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Estimating Cloth Simulation Parameters From a Static Drape Using Neural Networks

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ABSTRACT We present a neural network learning approach for estimating a set of cloth simulation parameters from a static drape of a given fabric. We use a variant of Cusick's drape, which is used in the fashion textile industry to classify fabric according to mechanical properties. In order to produce a large enough set of reliable training data, we first randomly sample simulation parameters using a Gaussian mixture model that is fitted with 400 sets of primary simulation parameters derived from real fabrics. Then, we simulate our modified Cusick's drape for each sample parameter set. To learn the training data, we propose a two-stream fully connected neural network model. We prove the suitability of our neural network model through comparisons of the learning errors and accuracy with other similar neural network and linear regression models. Additionally, to demonstrate the practicality of our method, we reproduce the drape shapes of real fabrics using the simulation parameters estimated from the trained neural networks.

INDEX TERMS Fabrics, computer simulation, parameter estimation, artificial neural networks, Cusick's drape.

I. INTRODUCTION

Cloth simulation is widely used in the fashion textile industry. For example, the development costs of a new garment design can be dramatically reduced by predicting the final drapes through a simulation and compensating for problems. To reproduce the drape characteristics of a real fabric through simulation, an appropriate set of simulation parameters for the fabric must be determined, which is the responsibility of the designer. Generally, simulation parameters represent the values of the physical and mechanical properties of the fabric. That means that the designer may need to measure the density, stretch stiffness, bending stiffness, and other properties of the fabric to determine the simulation parameters.

However, there are two problems with using the mechanical properties measured by the designer. First, expensive equipment such as the Kawabata estimating system (KES) is required to accurately measure the mechanical properties of fabric. It is not easy for ordinary users or personal designers to access these kinds of equipment. Second, because the physical mechanism of the cloth simulation is different from the mechanism of real cloth, simulated drapes are often different from real drapes, even if you enter the precise mechanical properties. One common ways for end users to ensure that their current set of simulation parameters is sufficient for the target fabric is to test the parameters on a simple drape such as the Cusick Drape Tester [1]. If the real drape and the simulated drape are visually similar, the current set of simulation parameters can be considered adequate. However, if the drapes are different, the end user cannot be sure of the suitability of the simulation parameter set. In practice, designers iterate to adjust the simulation parameters until they get a simulated drape similar to the real drape, but tuning cloth simulation parameters is notoriously difficult. Even automatic optimization for a single target fabric takes at least a few hours.

In this study, we present a neural network learning approach for estimating a set of cloth simulation parameters from a static drape of the target fabric. We use a variant of Cusick's drape to effectively learn the simulation parameters. Cusick's drape is mainly used in the fashion textile industry to classify fabric according to mechanical properties. The main advantage of Cusick's drape is that anyone who has a small fabric specimen can easily reproduce it. Additionally, the shape of Cusick's drape has a high correlation with the mechanical properties of fabric. For training, we introduce a neural network model designed to be optimal for learning the training data. To produce a large amount of training data, we first sample the simulation parameter sets from a generative model fitted with 400 primary parameter sets derived from real fabrics. Then, we simulate our modified Cusick's drape for each sampled parameter set.

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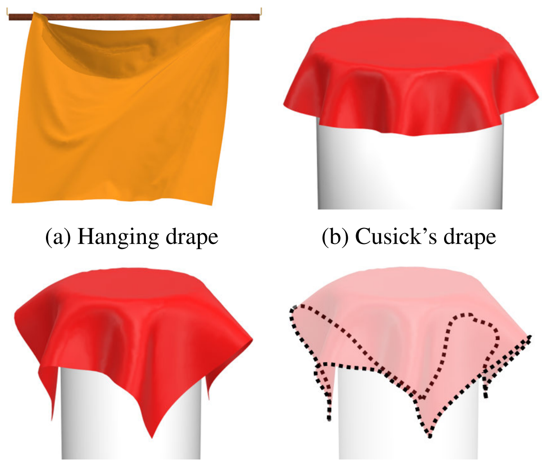

FIGURE 1. Comparison of simulated hanging drape, Cusick's drape, and our modified Cusick's drape.

To evaluate our neural network model, we compare the training accuracy and errors with those of other similar neural network and linear regression models. With the estimated simulation parameter sets, we simulate the modified Cusick's drape and compare them with the ground truth data to determine the drape reproducibility. Finally, to demonstrate the practicality of our method, we reproduce the drape shapes of real fabrics using the simulation parameters estimated from the trained neural networks.

II. BACKGROUND

KES [2] is the most representative instrument for measuring material. It precisely measures the mechanical properties of fabric, such as tensile strength, bending stiffness, and shear stiffness, as well as simple physical properties, such as frictional force and density. Most of these properties are the same as the simulation parameters used in general cloth simulators. Breen *et al.* [3] directly used KES measurements as simulation parameters to simulate various cloth drapes, but they ignored the difference between the mechanism of the virtual simulator and the mechanism of real cloth. However, our goal is not to measure the actual mechanical properties of a real fabric but to estimate the simulation parameters that reproduce the desired static drape.

