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Map Art Style Transfer with Multi-stage Framework

Chiao-Yin Shih · Ya-Hsuan Chen · Tong-Yee Lee

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Abstract We propose a multi-stage framework to create the stylized map art images. Existing techniques are successful in transferring style in photos. Yet, the noise in results and the harmonization in the generated art images still need to be investigated. We address these issues with a proposed algorithm that defines a good portrait for map art application in the initial round. A refinement strategy is then applied to produce the final map arts that meet the aforementioned expectations. Beside our plausible results, the objective evaluation presented in this paper shows that our proposed method can interactively achieve better and appealing map art results in the comparison with those of other works. In addition, our method can also create ocean or landscape stylized paintings using our map art collage.

Keywords map art images · NPR (Non-photorealistic rendering) · stylization · portraiture · deep learning

1 Introduction

From a style image and a content image, a new photo can be generated by transferring the reference style to the input content image. Producing such art images is not only an interesting research field but also a potential industry product. Modern artists generally use maps as background materials to create their multiple artworks. Robert Walden utilized the concept of ontology

Chiao-Yin Shih
National Cheng-Kung University, Tainan, Taiwan

Ya-Hsuan Chen
National Cheng-Kung University, Tainan, Taiwan

Tong-Yee Lee*
National Cheng-Kung University, Tainan, Taiwan

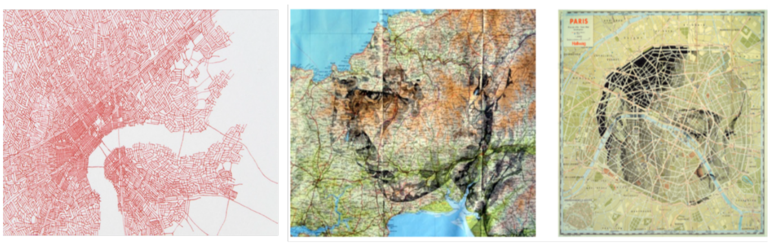
*Corresponding author and his email: tonylee@mail.ncku.edu.tw

to create his ontology road maps (shown in Figure 1(a)) and Ed Fairburn combines cartography and portraiture in his map art design. In particular, Ed Fairburn beautifully redraws and modifies intervenes with a range of original maps, especially creating gradual changes to contours, roads/streets, and other particular and natural patterns. These specially stylized drawing changes let his map art design to tease out the human feeling, giving a comfortable coexistence of photo and landscape and then to create appealing map art results such as Figure 1(b). However, such existing methods including conventional approaches and deep learning-based approaches remain challenges in the field of computer graphics, image processing, and multimedia.

Our current study is motivated by the Neural Style algorithm by [5]. Given a style image and a content image, such a map art system [5] generates a new image that has the content and the style are transferred from the two input images. Unlike the introduced style transfer technique in [5], we propose a multi-stage framework. The proposed method aims to overcome the noise as well as to gain a better harmonization in the map art results. In the first stage, we use an reference style image and a content image to generate an initial map art. Thereafter, a proposed refinement strategy is employed to produce the final map art result. Our contributions can be summarized in following three issues:

- A multi-stage framework to generate map art.
- We propose a method to extract a good feature map for our map art application.
- A new version of Gram matrix in style loss function to reduce the noise of map art results.

The remainder of this paper is organized as follows. In Section 2, non-photorealistic rendering technique and photographic style transfer are introduced by a brief discussion on the related studies. In Section 3, the multi-stage framework used in our proposed map art system is explained. In Section 4, the evaluation results are described and the discussion on our results follows. The conclusions and future work are presented in the last section.



(a) Robert Walden's work. (b) Ed Fairburn's work.

Fig. 1 Map art image examples.

2 Related work

Non-photorealistic rendering[1] (NPR) techniques have been intensively used to generate many artistic styles for images such as abstract, stroke-based and oil painting styles. Hertzmann [6] presented a survey of stroke-based rendering in 2D NPR research. Example-based NPR techniques [4, 18] have been very popular and successful in generating visually pleasing NPR results. The example-based approach transfers the styles of sample paintings to the synthesized paintings. In addition, several techniques have also been developed to render 3D models, for example, the polygonal mesh technique [3, 17, 2, 8] and the 3D points technique [1, 23]. These 3D NPR techniques draw different strokes over the surface of a 3D model, including line drawings, decal strokes, and hatching strokes. Furthermore, to overcome the difficulties in NPR, a novel technique presented by [24] generates painterly art maps (PAMs) for 3D non-photorealistic rendering. Their technique can automatically transfer brushstroke textures and color changes to 3D models from samples of a painted image. Later, [9] extended this work to achieve interactive visualization of anatomic models and adding stroke texture synthesis can enrich medical object illustrations. There are also some multimedia research on beautification of NPR on QR code design [12] and multimedia resizing [13].

Fig. 2 (a) Reference style image, (b) input content image, (c) input map, (d) our map art result.

