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Watercolor Image Processing Method for Big Data Analysis

Yunxia Zhang[1,a,*]

[1]Yanan University, The Luxun Institute of Art, The New Campus of Yanan University, Yanan, Shaanxi, 716000, China
[a]yunxia@yau.edu.cn
[*]Corresponding author

Abstract: *The colors in a watercolor painting are transparent. The watercolor style uses one layer of color over another to achieve a special transparent visual effect. Therefore, the watercolor pixel color change level is more complex, and the color edge is not apparent. The traditional image processing method is challenging to carry out high-quality image transformation, image coding, image compression, and image segmentation. This paper proposes a watercolor image processing method oriented to big data analysis. First, the collected watercolor image is preprocessed to eliminate background noise in the watercolor image. Then, the watercolor image is colorized through image semantic segmentation. Based on the semantic segmentation results, the images can be clustered by different layers. These layers are then colorized according to their properties. Finally, the colored layers are combined with a degree of transparency to get the final watercolor-style image. The watercolor obtained by this method is more consistent with the actual watercolor painting form and fully uses the advantages of big data analysis. The computer simulation of the watercolor painting process and the parallel deep learning method can significantly improve the algorithm's efficiency.*

Keywords: *Big Data Analysis, Image Colorization, Semantic Segmentation, Watercolor Image Processing*

1. Introduction

Watercolor painting was born in Britain and has gone through development for more than 200 years. From the birth of watercolor painting to the present has had a close relationship with real life. From the 16th century, applied to the overseas colonial expansion of watercolor terrain painting, to the 19th century, introduced China's moon plate painting, are the actual performance of the application of watercolor painting. Watercolor painting has essential undertaking in the practical field, such as architectural design, industrial design, commercial illustration, cartoon original painting, film, and so on [1,2]. These forms of watercolor expression are reflected in our life.

In the 21st century, many changes in traditional painting are no longer conventional innovations [3], having undergone qualitative changes in media carriers, creative concepts, creative methods, and visual expression languages. Since the early 1990s, they are using computer simulation to draw traditional painting art has become a hot topic in the field of graphics rendering. The development of the digital conventional painting simulation provides support for the virtual preview of traditional painting creation. Especially the simulation research on oil painting, watercolor painting, and other western painting art categories has achieved excellent visualization results. Digital technology diversifies traditional painting creation and makes the aesthetic sense of materials and texture more intuitive. The process of painting creation through digital technology can be integrated, interchanged, and reconstructed, which not only inspires artists' creation inspiration to deepen and optimize the theme of innovation, but also improves the efficiency of creation and accuracy.

The image processing method based on big data analysis has recently become a research hotspot [4]. Big data analytics refers to the analysis of large amounts of data. The advent of the era of big data has also laid a foundation for the development of artificial intelligence technology, such as machine learning [5], natural language processing [6], computer vision [7], robotics [8], and biometrics [9]. Some scholars have also proposed various schemes for watercolor generation by using these most advanced artificial intelligence technologies combined with big data analysis. For example, Scalera et al. studied the robotic painting system utilizing a sponge and the watercolor painting technique [10]. They proposed

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a contour-filling algorithm to finish the watercolor painting. Verdi et al. presented watercolor-like painting tools for the digital artist's generation [11]. Zhang et al. utilized the traditional image processing methods to change the color channels of color space (R, G, B channels) for generating watercolor images [12]. There are also some colorization schemes for changing the original image color, such as the interactive colorization method proposed by Reinhard et al. [13] and the blending and palettes method presented by Chang et al. [14]. However, these studies only focus on the color and palettes of watercolor paintings, ignoring the semantic information of watercolor paintings themselves. Although watercolor painting style has characteristics, they also have a distinct implied expression meaning similar to the traditional photos taken by our devices. Furthermore, these meanings of the watercolor painting contents are the concerned point of the audience. Accordingly, the main contributions of this paper are summarized as follows.

(1) A watercolor synthesis method based on semantic segmentation, similarity matrix, and a realistic image is proposed, which has high efficiency, a wide application range, and variable styles.