A. HANGING DRAPE VS. CUSICK's DRAPE

The relationship between drapes and the mechanical properties of fabrics has been actively studied in the fields of textile engineering and computer graphics. In the field of computer graphics, the ''hanging drape'' has been most commonly used, in which a rectangular fabric specimen hung on a horizontal bar flutters due to artificial wind (see Fig. 1(a)). Most studies have estimated simulation parameters such as bending stiffness and weight from a video of the hanging drape for a specific fabric [4]–[8]. The advantage of the hanging drape is that some physical properties, such as bending stiffness, are visually clear and can be perceived even with the naked eye. However, the downside is that it is difficult to recognize mechanical properties from a static image of a hanging drape [5], [8].

In the field of textile engineering, Cusick's drape [1] or a variant thereof has been used to analyze various physical properties of fabrics. Cusick's drape is formed by placing a circular fabric specimen over a small radius disk so that the edge of the specimen drops down (see Fig. 1(b)). Cusick's drape is mainly observed after being projected as a 2D image onto a horizontal plane. For various analysis methods for Cusick's drape, we refer to [9]. Numerous studies have demonstrated that Cusick's drape is highly correlated with most KES measurements [10]–[13]. For example, Lam *et al.* [14] proposed a method for estimating the Cusick's drape coefficient from mechanical properties of fabric using neural network learning. In addition, the Cusick's method has evolved into a device for dynamic drape measurement and 3D drape shape analysis [15]–[18]. We also use the 3D geometric information of a variant of Cusick's drape to estimate simulation parameters.

B. OPTIMIZING VS. SUPERVISED LEARNING

Estimation of fabrics' mechanical properties or simulation parameters has been studied through two major approaches. The first is an optimization approach, which iterates simulating and adjusting parameters until the desired drape is obtained. Bhat *et al.* [4] optimized simulation parameters to reproduce a desired hanging drape video. Wang *et al.* [19] and Miguel *et al.* [20] applied a certain force to fabric specimens using specially designed equipment to capture their deformations and then optimized the simulation parameters to reproduce the deformations. Mongus *et al.* [21] optimized the simulation parameters for the feature vector extracted from the Cusick's drape of a target fabric. Yang *et al.* [22] optimized simulation parameters to reproduce the shape of the drape in a photo of a person wearing clothes. These optimization techniques have the advantage of not requiring training data. However, they require a long computation time. The methods mentioned above can take from several hours to tens of hours to optimize for a single fabric. Therefore, this approach is impractical for quickly simulating a variety of fabrics to find the most suitable one.

The second approach is to learn from training data. Most previous studies have used a series of hanging drape images as training data. Bouman *et al.* [5] and Bi *et al.* [8] used dozens of real fabric data to learn bending stiffness and weight from hanging drape images. Since their objective was to estimate the actual mechanical properties of fabric, they did not check whether the estimated values are valid for use as simulation parameters. Yang *et al.* [7] presented a learning method for estimation of simulation parameters. Hanging drape videos were created through simulation and used as training data. Rather than estimating the simulation parameter values directly, they simplified the problem into one that classifies 54 types of fabrics.

Our method is similar to [7] in that it learns from a set of training data generated through simulation. However, instead

TABLE 1. The simulation parameters of our experiments.

Symbol	Definition	Unit	Purpose
S^u	Weft Stretch Stiffness	$\mathrm{g\,mm^2}$	Output (to be estimated)
S^v	Warp Stretch Stiffness	$\mathrm{g\,mm^2}$	
H	Shear Stiffness	$\mathrm{g\,mm^2}$	
B^u	Weft Bending Stiffness	$\mathrm{g\,mm^2\,s^{-2}\,rad^{-1}}$	
B^v	Warp Bending Stiffness	$\mathrm{g\,mm^2\,s^{-2}\,rad^{-1}}$	
B^h	Bias Bending Stiffness	$\mathrm{g\,mm^2\,s^{-2}\,rad^{-1}}$	
D	Density	$\mathrm{g\,m^{-2}}$	Input

TABLE 2. The statistics of the simulation parameter sets derived from 400 real fabrics. 1 000 000 $\mathrm{g\,mm^2}$ is the maximum limit of stiffness defined by the CLO3D simulation system.

Parameter	Mean	Std. dev.	Min.	Max.
S^u	131 010.96	158 742.72	1351.57	1 000 000.00
S^v	163 944.78	163 944.78	2783.85	1 000 000.00
H	75 064.22	120 353.45	638.27	1 000 000.00
B^u	1119.74	3009.62	33.57	43 753.10
B^v	1370.87	3244.53	45.78	43 753.10
B^h	1245.30	2712.10	45.78	27 932.70
D	214.02	66.44	53.03	393.43

of a video of the hanging drape, we use a static drape inspired by Cusick's drape, and we estimate simulation parameters directly rather than classify fabrics by type. Using a static drape makes it much easier to generate training data through simulation. In addition, forming a static drape of a specimen is more practical for end users compared to recording a video of cloth fluttering under a constant-intensity wind.

