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Portrait2Bust: DualStyleGAN-based portrait image stylization based on bust sculpture images

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Abstract

In cultural heritage, portrait paintings and busts are special genres of artworks which are used to show the appearance and expression of a human subject. The purpose of such artwork is to serve as remembrance of the person who is depicted in that portrait or bust. The bust can moreover serve as a 3D representation of a portrait painting. Therefore, it would be interesting to stylize a portrait painting based on a specific bust, i.e. the generation of a 2D image of a bust corresponding to the person depicted in the portrait image. In this paper, we analyze and discuss the stylization of portrait paintings and photographs of human faces with busts using a deep learning based style transfer approach. To capture the characteristics in the appearance of busts, we created a novel dataset of busts and used DualStyleGAN for the use cases of stylizing portrait paintings and stylizing human faces based on our novel bust style. Our experiments show the potential of this approach. Stylizing human faces as busts might not only be appealing to experts that might save time and effort for generating an initial stylization to refine later on, but also increase the engagement of novice users and exhibition visitors with cultural heritage.

CCS Concepts

• Computing methodologies → Machine learning; Image manipulation; Computer graphics; • Applied computing → Arts and humanities;

1. Introduction

Artistic portrait painting as well as the sculpting of busts are distinct forms of art where the idea is to artistically represent a specific human person with their characteristic appearance traits. Hence, there exists a strong co-relation between busts and portrait paintings. Realistic portraits especially of important persons already existed in Roman art long ago in the form of Verism [Ric55]. Verism is a realistic style of Roman art and showed imperfections in portraits such as warts, wrinkles and furrows. Verism was prevalent in many bust sculptures and hence stylizing a portrait painting with busts can provide a deeper understanding about the portraits during a certain era.

In this paper, we aim at the stylization of an artistic portrait painting or photographs depicting human faces respectively with busts using style transfer based on deep learning, i.e. the generation of a 2D image depicting a bust corresponding to the person depicted in the portrait image.

Exemplar-based portrait style transfer, i.e. transferring the style of an exemplar portrait onto a target face, has received a lot of attention in the past and enables applications such as transforming photographic portrait depictions into artistic ones and vice versa. In contrast to relying on time-consuming manual creation and the respectively required professional skills, automatic portrait style transfer significantly facilitates the task so that even novice users can generate stylized results. In turn, the stylization results could also serve as initial proposals for artists, who could focus on the final refinement of their work and save some time during the process. In particular, the rapid progress in machine learning has led to promising results for portrait style transfer based on neural image style transfer [GEB16, LW16, LYY*17, SED16] and image-to-image translation [CF21, KKKL19, LZW*21]. Neural image style transfer is a process of rendering the semantic content of one image with the style of another image, while image-to-image translation relies on the learning of a bi-directional mapping between the source domain (e.g. photograph of a face) and target domain (e.g. artistic portrait domain). Recently StyleGAN-based approaches [KLA19a, KLA*20, KAL*21, AQW19, YJLL22a] for style transfer have been demonstrated to produce promising results. StyleGAN has been designed as a progressive generative adversarial network (GAN) with neural style transfer,however, with lacking control of the stylization process. For our problem, we focused on a StyleGAN-based approach that allows controlling the stylization process in terms of a conditional stylization. Therefore, we used the DualStyleGAN [YJLL22a], which is based on a pre-trained StyleGAN method, due to its support for exemplar-based portrait style transfer with flexible control of the dual style paths

