GANs-based Clothes Design: Pattern Maker Is All You Need to Design Clothing

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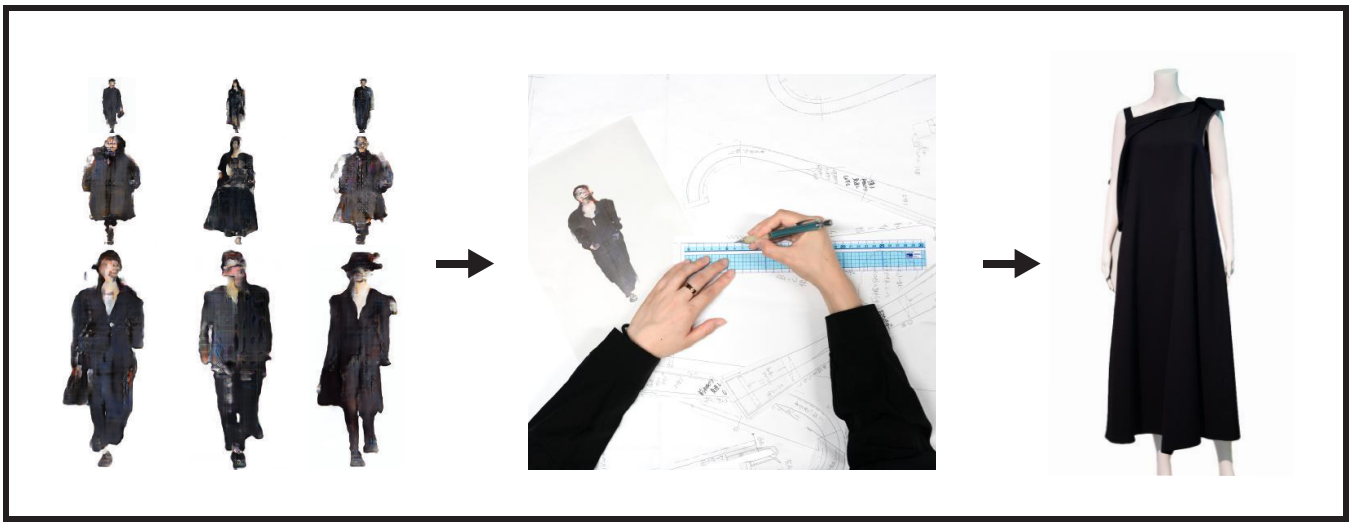

Figure 1: In clothing production from generated images by GANs, we investigated important factors in pattern creation.

ABSTRACT

Machine learning have been recently applied to multiple areas, including fashion. Fashion design by generated images makes it possible to inherit design without fashion designer and get inspiration, however, little research has been done on usage of machine learning for creation of designer clothing. The state-of-the-art works aim for high-definition output images. However in fashion design image generation, it has not been thoroughly investigated to what extent the quality of the generated image should be provided to the pattern makers that draw the costume pattern from the design images. Therefore, in this paper we propose a method of generation of clothing images for pattern makers using Progressive Growing of GANs (P-GANs) and conduct a user study to investigate whether the different image quality factors such as epoch and resolution affect the participants' confidence score. We discuss the results and possible applications of the developed method.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**;

KEYWORDS

fashion, clothes, pattern, pattern maker, Generative Adversarial Networks, deep neural network

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1 INTRODUCTION

Popular designers are loved and known by their unique styles and features. However, it is difficult to maintain the level of creativity in

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designing while preserving their own styles. Especially in fashion design, new clothing are announced globally every season in the form of fashion shows. Maintaining the characteristics of his own design in intense production schedule, while creating novel work is a big challenge for designers. Recently, in the field of machine learning, researches on image generation of clothing and designs using deep learning are actively conducted. Most of the researches have been made from a consumer's viewpoint, such as images discrimination of clothing using machine learning [31, 40], trend predictions [37], coordination articles [30]. On the other hand, few researches are done on the production process all the way from clipping to actual production of clothing from generated image.

