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Rendering and Reconstruction Based 3D Portrait Stylization

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***Abstract*—Both 2D images and 3D models are vital aspects of portrait applications. Existing style transfer methods principally emphasized 2D images, neglecting the urge for 3D style transfer. We propose rendering and reconstruction based 3D portrait stylization. And we present the first geometry-aware stereoscopic image stylization. Our framework requires one content image and one style image to obtain a 3D stylization portrait. In the first step, 3D face reconstruction produces a 3D face model. We excute stereoscopic rendering to the model and reserve the images and parameters. We propose to perform the perspective transformation on one style image to match two content images. Then we use disparity loss to conduct a geometry-aware stereoscopic stylization. Using stereoscopic stylization images, we calculate the 3D stylization portrait using a stereoscopic 3D reconstruction algorithm. Expect for portraits, the framework applies to models with simple shapes. Extensive experiments demonstrate the validity and robustness of our method.**

***Index Terms*—neural style transfer, 3D face modeling, stereoscopic image style transfer, stereoscopic 3D reconstruction**

I. Introduction

Style transfer aims at reproducing the content of given images using style characteristics extracted from style images. Harmonious texture and geometry information learned from style images shall be applied while preserving the semantics of the content images. Analogously, 3D model style transfer refers to modulating the texture and geometry of the content models according to the style information. The style examples could be images or models. In this paper, we only focus on image style examples, and model-to-model fusion [1] is not involved.

Gatys et al. [2] presented a pioneering artistic style transfer algorithm for images through optimizing the output image, in which a tradeoff is made between characteristics from content images and style images. Starting from it, fruitful researches adjusted the implementation details, such as features, losses [3]–[6]. Compared with the extensive number of studies on images, there have been few studies on 3D models [7]–[11].

In this paper, we demonstrate a 3D portrait stylization method concerning both texture and geometry style transfer.The 3D portraits could be generated using our method given a face image and a style image. We use [12] to reconstruct a preliminary 3D face model for stylization. A stereoscopic renderer renders the model into two images of different views, with parameters reserved. Perspective transformation aligns one style image into two images. Implementing disparity loss for stylization images achieves a high-quality geometry-aware stereoscopic image stylization. Finally, we use a stereoscopic 3D shape reconstruction algorithm to generate the stylization 3D portrait. Since the stereoscopic 3D shape reconstruction and stereoscopic image style transfer are not restricted to portraits, our method is applicable for the stylization of models with simple shapes.

The contributions of this work are as follows:

- We propose a 3D portrait stylization method without pretraining. We present the first geometry-aware stereoscopic image stylization. The method applies to general models with simple geometry.
- We demonstrate the effectiveness of our method on a range of portrait styles. Experiments also illustrate the applicability to general models with simple geometry.
- We introduce the idea of rendering and reconstruction to 3D model modification, which is capable of being extended to the migration of more style transfer methods.

II. Related Work

A. Geometry-aware Image Style Transfer

Starting from [2], style transfer has been studied extensively in recent years. Although fruitful results emerged, geometry deformation was neglected with the above style transfer methods except for style transfer for faces. [13] presented Deformable Style Transfer (DST), a novel approach that combines traditional texture and color transfer with spatial deformations. Based on DST, [14] presented a flexible and efficient non-parametric geometric deformation method. The speed was enhanced, and the texture and geometry styles were partitioned, facilitating more flexible style transfer. Although satisfactory results could be achieved, these methods only concerned images. We implement the image style transfer method to 3D stylization, which works well with 3D portraits and applies to other simple models.

B. 3D Style Transfer

Compared with image style transfer, 3D style transfer remains underexplored. To the best of our knowledge, few works were undertaken [7]–[11]. [7] provided Neural 3D Mesh

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Renderer (NMR), a renderer that includes 3D mesh editing operations such as 2D-to-3D style transfer. Using the renderer, the texture and geometry style could be edited simultaneously according to the style image. [8] constructed a differentiable triangle mesh renderer, which can backpropagate changes in the image domain to the 3D mesh vertex positions. [9] focused on differentiable image parameterizations. Models with style textures could be obtained while the algorithm does not alter vertex positions.