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(intrinsic and extrinsic styles). The features of the content image are controlled by the intrinsic style path and that of the style image by the extrinsic style path. So the intrinsic style path corresponds to the content path and the extrinsic style path corresponds to the style path in the normal style transfer paradigm. In our case, the 2D bust images and portrait images serve as style and content images respectively. We used the FFHQ dataset and created our own dataset of 2D bust images from minifactory [min23] for training our network. We crawled the web-site using selenium webdriver. The Flickr-Faces-HQ (FFHQ) is a high-quality image dataset of human faces and consists of 70,000 PNG images of resolution 1024 x 1024. The dataset has considerable variations in terms ethnicity, age and background. Our 2D bust image dataset consists of 698 images of resolution 720 x 720 and contains different kinds of busts with variations in age and gender. The DualStyleGAN network uses a pre-trained StyleGAN on FFHQ dataset to perform facial destylization and progressive fine-tuning to generate the checkpoints necessary to perform the style transfer. In the scope of our evaluation, we demonstrate the potential of this approach for visualizing portrait paintings or portrait photographs respectively in the style of a bust as well as the potential to provide proposals for novel busts. The main contributions of this paper are:

1. Stylization of an artistic portrait painting or photographs depicting human faces respectively with busts using style transfer based on deep learning and evaluation of potential for DualStyleGAN for this task.
2. Creation of novel bust dataset.

In the next section we describe the related work in the style transfer and StyleGANs. Section 3 describes the methodology used for style transfer using the DualStyleGAN. Dataset details used for training the network are described in Section 4. The use-cases for stylization of portrait paintings and face images from busts in the field of cultural heritage are described in Section 5. Generation of bust stylized data for data augmentation is presented in Section 6. In Section 7, we briefly discuss the use-cases we presented and, finally, Section 8 presents the conclusion and an outlook on future work in this area.

2. Related work

In the past few years, automatic portrait style transfer has received a lot of attention in literature and the main approaches can be categorized into image style transfer [LW16, LYY*17, SED16] and image-to-image translation [CF21, KKKL19, LZW*21].

StyleGAN [KLA19a], the current state-of-the-art face generator, allows the generation of high-resolution face images, where it is also able to automatically separate high-level attributes (e.g., pose) from stochastic variations (e.g., freckles, hair, etc.). This allows an efficient fine-tuning based on the requirements of fewer (i.e., only hundreds of) portrait images and some hours of training, while offering better image quality and better image resolution in comparison to to image style transfer and image-to-image translation models that aim at learning a bi-directional map- ping between the different domains. Furthermore, it also allows interpolation operations which can be used for style mixing between images.

Two subsequent versions of StyleGAN [KLA*20, KAL*21] focused on improving the quality of the images generated by the StyleGAN generator. The Image2StyleGAN [AQW19] includes a new embedding method which allows semantic editing operations that can be applied to images and has been used for both style and expression transfer. This network is able to transfer low-level features (color and texture), however, it fails to faithfully maintain the content structure of non-face images especially paintings.

More recently, DualStyleGAN [YJLL22a] also addressed the support for exemplar-based conditional fine-tuning with flexible weights to control the content and style images. Conditional fine-tuning the extrinsic style path and keeping the intrinsic path constant preserve the face features of the content image. The model uses modulative residual blocks which is robust to content loss [YJLL22a] ,that is, it will learn to capture and transfer more structure styles besides colors. A limitation of this method, however, is that non-facial features are not that well captured.

Style transfer has been used quite extensively to toonify human faces ([YJLL22b], [PA20], [YJLL22a]). To the best of our knowledge, there has been no previous work on stylizing portrait paintings and human faces using busts. We build our approach on the DualStyleGAN architecture [YJLL22a], since it best suits our goals regarding conditional style transfer from portrait images to 2D bust images by allowing us to better control the stylization of the content image by providing flexible weights which enables us to decide which features of the content image needs to be stylized and, together with a newly generated bust dataset, that allows us to stylize the portrait paintings and human faces with the busts in a controlled fashion.

3. Methodology

With our approach, we aim at the stylization of source images such as photographs or 2D facial depictions according to a target domain. Here we have a content image I (portrait painting or human face) and a style image S (bust) which are inputted to the intrinsic and extrinsic style path respectively as shown in Figure 2. The generator network takes both these inputs and generates the final stylized image.

