Parallel Processing Project

Sri Manjusha Tella

IMAGE STYLE TRANSFER USING TENSOR FLOW

1. Abstract

The basic idea of the image style transfer is to recompose the input images by inducing change and produce a new image which has both the content and features of the input images. This can be solved using the neural algorithm of artistic style and convolution neural networks. The neural networks consist of various layers which help in understanding the given image. We will have a neural network to which we are going to input two images namely a normal image and a style image. As a result, a mixed image is produced with the content and the texture from the two input images respectively. The resultant mixed mage is mainly composed of the content from the normal image and the texture or effects from the style image. This process makes us understand the abstraction level a layer in the network has achieved in its image understanding.

2. Introduction

Paintings has been honored and praised all over the world for its unique content and texture. This uniqueness can be applied to our original photos using the convolutional neural networks which is fun to work with and gives us a whole new image which consists the texture of our favorite painting. In simple words we are recreating images in another image's context. Gatys et al. has put forth an algorithm named Neural Style Transfer which combines the content of our original photograph and style or texture of our favorite painting. Their algorithm has been successfully implemented and has produced many creative images with the style of the given artwork. The basic idea of this algorithm is to start from a random noise as the initial value and later adjust the weights of the convolution neural network we are using to get our desired stylized image.

It is being known widely that the convolutional neural networks are the efficient neural networks for recognition of objects present within the images. These neural networks work by detecting the features and use nonlinear combinations to detect objects within images. Gatys et al. has showed in his analysis that the CNN has been trained to detect objects in images. But these various trained representations are independent of each other. This means we can use the trained neural network content representation from the previous stylized images to produce a brand new stylized image.

This technique is done iteratively and is based on the concept of weighing the loss functions and normalization of these functions. We tend to create several loss functions for both the input images which are optimized. The loss function of the normal image tries to minimize the loss difference of the features that are present in the normal image and that of the mixed image which as a result produces the same content (edges and highlights) of the normal image into the mixed image.

The style image loss function tries to minimize the loss difference between the matrices dedicated to both the style image and mixed image respectively. This matrix is used to transfer the texture features of the style image into the mixed image.

3. Background and Related Work

The recent research is with algorithms surpassing the performance of humans in image classification. The primary efficient working network for all these advances in image classification is the convolution neural networks which has its hierarchical operation of reconstructing the representation features of the image content. There are many layers in the CNN. Every layer consists of many filters which slide over the given input image and create an activation map for the input image to that respective layer. Thus, CNN's can develop abstract representations of various images by overlapping a number of these layers.

Gatys et al. has proposed a neural style algorithm which had run successfully and produced various stylized images. By using CNN’s, it is possible to create multiple textured images on the same input image as the layers consist the previous feature representations.

Recent work has advanced models which are efficient in digitizing images before inputting the image in to the style loss neural network. Enhanced work on these networks have given result to many new features such as multiple color transfer, content aware style transfer, several mobile applications recreating this style transfer algorithm and color preserving style transfer.

4. Methodology

The vgg16 architecture consists of many layers of convolution plus relational units which are separated by pooling areas and lastly ends in connected layers. These various layers are used for extraction of the style and content of images.

4.1 Content and style representation

The CNN's have feature detectors which slide over the image to produce a feature map which can be viewed as filtered or scanned version of the image. The object recognition trained network layers extract the features from the image to identify the content of the image. As the layers of the network increase we get a abstract higher level representation of the image content. In this content representation it is important that we can reconstruct the identified image, but we tend to lose the exact pixel information of the input image. The style representation can be found out by determining the gram matrix of the feature map of the image.

4.2 Style transfer method

This method produces a new image which is the output image O whose content is equal to the content image C and style equals the style image S. We now define the loss functions of the content image and style image which will show us the distance to our desired generation of style transfer image O. After calculating the independent loss functions the total sum of this function is derived by adding both loss functions. This total loss equation is essential for letting us know how to produce a good stylized image O.

5. Experiments and Analysis

The style transfer algorithm mainly depends on the gradient descent of the loss functions we have calculated. We use this gradient matrix to update the output image after given number of iterations. These loss functions are in the normalized form. The user will be able to set the weights of these loss functions so that the desired mixed image can be obtained.