There are a number of researches that aimed at creating new designs through image generation. However, few directed towards the process of actually producing the clothing. In the process of actual clothing production, often there is a pattern maker besides the main designer in sketching a pattern according to design picture.

Traditional fashion production can be briefly described in the following steps. First a design is visualized by the fashion designer in the form of a rough sketch. Next, a pattern maker draws a pattern with precise measurements of the clothing based on the design sketch. Finally, sewing craftsmen make the clothing based on that pattern. Kato et al.[17] have reported that a fashion design workflow (Figure 2) that replaces a design drawing of a designer in the first production process with image generation by generative adversarial networks (GANs), followed by a pattern maker produces a pattern based on it, and a sewing craftsman actually produce the clothing. They use images of clothing under the same brand as the dataset used for GANs learning to generate images that maintain the style of the source brand. In the study, they made clothing from referencing 128 px images generated using former image generation technique DCGAN [26]. Machine learning researchers are devoting much effort to generate high resolution image in hope of bringing it closer to the actual sketch. However, such tasks consume large amount of time and computation resources. These ultra high quality high resolution GAN image generation that is comparable to designer's takes a long time which simply is not realistic. It is estimated that a month of training is required using the current state of art GAN algorithm. In addition, as quoted above, it is possible to produce clothing even with the low resolution image generated by GANs as a design sketch. In the process, the impact of resolution of the generated image by machine learning on actual clothing production is questioned. Therefore, we conduct experiments on people who actually participate in clothing production. Based on the results, we clarify the degree of quality a pattern maker needs to draw an accurate patterns from the generated image. As a result, image resolution and epoch number are not the main factors in pattern making. However, the pattern makers who are experienced and knowledgeable in the source brand designs in pattern making using the generated images.

1.1 Contributions

- We surveyed how the quality of image generated by GANs affects pattern making process.
- Analysis of the user study is conducted by using mathematical models.

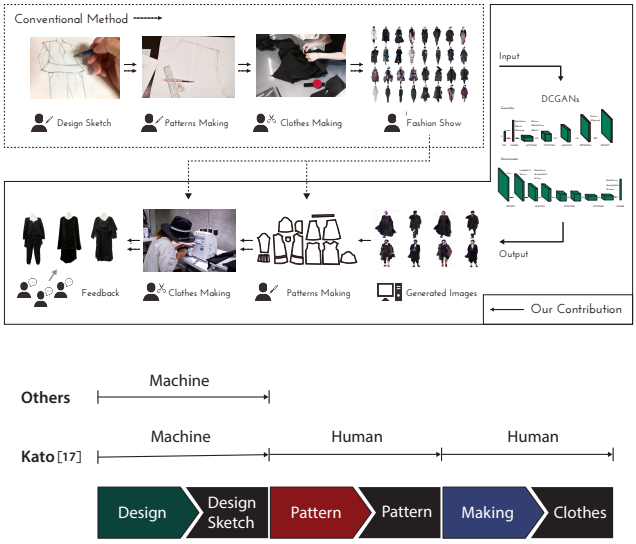

Figure 2: Kato et al. reported workflow to make clothing by using GANs. We surveyed the factors necessary for making clothing that were not discussed in that study.

- Extensive discussions of the major factors in clothing production from images generated by GANs based on the experimental results.

2 RELATED WORKS

2.1 Applications of Generative Models

Generative Adversarial Networks (GANs) [12] show impressive results in image generation [9], image to image translation [15, 33, 42], super resolution [19, 32], video generation [7, 8], painting [3] and text-to-image synthesis [27, 38, 39, 41].

State-of-the-art generation models already can generate sophisticated realistic images[16]. However, there are still no reliable applications of GANs in the real world. One common issue in applying GANs into practical uses is the limitation of the size and quality of available datasets. It is useful only if the minimum requirements are fulfilled.