We used the DualStyleGAN [YJLL22a] due to its possibility regarding conditional fine-tuning of the de-stylized target domain to fit the source domain. To reduce the discrepancy between the source and the target domain, destylization is used. During destylization plausible counterparts of the target domain (busts in our case) are found in the source domain (human faces and portrait paintings).

Destylization involves three steps as shown in Figure 1: In the initial stage, of *latent initialization*, the target domain (given as the domain of busts) is embedded into the StyleGAN's latent space g. Subsequently, a *latent optimization* is carried out, where the latent code z+ (which is the latent space embedding generated by the modified psp-encoder [RAP*21] on the FFHQ dataset as proposed in the DualStyleGAN [YJLL22a]) of the fine-tuned model g' is optimized to reconstruct the source. Finally,

Image embedding: The reconstructed face image g(z+) is also embedded according to initial embedding to further mitigate unreal facial details. The obtained face reconstruction exhibits reasonable facial details and, hence, can be used to supervise the deformation and abstraction of facial structures to mimic the input S.

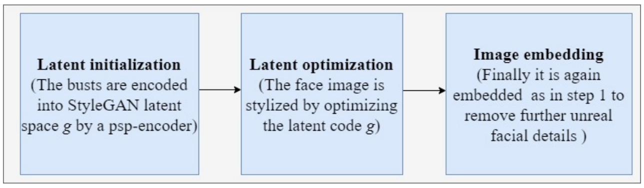

Figure 1: *The above diagram shows the steps involved in the de-stylization process*

For our approach,we used the pSp-encoder [RAP*21] for the embedding into the StyleGAN's latent space due to its higher robustness to face-irrelevant background details and distorted shapes [YJLL22a] The complete architecture of the DualStyleGAN is shown in Figure 2. The network consists of the instrinsic style path, generator network and the extrinsic style path. The instrinsic path and generator follow the original StyleGAN model [KLA19b] and are kept fixed during fine-tuning. The extrinsic style path captures important features like facial shapes and hair colors. The whole architecture can be represented as $G(E(I),E(S),w)$ where $w \in R^{18}$where I is the face image or artistic portrait painting, S is the bust image,w is a weight vector for flexible style combination of the two paths, G is the generator network, *E(I)* is the intrinsic style and *E(S)* is the extrinsic style path. The w is used control the degree of style, G represents the original pre-trained StyleGAN [KLA19a] with the FFHQ dataset and E represents the fine-tuning network for the stylization process.

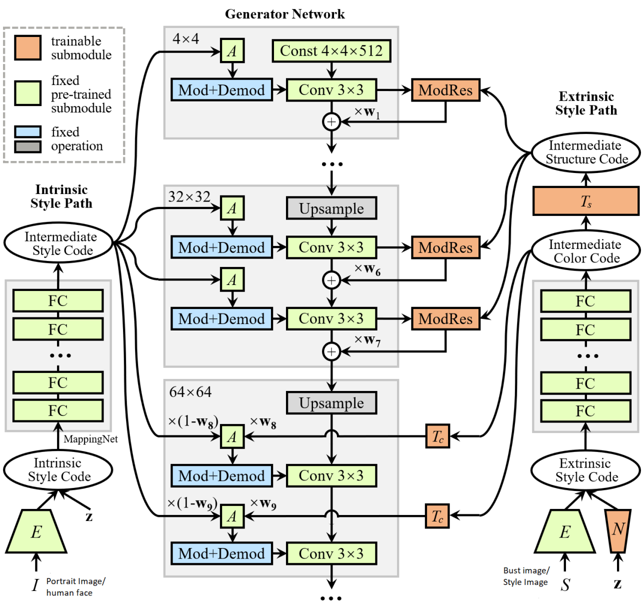

Figure 2: *The depicted diagram [YJLL22a] shows the network architecture for the DualStyleGAN.*

4. Training and Dataset

We used the *FFHQ dataset* [KLA19b] and a novel *Bust dataset* (see Figure 3), that we generated for this work, for training our network. For the creation of the *Bust dataset*, we downloaded bust images from minifactory. It consists of 698 bust images. De-stylization and progress fine-tuning of the *Bust dataset* was done on a NVIDIA GeForce RTX 3090 (24GB) graphics card. We used the same hyperparameters for the facial destylization, progressive fine-tuning and, latent optimization and sampling as proposed in the original DualStyleGAN [YJLL22a] implementation.

