

Application of Generative Adversarial Networks in Color Art Image Shadow Generation

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Abstract—In this research, we propose a framework based on Generative Adversarial Networks (GANs), known as the Color Shading Frame (CSF), to address the challenge of achieving ideal shadow effects in artistic creations. The CSF framework consists of two main components: Line Art Extraction and Shadow Composition. Line Art Extraction involves extracting line drawings from color images, while Shadow Composition aims to combine shadows with color images. Through these steps, the CSF framework enables the automatic generation of shadows with directional lighting effects. Experimental results demonstrate that, when utilizing neural networks as the line art extraction method, CSF outperforms traditional edge detection methods in handling noisy images with patterns resembling paper textures and images with gradients.

Keywords—GAN, Shadow generation, ShadeSketch, Line draft extraction

I. INTRODUCTION

In the realm of painting, shadows and lighting play pivotal roles as essential elements[1], imbuing artworks with depth, texture, and contextual information while conveying the atmosphere of the scene. Different shadow renderings can bestow varied meanings and lighting effects. However, creating shadows in paintings is a laborious and time-consuming process, requiring artists to painstakingly adjust the positions, shapes, and colors of shadows to convey the intended mood and scene of their artwork[2][3]. Consequently, the advent of techniques that can significantly shorten this process to a matter of seconds, such as 3D rendering[4] or neural networks, particularly Generative Adversarial Networks (GANs)[5], which utilize the adversarial interplay between discriminators and generators to reduce the extensive data needed for training, is of great significance.

Existing methods such as ShadeSketch[6] by Qingyuan Zheng et al., or SmartShadow[7] by Lvmin Zhang et al., although they can produce shadows on black and white line draft pictures, but for color pictures, a method that can produce obvious edge shadows is needed. Therefore, it is very urgent and necessary to develop a method for producing obvious edge shadows for color hand-painted pictures.

In this paper, we propose a neural network-based framework that effectively addresses the limitation of the ShadeSketch method in generating shadows on color art images. Through qualitative analysis, we demonstrate that the shadows produced by this framework exhibit enhanced depth and distinct edges compared to non-neural network-based methods. Additionally, when utilizing neural network

methods for line art extraction, this framework can handle various types of images, including those with noise, decorative patterns, solid blocks without contours, gradients, and produce fewer anomalous shadows.

II. METHOD

Since the existing method ShadeSketch has been able to successfully generate satisfactory shadows on black and white line drawings, to achieve the goal of “drawing shadows on color pictures,” it is only necessary to use a set of line drawing extraction methods to extract the color pictures before entering ShadeSketch. The drawing is converted to a black and white line drawing that ShadeSketch can handle. In addition, after the shadow map is generated by ShadeSketch, a method that can combine the color map and the shadow map is needed. Fig. 1 is the process and architecture of the Color Shading Frame (CSF), a framework designed for generating color shadows on artistic images. The input to the CSF is a color art image, which undergoes a line art extraction process to produce a line drawing. This line drawing is then used as an input to ShadeSketch, where the desired lighting direction is specified, resulting in a shadowed line art. In the final stage of the process, the shadowed line art is combined with the original color image, and through a composition process, the final output is achieved - a color image adorned with shadows.

To automatically extract line art from artistic images, edge detection methods are employed. Among these methods, the Canny edge detection algorithm[8] is commonly used, and we adopt it as one of the line art extraction techniques within the CSF framework. Canny edge detection is a composite edge detection algorithm, resembling a Gaussian function, and utilizes variational calculus. It possesses the following advantages:

1. Marks as many actual edges in the image as possible, including those caused by color differences.
2. Detects edges that closely approximate the actual edges in the image.
3. Ensures each edge is marked only once, avoiding detection of noise as edges.

However, applying Canny edge detection presents challenges. It does not guarantee that both strong and weak edges will fall within the same threshold range. Setting dual threshold parameters for each image becomes time consuming, and without specific parameter tuning for individual images, it fails to effectively handle noise, resulting in suboptimal shadow performance after processing with ShadeSketch.

