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Poster

Japanese Kanji Font Style Transfer based on GAN with Unpaired Training

Hiroki Sakai and Daisuke Niino and Takashi Ijiri

Shibaura Institute of Technology, Tokyo, Japan

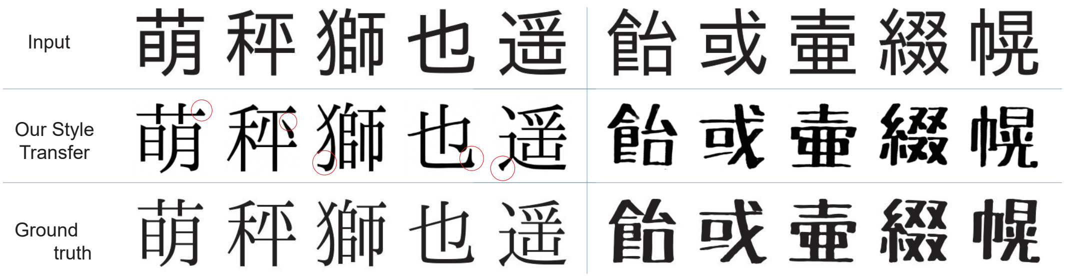

Figure 1: *The result of style transfers from IPA Gothic to IPA Mincho (left) and from IPA Gothic to Tanuki Yusei Magic (right).*

Abstract

To design a whole package of Japanese font is labor consuming, since it usually contains about 30k kanji characters. To support an efficient design process, this poster attempts to adopt a style transfer algorithm for font package completion. Given two font packages where one contains all characters and the other lacks a large part, we train CycleGAN to perform style transfer between the two packages and transfer the style from the former to the latter. To illustrate the feasibility of our technique, we performed style transfer experiments and achieved visually plausible results by using a relatively small training data set.

CCS Concepts
•***Computing methodologies*** $\rightarrow$ *Image processing;*

1. Introduction

When designing a font package, designers decide on an overall style and design each character such that it is consistent to the overall style. However, constructing a Japanese font package is very labor intensive because Japanese has approximately 50k kanji (Chinese characters used in Japanese), and a Japanese font package usually contains 30k kanji. Some free font packages do not cover enough kanji characters, which causes problems for practical use. To address such issues, we report on our attempt to automatically complete a font set by adopting a style transfer technique based on a generative adversarial networks (GAN) [GPAM*14].

Style transfer is a technique to modify an image to have a style of other images [ZPIE17, LBY*17, IZZE17]. Zhu et al. presented a novel approach called CycleGAN [ZPIE17]. Given two sets of images, it learns bijection from a set to the other by taking into account both forward and backward mapping. However, style transfer for Japanese kanji fonts has not been extensively discussed. Lyu et al. recently presented a style transfer technique to generate Chinese calligraphy images from standard Chinese font images [LBY*17]. They combined GAN with a deep auto-encoder and achieved high quality transfer results. However, their technique requires *paired* training data, i.e., pairs of characters in standard font and in calligraphy style. In contrast, we adopt a technique that involves unpaired training data to increase the size of the training data for the font-completion problem.

We attempted to complete a Japanese font set by assuming two font sets *set_A* and *set_B*, where *set_A* contains all kanji characters and *set_B* does not. In our scenario, *set_A* can be selected from current standard fonts and *set_B* is a newly designed font. We learn the font-style transfer from *set_A* to *set_B* and transfer images of characters in *set_A* to complete *set_B*. We adopt CycleGAN with

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a small modification for this purpose. To illustrate the feasibility of our technique, we selected three fonts with different styles, i.e., Ming (serif-like), Gothic (sans-serif-like), and handwriting fonts, and transfer their styles to a different one. If our technique learns accurate style transfer even when the size of *set_B* is small, it will reduce the workload for designers. To confirm the effect of the size of *set_B*, we learned style transfer multiple times by varying the size of *set_B* and measured the accuracy of this learning.