[11] constructed a large dataset of 6,100 3D caricature meshes and established a PCA model in the 3D caricature shape space. With human face photos, simple interaction controls the ratio of 3D caricatures' facial shapes. [10] presented a 2D-to-3D portrait style transfer algorithm. After pre-training, 3D stylization portraits are generated, given the content and style images.

III. Method

To deal with style transfer for the 3D object, it comes to our mind that transferring 3D objects into 2D images simplifies the problem. Using two cameras to capture one object, the stereoscopic reconstruction system reconstructs the 3D surface. Stereoscopic style transfer algorithms conduct image stylization with stereoscopic images. By combining both methods, the essence of our idea is to render 3D models into two images, execute style transfer and then reconstruct the stylization models. Fig. 1 shows the architecture of the proposed method, which consists of the following modules: 3D face reconstruction, stereoscopic rendering&perspective transformation, landmarks calculation, spatially guided stereoscopic image style transfer, and stereoscopic 3D model reconstruction.

A. Stereoscopic Rendering and 3D Reconstruction

In a stereoscopic 3D reconstruction system, the 3D coordinates of the object could be measured, knowing cameras parameters and the coordinates corresponding between two images. In our method, off-screen rendering(using PyTorch3d [15]) simulates the camera capture procedure. Setting the rendering parameters, a model is rendered into left and right content images I_l^c, I_r^c who have different view angles. For arbitrary 3D vertex $p_w^c = (x_w^c, y_w^c, z_w^c)$ in a content model, the rendered 2D pixel coordinates of the two images could be calculated, as stated in Eq. (1). $p_l^c = (x_l^c, y_l^c)$ and $p_r^c = (x_r^c, y_r^c)$ are pixel coordinates in images I_l^c, I_r^c. H_l, H_r are camera parameters matrix, s_l, s_r are scale factors [16]. In the off-screen rendering process, H_l, H_r,s_l, s_r are artificial settings.

$$s_l \begin{bmatrix} x_l^c \\ y_l^c \\ 1 \end{bmatrix} = H_l \begin{bmatrix} x_w^c \\ y_w^c \\ z_w^c \\ 1 \end{bmatrix}, s_r \begin{bmatrix} x_r^c \\ y_r^c \\ 1 \end{bmatrix} = H_r \begin{bmatrix} x_w^c \\ y_w^c \\ z_w^c \\ 1 \end{bmatrix}, \tag{1}$$

Using Eq. (1), the mapping between p_l^c and p_r^c could be calculated, which is denoted by Eq. (2), where T_{r2l}^c is a transform matrix. The point-to-point mappings are calculated for later stereoscopic style transfer for all the model vertexes visible in the rendered images.

$$p_l^c = T_{r2l}^c p_r^c, \tag{2}$$

B. Stereoscopic Image Style Transfer

We use disparity loss L_{disp} to execute a geometry-aware stereoscopic image style transfer and propose to perform the perspective transformation on the style image for alignment.

1) Disparity Loss for Spatial Consistency: The intermediate step of our 3D portrait stylization is image style transfer. To realize geometry aware 3D portrait stylization, we adopt DST [13] because it is a spatially guided style transfer method. During the stylization, transformation between original image pixel $p^c = (x^c, y^c)$ and style image pixel $p^s = (x^s, y^s)$ could be obtained. Given a content image I^c, a style image I^s and aligned keypoint pairs $P = \{p_1, ..., p_k\}$ (source) and $P' = \{p'_1, ..., p'_k\}$ (target), the image deformation is specified by 2D displacement vectors $\theta = \{\theta_1, ..., \theta_k\} = \{p'_1 - p_1, ..., p'_k - p_k\}$. Warped image $W(I, \theta)$ is produced by thin-plate spline interpolation which finds proper parameters w, v, b to minimize $\sum_{i=1}^{k} \parallel f_\theta(p_i + \theta_i) - p_i \parallel^2$ subject to a curvature constraint. And we get the mapping function Eq. (3), where ϕ is a kernel function which is chosen to be $\phi(r) = r^2 \log(r)$, p^o denotes the pixel coordinates in warped images and $p^c = f_\theta(p^o)$ denotes its inverse mapping in the original image [13].

