Auto-Encoder Guided GAN for Chinese Calligraphy Synthesis

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Abstract—In this paper, we investigate the Chinese calligraphy synthesis problem: synthesizing Chinese calligraphy images with specified style from standard font (e.g., Hei font) images (Fig. 1(a)). Recent works mostly follow the stroke extraction and assemble pipeline which is complex in the process and limited by the effect of stroke extraction. We treat the calligraphy synthesis problem as an image-to-image translation problem and propose a deep neural network based model which can generate calligraphy images from standard font images directly. Besides, we also construct a large scale benchmark that contains various styles for Chinese calligraphy synthesis. We evaluate our method as well as some baseline methods on the proposed dataset, and the experimental results demonstrate the effectiveness of our proposed model.

I. INTRODUCTION

Chinese calligraphy is a very unique visual art and an important manifestation of Chinese ancient culture which is popular with many people in the world. Writing a pleasing calligraphy work is so difficult that it always takes the writer many years to learn from the famous calligraphers’ facsimiles. Is there a way to synthesize calligraphy with specified style expeditely? We will explore an effective and efficient approach for calligraphy synthesis in this paper.

Automatic calligraphy synthesis is a very challenging problem due to the following reasons: 1) Various Chinese calligraphy styles. A Chinese character usually has thousands of calligraphy styles which vary from the shapes of component and the styles of strokes; 2) Deformations between the standard font image and calligraphy image. The standard font image and calligraphy image for the same character are only similar in relative layout of radicals of character but different in the layout and style of strokes.

Recently, there are some attempts [27], [25] to synthesize calligraphy automatically, which first extract strokes from some known calligraphy characters and then some strokes are selected and assembled into a new calligraphy character. The above mentioned methods are largely dependent on the effect of strokes extraction. However, the stroke extraction technology does not always work well when the Chinese character is too complex or the character is written in a cursive style (Fig. 1(b)) where the strokes are hard to separate and have to be extracted artificially [26].

Considering there are some shortcomings in stroke assemble based methods, we treat the calligraphy generation as an image-to-image translation problem and propose a new method which can generate calligraphy with a specified style from a standard Chinese font (i.e., Hei Font) directly without extracting strokes of characters. Over the past few years, many network architectures have been proposed and applied to different image-to-image tasks. However, those networks are all designed to handle the pixel-to-pixel problems, such as semantic segmentation, and poor performance is achieved when there are deformations between the input and target images (Fig. 1(c)).

To overcome these problems, we propose a deep neural network based model which consists of two subnets. The first one is an encoder-decoder network acting as image transfer, which encodes an input standard font image to a feature representation and then decodes the feature representation to a calligraphy image with specified style. The encoder-decoder network with similar architecture has been used in [9] and show that the feature representation is likely to compress the image content. This network architecture is sufficient to reconstruct an image. But considering that in our task the input images and output images only have the same relative layout among radicals but are different in the layout and style of strokes, it is hard for an encoder-decoder network to yield vivid calligraphy images. So besides the transfer who captures the layout of input standard font image, we also use another encoder-decoder network acting as autoencoder which inputs and reconstructs calligraphy images to guide the transfer to learn the detailed stroke information from autoencoder’s low level features. Finally, we train the two subnets together with reconstruct loss and adversarial loss to make the output look real.

In summary, the contributions of this paper are two aspects:
Firstly, we propose a neural network based method which can end-to-end synthesize calligraphy images with specified style from standard Chinese font images. Compared to some baseline methods, our approach achieves the best results with more realistic details. Secondly, we establish a large-scale dataset for Chinese calligraphy synthesis collected from the Internet. The dataset comprises of 4 calligraphy styles and each style contains about 7000 calligraphy images.