Among these previous studies, many NPR approaches concentrate on converting photographic images into artistic images. Photographic style transfer is mentioned as an NPR problem. Such research attempts to transfer the style of a reference style photo onto another input picture. Our current study is related to this problem and focuses on creating stylized map art images (as shown in Figure 2).

With the dramatic advances in deep learning – based approaches in recent years, many researches handle a large variety of image content while faithfully

[1] https://en.wikipedia.org/wiki/Non-photorealistic_rendering

transferring the reference style to the target images. Mentioned as the original work, [5] introduced a neural algorithm of creating artistic style images and their approach automatically learns the artistic styles through convolution neural network. Their method considers features of content and styles from the images, and then synthesizes the target image. Their approaches firstly used the pre-trained VGG-19 model [21] to extract the features from contents and styles of image. Then they iteratively minimizes the loss between the input and the target to make the target image have the information of the content and the style from the input. However, when simulating the style of the picture, the edges of output cannot be maintained well and distorted. Built upon the recent deep learning – based works on painterly transfer, [15] proposed to solve the problem of edge distortion and yields satisfying photorealistic style transfers. For synthesizing 2D images, [10] proposed a study to combine Markov random fields and convolutional neural networks (CNNMRF). Since this approach is based on small pieces of pictures, the results can be very detailed. Later, [16] presented a method to copy an object in a photo and paste it into a painting so that it still looks like a genuine painting in the style of the original painting. [25] proposed the Cycle-GAN method to produce amazing results in transferring an image with a painter's style. However, this approach is not stable, requires much more time and large number of unpaired content and style images for training. The study in [20] investigated a technique for transferring the painting from a head portrait onto another. This approach better captures the painting texture and maintains the integrity of facial structures. [14] proposed a robust approach for portrait style transfer that gets rid of dense correspondence and their approach is based on the guided image synthesis framework. Their method combines deep neural network with detected facial landmarks and can obtain accurate results for the whole image in portrait style transfer. To transfer Chinese painting, [11] presented a multi-scale neural network. Yet, their method is not end-to-end, and requires sketches or edges for input. To provide a comprehensive discussion on Neural Style Transfer, a detailed survey of the algorithms in this field is presented in [7]. For more discussion about other related work, please see [7].

In contrast to aforementioned works, we propose a multi-stage framework to generate map art results. Relying on the feature maps obtained from the well-known VGG-19 network [21], the good portraits for our map art application are extracted through the proposed strategy in our study. In addition, with the updated version of Gram matrix in style loss function, we can reduce the noise in output map art images and boost our map art results more harmonization.

3 Proposed Multi-stage framework

Given a reference style image and a content image, output of our system is a new map art. Our map art result has two properties: (1) the content is generated from input content image (2) the style is transferred from the input reference artwork. The proposed system consists of two stages in the terms of "*Initial stage*" and "*Refinement stage*", as shown in Figure 3. The initial stage's job is to generate an initial map art. Meanwhile, refinement stage's job is to produce final map art through refinement operation. Accordingly, three processes operated in two stages are portrait extraction, style transfer, and refinement. Specific operations of our multi-stage system are described in detail as follows.

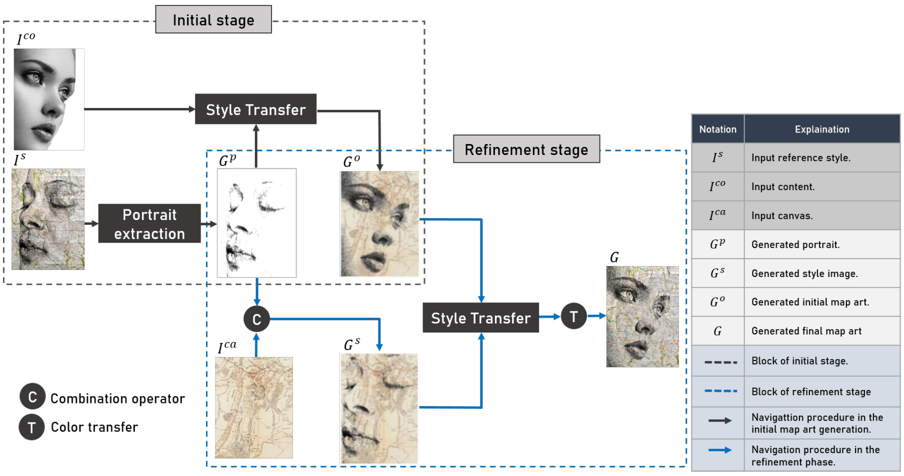


Fig. 3 System Overview.