$$p^c = f_\theta(p^o) = \sum_{i=1}^{k} w_i \phi(\parallel p^o - p_i - \theta_i \parallel) + v^T p^o + b \tag{3}$$

The keypoints matching between content and style images is the basis of the geometry-aware stylization. For portraits, face landmarks are appropriate to lead the stylization. In our method, Dlib [17] and the face-of-art [18] are respectively used for real human faces and other artistic images.

Combining Eq. (2) and Eq. (3), the pixels mapping between left and right warped stylization images(whole face region) could be denoted as Eq. (4), where p_l^o and p_r^o are pixel coordinates in stylization images. T_{r2l}^o in Eq. (5) is used as a shorthand.

$$\begin{aligned} p_l^c &= T_{r2l}^c p_r^c \\ f_{l\theta}(p_l^o) &= T_{r2l}^c f_{r\theta}(p_r^o) \\ p_l^o &= f_{l\theta}^{-1}(T_{r2l}^c f_{r\theta}(p_r^o)), \end{aligned} \tag{4}$$

$$p_l^o = T_{r2l}^o(p_r^o) \tag{5}$$

The loss function used by DST [13] is composed of five components: content loss $L_{content}(I^c, I^{ou})$, unwarped style loss $L_{style}(I^s, I^{ou})$, deformed style loss $L_{style}(I^s, I^o)$, deformation loss $L_{warp}(P, P', \theta)$, regularization term $R_{TV}(f_\theta)$,

$$\begin{aligned} L_{DST}(I^o, \theta, I^c, I^s, P, P') =& \alpha L_{content}(I^c, I^{ou}) \\ &+ L_{style}(I^s, I^{ou}) \\ &+ L_{style}(I^s, I^o) \\ &+ \beta L_{warp}(P, P', \theta) \\ &+ \gamma R_{TV}(f_\theta), \end{aligned} \tag{6}$$

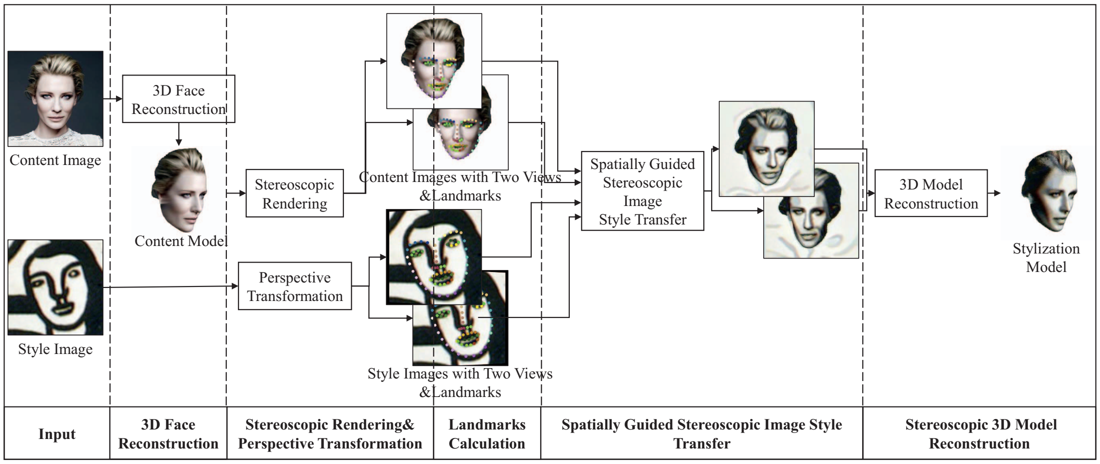

Fig. 1. Our Rendering and Reconstruction Based 3D Portrait Stylization consists of five parts: 3D face reconstruction, stereoscopic rendering&perspective transformation, landmarks calculation, spatially guided stereoscopic image style transfer, and stereoscopic 3D model reconstruction.