This model of image style transfer using TensorFlow and VGG-16 convolutional neural network model worked well. Implemented examples to observe the results produced so that the desired mixed image is being obtained as artistic output.

6. Results

Example – 1:

I have given a Panda image as the content image and a fall painting picture as my style image extracted from the internet and I have given the number of iterations as 60 and the results were as below.

```
Iteration: 0
Weight Adj. for Content: 1.85e-10, Style: 5.40e-30, Denoise: 8.51e-07
```


Content


Mixed


Style

```
. . . . . . . . . . .
Iteration: 10
Weight Adj. for Content: 2.73e-10, Style: 6.75e-29, Denoise: 4.16e-08
```


Content


Mixed


Style

```
. . . . . . . . . . .
Iteration: 50
Weight Adj. for Content: 1.51e-10, Style: 9.62e-29, Denoise: 3.79e-08
```


Content


Mixed


Style

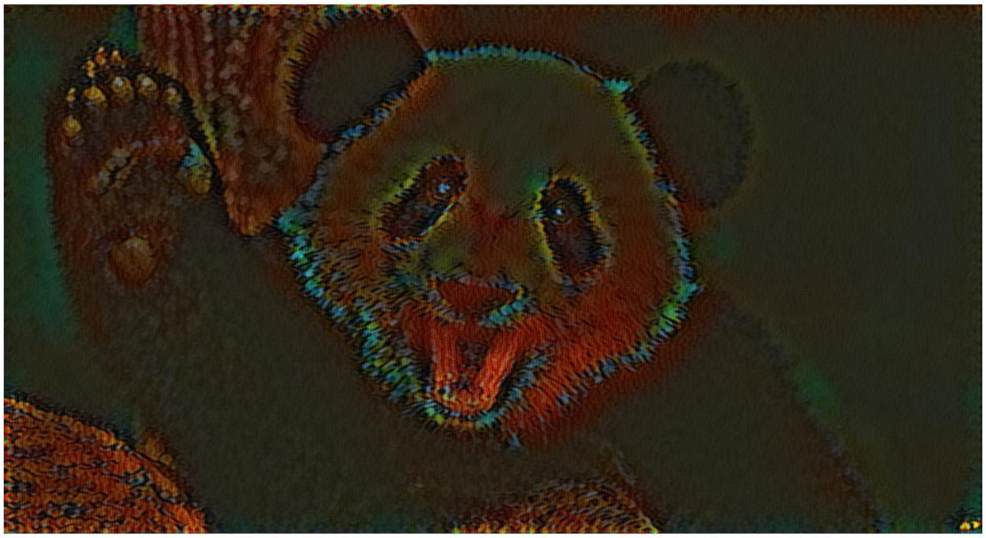
```
. . . . . . . . . .
Iteration: 59
Weight Adj. for Content: 2.03e-10, Style: 3.82e-28, Denoise: 3.94e-08
```


Content


Mixed


Style

Final image:



Wall time: 32min 46s

Example – 2:

I have given my Professor’s (Dr. Pablo Rivas) image as the content image and a tropical pattern as my style image extracted from the internet with a 1000 iterations and the results were as below.

Iteration: 0
Weight Adj. for Content: 7.14e-11, Style: 2.57e-29, Denoise: 8.01e-06

Content Mixed Style

```
Iteration: 999
Weight Adj. for Content: 1.66e-11, Style: 1.07e-27, Denoise: 1.01e-07
```

Content Mixed Style

```
Final image:
```

```
Wall time: 1h 30min 23s
```

7. Conclusion and Future Work

My experiments with the neural style transfer algorithm mainly show that potential and flexible nature of the convolutional neural networks. We are already seeing many mobile applications such as Prisma and various other websites where the style transfer is being implemented to produce stylized images. These networks can be extended further to enhance quality of the applications in fields of color preserving and multiple style transferring.

These extensions contain many interesting features and effects. However, many other interesting and advanced features may be established soon using this style transfer concept. One more future enhancement that can be applied to this style transfer is to produce different stylized effects in various regions on the same image. This will produce a more detailed image with different effects rather than one style effect.

8. Bibliography

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