2.2 Machine Intelligence Creativity

In the context of computational creativity, different algorithms have been proposed to investigate various effective ways of exploring and expanding the creative space. In some approaches, for example, [10, 23] uses an evolution process that iterates the algorithm to generate candidates, evaluate using fitness functions, and improve fitness scores of the next iteration. This process is called genetic algorithm framework. As pointed out by DiPaola and Gabora 2009[10], these algorithms' challenge is "how to write a logical fitness function that has an aesthetic sense". Some of the early systems used people to play the role of process guide in a closed loop [2, 13]. In these interactive systems, the computer searches for creative space and plays the role of an observer whose feedback is indispensable for

human being to promote the process. Recent systems highlight the role of perception and cognition in creative processes [5, 6, 14].

Creative Adversarial Network (CAN) [11] is a research that creates paintings which use model similar to DCGAN[26]. It was almost impossible to distinguish between generated by CAN and contemporary artists by human subjects according to the study.

2.3 Machine Intelligence & Fashion Design

In machine learning and fashion researches, there are many studies that learn the compatibility of fashion items for recommendation applications [24, 29, 34–36] and extract features of styles from co-purchase and outfit data [20, 21, 25]. In order to measure the compatibility between items, McAuley et al. [24] proposed a method to learn relationships among image features extracted by pre-trained Convolutional Neural Networks (CNN). Using a Siamese network, this feature extraction technology for compatibility learning has been improved in [34, 36].

To the best of our knowledge, there are no commercial project that are doing well in the project of making clothing using machine learning. A deep knowledge set on Google's fashion trend report and Zalando's [1] fashion trends was used to refine the design and ensure fashionability. However, Amazon's Project uses GANs based DNNs architecture [18] that internalize the properties of a particular style simply by looking at many examples and apply that style to existing clothing. Amazon's AI is still in the development stage.

Kato et al. [17] discussed the whole process of clothing production. The process was divided into three steps: designing, patterning, and making. In the designing step, GANs generated design images instead of human designers. Next in the patterning step, human pattern makers drew patterns, i.e. development diagram of clothing. The human pattern makers had to imagine 3D shapes of clothing from 2D design images. Finally, in the making step, human makers cut and sewed clothing based on the patterns. The result clothing were not easily distinguished from the original (human-designed) clothing, which concludes the originality of the designer was effectively reproduced. Their work demonstrated the whole process, however, no further investigation such as parameter optimization or survey of minimum quality of generated images had been conducted. Therefore, we aim to understand the major factors to make practical and usable clothing from generated images.

3 GENERATIVE ADVERSARIAL NETWORKS

The Generative adversarial network consists of a generator network G and a discriminator network D. Given training data x, G will take input from random noise z and try to generate data with distribution similar to x. The discriminator network D receives inputs from both x and the one generated from G and estimate the probability that the sample came from the training data, not G. G and D are trained at the same time: To adjust the parameters of D to maximize the probability of assigning the correct label to both the training example and the G sample, and to adjust the parameters of G to minimize $\log(1 - D(G(z))$. In other words, D and G play the following two player min-max game with value function $V(G, D)$.

Progressive Growing of GANs (P-GAN) [16] technique is popular since its release last year. The main idea of P-GAN is to gradually

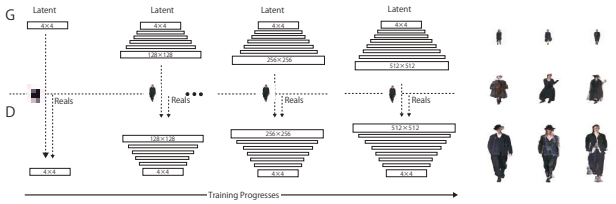

Figure 3: Our training begins with both generator (G) and discriminator (D) with low spatial resolution of 4×4 pixels. As training progresses, layers are gradually added to G and D to improve the spatial resolution of the generated image. All existing layers remain trainable throughout the process. Here, it refers to a convolution layer operating with $N \times N$ spatial resolution. This enables stable synthesis with high resolution and greatly speeds up training. One shows each three example images generated using progressive growth of 128×128 and 256×256, 512×512 pixel images.

and symmetrically grow the generator and discriminator in order to produce high resolution images. P-GAN begins with a very low resolution image (4×4), the quality improves for each new layer in the model, and fine-grained detail is added to the image generated in the previous stage. Promising results were obtained in the experiment of the CelebA dataset [22]. We employ P-GAN to generate 128×128 and 256×256, 512×512 pixel images using our specific brand runway dataset as training data. We follow the same experimental setup and structural details of the original P-GAN article [16].