where I^o is the stylization image, I^{ou} is the unwarped stylization image, θ parameterizes the spatial deformation, I^c is the content image and I^s is the style image, P (source) and P' (target) are aligned keypoint pairs. Hyperparameters α and β control the relative importance of content preservation and spatial deformation to stylization. Hyperparameter γ controls the amount of regularization on the spatial deformation [13]. $L_{content}$ and L_{style} refer to STROTSS [6]. The deformation loss L_{warp} denotes the Euclidean distance between source and target point coordinates. The regularization term R_{TV} uses total variation norm to encourage the points to move uniformly. For more details, we direct the reader to [13].

In our method, we define the disparity loss as the color numerical differences between the corresponding pixels(whole face region) in two images, as shown in Eq. (7). p_r^o denotes the pixel coordinate in the right stylization image, N denotes the number of target pixels. Taking the disparity loss and L_{DST} together, the objective function of our method is Eq. (8). Hyperparameters $\delta_1, \delta_2, \delta_3$ control the relative importance of 2D stylization and disparity.

$$L_{disp}(I_l^o, I_r^o) = \sum_{p_r^o} |I_l^o(T_{r2l}^o(p_r^o)) - I_r^o(p_r^o)|/N \tag{7}$$

$$\begin{aligned} Loss =& \delta_1 L_{DST}(I_l^o, \theta_l, I_l^c, I^s, P_l, P') \\ &+ \delta_2 L_{DST}(I_r^o, \theta_r, I_r^c, I^s, P_r, P') \\ &+ \delta_3 L_{disp}(I_l^o, I_r^o), \end{aligned} \tag{8}$$

2) Style Images Perspective Transformation for Spatial Consistency: Using one style image to align two content images is not sufficiently rigorous. Foreshortening effects caused by different view angles lead to inaccurate mappings. To eliminate this, we propose to take perspective transformation for style images.

The perspective transformation could be denoted as Eq. (9), where T_{s2l}^s and T_{s2r}^s are perspective matrices, I_l^s and I_r^s are transformed style images. Replacing style image with transformed style images, Eq. (8) could be modified to Eq. (10), where $P_l{}'$ and $P_r{}'$ are transformed keypoint pairs. After transformation with the same angles as content images, the keypoints matchings between two style images and two content images could be calculated more accurately. Standard iterative techniques such as stochastic gradient descent are used to minimize Eq. (10).

$$\begin{aligned} I_l^s &= T_{s2l}^s I^s \\ I_r^s &= T_{s2r}^s I^s, \end{aligned} \tag{9}$$

$$\begin{aligned} Loss =& L_{DST}(I_l^o, \theta_l, I_l^c, I_l^s, P_l, P_l{}') \\ &+ L_{DST}(I_r^o, \theta_r, I_r^c, I_r^s, P_r, P_r{}') \\ &+ L_{disp}(I_l^o, I_r^o), \end{aligned} \tag{10}$$

C. Stylization 3D Shape Reconstruction

In our method, the image stylization process only warps the original images, maintaining the relative position of pixels constant. This property promises the initial camera parameters applicable for the final 3D reconstruction.

In the rendering process, parameters I_l, I_r, T_{r2l}^c, H_l, H_r, s_l, s_r are reserved. Then stereoscopic image style transfer accomplishes style transfer which harmonizes left and right content images I_l^c, I_r^c, and produces stylization images I_l^o, I_r^o and stylization coordinates mapping T_{r2l}^o. Combining all these parameters H_l, H_r, s_l, s_r, I_l^o, I_r^o, T_{r2l}^o with Eq. (1), 3D points coordinates of stylization models $p_w^o = (x_w^o, y_w^o, z_w^o)$ could be calculated.

