Chinese Typography Transfer

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Abstract—In this paper, we propose a new network architecture for Chinese typography transformation based on deep learning. The architecture consists of two sub-networks: (1) a fully convolutional network (FCN) aiming at transferring specified typography style to another in condition of preserving structure information; (2) an adversarial network aiming at generating more realistic strokes in some details. Unlike models proposed before 2012 relying on the complex segmentation of Chinese components or strokes, our model treats every Chinese character as an inseparable image, so pre-processing or post-preprocessing are abandoned. Besides, our model adopts end-to-end training without pre-trained used in other deep models. The experiments demonstrate that our model can synthesize realistic-looking target typography from any source typography both on printed style and handwriting style.

I. INTRODUCTION

The design of Chinese typography is a very time-consuming task, with the majority of time spent on manually writing a large amount of Chinese characters as the benchmark by calligraphers. Typography designers are also faced with this large amount of work though they can design with the help of software. So more efficient methods are absolutely worthwhile to be investigated: with a few characters being artificially designed, can we directly synthesize the remaining characters with the same designed typography.

The vast majority of work about typography synthesis focused on simple English or Latin characters. While just a few exploration about Chinese typography synthesis since the complexity and diversity of Chinese characters. Some proposed methods viewed every character as the combination of many radicals and strokes. The synthesis of a target style typography was based on components assembling or generating every stroke similar to that in desired characters. Another model tries to transfer style between characters using deep recurrent neural network while it is also a stroke-based method which synthesized a character by generating its strokes sequentially. Generative Adversarial Network has been applied to many image generation tasks in recent years. zi2zi is the first real deep model viewing characters as images and using conditional GAN to transfer typography style.

Many disadvantages exist in previous methods. Stroke-based models rely heavily on the preceding structural segmentation of every character such as. These methods decompose both calligraphic characters and standard characters into radicals even strokes on training set, then the models infer the most appropriate radicals or strokes for a new character. The character generation process in stroke-based methods essentially is the assembling of radicals or strokes. Another stroke-based method greatly relies on the manually definition of key points in all essential strokes appeared in Chinese characters. In summary, stroke-based models explicitly learn the corresponding calligraphic representation of standard characters, such as the contour and orientation of radicals or strokes. Sequence-based model generates key anchor sequentially and recurrently by using RNN, then connect these anchor points in order to form the complete character. The RNN generated method can not generalize to different style characters except generating skeletons of characters.

Compared with stroke-based models, firstly, our model treats every character as an in-separate image without any preprocessing such as segmentation or anchor points definition. Secondly, the calligraphic characters are indeed generated intelligently instead of structurally integrated by the model.

The most relevant work of our model is zi2zi, there are lots of losses(more than 4) constructed in model. A sophisticated balance settings between every loss is an unavoidable process. However, our model just contains 2 losses and the model is not sensitive to the weights of each loss. The generation net used in zi2zi is embedded into an intermediate layer containing category and character feature the desired output needs. In addition, instead of pretrained model before fine tune, end-to-end training mode is adopted by our model.

The contributions of this paper are reflected in the following aspects:

- Firstly, we propose an end-to-end model which can directly transfer typography style from a standard printed fonts to any other printed or handwriting typography. The model consists of two deep neural network: transfer network and discriminator. The transfer-net is responsible for capture calligraphic style information from target characters and then reconstruct the desired fonts. The transfer-net can be seen as a generator, together with the introduced discriminator, we jointly train these two nets like GAN.
- Our model gets extraordinary transformation results both on printed style and handwriting style fonts and we also explore how less training samples can be used to get satisfied performance so that the designed period can be shortened for typography and we can imitating anyone’s handwriting style in the future.
- In addition, a large benchmarks of 1872 calligraphic fonts are constructed by our team.
II. RELATED WORK

