Realistic Sewing Pattern Generation and Dataset Construction for GAN-based Fashion Synthesis

Hikaru Suzuki[1†], Kazuma Miura[1], Alessandro Moro[2], Sarthak Pathak[3], and Kazunori Umeda[4]

[1]Precision Engineering Course, Graduate School of Science and Engineering, Chuo Univ.
(E-mail: h.suzuki@sensor.mech.chuo-u.ac.jp)
[2]RITECS, Tokyo, Japan
(E-mail: alessandromoro.italy@ritecs.co.jp)
[3]College of Engineering Shibaura Institute of Technology
(E-mail: spathak@shibaura-it.ac.jp)
[4]Department of Precision Mechanics, Faculty of Science and Engineering, Chuo Univ.
(E-mail: umeda@mech.chuo-u.ac.jp)

Abstract: In the process of garment production, creating sewing patterns which serve as design blueprints for clothing, from fashion sketches is a highly complex task that requires extensive experience and knowledge from garment makers. In this paper, we propose a method for generating sewing patterns from clothing images by constructing a dataset based on sewing patterns used in actual dressmaking and training an image generation model using Generative Adversarial Network (GAN).

Keywords: Deep learning, image generation, dataset, fashion synthesis

1. INTRODUCTION

In recent years, the diversification of fashion has led many designers to create unique works that resonate with consumers. However, in the fashion industry, trends change almost every season, necessitating the release of new designs accordingly. As a result, creating distinctive garments within tight schedules is considered challenging. Additionally, some individuals enjoy making clothes as a hobby. However, since garment production requires significant effort and time, many people find it difficult.

Fig. 1 illustrates the general workflow of garment production. First, a fashion sketch is drawn, followed by the creation of a sewing pattern based on the sketch. The fabric is then cut according to the sewing pattern, sewn together, and assembled into a completed garment. A sewing pattern serves as the blueprint for clothing and is an essential component in garment production. It is difficult for amateur hobbyists to create these sewing patterns and the learning curve is quite steep. This research aims to generate realistic sewing patterns automatically from designs/sketches to solve this problem.

Previously, Kato et al. [1] proposed a method for generating fashion designs while preserving brand identity using Generative Adversarial Network (GAN) [2]. They evaluated the difficulty of deriving sewing patterns from the generated images by employing professional pattern makers as test subjects. The results revealed that the difficulty of creating sewing patterns was more significantly influenced by the pattern makers 'knowledge and experience than by the quality of the generated fashion sketches. This issue also affects individuals who attempt to make clothing on their own, as a lack of experience in pattern drafting and insufficient knowledge of garment construction can limit their ability to create diverse designs.

† Hikaru Suzuki is the presenter of this paper.

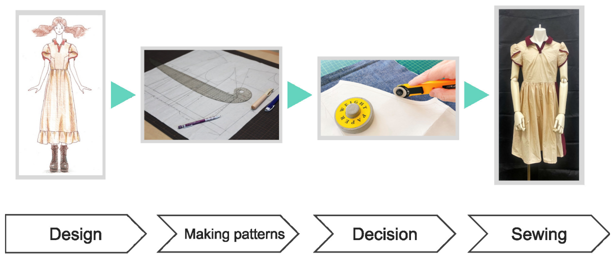


Fig. 1 The process of making clothes

LIJUAN et al. [3] proposed a method for predicting sewing patterns from clothing images using a 3D model dataset and a Transformer-based network [4]. However, the generated sewing patterns differed from those used in actual dressmaking, and the shapes of the garments in the input images were not accurately reflected in the sewing patterns. These issues stem from the fact that the dataset used did not contain sewing pattern information and lacked diversity in garment shapes.

In this paper, we construct a dataset that includes actual sewing patterns and a diverse range of garment shapes. We then propose a method for generating practical sewing patterns from clothing images by utilizing an image generation model based on deep learning that reproduces garment shapes.

