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A Hanbok Design and Improve the Results using GAN

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Abstract

In this study, Generative adversarial network (GAN) was used to design Korean traditional clothes, Hanbok. Style transfer methods are used to create Hanbok images based on contour images of Hanbok by learning domain translation between color domain and edge domain with GAN algorithm. Among the Style transfer methods, DiscoGAN was used. Furthermore, CycleGAN and SRGAN were used to improve the resulted images of DiscoGAN.

Keywords: GAN, Style Transfer, Design

I. INTRODUCTION

In the field of artistic creation, such as music and painting, which were considered as human domains, deep learning has been applied increasingly. Recently, the use of artificial intelligent (AI) in fashion design has been continuously conducted. This study developed a method of designing Hanbok using deep learning. Hanbok is a tradition Korean dress. Basic women's Hanbok consists of jacket (Jeogori) and skirt (Chima), and it can be changed depends on the situation and weather. The characteristics of Hanbok are unique texture, color combination and pattern. Therefore, we need a network that learns these features well.

The design has no right answer and creative results are expected. Thus, an unsupervised learning is proper to obtain new results rather than a supervised learning. Furthermore, new research is necessary for traditional costume design. Not only the unique textures and colors of the Hanbok, but also the characteristics of the traditional jackets and skirts should be learned successfully.

Therefore, this study pursues style transfer that transform input images into images with the desired characteristics using GAN, a representative unsupervised learning method. Afterwards, improved DiscoGAN results by using CycleGAN or adding SRGAN.

II. RELATED WORK

II.I Generative adversarial network (GAN)

Since its first appearance in 2014, GAN[1] has received a lot of attention. Its success in generation has led many methodologies and applications such as data augmentation, image up-sampling, and style-based generation and so on. A Generative Adversarial Network is a generative model that is trained using a generator and a discriminator. The generator aims to generate samples from a noise-based input and produce plausible samples that the discriminator thinks is real. The discriminator learns to differentiate generated examples from real examples. It aims to determine accurately whether the data produced by the generation model is real or false. Therefore, the generator can create plausible samples as the two models competitively trained.

II.II Style Transfer GAN

Style transfer is changing the style of images while maintaining the shape of the content images. There are many methods in style-transfer, and they are being developed. Representatively, there are Pix2Pix[2], DiscoGAN[3], and CycleGAN[4]. Pix2pix is a method to implement image to image translation using conditional adversarial networks(cGAN). Pix2pix uses the cGAN loss function to set the conditions for generating images in the generator and discriminator. By adding L1 loss between generated image and actual image, it gets more distinct result. Pix2pix needs a pair of the original images and the ground truth of changed images. However, it is rare to have ground truth images that you want to convert. DiscoGAN and CycleGAN use a method to bring the generated image back to itself so that it can be converted to different image styles even when the data is not in pairs. The key ideas of the two networks are the same. When different image domains A and B exist, learn to convert from domain A to domain B and then back to domain A. Also, B converts to domain A and then to domain B.

II. III Super Resolution GAN

Image super resolution can be defined as increasing the size of small images without quality drop or restoring high resolution images from low resolution images. Super Resolution GAN (SRGAN)[5] is a method to improve blurry images using GAN. While training, the original high resolution (HR) image is reduced to low resolution (LR) image and then restoring it back to the original HR image. SRGAN proposed a perceptual loss function. This trains the Generator function that generates an HR image from the LR input image. Therefore, when a new image comes in, super resolution is possible based on the existing trained Generator.

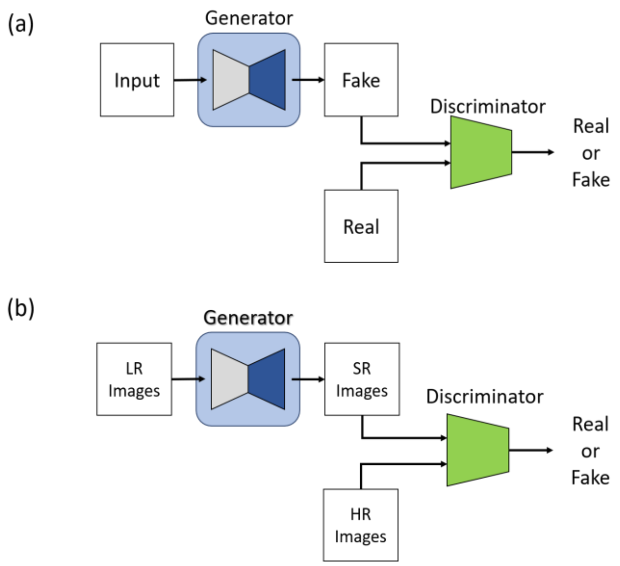

Fig.1. (a) Basic GAN Architecture. (b) Super Resolution GAN Architecture.