3.1 Portrait extraction

The first purpose of our map art system is to extract the portrait from the reference map art and then uses it for the style transfer step. Therefore, analyzing the information of the style in the reference map art is a prerequisite in our proposed method. For this process, the VGG-19 network [21] is used. This well-known network is trained with ImageNet dataset [19] and has excellent performance in image classification, object detection, etc. Besides, there are number of deep learning - based studies in style transfer adopted VGG-19 to extract features in their system. Thus, the pre-trained VGG-19 network is suitable to adequately extract features from style or content images. This network consists of 16 convolution layers and 5 pooling layers that form five convolutional blocks (as shown in Figure 4). [5] showed that the first few layers of VGG are sensitive to style of the image and later layers are sensitive to the content. Guided by this deep learning-NPR work, we utilize layer $conv1\_1$ in pre-trained VGG-19 to get features from the reference style image.

Each layer in VGG is applied by the different number of filters. In the demonstration of the VGG-19 network in Figure 4, we can see layer $conv1\_1$

uses 64 kernels. Thus, there are a total of 64 feature maps extracted at this layer for our map art application. Each feature map represents the different features of the corresponding image. The question here is which feature map

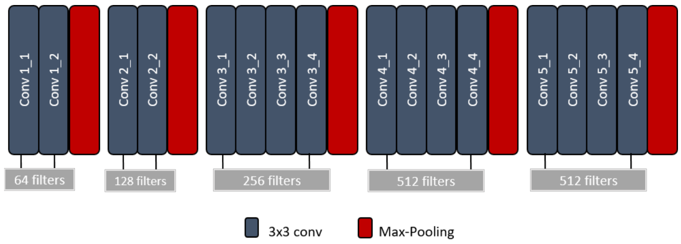


Fig. 4 VGG-19 convolutional neural network (CNN) with 16 convolution layers and 5 Max-pooling layers [21].

could be used as the extracted portrait for our map art application. To solve this issue, we measure the structural similarity index (SSIM) [22] between the aforementioned feature maps and a "*base image*". SSIM measurement is introduced in [22] to quantify the differences between two images. This score is in the range from 0 to 1. The higher of SSIM is, the two images are more similar. We use the terminology "base image" to refer to the image that contains the basic information of the reference map art such as edges, dots, etc. We do not directly use the reference style image in this process since it contains all of the image information. Utilizing this original image in SSIM will result in an extracted portrait with noise. Thus, we propose a kernel to filter the reference style image. The "base image" is strategically operated a convolution filter as followed:

$$g(x, y) = w * f(x, y) \tag{1}$$

, where $g(.)$ is the "base image", $f(.)$ is the reference map art, $*$ denotes the convolution operation, w is the filter kernel. The proposed kernel is defined as:

$$w = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -2 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

In image processing[2], kernels with different element values result in different effects on the same image . Motivated by this, we propose the kernel that meets our expectation in a "base image".

Once the "base image" is generated by equation (1), we adopt the structural similarity index measurement (SSIM) to specify the portrait (G^p) as followed:

$$G^p = max\big(s_i(g, F_i)\big) \tag{2}$$

[2] https://en.wikipedia.org/wiki/Kernel_(image_processing)

(1-a) (1-b) (2-a) (2-b)

Fig. 5 Visualization of "base image" that is generated from the corresponding reference map art. (-a) Reference map art, (-b) "base image" generated by our proposed kernel.

, where $s_i(.)$ is SSIM score; F_i is the i^{th} feature map at $conv1\_1$; $i = 1 \ldots 64$; g is the "base image" obtained from equation (1). Using equation (2), the feature map that has the highest SSIM score is utilized and selected as the portrait. With this strategy, we can specify the feature map that is most suitable to treat as the sample style for generating new stylized photo. Figure 5 demonstrates the visualization of the "base image" after employing the proposed filter on the reference style image. Taking the Figure 5 (1-a) as a sample input, the SSIM score between the corresponding "base image" and its feature maps are shown in Figure 6. In this chart, the 40^{th} feature map has the highest score, thus it is selected as the portrait in our map art application. Besides, the visualization for the set of feature maps and the extracted portrait on the mentioned sample input are depicted in Figure 7.

Fig. 6 SSIM score between "base image" and 64 feature maps of the sample input in Figure 5 (1-a). The red rectangle is a mark of the feature map that has the highest score, i.e., the 40^{th} feature map.

3.2 Style transfer

The second purpose of our map art system is to transfer the style in the extracted portrait to the input image. To achieve this, our style transfer process

Fig. 7 (a) The reference style image, (b) the set of feature maps ($F_1 \dots F_{64}$), (c) the selected feature map, i.e 40^{th} feature map.

is based on neural style transferring using CNN [5]. The objective function in [5] is minimized as follows:

$$I^* = \arg\min_I L_{total}(I_c, I_s, I) = \arg\min_I \alpha L_c(I_c, I) + \beta L_s(I_s, I) \quad (3)$$

In equation (3), I, I_c, I_s is the output map art, the input content image, and the input style image, respectively. L_c is the content loss function (i.e., makes the content of output the map art I equal to the input image I_c) and L_s is the style loss function (i.e., makes the style of the output map art I equal to the input style image I_s). We get the final output by minimizing L_c and L_s. Both α and β are the weights of content and style loss functions used to adjust the proportion between content and style. When α/β is bigger, the output and photo contents are closer. For more details, see [5].