II. RELATED WORK

1) Chinese Calligraphy Synthesis: In the past few years, many works on Chinese calligraphy synthesis have been proposed. In [27], Xu et al. propose a method based on shape analysis technique and hierarchical parameterization to automatically generate novel artistically appealing Chinese calligraphy artwork from existing calligraphic artwork samples for the same character. Xu et al. [25] propose a method to parameterize stroke shapes and character topology, and successfully transfer font style Kai into a specific user’s handwriting style by choosing the most appropriate character topology and stroke shapes for a character. Different from the above mentioned methods which follow the stroke extraction and stroke assembly pipeline, we input a standard font image to our model and output a calligraphy image directly.

2) Image-to-Image Translation: Image-to-image translation is an extensive concept which covers many tasks such as edge/contour extraction [24], [22], semantic segmentation [14], [18], artistic style transfer [11], [6], image colorization [15], [30] et al. in computer vision field. However, in those tasks, image-to-image translation problems are often formulated as pixel-to-pixel translation problem, where the input images and target images have the same underlying structure and without any deformations. In this paper, we focus on another scenario in image-to-image translation where there are deformations between the input and target images. To be specific, in our calligraphy synthesis task, the input standard font images and target calligraphy images only have the similar relative layout among radicals of the same characters but are different in the position and style of strokes.

3) Generative Adversarial Networks: Generative Adversarial Networks is proposed by [7] which has attracted great interest from the computer vision and machine learning community and has a rapid development [17], [20], [6], [4], [2]. GAN is not only used in unsupervised learning such as generate an image from random noise vector but also used with some image-to-image translation tasks [10], [19] to make the output look real. Like [10], [19], we train our image transfer using an adversarial loss as well as the reconstruction loss between the output images and target images to generate desirable results. To learn the deformation between the input images and target images, we also reconstruct the low level features of our transfer supervised by the low level feature from an autoencoder.

III. PROPOSED METHOD

In this section, we describe in detail the proposed method. As shown in Fig. 2, our module consists of two encoder-decoder networks which have similar network structure and can be trained together in an end-to-end way. We refer to the two subnets as Supervise Network and Transfer Network respectively, as Transfer Network is used to transfer a standard font image to a calligraphy image with specified style, and Supervise Network can provide supervision information for Transfer Network in training stage. Details of the two subnets are discussed below.

A. Supervise Network

The supervise network is an autoencorder network. The encoder consists of a series of Convolution-BatchNorm-LeakyReLU [20] blocks which takes a calligraphy image as
input and produces a $C \times 1 \times 1$ latent feature representation of that image, where $C$ is the dimension of the latent feature. The decoder is stacked by a series of Deconvolution-BatchNorm-ReLU [20] blocks, which takes the latent feature representation from encoder and outputs an image which is similar to the input image.

The architecture of the supervise network is a simple CNN based encoder-decoder network but has skip connections between each layer $i$ and layer $n-i$ as [10], where $n$ is the total number of layers of supervise network. The skip connections are essential for the supervise network to output images with photo-realistic details. We have experimented and verified that the simple encoder-decoder network can only output images with the rough layout but almost lost all stroke information, but our supervise network can generate correct strokes as input images. We argue that the feature maps of the bottleneck layer in the simple encoder-decoder lost fine details of input images but the spatial structure is kept, and that skip connections can provide the decoder with detailed information.

B. Transfer Network

The transfer network is also a CNN based encoder-decoder network which inputs a standard font image and generates a calligraphy-like image. The encoder and decoder are similar as the supervise network which is composed of a series of Convolution-BatchNorm-LeakyReLU and Deconvolution-BatchNorm-ReLU blocks respectively, but there is a little difference in skip connections.

Chinese characters have diverse and complicated layouts and are hard to transform to calligraphy image from standard font image even the two images have the same layout. Instead of concatenating the feature outputted by layer $i$ and layer $n-i$ directly, we use a residual block [8] to connect layer $i$ and layer $n-i$ and sum the feature yielded by the residual block and layer $n-i$ to enhance the capacity to learn the minute difference between the spatial architecture of standard font and specified calligraphy images.