III. SIMULATION MODEL AND PRIMARY DATA

In our experiments, we use the *CLO3D simulator* [23], which is widely used in the apparel industry. The CLO3D simulator is essentially an implementation of Baraff and Witkin's method with an implicit integration solver. In this method, cloth is modeled as anisotropic material; thus, some simulation parameters are independent of the direction (weft direction or warp direction). For more details, we refer to [24].

Table 1 shows the list of the simulation parameters subject to our experiments that have the greatest impact on static drape. The first six rows indicate the target parameters to be estimated: stretch, shear, and bending stiffnesses. Additionally, density is used as an input value in the training model. We will discuss density further in Section IV-C. All other parameters were fixed to the default values defined by the CLO3D simulator in all experiments.

We were provided with 400 simulation parameter sets from CLO Virtual Fashion Inc. that were derived from real knit fabrics. These simulation parameter sets were obtained by measuring the mechanical properties of the fabrics using the CLO Fabric Kit [25] and then converting the values into simulation parameters for CLO3D. The real fabrics contain a variety of natural fiber fabrics, synthetic fiber fabrics and blended yarn fabrics containing cotton, linen, wool, polyester, nylon, elastane and so on.

Although the 400 parameter sets will not be sufficient training data for our high dimensional nonlinear regression problem, we can learn an approximate distribution of the parameters of real fabrics from them. Table 2 shows the

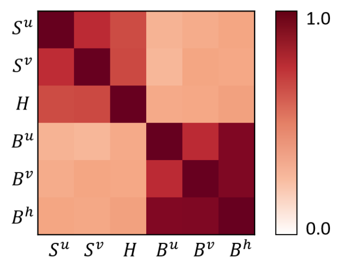

FIGURE 2. Correlation matrix between the simulation parameters.

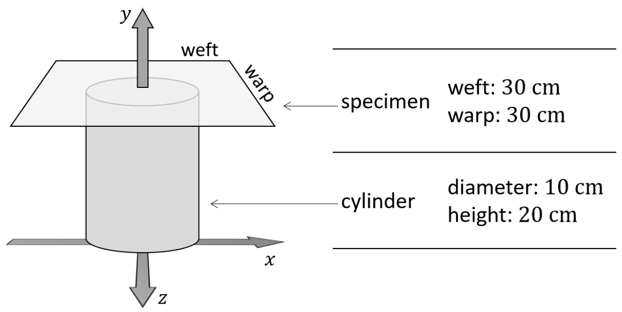

FIGURE 3. The initial state of the modified Cusick's drape.

statistics of the 400 parameter sets. The minimum, maximum, and standard deviation values show that these data cover a wide range of fabrics. Fig. 2 shows the correlation matrix between the six target parameters, which clearly indicates two groups of strongly correlated parameters: one is of S_u, S_v, and H and the other is of B_u, B_v, and B_h. However, the correlation between the two groups is relatively weak. We use these primary data to generate a larger set of training data with similar distribution (see Section V-A).

IV. DRAPING AND FEATURE VECTOR

In this section, we explain our method of draping fabric specimens and the definition of a feature vector consisting of the boundary curve of the drape and the density of the fabric.

A. MODIFIED CUSICK'S DRAPE

In the original Cusick's drape, a fabric specimen cut into a circle with a radius of 15 cm is placed on a circular base plate with a radius of 9 cm to form a drape. The width of the unsupported area of the specimen is 6 cm, which is narrower than that of our drape. Cusick's drape is observed mainly by projecting it onto a two-dimensional plane from the top-down direction. Therefore, the wider the area where the fabric specimen flows downward, the greater the possibility that the edge cannot be observed due to perspective effect. To avoid this, it is necessary to limit the width of the specimen size.

However, we do not need to limit the area where the specimen flows because the feature vector is extracted while maintaining the 3D shape without observing the drape by projecting it in 2D. In our method, we use a square-shaped specimen of 30 cm × 30 cm. One pair of parallel sides should coincide with the weft direction and the other pair should coincide with the warp direction of the fabric. Additionally, we reduce the radius of the base plate to 5 cm to enlarge

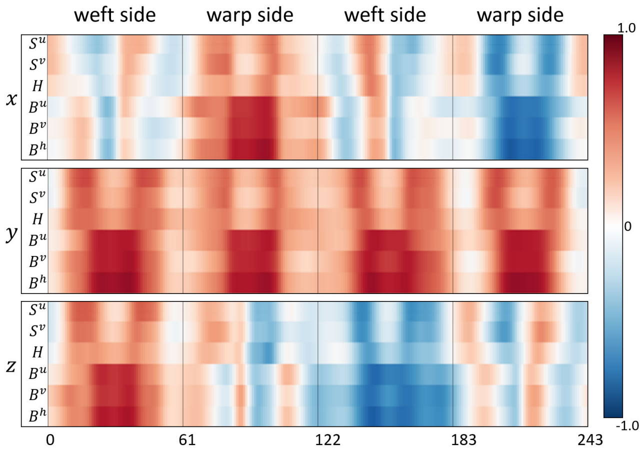

FIGURE 4. Correlation matrix between the simulation parameters and the boundary vector.

the draping area. Fig. 3 represents the initial state of our drape experiment. In the simulation, the weft direction and the warp direction are aligned with the z and x axes of the world coordinates, respectively.