Contrast to [5], we perform style transferring based on our portrait extracted from the first step. Using CNN, a given input image $\vec{x}$ is encoded in each layer of CNN by the filter response to that image. The response in a layer l can be stored in a matrix $F^l \in R^{N^l M^l}$ where F^l_{ij} is the activation of the i^{th} filter at position j in layer l. However, using CNN, the extracted portrait of the map art is usually composed of discontinuous patterns. When converting the image (Figure 8(b)) based on this extracted portrait (Figure 8(a)), the transferred image is easily affected by these unpleasant discontinuous patterns, and there is some noise in the transferred image (Figure 8(c)) after the conversion. Therefore, we subtract feature from its standard deviation to reduce this noise generation.

$$G(F^l(I_s)') = [F^l(I_s)' - std(F^l(I_s)')][F^l(I_s)' - std(F^l(I_s)')]^T \quad (4)$$

The equation (4) is called the Gram matrix in [5]. After using the method mentioned above, the output image still looks gray, i.e., dark (as in Figure 8 (d), in order to alleviate this problem, as shown in equation (5), we multiply the $l+1$ layer instead of multiplying by the l layer in equation (4) and then get the final transferred result in Figure 8 (e). The idea of our proposed neural style transferring can be illustrated in Figure 9. The equation (5) is our new Gram matrix in this paper:

$$G(F^l(I_s)^{'}) = [F^l(I_s)^{'} - std(F^l(I_s)^{'})][F^(l+1)(I_s)^{'} - std(F^(l+1)(I_s)^{'})]^T \quad (5)$$

['hbt!']

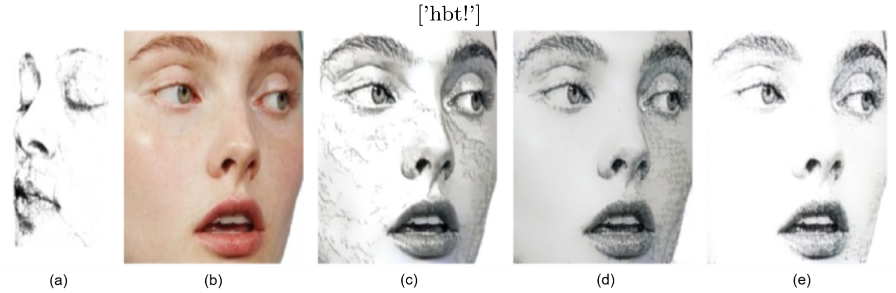


Fig. 8 Style transferring photo (b) according to (a) style. (c) is the original Gram matrix function (equation (4)), (d) is the subtracted std function, and (e) is the transposed matrix function (equation (5)) multiplied by the different layer features. The noise seriously occurs on (c) face, (d) is too dark, and (e) is brighter than (d).

3.3 Refinement

To make the final output map art more harmonious to the reference map art, we propose to refine the initial result. We feed input images into the style transfer model the second time to get the final map art. However, in this phase, the map art result obtained from initial stage is treated as a content image. As the notation table we show in Figure 3, we use it as an initial result (G^o). Meanwhile, the style image (G^s) is generated by pasting the extracted portrait (G^p) on an input canvas (I^{ca}). Once content image and style image are achieved, they are fed into the style transfer model to produce the final output map art (G). We regard to note that, the Gram matrix we improve in equation (5) is also employed in this refinement stage. Finally, to boost the final output map art to be more harmonious to the input reference map art (I^s), the color of G is converted to the color of I^s.

We demonstrate the effectiveness of the refinement part in Figure 10. It is obviously shown that, by strategically substituting the inputs of the style transfer model, we obtain a better result (Figure 10 (e) compare to the initial map art result (Figure 10 (d). Accordingly, the final output is more harmonious to the input reference map art by color converting operator (as shown in Figure 11).

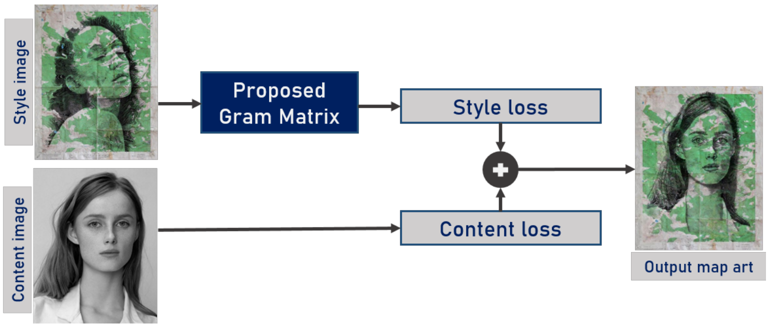


Fig. 9 The demonstration of the style transfer model employed in our system.