5. Use Cases

In this section, we define and analyze two uses cases of style transfer which may be of relevance in the field of cultural heritage. We used a manual evaluation process as there is no prior work to our knowledge in the field of bust stylization using style transfer. We propose a use-study as future work to improve the evaluation process and in that case we need experts in the field of cultural heritage. So we propose a manual evaluation here to get first impressions how a bust stylized portrait or human face looks like.

5.1. Use Case I: Visualizing a portrait painting as a bust

This use case addresses the question how a particular portrait painting would look like when we adapt it to a specific bust, i.e. we want to stylize the portrait painting so that it matches the features of the bust. In order to do so, we take the portrait painting as the content image and the bust as style image. For our use case, we chose a painting of Julius Caesar from openart. The StyleGAN latent space re-projection of the embedding and corresponding bust image is shown Figure 4. Finally, after applying the style transfer by running the DualStyleGAN with all weights set 1, we obtain the result depicted in Figure 5.

Stylizing a bust with portrait paintings could be interesting for cultural heritage to understand the correspondence between busts and paintings of a particular era. Furthermore, other deep learning methods could be used to convert the stylized 2D image into 3D models. Exemplary deep learning method could be 3D morphable models [EST*20]. So one could convert the 2D portrait into a 3D bust model which could be added to different scenes and rendered with different material and lighting parameters.

5.2. Use Case II: Visualizing a human face as a bust

The idea of this use-case is to engage the audience or people in museums by focusing on different dimensions of user experience [RMM20]. Exemplary efforts to increase public engagement with cultural heritage include personalized immersive interactive experiences of cultural heritage [BRR*19] including haptics-enhanced immersive Virtual Reality (VR) experiences of artifacts [KKW21, AB22] or haptic artifact experiences for visually impaired people [SE19], interactive 3D artefact puzzles [RESLW21], interactive digital art [TK21], immersive VR educational games [TAC*20, PP22, PMP22], interactive digital storytelling [RBO*19, PGN*21], Augmented Reality (AR) enhanced experiences of artworks [EDB*19, ESD*22], AR-enhanced

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Figure 3: *The figure shows some samples from the* Bust dataset *that we used for training our network.*

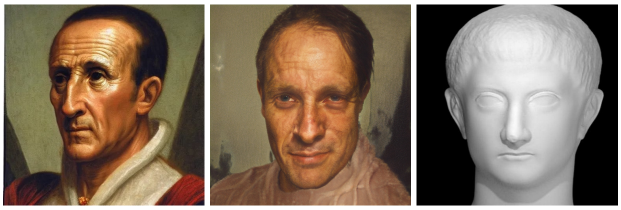

Figure 4: *The portrait painting (left),the corresponding projection in StyleGAN latent space (middle) and the bust image used to guide the stylization (right).*

Figure 5: *The above figure shows the result of style transfer of the portrait image (content image) and bust image (style image) as shown in Figure 4.*

books [NKA*22] and AR-enhanced pop-up books [HREJ20] as well as experiences of user-generated content [CHES20, Haz23] or user interaction with chatbot platforms [GBB19]. Here, we want to stylize a human face as a representation of a bust. Most people might be interested to see how a bust of them could look like. A respective 3D model could then be viewed in a normal screen or in a virtual/augmented reality setup. This might increase the engagement of visitors in museums and could be more interesting for certain people.

To approach the respective stylization, we follow a similar style transfer as for use case I. The human face is stylized using a bust and the corresponding results are presented in Figures 6 and 7.