III. EXPERIMENTS

III.I. Dataset

Edge and color images of Hanbok are desired for data set for edge to Hanbok style transfer. Therefore, data set is consisted of color images and extracted outline images using Holistically-nested Edge Detection (HED)[6]. HED is an edge detection method learned through end-to-end neural network. Therefore, it can extract constant edges. This method overcomes the drawbacks of the Canny edge, which requires appropriate threshold values according to the images. The images obtained through HED were more accurate at the clothes boundaries and had less noise (Figure 2). In addition, the contrast of HED images makes it easier to see the overall shape. Hanbok and edge images used for training were 4272 each, 4073 train images and 200 test images. Transformation between hanbok and edge images were learned with this data set.

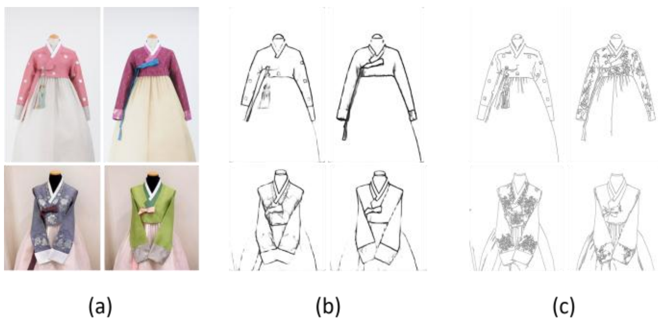

Fig.2. (a) Original color Hanbok images. (b) Edge images using HED. (c) Edge images using canny edge detection.

III.II. DiscoGAN

DiscoGAN uses GAN to discover relationships between different domains. When different image domains A and B exist, the A domain is mapped to B ($x_{AB} = G_{AB}(x_A)$), and then B is mapped to A ($x_{ABA} = G_{BA}(x_{AB})$). DiscoGAN learns by adding reconstruction loss to general GAN loss. GAN loss is used to train the generator so that the discriminator considers the data transformed from the A domain to the B domain is real. Reconstruction loss is the difference between x_A and x_{ABA} used to return to the starting domain(A).

Fig.3. Characteristics of Hanbok image designed using DiscoGAN. (a) Edge images and color images made with DiscoGAN. (b) The result is only an image of the domain and not related to the input. (c) The resolution of the resulting image is low.

III. III. CycleGAN

In the case of DiscoGAN, it was mapped in one direction, resulting in a meaningless mapping result. Therefore, in order to be meaningful, the mapping must be done in both directions. CycleGAN is a cyclic structure that maps the results back. That is, learn the bidirectional mapping to return to the original state. Also, unlike DiscoGAN, cycle-consistency loss transforms the style without changing the shape. As a result of learning, the shape was almost unchanged, and it produced the characteristics of Hanbok such as colorful colors, patterns of Hanbok, and wrinkles.

In Figure 4, the resolution is relatively high, and the shape and texture of the hanbok is very similar to the actual hanbok. On the other hand, it created a new type of hanbok different from the existing hanbok. In Figure 4 (b), it shows a color or pattern of tie that did not exist in the data set. In (c), we can see that the texture and pattern of the skirt is newly created. In other words, it has obtained better results than DiscoGAN. Therefore, it is suitable for designing a new hanbok while restyling the edge image to a color image, which is the goal of this paper.

Fig.4. Characteristics of Hanbok image designed using CycleGAN. (a) Edge images and color images made with CycleGAN. (b) Design of ties that are not in the data set. (c) New pattern or texture of the skirts that are not in the data set

III. IV. DiscoGAN with SRGAN

SRGAN was added to solve the disadvantage of the low resolution of DiscoGAN. During training, when the original Hanbok image is given as input, SRGAN lowers the resolution of the image. Then the generator of SRGAN learns how to return it to the original image resolution. Therefore, using well-trained generator can improve low resolution images. In other words, the generator learned through SRGAN is used to improve the result of DiscoGAN.

If you look at Figure 5, the resolution has been increased, so it creates a more realistic hanbok image. Looking at the images of Hanbok in (b), the colors became clear and the boundaries between the skirts, jackets, and ties became clear.

Fig.5. Improving DiscoGAN results with SRGAN. (a) Results of DiscoGAN. (b) Results of SRGAN

IV. CONCLUSION

This study demonstrated GAN can be used to design Korean traditional clothes, Hanbok. We experimented with three representative GANs using the style transfer methods. Although the results resolution of discoGAN was not good, CycleGAN shows better results through cycle-consistency. Furthermore, better results were obtained by using SRGAN which makes high resolution images from low resolution result images of DiscoGAN. This paper shows that there are many methods to design Hanbok and results can be better if Style transfer GAN combine with other GAN algorithms.

If style transfer is used, not only edge to hanbok, but various designs will be possible. It can be applied in various ways such as converting from Korean hanbok to male hanbok, designing Hanbok style modern clothes, and designing Hanbok style products. Also, GAN algorithms such as TextureGAN can be applied for various designs to better utilize traditional patterns and textures. If go further, we will be able to implement a network specialized in hanbok design which will help Hanbok designers develop their designs.

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