3.1 Training

We collected images of a specific brand [1] announced between 2014 and 2017. We used web scraping Python code to collect and compile over 1000 images as the training dataset. Several steps were performed to pre-process the images for training. We paint the background white so that only the model and clothing are isolated, and resize it into full color image of 512×512 (dataset is uploaded as supplemental material).

We implemented our network using Chainer[2], a deep learning framework. We followed implementation and training procedure as described in the recent work by Karras et al. [16]. Training was done with a batch size of 2, using Adam with hyper parameters (α=0.0002, $\beta_1 = 0$, $\beta_2 = 0.99$, $\epsilon = 1e-08$). We run 3 types of epochs (500, 1000, 1500) on a NVIDIA Titan V100 GPU in order to evaluate the quality of each epochs generated images in later experiments.

4 EXPERIMENT

We examined the relationship between resolution of images generated by GANs and the number of epochs, which is the learning time of GANs, to the ease of pattern making. Also, in order to evaluate how interpretation of images changes based on individual differences, we asked them to self-evaluate their knowledge about the learning source brands.

[1] https://www.zalando.co.uk (last accessed January 9, 2018)

[2] https://chainer.org/ (last accessed September 10, 2018)

Figure 4: Generated images shown to participants. Three images each combining the conditions of 128px, 256px, 512px, 500epoch, 1000epoch, 1500epoch were showed and evaluated the ease of pattern drawing in five stages. 27 images are evaluated by each participant.

A set images from 500, 1000, and 1500 epoch, with a resolution of 128px, 256 px, and 512 px generated at each epoch number respectively, a total 27 images are prepared. Each generated image is randomly arranged to each subject. We conduct the survey through Google form and made a 5-point evaluation of 1 (no pattern can be drawn) to 5 (well drawn pattern) (Figure 4). After 27 images evaluation, we asked about how much knowledge of the learning source brand design and pattern do they have, 1 (absolutely unknown) from 5 stages (very familiar).

4.1 Participants

We recruited professional pattern makers from pattern makers online crowdsourcing site. Twenty eight participants (16 females, 12 males) participated in the experiment. All participants are experienced professional pattern maker. The participants' length of worker as a pattern maker was between 3 and 39 years (M = 17.3, SD = 9.1).

4.2 Results and Statistical Analysis

Results are shown in Figure 5. We used SPSS Statistics version 24 for analysis. First, we analyzed the interaction effect between resolution and epoch with two way ANOVA. The sphericity assumption was supported by Mauchly's test of sphericity at the 5% level, or the degrees of freedom were corrected using the Greenhouse-Geisser estimates of sphericity. A comparison of epoch and resolution showed no significant interaction effect ($F(4,188) = 1.166$, $p > 0.05$). Second, we analyzed main effect of resolution and epoch respectively with two way ANOVA by fixing one side. By fix resolution, epoch showed no main effect ($F(2, 94) = 0.052$, $p > 0.05$). Post-hoc Bonferroni test suggested no significant difference in every combinations of epochs ($p > 0.05$). From this point, since the main effect was not observed at every resolution, we interpreted epoch do not affect the score of ease of drawing the pattern.

By fixing the epoch, resolution showed main effect ($F(2, 94) = 5.501$, $p < 0.05$). Post-hoc Bonferroni test suggested no significant difference for any combinations of resolution for any epochs ($p > 0.05$). At this point, with the exception that there is an increment in resolution, because the significant difference was not seen, we interpreted resolution do not affect the score of ease of drawing the pattern. Because there is a main effect, there is a possibility that a significant difference may be obtained if the resolution is made higher, any meaningful result maybe offset because it requires a large amount of calculation resources to output an image with a resolution exceeding 512 px. Also, it is obvious that the details will be unrecognizable if we look at images with very low resolution. Because of this reason it is difficult to make clothing using small images, so there is no need for 64px or lesser resolution comparison.