One advantage of a square-shaped specimen is that the weft and warp directions can be easily distinguished from each other. This is important because the parameters to be estimated are defined for each direction. The other advantage is that more draping area potentially leads to more diversity in the shapes of drapes. Fig. 1 shows the simulated results with Cusick's drape (a) and our drape (b) using the same parameter set. In our method, the corner area of the squared specimen weighs more than the rest of the area. As a result, the shape of the drape varies depending on the weight distribution. To compare the diversity in the shapes of drapes, we simulated Cusick's method and our method with the 400 primary parameter sets and compared their variance. The variance was computed by averaging the variances of each element of the boundary vectors (see Section IV-B). The variance with Cusick's method was 68.87, while the variance with our method was 144.00.

B. BOUNDARY VECTOR

Under the assumption that the boundary curve of a drape is uniquely determined by the entire shape of the drape, we use only the boundary curve to represent one drape datum (see Fig. 1(d)). We sample the boundary curve with 244 3D points at 5 mm intervals represented as a 732-dimensional vector. The interval size was determined through experiments. In order to verify whether it is valid to estimate the simulation parameters with the boundary vectors, we visualize the correlation matrix between the simulation parameters and the boundary vectors using the 400 primary data on Fig. 4 in which the boundary vector is separated into three axis components (x, y, and z). Clear correlations can be seen between the boundary vectors and the simulation parameters. Since the sampling starts from one corner of the squared fabric specimen and travels along the boundary, the boundary vector can be divided into two weft sides and two warp sides. It can be clearly seen that the x coordinates have stronger correlations in the warp sides than in the wept sides, while z coordinates have stronger correlations in the wept sides than in the warp sides. This is because in our modified Cusick's drape, the warp and weft directions are perpendicular to the x and z axes, respectively.

There are several ways to capture the boundary vector of a fabric specimen. In the case of a simulated one, we can simply sample the vertices on the boundary of the mesh model. In the case of real fabric, we may reconstruct the boundary curves from pictures. Since the fabric is in a static state and we know the original shape and size, it will be relatively easy to solve the problem. Alternatively, we can simply scan 3D boundary shapes with a scanning device. We will demonstrate examples of scanning in Section VI-C.

C. DENSITY

Most cloth simulation models include density as one of the simulation parameters because the weight of a fabric has a great influence on a draping result. We use density as an input value of the learning model instead of output value to be estimated. The density of a given specimen can be easily obtained by dividing the mass by the area. Using density as a fixed input value significantly reduces the ambiguity of the parameter estimation. For example, more drooping down could be due to lower stiffness or higher density. With a fixed density, this ambiguity is removed. Finally, the feature vector for a fabric specimen is composed of the boundary vector and the density, and its size is 733.

V. TRAINING

In this section, we explain the details of our training method. We use a generative model that is fitted with the 400 primary data to produce a sufficient number of training data. Additionally, we introduce a neural network model optimized for learning the data.

A. DATA GENERATION

We fit a Gaussian mixture model (GMM) with the primary data, then randomly sample the simulation parameters according to the GMM's probability distribution. In our experiment, the number of GMM clusters was set at five, which was determined using the Akaike information criteria [26]. The advantage of using a GMM generative model is that the problem of data bias can be avoided by sampling the same number of parameter sets for each cluster. With the sampled parameter sets, the modified Cusick's drapes can be simulated. The entire set of the generated data, **G**, is defined as follows:

$$\mathbf{G} = \{(\mathbf{p}_0, \mathbf{q}_0), (\mathbf{p}_1, \mathbf{q}_1), \ldots, (\mathbf{p}_n, \mathbf{q}_n)\}, \tag{1}$$

$$\mathbf{p}_i = \{\Omega_i, D_i\} \in \mathbb{R}^{733}, \tag{2}$$

$$\mathbf{q}_i = \{S_i^u, S_i^v, H_i, B_i^u, B_i^v, B_i^h\} \in \mathbb{R}^6, \tag{3}$$

where $(\mathbf{p}_i, \mathbf{q}_i)$ is the pair of the i'th input and output data for the training model, and Ω_i is the boundary vector of the i'th drape.

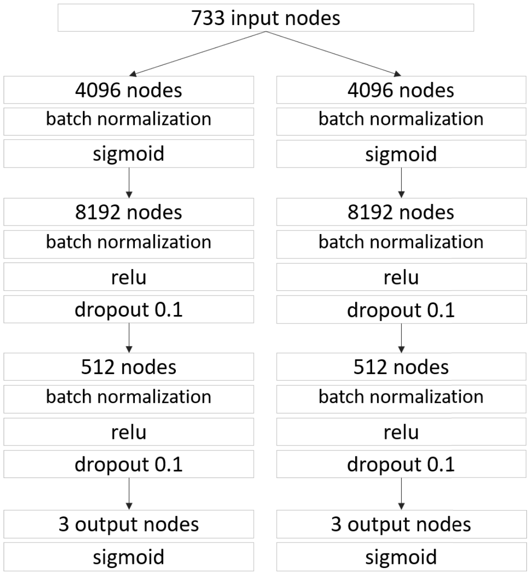

FIGURE 5. The structure of the neural networks.

