Digital Image Processing Project: Image Style Transfer

Nguyễn Trọng Nghía Lê Chí Anh

Abstract

This project focuses on Digital Image Processing, specifically exploring the topic of Image Style Transfer. Utilizing Convolutional Neural Networks (CNNs), the system identifies objects within an image and integrates the artistic style of a separate style image. By extracting features from both the original and style images, the project creates a combined output that blends the content of the original image with the aesthetics of the style image.

1. Introduction

Our problem is when we have two images A and B. Image A is the image that needs to be redrawn, renewed in the same style as Image B. After the image transfer process, the new image C is produced, which has the original object of Image A and the style or detail of Image B. We used a pre-trained model. The model used VGG-19, and the training dataset was ImageNet. We simply used this model and configured some parameters to match the paper we read. We faced challenges when using the pre-trained model, such as understanding and configuring the code. We used three indexes to evaluate: content loss, style loss, and total loss.

2. Related Work

Generative Adversarial Networks (GANs) have demonstrated remarkable success in tasks such as image generation and translation. A GAN typically comprises two components: a generator and a discriminator. The generator creates images, while the discriminator evaluates whether these images are real (matching the distribution of the training data) or fake (synthetically generated). The goal is for the generator to produce images that are indistinguishable from real ones, making it impossible for the discriminator to differentiate between them. While effective for generating and transforming images, this approach is too advanced for our scope. We opted for a simpler approach using VGG-19.

3. Proposed Method

In our approach, we utilized the VGG-19 model pre-trained on the ImageNet dataset as the backbone for feature extraction. The pipeline consists of three main components: input preprocessing, feature extraction, and style transfer optimization.

We represented images as tensors in PyTorch, where each image was resized to a fixed resolution of 512x512 pixels for consistency. The feature maps extracted from the convolutional layers of VGG-19 were stored as multi-dimensional tensors. To compute the style representation, we calculated the Gram matrix from the extracted feature maps.

The style transfer process involves several steps.

Input preprocessing normalizes the input images (content image A and style image B) using the mean and standard deviation of the ImageNet dataset.

Feature extraction is performed using the VGG-19 model. Content features are extracted from a specific layer (e.g., conv4_2), while style features are extracted from multiple layers (e.g., conv1_1, conv2_1, conv3_1, conv4_1, conv5_1).

Loss computation includes three components:

The content loss measures the difference between the content features of the output image and content image A.

The style loss measures the difference between the Gram matrices of the style features of the output image and style image B.

The total loss is calculated as the weighted sum of the content and style losses.

Loss Function: The loss function in the paper *Image Style Transfer Using Deep Convolutional Neural Networks* is defined to optimize the style transfer process. It combines three main components:

1. **Content Loss:** Content loss preserves the content and structure of the original image (content image). It is defined as the squared difference between the feature maps of the generated image P and the content image C, calculated from a specific layer (e.g., $conv4\_2$):

$$\mathcal{L}_{content} = \frac{1}{2} \sum_{i,j} (F_{ij}^l - P_{ij}^l)^2$$

where: - F_{ij}^l: Feature map of the output image at layer l. - P_{ij}^l: Feature map of the content image at layer l.

2. **Style Loss:** Style loss measures the difference between the style features of the generated image and the style image. Using the Gram matrix to capture the correlations between feature maps, the style loss is computed as:

$$\mathcal{L}_{style} = \sum_l w_l \frac{1}{4N_l^2 M_l^2} \sum_{i,j} (G_{ij}^l - A_{ij}^l)^2$$

where: - G_{ij}^l: Gram matrix of the generated image at layer l. - A_{ij}^l: Gram matrix of the style image at layer l. - w_l: Weight of layer l in the total style loss.

3. **Total Variation Loss (optional):** Total variation loss is used to smooth the output image and reduce noise:

$$\mathcal{L}_{tv} = \sum_{i,j} \left((I_{i,j+1} - I_{i,j})^2 + (I_{i+1,j} - I_{i,j})^2 \right)$$

4. **Total Loss:** The total loss combines all components:

$$\mathcal{L}_{total} = \alpha \mathcal{L}_{content} + \beta \mathcal{L}_{style} + \gamma \mathcal{L}_{tv}$$

where α, β, and γ are weights balancing the content, style, and smoothing losses.

