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Deep Learning Based Color and Style Transfer: A Review and Challenges

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Abstract – Deep learning methods have been applied in many fields in recent years, and successful results have been obtained. Image processing is one of these areas. One of the image processing applications using deep learning is color and style transfer. Color and style transfer is aimed at transferring the color and texture from the source image to another image (the target image). In color transfer, the colors in the source image are transferred, while in style transfer, texture is transferred as well as color. In the literature, color transfer has been studied for many years, and traditional methods such as PCA have been used in addition to deep learning. On the other hand, studies about the style transfer are relatively new and mostly realized by using deep learning methods. In this study, color and style transfer studies in the literature are examined. The methods used in these studies are mentioned, and the current problems in this field are shared.

Keywords *– Color Transfer, Neural Style Transfer, Image Colorization, Image Recoloring, CNN.*

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I. INTRODUCTION

The development of technologies such as artificial intelligence and image processing has made it possible to modify images [1], [2]. As a result of these advancements, aspects like the colorization of black and white images, the recoloring of colored images, and the transfer of color and style between images have gained popularity. As digital images can be seen as a well-known artwork using style transfer, color transfer can make a recolored image. In this paper, literature review about color and neural style transfer have been addressed. In the context of colorization, limitations and challenges of these studies have been discussed.

Color and style transfer problems are very comprehensive and hot topics and there are many studies in the literature on this subject. Graphics in Figure 1 present the number of manuscript's numbers of in the Scopus journals lists between 2014 and 2024 which include “neural style transfer” and “image color transfer” keywords, respectively.

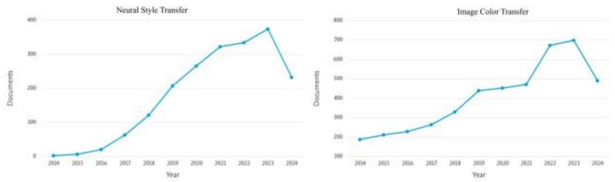

Fig. 1 Number of publications between 2014 and 2024 [3]

Figure 1 shows the number of publications for the last decade. As seen in Figure 1, the number of studies on this topic has been steadily increasing (except for 2024). Considering that 2024 is not yet complete, we expect that there will be more publications on color and style transfer at the end of this year than in 2023.

The rest of the paper is organized as follows: in Section 2, the neural style transfer and literature review about the neural style transfer are explained; in Section 3, the image color transfer and literature review about the image color transfer are explained, in Section 4, encountered difficulties about color and neural style transfers are presented, in Section 5, the conclusions are given.

II. NEURAL STYLE TRANSFER

Neural Style Transfer (NST) is the process of transferring the style of one image to another by the neural network methods [4]. This process requires a style and a context image. The artistic style, colors and texture features of the style image are considered without changing the content and structural features of the context image. Usually, deep learning algorithms are used to extract the features of the context and style images. The features of the style image are transferred to the context image and a target image is generated by doing this [5]. Today, it is possible to use the style of a painting by a famous artist who is no longer alive to obtain multiple target images that look as if they were drawn by the artist [6][7]. Figure 2 shows an example of NST [8].

The first and second column in Figure 2 shows the content and style image respectively, and the last column shows the target image obtained after the NST. The images in Figure 2 are generated using the method proposed by Gayts et al.

Fig. 2 An example of NST

There are many deep learning-based methods such as convolutional neural network (CNN), Generative Adversarial Network (GAN), Variational Autoencoder, Transformer, and Attention mechanism for the implementation of style transfer [4]. These methods are typically used in the RGB color space. Gatys et al. conducted the first study on NST in 2015 [9]. CNN-based VGG16 model was used in this study. An image depicting the Neckarfront in Tübingen was used as a content image. JMV's Shipwreck of the Minotaur, Vincent van Gogh's Starry Night, Edvard Munch's Scream, Pablo Picasso's Seated Nude Woman, and Wassily Kandinsky's Composition VII were selected as style images. The artistic styles in the style images were transferred to the content image.

Zhang et al. colorized anime images using Residual U-net and Auxiliary Classifier GAN (AC-GAN) algorithms [10]. Because anime images are randomly colored using the style transfer method, in this study, areas in the anime image were classified and colored by hair, eyes, clothing, and skin color. VGG model was used for the classification process. However, it was observed that the VGG model is feasible for classification of photographs, but not for drawings. In addition, it was observed that because the obtained colorized images were blurred, quality of these images were low.

