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Neural Style Transfer using Deep Learning with CNN and Streamlit

[1]Zubair Iqbal, [2] Satyam Rastogi, [3] Anshdeep Tyagi, [4] Anubhav Shukla, [5] Anil Kumar

[1]Assistant Professor, [2]Student, [3]Student, [4]Student, [5]Student
[1,2,3,4,5]Computer Science & Engineering Department,
[1,2,3,4,5]Moradabad Institute of Technology, Moradabad, U.P., India

Abstract: In the field of two-dimensional image and video processing, convolution neural networks have been successfully applied to generate novel images by composing content and style of two different sources, a process called artistic or neural style transfer. However, a usage of these methods for three-dimensional objects is not straightforward due to the unstructured mesh representations of typical shape data. Hence efficient geometry representations are required to use neural network-based style transfer concepts for three-dimensional shapes and to enable the fast creation of style options for instance in a product ideation process. In this paper an overview of current state-of-the-art shape representations is presented with respect to their applicability of neural style transfer on three-dimensional shape data. Combinations of three-dimensional geometric representations with deep neural network architectures are evaluated towards their capability to store and reproduce content and style information based on previously proposed reconstruction tests.

***Index Terms* - Neural Style, Deep Learning, CNN, Streamlit.**

I. Introduction

Tensor Flow is an end-to-end open source platform for machine learning. It has a comprehensive, flexible ecosystem of tools, libraries and community resources that lets researchers push the state-of-the-art in ML and developers easily build and deploy ML powered applications. Matplotlib is for visualizing the images in our Jupiter notebook. It also allows us to save the plots if we want to keep a record of the process. Numpy is a scientific library that needs to be installed. It is one of the top libraries that work in the backend. Since images are made of pixels and are collected as multi-dimensional arrays, the Numpy library helps us work on this kind of array. Tensor Flow is a machine learning ecosystem developed by Google developers and software engineers. Many giant companies are using Tensor Flow for their businesses. Tensor Flow Hub is a repository of trained machine learning models ready for fine-tuning and deployable anywhere. It is a part of the Tensor Flow umbrella. PIL is an image processing library. Very helpful library, especially when working on computer vision projects. It is installed as pillow. We will use PIL when exporting our final result.

II. LITERATURE SUREY

Any optimization of gradient descent methods involves selecting a learning rate. Tuning the learning rate can quickly become repetitive with deeper models of image classification, does not necessarily lead to optimal convergence. We proposed in this paper, a modification of the gradient descent algorithm in which the Nest rove step is added, and the learning rate is update in each epoch. Instead, we learn learning rate itself, either by Armijo rule, or by control step. Our algorithm called fast gradient descent (FGD) for solving image classification with neural networks problems, the quadratic convergence rate o(k2) o(k2) of FGD algorithm are proved. FGD algorithm are applicate to a MNIST dataset. The numerical experiment, show that our approach FGD algorithm is faster than gradient descent algorithms.

In fine art, especially painting, humans have mastered the skill to create unique visual experiences through composing a complex interplay between the content and style of an image. Thus far the algorithmic basis of this process is unknown and there exists no artificial system with similar capabilities.

However, in other key areas of visual perception such as object and face recognition near-human performance were recently demonstrated by a class of biologically inspired vision models called Deep Neural Networks. Here we introduce an artificial system based on a Deep Neural Network that creates artistic images of high perceptual quality. The system uses neural representations to separate and recombine content and style of arbitrary images, providing a neural algorithm for the creation of artistic images.

Moreover, in light of the striking similarities between performance-optimized artificial neural networks and biological vision, our work offers a path forward to an algorithmic understanding of how humans create and perceive artistic imagery.

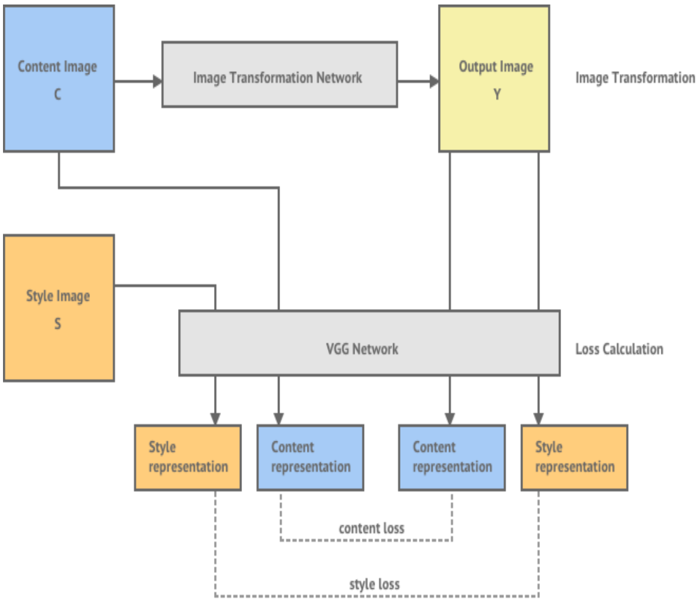

Figure 2.1: Neural Style Transfer

III. MACHINE LEARNING ALGORITHM IS USED

Gradient Descent algorithm

Neural Algorithm Prepare Your Paper Before Styling

Gradient Descent Algorithm

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Neural Algorithm

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IV. APPLICATIONS

Due to the visually plausible stylised results, the research of NST has led to many successful industrial applications and begun to deliver commercial benefits. In this section, we summarise these applications and present some potential usages.