B. NORMALIZATION

According to a study by Hu and Chan [10], the Cusick's drape coefficient show a high correlation with the logarithm of the mechanical properties of fabric. In addition, according to Bouman *et al.* [5] and Bi *et al.* [8], human-perceived change of draping is generally proportional to the logarithm of the bending stiffness of the fabric. Based on these studies, we normalize p_i and q_i as follows:

$$\mathbf{p}_i' = \mathrm{N}_{[0,1]}(\mathbf{p_i}), \tag{4}$$

$$\mathbf{q}_i' = \mathrm{N}_{[0,1]}(\mathrm{L}(\mathbf{q_i})), \tag{5}$$

where $\mathrm{L}(\cdot)$ is an element-wise logarithm and $\mathrm{N}_{[0,1]}(\cdot)$ is a min-max normalization scaling the range to [0, 1].

C. NEURAL NETWORKS

Our neural network model consists of two streams of fully connected neural networks with three hidden layers. Fig. 5 shows the details of the neural network model. The outputs of the first stream are the normalized S^u, S^v, and H, and the outputs of the second stream are the normalized B^u, B^v, and B^h. This separation is based on our observation that each group of three outputs has a strong self-correlation, whereas the correlation between the two groups is relatively weak (see Fig. 4). The numbers of hidden layers and nodes, the types of activations and other hyperparameters were optimized experimentally.

VI. RESULTS AND DISCUSSION

We generated 100,000 data pairs by using the GMM (20,000 data pairs for each GMM cluster) and simulating the drapes. In the simulation, a fabric specimen was modeled as a triangular mesh with 5 mm vertex distance, and the time step was set at 0.33 s. The initial state of the simulation was same as shown in Fig. 3. The termination condition was defined as when there was no significant change in the position of any vertex. The maximum simulation frame was limited to 4,000 in case the speed of the vertex was not reduced by oscillation. The whole simulation was done in parallel using 100 CPUs and took about 42 hours. We excluded some of the data diverged during the simulation. Of the total data, 10% was randomly selected as test data and 90% was used as training data.

TABLE 3. The errors (RMSE), accuracy (R^2), and numbers of learnable parameters for each model.

Model	Train RMSE	Train R^2	Test RMSE	Test R^2	Learnable parameters.
SNN	**0.01479**	**0.98503**	**0.01975**	**0.97335**	**81.58M**
NN	0.01454	0.98580	0.01990	0.97323	157.08M
SNN/2	0.01599	0.98318	0.02095	0.97065	21.92M
SNN/4	0.01997	0.97324	0.02371	0.96217	6.24M
SNN/B	0.01783	0.97854	0.02271	0.96519	78.58M
LR	0.03629	0.90878	0.03997	0.88908	4,404
LR-D	0.04557	0.86396	0.04908	0.84118	4,398

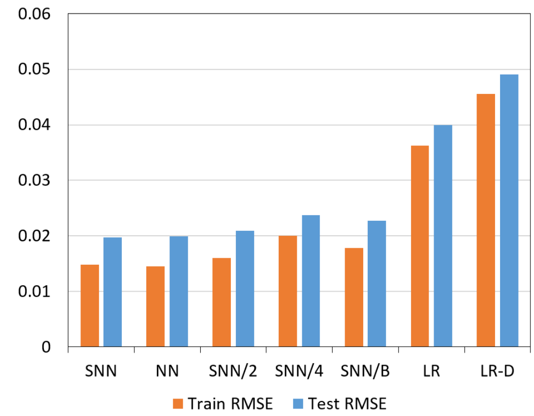

FIGURE 6. Comparison of the RMSEs of models.

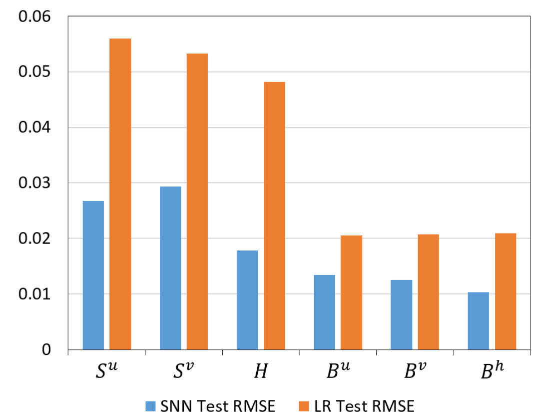

FIGURE 7. Comparison of the RMSEs of SNN and LR by simulation parameter.