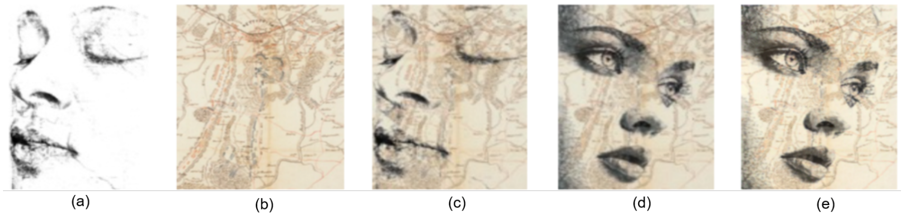


Fig. 10 (a) generated portrait, (b) input canvas, (c) generated style image, (d) initial map art, (e) final map art.

Fig. 11 (a) input style image, (b) the final map art before color transferring, (c) the final map art after color transferring.

4 Experimental Results

We begin this section by an objective evaluation. Later, a discussion on our results as well as an objective evaluation-based is presented.

4.1 Objective evaluation

We conduct user studies to quantitate the quality of our results. Beside our method, two typical methods for this map art application are chosen in this survey. They are [5] (Neural Style) and [10] (CNNMRF). The source code of these two methods are published by the authors, thus they are trustful enough to use. A total of 50 participants are invited to join in our user studies. They are of different ages (age range of 20-35) and background. Our map art data contains 15 sets. Each set consists of an input style image, an input content image, and a map art result. We apply three methods ([5], [10], and our method) to all these 15 sets. We run two user studies to (1) measure the harmonization of our results, and (2) compare our results with the two mentioned methods.

In the first study, we show the participants three images in a set, which consists of a reference style image, a content image, and a map art result generated by our system. We ask them to independently evaluate the harmonization of our results and annotate as one of the following five levels: *bad, poor, acceptable, good, excellent*, which correspond to scores of $0, 0.25, 0.5, 0.75$, and 1, respectively. Thereafter, we compute the average score from 50 participants as the harmonization evaluation of each map art result in our data. The higher score means better harmonization quality.

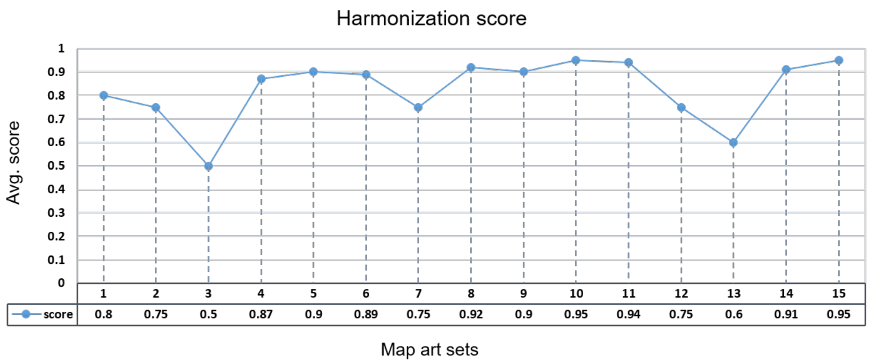


Fig. 12 Evaluate the harmonization evaluating scores of our results.

The objective evaluation of comparison is conducted on the second user study. In this study, for each map art set, we first show the participants the reference style image and the content image. Following were three map art results generated by the three aforementioned methods. The map art results were displayed in random order to prevent participants from inferring the map art method. The participants were not provided any method information. We simply ask them to choose which map art result that they had a perceptual feeling it is the best among the three tested map art images. We received 50 answers on 15 map art sets. The number of votes on a map art result is performed in percentage. That is, a method that has a higher percentage means map art result generated from that method is better. The quantitative results are shown in Figure 16.

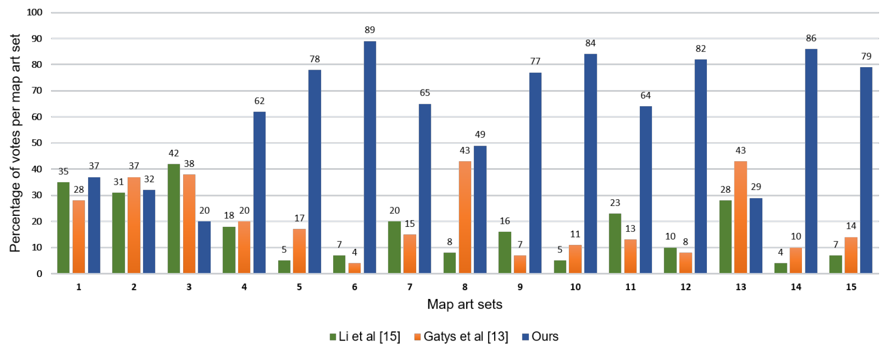


Fig. 13 Objective evaluation of comparison between previous results and ours.