Considering the limitations of the Canny method, an approach is required that can automatically determine line

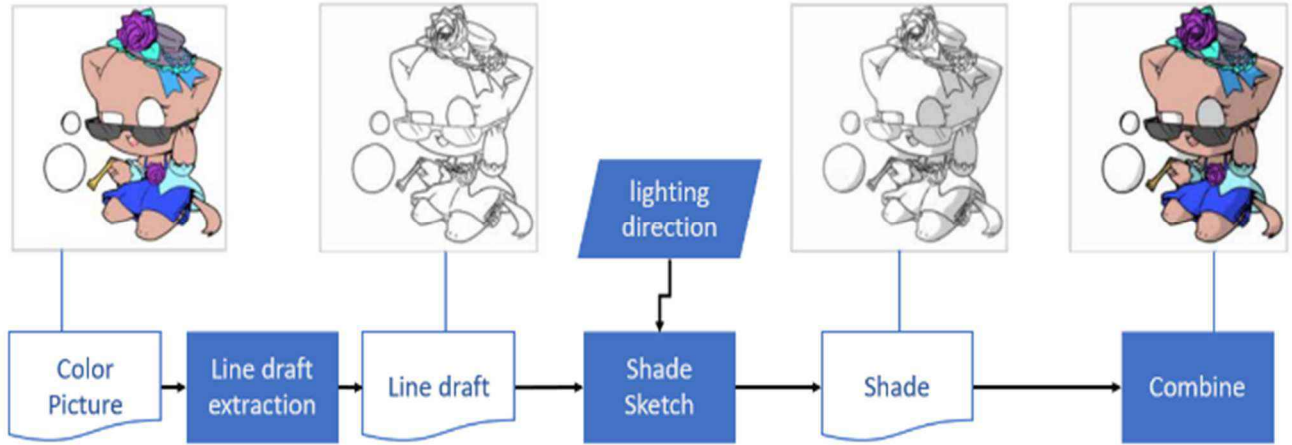


Fig. 1 | CSF architecture diagram. This is the process and architecture of the Color Shading Frame (CSF), a framework designed for generating color shadows on artistic images. The input to the CSF is a color art image, which undergoes a line art extraction process to produce a line drawing. This line drawing is then used as an input to ShadeSketch, where the desired lighting direction is specified, resulting in a shadowed line art. In the final stage of the process, the shadowed line art is combined with the original color image, and through a composition process, the final output is achieved - a color image adorned with shadows.

strength without the need for parameter settings. Data-driven neural networks can judge line importance from an artistic perspective, resembling human artists' judgment. Therefore, we opted for the SketchKeras method based on VGG-16[9], which integrates high-pass filtering and the Holistically-Nested Edge Detection algorithm[10] and is specifically trained on images with an anime-style. It not only eliminates noise but also adjusts line thickness and intensity, yielding outputs resembling human artistic creations. In the subsequent line art extraction, we will further compare the results of these two methods.

After processing with ShadeSketch, the grayscale shadow image needs to be combined with the flat-colored artwork. The combination is achieved by overlaying the shadow image onto the flat-colored image and subsequently performing color value enhancement operations. The color value enhancement algorithm is as follows:

$$\hat{C} = w \times S \times C \quad (1)$$

Where \hat{C} represents the result of combining the color image with the shadow image, C denotes the RGB values of the color image, and S represents the grayscale intensity of the shadow image. The RGB values range from 0 to 1, and each pixel's RGB value is multiplied by the grayscale intensity of the shadow image. As the RGB values corresponding to shadow regions are all smaller than 1, the result of multiplication darkens the image. To avoid excessively darkening the overall composition, a weighting factor, w , is introduced for adjustment.

Furthermore, we need to pay additional attention to the output of ShadeSketch. If the shadow image is directly combined with the color image without prior removal of the line art, it may introduce unintended black lines at edges where no prominent black lines exist. the unprocessed shadow image (without line art removal) may produce artificial edges in regions lacking distinct boundaries. This phenomenon could adversely affect the result, especially for certain art styles that do not feature prominent lines. Hence,