A. TRAINING ACCURACY

To confirm how well our neural network model fits the training data, we compared the errors and accuracy with slightly modified neural network models and linear regression models. Table 3 summarizes the results. For all neural network models, we trained for 100 epochs with 32 batch sizes and used the mean square error loss function and the

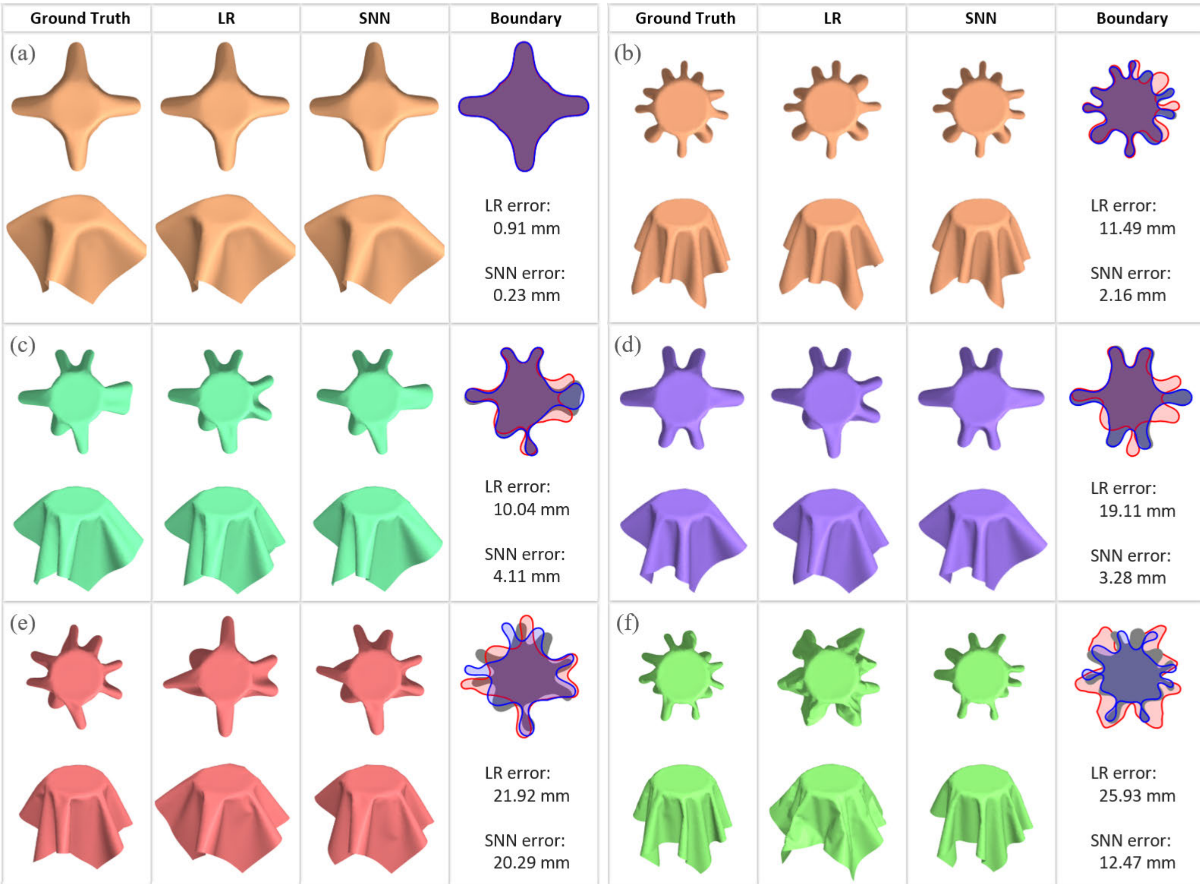

FIGURE 8. Selected simulated results of 200 test data.

Adam optimizer. The linear regression models were fitted using the least square method. We measured the root mean square error (RMSE) and the coefficient of determination (R^2) of the training data and the test data for each model. The last column of Table 3 shows the number of learnable parameters for each model. The RMSE values are also plotted in Fig. 6 for a visual comparison. Since the RMSE was calculated from the normalized parameters, the relative differences are more important than the absolute values.

SNN means our two-stream fully connected neural network model. NN means a general fully connected neural network model (single stream) with the same numbers of nodes and hidden layers as in SNN. There is no significant difference in RMSE and R^2 values between the SNN and NN models. However, SNN outperforms NN in terms of computational and memory efficiency, as SNN includes about half as many learnable parameters as NN. Using a computer with an Intel i7-8700 (3.2 GHz) processor, 16 Gb RAM, and a GTX 1060 graphics card, it took about two hours to train SNN for 100 epochs, and about four hours to train NN for the same epochs.

The SNN/2 and SNN/4 mean the models that have the same structure as SNN, but the numbers of nodes in the hidden layers are reduced to one half and one quarter, respectively. The SNN/B means the model in which we widened the sampling

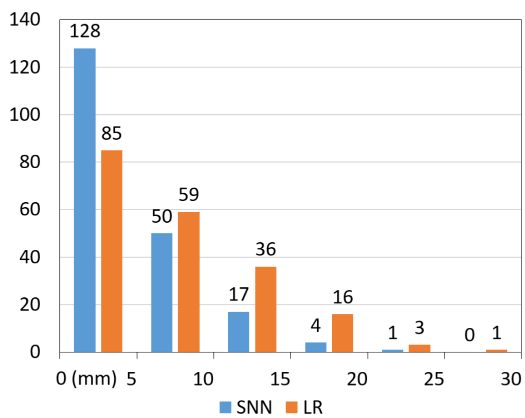

FIGURE 9. Histograms of the boundary vector errors.

intervals of the boundary curve to 10 mm, reducing the size of the boundary vector by half. Thus, SNN/B is identical to SNN except for the input layer. The results show that reducing the number of nodes or the sampling rate leads to higher error (RMSE) and lower accuracy (R^2). However, adding more nodes to SNN or narrowing the sampling intervals did not lead to any significant improvement in our experiments.