The standard font image and the corresponding calligraphy image always have the same character component structure but vary greatly in the layout and style of strokes. The high level features in encoder carry layout information of the input standard font images, but it is not enough to generate calligraphy images with clear strokes and specified style when the model is only supervised by the target calligraphy image. So we use the above supervise network to guide the transfer network. Let $S = \{s_1, s_2, \ldots, s_k\}$ and $T = \{t_1, t_2, \ldots, t_k\}$ denote the low level feature representations yielded by supervise network and transfer network’s decoder respectively. We use $s_j$ to supervise $t_j$ in order to guide the decoder of transfer network to learn the feature representations which carry the layout and style of strokes, layer by layer.

Generative Adversarial Network (GAN) is recently proposed by [7] and has been widely used in image generation tasks [13], [23], [29], [10]. Adversarial loss has the effect of learning the same distribution of the ground truth distribution, which can make the output images look real. [10], [19] have shown that an image transfer with an adversarial loss can output much sharper results than the one only with L1 loss. We can adjust our transfer network to a GAN framework easily with an additional discriminative model. We treat transfer network as generator $G$ and use a deep network as discriminative model $D$ following [20]. In our work, the generator $G$ is optimized to output images which have the same distribution as truth calligraphy images by generating images that are difficult for the discriminator $D$ to differentiate from real images. Meanwhile, $D$ is conditioned on the input standard font images and optimized to distinguish real images and fake images generated by $G$.

C. End-to-End Joint Training

We train the two subnets jointly in an end-to-end way. Given a pair of training sample $(x, y)$ which is composed of a standard font image $x$ and a calligraphy image $y$ for the same character.

For the supervise network, we take calligraphy image $y$ as input and the objective is to reconstruct $y$. We use L1 loss as our reconstruction loss rather than L2 loss as L1 tends to yield sharper and cleaner image. Let $A(\cdot)$ be the supervise network, the objective of the supervise network can be expressed as:

$$L_{supervise} = \mathbb{E}_{y \sim \text{pdata}}(y) || y - A(y) ||_1$$

For the transfer network, we input standard font image $x$ and take calligraphy font image $y$ as ground truth. We also reconstruct the low level feature $S$ from the supervise network. We define the reconstruction loss function as:

$$L_{reconstruct} - 1 = \mathbb{E}_{t_1 \sim \text{pdata}}(t_1) || t_1 - s_1 ||_1$$

...  

$$L_{reconstruct} - k = \mathbb{E}_{t_k \sim \text{pdata}}(t_k) || t_k - s_k ||_1$$

$$L_{reconstruct} = \lambda_1 \times L_{reconstruct} - 1 + \ldots + \lambda_k \times L_{reconstruct} - k$$

Besides, we define our adversarial loss as:

$$L_{adversarial} = \mathbb{E}_{y \sim \text{pdata}}(y) [\log D(x, y)] + \mathbb{E}_{x \sim \text{pdata}}(x) [\log (1 - D(x, G(x)))]$$

So, our final objective is:
\[ G^* = \arg \min_G \max_D \mathcal{L}_{adversarial} + \lambda_s \mathcal{L}_{supervise} + \lambda_r \mathcal{L}_{reconstruct} \]

**D. Implementation details**

In this paper, all images are scaled to 256 × 256 and converted to binary images before being fed into the model. In addition, we employ data augmentation to artificially enlarge the dataset for the purpose of reducing overfitting. We flip the image horizontally with probability of 0.5.

The encoder of supervise network and transfer network both have 8 stacked Convolution-BatchNorm-LeakyReLU blocks, which yield 1 × 1 latent feature representations of the input calligraphy images and standard font images respectively. The decoder of supervise network and transfer network both have 7 stacked Deconvolution-BatchNorm-ReLU blocks and followed by a Deconvolution layer which will generate 256 × 256 binary images. All Convolution and Deconvolution layers in the above mentioned part have 4×4 kernel size and 2×2 stride. The residual block in transfer net consists of Convolution, Batch normalization and ReLU layers as [8] and only exists between the layers whose feature map size are 2 × 2 and 4 × 4 of encoder and decoder. The architecture of D is adapted from [20]. 7 stacked Convolution-BatchNorm-ReLU blocks are used and followed by a convolution layer and output the probability of the input images like real.