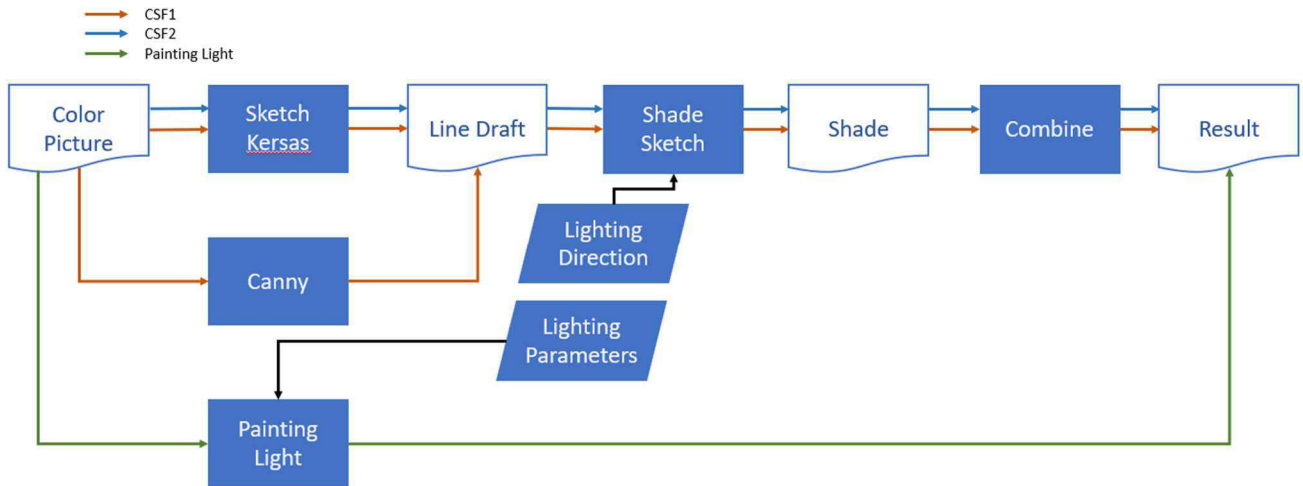


Fig. 2 The process of comparing various methods.

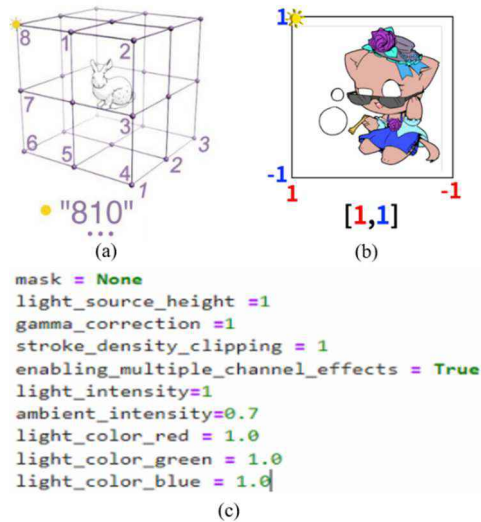


Fig. 3 Experimental lighting parameters.

before performing the combination process, we preprocess the shadow image by removing the line art to prevent the generation of unnecessary black lines.

III. EXPERIMENT

In this study, we conduct a comparative analysis of two line art processing methods within the CSF framework, and we compare them with the existing color image shadow generation method, PaintLight. The comparison is accompanied by qualitative analysis to evaluate the performance and effectiveness of the different approaches. As shown in Fig. 2, CSF1 involves a color art image, extracting

its line art using the Canny method, and providing the lighting direction to ShadeSketch for generating a shadowed line art. During the composition phase, the line art is removed from the shadowed image, and a color value enhancement operation combines the original color image and the shadowed image, resulting in a color image with shadows. Similarly, CSF2 follows the same process, but utilizes the SketchKeras method for line art extraction. The third method, PaintingLight, is an existing technique that directly generates color images with shadows by inputting lighting parameters. Unlike CSF1 and CSF2, PaintingLight does not involve line art extraction or the creation of shadowed images.

For our experimentation in shadow generation, we curated a dataset from Danbooru2021[11], specifically filtering images labeled with "Flat_Color," which indicate color images without shadows or variations due to lighting. We excluded images containing adult content, resulting in a final dataset of 2,692 images from a pool of 4 million images. These selected images can be categorized into various classes, including those with noise, decorative patterns, solid color blocks without contours, and gradients. We will employ three methods, namely Canny, SketchKeras line art extraction, and the existing color image shadow generation method, PaintingLight, to compare and analyze the outcomes on this dataset.

Fig. 3 is the experimental lighting parameters. Fig. 3a The representation of the lighting direction in the PaintingLight method is composed of three numerical values. The first number denotes the direction in the plane, the second number signifies the depth in the plane, and the third number indicates a special orientation. Specifically, the value "1" corresponds to the front-facing direction of the object, "2" represents the back-facing direction, and "0" denotes other orientations. Fig. 3b It is important to note that the positive and negative