Karadağ et al. compared the NST performance of VGG16, VGG19 and ResNet50 models using different optimization algorithms. Leonardo da Vinci's Mona Lisa, Pablo Picasso's Weeping Woman, Vincent van Gogh's Cypresses and Edvard Munch's Scream were used as style images. An image of an asphalt road was chosen as the content image. The best visual performance was achieved with the VGG19 model using the Stochastic Gradient Descent (SGD) optimization algorithm. The fastest results in terms of time were obtained using the ResNet50 model and the SGD optimization algorithm [11].

Lian and Ciu transferred the colors of hair, clothing, skin, and other features of characters in anime images to grayscale anime images. In this study, the Spatially Adaptive (DE) Normalization (SPADE) method was proposed for style transfer. It was reported that the colorized images obtained were consistent with the style image and exhibited good visual quality. However, upon examining the resulting images, it was observed that the shades of the colors in the style image and the target image did not match precisely, leading to tonal differences between the colors [12].

JinKua et al. performed style transfer and colorization in their study. The VGG19 model was used for style transfer. The style transferred black and white image was colorized by estimating the a* and b* channels in the La*b* color space. Then, the resolution of the resulting images was increased using the CNN algorithm [13].

Ke et al. proposed the Neural Preset method to solve the problems of style transfer methods such as high memory requirements and time consuming. The proposed method consists of two components. One of these components is deterministic neural color mapping. This component reduces error, blur and distortion by providing a consistent color mapping in each pixel. The other component is a two-stage pipeline for color normalization and stylization. It has been reported that the proposed method has advantages over existing techniques, such as preserving image textures, providing color properties more consistent with style images. However, it has limitations in style transfer between different colors and local color matching [14].

Virtusio et al. proposed the Neural Style Palette (NSP) method. Existing NST methods produce a limited variety of outputs. The proposed method aimed to generate various stylized images from a single style image input. A sample user interface was also developed in the study. Consequently, a user-interactive style transfer method was proposed, enabling users to maximize, minimize, or remove certain style features. [15].

Deng et al. proposed a transformer-based approach StyTr2 for NST. This approach utilized two distinct transformer encoders: content and style transformer encoders. These encoders process content and style sequences separately, while the transformer decoder stylizes content sequences according to style sequences. It has been reported that the proposed method was more successful than traditional CNN-based models but slower in terms of speed. [16].

Fu focused on the blurring problem encountered in traditional methods in style transfer studies. He proposed a CycleGAN-based method to solve the blurring problem [17]. Huang et al. proposed a method called QuantArt to improve the visual fidelity of NST. They reported that they adopted a vector quantization-based approach to ensure that the latent features of the target image generated in the proposed method are closer to the real distribution. The method was tested for digital image-to-artwork, artwork-to-artwork, and digital image-to-digital image style transfer operations, in [18].

Fang et al. colorized anime images using the style image and the coloring style given in the text. In this study, a GAN-based method with one generator and two discriminator networks was proposed. The generator network was designed using U-Net architecture. As input, the drawing was stylized and colored by taking the anime image and the coloring style in the text. One of the discriminative networks was used for color and the other for style. When the results of the study were examined, it was observed that some images had problems due to blur and color tones [19].

Zheng and Zhang colorized flower images. They proposed a two-stage method for drawing extraction and colorization. In the first stage, drawing was considered a type of style rather than edge detection algorithms. CNN-based style transfer method was used to obtain the drawing. In the second stage, image colorization was performed with GAN-based style transfer. It has been reported that the two-stage method captures the color tone and outlines better than the one-stage method. However, in some cases, the two-stage method was not able to preserve the color features of the content images [20].

Luan et al. performed style transfer between images using a deep learning approach. To improve the success of the style transfer, the colors or pixels in local regions of the image were changed by linear transformations. Furthermore, the approach is supported by semantic segmentation. The proposed method was tested in many scenarios, and realistic results were obtained [21]. Wang et al. presented a multimodal transfer method for fast and efficient transfer of artistic styles to daily photographs. In style transfer studies, a problem in high-resolution images is that local regions appear less like the desired artistic style. In this study, an approach that learns style cues (such as color, texture structure) at various scales was proposed to solve this problem [22].

Ciu presented a deep learning-based style transfer method based on HSV color space. The proposed method aimed to exploit the strengths of the HSV color space model in representing color types. In [23], the L2 distance between the H factor in the HSV color model of the style-transferred image and the content image is added to the loss function. As a result of the tests, it was reported that proposed algorithm preserves the color tone of the original content image.