4.1 Social Communication

One reason why NST catches eyes in both academia and industry is its popularity in some social networking sites,e.g., Facebook and Twitter. A recently emerged mobile ap-plication named Prisma is one of the first industrial applications that provide the NST algorithm as a service.Due to its high stylisation quality, Prisma achieved great success and is becoming popular around the world. Some other applications providing the same service appeared one after another and began to deliver commercial benefits, e.g., a web application Ostagram requires users to pay for a faster stylisation speed. Under the help of these industrial applications people can create their own art paintings and share their artwork with others on Twitter and Facebook, which is a new form of social communication. There are also some related application papers: introduces an iOS app Pictory which combines style transfer techniques with image filtering; further presents the technical implementation details of Pictory; [demonstrates the design of another GPU-based mobile app ProsumerFX. The application of NST in social communication rein-forces the connections between people and also has positive effects on both academia and industry. For academia, when people share their own masterpiece, their comments can help the researchers to further improve the algorithm. More- over, the application of NST in social communication also drives the advances of other new techniques. For instance, inspired by the real-time requirements of NST for videos, Facebook AI Research (FAIR) first developed a new mobile- embedded deep learning system Caffe2Go and then Caffe2 (now merged with PyTorch), which can run deep neural networks on mobile phones [104]. For industry, the applica- tion brings commercial benefits and promotes the economic development. 7.2 User-assisted Creation Tools Another use of NST is to make it act as user-assisted creation tools. Although there are no popular applications that applied the NST technique in creation tools, we believe that it will be a promising potential usage in the future. As a creation tool for painters and designers, NST can make it more convenient for a painter to create an artwork of a particular style, especially when creating computer-made artworks. Moreover, with NST algorithms, it is trivial to produce stylised fashion elements for fashion designers and stylised CAD drawings for architects in a variety of styles, which will be costly when creating them by hand. 7.3 Production Tools for Entertainment Applications. Some entertainment applications such as movies, anima- tions and games are probably the most application forms of NST. For example, creating an animation usually requires 8 to 24 painted frames per second. The production costs will be largely reduced if NST can be applied to automatically stylise a live-action video into an animation style. Similarly, NST can significantly save time and costs when applied to the creation of some movies and computer games.

There are already some application papers aiming at introducing how to apply NST for production, e.g., Joshiet al. explore the use of NST in redrawing some scenes in a movie named Come Swim [105], which indicates the promising potential applications of NST in this field. In [106], Fiˇseret al. study an illumination-guided style transfer algorithm for stylisation of 3D renderings. They demonstrate how to exploit their algorithm for rendering previews on various geometries, autocomplete shading, and transferring style without a reference 3D model.

V. Proposed Solution

In this work, we have implemented Gatys' neural style transfer algorithm and explored the impact of hyper parameter setting on the output. We implemented a spatial control extension to Gatys' algorithm and showcased successful and unsuccessful examples of adding spatial control to neural style transfer. Gatys' method is capable of arbitrary style transfer, and produces high quality output, but has high computational cost (> 1 hour CPU runtime for 500x500 image, approximately 300 iterations). All our output images are limited in resolution and contains residual noise from random image initialization. Additionally, each pair of style, content images requires custom hyper parameter tuning in order to obtain the most visually impressive result. Our spatial control method requires the user to generate two additional input masks. It enables us to obtain higher quality output for some examples, but introduces distortion at the mask boundaries, and may fail spectacularly if the target style is too photorealistic, or if image resolution is too low.

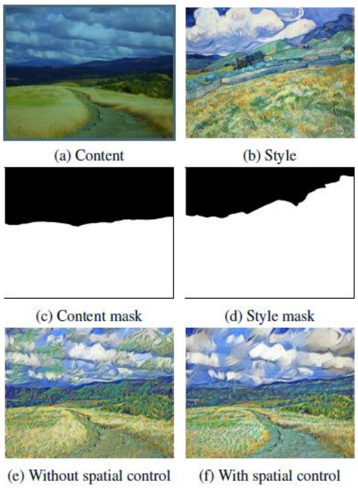

Figure 2.1: Spatial Control Example.

VI. CONCLUSION

NST, one of the exhilarating AI applications adopted for artistic use of photos and videos, has started capturing the attention of GANs researchers in the last few years. These papers consisted of a comprehensive study of GANs and Video NST, divided into four parts. Initially, the working of GANs has been explained and its recent development on the different types of models for NST on mobile devices like CartoonGAN, Artsy-GANs, etc. The unpaired images can be used for training GANs using CycleGANs. Furthermore, adding ''temporal losses'' allows consistency between adjacently generated frames as seen over multiple architectures. Then the GANs improvement papers, explaining how Spatial, Color, and Scale control can allow better image generation. Lastly, how NST can be applied over mobile devices in real-time using GANs has been explained. However, real-time NST on mobile devices with a reasonable frame rate is still relatively difficult to achieve. As time progresses, low power devices and devices with a smaller footprint will perform and handle large-scale computation better. This will be an exciting avenue to investigate, considering NST can be used in Augmented Reality. Non-iterative video NST is a good topic for future research since it can considerably reduce the time required to process videos. Since NST has vast potential, its research would see growing exponentially in coming years.

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