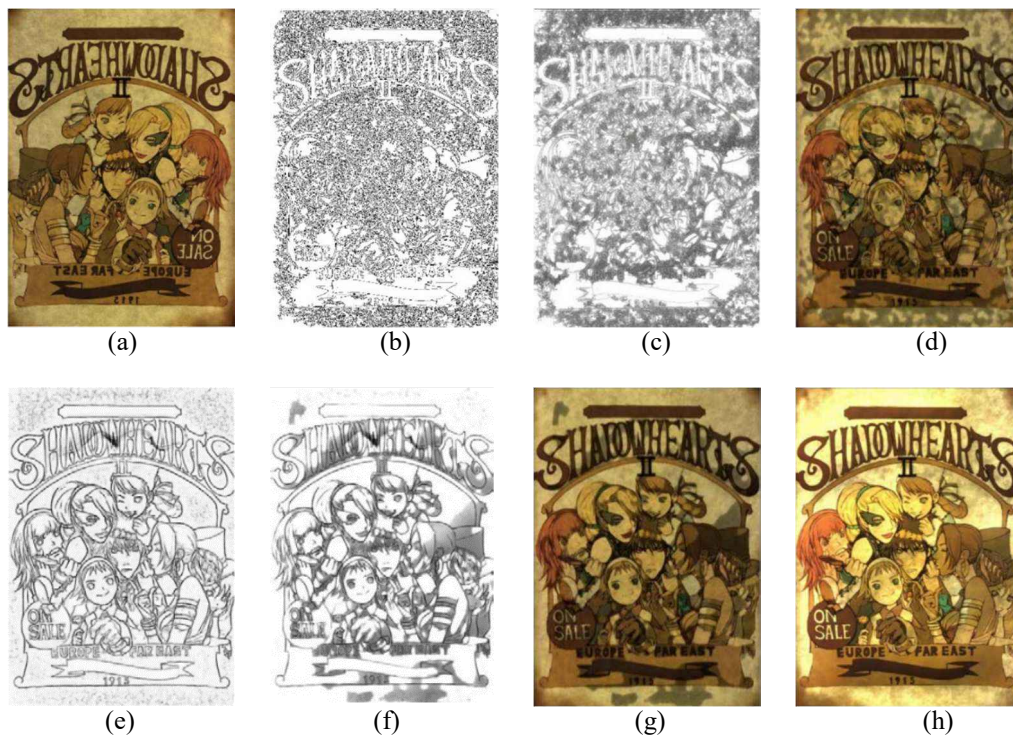


Fig. 4 The results of the experiment with the image with the paper texture.

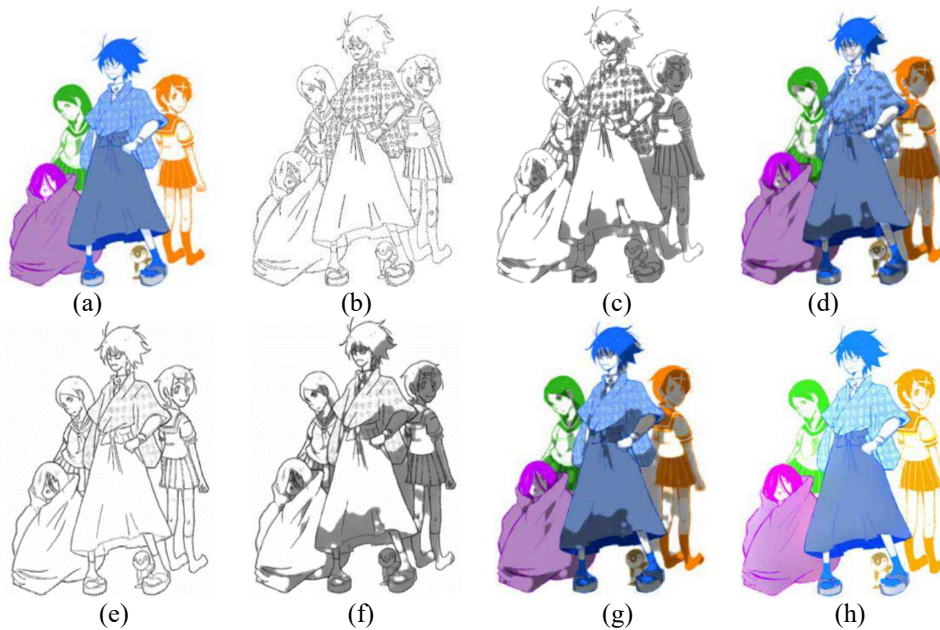


Fig. 5 The results of experiments with pictures with decorative patterns.