4.2 Discussion

In term of harmonization, we show the harmonization score of our results in Figure 12. The score of each result is normalized in the range from 0 to 1. Based on the scores in this figure, most of our map art results are harmonization. Even three of our results do not have a high score they are still in acceptable level.

Based on the objective evaluation from participants in this Figure 13, most of our results are better than two compared methods. With the utilization of the good feature maps, the map art results obtained from our system have a better performance. The highest score is given to the 6^{th} map art. Figure 14 depicts the results of this map art set. The generated portrait image, Figure 14 (2-b), contains more information on the input reference style image (Figure 14 (2-a)). Consequently, the map art result (Figure 14 (2-d)) not only preserves the content in the input content image (Figure 14 (2-c)) but also has a good harmonization. Nevertheless, if the extracted portrait falls in the lack of information of the input reference style image (as shown in the first row of Figure 14), map art result does not have a good performance, such as the 3^{rd} map art set in Figure 13. We visualize the data of this map art set in Figure 14.

In term of execution time, our method takes 8 to 10 seconds to obtain a result. CNNMRF [10] runs for about 70 to 90 seconds and Neural Style [5] takes longer (about 3 to 4 minutes). Figure 15 and Figure 16 shows more results created by the proposed method. In addition, an artist Matthew Cusick creates figure or landscape paintings using map collage. We combine the photo with a single map and use our method to transfer the background map color into a style and by this way we can produce similar results to his work style as shown in Figure 17. Finally, we show a bad example in Figure 18. In this example, we put the portrait on the map without considering the content of the map, so if we need to consider the edges on the map (a) to paint the map art of the portrait, we can't make a similar artistic style in (c).

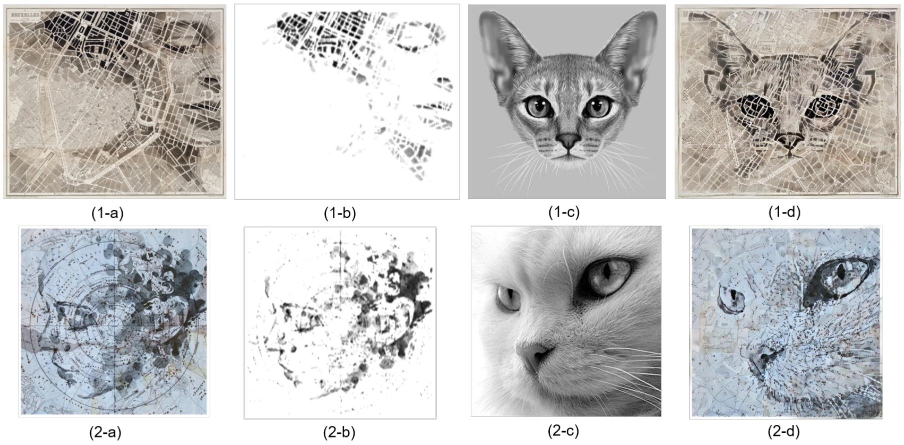


Fig. 14 The demonstration of the 3^{rd} and 6^{th} map art set inferred from Figure 13. The first row represents for the 3^{rd} set, and the second row is the 6^{th} set. (-a) the input reference style image, (-b) the generated portrait, (-c) the input content image, (-d) map art result.

