AUTOMATIC GENERATION OF CHINESE HANDWRITING VIA
FONTS STYLE REPRESENTATION LEARNING

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ABSTRACT

In this paper, we propose and end-to-end deep Chinese font generation system. This system can
generate new style fonts by interpolation of latent style-related embedding variables that could achieve
smooth transition between different style. Our method is simpler and more effective than other
methods, which will help to improve the font design efficiency.

Keywords Chinese Fonts · Generation · Handwriting · Font Style · Representation Learning

1 Introduction

Language is a unique symbol of human civilization. Writing system is the development of the language. Writing
system usually has many different fonts. Unlike the English font library that has only 26 alphabets, Chinese font library
contains tens of thousands of characters. There are also thousands of commonly used characters. Making a new style
font library is a difficult and time-consuming job due to the huge amount of Chinese characters. Designing a new font
of Chinese character require a lot of human design and adjustment to draw each character. It is necessary to find an
automation method to help the font designing for Chinese character.

In the last few years, the development of deep learning make it possible in automatic image style transfer. Several
researcher have intended to generate Chinese fonts by using different deep learning method. Jiang et.al. using a U-net
model realize end-to-end Chinese character mapping, that automatically generate the whole GB2312 font library that
consists of 6763 Chinese characters from a small number of characters written by the user. [1]. Jiang develop an
efficient and generalized deep framework W-Net, that is capable of learning and generating any arbitrary characters
sharing the style similar to the given single font character[2]. Sun et. al. also propose a variational auto-encoder
framework to generate Chinese characters[3].

These methods are based on such an assumption that the latent features of a Chinese character can be disentangling into
content-related and style-related components. Combining different parts content-related and style-related components
can construct new style fonts. In this paper, we propose and end-to-end deep Chinese font generation system. This
system can generate new style fonts by interpolation of latent style-related embedding variables that could achieve
smooth transition between different style. Our method is simpler and more effective than other methods, which will
help to improve the font design efficiency[3, 4, 5, 6, 7, 8, 9].
2 Method Description

Due to the complicated structures of Chinese characters, it is not easy to transfer deep learning methods widely used in image synthesis to this job. The main problem is that the style and content features of Chinese characters are complexly entangled. The present deep learning methods, such as cross-domain disentanglement\[10\], Dientangled Representation\[11\], U-Net model[12], are not well suited for Chinese character synthesis.

In this paper, we use an encoder-decoder model to map Chinese characters from one type to another type, such as Song fonts to Kai fonts. The mapping only transfers the character style, the characters have the same content. During the mapping training, the encoder-decoder model will extract the fonts style features in the latent space. When we find the right model parameters, we embed a font style one-hot vector in the latent space. Then we retrain the model with style embedding. This process can be seen as an artificial entanglement process, that entangles the style and content features of the characters.

Our method contains three steps. First, we use a U-Net encoder-decoder model to extract the font feature vectors for about 40 different types of fonts. Then, we concatenate an one-hot vector to the feature vectors and retrain the model. The one-hot vector encoding about 40 different fonts style. Finally, we can change the one-hot style vector to arbitrary embedding vectors, and synthesize new style fonts which have mixed styles of different fonts.

2.1 U-net encoder-decoder model

The U-net encoder-decoder architecture is shown in Figure 1. The input of the network is an Song style Font with 256x256 pixels. The Font through an 8-layers convolutional encoder. The output of the encoder is 5x5x512 features vectors. This features concatenate a one-hot style embedding are input to the decoder. After similar 8-layers deconvolution, the decoder output a new style fonts.

3 Experiments results

Figure 2 is the two different outputs of the model. The input is all the Hei style fonts. Figure 3 is the Song style fonts. Song style have a similar style feature of Hei. Figure 4 is XingKai style, that has very different characteristics style with the Hei style. This two output examples show that the model has a good ability to generate new fonts.

The style transfer have been show in Figure 5. The first three columns are the input fonts. The middle three columns is the output of our model. The last three columns is the style fonts, which features is embedding in the one-hot vectors. This results indicate that our model can control the output fonts through the one-hot embedding vectors.

Figure 6 show the generate fonts of multiple different styles. All the generated fonts have no missing strokes, and the font feature details are perfect. The input fonts is all Hei style fonts for those multiple generation fonts. These multiple generation fonts show that the control of the style embedding vector is very good.

Since the above results show the one-hot embedding vector already have stable control ability over the generation fonts, we can explore whether the embedding vector can be used to achieve the style transition between two fonts.
Figure 2: Hei style fonts generation

Figure 3: Xing style fonts generation
Figure 4: Hei style to Xing style transfer

Figure 5: multiple different styles generation
When the input embedding label is [1,0,...], the network will convert the source input font text sample to the target font text sample with label 0 during training, and if the the input embedding label is [0,1,0,...], the source font sample is converted into the target font sample with the label 1. So does the input embedding label [0.5,0.5,0,...] mean that the output style is the mixture of the two fonts? Figure 6 shows the generation of the fonts when the embedding labels are assigned different values, such as [0.2,0.5,0.7,...]. The results indicate that the font styles can be controlled through assigned different values in the embedding vector.

3.1 Conclusion

Our paper proposed a novel and simple method to automatic generate new Chinese fonts from existing font libraries. The results demonstrated that our method is capable of generating new high-quality fonts.

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References

[1] Yue Jiang, Zhouhui Lian, Yingmin Tang, and Jianguo Xiao. DCFont: An End-To-End Deep Chinese Font Generation System. SIGGRAPH Asia 2017 Technical Briefs on - SA’17, pages 1–4, 2017.
[2] Shun-ichi AMARI. W-Net: One-Shot Arbitrary-Style Chinese Character Generation with Deep Neural Networks. Journal of the Society of Mechanical Engineers, 90(823):758–759, 2017.
[3] Danyang Sun, Tongzheng Ren, Chongxuan Li, Jun Zhu, and Hang Su. Learning to Write Stylized Chinese Characters by Reading a Handful of Examples. 2017.
[4] Pengyuan Lyu, Xiang Bai, Cong Yao, Zhen Zhu, Tengteng Huang, and Wenyu Liu. Auto-Encoder Guided GAN for Chinese Calligraphy Synthesis. Proceedings of the International Conference on Document Analysis and Recognition, ICDAR, 1:1095–1100, 2018.
[5] Li Deng, Liyi Wang, and Zhaolin Ren. Chinese Calligraphy Font Classification and Transformation.
[6] Yuan Guo, Zhouhui Lian, Yingmin Tang, and Jianguo Xiao. Creating New Chinese Fonts based on Manifold Learning and Adversarial Networks. 2018.
[7] Bo Chang. Rewrite2 A GAN based Chinese font transfer method. pages 1–9.
[8] Bo Chang. Generating Handwritten Chinese Characters using CycleGAN.
[9] Samaneh Azadi, Matthew Fisher, Vladimir Kim, Zhaowen Wang, Eli Shechtman, and Trevor Darrell. Multi-Content GAN for Few-Shot Font Style Transfer.
[10] Abel Gonzalez-Garcia, Joost van de Weijer, and Yoshua Bengio. Image-to-image translation for cross-domain disentanglement. (Nips), 2018.
[11] Hsin-Ying Lee, Hung-Yu Tseng, Jia-Bin Huang, Maneesh Kumar Singh, and Ming-Hsuan Yang. Diverse Image-to-Image Translation via Disentangled Representations. 2018.
[12] Patrick Esser and Ekaterina Sutter. A Variational U-Net for Conditional Appearance and Shape Generation.