2. METHOD

2.1. Method overview

In this paper, we propose a method for creating sewing patterns, focusing on dresses. The reason for this is that if the input image contains several garments (e.g. shirt and trousers), each garment needs to be divided before the sewing pattern is generated, which complicates the process before the image is passed to the image generation

Fig. 2 Example of an output image

model. On the other hand, a dress, on the other hand, can be used as input to the sewing pattern generation model as it is, as the whole body outfit is completed in one dress, so there is no need to split the garments in the image. As the main focus of this study is first on the construction of the sewing pattern generation model and the evaluation of its accuracy, a relatively simple task setting that does not require any pre-processing is considered desirable, and the research target is therefore focused on dresses. First, we generate images of dresses with various shapes along with their corresponding sewing patterns. Then, we use this data to construct a dataset and train a deep learning model, specifically pix2pix [5]. Through this approach, we aim to generate sewing patterns corresponding to input garment images.

2.2. Dataset

In this subsection, we describe our proposed dataset generation method. The output images consist of sewing patterns for dresses. Each dress is divided into three components: the bodice, sleeves, and collar. We design 10 types of bodices, 8 types of sleeves, and 5 types of collars. The generated sewing patterns are scanned, edited, and compiled into a single image representing the dress's complete sewing pattern. This compilation aligns with the input-output format required by the pix2pix [5] model used in this study. Additionally, the placement of the bodice, sleeves, and collar within each output image is standardized to facilitate model learning. An example of an output image is shown in Fig. 2.

Next, the input images consisting of dress illustrations, are created. Similar to the output images, each dress is divided into bodice, sleeves, and collar components, with 10 types of bodices, 8 types of sleeves, and 5 types of collars. These components are then edited and combined to create complete dress images. The process of creating the input images is illustrated in Fig. 3.

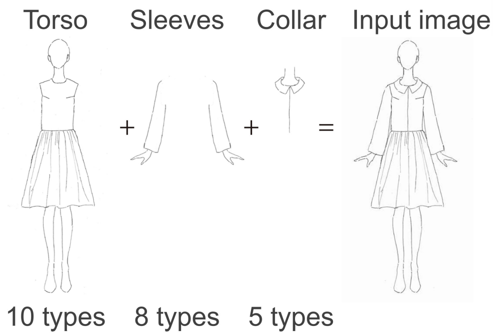


Fig. 3 Making an input image

2.3. pix2pix

pix2pix [5] is a type of Conditional Generative Adversarial Network (CGAN) [6] developed by Isola et al., capable of performing various image-to-image translation tasks. It is particularly suited for generating output images corresponding to given input images. Traditionally, different tasks required manually designing specific loss functions, but CGAN [6] eliminates this need by automatically learning the loss function from data. Due to this advantage, pix2pix [5] incorporates CGAN [6].

In this study, we utilize pix2pix [5] to train a model for generating sewing patterns from clothing images.

3. EXPERIMENT

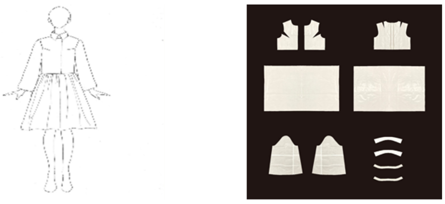
We verified the proposed method for generating sewing patterns from images by constructing a dataset and training the pix2pix [5] model. Furthermore, based on the experimental results, experienced garment makers evaluated the generated images to assess the effectiveness of the proposed model.

3.1. Dataset construction

We created the experimental dataset using the method described in subsection 2.2. First, we generated the output data, which consists of sewing patterns. The sewing patterns were designed based on references from fashion literature [7].

For the input data, all garment line drawings were hand-drawn using only a black ballpoint pen on white A4 paper. The human figures wearing the dresses in the input images were drawn using a common template, ensuring uniform body proportions across all images.

The completed input and output data was then scanned and imported into a computer, where they were edited and combined to generate images of dresses with diverse shapes alongside their corresponding sewing patterns.
Adobe Photoshop and Illustrator were used for image editing and composition. Additionally, both input and output data were standardized to the PNG format.



(a) Input image (b) Actual sewing pattern

Fig. 4 Input image and corresponding actual sewing pattern

Fig. 5 Generated image

3.2. Experimental conditions

The dataset created in subsection 3.1, consisting of 110 images, was divided into 88 training images, 11 validation images, and 11 test images. To prevent bias in garment shapes within each subset, the data was manually distributed.