The method was implemented in Torch [5]. In our experiment, we supervise the decoder of transfer net from the layer with feature map size 16 × 16 to 128 × 128 and set \( \lambda_1 \ldots \lambda_k \) to 1, and set \( \lambda_s \) and \( \lambda_r \) to 100. We choose initial learning rate of 0.002 and train the proposed model end-to-end with Adam [12] optimization method. This model was trained with batch size set to 16 until the output tends to be stable in training phase. When testing, only the transfer network is used to generate calligraphy images. We also use a median filter to denoise the output image as a post-process method to make the results cleaner.

**IV. EXPERIMENTS**

In this section, we propose a new benchmark for Chinese calligraphy generation and evaluate our algorithm on the proposed dataset. Besides, we also compare our method with other neural network based image translation methods to prove the effectiveness of our approach.

**A. Dataset**

As far as we know, there are no existing public datasets for Chinese calligraphy images generation with specified style. Therefore we propose a new dataset for calligraphy images automatic generation collected from the Internet. This dataset contains 4 subsets which are written by 4 famous calligraphers in ancient China, namely Mi Fu, Zhao Zhiqian, Liu Gongquan and Shen Yinmo in different style. Some samples from 4 subsets are shown in Fig. 5. What we can see is that the styles of 4 subsets vary from one to another and cover a few categories, such as running script, official script and regular script. As shown, running script shows enormous shape transformation. Official script exhibits wide and flat shapes. Its characters are usually horizontally long and vertically short. Regular script is more clear and neat which is mostly similar to printed fonts. Each subset in our proposed benchmark contains about 7000 images and is split into two set: training set and validation set. We randomly select 6000 images as training set and the rest images are treated as validation set for each style and ensure that the training set and validation set have no overlap in characters.

For convenience, we call this dataset Chinese Calligraphy Synthesis-4(CCS-4).

**B. Baseline Methods**

1) **Rewrite** : Rewrite [1] is a neural style transfer for Chinese font which is effective to transfer a typographic font to another stylized typographic font. It is a simple top-down convolution network with big convolution kernel size and
1 \times 1 \text{ stride}. Each Convolution layer in Rewrite is followed by
Batch Normalization layer and a ReLu layer. The architecture
of Rewrite is stacked by some above mentioned convolution
blocks and end up with a 2\times2 MaxPooling layer then followed
by a Dropout layer and a Sigmoid layer. The network is
minimized by L1 loss and total variation loss.

2) Encoder-Decoder Network: Encoder-Decoder network
is an effective image-to-image translation model and has been
widely used and studied for many image translation tasks,
such as semantic segmentation [18], edge extraction [28],
image colorization [10], image restoration [16] and image style
transfer [8] etc. We use the architecture proposed by [10]
as a baseline and train the model with L1 loss and adversarial
loss.

3) UNet: UNet is proposed by [21] and is an extension of
the simple encoder-decoder method. In [10], skip connections
are used to connect encoder and decoder, based on the fact
that in an image translation task, the input and output differ
in surface appearance, but both are renderings of the same
underlying structure. Besides, the network is also optimized
with L1 loss and adversarial loss.

C. Evaluation and Discussions

We evaluate our proposed method as well as other baselines
on the CCS-4 dataset. We use the font style Hei as character’s
standard font for each method, as Hei font has the least
style structures, even thickness and reduced curves. So using
Hei font as character’s standard font can avoid the similarity
between input font style and output calligraphy style, which
may increase the difficulty of calligraphy generation but can
evaluate the robustness and effectiveness of the evaluated
methods.