directions of the X and Y axes are not determined based on mathematical coordinate systems but rather governed by the program's code, where the sun icon denotes the position of the light source. The PaintingLight method allows for the adjustment of various parameters as depicted in Fig. 3c. In this experiment, the CSF1 and CSF2 methods employ ShadeSketch to represent the lighting direction, as depicted in Fig. 3a. For the current study, the chosen lighting direction is 810, located in the upper right corner in front of the object. Regarding line art extraction, CSF1 utilizes Canny with dual threshold parameters of 100 and 20, which have been determined as suitable for extracting line art from the dataset images. Conversely, CSF2 adopts SketchKeras, an automatic method that requires no adjustable parameters. In the PaintingLight method, the calculation of shadow effects involves the use of 11 parameters, as illustrated in Figure 3c, and the representation of the lighting direction is shown in Figure 3b. For this particular experiment, the selected lighting direction is [1,1]. The PaintingLight method generates shadow effects based on lighting parameters, but unlike CSF1 or CSF2, it is unable to produce distinct edged shadows and may even result in overexposed effects on certain high-brightness images. When using CSF to generate satisfactory shadows, it is essential to pay attention to the following aspects, even if CSF1 and CSF2 produce similar and anomaly-free shadows:

1. Avoid overly complex and cluttered lines within closed figures, which may obscure the object's structure.
2. Prevent the presence of noise, such as paper texture.
3. Minimize excessive color variations that can create edges, such as patterns on clothing or background decorative elements.

After processing a total of 2694 images, we used the Structural Similarity Index SSIM algorithm[12] to calculate the similarity between the shadow images generated by CSF1 and CSF2. It was found that 128 images had a similarity value lower than 70%. This subset of images includes those with

decorative patterns, distinct gradient variations, noise, solid color blocks without lines, and images containing multiple elements or other types of compositions.

Fig. 4 is the results of the experiment with the image with the paper texture. Fig. 4a is the original image. Fig. 4b is the line draft image extracted the lines by Canny method in CSF1. The shadow image generated by CSF1 through the line draft shown in Fig. 4c. Fig. 4d is the result of CSF1 combining the original image with the shadow image. Fig. 4e is the line draft image extracted in CSF2. Fig. 4f shows the shadow image generated by CSF2 from Fig. 4e. Fig. 4g The result of CSF2 combining the original image with the shadow image Fig. 4f. Fig. 4h is the result of generated by PaintingLight. In Figure 6a, it can be observed that ShadeSketch generates fragmented or unintended shadows around detected lines. This phenomenon occurs when artists add paper-like texture to their digital artworks to achieve specific visual effects. If the parameters of the Canny edge detection method are not adjusted appropriately, these textures may be detected as stroke edges by the Canny algorithm, leading to the creation of shadows by ShadeSketch around these areas.

Fig. 5 is the results of experiments with pictures with decorative patterns. Fig. 5a is the original image. Fig. 5b is the line draft image in CSF1. Fig. 5c is the shadow image generated by CSF1. Fig. 5d is the result of CSF1 combining the original image with the shadow image. Fig. 5e is the line draft image in CSF2. Fig. 5f is the shadow image generated by CSF2. Fig. 5g is the result of CSF1 combining the original image with the shadow image. Fig. 5h The result of directly using PaintingLight to generate shadow. In Figure 5a, fragmented and incomplete shadows can be observed on both the background and the clothing of the character. This occurs because artists often incorporate non-disruptive patterns into the surfaces of objects or backgrounds to enhance visual appeal. These patterns are similar to paper textures but possess regular and repetitive designs, categorizing them as decorative patterns. It is essential to note that artists typically do not outline these patterns with distinct lines; instead, they are distinguished using various colors.

Due to the nature of the Canny edge detection method, shadows resulting from color differences can also be detected as edges. In contrast, SketchKeras treats such color variations as less critical lines and reduces their prominence in the edge detection result. Consequently, when processed by ShadeSketch, the shadows generated around these areas appear more complete compared to Canny's output.

CONCLUSION

This research framework addresses the limitation of ShadeSketch's inability to generate shadows on color hand-drawn images. Chapter 3 provides a detailed explanation of the necessity of each module, and the experimental results demonstrate that employing neural network-based line art extraction methods, such as SketchKeras, outperforms Canny in handling textures and patterns, thus enhancing the efficacy of line art extraction.

Currently, while we can control the direction of the light source, we lack the ability to control the brightness of the light source and the resulting shadows, which poses a significant challenge for artists. Future work could involve incorporating user interfaces and light source brightness controls to make the method more user-friendly. Alternatively, introducing Convolutional Neural Networks (CNNs) to automatically identify camera movements in continuous animation images could enable automatic parameter adjustment for light source directions after specifying it in the first frame. Moreover, we could explore another color-based approach, such as the one proposed by Paul Centore, which considers the artist's adjustments to shadow color based on object and light source colors, including changes in brightness, saturation, and hue. This could further enhance the aesthetic appeal of the final output.

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