The reconstructed models shall contain noise caused by the mapping deviations between warped images. To eliminate the noise in the models, Tabin [19] is used to smooth the results. Compared with geometry changes we are concerned about, the influences caused by the smooth algorithm are ignorable.

IV. Experiments

In this section, we validate the effectiveness of our method by comparisons, ablation studies, and perceptual studies. Human portraits images and face images are from face-of-art

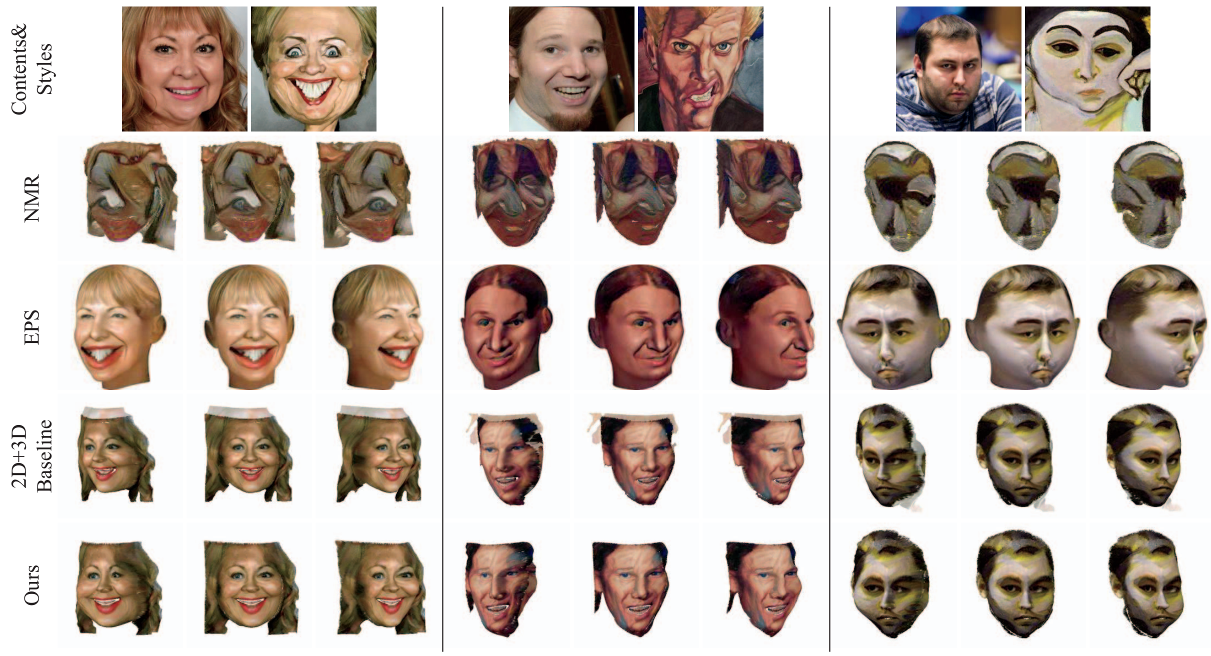

Fig. 2. Comparison with 3D geometric stylization methods. From top to bottom: content and style images, Neural 3D Mesh Renderer (NMR), Exemplar-Based 3D Portrait Stylization (EPS), the 2D+3D baseline ([13] to stylize both geometry and texture of the image, and then [12] to reconstruct the face), and ours.

[18] and CelebA-HQ [20]. Some content and style images are from [10]. Rendered images and style images are resized to 512×512. The code is accomplished using PyTorch on a single Nvidia 3080 GPU.

A. Comparisons

There is a great deal of research aiming to reconstruct the 3D face model from a single image. When it comes to arbitrary 3D face styles transfer, to the best of our knowledge, only [10] proposed Exemplar-Based 3D Portrait Stylization(EPS). Universal method Neural 3D Mesh Render(NMR) [7] also could be used to generate the stylization portrait with one face model and one style image. We use Deep 3D Portrait From a Single Image [12] to obtain an initial method for NMR. And the baseline method for 3D portrait generation is to combine 2D style transfer and 3D face reconstruction algorithms. We use DST [13] to obtain stylization portraits and Deep [12] to reconstruct the 3D face models.