Figure 6: *The face image (left),the corresponding projection in StyleGAN latent space (middle) and the bust image used to guide the stylization (right).*

Figure 7: *The above figure shows the result of style transfer of the face image (content image) and bust image (style image) as shown in Figure 6.*

6. Generation of Bust-stylized Data

Using our fine-tuned DualStyleGAN network one can also generate random human faces stylized with busts. This might be used for data augmentation when less representative data is available for training a certain deep learning network. Figure 8 shows bust stylized human faces using the fine-tuned DualStyleGAN network with our *Bust dataset* [min23].

7. Discussion

Figure 5 indicates that the results of style transfer might be plausible. In our experiments, we observed that the style transfer works better for human faces when compared (empirically) to that of portrait paintings as our network has been pre-trained with the FFHQ dataset which captures human faces rather than portrait paintings. If we would pre-train our network with portrait paintings, then the results could be better. As mentioned before in the use cases, we intend to convert 2D stylized busts of paintings into 3D models. In that case, we additionally would like the materials to be transferred to the corresponding 3D busts. The DualStyleGAN network allows us to preserve the pose and color of the content image and a result of such a style transfer is shown in Figure 9. We see from the results of Figure 9 that the stylized portrait painting matches more to the portrait painting than the bust. Hence we want to apply the inverse style transfer that is to stylize the bust image with a portrait painting in this case. In order to do so, we need to have the bust as content image and the portrait painting as style image. So the de-stylization and progressive fine-tuning has to be applied on the portrait paintings. This could be a nice extension of this network as one can also get the colors mapped correctly to busts in that case. Finally, converting such a colored bust into a 3D model would let us see a photo-realistic 3D rendering of a portrait painting.

8. Conclusion and Future Work

In this paper, we evaluated two scenarios where style transfer using a StyleGAN based approach (DualStyleGAN) pertaining to cultural heritage can be achieved. The analysis shows that style transfer between both human faces and portrait paintings work to varying degree of accuracy and as a next step, would require to be tested by cultural heritage experts to validate respective applications. To the best of our knowledge, our work is the first study to investigate how well style transfer performs for human face/portrait stylization based on a *Bust* style. Our approach allows controlling the style features between the bust image and the corresponding face/portrait painting image by varying the weights. Users of this tool can vary the weights according their preferences.

An obvious improvement would be the visualization of the result in 3D which gives the user a complete different insight of the 2D portrait image. Such 3D models along with lighting and proper materials when viewed under augmented reality and virtual reality setups could be appealing to visitors of a museum. The method could also be used for data augmentation by generating synthetic data of paintings/faces stylized by busts. Conservational scientist often find similar pigments in other artworks like paintings and want to digitally restore such busts. Furthermore, we could also focus on the reverse process, i.e. to stylize a bust using a portrait painting, with

Figure 8: *The above figure shows some samples from the bust dataset that we used for training our network.*

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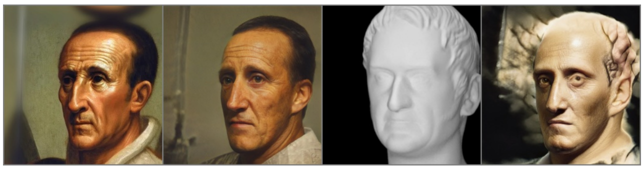

Figure 9: *The figure shows the style transfer where the original color and pose of the content image (portrait painting) is preserved.*

a similar approach, which could help conservational scientists to restore such busts which have lost its polychromy. The method has obvious limitations inherited from the use of the DualStyleGAN, which includes the fact that non-facial features are not properly captured, e.g. the noses are sometimes very abstract, and the suffering from a data bias problem. Nevertheless, our study provides first impressions of style transfer using StyleGAN based approach for paintings and the possible improvements for applying this approach in the field of cultural heritage. Our approach can save a lot of time and effort as compared to manually creating respective stylizations.

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