Liao and Huang focus on the CycleGAN algorithm to perform style transfer. Also, they included comparisons of various loss functions [24]. NST studies usually focus on color and texture transfer and ignore other components of style. Liu et al. proposed a new network architecture that enables the transfer of both texture and geometric style. As a result of the tests, it was reported that the proposed method improves the qualitative expressive power of stylized images and shows more similarity to the target styles than other algorithms. However, some styles such as Cubism were out of the scope of this method [25].

Han et al. proposed depth extraction generative adversarial network (DE-GAN) model. In the proposed model, they applied multiple feature extractors such as U-Net, multi-item extractor, Fast Fourier Transform and MiDas depth estimation network to extract color, texture, depth features and shape masks from style images. After experimental comparisons with StyleGAN and CycleGAN, it was reported that the images produced using DE-GAN have higher image quality. However, it was reported that the DE-GAN model is a general artistic style transition network and has a worse transition effect compared to some specialized style transition methods such as CartoonGAN [26].

III. IMAGE COLOR TRANSFER

Image color transfer is the process of changing the color content of the target image by transferring the colors of the source image to the target image [27]. In the image color transfer, only color is transferred, while in the style transfer process, features of the style image such as color and texture are transferred. Figure 3 shows an example of color transfer [28].

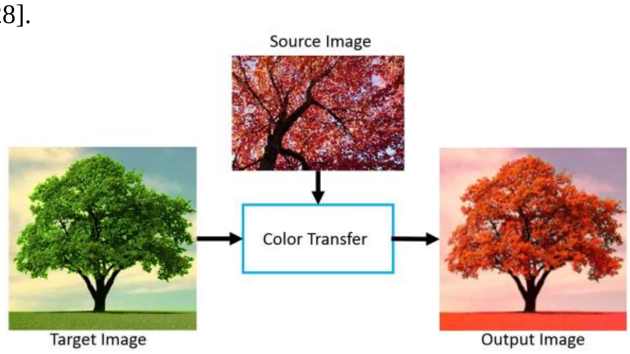

Fig. 3 An example of image color transfer

Today, color transfer is usually performed using deep learning algorithms, but it can also be performed based on statistical information, user interaction or hybrid methods [29]. One of the important studies on color transfer was conducted by Reinhard et al. in 2001. In this study, color transfer was performed using statistical information (color mean and standard deviation) in the image. It was reported that the proposed method was applied in the lαβ color space [30]. Abadpour and Kasaei also performed color transfer between images using Principal Component Analysis (PCA) dimensionality reduction method. In the study, both grayscale images were colored, and color images were recolored [31].

An and Pellacini proposed a framework in which the user marks the colors with a brush on the source and target image and performs color transfer from the target image to the source image according to the marked areas. It was reported that the proposed framework matches color distributions using a transfer function for each pair of brushes and minimizes visible distortions [32]. Arbelot et al. proposed a method for color transfer and colorization in their work. The proposed method performs local color transformations between input and reference images using an edge-aware texture descriptor. However, it was reported that the lack of sufficient similarity between the input and reference images in the proposed method negatively affects the success of color transfer [33].

Xu et al. proposed a Color Network Model to transfer colors from an image to another. This model consists of two sub-networks: source network, which describes the color information of the reference image, and target network, which indicates the target object to be colored. Color extraction from the reference image was performed with the k-means algorithm. In the study, the k-means algorithm was applied twice to perform color extraction. The limitations of the study are the evaluation of the colorized image by the designer and the many parameters that are manually determined in the process. For example, parameters such as the number of groups determined by the designer in the colorization process are manually entered. In addition, the k parameters of the k-means clustering algorithm used to extract the colors from the reference image were also determined by the designer [34].

Gu et al. reported using the Gaussian Mixture Model (GMM) algorithm for pixel-wise color transfer. They found that the proposed method produced successful results and that multiple transfer results could be obtained. However, they noted that the method struggles to produce the desired results when there are very similar color tones between the two input images [35]. Xiao and Ma focused on the fidelity problem in the color transfer. A gradient preservation algorithm was proposed to solve this problem. The algorithm was formulated as a two-stage optimization problem to achieve these goals. Furthermore, a new metric was introduced in the study to objectively evaluate the fidelity of global color transfer algorithms [36].

Lee et al. proposed a deep neural network method that uses histogram similarity for color transfer. The proposed method was tested for different scenarios where the relationship between the source and reference image was strongly correlated, weakly correlated and uncorrelated. As a result of the tests, it was reported that the method showed moderate performance for all cases and was comparable to specialized state-of-the-art color transfer methods [37]. Yin et al. proposed a color transfer method based on CNN algorithm to remove blur in images. They reported that the brightness and clarity of a blur image can be effectively recovered with this process [38].