LR means a linear regression model fitted with the data pairs of p_i and q_i. LR-D also means a linear model but was

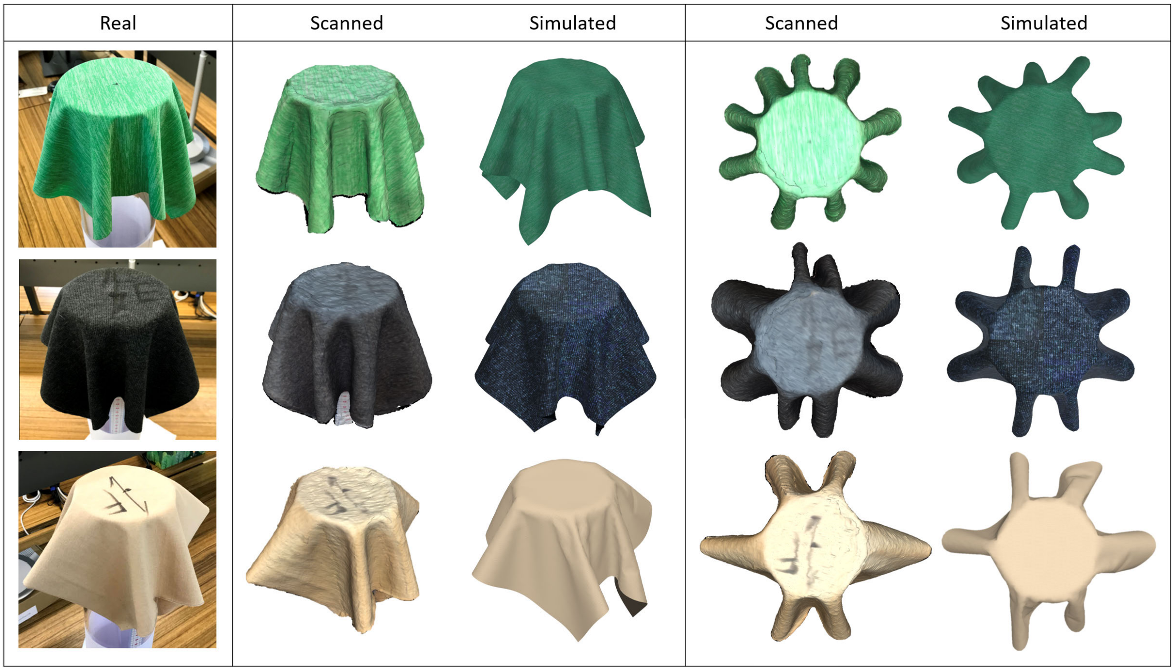

FIGURE 10. Comparison of the drapes formed by the real fabrics and simulated versions using the estimated simulation parameters.

trained without the density in the input vector. The linear regression models resulted in significantly higher RMSEs than all other neural network models. This means that the data has nonlinearity and those neural network models could learn the nonlinearity. LR-D shows even higher RMSE than that of LR, which proves that using density as an input value reduces the ambiguity of estimating.

Fig. 7 shows the RMSEs of SNN and LR for each simulation parameter. In the LR results, the errors for S^u, S^v, and H are about 2.5 times higher than the errors for the other variables. This means that the nonlinearity of S^u, S^v, and H is particularly high. In the SNN results, the errors for S^u, S^v, and H are lower, and the difference between the errors for the parameters is also significantly lower.

B. DRAPING ACCURACY

To evaluate the draping results, we randomly selected 200 data of the total test data and then estimated the simulation parameters using the SNN and LR models. Finally, with the estimated simulation parameters, we again simulated the modified Cusick's drape. Fig. 8 presents 6 examples of 200 (please refer to the supplementary material for the complete list). The "Ground Truth" column presents the drape of the test data and the "LR" and "SNN" columns present the estimated drapes from the LR and SNN models, respectively. In the "Boundary" column, we overlay the three boundary vectors projected on the horizontal plane to clearly show the differences between the estimated ones and the ground truth. The gray, red, and blue areas represent the boundary vectors of the ground truth, LR, and SNN estimations, respectively. In the same column, the mean errors of the estimated boundary vectors are presented. The mean error was calculated by averaging the distances from the 3D points on the ground truth boundary vector to the corresponding 3D points on the estimated boundary vector.

(a) Scanning the 3D model. (b) Fitting a Bézier spline.

FIGURE 11. Extracting the boundary vector from the real fabric specimen.

Fig. 8(a) shows a case where the mean error of the SNN estimate is minimal. In this case, the three boundary vectors are overlapped almost exactly. Fig. 8(b), (c), and (d) show cases where the mean errors of the SNN estimates are less than 5 mm, but the mean errors of the LR estimates are higher than that. Through the results, we found that if the mean error was less than 5 mm, the estimated drape was visually almost identical to the ground truth, and the estimated drapes with errors less than 10 mm were still visually similar to the ground truth. Fig. 9 shows the histograms of the mean errors. 64.0% (128 out of 200) of all the SNN estimates exhibited errors less than 5 mm, whereas only 42.5% (85 out of 200) of the LR estimates exhibited less than that.