(2) A set of big data analysis systems for watercolor painting is established, which can effectively connect semantic information with watercolor painting.

The rest of the paper is organized as follows. Section 2 gives the methodology. The experiment is implemented in Section 3, and Section 4 gives the conclusion of this paper.

2. Methodology

This paper first collects the publicly available semantically segmented datasets, including the Gaofen Image dataset [15], Stanford Background dataset [16], COCO dataset [17], and KITTI dataset [18]. Then, this data is used to train a semantic segmentation network.

The overview of the watercolor painting big data analysis platform is shown in Figure 1. As shown in Figure 1, the system is composed of four functional layers. First, the big data analysis platform layer is responsible for the data collection, collation, storage, release, and interconnection transmission, which is the system's foundation. The second layer is the data layer, which is mainly responsible for constructing datasets, labeling, and so on. The data layer is the key and foundation of the application layer. The application layer primarily uses these data to implement various functional tasks, such as semantic segmentation, classification, object recognition, 3D reconstruction, etc. Behind these applications, layers are a series of background big data analysis algorithms, i.e., background big data analysis layer.

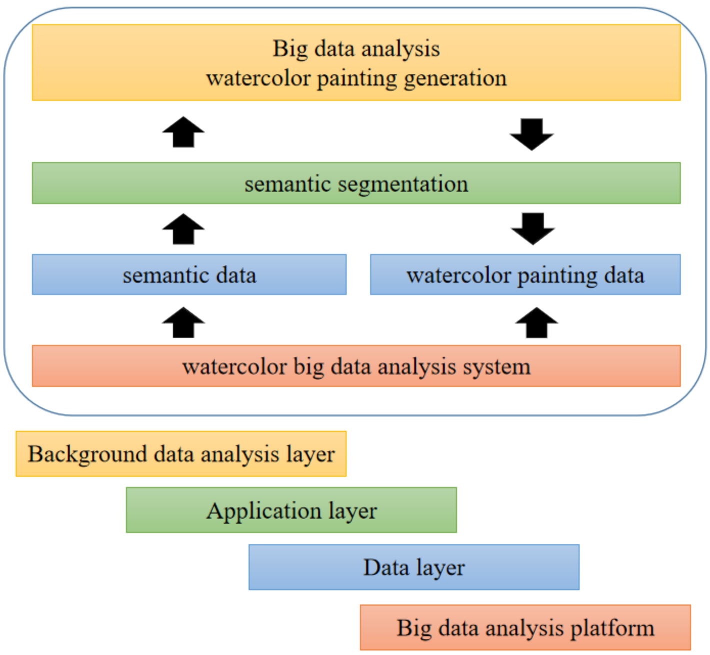

Figure 1: The overview of the watercolor painting big data analysis platform.

This paper uses the prominent architecture of conditional adversarial networks [19]. In conditional

GAN, the self-attention mechanism is structured by the generator [20]. Then, according to the needs of the task, the vision is kept focused on. The change of vision can help us obtain richer context information, which is not well reflected in the existing semantic segmentation network. Therefore, self-attention is used to extract the original attended feature. Then, the Resnet block is utilized as the following feature-extracting unit. Based on this, this paper puts forward the self-attention-based generator method for semantic segmentation. The self-attention module first processes the input image. Then the features are passed through the encoder and decoder. The encoder and the decoder are composed of Resnet blocks. The output of the generator is the segmentation result. This paper's semantic segmentation task is formulated as a classification problem. The number of categories of semantic segmentation is the number of classifications. The result is the semantic segmentation by pixel so that the semantic segmentation image can be obtained.

After translating the realistic image to a semantic image, this semantic information should be associated with the realistic image and the watercolor image color. Therefore, an association network is proposed. The inputs include the realistic image and the generated semantic image. The network structure also adapts the Resnet block architecture. These two inputs share the same weights and get the exact size feature. Then, the two features are concatenated after the feature extraction. Finally, the combined feature feeds into the last two association layer to get the association information. In this process, the original input feature is also added to the input of the first layer, which can preserve more of the original data.