The learning model used was pix2pix [5], and the loss function was kept as per the default settings of pix2pix [5]. The batch size, representing the number of samples shown per training iteration, was set to 1. The number of training epochs was set at 20,000 epochs.

3.3. Experimental results

Fig. 4 and Fig. 5 show the sewing pattern generation results using the model trained with 20,000 epochs. In Fig. 4, (a) represents the input image, while (b) shows the actual sewing pattern corresponding to the input image. Fig. 5 presents the sewing pattern image generated by the model developed in this study.

3.4. Evaluation of the proposed method

In this section, we evaluate the sewing pattern generation model developed in this study. Using the 11 test images from the dataset created for model training, we generated sewing patterns using the proposed model with 20,000 epochs. Note that none of the test images were included in the training data, ensuring all images used for evaluation were entirely new. This section assesses the model's performance using the generated sewing pattern images.

In image generation tasks, a common evaluation method involves assessing pixel-wise similarity between the generated image and the ground truth image. However, since this study aims to evaluate whether the generated sewing patterns are practical and accurately represent the clothing's shape, pixel-wise similarity may not provide an accurate assessment. In this paper, we evaluate the proposed method through a qualitative evaluation of patterns generated by experienced garment makers.

The sewing patterns were divided into four parts: the upper body (bodice), lower body (skirt), sleeves, and collar. The evaluation was conducted based on two criteria:

1. **Recognizability**: It was assessed whether each part of the generated sewing pattern (body, skirt, sleeves and collar) could be clearly identified as a component of the garment. Specifically, the criterion was whether the shape and structure of the sewing pattern visually indicated its function and role as a part of the sewing pattern, and whether a person with expert knowledge could look at it and immediately judge which part it corresponded to. If it was difficult to discriminate or if the shape was not established as a part, it was judged to have low recognisability.

2. **Shape Accuracy**: It was evaluated whether each part of the generated sewing pattern (body, skirt, sleeves and collar) adequately reflected the shape and structure of the garment in the input image. Specifically, the correct sewing pattern (actually designed data) corresponding to the input image and the sew-
ing pattern generated by the model were visually compared and evaluated by a person experienced in garment production. The focus of the evaluation was on whether the silhouettes matched and the proportions and balance of each part were accurately reproduced.

Table 1 presents the evaluation results for whether practical sewing patterns were generated for each part across all 11 test images. Some test images included garments without sleeves or collars. Therefore, a hyphen ("-") is used in the corresponding cells for images without sleeves or collars.

Table 2 shows recognizability, representing the probability of generating recognizable sewing patterns for each part across the 11 test images.

From Table 1 and Table 2, it can be seen that the generation rate for lower body sewing pattern is 100% , meaning that a practical sewing pattern was generated for all generated images. However, the generation rates for sleeves and collars were significantly lower. Notably, none of the 11 generated images successfully produced a sewing pattern for the collar. This result indicates that the proposed model struggled to generate sewing patterns for smaller components. Fig. 6 presents examples where the upper body and sleeves were not generated correctly.

Although the shapes resembling the upper body and

Table 1 Is the generated image a practical sewing pattern?

No.	Upper Body	Lower Body	Sleeve	Collar
0	✓	✓	✓	✗
1	✓	✓	✓	✗
2	✓	✓	✓	✗
3	✓	✓	–	✗
4	✓	✓	✓	✗
5	✓	✓	✓	✗
6	✓	✓	✓	✗
7	✓	✓	✓	✗
8	✗	✓	✗	✗
9	✗	✓	✗	✗
10	✓	✓	✓	✗

Table 2 Recognizability of sewing patterns for each part

	Upper Body	Lower Body	Sleeve	Collar
Rate	81.8%	100.0%	80.0%	0%

Fig. 6 Example of failure to generate a practical sewing pattern

sleeves are somewhat recognizable, the images are distorted and unsuitable for practical sewing patterns. Among the 11 generated images, two exhibited such distortions.

Next, Table 3 presents the evaluation results for whether the generated sewing patterns accurately reflected the garment's shape for each part across all 11 test images. Additionally, Table 4 shows the Shape Accuracy, representing the probability that the sewing patterns of each part accurately reproduced the garment's shape in the input image. For parts where no practical sewing pattern could be generated, the corresponding cells are marked with a hyphen ("-") to indicate that they were excluded from that evaluation.