We compare our method with NMR, EPS, and the 2D+3D baseline in Fig. 2. Images in the first row are content images and style images. From top to bottom, stylization models using different methods are shown. Content images, style images, and EPS results are cited from [10]. NMR produces results with scaly geometry deformations and chaotic texture. Due to ignoring semantic information, NMR can not achieve an ideal texture transfer. Results of the 2D+3D baseline method are acceptable, but no geometry stylization arises. The 2D+3D baseline method treats an artistic portrait as a real human photo. The statistic model for real faces can not handle enormous distortions. EPS and ours achieve good results in texture and geometry, although the details may vary. EPS deals with details better, while ours preserves identification better. Moreover, EPS produces a whole head while ours produces faces with hair.

B. Ablation on Geometry-aware Stereoscopic Image Style Transfer

Consistency between two stylization images is ideal in stereoscopic image style transfer. We propose two designs. The first is to use disparity loss, and the second is to take perspective transformation for style images. No one has suggested geometry-aware stereoscopic image style transfer, so we conduct ablation experiments without comparisons with others.

To verify their effectiveness, we compared the results of these two designs in Fig. 3. Images in the first column are content images and style images. From left to right, stylization images using different methods and zooming results are shown. DST produces nonmatched stylization results. Disparity loss decreases the large-scale inconsistencies. Perspective transformation improves the details. The disparity loss promises high consistency in color and geometry but smooths out some color features from style images. Perspective transformation is helpful to retain more style color features. For example, the disparity loss ensures eye geometry consistency while the perspective transformation improves the cheek color in the second sample.

C. Perceptual Study

For image style transfer, evaluating the quality of the stylization results is still a challenging problem. Mathematical

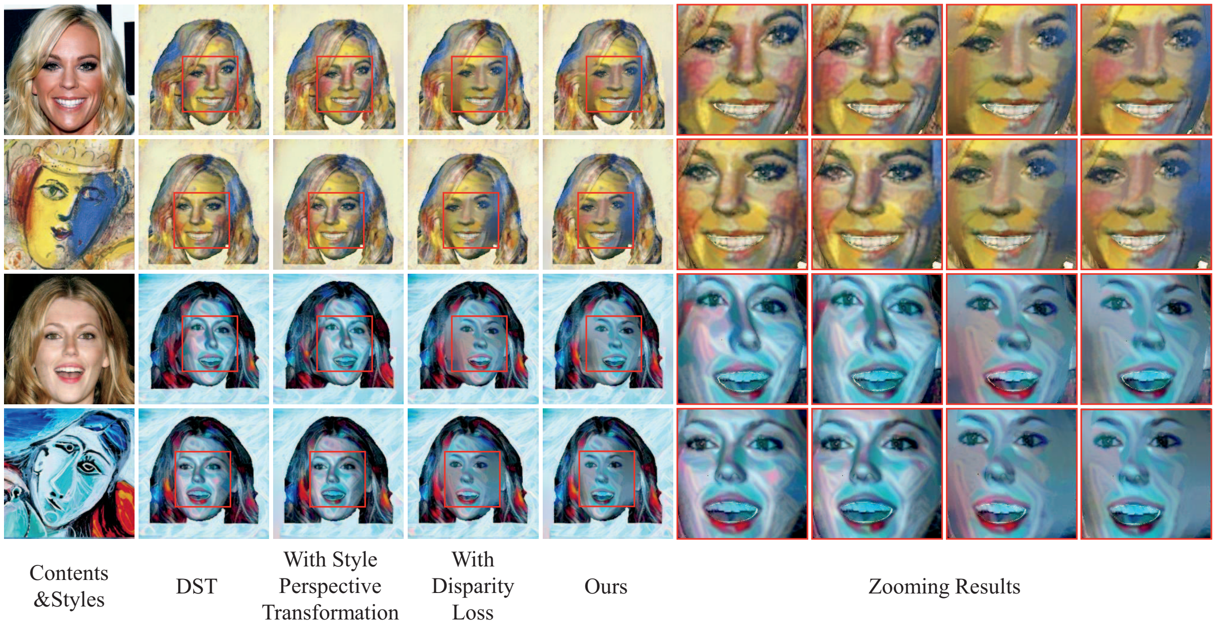

Fig. 3. Comparisons on stereoscopic image stylization. We compare our results using perspective transformation and disparity loss with the results using DST, the results using perspective transformation, and the results using disparity loss.