Fig. 8(e) and (f) show cases where the mean errors of the SNN and LR estimates, respectively, were maximal. In general, the test data sampled with a lower probability in the GMM tends to exhibit a higher error. For example, in the case of (e), the density was 27.3 g m^{-2}, which is far below the minimum densities of the 400 real fabrics (see Table 2).

FIGURE 12. Comparison of the real dress and the simulated dress using the estimated simulation parameters.

C. QUALITATIVE EVALUATION WITH REAL FABRICS

For the qualitative evaluation, we conducted experiments used three fabric specimens with distinct differences in the shapes of the drapes (see the first column of Fig. 10). They are 100% cotton knit fabrics of different thicknesses and densities. When trying to form the modified Cusick's drape with a real fabric specimen, the drape shape may vary depending on how it falls. It is important to drop the four corners of the specimen at the same time from the same height. To do this, two people each held two corners with both hands and then released the corners at the same time. We repeated this process several times for one specimen and chose the drape shape that appeared most often. Alternatively, a device similar to the Cusick's drape meter can be built to simplify the process.

To extract the boundary vector from the real drape, we first reconstructed the 3D meshes of the drapes using a general tablet device equipped with a depth sensor as a 3D scanner. (see Fig. 11(a)). The second and fourth columns in Fig. 10 shows the scanned meshes. Then, we manually fitted a Bézier spline along the boundary of the mesh (see Fig. 11(b)). With the boundary vectors and the density of the real specimens, we estimated the simulation parameters using the SNN model and then reproduced the modified Cusick's drapes through the simulation to visually compare with the real drapes. The third and fifth columns of Fig. 10 show the results. Although there is a difference in degree, the shapes of wrinkles are generally similar to the real drapes in all three cases.

To verify the practicality of our method, we made a life-size dress with the same fabric as the green specimen in Fig. 10. Additionally, the identical virtual dress was simulated with the predicted parameters. Fig. 12 compares the pictures of the real dress and the captured images of the simulated dress. As shown, the wrinkle shapes apparent in both dresses are fairly similar.

VII. CONCLUSION

In this study, we presented a supervised learning approach that estimates simulation parameters from a modified Cusick's drape of a fabric specimen. CLO3D was used as the simulator, and six simulation parameters that have a great influence on the formation of static drape were targeted. In order to generate reliable training data, a generative GMM was created based on a primary data set measured from 400 real fabrics, and new parameters were randomly sampled from them. The training data were generated by simulating the modified Cusick's drape with each sampled parameter set and extracting feature vectors. We proposed a two-streamed fully connected neural network model, which was optimally designed for the training data. The experimental results using the test data showed high accuracy, and we verified the practicality through experimental results using real fabrics.

VIII. FUTURE WORK

The 400 primary data included fabrics with a wide range of mechanical properties, but all were knit fabrics. Because the physical structure of woven fabric is different from knit fabric, we cannot assume that woven fabrics will also work well with our method without any in-depth experimentation and verification. We plan to update the primary data set with real woven fabric data and verify whether our method can be applied as it is. We may need to improve the neural network model to be applicable to both knit and woven fabrics at the same time, or we may need to develop an independent learning model for woven fabrics.

In our experiments, the extracting of the boundary vector from the real fabric was conducted by an expert with experience in virtual garment design, who could complete a believable 3D boundary curve even if the scanned mesh had holes and crushed parts due to the low quality of the 3D scanning. This task would be difficult for non-experts. To resolve this issue, we plan to automate the process of extracting 3D boundary curves. We may be able to develop a reconstruction algorithm specialized for the boundary curves of fabrics. Alternatively, adding a small amount of noise to the training data may improve the robustness of our training model.

In this study, we aimed to estimate the simulation parameters from only one static drape as much as possible in order to maximize practicality. However, our modified Cusick's drape may not be suitable for all types of fabrics. For example, some fabrics curl on the edges when they are cut. Severe curls will interfere with the formation of our modified Cusick's drape. One way to reduce the interference is to use a wider fabric specimen. For example, Mozafary *et al.* [27] used a skirt-shaped drape to check the simulated results for a fabric with curls. We will continue to explore new static drapes that are applicable for more types of fabrics.

In some cloth models, stretch stiffness and bending stiffness are defined by more than one parameter [19]. We also plan to expand our method to estimate a larger number of parameters. To do this, we will explore new drapes that show different physical characteristics of a given fabric and train with multiple static drapes at the same time to increase the diversity of expressions. We will also apply our method to other types of simulation models, such as soft body simulation.

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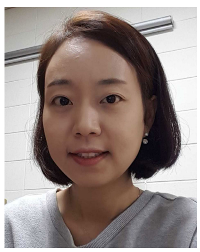

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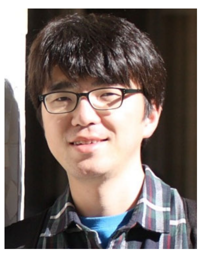

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