Finally, the influence of pattern maker's knowledge was analyzed by one-way ANOVA. Result shows a main effect of pattern makers knowledge score ($F(4,1021) = 46.4$, $p < 0.05$). Post-hoc Tukey's HSD test suggested knowledge score showed no significant difference between score group 3 and group 4, and group 3 and group 5 ($p > 0.05$). There was significant difference in other combinations of knowledge score ($p < 0.01$). From this point, ignoring that there is no significant difference between 3 and 4, and 3 and 5, knowledge affect the score of ease of drawing the pattern.

From these results, we found that the ease of pattern drawing from generated images depends on knowledge of pattern maker, and lesser on the quality of generated image.

4.3 Patterns Makers Opinions

We interviewed the participants who have a pattern making experience with the brand of the learning source and concluded that it is easier to draw patterns from the generated images if they had an average score of 2.8 or more.

Also, by interviewing other pattern makers, it was found that the score could be improved by including the material and the rough size of the clothing.

(Pattern maker 1: Female, 31, design experience 10 years)

Because there is accumulation of shapes of silhouettes and patterns that I have came up with patterns that I have been making with the brands up to now, it may seem easy to understand even if it is a rough design image. Judging that it does not resemble any shape of the past clothing, arranging it while obtaining inspiration from the generated image, I had to think about how to draw the pattern. 1, 2, 3 in 5 stages have a high dependence rate of pattern maker's design (the rate of pattern maker's own bias), while 4 and 5 show the ratio of the design of the generated image to the pattern design is around half to half.

(Pattern maker 2: male, 30s, design experience 12 years)

If you do work from the viewpoint of a pattern maker, I think that it will be 2 to 3 if there is not only a design picture but also a used material and rough size setting.

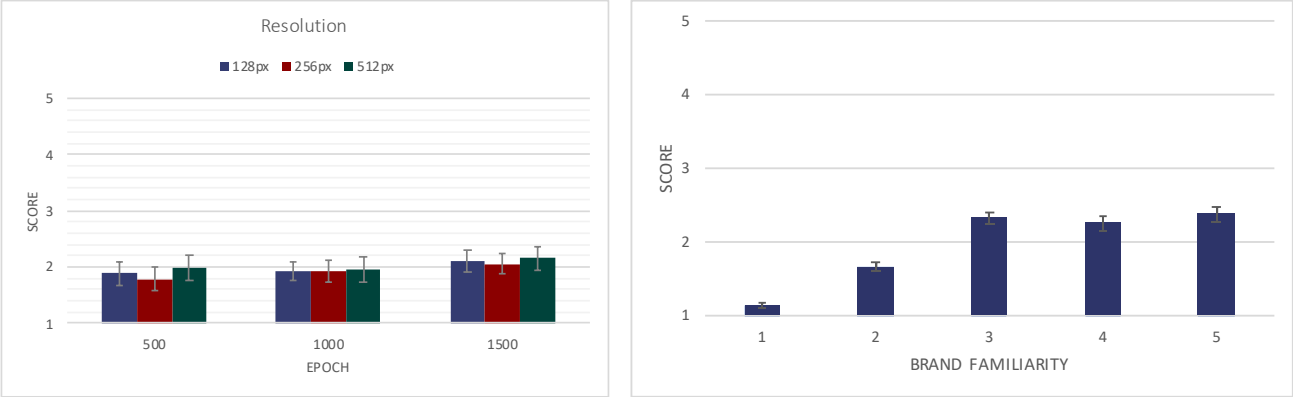

Figure 5: Left: Result of the questionnaire response on resolution and epoch. Right: Pattern maker's knowledge about learning source brand.

5 DISCUSSIONS

5.1 General Discussion

In the experiment, the ease of drawing the pattern from the generated image by GANs was evaluated by factors such as resolution and epoch. Analysis of the interaction effect between resolution and epoch using two way ANOVA showed no interaction. Next, when we take a test for each factor, epoch and resolution did not show a main effect. From here, there were no thresholds for each of the three levels of resolution and three levels of epoch numbers, and it turned out that when drawing a pattern from the image, it is not related to the quality of the generated image.