Liu et al. performed deep learning based emotional color transfer. The deep learning model reportedly consists of four main networks: a low-level feature network, an emotion classification network, a fusion network, and a colorization network. Since the training set of the emotional colorization network was manually created, it was noted that the training and test sets are limited. As a result of, they indicated that they aim to achieve more accurate results by expanding the training set of the emotional colorization network [39]. Zhang et al. proposed a deep learning-based color transfer method for recoloring 3D models. The proposed model consists of two modules: Color Transfer Network and 3D Texture Optimization Module [40].

IV. CHALLENGES IN COLOR AND NEURAL STYLE TRANSFER

NST and image colorization are important research topics in image processing. In the literature, it is observed that various studies have been carried out by considering these two separate topics together. When these studies are examined, it is observed that style transfer and colorization have various difficulties, limitations and disadvantages. NST aims to apply the style of another image while preserving the content of an image, while colorization aims to color an image in black and white or drawing form with appropriate colors.

Color transfer is the process of changing the colors of the target image with respect to the reference image [27]. This image editing process is currently used in many different fields such as colorization of grayscale images, recoloring of color images [37], image de-blurring [38], image stitching [41][42]. However, colorization by color transfer has some limitations and challenges. Some of these limitations that we have encountered in the literature are as follows:

- *Computational cost:* For color and neural style transfer generally deep learning-based methods are used. These methods require a large amount of computing power and memory, especially when they are trained on large datasets. This can make the process time-consuming and more costly. For example, style transfer of a high-resolution image may require a high computational cost[14], [21], [22], [37].
- *Re-editing the output images:* One of the challenges is that the images obtained after color and neural style transfer operations can't be edited in real time or afterwards according to user requirements [33].
- *Lack of control:* In color and neural style transfer, images are perceived as a whole, and the transfer process is usually applied to the entire target image. Thus, it may be difficult to select local regions of the image to be colored and to assign colors to the selected regions in terms of control. However, it is possible to perform style and color transfer to certain regions of the image. For example, Ding et al. applied segmentation separated foreground objects. Then, they applied style transfer to the background and color transfer to the foreground objects [43].
- *Unnatural image outputs:* As a result of the neural style and color transfer, problems such as unnatural appearance of the output image, low image quality and resolution, or blurred image may be encountered [10], [12], [19], [21]. Such problems cause the images to look like unnatural. Figure 4 shows the unnatural images obtained after NST.
- *Color tone differences*: When transferring color and style from the source image to the target image, problems such as mismatched color tones can occur [10], [12]. Color and style transfer algorithms usually try to match the color palette of the target image with the color palette of the source image. However, in this process, some color tones of the style image may be lost, or color deviations may occur. Figure 5 shows the color tone differences in the target image after NST.

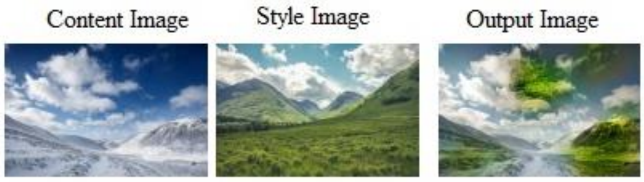

Fig. 4. Unnatural images obtained after NST [21]

Figure 4 shows green color tones in the cloud parts of the output image, so an artificial image was obtained. The output image was generated using the CNN algorithm.

Fig. 5 Image obtained after NST [10]

Analyzing the images in Figure 5, it is observed that the colors in the style image and the colors in the output image do not match each other in terms of tone, and some colors in the reference image are not included in the output image.

- *Visual fidelity problem:* The concept of fidelity can be defined as the accuracy with which the output image reflects the scene in the content image and the color distribution in the style image [18]. The more the output image obtained after the style transfer process resembles the style and content images, the higher the visual fidelity. This issue has been addressed in the literature, particularly in [18], [44], [45].

V. CONCLUSION

In this study, the studies in the literature on color and neural style transfer are discussed within the scope of image colorization. When the studies in the literature are examined, it has been seen that style and color transfer processes have various limitations and difficulties. The literature has encountered difficulties such as generating unnatural images, loss of fine details, difficult control, high computational cost, and color tone differences. To overcome these challenges, real-time, efficient methods can be developed that optimize computational costs and take user feedback into account. New research can be done on these issues. This literature review is intended to guide researchers who want to work in this field. Future works will aim to overcome these challenges by proposing innovative algorithms and techniques that balance efficiency and quality.

Statement of Conflicts of Interest

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The authors declare that this study complies with Research and Publication Ethics

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