We can get the association information between the realistic and semantic images. However, this information is pixel-wise after the construction of the association network. There is no similarity between each pixel and the whole image. Therefore, in this paper, we propose a similarity network to get the similarity between each pixel of two images. The similarity network extracts the features of the two association information at a higher level, respectively, and then the size gradually transforms into a vector. At this time, two vectors are obtained, and then the cross-product of the two vectors is used to obtain a similarity matrix. Then the element's value is changed to the range of -1 to 1. To achieve unsupervised training, we subtracted the similarity matrix from the label image and the similarity matrix from the generated semantic image. Then we set the trace of the matrix as their negative. The loss function is defined as the sum of the elements of the matrix.

After getting the similarity, we can utilize this weight to colorize the original image. In this process, we have already translated the semantic information into the similarity matrix. Therefore, the similarity matrix can keep the segmentation edge for each classification. Here, we add the RGB value to the original image using a preset color palette weighted by a similarity matrix. The final output image is the final watercolor style image.

3. Implementation

The original image resolution of the dataset was different from different. Therefore, we first resize the image to the exact resolution. In this way, input of different resolutions can be provided, and the relationship of two times ensures that the input of any scales has a noticeable difference in feeling when extracting features. However, too low image resolution will lead to the loss of small objects. All the networks are implemented by PyTorch 1.9.0 on the Ubuntu system. We use two 1080 Ti GPUs to train our network. The batch size of the segmentation task is set to 8. The epoch is formed to 300. We utilize each dataset to train the network and get different parameter models. This is because different dataset has a different number of classification. We use the ADAM optimizer with the learning rate of 1×10^{-5}. For association network training, we set the batch size as 64 and the learning rate as 1×10^{-4}, The epoch is set to 50k. The optimizer is also the ADAM. For the similarity matrix network, we use unsupervised training methods. In the training process, the learning rate decays to one-tenth after every 100 epochs. The batch size is set to 64 with two GPU. We utilize the python and OpenCV libraries in the final image processing step to implement the algorithm. Figure 2 is an example result of our method. The result shows that our approach is practical.

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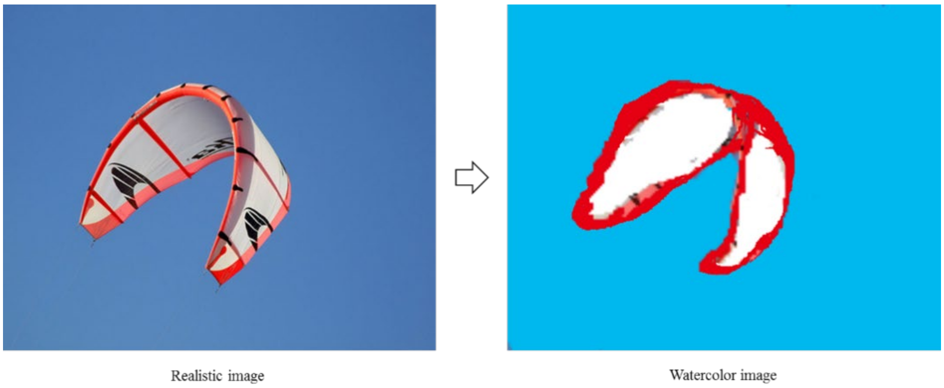

Figure 2: The experimental result.

4. Conclusion

This paper proposes a watercolor image processing method for big data analysis. The proposed system includes four layers, i.e., big data analysis platform, data layer, application layer, and background data analysis layer. Based on this structure, we present our watercolor image processing method. We first propose a translation network that can translate the realistic image to the semantic image. Then, the proposed association network can effectively establish a specific association between the original image and semantic category. We also suggest a similarity matrix estimation network with unsupervised learning. Finally, we utilize this information extracted by the above image processing methods. We can create a watercolor-style image based on the realistic image. The experimental results show that our approach is practical.

Data Availability

All data used to support the findings of the study is included within the article.

Conflicts of Interest

The author declares no conflicts of interest in this paper.

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