Next, since the influence of pattern maker's knowledge was significant among almost all groups, our result showed that the major factor when drawing a pattern from a generated image is the pattern maker's knowledge of the brand. This result 5 showed about brand familiarity and score. It is found that they can make patterns from generated images if the brand familiarity scored over 3. Conversely, pattern makers who are not familiar with the brand design, were not able to draw the pattern easily. Therefore, it is more important to have pattern makers with prior knowledge to the brand design and brand pattern when making clothing based on design images generated from machine learning. As this study focus greatly on efficiency in both time and cost for automation of clothing production, long hours and high computing powered training is not practical. From this we can deduce that in the clothing production, unless a more efficient image generation network algorithm is implemented, there is not much need to spend computation resources to increase the resolution of the generated image instead more resources should be directed to pattern makers selection. In other words, even if it is a rough generated image, if the pattern makers who are familiar with the brand, patterns can still be drawn by combining experience and design inspiration. However this is expected to change drastically as high resolution and detail image generation becomes easily attainable.

5.2 Pattern Makers

In fact, in our workflow, images are generated with a specific brand as dataset, patterns are drawn from the image by pattern maker, and clothing are made by sewing craftworker. It is important to treat both excellent professional pattern makers with collection brand experience and the selection of cloth material used for sewing as two important elements. Professional pattern makers with collection brand experience have the ability to draw more complicated and detailed patterns than professional pattern makers without. In the fashion world, clothing are more like an art piece than just a garment in the famous show such as Paris collection. The collection brand's pattern makers are often found interpreting the designer's intention from the abstract designer's sketch and they would then make the pattern that expressed in the form of clothing that one can actually wear. Since the pattern makers are the one with the skill to materialize the designer's sketch, it is possible to draw complicated and detailed patterns based on the intention of the brand in the situation of drawing patterns from abstract images generated by machine learning. On the other hand, pattern makers who are not experienced in collection brands shows patterns of clothing designs that are not composed of general and complex lines, so the range of expression in pattern design is reduced compared to the experienced ones. Therefore, it is difficult to draw a pattern that is faithful to the original brand's clothing from the features extracted in rough image. Therefore, it is more likely for the experienced pattern makers of collection brands to be able to draw the patterns from our generated image.

From here we elaborate based on the opinions from the pattern makers. Pattern maker of the original brand, who has been in service for 10 years, first focuses on the characteristics of the parts of the clothing and identify it as a category such as V-neck, skirt, jacket, pants etc. . Then, combined with what the pattern maker has produced so far, he would draw a pattern that is relevant to the source brand. As it is also shown in the results of the experiment, it is important that one have experience in making the clothing of the learning source brand. Also, typically, the sketch picture in fashion design has a lower abstraction level than the generated image

and more specifically instructed to the features of the brand and designer's intention. Among the very experienced pattern makers, we received positive opinions such as the degree of freedom is high and interesting in pattern production from the abstract generated image. In other words, the higher the abstraction level in the generated image, the greater the proportion of ideas of the pattern maker exerts on the drawn pattern, which the dependence on pattern makers experience and skill will increase. In contrast to design, patterns typically require high quality with numbers of realistic scales to produce clothing , so patterns can hardly be automated. Therefore, we propose that pattern makers are the most important aspect in drawing pattern from highly abstracted generated image.