Chinese Characters Synthesis In [14], sample Chinese characters were decomposed into hierarchical components which may appear in other samples. A target character generation is a process of assembling all needed components which segmented from training samples. The algorithm tries to compare different possible ways of this combination and evaluate likeness of the combination results and choose the optimal one as the eventual result. [16] builds a Chinese Character Radical Composition Model based on the standard printed characters. Then samples from handwriting characters are segmented based on the model and non-samples handwriting characters can eventually generated by the previous segmented radicals from samples. [13] needs to represent the shapes of individual strokes and the typology of every character. The model then infers the character’s typology and shapes of all its constituent strokes. At last they assemble the strokes into a calligraphic rendition of the character. [12] proposed a method based on manually strokes extraction. Same number of key points in every stroke are extracted both on the reference and target character. Then the loss between these two groups of key points was calculated to minimize. Namely the style of target Calligraphy was represented as the relative locations of key points in every stroke. These stroke-based models need to segment every character into components it includes. This preceding segmentation is very complex and time-consuming and it always cannot correctly decompose some complicated characters. [15] proposed a model which used recurrent neural network(RNN) as both discriminator for recognizing Chinese characters and generator for drawing Chinese characters. It is also a stroke-based model which generated strokes of one character sequentially. But this method just generated characters without any typography style. Recently, Generative Adversarial Network(GAN) has been applied to many image generation task. “zi2zi” is the first model transferring Chinese calligraphy by using conditional GAN with auxiliary classifier to capture style information of target characters. An encoder and and decoder are involved in generator with style information and character information forming the intermediate embedding layer. However, it performs well on synthesis of thick typography style rather than hand-writing style fonts since the embedding layer can not preserve enough structural information for recovering in decoder. Our model with a fully convolutional network obtains amazing transformation performance even on hand-writing fonts.

Image Style Transfer Many works have been exploring style transformation between images such as: [3], [7], [6], [11] etc. Cross domain transfer[11] and Image-to-image[6] are relevant to our work. Generative Adversarial Net is the primary model both in [6] and [11]. [6] use GAN translate the edges of an objection into corresponding photos with color, changing an abstracted images such as cityscapes into scene images, etc. [11] map the semantic content from original domain to a new domain. Many Image segmentation tasks can also be viewed as the transformation between images, such as [8]. Most of these work focused on natural images while our work is about Chinese characters which are characterized by many sophisticated and compact structure, so it is a challenge to capture style information and obtain good generalization performance on test set.

III. METHOD DESCRIPTION

We will illustrate details of our proposed model in this section. Our model consists of two sub-nets: Transfer
Network and Discrimination Network. Transfer net implements the purpose for changing style information(e.g., thickness, contour, orientation, connection) of standard printed characters(namely source domain) into another quite different style which may exhibit individual characteristics of hand-writer(namely target domain). Discrimination net polishes the generated characters as a decorator since characters generated by Transfer net may be a little twisty or blurry on test dataset especially some of Cursive Script. The whole model is showed in Figure 1. Further explanations are demonstrated below.

A. Transfer Network

The separation of content/style information is important in most researches about style transfer or domain transfer. For task about English letters or digits(e.g. MNIST or SVHN), simple classification models can be trained as content extractors[11] because just a few classes included in these data. For task about natural image transformation, a pre-trained network on Image-Net can extract content information[3]. While for thousands of Chinese characters, two mentioned methods above are not good choices since it is hard to train a classification model to distinguish every character and pre-trained model based on other dataset also cannot extract complete content information from just single character.

We adopt a fully convolution net(FCN) structure in Transfer Network to solve this separation problem perfectly. Instead of training two networks for extracting content/style information respectively, this FCN structure captures unique calligraphic style correctly, meanwhile preserves structure information as intact as possible. The first half part of transfer-net is similar to encoder: convolution layers with following batch-normalization and exponential linear units. Standard source characters are transformed into essential skeletons in the first two convolutional outputs and then further abstracted until to a $4 \times 4 \times 512$ space instead of a embedded fully connection layer. Experiments verify that fully connected embedding destroys topological structure, leading to inaccurate relative locations of strokes since the limited representation of 1-D feature vector compared to 2-D feature map. The latter half part of transfer-net is composed of a series of up-sample(also named transpose-convolution) and convolutional layers. Borrowing from U-Net[10], skip connection strategy is effective on recovering details in characters, especially in some case of complex characters with compact structure. The decoder is deeper than encoder considering that it is more difficult to recover the target domain character from intermediate hidden space.