2. Method and Experiments

We assumed two character image sets of two different fonts *set_A* and *set_B*. *Set_A* contains all kanji characters and *set_B* does not. Each character is represented with a 256×256 image. To construct training data, we resize each image to 143×143 and obtain multiple 128×128 images by cropping the resized image at different positions. We learn the style transfer between *set_A* and *set_B* by adopting CycleGAN [ZPIE17]. Note that the original CycleGAN flips images to augment the training data set; however, kanji characters are asymmetric, so we skip this process.

To illustrate the usefulness of our technique, we conducted experiments on font-style transfer. We selected three fonts with different styles, i.e., *IPA Gothic*, *IPA Mincho*, and *Tanuki Yusei Magic*. Figure 1 (left) shows the results when we used IPA Gothic for *set_A* and IPA Mincho for *set_B*. Similarly, Figure 1 (right) shows the results when we used IPA Gothic for *set_A* and Tanuki Yusei Magic for *set_B*. Note that the Japanese government defines 2136 kanji as *regular-use kanji*. We used these kanji for *set_A* and 500 characters (randomly selected from the 2136) for *set_B*.

Figure 1 shows our style transfer results where we selected characters not included in the regular-use kanji and transferred their styles. The results indicate that we achieved visually plausible font images. Especially, as in the circles in Figure 1, our technique accurately adjusted the thicknesses of strokes and reconstructed the decorative effects shown at specific stroke motions.

To confirm the effect of the size of set_B on the training accuracy, we conducted another experiment. We chose *MS Gothic* for *set_A* and *MS Mincho* for *set_B*. We used the 2136 regular-use kanji for *set_A* and a randomly selected N characters for *set_B*. After training, we selected 100 characters from *MS Gothic* that were not used for training, transferred their style, and measured the errors. We used the mean squared difference of pixel values for the error metric. We set N = 100, 200, 300, 400, 500, 1000, 1500, and 2000. For each N, we conducted style transfer learning three times and measured the errors. Figure 2 summarize the error values with respect to the size of *set_B*. When the size of *set_B* increased, the error rate decreased, and accurate style transfer was achieved. The decrease in the error rate slowed considerably when $N = 500$.

3. Conclusions

We proposed a style transfer technique for Japanese kanji font completion. Given two image sets of different fonts, we train style transfer by using an unpaired image-to-image translation technique and complete a set by transferring images in the other set. We achieved visually plausible completion by using a relatively small training data set.

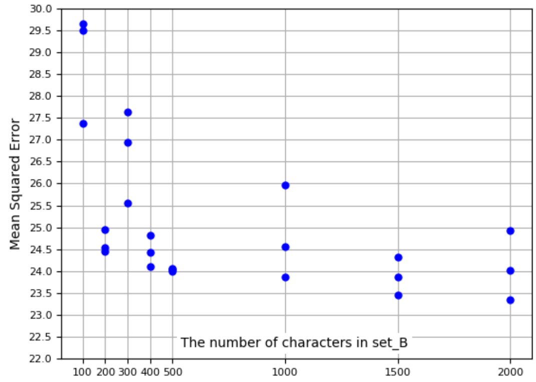

Figure 2: *Errors of style transfer experiments with different N.*

Figure 3: *Visible errors in style transfer.*

Limitations and future work. We found limitation in deformation of each stroke; when the shapes of corresponding strokes differ significantly, our technique only modifies the style of the stroke and fails to deform it (circles in Figure 3). We also observed appearance and disappearance of wrong strokes (red arrows in Figure3). In the future, we would like to modify the network structure and loss function to deal with the stroke deformation and reduce the wrong stroke appearance/disappearance. Our future work contains to perform comparison with our method (i.e., training with unpaired data set) with style transfer methods with paired data set. Furthermore, to develop a hybrid technique by combining paired and unpaired training methods for more accurate and robust font style transfer is our interesting future direction.

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