5.3 Dataset

From the learning source brands, we found that it is easier to output results that match the brand image using a source brand with a certain unified design that does not change drastically every season. Therefore, the idea of drawing a pattern by combining a generated image with the brand image and brand design is increasing. In this paper, we used the dataset of a certain brand [1] image. The reason for using this brand's dataset is that the generated images are easier to recognize because of the obvious brand features. This specific learning brand, both men's and women's, all season black, is a brand that is unified with a relatively oversized silhouette design. Therefore, when clothing design is included in the data set, the color of commonality is high, and it is easy to extract the features by machine learning. If learning is performed with brands that do not have recognizable features that are easy to understand, there is a concern that designs that inherit the characteristics of source brands can not be created. Moreover, in case where designs of all seasons of both men's and ladies' are not unified, extraction of features is difficult by machine learning, resulting difficulty in brand identification. Therefore, when extracting features by performing image generation of a specific brand, it is considered better to use brands of relatively unified designs as source learning brand. In terms of generating an image that inherits the features of a designer's work, within the scope of the experiment conducted this time, it is not possible to extract the potential features that are unrecognizable by human eyes with machine learning. It also means that human resources such as pattern makers are as equally important.

5.4 Evaluation of GANs Generated Image

Evaluation of images generated by GANs is a difficult problem. When comparing the dataset and the generated image by mean squared error or PSNR, there is a problem that a blurred image tends to be generated [4]. In addition, even if an image with a bad score is generated numerically, it sometimes looks beautiful when people see it. In general, evaluation of the generated image of GANs is done by Inception score [28] etc. However, this time we can not use Inception score because we prepared the dataset ourselves. Good indicators should be proposed so that scores of images that look reasonable when viewed by humans, and can be used for a wide range of dataset.

5.5 Future Work

When making clothing with one brand's design creation image like the image we generated this time, the selection of cloth is also an important factor to obtain the characteristic. For example, clothing based on the same pattern Even if you make the cloth, if you use cloth of hemp material and gaba, hemp dress becomes thin, material is flickering design, drape becomes a beautiful silhouette design. If you use polyester gaba, it is a material with tension on the fabric and it is difficult to stretch, so it will be designed to keep the line beautifully. In other words, to make final clothing output that make the most of the goodness of design and pattern, selection of cloth is a very important factor. If we select the optimized cloth based on the generated image and pattern automatically by machine learning, we think that we will make clothing optimized for design, pattern, and place and occasion when wearing. Since the number of data sets and computer resources are limited in this research, the resolution of the generated image and the number of epochs of learning are limited. It is difficult to gather sufficient data by web collection only to gather data sets with uniform conditions such as the position and background of the model that is the object with just one brand of clothing. However, by securing enough computer resources to gather hundreds of thousands of datasets and to converge learning using that dataset, the degree of capture of the resolution of the generated image and the features of the brand is improved , The conclusion may change. Also, although it is possible to draw patterns even from low-resolution images with few learning times, increasing the number of learning times improves the quality of feature extraction in designs, and moreover, it is possible for brands and designers used for data sets An image that captures the features of the design is generated, and for a parameter called a degree of agreement with the characteristics of the brand, there is a possibility that a significant difference appears in the epoch number. There is room for discussion as to whether pattern automation can be automated by machine learning. In other words, in this flow, it can be said that it is possible to generate a pattern from the generated image. In addition, it may be possible to automatically generate a pattern tied to the generated design image by learning pattern data and sketch image as bilateral translation. In order to realize this, a large amount , It is necessary to construct a scheme that can obtain large quantities of pattern data drawn on the paper which is usually discarded as an intermediate product in digitally processable form. By automating all of the generated image, pattern generation, and cloth selection by machine learning, the production cost of expensive brands suddenly lowered, in return high quality clothing becomes readily available around the world. It is conceivable that a big revolution will occur in the fashion industry.

6 CONCLUSION

In this study, we reveal that it is more efficient to invest in pattern maker selection than computer resource when making clothing from abstract generated images. The images generated by GAN at its current state requires a high computational cost while yielding mediocre results in pattern making process as shown in the previous section. From the result, we can deduce that when a pattern maker draws a pattern using an abstract generated image by GANs,

resolution and epoch number are not the most important factors now. It was found that it is possible to draw a pattern from the generated image of lower quality by a pattern maker with prior knowledge of the source brand. Therefore, from the viewpoint of cost performance, it was found that it is better to cost a pattern maker with source brand design knowledge and experienced pattern drawing than to invest in computing resources to improve the quality of the generated image. The result reconfirm the importance of pattern maker's knowledge in the process of making clothing.

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