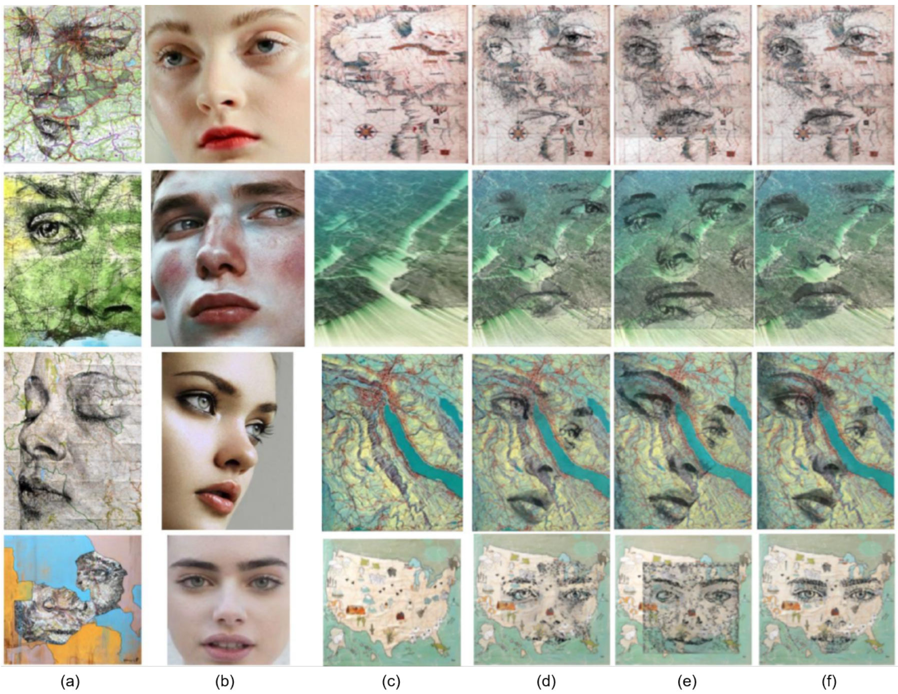


Fig. 15 Our experimental comparison: (a) input map art (b) a new photo (c) a new map, (d) is created by [13] and (e) is by [15] and (f) our result.

5 Conclusion and Future work

In this paper, we have presented a multi-stage framework for map art style transfer, which can be used to reduce the noise map art images and produce

(a) (b) (c) (d)

Fig. 16 More results created by the proposed method, (a) input style image, (b) input map, (c) input content image and (d) our result.

a better harmonization in such these results. The proposed framework utilizes a reference style image and a content image to produce an initial map art. A refinement strategy is then employed to generate better map art images. We demonstrate the effectiveness of our framework by an objective evaluation with those of other works. Experimental results prove that the proposed scheme performs well among other methods. We finally show a bad example and in the future, we plan to explore a solution to cope with this problem. Besides, it will be interesting to first remove the original photo from map art to re-generate the map and then combine a new photo with this re-generated map. It will be more challenging how to recover the original map successfully and create a new map art with this regenerated map in our future research.

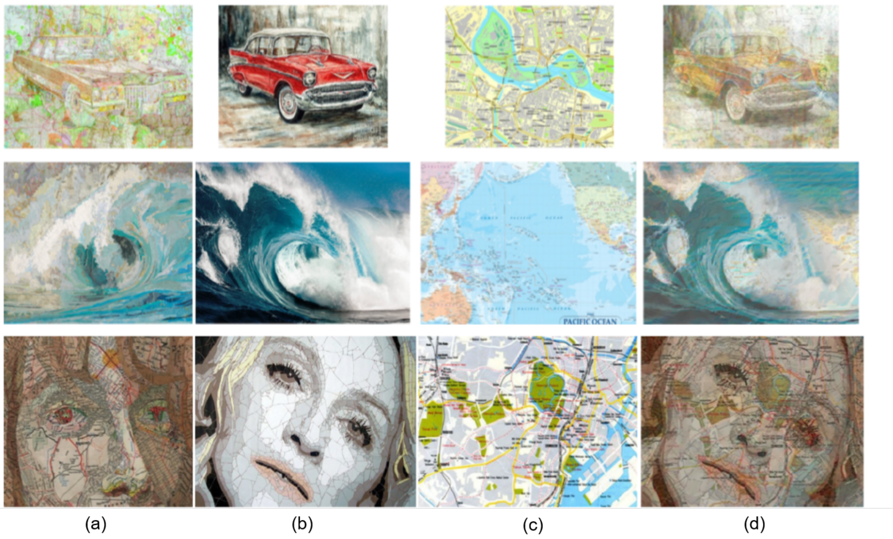


Fig. 17 Extra application to create similar result by Matthew Cusick. (a) Matthew Cusick's result, (d) Our map art result generated from input style image (b) and input content (c).

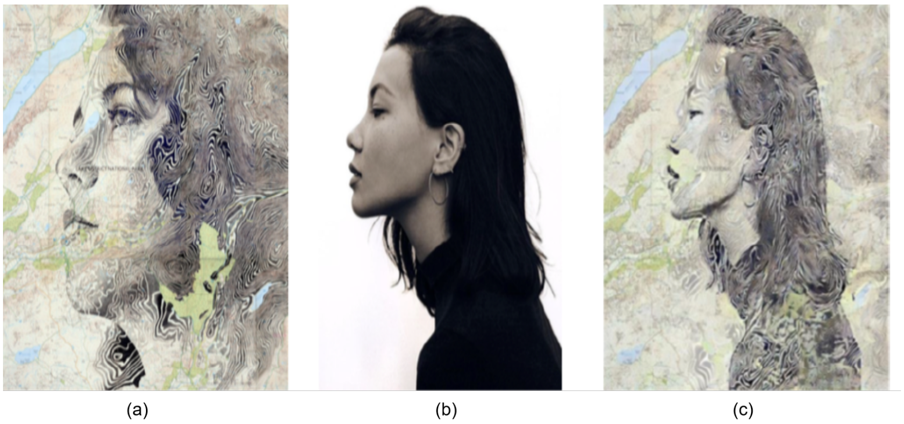


Fig. 18 Bad example. Although the result on the right is also an effect of strips, it does not consider the edges on the map and the artistic sense of the strips are not as smooth as the left picture.

