed batch size

Figure 3 displays the results of the PSNR metric evolution with respect to the epoch, ranging from 1 to 50, with a fixed batch size value of 1. In blue (respectively orange), it is the curve corresponding to the average PSNR of the images used during training (respectively during testing). The green curve represents the average between training and testing.

After analyzing the curve, it was found that the epoch value of 40 was selected.

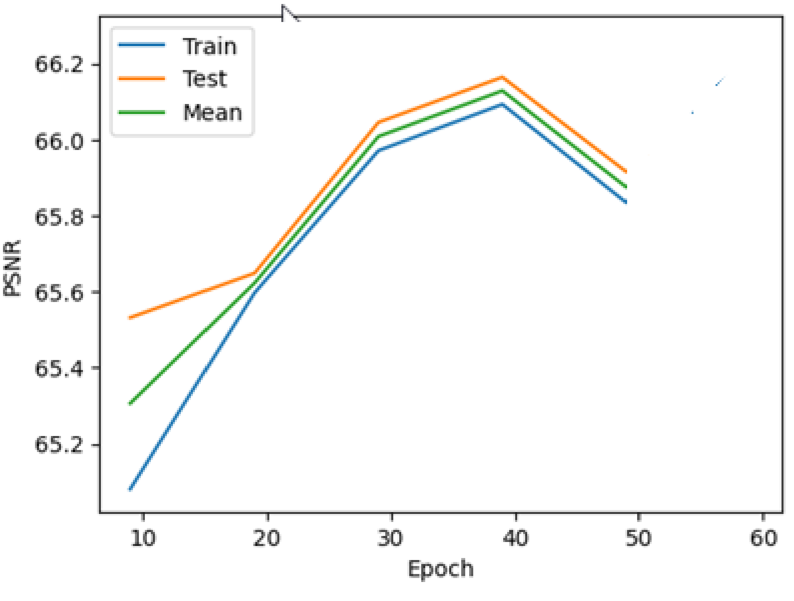

Figure 3 : PSNR Evolution Curve with respect to Epoch

3.2. The result of the PSNR evolution with respect to the batch size parameter

Figure 4 shows the result of the PSNR evolution with respect to the batch size parameter, with the epoch value fixed at 40. Like in Figure 3, there are three curves corresponding to training, testing of the model, and the average between the two.

It was observed that the curve decreased, and the batch size value of 1 corresponded to the maximum PSNR. This value was therefore chosen.

Thus, in the context of this research, the best model performance was achieved with the parameters batch size 1 and epoch 40.

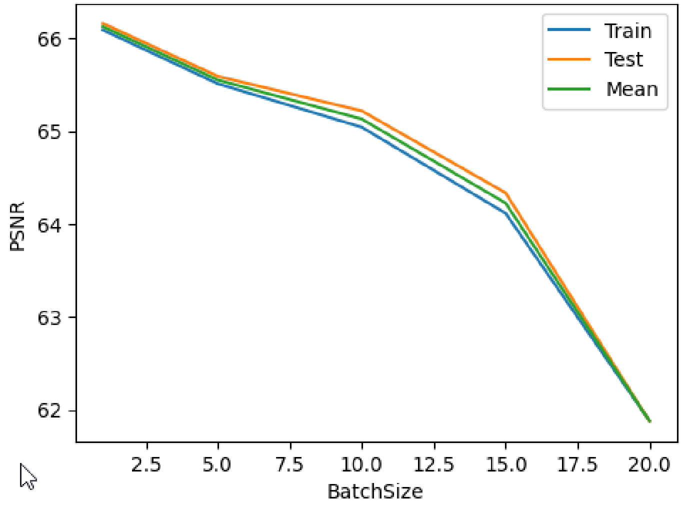

Figure 4: PSNR Evolution Curve with respect to batch size

3.3. An example of SRGAN model result with the parameters obtained

Figure 5 represents an example of an image triplet: a low-resolution image, an image predicted by the SRGAN model after training and testing, and the expected high-resolution image. The parameters of the SRGAN model were 1 for the batch size and 40 for epoch. The other parameters of the SRGAN model were set to the default values of the SRGAN model.

Through this example, could be concluded that after training and testing the model, it was capable of significantly enhancing an image.

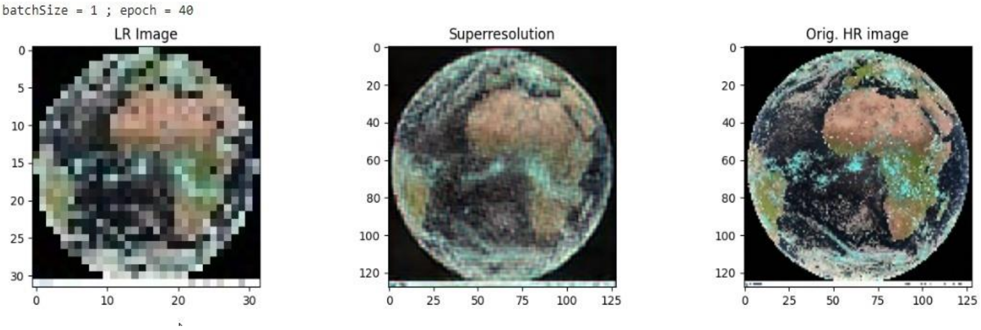

Figure 5: Image triplet: low-resolution image, image predicted by the SRGAN model with the selected batch size and epoch parameters, and the corresponding high-resolution image.

4. Discussion

The SRGAN algorithm was first invented in 2017 by Christian Ledig. At the time of its invention, the model was applied using one hundred image pairs. In this research, the SRGAN model was also trained using sequences of images from geostationary meteorological satellites. The number of image pairs used matched that of the creator's original SRGAN model. These image pairs consisted of sequences of both low-resolution and high-resolution images taken by the same geostationary meteorological satellite. It is worth noting that other researchers in the field sometimes use image processing techniques to blur images in order to create pairs of low-resolution and high-resolution images. Others use images captured by two instruments with different resolutions.

In this study, the PSNR (Peak Signal-to-Noise Ratio) metric was used to compare the output image from the model with the expected high-resolution image. It is important to mention that other metrics, such as MSE (Mean Squared Error) [17] and SSIM (Structural Similarity Index) [18], are also used for evaluation.

5. Conclusion

In this study, the training of the SRGAN model was conducted using our own datasets. It consisted of two hundred pairs of images from the geostationary meteorological satellite METEOSAT to enhance image resolution. The objective of this work was to determine the batch size and epoch parameters of the SRGAN model that yield the best modeling.

After the training and testing process, we conclude that the trained SRGAN model allow us the best image when parameters batch size equals to one and epoch equals to forty.

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