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Image Textural Style Transfer using Neural Network

Shubham Bhatnagar, Shubham Upadhyay, Surya Prakash Gupta, Prof. G. V. Bhole, Piyush Singh
Dept. of Information Technology, Bharati Vidyapeeth University, College of Engineering, Pune, Maharashtra, India

Abstract— In this survey paper, the purpose was to present the context aware algorithm based textural style transfer based on sporadic representation of texture fusion. The ideology behind this is to blend the style which is identified from a reference image to a source image, while the scenic attributes of the source image are conserved. The sporadic representation focuses on the extraction of the texture or style from a reference or example image(s). The actual fusion takes place of the extracted style component with the source image where the settings are optimized to conserve the true scene structure. Here, the textural style transfer is performed automatically without the required knowledge of user interest.

Keywords— Tensorflow, Machine Learning, Neural Networks, Style Transfer, VGG.

I. INTRODUCTION

Looking at the cool images that people post these days on internet which look more like a work of art or a painting by famous artists, there is whole lot of complex algorithms running underneath which are more context based and are capable of retaining the structure of the image.

The way that photo filters typically works is adding a new layer on top of the original layer and compressing and meshing them up conserving the structure of the image. These layers might have new colors or new textures in it. But these artsy filters are so much more amazing and complicated than that. In fact, they are not even filters, what's actually happening is something called style transfer. These so called “filters” commonly found in digital cameras where the user can interactively edit their photos in an artistic fashion.

Keeping in mind the various IPR(Intellectual Property Rights) issues and the various challenges for the user to create those artistic images and use them, the example based system is proposed, which reduces the amount of work and time for user to create the desired art of the image. Even though the production softwares like Adobe Photoshop which

provides a wide range and scope for these artistic filters have been proved to be inconvenient for the general user who is unaware of the use of such softwares.

There are other research work which have provided the similar kind of work , but are not practically possible, or even if they are, they are not desirable and could not achieve the quality of transfer as required.

II. LITERATURE SURVEY

The creation of interesting abstract representation of synthetic as well as natural scenes is discussed in here. Various methods for creating still and moving abstract pictures of photographs and stitched scenes.

The aim is to make the images effective, speaking images that communicate. By interactively computing a picture, we can choose and engineer the visual data to get rid of diverting details, render indication about surface emplacement, and impact the user's cognizance of the theme.[1]

The further work includes the process of image quilting for the texture or pattern the users are trying to use. This is done in order to produce a perfect and novel impression of a new image by seaming small patches of the reference image. The method mentioned here is “*quilting”* for rapid and easy synthesis, an algorithm which produce accurate results for an array of textures. The second continuation of the algorithm aim to provide texture transfer i.e. rendering an image with the texture taken from another image. It does not require other information such as 3d depth etc.

The brief nature of the algorithm is like acquiring blocks from the sample texture image, then placing those blocks randomly adjacent to each other for a ratio generalized texture, the neighboring blocks are overlapped for the constraint and at last, cutting the edges for the minimum error by computing the minimum cost path through error surface. The image to be manipulated goes through a raster scan order in terms of blocks, which is the only parameter the user can control. Randomly picking up of block with some error tolerant mechanism. The mechanism for the “quilting” proposed here works fine with all the samples of texture and images.[2]

The previous algorithm was further improved by orders of quick performance. The prior knowledge of the physical formation of the textures, they were easily synthesized by “*acceleration using Tree-Structured Vector Quantization (TSVQ).”* The textures could be produced in more efficient time even on the standard configurations. The texture model used here is Markov Random Fields(MRF) which have proved to cover the widest range of texture types. Also to avoid the further “*probability construction” and sampling ,* a pre-synthesis procedure has been deployed. [3]

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Further, the source image is processed by a framework which takes help of examples , called as "*Image Analogies."* There are two very significant stages involved , *Design* and *Application* phases. The images are in pair , where one image is the *filter-version* of the respective image. These samples of image data is used for training the framework to identify and apply the texture or filter. These filters are learnt by framework to create an analogous patterned image of the input image. The wide variety of patterns of different image pairs help in choosing from a variety of filters available for a user. There are also few textures which are improved and synthesized using previous textures. Some filters which are artistic filters, based on the paintings and drawings from the real world. Further it is also proposed for painting the texture by numbers from a real world scenes using a painting interface.[4]

The next big thing to deal with was the *color correction* which was tackled using a color transfer technique. This is simply based on the statistical analysis to imply one image's color properties on another image by choosing a suitable image for the source. This strategy simply works on a color space of three channel image , and their correlations amongst the various values are calculated so that the aspect of the pixel's color change in a coherent way. This is achieved by minimizing the correlation between the channels for all the real life scenes. The space on which it actually works was data driven by human appreciation of processing of real scenes.