Finally, optimization is conducted using the L-BFGS optimizer. The pixels of the output image are iteratively updated to minimize the total loss.

4. Experiment

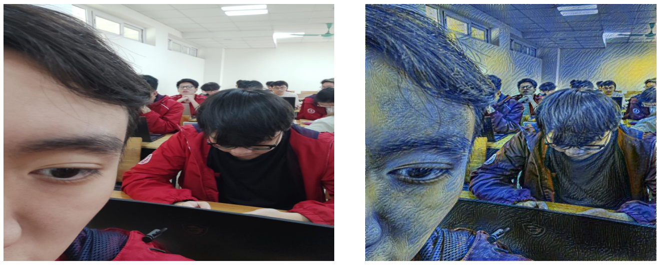
For the style transfer task, we used two images: a content image representing the structure and main content, such as a photograph of a dancing figure, and a style image, an artwork image used to transfer the stylistic elements to the content image. Both images were resized to 512x512 pixels for consistency during processing.

Loss Function We implemented the style transfer algorithm using the VGG-19 model pre-trained on ImageNet. The results include content loss, which measures the difference in content features between the generated image and the original content image; style loss, which measures the difference in style features between the generated image and the style image, calculated using the Gram matrix; and total loss, which is a combination of content and style losses used for optimization.

The generated image successfully retained the structural content of the content image while adopting the stylistic features of the style image. Below is an example of the input and output, including the content image, the style image, and the generated image

5. Evaluation

To evaluate the effectiveness of our style transfer approach, we focused on three key metrics: content preservation, style adherence, and computational efficiency.



Content Image

Style Image

Figure 1. The content image (left) and style image (right) used for the style transfer.

Content Preservation: The content loss measures how well the content of the original image has been preserved after style transfer. As expected, the content features of the generated image closely matched those of the original content image. The VGG-19 model's layers, particularly conv4_2, proved effective at capturing the high-level content information of the image, allowing for a smooth transfer of the structural elements from the content image.

Style Adherence: The style loss measures how well the stylistic features of the style image have been transferred to the content image. Using the Gram matrix, we were able to successfully replicate the textures, color patterns, and brushstrokes of the style image. The results show that the generated image adopted the style of the artwork image, maintaining recognizable stylistic features, such as color schemes and brushstroke textures, while preserving the content of the original image.

Computational Efficiency: The style transfer process, although computationally intensive, was completed within a reasonable time frame, particularly when using a CPU for the optimization steps. The optimization process was found to converge in about 300 iterations, which varied depending on the complexity of the images used. Although the model does require substantial computational resources, the results indicate a balance between quality and computational feasibility.

Overall, the style transfer method proved successful in transferring the artistic style while preserving the content of the image. The key strengths of our approach are its simplicity and efficiency, especially with the pre-trained VGG-19 model. However, further improvements could be made in handling extreme cases, such as highly complex images or very fast convergence times for certain configurations.

6. References

1. Image Style Transfer Using Convolutional Neural Networks: `https://cv-foundation.org/openaccess/content_cvpr_2016/papers/Gatys_Image_Style_Transfer_`

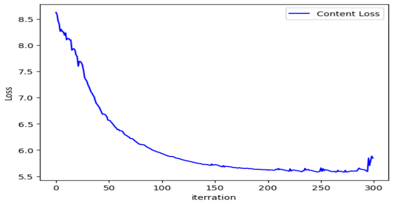


Figure 2. content loss

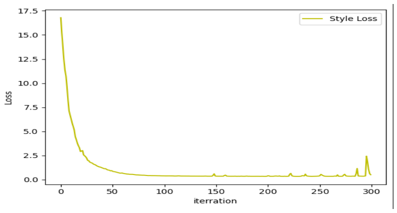


Figure 3. style loss

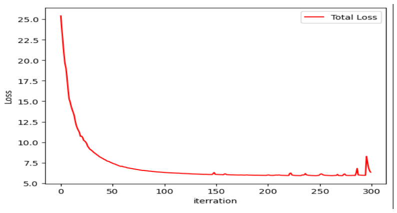


Figure 4. total loss

`CVPR_2016_paper.pdf`

2. GitHub code: `https://github.com/Aleadinglight/Pytorch-VGG-19/blob/master/VGG_19.ipynb`