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References

1. M.-T. Chi and T.-Y. Lee. Stylized and abstract painterly rendering system using a multiscale segmented sphere hierarchy. *IEEE transactions on*

visualization and computer graphics, 12(1):61–72, 2005.

2. D. Cornish, A. Rowan, and D. Luebke. View-dependent particles for interactive non-photorealistic rendering. In *Graphics interface*, volume 1, pages 151–158, 2001.
3. O. Deussen and T. Strothotte. Computer-generated pen-and-ink illustration of trees. In *Proceedings of the 27th annual conference on Computer graphics and interactive techniques*, pages 13–18, 2000.
4. A. A. Efros and W. T. Freeman. Image quilting for texture synthesis and transfer. In *Proceedings of the 28th annual conference on Computer graphics and interactive techniques*, pages 341–346, 2001.
5. L. A. Gatys, A. S. Ecker, and M. Bethge. Image style transfer using convolutional neural networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2414–2423, 2016.
6. A. Hertzmann, C. E. Jacobs, N. Oliver, B. Curless, and D. H. Salesin. Image analogies. In *Proceedings of the 28th annual conference on Computer graphics and interactive techniques*, pages 327–340, 2001.
7. Y. Jing, Y. Yang, Z. Feng, J. Ye, Y. Yu, and M. Song. Neural style transfer: A review. *IEEE transactions on visualization and computer graphics*, 2019.
8. R. D. Kalnins, L. Markosian, B. J. Meier, M. A. Kowalski, J. C. Lee, P. L. Davidson, M. Webb, J. F. Hughes, and A. Finkelstein. Wysiwyg npr: Drawing strokes directly on 3d models. In *Proceedings of the 29th annual conference on Computer graphics and interactive techniques*, pages 755–762, 2002.
9. T.-Y. Lee, C.-R. Yan, and M.-T. Chi. Stylized rendering for anatomic visualization. *Computing in Science & Engineering*, 9(1):13–19, 2007.
10. C. Li and M. Wand. Combining markov random fields and convolutional neural networks for image synthesis. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 2479–2486, 2016.
11. D. Lin, Y. Wang, G. Xu, J. Li, and K. Fu. Transform a simple sketch to a chinese painting by a multiscale deep neural network. *Algorithms*, 11(1):4, 2018.
12. S.-S. Lin, M.-C. Hu, C.-H. Lee, and T.-Y. Lee. Efficient qr code beautification with high quality visual content. *IEEE Transactions on Multimedia*, 17(9):1515–1524, 2015.
13. S.-S. Lin, I.-C. Yeh, C.-H. Lin, and T.-Y. Lee. Patch-based image warping for content-aware retargeting. *IEEE transactions on multimedia*, 15(2):359–368, 2012.
14. M. Lu, F. Xu, H. Zhao, A. Yao, Y. Chen, and L. Zhang. Exemplar-based portrait style transfer. *IEEE Access*, 6:58532–58542, 2018.
15. F. Luan, S. Paris, E. Shechtman, and K. Bala. Deep photo style transfer. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 4990–4998, 2017.
16. F. Luan, S. Paris, E. Shechtman, and K. Bala. Deep painterly harmonization. In *Computer Graphics Forum*, volume 37, pages 95–106. Wiley Online Library, 2018.

17. B. J. Meier. Painterly rendering for animation. In *Proceedings of the 23rd annual conference on Computer graphics and interactive techniques*, pages 477–484, 1996.
18. E. Praun, H. Hoppe, M. Webb, and A. Finkelstein. Real-time hatching. In *Proceedings of the 28th annual conference on Computer graphics and interactive techniques*, page 581, 2001.
19. O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A. C. Berg, and L. Fei-Fei. ImageNet Large Scale Visual Recognition Challenge. *International Journal of Computer Vision (IJCV)*, 115(3):211–252, 2015.
20. A. Selim, M. Elgharib, and L. Doyle. Painting style transfer for head portraits using convolutional neural networks. *ACM Transactions on Graphics (ToG)*, 35(4):1–18, 2016.
21. K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*, 2014.
22. Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli. Image quality assessment: from error visibility to structural similarity. *IEEE transactions on image processing*, 13(4):600–612, 2004.
23. H. Xu, N. Gossett, and B. Chen. Pointworks: Abstraction and rendering of sparsely scanned outdoor environments. In *Rendering Techniques*, pages 45–52, 2004.
24. C.-R. Yen, M.-T. Chi, T.-Y. Lee, and W.-C. Lin. Stylized rendering using samples of a painted image. *IEEE Transactions on Visualization and Computer Graphics*, 14(2):468–480, 2008.
25. J.-Y. Zhu, T. Park, P. Isola, and A. A. Efros. Unpaired image-to-image translation using cycle-consistent adversarial networks. In *Proceedings of the IEEE international conference on computer vision*, pages 2223–2232, 2017.