evaluations may have a strong bias against human subjective feelings. More researchers adopt human evaluation studies, which is more reasonable. Considering this and inspired by EPS [10], we conducted a perceptual study to evaluate our method.

In this paper, only NMR [7], EPS [10], and 2D+3D baseline are compared with our method. NMR is a universal style transfer method that does not consider semantics information. 2D+3D baseline method does not produce geometry stylization. Considering this, perceptual study comparisons are between EPS and ours.

Twenty pairs of content and style images were selected randomly to perform the study. In the user study, we rendered the stylization models in three views, and the content and style images were shown separately, together with four similar images. Users shall select the most similar images from the five options. The content recognition rate (CR) and the style recognition rate (SR) were used to demonstrate the visual effect of the stylization. Results were collected from 50 users. The average content recognition rate of EPS is 87.30%, and ours is 87.90%. The average style recognition rate of EPS is 81.501%, and ours is 82.00%. Compared with EPS, our method could obtain competitive results.

D. Run Time

Table I lists the average runtime of each step for one example. The performance of NMR and our method were tested on an NVIDIA 3080 GPU. The runtime performance of EPS is cited from [10], which was tested on an NVIDIA Tesla V100 GPU. As shown in Table I, time-consuming pre-training is needed in EPS but not in NMR and our method. EPS and ours consume the same time for landmarks calculation. NMR is the most time-consuming for running, EPS is medium, and ours is the fastest.

TABLE I
THE AVERAGE PROCESSING TIME OF THREE METHODS.

Step	Pre-training	Landmarks Calculation	Run
NMR	without	without	1240.5s
EPS	20 hours	0.2s	257.0s
Ours	without	0.2s	156.3s

E. Experiments with General Models

Our method applies to general models. Our method only deals with single face due to the FOV. We use Neural Best-Buddies(NBB) [21] for finding corresponding points between two image. With keypoints matching, stylization for images with general objects could be implemented.

Simple experiments were carried out to illustrate the usability of our method for general models, as shown in Fig. 4. The first line is the content model(Stanford Bunny [22]), and the second-line shows style images from [13]. For texture, our method transfers the features of the object in style images, and NMR learns features of the full images(including background). For the geometry, NMR leads to scaly geometry changes while largish deformations are resulted using our method. For example, two bunnies have different shapes of faces and heights.

Fig. 4. Comparison with 3D geometric stylization methods for general models. From left to right: content model, style images, multi-views results of NMR and ours.

V. LIMITATIONS

There are some limitations to our method. Firstly, landmarks of faces may be affected by the angle of the head. And landmarks of portraits vary according to the artists. Our method expects the content and style face images to share similar head poses for better stylization results.

Secondly, FOV restricts the applicability to single surfaces. Shaded areas are challenging for stylization because they are invisible in rendered images. Although carrying out multiple calculations around the object may be helpful for global surface stylization, how to deal with the synchronous optimization of plenty of images remains to be solved.

VI. CONCLUSIONS

In this paper, we present a 3D portrait stylization algorithm. We present the first geometry-aware stereoscopic image stylization. We introduce the stereoscopic 3D rendering and reconstruction process into 3D style transfer. By combining these two algorithms, our method can generate 3D stylization portraits. The proposed method takes one face image and one portrait image as input, produces 3D portraits with geometry and texture styles exaggerated from the reference image while preserving the content of the face. The algorithm is workable for models with a simple surface. Our method still has limitations. How to enhance the effectiveness and usability of our method, need to be further studied.

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