B. Discriminator Network

After Generative Adversarial Network being proposed in 2014, it has been widely applied to many tasks relevant to image generation. The adversarial training procedure makes generator produce fake data sharing the identical distribution of real data. Some methods accomplished Chinese style transformation based on an ACGAN[9]. In our previous work, the transfer-net achieves transformation purpose in some degree but there is some noise attached in characters’ background and some strokes are little twisty. So we introduce Discriminator which receives generated characters from transfer-net as input. Discriminator tries to distinguish which inputs come from target domain and which ones come from Transfer net, meanwhile the transfer-net tries to optimize itself for producing more realistic samples to cheat Discriminator. This adversarial loss is defined just like GAN and it is very effective in two aspects: (1)removing blurry noise from characters; (2) fine tuning the direction of some poor generated strokes.

C. Optimization Jointly

We optimize Transfer Network and Discriminator jointly rather than two divided steps. Two loss functions are implemented by model. The transfer loss is the measure between generated characters and corresponding ones in target domain. In the period of data pre-processing, every pixel in both source and target character images is normalized ranging from 0 to 1. Cross entropy loss is chosen by our model since the transfer problem can be viewed as a logical regression problem in every pixel if we binarize the images. It is noticed that a weighted parameter $\lambda_t$ is introduced into the cross entropy loss for balancing the unbalanced proportion of positive/negative pixels in every calligraphic style. We do this based on the observation that some calligraphic style are thin while some may be very thick. The transfer loss is defined as:

$$
\min_T V_t(T) = \mathbb{E}_{(s,t)}[-t\lambda_p \cdot (\log \sigma(T(s))) - (1 - t) \cdot \log(1 - \sigma(T(s)))]
$$

(1)

This loss request pair-wise samples $(s,t)$, where $s \sim P_{source\_domain}(s), \ t \sim P_{target\_domain}(t)$. $T$ is function of transfer-net and $\sigma$ is $sigmoid$ activation. $\lambda$ is a trade-off parameter controlling the penalty by up-weighting or down-weighting the cost of a positive error relative to a negative error.

The adversarial loss follows a two-player minimax game with valued function $V(G,D)$ just like GAN:
\[
\min_T \max_D V_2(D, T) = \\
E_{t \sim p_{\text{target}}(t)}[\log D(s)] + E_{s \sim p_{\text{source}}(s)}[\log(1 - D(T(s)))]
\]  
(2)

We optimize these two objection jointly, while the losses are combined into 2 groups:

\[
L_{\text{generation}} = \min_T [\lambda_1 V_1(D, T) + E_{s \sim p_{\text{source}}(s)}[\lambda_2 \log(1 - D(T(s)))]]
\]  
(3)

\[
L_{\text{discriminator}} = \max_D \lambda_3 V_2(D, T)
\]  
(4)

\(L_{\text{generation}}\) is minimized to update parameters in transfer-net, while \(L_{\text{discriminator}}\) is minimized to update parameters in discriminator. \(\lambda_1, \lambda_2\) and \(\lambda_3\) work as the trade-off parameters. Experiments demonstrate that this optimization strategy obtained better clear results.

IV. EXPERIMENTS

A. Transfer performance on calligraphic style

In calligraphic style transfer tasks, 60%, approximate 3000 characters of the source dataset and corresponding 60% of the target dataset are used for training. The evaluation is done on the random 64 characters sampled from test split(40%) of source dataset, comprised of 2000 characters. Calligraphic style fonts are all characterized with some thick strokes compared with our source domain, so the positive/negative pixels are nearly balanced in desired output. We set parameter \(\lambda = 1.1\) in cross entropy loss. Figure IV-A shows the transfer result on XingKai fonts.

B. Transfer performance on printed style

Compared with calligraphic style fonts, handwriting fonts are extremely thin with connections between strokes. Since the unbalanced positive/negative pixel in desired output, we set parameter \(\lambda = 0.6\) in cross entropy loss to trade off the penalty. Figure 3 shows the transfer results on one handwriting fonts.