Application of this technique has proved to be outstanding , even on (for example) converting a daylight image into night scene. This color space *laß can also be used for color quantization.*[5]

This *example based color transfer* was further formulated in two-step process, CAT(Chromatic Adaptation Transform) and mapping. The CAT process was designed to acquire pixels which match between the example images and the source image. Then, optimized mapping of the prevalent colors from the correlated color palettes using *thin plate splines.* To obtain a consistent color mapping , various semantic thresholds are applied which are implied in a fluid manner. The method performs extremely well leaving behind the state of art techniques for even the complex images and have been assessed by the measure, proving to be able to conserve the structure while transferring color. The change is limited to the luminescence channel, leaving no artifacts unlike the state-of-art algorithms. The proposed work equally works well for the video also.[6]

The other novel method of color transfer was also studied which also involves feature detection along with color transfer. The approach is more cluster based method of *style transfer*. The main focus of the work is preserving the light as well as color variation in the image styles. The image is divided to *Gaussian distributed clusters* by keeping in mind the features of the image to be conserved accurately. There is also included a mechanism of the classification step of the algorithm which help identifies the various feature of the image. Each group of cluster of respective identity , a *parametric color transfer* and *local chromatic adaptation transform* mechanisms are applied. The results are pretty amazing with the expected and aesthetic images which are artifacts free, totally following the style of reference images.[7]

A *Super Resolution* algorithm for a single image, based on self-learning by example and sparse representation was proposed. No high resolution training was required as the method use of learned dictionary which exploits the use of self image and self exemplar. The proposed method is faster than most present algorithms and the performance and computing efficiency is outstanding for the natural scenes.[8]

The *sparse representation* plays an important role in defining the work done in here. This is also used in image decomposition and separation . The method over here uses an analysis method called as Morphological Component Analysis which decomposes a signal into its sub parts. The method makes an assumption over mono-channel signal of being made if various layers which tend to morph individually. Two factors which play role in success of these methods are very significant , *sparsity* and *morphological diversity*. To brief, each part is distinctively represented in their respective domain and other one is incapable of representing other attributes of the mixture. MCA provides for repeated thresholding which aims at decoupling the signal matter.[9]

There were certain cases where the rain removal from a video as well as images were important to get the best result through MCA [9]. Here the attempt has been made using a single image which is very challenging to remove the rain. Framework for a single image based rain removal using MCA , where the contents are morphologically divides into high and low frequencies also using a bilateral filter[11]. Further the High Frequency component is divided into rain as well as non rain component, by example based learning and *sparse representation.* The rain component from the image and video were successfully removed and also achieved preserving original image details. [10]

The Bilateral Filtering help in achieving images with the smooth corners with non linear patterns of close image attributes. The method is easy and non repetitive, includes grey channels and the respective colors and separation value range. Unlike filters, these can imply the LAB color space and conserve edges for human perception. Unlike the standard filtering, there are no unwanted colors accumulated on the edges and also reduces them in the picture itself. [11]

The system is based on an artificial intelligence which incorporates a Deep Neural Network which creates high quality artsy images which human percept easily. The system makes use of neural methods for partitioning and stitching up style and the content of images. Mostly using Convolutional Neural Networks, where each layer is expert in recognizing different attributes of the images from input as well as the example library which is incremental. The information is stored in a hierarchical manner, which makes it easy for the layers to identify the attributes in a feed-forward manner. These layers can be assumed as a filters. After a system gets trained , it increasingly gets better at recognizing the objects and the content based pixel values. The feature correlation mechanisms helps in achieving faster results. It also gets more smart in extracting texture and style from a reference image and capturing texture information. The two important steps are content and style reconstruction.The results of the method proposed here were astonishingly amazing and outstanding and achieved better results with the faster performance.[12]

III. CONCLUSIONS

In this paper, a method is proposed in which a framework is developed which decomposes a reference image into style and non-style components. The extracted style component is matched with the example images which contain texture patterns. The incremental learning for the decomposition of style using sparse representation based MCA. Then a context aware algorithm takes place to transfer the style component from reference image to the source image based on the manipulation of previous examplar. It also conserves the image context during synthesis if style on source image. The system works well enough without the user intervention. The method also caters to high and low frequency domain in luminance channel automatically transferring style.

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