According to Table 3 and Table 4, the reproduction

Table 3 Is the sewing pattern faithful to the garment's shape?

No.	Upper Body	Lower Body	Sleeve	Collar
0	✗	✓	✗	–
1	✗	✓	✗	–
2	✓	✓	✗	–
3	✗	✗	–	–
4	✗	✓	✓	–
5	✓	✓	✗	–
6	✓	✓	✗	–
7	✗	✓	✗	–
8	–	✗	✗	–
9	–	✗	✗	–
10	✗	✓	✗	–

Table 4 Shape Accuracy of sewing patterns for each part

	Upper Body	Lower Body	Sleeve	Collar
Rate	33.3%	72.7%	10.0%	–

rate for the lower body sewing patterns was 72.7%, the highest among all parts. In contrast, the upper body reproduction rate was notably low at 33.3%. The instances where the sewing patterns failed to reflect the shape of the upper body are shown in Fig. 4 and Fig. 5.

The actual upper body sewing patterns had two variations: one with a separated left upper part and another with a single connected part. However, the model often generated a single connected piece even when the actual pattern had separated parts. This result suggests that the proposed method struggled to learn fine-grained differences in pattern structure.

This result suggests that the proposed method struggled to learn fine-grained differences in pattern structure. Furthermore, the reproduction rate for the sleeves was only 10.0%, meaning that out of the 10 sleeve patterns in the generated images, only one accurately reflected the shape of the input image. This further demonstrates the difficulty of generating detailed sewing patterns for smaller parts using the proposed method.

3.5. Discussions

Based on the experimental results, it can be concluded that the proposed method in this study is partially capable of generating sewing patterns that correspond to the garment shapes in the input images. However, challenges remain, such as errors in the sewing patterns for detailed parts like sleeves and collars, or instances where no sewing pattern is generated at all.

One possible cause of these issues is the approach of combining the sewing patterns into a single image for training the pix2pix [5] model. This may have resulted in the model learning without understanding which part of the sewing pattern corresponds to which part of the garment.

To address this issue, a new approach can be considered where the garment is divided into individual parts, and a separate sewing pattern is generated for each part. Additionally, during the training of the deep learning model, it is proposed to use annotated images for both input and output, indicating each garment part. By doing so, the model will be able to learn the detailed shapes of each garment component more effectively, ultimately aiming to generate sewing patterns that more accurately reflect the actual garment shapes.

4. CONCLUSION

In this paper, we proposed a method to generate sewing patterns that faithfully reproduce the shape of the garment from images using a deep learning model. The experimental results demonstrated that the proposed dataset and method could partially generate sewing patterns that accurately reflect the shape of the garment in the input images. However, challenges remain, such as difficulties in generating detailed sewing patterns for small parts and the inability to generate patterns that consider the overall shape of the garment.

In the future, we aim to generate practical sewing patterns that better align with garment shapes by improving both the dataset and the learning model used in this study.

REFERENCES

[1] Natsumi Kato, *et al.*, “Gans-based clothes design: Pattern maker is all you need to design clothing,” Proceedings of the 10th augmented human international conference, pp. 1–8, 2019.

[2] Goodfellow, Ian, *et al.*, “Generative adversarial nets,” Advances in neural information processing systems 27, vol. 27, 2014.

[3] Liu, Lijuan, *et al.*, “Towards garment sewing pattern reconstruction from a single image,” ACM Transactions on Graphics, vol. 42, no. 4, pp. 1–13, 2023.

[4] Vaswani, Ashish, *et al.*, “Attention is all you need,” Advances in Neural Information Processing Systems, vol. 30, 2017.

[5] Isola, Phillip, *et al.*, “Image-to-image translation with conditional adversarial networks,” Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 5967–5976, 2017.

[6] Mirza, Mehdi, *et al.*, “Conditional generative adversarial nets,” arXiv preprintarXiv:1411.1784, 2014.

[7] Harumi Maruyama, ”Shijo Pattern Juku Vol.4: One-Piece Edition,” Bunka Publishing Bureau, 2018.