In this section, we will evaluate our model’s performance. A standard FangSong font is constructed to be fed in the model as input. FangSong fonts are balanced in width and structure, so it is appropriate to use them as source domain. 6 different style fonts including printed type(3) and handwriting type(3) are also constructed according to their TTF scripts as target domain. Every script includes 5000 characters frequently used in our daily life. Different from style transfer tasks for natural image, which we cannot find a good objective criteria, Chinese calligraphic style task has corresponding ground truth for every input as our reference, so mean square error(MSE) is used as our evaluation standard in test set.

Structural details of model are showed in Table I. The architecture of \textit{Transfer} net consists of two parts: encode and decode. In encode part, a \(64^2 \times 1\) character image will be convolved to \(4^2 \times 512\) feature map by 8 convolutional
Experiments result under different configuration. (a) Left: Our generated results; Center: Results without skip connections; Right: Results without adversarial loss. (b) Some characters generated in different cases are magnified particularly for details. Top: Our generated results; Center: Results without skip connection; Bottom: Results without adversarial loss.

(a) Experiments result under different configuration
(b) Magnified characters for comparing details

Fig. 4. Experiments result under different configuration. (a) Left: Our generated results; Center: Results without skip connections; Right: Results without adversarial loss. (b) Some characters generated in different cases are magnified particularly for details. Top: Our generated results; Center: Results without skip connection; Bottom: Results without adversarial loss.

layers with $64, 64, 128, 128, 256, 256, 512, 512$ filters respectively. In decode part, previous $4^2 \times 1$ feature map is gradually de-convolved, with skip-connection and convolutional layers in it. The architecture of Discriminator net consists of 4 convolutional layers and a FC layer with 256 outputs. Each convolutional layer is followed by Batch Normalization[5] and ELU[2] non-linearity.

C. Effect of adversarial loss and skip connection

Skip connection The skip connection trick introduced in U-Net has got amazing performance on image segmentation task[10] and image-to-image generation task[6]. This skip connection trick improves our performance on fonts transfer task since it is able to recover the details, such as subtle strokes, connections in characters (see Figure 4). We visualize first two connection feature maps for analysis. It is illustrated in Figure IV-B(a) that in the 1st skip connection layer, the previous $64^2 \times 1$ feature map is clear in texture, preserving sharp edge information, while the posterior feature map is blurry and some local texture are disconnecting. So by connecting this layer to latter layer, local region in latter feature map may be compensated with some lost details.

Adversarial Loss Many tasks about image generation adopt adversarial method for training recently. A discriminator tries to correctly draw a distinction between the real fonts (target domain) and the fake fonts (generation) while the generator improves itself for cheating the discriminator as much as possible so that the generator captures some feature representing the real ones. For our model, the optimization of this adversarial loss release the overfitting in test set. Figure IV-B(b) demonstrates that the configuration with adversarial loss leads to lower reconstruction loss in the latter period of training. Compared with generated fonts without adversarial loss, our transfer results become more realistic with less twisty on some strokes and less noise on the background, see Figure 4.

D. Performance on different number of training set

Our purpose is to do font transfer task by using as less samples as possible. So different proportion training samples are divided from the whole dataset. And the remaining ones are validation and test set. We evaluate the performance of the model on 3 different number of training set: (1) 3000 samples (60%) are trained on the model; (2) 2000 samples (40%) are trained on the model; (3) 1000 samples (20%) are trained on the model. The MSE loss curve demonstrated that (1) and (2) obtained very close performance, we can also confirm it according to Fig[4]. However if we decrease the training numbers to only 10%, the performance will greatly deteriorate.

V. CONCLUSION AND FUTURE WORK

In this paper, we propose a style transfer model for Chinese characters, which can change the standard printed style characters into other various style characters including printed fonts.
even handwriting fonts. The model we proposed is a generic framework including a transfer-net and a discriminator being trained jointly and end-to-end. Experiments results demonstrated that our model can be used to automatically generate high-quality printed style or handwriting style fonts libraries which include huge amount of machine-generated characters that are indistinguishable from original real fonts.

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Fig. 7. More experiment results on printed style fonts

Fig. 8. More experiment results on handwriting style fonts