1) Qualitative Results: We train a model for every above
mentioned baseline methods as well as our method on the
four subsets individually. We show some samples generated
by the baseline methods and our proposed method in Fig. 3.
Our method achieves the best results on all the subsets.

Specifically, Rewrite and Encoder-Decoder method achieve
the worst results. The images generated by Rewrite and
Encoder-Decoder only have the right spatial structure of Chi-
nese character component but the layout and style of strokes
are far from satisfactory. As Fig. 4 shows, In Mi Fu and Zhao
Zhiqian subsets, almost all strokes can not match the ground
truth strokes.

The UNet method achieves a better result than the Encoder-
decoder result. Some results are close to ground truth both in
global style and local stroke style but have a small part of
wrong strokes on the Zhao Zhiqian, Liu Gong quan and Shen
Yinmo subsets. However, the results on Mi Fu subset is a little
unsatisfactory. We argue that the layout of strokes in Zhao Zhi-
qian, Liu Gongqu and Shen Yinmo are very similar to the
strokes of the standard font, which is much easier to transform
for the translation invariance of CNN. But there are significant
differences between the standard font and Mi Fu calligraphy
which may be too hard for UNet to learn.

The best results are obtained by our method. Even evaluated
on Mi Fu subset, our model can still generate images with
the similar style of the global image and the local stroke. In
some scenes, such as the input character has complex stroke
structure, our method still can handle well.

2) Effect of The Supervise Network: In practice, low level
features are hard to learn well in ordinary autoencoder models,
so we add Supervise Network in our model as a reference
to guide the transfer network to learn detail layout and style
of strokes. In Fig. 5, we compare our model with the one
without Supervise network while other parts maintain the same
design. In the aspect of perceptual quality of the generated font
images, our model beats the one without Supervise network
which holds a general structure of the character while having
some wrong fine details.

3) Effect of The Adversarial Loss: From the results shown
in the Fig. 6, we can see that the introduction of GAN Loss
helps to improve the quality of the generated image. It is
obvious that there are more valid vivid details of the characters
are added and the generated image tends to be more sharp with
much less blur. Take the first column as example, we can see
that the generated image is similar with the ground image in
shape layout but loses some details. However, after adding
GAN Loss, the image generated is more sharp and detailed.
We can draw the conclusion that GAN Loss helps the generator
mitigate the blur and add the details which cannot be captured
only with the L1 Loss.

4) Analysis of The Standard Font: Our approach achieves
desirable results when we use Hei Font as the standard font.
Here, we use a different font as our standard font to explore
the affect of the standard font. As shown in Fig. 7, we use
Kai font as the standard font, and our model can still output
photo-realistic calligraphy images which shows the robustness
of our method.
In this paper, we propose a model consisting of two subnets: transfer network and supervise network to synthesize Chinese calligraphy. The transfer network can transfer a standard font image to a calligraphy image with specified style and the supervise network can learn detailed stroke information. The two subnets can be trained together. Compared with recent Chinese calligraphy generation works, our approach can generate Chinese calligraphy images from standard font images directly. Besides, we also establish a benchmark for Chinese calligraphy generation and evaluate our method as well as other baseline approaches on the proposed dataset, our method achieves the best results. In the future, we will investigate methods that can handle large deformation between the input target images and expand our method to more general problems.

V. CONCLUSION

In this paper, we propose a model consisting of two subnets: transfer network and supervise network to synthesize Chinese calligraphy. The transfer network can transfer a standard font image to a calligraphy image with specified style and the supervise network can learn detailed stroke information. The two subnets can be trained together. Compared with recent Chinese calligraphy generation works, our approach can generate Chinese calligraphy images from standard font images directly. Besides, we also establish a benchmark for Chinese calligraphy generation and evaluate our method as well as other baseline approaches on the proposed dataset, our method achieves the best results. In the future, we will investigate methods that can handle large deformation between the input target images and expand our method to more general problems.

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